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Asymmetric mean-reversion and contrarian profits: ANST-GARCH approach

Kiseok Nam [a,*], Chong Soo Pyun [b], Augustine C. Arize [c]

[a] *Department of Economics and Finance, College of Business Administration, University of Texas-Pan American, Edinburgh, TX 78539-2999, USA*

[b] *University of Memphis, Fogelman College of Business, Memphis, TN 38152, USA*

[c] *Department of Business Administration and Management Information Systems, College of Business and Technology, Texas A&M University-Commerce, Commerce, TX 75429-3011, USA*

Abstract

This paper investigates the time-series evidence of asymmetric reverting patterns in stock returns that is attributable to "contrarian profitability." Using asymmetric nonlinear smooth-transition (ANST) GARCH(M) models, we find that, for monthly excess returns of US market indexes over the period of 1926:01–1997:12, negative returns on average reverted more quickly, with a greater reverting magnitude, to positive returns than positive returns revert to negative returns. The results are quite consistent when the models are implemented not only for the different sample periods, such as 1926:01–1987:09 and 1947:01–1997:12, but also for portfolios with different characteristics, such as different firm-size portfolios and Fama–French risk-adjusted factor portfolios. We interpret the asymmetrical reversion as evidence of stock market overreaction.

JEL classification: G14; C40; C51

Keywords: Asymmetric GARCH model; Asymmetric mean reverting; Contrarian portfolio strategy; Stock market overreaction

1. Introduction

Since DeBondt and Thaler (1985) documented that a portfolio of "loser" stocks outperforms a portfolio of "winner" stocks, a large body of literature has shown that a simple trading strategy of buying "recent losers" and selling "recent winners" yields a

* Corresponding author. Tel.: +1-956-318-5317; fax: +1-956-384-5020.

E-mail address: knam@panam.edu (K. Nam).

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substantial excess profit (i.e., contrarian profit) in both short-term and long-term investment horizons.[1] Despite the apparent usefulness of the strategy, interpretation of the contrarian profitability is still in a debate between the two competing hypotheses: the time-varying rational expectation hypothesis and the stock market overreaction hypothesis.[2]

What is in dispute is whether the predictability of price reversals reflects the market overreaction or the pricing behavior on the part of rational investors. If the price reversals reflect investors' irrational pricing resulting from extreme optimism or pessimism, then the contrarian profit is seen as a specific consequence of market overreaction.[3] In contrast, under the time-varying rational expectation, the price reversals should be attributed to the adjustments of rational investors in response to the changing volatility.[4]

The dispute emanates in part from different analytical perspectives that researchers consider pivotal in explaining the contrarian profitability vis-a-vis portfolio strategies. Although the contrarian profits are closely related to the mean-reverting behavior in stock returns, few studies have investigated the time-series property of the return dynamics, which might explain the source of the contrarian profitability. Taking a different approach, with a focus on the direct measurements of an asymmetric reverting component in stock returns from the raw time-series data, this paper presents supportive evidence for validating the contrarian profitability suggested by DeBondt and Thaler (1985).

According to our preliminary tests, stock indexes exhibit an apparent asymmetric reverting pattern in their return behavior. For the value-weighted index over the period of 1926:01–1997:12, there were 158 (125 for the equal-weighted index) four-consecutive-month rises as compared to only 25 (45 for the equal-weighted index) four-consecutive-month declines; 233 (198 for the equal-weighted index) three-consecutive-month rises as opposed to only 59 (92 for the equal-weighted index) three-consecutive-month declines; and 353 (306 for the equal-weighted index) two-month rises against 134 (186 for the equal-weighted index) two-month declines.[5] This overwhelming asymmetry in the reverting pattern from the return time series is so revealing that we may be able to adduce these asymmetries for the possible source of the contrarian profitability.

Recent developments in the GARCH models make it possible to identify the asymmetric patterns that may otherwise go undetected in the conventional time-series analysis. In particular, the asymmetric nonlinear smooth-transition (ANST) GARCH(M) model suggested in this study provides an efficient and parsimonious means of investigating the issue at hand. It allows a nonlinear specification to capture an asymmetry in both the conditional mean and variance processes in response to a positive and negative return shock.

This paper hypothesizes that the relative profitability of "loser" stocks is attributed to an asymmetric reverting property of their return dynamics. More importantly, the

[1] See Lehmann (1990), Jegadeesh (1990) and Chopra et al. (1992).

[2] Another hypothesis is that contrarian/momentum strategies are not profitable after transaction costs.

[3] Poterba and Summers (1988), Turner et al. (1989) and De Long et al. (1990).

[4] The argument of time-varying risk premium was first suggested by Pindyck (1984) and supported by other studies, such as French et al. (1987), Fama and French (1988), Ball and Kothari (1989), Cecchetti et al. (1990), Haugen et al. (1991), Campbell and Hentschel (1992) and Veronesi (1999).

[5] This asymmetry is still persistent in the daily and weekly index returns.

asymmetry is an intrinsic property of return dynamics, which is predictable ex ante. The findings of this paper from the monthly excess returns of market indexes over the period of 1926:01–1997:12 are: (a) stock returns exhibit a strong asymmetric reverting pattern in which a negative return reverts more quickly, with a greater reverting magnitude, than positive returns revert to negative returns; (b) the asymmetric reverting behavior of stock returns is indeed exploitable by the contrarian portfolio strategy; (c) the results are not sensitive to the two sub-periods, the pre-87 Crash period and the post-war period; (d) the results are not associated with the negative relationship between volatility and serial correlation in stock returns; and (e) the results are still significant and unaffected by other return series with different characteristics, such as firm-size portfolio returns, Fama and French's factor portfolio returns, the industry portfolio returns, and an inflation-adjusted real return series of market index.

The remainder of this paper is as follows. Section 2 presents a testing hypothesis for the asymmetric return reversals. Section 3 describes the extended ANST-GARCH(M) models actually implemented in this study, and Section 4 reports estimation results and their interpretations with diagnostics. Section 5 discusses the robustness of results and Section 6 presents a discussion of the validity of the two competing hypotheses on the asymmetry explored in this study. Section 7 concludes the paper.

2. Literature and testable hypotheses

Many factors, such as differential riskiness (time-varying conditional beta), seasonality (e.g., January effect), firm size and measurement bias from bid-ask bounce, have been identified as being attributable to the relative profitability of the "winner–loser" portfolio. For example, Zarowin (1989) challenges the investor overreaction by arguing that the substantial positive abnormal return of the winner–loser portfolio is due to both the size effect and the January effect.[6] Conrad and Kaul (1993) find that DeBondt and Thaler (1985) suffer from a methodological drawback that profits of the winner–loser portfolio are upward biased due to the bid–ask spread bias. Chan (1988), Ball and Kothari (1989) and Cho and Engle (1999) attribute the contrarian profitability to the differential riskiness of stock returns induced by the leverage effect. They argue that the relative profitability of the winner–loser portfolios can be explained by the shifts in riskiness due to a predictable asymmetry in the conditional betas in responding to negative and positive abnormal returns.[7] However, several studies, including DeBondt and Thaler (1987, 1989), Chopra et al. (1992) and Braun et al. (1995), show that the leverage effect in the conditional beta is not sufficient to account for the stock market overreaction to winners and losers. On the other hand, Lo and MacKinlay (1990) argued

[6] Other studies document a negative correlation between the size of firms and their return performances; namely, smaller firms tend to outperform larger firms. See Banz (1981) and Keim (1983).

[7] While Chan (1988) and Cho and Engle (1999) suggest that a positive covariance between the conditional beta and market risk premium affect the time-varying expected returns, Ball and Kothari (1989) do not detect the relationship.

that, since the positive cross-autocorrelation with a lead-lag effect across individual securities can lead to contrarian profitability, the existence of contrarian profits does not necessarily support the stock market overreaction.

Several studies have focused on the possibility of correlation between future volatility and return serial correlation. LeBaron (1992) explores the negative relationship between future volatility and serial correlation in daily and weekly frequency of stock returns. Campbell et al. (1993) show a negative correlation between the serial correlation of daily stock returns and future volatility. On the other hand, Sentana and Wadhwani (1992) document that stock returns measured by hourly and daily frequencies exhibit a positive (negative) autocorrelation when volatility is low (high).[8]

In this study, we hypothesize that stock returns exhibit an asymmetric reverting pattern in terms of both reverting tendency (or speed) and magnitude; a negative return is on average more likely to revert, with a greater reverting magnitude, to positive returns than are positive returns to revert to negative returns.[9] Asymmetric reverting patterns in return dynamics cannot be captured by the conventional autoregressive model restricted by the constant serial correlation coefficient. Rather, it requires a nonlinear autoregressive model that allows serial correlation to change in response to a prior positive and negative return shock.[10]

Suppose that the dynamics of a stock return evolve with the following nonlinear autoregressive process:

$$R_t = \mu + \phi^{-} R_{t-1} + \varepsilon_t, \quad \text{if } \varepsilon_{t-1} < 0$$

$$R_t = \mu + \phi^{+} R_{t-1} + \varepsilon_t, \quad \text{if } \varepsilon_{t-1} \geq 0,$$

where $|\phi^-| < 1$ and $|\phi^+| < 1$ for stationarity condition of R_t. This specification allows a different autoregressive process for R_t under a prior positive and negative return shock, such that serial correlation is measured by ϕ^- when $\varepsilon_t < 0$, while it is measured by ϕ^+ when $\varepsilon_t > 0$. An asymmetric reverting pattern considered here implies $\phi^+ > \phi^-$; i.e., serial correlation under a negative return shock is less than serial correlation under a positive return shock. The condition $\phi^+ > \phi^-$ reveals important information on the asymmetric

[8] Presenting a model where some traders follow feedback strategies, Sentana and Wadhwani (1992) show that the demand for shares by traders with different feedback strategies and differing volatility will switch the sign in the serial correlation of returns.

[9] Many studies of stock return volatility have documented the asymmetric effect of a positive and negative return shock on the volatility process known as "the leverage effect", which implies that an unexpected negative return shock causes a higher return volatility. Thus, we consider not only asymmetry in the reverting pattern of the mean process but also asymmetry in the volatility response of the variance process. We specify the ANST-GARCH model to simultaneously capture the asymmetric effect of a positive and negative return shock on both the conditional mean and variance process.

[10] LeBaron (1992) and Sentana and Wadhwani (1992) show that the serial dependence of stock returns exhibits a time-varying pattern, which can be captured better by the nonlinear autoregressive process.

reverting patterns in return dynamics, which would be a critical source of the contrarian profitability.

First, since ϕ^+ and ϕ^- measure the reverting tendency (or speed) of R_t under a prior positive and negative return shock, respectively, the condition $\phi^+ > \phi^-$ implies that a negative return is on average more likely to revert than the same magnitude of a positive return. For example, the condition $\phi^+ > \phi^-$ with both $\phi^+ > 0$ and $\phi^- > 0$ implies that a negative return shock is relatively less persistent than is the same size of a positive return shock, whereas the condition $\phi^+ > \phi^-$ with $\phi^+ > 0$ and $\phi^- < 0$ implies that a negative return shows a much stronger reverting tendency, while a positive return shows persistence.

Second, the condition of $\phi^+ > \phi^-$ implies that the reverting magnitude of negative returns is greater than the reverting magnitude of positive returns. Let $R_{t-1} = \mu = 0$ for convenience such that $R_t = \varepsilon_t$. Let ε_t^- denote the negative return shock (i.e., $\varepsilon_t < 0$), and ε_t^+ the same magnitude of positive return shock at time t (i.e., $\varepsilon_t > 0$), such that $\varepsilon_t^+ = -\varepsilon_t^-$. Then, the conditional expected return is denoted as $E(R_{t+1} | \varepsilon_t) = \phi^- \varepsilon_t^-$ if $\varepsilon_t < 0$ or $-\phi^+ \varepsilon_t^+$ if $\varepsilon_t > 0$. From the stability condition of autoregressive process, the reverting magnitude of return expected at time $t+1$ can be measured by the difference between R_t and $E(R_{t+1} | \varepsilon_t)$, which is $R_t - E(R_{t+1} | \varepsilon_t) = (1 - \phi^+)\varepsilon_t$ if $\varepsilon_t > 0$ and $(\phi^- - 1)\varepsilon_t^-$ if $\varepsilon_t < 0$, respectively.[11]

If the reverting magnitude (in absolute value) of negative returns is greater than the reverting magnitude of positive returns, then the comparison in the reverting magnitude can be expressed as $|R_t - E(R_{t+1} | \varepsilon_t < 0)| > |R_t - E(R_{t+1} | \varepsilon_t > 0)|$. Since $R_t - E(R_{t+1} | \varepsilon_t > 0) < 0$ and $E(R_{t+1} | \varepsilon_t > 0) - R_t > 0$, the above inequality is equivalent to $(\phi^- - 1)\varepsilon_t^- > (1 - \phi^+)\varepsilon_t^+$ or $\phi^+ > \phi^-$. Hence, $\phi^+ > \phi^-$ confirms that the reverting magnitude of negative returns is greater than that of positive returns.

Therefore, the testing condition for our hypothesis is $\phi^+ > \phi^-$, which implies that a negative return is on average more likely to revert, with a greater reverting magnitude, to a positive return than the same size positive return reverts to a negative return. This implies that the condition ($\phi^+ > \phi^-$) justifies the outperformance of the loser stocks. In this context, the contrarian profit is merely a result of trading strategy exploiting this asymmetry property, which is intrinsic in return dynamics.

3. Asymmetric nonlinear smooth transition (ANST) GARCH(M) model

3.1. Asymmetric reverting pattern of return dynamics

Our modeling strategy is to capture asymmetry in both the conditional mean and variance process, asymmetric return reversals in the conditional mean equation and the asymmetric volatility response in the conditional variance equation. For an excess (or

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[11] The reverting magnitude of a stationary series that is implied by a constant serial correlation is symmetrical to positive and negative innovation; i.e., $\phi^+ = \phi^-$.

expected) return series R_t, we specify the following asymmetric nonlinear smooth-transition (ANST) GARCH model:

Model 1

$$R_t = \mu + [\phi_1 + \phi_2 \cdot F(\varepsilon_{t-1})] \cdot R_{t-1} + \varepsilon_t, \tag{1a}$$

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + a_2h_{t-1} + [b_0 + b_1\varepsilon_{t-1}^2 + b_2h_{t-1}] \cdot F(\varepsilon_{t-1}), \tag{1b}$$

where $F(\varepsilon_{t-1})=\{1+\exp[-\gamma(\varepsilon_{t-1})]\}^{-1}$, and ε_t is a white noise series denoting a collective measure of news into the market at time t. By definition, $\varepsilon_t = v_t \cdot \sqrt{h_t}$ with $\varepsilon_t \sim N(0, \sqrt{h_t})$, such that $v_t \overset{\text{iid}}{\sim} N(0,1)$.

The changing serial correlation is measured by $\phi_1+\phi_2 \cdot F(\varepsilon_{t-1})$, which varies between ϕ_1 and $(\phi_1+\phi_2)$ with $0<F(\varepsilon_{t-1})<1$; when $\varepsilon_{t-1}<0$ causing $F(\varepsilon_{t-1})=0$, serial correlation is measured by ϕ_1, while it is measured by $\phi_1+\phi_2$ when $\varepsilon_{t-1}>0$ with $F(\varepsilon_{t-1})=1$. Stationarity of R_t is satisfied with the condition $|\phi_1+\phi_2 \cdot F(\varepsilon_{t-1})|<1$, which is $|\phi_1|<1$ with $\varepsilon_{t-1}<0$ causing $F(\varepsilon_{t-1})=0$, or $|\phi_1+\phi_2|<1$ with $\varepsilon_{t-1}>0$ causing $F(\varepsilon_{t-1})=1$.

Volatility persistence is measured by the $[a_1+b_1 \cdot F(\varepsilon_{t-1})]+[a_2+b_2 \cdot F(\varepsilon_{t-1})]$, which is a_1+a_2 under a prior negative shock causing $F(\varepsilon_{t-1})=0$ or $(a_1+b_1)+(a_2+b_2)$ under a prior positive return shock causing $F(\varepsilon_{t-1})=1$. Thus, $b_1+b_2<0$ captures the asymmetric volatility response to positive or negative return shock. It should be noted that the transition mechanism, which is controlled by the function $F(\varepsilon_{t-1})$, in the variance process generates different states of volatility persistence. This particular volatility–transition process is capable of capturing the asymmetric volatility response in a smoother and more flexible fashion than the other asymmetric GARCH models.[12]

The parameter γ governs the speed of transition between volatility regimes, such that, the greater the value of γ, the faster the transition between volatility regimes. When the value of γ approaches ∞, Eq. (1b) with $b_0=b_2=0$ degenerates into the modified GARCH (1,1) model (hereinafter GJR model) by Glosten et al. (1993).[13] Elements of smooth transition with a logistic function are also found in the modified model by Gonzalez-Rivera (1998). As compared to her model, ours is based on more general specifications in that our model becomes the same as that of hers when $b_0=b_2=0$.

The main advantage of Model 1 is that it incorporates the asymmetry in both mean and variance into specification, such that the effect of return shock on both the conditional mean and the variance is simultaneously measured. For example, when a large-size negative return shock is realized, serial correlation is measured by ϕ_1 (or $\phi_1+\phi_2$ with a

[12] For any negative return shock yielding $0<F(\varepsilon_{t-1})<0.5$, the current volatility is described as a "high-persistence-in-volatility regime." In contrast, for $\varepsilon_{t-1}>0$ causing $0.5<F(\varepsilon_{t-1})<1$, the current volatility is described as a "low-persistence-in-volatility regime." When $\varepsilon_{t-1}=0$, the value of $F(\varepsilon_{t-1})$ is 0.5, implying that current volatility h_t is half way between the upper and lower regimes. For more details, see Nam (1998) and Anderson et al. (1999).

[13] In the GJR model, the derivative in the indicator function is not defined (unbounded), violating the differentiability assumptions underlying the derivation of the robust standard errors. Thus, statistical inference under the GJR model is quite uncertain when conditional heteroskedasticity is present.

positive return shock), while the leverage effect is measured by a_1+a_2 (or $a_1+b_1+a_2+b_2$ with a positive return shock).[14]

The testing condition of $\phi^+>\phi^-$ in Section 2 for our hypothesis is equivalent to $\phi_2>0$ with Model 1, which confirms the asymmetric return reversals that a negative return is more likely to revert, with a greater reverting magnitude to a positive return than positive returns revert to negative returns.[15] If $\phi_1<0$ given $\phi_2>0$, then it implies that negative returns exhibit a strong reverting behavior.[16]

It has been known that time variations in expected returns are partly attributed to the adjustments in the changing volatility; i.e., the time-varying rational expectation hypothesis. Thus, we estimate the following ANST-GARCH-M model to evaluate the asymmetric reverting pattern, even in the presence of the time-varying volatility effect on the expected return:[17]

Model 2

$$R_t=\mu+[\phi_1+\phi_2\cdot F(\varepsilon_{t-1})]\cdot R_{t-1}+\delta\cdot\sqrt{h_t}+\varepsilon_t, \tag{2a}$$

$$h_t=a_0+a_1\varepsilon_{t-1}^2+a_2h_{t-1}+[b_0+b_1\varepsilon_{t-1}^2+b_2h_{t-1}]\cdot F(\varepsilon_{t-1}), \tag{2b}$$

where δ measures the effect of the time-varying volatility on the expected returns. Thus $\phi_2>0$ with $\delta\neq 0$ confirms that the asymmetric reverting pattern is not associated with the time-varying rational expectation hypothesis.

3.2. Negative relationship between volatility and serial correlation

As mentioned in Section 2, LeBaron (1992), Campbell et al. (1993) and Sentana and Wadhwani (1992) find a negative correlation between the return serial correlation and future volatility in hourly, daily and weekly frequencies of stock returns. Since a prior negative return shock, as compared to a prior positive return shock, causes a greater volatility resulting from the leverage effect, our result on the asymmetric reverting pattern in stock returns may also be imputable to the negative correlation between future volatility and return serial correlation. In order to ascertain that volatility per se significantly affects the degree of reverting pattern in monthly return series, we implement the following model:

Model 3

$$R_t=\mu+\left[\phi_1+\varphi\sqrt{h_t}\right]\cdot R_{t-1}+\varepsilon_t \tag{3a}$$

$$h_t=a_0+a_1\varepsilon_{t-1}^2+a_2h_{t-1}+[b_0+b_1\varepsilon_{t-1}^2+b_2h_{t-1}]\cdot F(\varepsilon_{t-1}), \tag{3b}$$

[14] We have tested the null hypothesis that γ has the same value across the mean and variance equations. The LR test failed to reject the null of the same value of γ across the mean and variance equations. This implies that the speed of asymmetric return reversal is not necessarily different from the speed of volatility transition in responding to a prior positive and negative return shock.

[15] $\phi^+>\phi^-$ implies $\phi_1+\phi_2>\phi_1$; hence, $\phi_2>0$.

[16] If $\phi_2=0$, then there is no asymmetric pattern, such that return reversal is symmetrical.

[17] We are grateful to an anonymous referee for his insightful suggestion on this new line of inquiry with the ANST-GARCH-M model, which we have incorporated in estimation.

where the sign of φ captures the relationship between future volatility and serial correlation. If φ is negative, then the asymmetric reverting property may be attributable to the volatility effect. However, if $\varphi \geq 0$, asymmetry is independent of the negative relationship between return serial correlation and future volatility.

With Model 4 below, we further examine whether or not this asymmetric reverting pattern is still significant when the effects of volatility are allowed to influence return serial correlation.

Model 4

$$R_t = \mu + \left[\phi_1 + \phi_2 F(\varepsilon_{t-1}) + \varphi\sqrt{h_t}\right] \cdot R_{t-1} + \varepsilon_t \tag{4a}$$

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + a_2 h_{t-1} + [b_0 + b_1\varepsilon_{t-1}^2 + b_2 h_{t-1}] \cdot F(\varepsilon_{t-1}). \tag{4b}$$

In the model, parameters of both volatility effect and asymmetric reverting pattern are specified in the mean equation so that a possible statistical link between future volatility and asymmetric patterns can be examined. If $\phi_2 = 0$, the asymmetry is associated with the volatility effect. If ϕ_2 is positive, regardless of the sign of φ, it confirms that the relationship between future volatility and return serial correlation is irrelevant for the asymmetric reverting pattern observed.

4. Empirical applications

4.1. Data description

We use monthly excess returns of the value-weighted and equal-weighted market portfolio indexes of the NYSE, AMEX and NASDAQ from the CRSP tape over the period from 1926:01 to 1997:12. The monthly excess return series is constructed by subtracting the 1-month US Treasury bill returns reported by the Ibbotson Associates from each monthly nominal index return. All the excess return series are computed as percentage returns.

Many studies have shown that the effect of the 1987 October shock could be critical in their studies with results sensitive to the inclusion or exclusion of the shock. For example, Franses and Dijk (1996) show that estimation results with the GARCH models are sensitive to the inclusion and exclusion of the 1987 shock. On the other hand, Kim et al. (1991) show that the evidence of mean reversion behavior in stock prices is entirely a pre-war phenomenon. Thus, we use the sub-period analysis: 1926.01–1987.09 (pre-87 Crash period) and 1947:01–1997:12 (post-war period) to check the possibility that our results could be sensitive to a different sample period. In addition, for checking a possible firm-size effect on the asymmetric reverting pattern, we use monthly excess returns of the two selective portfolios out of 10 firm-size portfolios that are categorized by NYSE-determined-size deciles for the period of 1926:01–1997:12.

Table 1 reports the descriptive statistics and shows that excess returns of all the market indexes exhibit significant excess kurtosis and positive first-order autocorrelation, which are commonly found in short-horizon stock return series. These statistical properties

Table 1
Summary statistics for monthly nominal and excess market index returns

Statistics	Nominal value-weighted returns	Nominal equal-weighted returns	1-month T-Bill returns	Excess value-weighted returns	Excess equal-weighted returns
Full-period: 1926.01–1997.12					
Observations	864	864	864	864	864
Mean	0.634	1.034	0.336	0.295	0.694
Standard deviation	5.496	7.554	0.304	5.499	7.565
Skewness	0.216	1.647	1.235	0.253	1.682
Kurtosis	11.128	18.259	6.319	11.163	18.379
1st order	0.106	0.206	0.889	0.109	0.210
Autocorrelation	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)
Sub-period: 1926.01–1987.09					
Observations	741	741	741	741	741
Mean	0.585	1.022	0.316	0.269	0.737
Standard deviation	5.698	7.926	0.316	5.701	7.935
Skewness	0.340	1.703	1.435	0.378	1.746
Kurtosis	10.792	17.236	6.615	10.790	17.400
1st order	0.109	0.201	0.886	0.112	0.203
Autocorrelation	(0.003)	(0.000)	(0.000)	(0.002)	(0.000)
Sub-period: 1947.01–1997.12					
Observations	612	612	612	612	612
Mean	0.742	0.965	0.442	0.300	0.524
Standard deviation	4.071	5.095	0.290	4.089	5.111
Skewness	– 0.399	– 0.130	1.424	– 0.468	– 0.193
Kurtosis	5.200	6.616	6.838	5.304	6.606
1st order	0.044	0.197	0.870	0.054	0.202
Autocorrelation	(0.271)	(0.000)	(0.000)	(0.184)	(0.000)

Monthly nominal return series are value-weighted. Both this and the equal-weighted market indexes retrieved from the CRSP tapes cover the sample period of 1926.01–1997.12. Both indexes are computed from the NYSE, AMEX and NASDAQ stocks. The excess return series is computed by subtracting the nominal index returns from 1-month Treasury bill return reported by Ibbotson Associates. All returns are computed as percentage value. The value in the parentheses is the p-value for the Ljung–Box Q test.

indicate that the dynamics of stock returns can be described with an autoregressive process under conditional heteroskedasticity.

4.2. Empirical results and interpretations

4.2.1. Asymmetric reverting pattern

We use Gauss 386i programming for the maximum likelihood estimation method with the provision of analytical derivatives of the parameters. All statistical inferences are based on the Bollerslev and Wooldridge (1992) robust standard errors obtained from the parameter derivatives for the log-likelihood function under the normality assumption of distribution.

Table 2 reports estimation results of Models 1 and 2 for the entire period between 1926:1 and 1997:12. From the table for Model 1, ϕ is positive and statistically significant

Table 2
Parameter estimates of Models 1 and 2 for the full-period of 1926:01–1997:12

Coefficients	Model 1		Model 2	
	VWRET	EWRET	VWRET	EWRET
μ	0.248 (7.459)	0.075 (17.920)	0.160 (7.186)	0.016 (0.351)
ϕ_1	−0.080 (−9.975)	0.004 (0.795)	−0.043 (−11.742)	0.099 (13.201)
ϕ_2	0.119 (6.719)	0.306 (34.750)	0.150 (18.463)	0.266 (20.458)
δ			0.030 (4.980)	−0.028 (−2.563)
a_0	0.000 (0.895)	0.025 (0.031)	0.000 (0.885)	0.014 (0.242)
a_1	0.101 (3.368)	0.097 (2.939)	0.104 (3.226)	0.111 (2.780)
a_2	1.037 (30.825)	1.082 (23.820)	1.035 (32.717)	1.074 (22.130)
b_0	2.642 (2.757)	2.799 (2.097)	2.656 (2.388)	2.562 (3.197)
b_1	−0.011 (−0.186)	−0.012 (−0.217)	−0.024 (−0.381)	−0.047 (−0.886)
b_2	−0.369 (−4.334)	−0.412 (−2.266)	−0.372 (−4.012)	−0.375 (−3.949)
γ	237.667 (3.179)	224.721 (4.265)	257.375 (2.235)	158.347 (3.779)
LLV	−2531.59	−2724.26	−2528.69	2723.84

The conditional variance equation is $h_t = a_0 + a_1\varepsilon_{t-1}^2 + a_2 h_{t-1} + [b_0 + b_1\varepsilon_{t-1}^2 + b_2 h_{t-1}] \cdot F(\varepsilon_{t-1})$, where $F(\varepsilon_{t-1}) = \{1 + \exp[-\gamma(\varepsilon_{t-1})]\}^{-1}$. The conditional mean equations for Models 1 and 2, respectively, are specified as follows:

$$\text{Model 1}: \; R_t = \mu + [\phi_1 + \phi_2 F(\varepsilon_{t-1})] \cdot R_{t-1} + \varepsilon_t$$

$$\text{Model 2}: \; R_t = \mu + [\phi_1 + \phi_2 F(\varepsilon_{t-1})] \cdot R_{t-1} + \delta \cdot \sqrt{h_t} + \varepsilon_t.$$

VWRET is monthly excess returns of value-weighted index, and EWRET is monthly excess returns of equal-weighted index. The values in parentheses are the Bolleslev–Wooldridge t-statistics, and LLV is the log-likelihood value.

at the 1% level for both indexes, suggesting that stock returns exhibit an asymmetric reverting pattern. For the value-weighted index, the estimated value of ϕ_1 is negative and statistically significant at the 1% level. Note that ϕ_1 measures return serial correlation under a negative return shock. The result for the value-weighted index shows that return serial correlation is -0.080 under a negative return shock and about 0.04 (sum of ϕ_1 and ϕ_2) under a positive return shock. As mentioned in Section 2, this result implies that a negative return shock exhibits a stronger reverting behavior in terms of both its speed and magnitude, as compared to a positive return, which exhibits a pattern of persistence. This finding is consistent with the reverting pattern observed in the raw data, in which a negative return is more likely to revert than a positive return.[18]

Table 2 also contains the estimation results from implementing Model 2.[19] They show that the asymmetric reverting pattern is still significant, even with the ANST-GARCH-M

[18] Koutmos (1998) also conducts the leverage effect of return shock on serial correlation for the nine national index return series. Allowing asymmetry in both the conditional mean and variance equations governed by a single indicator function, he finds a dramatic reduction in the positive serial correlation following a negative return shock. However, he does not evaluate it in relation to the contrarian profitability.

[19] For the value-weighted index, δ is positive and statistically significant at the 1% level. This result is consistent with the findings by Scruggs (1998). Using the EGARCH-M model that includes excess returns on a long-term government bond as an instrument variable for the second factor affecting the risk–return relation, Scruggs shows that the partial relationship between the market premium and conditional market variance is positive and statistically significant.

model. The estimation results of Models 1 and 2 are very similar to each other, indicating that the asymmetric reverting pattern observed is not sensitive to the different model specification. The results from Model 2 show that ϕ_2 is positive and statistically significant at the 1% level for both indexes, thereby confirming the asymmetric reverting behavior of returns even with the presence of a time-varying risk premium for changing volatility. It also shows that the estimated return serial correlation under a prior positive return shock is positive for both indexes, implying that a positive return exhibits a pattern of persistence; $\phi_1+\phi_2=0.107$ for the value-weighted index and $\phi_1+\phi_2=0.365$ for the equal-weighted index.

One interesting finding is that for both Models 1 and 2, while the estimated value of ϕ_1 is positive for the equal-weighted index, it is negative for the value-weighted index, with a statistical significance at the 1% level. This indicates that the value-weighted index exhibits a stronger reverting behavior of a negative return than does the equal-weighted index. Given that large firms have a higher weight in the value-weighted index, the result suggests that there is more reversion in large firms than in small firms.[20]

The asymmetric volatility response is captured by $b_1+b_2<0$ in the conditional variance equation, with a statistical significance for all estimations. This implies that the ANST-GARCH model is suitable for capturing the leverage effect, generating different volatility persistence under a prior positive and negative return shock. It should be noted that a high estimated value of the parameter γ is indicative of an instantaneous transition between volatility regimes.

Table 3 reports estimation results of Models 1 and 2 for the two sub-periods. Panel A shows parameter estimates for the pre-87 Crash period of 1926:01–1987:09, while Panel B shows parameter estimates for the post-war period of 1947:01–1997:12. The estimation results for the pre-87 Crash period show that for both indexes ϕ_2 is positive and statistically significant at the 1% level for both Model 1 and Model 2. These results are still consistent with those for the post-war period. Therefore, sub-period estimation results suggest that the asymmetric pattern of return reversal is consistent and robust in return dynamics.

The persistence of positive return is also confirmed for both periods. The estimated value of $\phi_1+\phi_2$ is positive for both indexes under Models 1 and 2. Except for the equal-weighted index, ϕ_1 for both periods is still negative and statistically significant (except for the value-weighted index for the post-war period) under both Model 1 and Model 2.[21]

[20] To examine the effect of the January seasonality on the asymmetry, we estimate Model 2 by adding a January dummy variable in the conditional mean and variance equations. Estimations over 1926:01–1997:12 show mixed results that, while the asymmetry in the value-weighted index is dissipated with $\phi_2=0.013$ (p-value: 0.340), the asymmetry in the equal-weighted index is still significant, with $\phi_2=0.229$ (p-value of 0.007).

[21] Kim et al. (1991) show that the evidence of mean reversion behavior in stock prices is entirely a pre-war phenomenon. While they focus on the mean reverting behavior as a global property of return dynamics that is measured by a constant serial correlation, we are primarily concerned with the asymmetric reverting property, which is measured by the changing serial correlation under a prior positive and negative return shock. Therefore, our empirical result of strong asymmetric return reversal for the post-war period would not necessarily be subject to their result.

Table 3
Parameter estimates of Models 1 and 2 for sub-periods

Coefficients	Model 1		Model 2	
	VWRET	EWRET	VWRET	EWRET
Panel A. Parameter estimates for the sub-period of 1926:01–1987:09				
μ	0.235 (5.124)	−0.014 (−0.866)	0.193 (5.784)	−0.061 (−0.416)
ϕ_1	−0.083 (−7.970)	0.103 (23.500)	−0.037 (−6.511)	0.108 (6.358)
ϕ_2	0.127 (5.332)	0.209 (17.520)	0.137 (7.947)	0.204 (7.477)
δ			0.029 (6.790)	0.009 (0.328)
a_0	0.001 (1.277)	0.002 (0.336)	0.000 (1.331)	0.080 (0.419)
a_1	0.120 (3.416)	0.158 (3.700)	0.124 (3.485)	0.159 (3.688)
a_2	1.030 (30.836)	1.036 (22.059)	1.030 (29.948)	1.034 (21.681)
b_0	2.715 (3.252)	2.418 (2.760)	2.807 (2.888)	2.308 (2.455)
b_1	−0.051 (−0.857)	−0.081 (−1.421)	−0.058 (−0.979)	−0.081 (−1.399)
b_2	−0.362 (−4.743)	−0.344 (−3.162)	−0.379 (−4.252)	−0.342 (−3.118)
γ	178.648 (4.525)	117.360 (4.179)	197.673 (3.396)	97.746 (1.482)
LLV	−2184.24	−2358.20	−2181.63	−2358.02
Panel B. Parameter estimates for the sub-period of 1947:01–1997:12				
μ	0.035 (2.384)	0.106 (3.608)	0.004 (0.019)	0.204 (2.775)
ϕ_1	−0.017 (−0.613)	0.160 (16.952)	−0.032 (−2.154)	0.149 (15.804)
ϕ_2	0.092 (3.281)	0.136 (9.310)	0.123 (10.270)	0.161 (12.734)
δ			−0.024 (−0.452)	−0.036 (−2.712)
a_0	21.502 (3.205)	1.577 (0.472)	22.409 (5.039)	1.701 (0.522)
a_1	0.117 (1.557)	0.032 (0.586)	0.115 (1.490)	0.031 (0.545)
a_2	0.040 (0.145)	1.147 (14.001)	0.009 (0.086)	1.149 (14.842)
b_0	−12.958 (−1.840)	2.056 (0.524)	−13.975 (−2.934)	1.921 (0.508)
b_1	−0.117 (−1.353)	−0.017 (−0.173)	−0.115 (−1.308)	−0.019 (−0.197)
b_2	0.059 (0.190)	−0.539 (−3.272)	0.095 (0.527)	−0.540 (−3.462)
γ	126.215 (2.349)	187.283 (4.110)	132.466 (2.795)	178.618 (2.921)
LLV	−1688.08	1797.85	−1687.80	1797.05

The conditional variance equation is $h_t = a_0 + a_1\varepsilon_{t-1}^2 + a_2 h_{t-1} + [b_0 + b_1\varepsilon_{t-1}^2 + b_2 h_{t-1}]\cdot F(\varepsilon_{t-1})$, where $F(\varepsilon_{t-1}) = \{1+\exp[-\gamma(\varepsilon_{t-1})]\}^{-1}$. The conditional mean equations for Models 1 and 2, respectively, are specified as:

$$\text{Model 1}: \ R_t = \mu + [\phi_1 + \phi_2 F(\varepsilon_{t-1})]\cdot R_{t-1} + \varepsilon_t$$

$$\text{Model 2}: \ R_t = \mu + [\phi_1 + \phi_2 F(\varepsilon_{t-1})]\cdot R_{t-1} + \delta\cdot\sqrt{h_t} + \varepsilon_t.$$

VWRET is monthly excess returns of value-weighted index, and EWRET is monthly excess returns of equal-weighted index. The values in parentheses are the Bolleslev–Wooldridge t-statistics, and LLV is the log-likelihood value.

We perform stability tests of parameter estimates on two sub-periods with equal observations (432 observations for each period).[22] Table 4 reports the likelihood ratio statistics for testing the null of equality of all parameter estimates in the conditional mean and variance equations and the null of equality of parameters only in the conditional mean equation over the two sub-periods. The null of equality of all parameter estimates in the

[22] We are indebted to a referee who suggested this stability test.

Table 4
Stability tests for parameter estimates Models 1 and 2 for the full-period of 1926:01 – 1997:12

	Model 1	Model 2
Value-weighted excess index returns		
Equality in all parameter estimates[a]	29.89 (0.001)	30.88 (0.001)
Equality in parameter estimates of the conditional mean equation[b]	6.50 (0.090)	8.48 (0.075)
Equal-weighted excess index returns		
Equality in all parameter estimates[a]	26.61 (0.003)	31.32 (0.001)
Equality in parameter estimates of the conditional mean equation[b]	7.62 (0.055)	8.76 (0.067)

[a] The restricted estimation for testing equality of all parameter estimates is the estimation of Models 1 and 2 for the full period of 1926:01 – 1997:12, while the unrestricted estimation is the separated estimation of Models 1 and 2 for each of the two sub-periods, each with the same numbers of 432 observations. The likelihood ratio for testing equality of all parameters is asymptotically distributed as $\chi^2_{(10)}$ for Model 1 and $\chi^2_{(11)}$ for Model 2. The *P*-values are in parentheses.

[b] The restricted models for testing equality of time-varying serial correlation parameters are Models 1 and 2, while the unrestricted model is as follows:

$$\text{For Model 1}: \; R_t = [\mu_1 + (\phi_1 + \rho_1 F) \cdot R_{t-1}] + [\mu_2 + (\phi_2 + \rho_2 F) \cdot R_{t-1}] \cdot \mathrm{DUM}_t + \varepsilon_t$$

$$\text{For Model 2}: \; R_t = \left[\mu_1 + (\phi_1 + \rho_1 F) \cdot R_{t-1} + \delta_1 \sqrt{h_t}\right] + \left[\mu_2 + (\phi_2 + \rho_2 F) \cdot R_{t-1} + \delta_2 \sqrt{h_t}\right] \cdot \mathrm{DUM}_t + \varepsilon_t,$$

where the conditional variance equation is $h_t = a_0 + a_1 \varepsilon^2_{t-1} + a_2 h_{t-1} + [b_0 + b_1 \varepsilon^2_{t-1} + b_2 h_{t-1}] \cdot F(\varepsilon_{t-1})$, where $F(\varepsilon_{t-1}) = \{1 + \exp[-\gamma(\varepsilon_{t-1})]\}^{-1}$. DUM_t is a dummy variable that takes a value of 1 for the first 432 observations and 0 for the second 432 observations. The likelihood ratio for testing equality of parameters in the mean equation is asymptotically distributed as $\chi^2_{(3)}$ for Model 1 and $\chi^2_{(4)}$ for Model 2.

conditional mean and variance equations is rejected for both Model 1 and Model 2. However, for both indexes the null of equality of the mean equation parameters over the two sub-periods is not rejected at the 1% level for both Model 1 and Model 2. This implies that the asymmetric pattern of return reversals does not differ across the two sub-periods, even with return dynamics of each period characterized by a different conditional volatility process.

We also perform a series of diagnostics with the Ljung–Box *Q* tests on the normalized residuals and the squared normalized residuals from each of the two model specifications. The Ljung–Box $Q(12)$ statistic on v_t checks serial correlation in the normalized residuals, while the same statistics on the squared normalized residuals, v_t^2, check whether serial dependence in the conditional variance process is well captured by the conditional variance equations in the two models. Diagnostic results are reported in Table 5, showing that all the estimations for the full-period pass the Ljung–Box $Q(12)$ test at the 1% level on both v_t and v_t^2, from which we conclude that our ANST-GARCH(M) model specifications well capture the serial dependence of the conditional mean and variance process.

Table 5
Diagnostics: Models 1 and 2 for different time periods

Summary statistics	Model 1		Model 2	
	VWRET	EWRET	VWRET	EWRET
Full-period (1926:01–1997:12)				
Skewness of v_t	−0.619	−0.410	−0.634	−0.390
Kurtosis of v_t	5.292	5.838	5.317	5.576
Ljung–Box Q(12) test on v_t	14.307 (0.282)	14.119 (0.293)	14.167 (0.290)	17.075 (0.147)
Ljung–Box Q(12) test on v_t^2	8.422 (0.750)	5.212 (0.951)	8.574 (0.739)	5.984 (0.917)
Sub-period 1 (1926:01–1987:09)				
Skewness of v_t	−0.414	−0.168	−0.412	−0.167
Kurtosis of v_t	3.972	4.076	3.997	4.069
Ljung–Box Q(12) test on v_t	16.364 (0.090)	18.100 (0.100)	19.661 (0.074)	18.260 (0.108)
Ljung–Box Q(12) test on v_t^2	11.779 (0.300)	9.500 (0.660)	18.430 (0.103)	9.540 (0.656)
Sub-period 2 (1947:01–1997:12)				
Skewness of v_t	−0.344	−0.466	−0.333	−0.456
Kurtosis of v_t	3.850	5.804	3.792	5.739
Ljung–Box Q(12) test on v_t	12.117 (0.436)	12.363 (0.417)	11.901 (0.454)	12.440 (0.411)
Ljung–Box Q(12) test on v_t^2	19.289 (0.082)	3.676 (0.989)	19.273 (0.082)	3.712 (0.988)

VWRET is monthly excess returns of value-weighted index, and EWRET is monthly excess returns of equal-weighted index. The values in parentheses are the p-values for the Ljung–Box Q test.

In summary, the following are the notable findings from the estimation results of Model 1 and Model 2:[23]

(1) Monthly excess returns exhibit a strong asymmetric reverting pattern.

(2) The asymmetric reverting pattern is still significant, even if adjustments of excess returns to changing volatility are allowed.

(3) For the value-weighted index, the excess return series exhibits a negative return serial correlation, hence a stronger mean-reverting tendency, under a prior negative return shock. It shows persistence with a positive return serial correlation under a prior positive return shock.

(4) The results are consistent over the two different sample periods, the pre-87 Crash and the post-war period.

All of these findings confirm the asymmetric reverting pattern that a negative return on average reverts more quickly, with a greater reverting magnitude, to a positive return than will positive returns revert to negative returns. More importantly, these findings support the outperformance of "loser" stocks, which is a key empirical presumption of the contrarian profitability.

4.2.2. Relationship between future volatility and return serial correlation

With Models 3 and 4, we examine the possibility that the asymmetric reverting pattern can be attributed to the negative relationship between future volatility and return serial correlation, which is explored by LeBaron (1992), Sentana and Wadhwani (1992), and

[23] Our examination of asymmetry during the World War II period (1940:01–1945:12) showed that, while asymmetry is significant for the entire period, it is more pronounced during the war period.

Table 6
Parameter estimates of Models 3 and 4 for the full-period of 1926:01–1997:12

Coefficients	Model 3		Model 4	
	VWRET	EWRET	VWRET	EWRET
μ	0.414 (17.169)	0.129 (13.614)	0.287 (6.288)	−0.006 (−0.629)
ϕ_1	−0.005 (−1.258)	0.261 (14.040)	0.024 (2.467)	0.003 (0.479)
ϕ_2			0.065 (4.170)	0.317 (16.184)
φ	0.007 (9.026)	−0.000 (−0.094)	0.004 (3.185)	−0.009 (−5.970)
a_0	0.000 (1.126)	0.065 (2.010)	0.000 (1.293)	0.000 (0.311)
a_1	0.129 (4.188)	0.170 (3.694)	0.141 (3.531)	0.148 (3.720)
a_2	1.021 (25.464)	1.041 (21.186)	1.021 (23.338)	1.026 (22.743)
b_0	2.362 (3.453)	2.356 (1.665)	2.446 (3.042)	2.269 (2.817)
b_1	−0.053 (−1.215)	−0.104 (−1.761)	−0.077 (−1.209)	−0.060 (−1.015)
b_2	−0.335 (−3.739)	−0.342 (−3.040)	−0.343 (−3.640)	−0.327 (−3.110)
γ	224.716 (2.675)	155.270 (1.839)	94.272 (2.961)	204.433 (3.675)
LLV	−2183.80	−2363.16	−2182.23	−2359.06

The conditional variance equation is $h_t = a_0 + a_1\varepsilon_{t-1}^2 + a_2 h_{t-1} + [b_0 + b_1\varepsilon_{t-1}^2 + b_2 h_{t-1}]\cdot F(\varepsilon_{t-1})$, where $F(\varepsilon_{t-1}) = \{1+\exp[-\gamma(\varepsilon_{t-1})]\}^{-1}$. The conditional mean equations for Models 3 and 4, respectively, are specified as follows:

$$\text{Model 3}: \; R_t = \mu + \left[\phi_1 + \varphi\sqrt{h_t}\right]\cdot R_{t-1} + \varepsilon_t$$

$$\text{Model 4}: \; R_t = \mu + \left[\phi_1 + \phi_2 F(\varepsilon_{t-1}) + \varphi\sqrt{h_t}\right]\cdot R_{t-1} + \varepsilon_t.$$

VWRET is monthly excess returns of value-weighted index, and EWRET is monthly excess returns of equal-weighted index. The values in parentheses are the Bolleslev–Wooldridge t-statistics, and LLV denotes the log-likelihood value.

Campbell et al. (1993). The estimation results of Model 3, reported in Table 6, show a conflicting result regarding the relationship between future volatility and return serial correlation; while the value-weighted index exhibits a positive relation, with a statistical significance at the 1% level, the equal-weighted index shows a negligible relation, with φ almost zero. This implies that the relationship between future volatility and return serial correlation may not be deterministic for monthly returns.

With Model 4, we further examine the irrelevance of the volatility effect on the asymmetric reverting pattern observed. The estimation result of the model is reported in Table 7. It confirms that the relationship between volatility and serial correlation in

Table 7
Diagnostics for Models 3 and 4 for the full-period of 1926:01–1997:12

Summary statistics	Model 3		Model 4	
	VWRET	EWRET	VWRET	EWRET
Skewness of v_t	−0.612	−0.574	−0.603	−0.527
Kurtosis of v_t	5.174	7.090	5.143	7.012
Ljung–Box Q(12) test on v_t	12.772 (0.386)	16.112 (0.186)	13.350 (0.344)	18.786 (0.094)
Ljung–Box Q(12) test on v_t^2	12.629 (0.397)	4.856 (0.963)	10.378 (0.583)	4.617 (0.970)

VWRET is monthly excess returns of value-weighted index, and EWRET is monthly excess returns of equal-weighted index. The values in parentheses are the p-values for the Ljung–Box Q test.

monthly excess index returns is not deterministic; while the value-weighted index exhibits a positive relation, the equal-weighted index shows a negative relation. More importantly, estimation results show ϕ_2>0 for both indexes, with a statistical significance at the 1% level. This implies that the asymmetric pattern in return reversals is still significant, even with a volatility effect allowed in return reversals. This confirms the irrelevancy of the volatility effect on the pattern of asymmetric mean reversions.

Diagnostics on the normalized residuals and the squared normalized residuals from Models 3 and 4 are reported in Table 7, which shows that all estimations pass the Ljung–Box $Q(12)$ test on both v_t and v_t^2. This indicates that Models 3 and 4 capture well the serial dependence of the mean and variance process of return dynamics.

5. Robustness of the results

5.1. Firm-size portfolio returns

Many studies have documented that there exists a negative correlation between firm size and its return performance; smaller firms tend to outperform larger firms. If the stock market overreacts to extreme earnings, and there exists a negative correlation between a firm's size and its earning performances, the evidence on the investor overreaction reported by DeBondt and Thaler can be construed as another manifestation of the size effect. To examine the above possibility, Zarowin (1989, 1990) replicates the DeBondt and Thaler samples by size and finds that, while the portfolios of the poorest earners do outperform the portfolios of the best earners, the poorest earners' portfolios are also significantly smaller in size than the portfolios of the best earners. Zarowin argues that the size effect, not overreaction to earnings, is responsible for the relative profitability of loser and winner portfolios reported by DeBondt and Thaler.[24]

In order to examine the size effect suggested by Zarowin, we estimate Models 1 and 2 for returns from the two different size portfolios selected from the ten NYSE-determined size decile: size decile 1 (smallest decile) and size decile 10 (largest decile). Although this particular estimation procedure does not fully validate the arguments related to the size effect or the market-overreaction hypothesis, the relative magnitude in the estimated value of ϕ_2 for different size portfolios will provide useful information about a possible link between the size effect and the asymmetric reverting pattern. For example, Zarowin's argument can be partly validated if the estimated value of ϕ_2 from Models 1 or 2 is found to be greater for the small-size portfolio (i.e., the NYSE size decile 1) than for the large-size portfolio (the NYSE decile 10); small-size portfolio exhibits a greater magnitude of asymmetric return reversal than does the large-size portfolio.

Table 8 reports the estimation results, which show that for the two size portfolios, ϕ_2 is positive, with a statistical significance at the 1% level under both Model 1 and Model 2. In a comparison between the smallest-and the largest-size portfolios, the asymmetric reverting pattern is much stronger in the largest-size portfolio; for the smallest-size

[24] Zarowin (1990) also shows that the relative profitability among firm size portfolios occurs almost exclusively in January.

Table 8
Parameter estimates of Models 1 and 2 to the firm-size portfolios for the period of 1926:01–1997:12

Coefficients	Model 1		Model 2	
	Size 1	Size 10	Size 1	Size 10
μ	0.457 (26.618)	0.177 (6.692)	0.303 (13.310)	−0.002 (−0.068)
ϕ_1	0.083 (35.584)	−0.084 (−30.169)	0.107 (13.363)	−0.077 (−25.987)
ϕ_2	0.135 (20.463)	0.188 (42.663)	0.150 (18.617)	0.286 (58.375)
δ			0.090 (4.637)	0.012 (3.541)
a_0	2.151 (0.615)	2.723 (1.497)	2.174 (1.090)	2.178 (1.300)
a_1	0.130 (3.452)	0.108 (3.363)	0.116 (2.855)	0.103 (3.060)
a_2	0.944 (8.887)	0.981 (17.393)	0.958 (12.490)	1.018 (21.645)
b_0	−1.250 (−0.220)	−1.915 (−0.715)	−2.210 (−0.402)	−0.903 (−0.337)
b_1	−0.049 (−0.721)	−0.015 (−0.340)	−0.020 (−0.327)	−0.025 (−0.513)
b_2	−0.173 (−1.024)	−0.227 (−2.171)	−0.218 (−1.741)	−0.291 (−3.110)
γ	216.833 (2.207)	104.347 (3.996)	214.279 (2.377)	108.926 (4.213)
LLV	−2688.96	−2701.91	−2688.31	−2692.60

The conditional variance equation is $h_t = a_0 + a_1\varepsilon_{t-1}^2 + a_2 h_{t-1} + [b_0 + b_1\varepsilon_{t-1}^2 + b_2 h_{t-1}]\cdot F(\varepsilon_{t-1})$, where $F(\varepsilon_{t-1}) = \{1+\exp[-\gamma(\varepsilon_{t-1})]\}^{-1}$. The conditional mean equations for Models 1 and 2, respectively, are specified as:

$$\text{Model 1}: \; R_t = \mu + [\phi_1 + \phi_2 F(\varepsilon_{t-1})]\cdot R_{t-1} + \varepsilon_t$$

$$\text{Model 2}: \; R_t = \mu + [\phi_1 + \phi_2 F(\varepsilon_{t-1})]\cdot R_{t-1} + \delta\cdot\sqrt{h_t} + \varepsilon_t.$$

Monthly return series of the 10 firm-size portfolios are retrieved from the CRSP tape. The portfolios are generated by ranking all eligible stocks by capitalization and then dividing them into 10 portfolios. Size 1 is the first portfolio containing the lowest capitalization stocks, while Size 10 is the last portfolio containing the highest capitalization stocks. The values in parentheses are the Bolleslev–Wooldridge *t*-statistics, and LLV is the log-likelihood value.

portfolio $\phi_2 = 0.135$ under Model 1 and 0.15 under Model 2, and for the largest-size portfolio $\phi_2 = 0.188$ under Model 1 and 0.286 under Model 2. The likelihood ratio test for the null of equality in ϕ_2 for both small and large portfolios showed a strong rejection of the equality.[25] It means that our findings do not support Zarowin's argument regarding a possible impact of size effect on the asymmetric reverting pattern.

For the two smallest- and largest-size portfolios, serial correlation under a prior positive return ($\phi_1 + \phi_2$) is positive, implying that positive returns exhibit persistence. The largest-size portfolio shows $\phi_1 < 0$, with a statistical significance at the 1% level. These findings suggest that the asymmetric pattern of return reversals is much stronger in larger-size portfolios. Interestingly, these findings are consistent with the findings reported in Section 4.2.1 that a stronger mean reverting pattern is observed in the value-weighted index than in the equal-weighted index, in which large firms have a higher weight.[26]

[25] We performed the log-likelihood ratio (LR) test on the null of the equality between small and large portfolios with the unrestricted model; this is essentially the same model specification for the stability test in Section 4.2.1. The only difference between the stability test in Section 4.2.1 and this (size effect) test is that, while the LR test for stability is performed on the null for the two different time periods, the LR test for size effect is performed on the null for the two different size (small and large) portfolios.

[26] Estimation results for the rest of firm-size portfolio returns are provided in Appendix A. Table in Appendix A reports the value of important parameter estimates in the conditional mean equation of Model 2 for the returns of size decile 2 through size decile 9.

A stronger reverting pattern found in the large-size portfolios (or weaker reverting pattern in the small-size portfolios) with Models 1 and 2 could be a reflection of relative risk–return tradeoff inherent in different size portfolios, i.e., the small firm-size portfolio is exposed to greater riskiness than the large firm-size portfolio under investigation. When confronted with a negative return shock, average investors tend to require a higher premium for the small-size portfolio, which in turn reduces the reverting tendency of the small firm-size portfolio returns relative to the large firm-size portfolio. The latter is also generally exposed to fewer business and financial risks. One corollary that can be deduced from the stronger reverting pattern in the large-size portfolio is that large capitalization stocks of so-called "recent losers" can be good candidates for investors using a contrarian portfolio strategy.

Table 9 reports summary statistics for the nominal and excess returns for the two selective size portfolios and diagnostics on the normalized residuals and the squared normalized residuals from the estimation of Models 1 and 2. The Ljung–Box $Q(12)$ test on both v_t and v_t^2 indicates that both model specifications well capture the serial dependence in conditional mean and variance processes.

5.2. Portfolio returns adjusted for common-risk factors, industry and inflation

In this section, we examine the sensitivity of empirical results for Models 1 and 2, with other return series such as Fama and French's factor portfolio returns, the industry portfolio returns and an inflation-adjusted real return series of market index. For Fama and French's factor portfolio returns, we choose two portfolio returns, SMB (portfolio

Table 9
Summary statistics and diagnostics: firm-size portfolios between 1926:01 and 1997:12

Panel A: Summary statistics for the nominal and excess returns of two selective firm-size portfolios

	Nominal returns for size 1 portfolio	Nominal returns for size 10 portfolio	Excess returns for size 1 portfolio	Excess returns for size 10 portfolio
Observations	864	864	864	864
Mean	1.172	1.169	0.865	0.857
Standard deviation	6.961	7.142	7.002	7.189
Skewness	0.855	1.020	0.920	1.081
Kurtosis	13.846	15.448	13.948	15.554
1st order	0.171	0.155	0.171	0.156
Autocorrelation	(0.000)	(0.000)	(0.000)	(0.000)

Panel B: Diagnostics

Summary statistics	Model 1		Model 2	
	Size 1	Size 10	Size 1	Size 10
Skewness of v_t	−0.635	−0.751	−0.569	−0.647
Kurtosis of v_t	6.072	6.640	5.676	5.878
Ljung–Box $Q(12)$ test on v_t	9.468 (0.663)	16.363 (0.178)	12.020 (0.444)	10.407 (0.580)
Ljung–Box $Q(12)$ test on v_t^2	6.734 (0.875)	5.626 (0.934)	6.435 (0.893)	6.048 (0.914)

The values in the parentheses are the p-value for the Ljung–Box Q test.

Table 10
Summary statistics for portfolio returns with different characteristics

	SMB	HML	RVW	MANUF	UTIL	SHOP	MONEY	OTHER
Period	26:7–97:12	26:7–97:12	26:1–97:12	26:7–97:12	26:7–97:12	26:7–97:12	26:7–97:12	26:7–97:12
Observations	858	858	864	858	858	858	858	858
Mean	0.393	0.201	0.731	1.063	0.907	1.046	1.113	0.867
Standard deviation	3.470	3.190	5.521	5.785	5.833	6.109	6.918	5.067
Skewness	2.144	2.505	0.321	0.482	0.104	− 0.046	0.661	0.333
Kurtosis	20.945	28.529	10.984	12.464	10.848	8.651	15.506	10.566
1st order autocorrelation	0.197 (0.000)	0.105 (0.002)	0.112 (0.001)	0.088 (0.010)	0.115 (0.001)	0.142 (0.000)	0.158 (0.000)	0.115 (0.001)

SMB, representing the size-related risk factor, is an average monthly return on three small firm-size portfolios minus the average monthly return on three large firm-size portfolios. It represents the size-related risk factor. HML, representing the risk factor in returns related to book-to-market equity, is an average monthly return on two value (high book-to-market equity) portfolios minus the average monthly return on two growth (low book-to-market equity) portfolios. See Fama and French (1992, 1993). RVW denotes inflation-adjusted real return series, which is generated from value-weighted market index returns less the monthly inflation rate computed from the consumer price index (from the CRSP tape).
MANUF denotes the portfolio returns for the Manufacturing with the SIC 2000–3999, UTIL the portfolio return for the Utility industry with the SIC 4900–4999, SHOP the portfolio return for the Wholesale, Retail, and Some Services industry with SIC 5000–5999 and 7000–7999, MONEY the portfolio return for the Finance industry with SIC 6000–6999, and OTHER is for the Agricultural, Mines, Oil, Construct, Transport, Telecom, Health and Legal Services industry.

returns related to size factor) and HML (portfolio returns related to book-to-market equity factor).[27] These portfolio returns mimic common risk factors in returns related to size and book-to-market equity, respectively. We also select the five industry portfolios—the Manufacturing (SIC 2000–3999), the Utilities (SIC 4900–4999), Wholesale, Retail and Some Services (SIC 5000–5999 and 7000–7999), the Finance industry (SIC 6000–6999), and the Agricultural, Mines, Oil, Construct, Transport, Telecom, Health and Legal Services industries.[28] Finally, we employ the inflation-adjusted real return series, which is generated from value-weighted market index returns less the monthly inflation rate computed from the consumer price index. Table 10 reports the descriptive statistics and shows that all the series exhibit nonnormality. Specifically, Fama and French's factor portfolio return series show a significant level of excess kurtosis and positive skewness, due to their risk characteristics.

[27] Fama and French (1992, 1993) identify three common risk factors for stocks, the overall market factor and factors related to firm size and book-to-market equity. They generate a corresponding portfolio return series for each of three risk factors; an excess market return (value-weighted market portfolio return less 1-month T-bill return) as a proxy for the market factor, an average return (SMB) on three small firm-size portfolios minus the average return on three large firm-size portfolios for the size-related factor and an average return (HML) on two value (high book-to-market equity) portfolios minus the average return on two growth (low book-to-market equity) portfolios for risk factor in returns related to book-to-market equity.

[28] French provides data and descriptions of the risk factor portfolio returns and industry portfolio returns at the following website; http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 11
Parameter estimates of Models 1 and 2 for portfolio returns with different characteristics

Panel A: Parameter estimates of Model 1

Coefficient	SMB	HML	RVW	MANUF	UTIL	SHOP	MONEY	OTHER
μ	−0.333	0.155	0.458	0.978	0.754	0.464	0.692	0.499
	(−4.096)	(2.501)	(35.948)	(27.415)	(33.675)	(9.874)	(7.168)	(25.767)
ϕ_1	−0.127	−0.037	−0.001	0.029	−0.018	0.049	0.055	0.008
	(−5.734)	(−3.051)	(−1.046)	(4.675)	(−9.492)	(10.074)	(4.497)	(1.825)
ϕ_2	0.454	0.120	0.130	0.050	0.133	0.134	0.117	0.190
	(6.889)	(5.488)	(11.081)	(3.747)	(20.009)	(13.944)	(3.374)	(26.811)
a_0	0.000	0.000	0.001	0.021	0.005	0.008	0.002	0.000
	(1.145)	(0.491)	(0.535)	(0.956)	(0.413)	(0.535)	(1.039)	(1.418)
a_1	0.150	0.133	0.122	0.130	0.083	0.116	0.186	0.108
	(1.768)	(3.008)	(3.314)	(3.662)	(3.088)	(3.099)	(3.262)	(3.359)
a_2	0.888	0.957	1.002	0.972	0.986	0.998	1.006	1.041
	(13.929)	(17.317)	(27.678)	(25.839)	(32.365)	(18.688)	(20.011)	(13.179)
b_0	0.139	0.442	1.965	2.123	0.816	1.303	3.371	2.302
	(0.679)	(1.912)	(2.513)	(2.201)	(1.987)	(2.118)	(3.116)	(2.007)
b_1	−0.138	−0.085	−0.044	−0.063	0.014	−0.024	−0.079	−0.037
	(−2.382)	(−2.366)	(−0.771)	(−1.005)	(0.371)	(−0.504)	(−1.112)	(−0.559)
b_2	0.075	−0.136	−0.271	−0.216	−0.190	−0.226	−0.387	−0.356
	(1.230)	(−1.772)	(−3.283)	(−2.662)	(−2.144)	(−2.412)	(−4.373)	(−1.789)
γ	212.270	106.357	178.456	77.013	96.265	67.123	51.694	128.409
	(2.865)	(2.897)	(3.087)	(2.849)	(1.980)	(2.202)	(2.221)	(2.946)
LLV	−2061.88	−2089.01	2543.26	−2565.75	−2492.14	−2622.75	−2634.87	−2464.08

Models 1 is specified as

$$R_t = \mu + [\phi_1 + \phi_2 F(\varepsilon_{t-1})] \cdot R_{t-1} + \varepsilon_t$$

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + a_2 h_{t-1} + [b_0 + b_1\varepsilon_{t-1}^2 + b_2 h_{t-1}] \cdot F(\varepsilon_{t-1}),$$

where $F(\varepsilon_{t-1})=\{1+\exp[-\gamma(\varepsilon_{t-1})]\}^{-1}$.
See notes to Table 10 for the descriptions of SBM, HML, RVW, MANUF, UTIL, SHOP, MONEY, and OTHER. The values in parentheses are the Bolleslev–Wooldridge t-statistics, and LLV is the log-likelihood value.

Table 11, Panels A and B show the parameter estimates of Models 1 and 2, respectively, for the above eight series. From Panel A, it is seen that ϕ_2 is positive and statistically significant at the 1% level for all eight return series, confirming the pattern of asymmetric reverting in return dynamics. The estimated value of $\phi_1+\phi_2$ (i.e., a serial correlation under a prior positive return shock) is also positive for all series, which confirms that a positive return exhibits a pattern of persistence. The statistics for Fama and French's factor portfolio returns (SMB and HML) show $\phi_1<0$ with a statistical significance at the 1% level, indicating a strong reverting tendency associated with a negative return shock.[29] Among the industry portfolios, only the Utility industry portfolio

[29] Interestingly, SMB (portfolio returns related to size factor) shows a much stronger asymmetry than HML (portfolio returns related to book-to-market equity factor).

Panel B: Parameter estimates of Model 2 for portfolio returns with different characteristics

Coefficient	SMB	HML	RVW	MANUF	UTIL	SHOP	MONEY	OTHER
μ	− 1.407	− 0.206	0.301	0.479	0.541	0.677	0.552	0.297
	(− 14.674)	(− 2.664)	(9.275)	(6.382)	(35.345)	(12.354)	(8.411)	(5.132)
ϕ_1	− 0.061	0.015	0.040	0.059	0.004	0.057	0.063	− 0.040
	(− 3.784)	(1.335)	(4.221)	(10.716)	(0.843)	(5.121)	(7.194)	(− 2.066)
ϕ_2	0.287	0.112	0.033	0.034	0.079	0.096	0.095	0.213
	(9.644)	(3.792)	(3.028)	(4.633)	(6.140)	(7.334)	(9.680)	(7.167)
δ	0.474	0.158	0.090	0.113	0.063	0.021	0.037	0.089
	(10.140)	(4.312)	(6.091)	(6.811)	(3.739)	(2.567)	(4.077)	(5.642)
a_0	0.001	0.002	0.006	0.001	0.003	0.000	0.001	0.000
	(0.967)	(0.337)	(0.648)	(0.315)	(0.477)	(0.639)	(0.911)	(1.692)
a_1	0.117	0.144	0.121	0.129	0.081	0.102	0.174	0.102
	(2.691)	(3.046)	(3.291)	(3.779)	(3.120)	(3.201)	(3.123)	(3.260)
a_2	0.902	0.947	1.003	0.994	0.997	1.012	1.017	1.072
	(13.667)	(18.104)	(25.266)	(30.435)	(31.830)	(24.363)	(21.191)	(13.649)
b_0	0.113	0.492	2.323	2.979	0.898	1.314	3.500	3.661
	(3.316)	(2.090)	(2.802)	(2.426)	(2.031)	(2.379)	(3.354)	(2.143)
b_1	− 0.138	− 0.099	− 0.044	− 0.069	0.019	0.001	− 0.066	− 0.001
	(− 3.539)	(− 2.614)	(− 0.758)	(− 1.295)	(0.488)	(0.012)	(− 0.978)	(− 0.018)
b_2	0.090	−0.130	− 0.294	− 0.291	− 0.216	− 0.257	− 0.407	− 0.521
	(1.795)	(− 1.947)	(− 3.378)	(− 3.206)	(− 2.439)	(− 3.699)	(− 5.056)	(− 2.236)
γ	376.377	171.002	265.335	236.438	137.018	178.327	82.519	143.866
	(3.608)	(2.981)	(2.745)	(2.586)	(2.315)	(2.152)	(2.910)	(2.180)
LLV	− 2054.86	− 2087.17	2542.74	− 2563.15	− 2491.23	− 2619.47	− 2634.11	− 2461.65

Models 2 is specified as

$$R_t = \mu + [\phi_1 + \phi_2 F(\varepsilon_{t-1})] \cdot R_{t-1} + \delta\sqrt{h_t} + \varepsilon_t$$
$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + a_2 h_{t-1} + [b_0 + b_1\varepsilon_{t-1}^2 + b_2 h_{t-1}] \cdot F(\varepsilon_{t-1}),$$

where $F(\varepsilon_{t-1})=\{1+\exp[-\gamma(\varepsilon_{t-1})]\}^{-1}$.
See notes to Table 10 for the descriptions of SBM, HML, RVW, MANUF, UTIL, SHOP, MONEY, and OTHER. The values in parentheses are the Bolleslev–Wooldridge t-statistics, and LLV is the log-likelihood value.

shows the strong reverting tendency of a negative return shock. Finally, the estimation result for the inflation-adjusted real returns shows ϕ_1 close to zero, which indicates that when a negative return shock occurs, return dynamics tend to exhibit a white noise process, i.e., a random walk process of the stock price. The empirical result of $\phi_2>0$ from the estimation of inflation-adjusted real returns implies that the asymmetry is not associated with the effect of inflation expectations on the risk premium.

Panel B shows similar results of asymmetry for all eight series for Model 2. Although the magnitude of ϕ_2 is in general smaller with Model 2 than that with Model 1,[30] ϕ_2 is still positive and statistically significant at the 1% level, with $\phi_1+\phi_2>0$ for all series. In short,

[30] Only OTHER industry portfolio shows that the magnitude of ϕ_2 is greater with Model 2 than is that with Model 1.

Table 12
Summary statistics and diagnostics for portfolio returns with different characteristics

Summary statistics	SMB	HML	RVW	MANUF	UTIL	SHOP	MONEY	OTHER
Model 1								
Skewness of v_t	0.481	0.642	− 0.520	− 0.422	− 0.117	− 0.328	− 0.451	− 0.462
Kurtosis of v_t	6.654	6.546	4.985	4.962	4.119	5.019	4.687	4.806
Ljung–Box $Q(12)$	12.749	15.773	15.343	13.228	14.032	9.615	12.709	19.215
test on v_t	(0.310)	(0.202)	(0.223)	(0.353)	(0.299)	(0.650)	(0.391)	(0.083)
Ljung–Box $Q(12)$	5.954 *	3.947	12.106	13.849	13.066	4.619	7.979	7.859
test on v_t^2	(0.652)	(0.984)	(0.437)	(0.310)	(0.364)	(0.970)	(0.787)	(0.796)
Model 2								
Skewness of v_t	0.382	0.647	− 0.499	− 0.438	− 0.125	− 0.311	− 0.439	− 0.379
Kurtosis of v_t	5.842	6.443	4.885	5.051	4.079	4.766	4.703	4.524
Ljung–Box $Q(12)$	15.724	15.615	17.199	14.731	15.131	9.089	13.519	17.966
test on v_t	(0.204)	(0.210)	(0.142)	(0.256)	(0.234)	(0.695)	(0.332)	(0.117)
Ljung–Box $Q(12)$	11.650 *	3.585	12.974	13.918	13.433	4.433	6.913	9.717
test on v_t^2	(0.167)	(0.990)	(0.371)	(0.306)	(0.338)	(0.974)	(0.863)	(0.641)

* The Ljung–Box Q(8) test on v_t^2 is performed. The values in parentheses are the p-value for the Ljung–Box Q test. See notes to Table 10 for the descriptions of SBM, HML, RVW, MANUF, UTIL, SHOP, MONEY, and OTHER.

the estimation results of Models 1 and 2 for all eight series indicate that asymmetric return reversal is a consistent and robust pattern in return dynamics.

Table 12 reports diagnostics on the normalized residuals and the squared normalized residuals from estimation of Models 1 and 2. The Ljung–Box $Q(12)$ test on both v_t and v_t^2 indicates that both Models 1 and 2 with the ANST-GARCH(M) specification well capture the serial dependence in the conditional mean and variance processes for all series.

6. Discussion

Our estimation results raise a critical question: "Can the observed asymmetry in short-horizon returns be justified under the time varying rational expectation hypothesis?" Under the time-varying rational expectation hypothesis, time variations in short-horizon stock returns should be associated with the rational pricing behavior of investors, who revise their risk premium in response to the changes in expectation of future volatility.[31] Thus, the asymmetric reverting pattern following a prior return shock should be related to the adjustment of risk premium to the changing volatility. However, our empirical

[31] In order to cast a substantial relationship between future volatility and changes in risk premium, the time-varying rational expectation hypothesis requires some strong assumptions for the dynamic behavior of stock returns. These are no effect of the expected dividend shocks on the expected returns, negative correlation between the expected returns and the current stock prices and a positive relationship between expected returns and the expected future volatility; see Fama and French (1988) and Fama (1991).

estimations show that the asymmetric reverting pattern is not related to the time-varying risk premium.

First, if the asymmetric reverting pattern is a reflection of the investors' rational pricing to the changing volatility, then the asymmetry should be dissipated under the ANST-GARCH-M model. However, estimation results of Model 2 (ANST-GARCH-M model) show that the asymmetric reverting pattern in stock returns is still significant, even with expected returns to be adjusted to the changing volatility, thereby revealing irrelevancy of the time-varying rationality for the observed asymmetry.

Second, under the time-varying rational expectation hypothesis, a fall in price causing a higher future volatility must be accompanied by another price decline. That is, given the positive relationship between future volatility and risk premium, an excess volatility caused by a fall in price should raise risk premium, which in turn reduces the concurrent stock prices. However, our findings show that a negative return is more likely to be followed by a positive return, which implies a quick reversion of negative returns.

Thirdly, when the pattern of asymmetry is evaluated for risk-aversion parameter, it is found that the risk premium under a negative return shock is found to be less than the risk premium under a positive return shock.[32] This finding suggests that, for stocks with a recent price drop, investors might have an optimistic expectation on future performance of the stocks.

In summary, under the notion of rational pricing behavior, the return dynamics should exhibit persistence, a tendency that a negative return is, on average, accompanied by another negative return, while a positive return is accompanied by another positive return. However, the asymmetric reverting patterns found in this section do not lend support to rational pricing behavior by investors. While our time-series findings on the asymmetry in the risk-aversion parameter are quite pervasive, it should be noted that they are tentative and that their implications merit further empirical research.

7. Summary and conclusions

This paper has explored the asymmetric reverting property of short-horizon expected returns in univariate time series and has shown that the asymmetric return reversals can be exploited for the contrarian profitability. Specifying the ANST-GARCH model that allows the leverage effect on both the mean and variance equations with time-varying parameters, we found that monthly excess returns of the value-weighted and equal-weighted indexes exhibit a strong asymmetric reverting pattern over the period from 1926:01 to 1997:12. The asymmetry implies that a negative return on average reverts

[32] The pattern of asymmetry adjusted for risk-aversion parameter was evaluated with: $R_t = \mu + [\delta_1 + \delta_2 F(\varepsilon_{t-1})] \cdot \sqrt{h_t} + \varepsilon_t$ and $h_t = a_0 + a_1\varepsilon_{t-1}^2 + a_2 h_{t-1} + [b_0 + b_1\varepsilon_{t-1}^2 + b_2 h_{t-1}] \cdot F(\varepsilon_{t-1})$. We find that δ_2 is positive and statistically significant at the 1% level, confirming that the pattern of changes in the risk-aversion parameter is also asymmetrical. The authors are indebted to an anonymous referee on this test.

more quickly, with a greater magnitude, to a positive return than positive returns will revert to negative returns. The results corroborate the arguments for the contrarian profitability.

We found that the asymmetrical patterns of return reverting are sensitive neither to the different sample period, such as the pre-87 Crash period and the post-war period, nor to different portfolio samples adjusted for differences in the size of firms, risk factors, industry characteristics and inflationary impacts. More specifically, we found robust patterns of asymmetry in return reversal for the pre-87 crash period between 1926:01 and 1987:09 as well as for the post-war period between 1947:01 and 1997:12.

Our findings are not consistent with Sentana and Wadhwani (1992) and LeBaron (1992) in that the asymmetric pattern is not associated with the negative relationship between the predictable volatility and serial correlation in returns. The asymmetry is still significant, even in the presence of the volatility effect. Interestingly, the relationship between the future volatility and serial correlation in monthly index returns explored in this paper is indeterminate, implying that the empirical relationship could be sensitive to the data frequencies.

Our findings do not support Zarowin (1990), that an effect of firm size is responsible for the relative profitability of the loser–winner portfolio strategy. The parameter estimates for the two different NYSE decile portfolios we obtained with the ANST-GARCH models and their diagnostic tests show that asymmetric patterns of return reversal are much stronger with large-size portfolios than with small-size portfolios. This result suggests that contrarian strategies should mostly be performed on large-firm stocks.

We also tested empirical robustness of the asymmetric reverting pattern, using data inputs with different characteristics such as Fama and French's factor portfolio returns, industry portfolio returns and an inflation-adjusted real return series of a market index. We found all the portfolios exhibited a strong reverting tendency with a negative return shock and a tendency for persistence with a positive return shock, confirming asymmetry in return reversals. Specifically, the empirical result from inflation-adjusted real returns suggested that asymmetry in return reversals was not associated with the effect of a risk premium related to inflation expectations.

In conclusion, our time-series evidence of asymmetric reverting behavior of monthly excess returns countenance a strong argument for the contrarian portfolio strategy. This paper does not seek any potential explanation for the validity of the asymmetric return reversal found in this study. However, viewed from the fact that the time-series evidence of uneven reverting pattern is not justified under the time-varying rational expectation hypothesis, it is difficult to negate the validity of stock market overreaction as a relevant explanation of contrarian profitability.

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Appendix A. Firm-size portfolios Model 2

Coefficients	μ	ϕ_1	ϕ_2	δ
Size 2	0.236 (5.374)	0.034 (0.822)	0.188 (4.645)	0.027 (1.394)
Size 3	0.074 (1.018)	0.003 (0.198)	0.090 (5.034)	0.093 (8.043)
Size 4	0.230 (17.054)	−0.044 (− 10.618)	0.077 (16.554)	0.023 (6.500)
Size 5	0.247 (1.023)	0.036 (1.166)	0.015 (0.239)	0.076 (2.769)
Size 6	0.115 (0.382)	0.188 (13.032)	0.055 (1.670)	0.061 (1.832)
Size 7	− 0.243 (− 2.652)	0.044 (6.689)	0.165 (16.811)	0.106 (7.583)
Size 8	− 0.277 (− 3.616)	0.034 (5.608)	0.241 (37.983)	0.035 (2.489)
Size 9	−0.230 (− 3.301)	− 0.009 (− 1.074)	0.302 (11.534)	0.058 (9.011)

Model 2 is specified as

$$R_t = \mu + [\phi_1 + \phi_2 F(\varepsilon_{t-1})] \cdot R_{t-1} + \delta\sqrt{h_t} + \varepsilon_t$$

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + a_2 h_{t-1} + [b_0 + b_1\varepsilon_{t-1}^2 + b_2 h_{t-1}] \cdot F(\varepsilon_{t-1}),$$

where $F(\varepsilon_{t-1}) = \{1 + \exp[-\gamma(\varepsilon_{t-1})]\}^{-1}$.

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