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Asymmetric return dynamics and technical trading strategies

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Abstract

We investigate the profitability of technical trading strategies based on an asymmetric reverting property of stock returns. We identify an asymmetry in return dynamics for daily returns on the S&P 500 index. Return dynamics evolve along a positive (negative) unconditional mean after a prior positive (negative) return. The trading strategies based on this asymmetry generate a positive return for buy signals, a negative return for sell signals, and a positive return for the spread between buy and sell signals. Our results imply that the observed asymmetry in return dynamics is the main source of profitability for the implied strategies, thereby corroborating arguments for the usefulness of technical trading strategies.

JEL classification: C53; G10; G14
Keywords: Technical trading strategies; Asymmetric reverting property; Nonlinear autoregressive models; Stock return predictability

1. Introduction

Various studies have documented the profitability of technical trading strategies. The usefulness of these strategies in equity markets relies on the presumption that profitable patterns in market prices can be identified and will continue in the future.

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Hence, technical analysis must be able to predict movements in market prices based upon identifiable patterns. [1]

Brock et al. (1992) showed that simple technical trading rules based upon the movements of a short-run and a long-run moving average have predictive ability with regard to a century of daily data on the Dow Jones industrial average. They found that buy signals consistently generate positive returns and sell signals lead to negative returns. Using bootstrap simulations of various null equilibrium pricing models, they also show that profits from the technical trading rules are not adequately explained by the popular parametric models for the return generating process. [2]

According to the moving average rules, buy and sell signals are produced by the relationship between a short-period and a long-period moving average. A buy (sell) signal occurs when the short-period moving average is above (below) the long-period moving average. There are numerous variations of this basic strategy, such as introducing a band width around the moving average or changing the length of the short- and long-period. The trading range break-out rule triggers a buy (sell) signal if the stock price moves above (below) a resistance (support) level.

Numerous studies on technical trading employ moving average rules. Several recent studies, however, examine the profitability of technical trading rules based upon Neural Network models. For example, Gençay (1998a) and Fernández-Rodríguez et al. (2000) used Neural Network models to determine buy and sell signals and showed that this technical trading rule is always superior to a naïve buy-and-hold strategy. Also, using feedforward network and nearest neighbors regressions, Genay and Stengos (1997, 1998) found that simple technical trading rules have a significant predictive power in forecasting returns.

Interestingly, Gençay (1998b) and Gençay and Stengos (1997) found evidence of nonlinear predictability of buy and sell signals in forecasting daily returns on the Dow Jones industrial average. Most bootstrap tests on the profitability of technical trading rules assume a linear dynamic relationship for the returns process and fail to explain the source of profitability. For example, Brock et al. (1992) did not consider nonlinearity in return dynamics for the bootstrap simulations of the four popular null models. They did indicate that the linear autoregressive models for the conditional mean process failed to explain the profitability of the technical trading rules. However, they mentioned that the result of positive (negative) buy (sell) returns indicate the existence of an asymmetric nature in return dynamics, and nonlinear models incorporating asymmetric dynamics might explain the source of profits. Thus, these studies suggest that the return generating process is better characterized by nonlinearities, and technical trading rules exploiting nonlinearities may generate positive returns.

There is growing interest in the nonlinear stochastic process of return dynamics. Several recent studies indicate that predictable components of stock returns are

[1] Many studies have examined the profitability of technical trading rules for the currency market investments (see Olson, 2004; LeBaron, 1999; Gençay, 1999; Kho, 1996; Taylor and Allen, 1992).

[2] Using UK data, Hudson et al. (1996) show that technical trading rules do not generate excess after-transaction profits.

stochastically nonlinear and better explained by an asymmetric dynamic process. Specifically, Nam et al. (2001, 2002) identify an asymmetry property of US stock market returns. They show that positive returns tend to persist longer than negative returns. Thus, momentum generally lasts longer for upward trends in the market. Sarantis (2001) found an asymmetry in annualized returns for the G7 countries' market indices. Also, Koutmos (1998), Sentana and Wadhwani (1992), and LeBaron (1992) explore nonlinearity in autoregressive processes of high frequency return series.

Our preliminary examination of daily S&P 500 market index returns overwhelmingly affirms an asymmetric reverting pattern. For daily returns over the entire period of 01/03/29–12/31/98, there were 798 five-consecutive-day rises as compared to only 476 five-consecutive-day declines; 1506 four-consecutive-day rises as opposed to only 990 four-consecutive-day declines; 2859 three-consecutive-day rises as opposed to only 2089 three-consecutive-day declines; and 5356 2-day rises against 4311 2-day declines. Similar to the patterns in Nam et al. (2001, 2002), this asymmetry indicates that a positive return is likely to persist longer than a negative return. [3]

Based on these findings, it is reasonable to hypothesize that (a) the dynamic process of index returns is better characterized by nonlinearity induced from an asymmetric reverting property, and (b) the asymmetric reverting property of stock returns can be used to generate profitable technical trading strategies before transaction costs.

Our paper focuses on a possible link between the asymmetric dynamic process of stock returns and profitable technical trading strategies. The primary objective of this study is to determine whether the predictable asymmetry in return dynamics can be used to develop profitable technical trading strategies.

We find that daily returns exhibit an asymmetric dynamic process in responding to prior positive and negative returns. More importantly, the asymmetric stochastic pattern of stock returns can be exploited to yield above average investment returns. The trading rules used to identify market positions are controlled by the holding-period return over a prior number of days and also by the number of consecutive days with the same positive or negative return. [4]

Our standard tests indicate that the strategies exploiting asymmetric reverting patterns generate profitable buy and sell signals. [5] Results show that most of the strategies implemented generate a positive return for buy signals and a negative return of sell signals. These results are consistent even when breaking the sample into two sub-periods.

[3] Table 1 shows preliminary results of the asymmetry in daily S&P 500 market index returns over the entire period and two sub-periods.

[4] It should be noted that typically the terms "momentum" and "contrarian" are used for the portfolio trading rules. The corresponding terms for a single stock or an index trading are "positive feedback" and "negative feedback" trading. Positive feedback traders buy a specific stock when its price rises, while negative feedback traders buy a specific stock when its price falls. Thus, these terms are somewhat interchangeable; positive feedback trading is a momentum-type strategy and negative feedback trading is a contrarian-type strategy. For more details on the momentum and contrarian strategies (see DeBondt and Thaler, 1985, 1987; Jegadeesh, 1990; Lehmann, 1990; Jegadeesh and Titman, 1993, 2001).

[5] It should be noted that *profitable buy and sell signals* implies *potential profitability*, which reflects that we do not consider transaction costs in our analysis.

The paper is organized as follows: Section 2 presents various nonlinear autoregressive models that are implemented to capture various asymmetric reverting patterns in return dynamics. Section 3 provides estimation results of the models and interpretations. Section 4 discusses various technical trading strategies implied from the observed asymmetry patterns and reports empirical results concerning the predictability of these strategies. Our concluding remarks are provided in Section 5.

2. Asymmetric reverting patterns

Initial tests on daily returns of the S&P 500 market index show a strong asymmetric pattern in return dynamics. Positive returns tend to persist longer than negative returns. Table 1 shows preliminary results of asymmetry that is apparent by looking at consecutive 2-day, 3-day, 4-day, and 5-day positive versus negative return series. Also, for 2-day, 3-day, 4-day, and 5-day holding periods, the number of positive return periods is larger than the number of negative return periods in each case. For daily returns over the entire period of 01/03/29–12/31/98, there were 798 five-consecutive-day rises as compared to only 476 five-consecutive-day declines; 1506 four-consecutive-day rises as opposed to only 990 four-consecutive-day declines; 2859 three-consecutive-day rises as opposed to only 2089 three-consecutive-day declines; and 5356 two-consecutive-day rises against 4311 two-consecutive-day declines. The asymmetry is also apparent in the two sub-periods shown in Table 1.

An asymmetric pattern in return dynamics cannot be captured by the conventional autoregressive models restricted by the constant serial correlation coefficient. Capturing the asymmetry requires a nonlinear autoregressive specification that

Table 1
Number of cases for the asymmetric pattern with prior returns

	Full-period (01/03/29–12/31/98)		First sub-period (01/03/29–01/16/62)		Second sub-period (01/17/62–12/31/98)	
	Positive	Negative	Positive	Negative	Positive	Negative
Consecutive return patterns						
2-Day returns	5356	4311	2582	2038	2774	2271
3-Day returns	2859	2089	1317	937	1542	1151
4-Day returns	1506	990	671	414	835	576
5-Day returns	798	476	345	185	453	291
Holding-period return patterns						
2-Day returns	10106	8485	5076	4210	5030	4273
3-Day returns	10259	8347	5130	4170	5129	4174
4-Day returns	10430	8177	5218	4083	5211	4091
5-Day returns	10512	8095	5283	4018	5229	4072

The numbers for positive and negative figures are based upon overlapping periods for both consecutive and holding-period return patterns. For example, 1 case of three consecutive positive daily returns is also counted as 2 cases of two-consecutive-positive daily returns. Also, there are few zero m-days holding-period returns in our samples, which are not included in return patterns in this table.

allows the coefficient on the serial correlation term to change in response to a prior positive or negative return pattern for a certain horizon. To capture the asymmetric pattern in return dynamics, we specify the following five models of nonlinear, autoregressive processes for a stock return, R_t:

Model 1:

$$R_t = (c_0 + \phi_1 R_{t-1}) + (c_1 + \rho_1 R_{t-1}) \cdot m_t + \varepsilon_t.$$

Model 2:

$$R_t = \left(c_0 + \sum_{i=1}^{2} \phi_i R_{t-i}\right) + \left(c_1 + \sum_{i=1}^{2} \rho_i R_{t-i}\right) \cdot m_t + \varepsilon_t.$$

Model 3:

$$R_t = \left(c_0 + \sum_{i=1}^{3} \phi_i R_{t-i}\right) + \left(c_1 + \sum_{i=1}^{3} \rho_i R_{t-i}\right) \cdot m_t + \varepsilon_t.$$

Model 4:

$$R_t = \left(c_0 + \sum_{i=1}^{4} \phi_i R_{t-i}\right) + \left(c_1 + \sum_{i=1}^{4} \rho_i R_{t-i}\right) \cdot m_t + \varepsilon_t.$$

Model 5:

$$R_t = \left(c_0 + \sum_{i=1}^{5} \phi_i R_{t-i}\right) + \left(c_1 + \sum_{i=1}^{5} \rho_i R_{t-i}\right) \cdot m_t + \varepsilon_t.$$

Each model represents a nonlinear AR(m) model for $m = 1, \ldots, 5$, and allows both constant term and serial correlation coefficients to vary in response to prior positive and negative return patterns. To implement the five models, we define four different cases of prior return patterns: Case PH-m (Case NH-m) denotes the patterns of asymmetry identified under the previous m-day positive (negative) holding period return. Case PC-m (Case NC-m) denotes the patterns of asymmetry identified under prior m-consecutive positive (negative) day returns.

There are five models to be estimated for each of four cases, and the condition that satisfies $m_t = 1$ determines the corresponding model to be estimated. For example, Case PH-3 represents a prior 3-day holding period return, and $m_t = 1$ only if the previous 3-day holding period return, defined as $R_{t-1} + R_{t-2} + R_{t-3}$, is positive. [6] The corresponding model to be estimated is Model 3 under the PH-m Case. Likewise, for the NC-3 Case (asymmetry identified under the prior 3-consecutive negative daily returns), $m_t = 1$ only if $R_{t-1} < 0$, $R_{t-2} < 0$, and $R_{t-3} < 0$. Note that Case PH-1 and Case NH-1 are identical to Case PC-1 and Case NC-1, respectively.

[6] Appendix A provides conditions for $m_t = 1$ for all four cases.

For each case, return serial correlation is measured by $\sum_{i=1}^{m}\phi_i + \sum_{i=1}^{m}\rho_i$ under $m_t = 1$ and $\sum_{i=1}^{m}\phi_i$ under $m_t = 0$ for all five models. For example, the return serial correlation for the PH-3 Case is measured by $\phi_1 + \phi_2 + \phi_3 + \rho_1 + \rho_2 + \rho_3$ under a positive 3-day holding period return and by $\phi_1 + \phi_2 + \phi_3$ otherwise. For the NC-3 Case the return serial correlation is measured by $\phi_1 + \phi_2 + \phi_3 + \rho_1 + \rho_2 + \rho_3$ under the prior 3-consecutive negative daily returns and by $\phi_1 + \phi_2 + \phi_3$ otherwise. Thus, asymmetry in return dynamics is captured by $\sum_{i=1}^{m}\rho_i \neq 0$, which represents additional predictive power for the return estimating process. The sum of autocorrelation coefficients under each model reveals either persistence or reversion information of return dynamics using the prior return patterns.

Once an autoregressive process of a return series is identified for $m_t = 0$ and 1, its unconditional mean implied by the autoregressive process can be calculated. The implied unconditional mean of R_t under each model is $c_0/(1 - \sum_{i=1}^{m}\phi_i)$ for $m_t = 0$ and $(c_0 + c_1)/[1 - (\sum_{i=1}^{m}\phi_i + \sum_{i=1}^{m}\rho_i)]$ for $m_t = 1$. For example, the unconditional mean for Case PH-2 can be derived as $c_0/[1 - (\phi_1 + \phi_2 + \rho_1 + \rho_2)]$ under a positive 2-day holding period return and $c_0/[1 - (\phi_1 + \phi_2)]$ otherwise.

It is not surprising that under an asymmetric autoregressive process, return dynamics evolve with a different unconditional mean. The importance of asymmetry is that it not only enhances the predictability of returns, but it also provides information on the profitability of the implied technical trading strategy. It should be noted that, while predictability is measured by the autoregressive coefficients, profitability is analyzed by the unconditional mean.

Predictability, however, does not imply profitability of the implied strategy. An objective of this paper is to examine the profitability of the implied trading strategy for each of the four cases. Suppose that the unconditional mean return is positive under $m_t = 1$ for the PH-2 Case and negative under $m_t = 1$ for the NH-2 Case. [7] This implies that one can expect, on average, a positive return after a positive 2-day holding period return and a negative return after a negative 2-day holding period return. The possible payoff of these strategies is that the PH-2 Case generates a positive return, and the NH-2 Case generates a negative return.

3. Estimations

3.1. Data descriptions

The daily return series of the S&P 500 market index from 01/03/29 to 12/31/98 is used for estimation. We divide the full-period into two sub-periods (9306 observations for each sub-period). The first sub-period covers 01/03/29–01/16/62, and the

[7] Since Case PH-*m* and Case NH-*m* have a mirror image, the condition $m_t = 0$ under Case PH-*m* is the same as $m_t = 1$ under Case NH-*m*. However, this is not the case for the Case PC-*m* and the Case NC-*m*, where asymmetry is identified with the prior consecutive return patterns.

Table 2
Summary statistics for daily S&P 500 market index returns

Summary statistics	Full-period (01/03/29–12/31/98)	First sub-period (01/03/29–01/16/62)	Second sub-period (01/17/62–12/31/98)
Observations	18612	9306	9306
Mean	0.000275	0.000198	0.000349
Standard deviation	0.011286	0.013269	0.008870
Skewness	−0.1193	0.2785	−1.3919
Kurtosis	23.1606	16.4111	39.3330
$\rho(1)$	0.056***	0.033***	0.106***
$\rho(2)$	−0.038***	−0.044***	−0.027***
$\rho(3)$	−0.008	−0.006	−0.012
$\rho(4)$	0.025***	0.044***	−0.017*
$\rho(5)$	0.013*	0.015	0.009
Bartlett Std.	0.0073	0.0104	0.0104

$\rho(j)$ is the estimated autocorrelation at lag j. "Bartlett Std." refers to the Bartlett standard error for the autocorrelation, and is computed as $1/\sqrt{N}$. *** and * imply a statistical significance at the 1% and the 10% level, respectively, for a two-tailed test.

second sub-period covers 01/17/62–12/31/98. Sub-period analysis is performed to insure that empirical results are not dominated by an atypical period.

Table 2 reports the descriptive statistics of daily nominal returns of the index for the entire period and two sub-periods. It shows that daily returns exhibit excess kurtosis and a significant autoregressive process for the full-period and both sub-periods. While the first and second autocorrelation coefficients, $\rho(1)$ and $\rho(2)$, are statistically significant at the 1% level for all sample periods, the third order autocorrelation coefficient, $\rho(3)$, is not significant. Also, except for the second sub-period, the fourth order autocorrelation coefficients are statistically significant at the 1% level based upon the estimated Bartlett standard deviation. The sum of autocorrelation coefficients is positive for all three periods. This indicates that daily return dynamics of the index exhibits a persistence, which implies that a positive (negative) return tends to be followed by another positive (negative) return. It should be noted that the constant autocorrelation coefficient does not describe the asymmetric property of the return process, which is reported in Table 1.

3.2. Estimation results and interpretations

Table 3 shows estimation results of Models 1–5 for the entire period. Daily returns exhibit strong asymmetry. Positive returns are likely to persist longer than negative returns. This asymmetry, if present for all five models, should be captured by $\sum_{i=1}^{m}\rho_i > 0$ and $\sum_{i=1}^{m}\phi_i + \sum_{i=1}^{m}\rho_i > 0$ under both the PH-m Cases and PC-m Cases and by $\sum_{i=1}^{m}\rho_i < 0$ and $\sum_{i=1}^{m}\phi_i + \sum_{i=1}^{m}\rho_i < 0$ under both the NH-m Cases and NC-m Cases.

Panel A shows the estimation results of Models 1–5 for the PH-m Cases and the NH-m Cases, where the asymmetry is identified with the prior m-day holding-period return pattern. Thus, $m_t = 1$ with a prior positive m-day holding-period return under

Table 3
Parameter estimates for daily S&P 500 index returns over the full-period (01/03/29–12/31/98)

	Case PH-*m*					Case NH-*m*				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A. Holding period return patterns										
c_0 (×100)	−0.066	−0.107	−0.115	−0.075	−0.074	0.046	0.069	0.073	0.063	0.074
	(−4.34)	(−6.57)	(−6.93)	(−4.42)	(−4.29)	(3.18)	(4.60)	(4.79)	(4.12)	(4.78)
ϕ_1	−0.021	−0.011	−0.013	0.023	0.018	0.070	0.061	0.074	0.057	0.064
	(−1.60)	(−0.93)	(−1.16)	(2.10)	(1.67)	(5.27)	(4.97)	(6.09)	(4.80)	(5.46)
ϕ_2		−0.116	−0.111	−0.106	−0.096		−0.040	−0.037	−0.013	−0.021
		(−9.36)	(−9.46)	(−9.46)	(−8.79)		(−3.34)	(−3.14)	(−1.09)	(−1.83)
ϕ_3			−0.045	−0.014	−0.029			−0.024	−0.037	−0.023
			(−3.71)	(−1.19)	(−2.55)			(−2.08)	(−3.23)	(−2.00)
ϕ_4				−0.009	0.010				0.019	0.000
				(−0.75)	(0.89)				(1.71)	(0.00)
ϕ_5					−0.003					−0.013
					(−0.24)					(−1.16)
c_1 (×100)	0.118	0.175	0.188	0.138	0.147	−0.115	−0.176	−0.188	−0.139	−0.147
	(5.54)	(7.95)	(8.33)	(6.03)	(6.39)	(−5.34)	(−7.96)	(−8.35)	(−6.05)	(−6.39)
ρ_1	0.088	0.072	0.087	0.034	0.047	−0.093	−0.072	−0.087	−0.034	−0.047
	(4.63)	(4.20)	(5.27)	(2.14)	(2.96)	(−4.90)	(−4.22)	(−5.27)	(−2.14)	(−2.96)
ρ_2		0.076	0.074	0.093	0.075		−0.076	−0.074	−0.093	−0.075
		(4.43)	(4.46)	(5.73)	(4.67)		(−4.45)	(−4.47)	(−5.73)	(−4.67)
ρ_3			0.022	−0.023	0.006			−0.022	0.023	−0.006
			(1.30)	(−1.39)	(0.35)			(−1.30)	(1.39)	(−0.35)
ρ_4				0.028	−0.010				−0.028	0.010
				(1.71)	(−0.64)				(−1.71)	(0.64)
ρ_5					−0.010					0.010
					(−0.61)					(0.61)
F-STAT	21.48	30.36	29.22	11.29	5.86	23.97	30.57	29.26	11.30	5.86
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
ψ_0	0.088	0.148	0.183	0.132	0.108	−0.093	−0.148	−0.183	−0.132	−0.108
ψ_1	0.067	0.021	0.014	0.026	0.008	−0.023	−0.127	−0.170	−0.106	−0.101
μ_1	0.056	0.069	0.074	0.065	0.074	−0.067	−0.095	−0.098	−0.069	−0.066

Panel B. Consecutive return patterns

c_0 (×100)	−0.066	−0.015	0.024	0.026	0.027	0.046	0.021	0.016	0.022	0.023
	(−4.34)	(1.44)	(2.60)	(3.01)	(3.17)	(3.18)	(2.03)	(1.84)	(2.51)	(2.71)
ϕ_1	−0.021	0.055	0.060	0.058	0.058	0.070	0.084	0.089	0.074	0.061
	(−1.60)	(6.26)	(7.67)	(7.78)	(7.89)	(5.27)	(9.18)	(11.0)	(9.67)	(8.23)
ϕ_2		−0.034	−0.035	−0.040	−0.039		−0.015	−0.016	−0.033	−0.038
		(−3.77)	(−4.44)	(−5.23)	(−5.27)		(−1.74)	(−2.06)	(−4.38)	(−5.08)
ϕ_3			−0.002	−0.002	−0.002			−0.015	0.004	−0.001
			(−0.21)	(−0.31)	(−0.32)			(1.91)	(0.54)	(−0.10)
ϕ_4				0.027	0.027				0.029	0.028
				(3.57)	(3.59)				(3.90)	(3.71)
ϕ_5					0.010					0.013
					(1.39)					(1.80)
c_1 (×100)	0.118	0.106	0.127	0.099	0.154	−0.115	−0.176	−0.352	−0.352	−0.184
	(5.54)	(4.27)	(3.59)	(1.87)	(2.03)	(−5.34)	(−6.55)	(−8.93)	(−5.39)	(−1.80)
ρ_1	0.088	0.010	−0.028	0.014	−0.005	−0.093	−0.101	−0.189	−0.235	−0.040
	(4.63)	(0.44)	(−0.82)	(0.26)	(−0.06)	(−4.90)	(−4.81)	(−6.86)	(−6.44)	(−0.60)
ρ_2		−0.100	−0.120	−0.038	−0.057		−0.154	−0.241	−0.138	0.013
		(−4.52)	(−3.77)	(−0.69)	(−0.71)		(−6.63)	(−7.62)	(−2.71)	(0.18)
ρ_3			−0.011	−0.070	−0.077			−0.110	−0.194	−0.048
			(−0.32)	(−1.39)	(−0.97)			(−2.99)	(−3.47)	(−0.61)
ρ_4				0.061	−0.061				0.046	−0.112
				(−1.26)	(−2.13)				(0.82)	(−1.33)
ρ_5					0.007					−0.247
					(0.11)					(−2.87)
F-STAT	21.48	11.09	12.92	4.39	6.57	23.97	87.76	162.79	48.58	13.80
(p-value)	(0.00)	(0.00)	(0.00)	(0.04)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ψ_0	0.088	−0.090	−0.159	−0.033	−0.193	−0.093	−0.255	−0.540	−0.521	−0.434
ψ_1	0.067	−0.069	−0.136	0.010	−0.139	−0.023	−0.186	−0.482	−0.447	−0.371
μ_1	0.056	0.085	0.133	0.126	0.159	−0.067	−0.131	−0.227	−0.228	−0.117

ψ_0 is the sum of asymmetry autocorrelation coefficients, i.e., $\psi_0 = \sum_{i=1}^{m} \rho_i$. F-STAT denotes the F-statistics for the null of $\psi_0 = 0$ for each corresponding model. ψ_1 is the sum of autocorrelation coefficients when $m_t = 1$, and is calculated as $\psi_1 = \sum_{i=1}^{m} \phi_i + \sum_{i=1}^{m} \rho_i$. μ_1 denotes the unconditional mean return when $m_t = 1$, and is calculated as $\mu_1 = (c_0 + c_1)/(1 - \psi_1)$.

the PH-*m* Case, and $m_t = 1$ for a prior negative *m*-day holding-period return under the NH-*m* Case. ψ_0 is the sum of asymmetry autocorrelation coefficients, i.e., $\psi_0 = \sum_{i=1}^{m} \rho_i$, [8] which adds additional predictive power. *F*-STAT denotes the *F*-statistics for the null hypothesis $\psi_0 = 0$, i.e., no asymmetric reverting pattern. All *F*-statistics are statistically significant at the 1% level, except for Model 5 which is significant at the 5% level. Thus, each of the five nonlinear autoregressive models have strong explanatory power for the asymmetric reverting components of returns identified with a prior positive and negative holding-period return pattern.

ψ_1 measures the sum of autocorrelation coefficients under $m_t = 1$ for each model, i.e., $\psi_1 = \sum_{i=1}^{m} \phi_i + \sum_{i=1}^{m} \rho_i$. Thus, for the PH-*m* Cases, ψ_1 measures return serial correlation under a prior positive *m*-day holding-period return. For the NH-*m* Cases, ψ_1 measures return serial correlation under a prior negative *m*-day holding-period return. The results indicate that index returns exhibit *positive* serial correlation under a prior positive *m*-day holding-period return and *negative* serial correlation under a prior negative *m*-day holding-period return. In other words, positive and negative returns tend to persist.

$\mu_1 (= (c_0 + c_1)/(1 - \psi_1))$ denotes the unconditional mean return for $m_t = 1$. The results show $\mu_1 > 0$ for the PH-*m* Cases and $\mu_1 < 0$ for the NH-*m* Cases; a positive unconditional mean under a prior positive holding-period return and a negative unconditional mean under a prior negative holding-period return.

Panel B in Table 3 shows the estimation results of Models 1–5 for the PC-*m* Cases and the NC-*m* Cases, where the asymmetry is identified by prior *m*-consecutive positive or negative daily returns. For the PC-*m* Cases, m_t takes a value of 1 with prior *m*-consecutive positive daily returns, while for the NC-*m* Cases, m_t takes a value of 1 with prior *m*-consecutive negative daily returns. The *F*-statistics for testing the null hypothesis of $\psi_0 = 0$ are all statistically significant at the 1% level, except for Model 4 in the PC-*m* Case which is significant at the 5% level. However, the reported values of ψ_0 and ψ_1 in the PC-*m* Cases does not confirm the desirable result of $\psi_0 > 0$ and $\psi_1 > 0$ (persistence of a positive return). Except for Model 1, all models under the PC-*m* Cases show inconsistent results. The result under the NC-*m* Cases is consistent with $\psi_0 < 0$ and $\psi_1 < 0$. Panels A and B indicate that in general the desirable asymmetry is not well identified with the prior consecutive daily return pattern, but rather is better captured by the prior holding period return pattern.

Table 4 reports parameter estimates for the two sub-periods. Panels 1 and 2 show the results for the first and second sub-periods. Panels 1A and 2A display the estimation results for the PH-*m* Cases and the NH-*m* Cases. Panels 1B and 2B report the results for the PC-*m* Cases and the NC-*m* Cases. The results indicate that the returns have strong asymmetric reverting patterns in the autoregressive process with some variation in the magnitude of parameter estimates. More importantly, for all PH-*m* Cases and PC-*m* Cases, $\mu_1 > 0$, and for all NH-*m* Cases and NC-*m* Cases,

[8] The sum of autocorrelation is $\sum_{i=1}^{m} \phi_i$ under $m_t = 0$ and $\sum_{i=1}^{m} \phi_i + \sum_{i=1}^{m} \rho_i$ under $m_t = 1$. Thus, $\sum_{i=1}^{m} \rho_i = 0$ indicates no asymmetry in return dynamics.

Table 4
Parameter estimates for daily S&P 500 index returns for sub-periods

	Case PH-*m*					Case NH-*m*				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Panel 1: First sub-period (01/03/29–01/16/62)										
Panel 1A. Holding period return patterns (01/03/29–01/16/62)										
c_0 (×100)	−0.061	−0.119	−0.156	−0.096	−0.086	0.023	0.058	0.077	0.070	0.085
	(−2.43)	(−4.46)	(−5.70)	(−3.41)	(−3.01)	(0.93)	(2.40)	(3.16)	(2.87)	(3.46)
ϕ_1	−0.029	−0.035	−0.043	−0.000	−0.016	0.057	0.048	0.055	0.033	0.053
	(−1.55)	(−2.07)	(−2.72)	(−0.02)	(−1.07)	(3.11)	(2.84)	(3.30)	(1.98)	(3.23)
ϕ_2		−0.105	−0.103	−0.104	−0.091		−0.045	−0.053	−0.023	−0.033
		(−6.01)	(−6.24)	(−6.52)	(−5.88)		(−2.70)	(−3.26)	(−1.38)	(−2.03)
ϕ_3			−0.062	−0.025	−0.034			−0.011	−0.026	−0.017
			(−3.58)	(−1.52)	(−2.13)			(−0.71)	(−1.64)	(−1.08)
ϕ_4				0.029	0.058				0.019	−0.007
				(1.70)	(3.51)				(1.27)	(−0.48)
ϕ_5					0.010					−0.017
					(0.59)					(−1.16)
c_1 (×100)	0.091	0.178	0.233	0.167	0.171	−0.086	−0.178	−0.235	−0.166	−0.171
	(2.61)	(4.94)	(8.33)	(4.46)	(4.54)	(−2.43)	(−4.93)	(−6.37)	(−4.44)	(−4.54)
ρ_1	0.082	0.083	0.098	0.033	0.069	−0.087	−0.083	−0.099	−0.033	−0.069
	(3.09)	(3.45)	(4.27)	(1.47)	(3.11)	(−3.28)	(−3.48)	(−4.27)	(−1.47)	(−3.11)
ρ_2		0.060	0.050	0.081	0.058		−0.061	−0.050	−0.081	−0.058
		(2.51)	(2.16)	(3.55)	(2.58)		(−2.53)	(−2.17)	(−3.55)	(−2.58)
ρ_3			0.050	−0.001	0.017			−0.051	0.001	−0.017
			(2.16)	(−0.04)	(0.73)			(−2.16)	(0.04)	(−0.73)
ρ_4				−0.009	−0.065				0.009	0.065
				(−0.41)	(−2.89)				(0.41)	(2.89)
ρ_5					−0.027					0.027
					(−0.22)					(1.22)
F-STAT	9.57	14.42	17.60	3.48	10.68	10.74	16.66	17.68	3.49	10.68
(p-value)	(0.00)	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.00)
ψ_0	0.082	0.143	0.198	0.104	0.052	−0.087	−0.144	−0.200	−0.104	−0.052
ψ_1	0.053	0.003	−0.010	0.004	−0.021	−0.030	−0.141	−0.209	−0.101	−0.073
μ_1	0.032	0.059	0.076	0.071	0.083	−0.061	−0.105	−0.131	−0.087	−0.080

Table 4 (*continued*)

	Case PC-*m*					Case NC-*m*				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Panel 1B. Consecutive return patterns (01/03/29–01/16/62)										
c_0 (×100)	−0.061	0.019	0.017	0.018	0.020	0.023	−0.005	−0.003	0.012	0.013
	(−2.43)	(1.44)	(1.16)	(1.27)	(1.46)	(0.93)	(−0.32)	(−0.23)	(0.87)	(0.95)
ϕ_1	−0.029	0.039	0.039	0.035	0.035	0.057	0.066	0.069	0.043	0.038
	(−1.55)	(3.13)	(3.57)	(3.32)	(3.39)	(3.11)	(5.20)	(6.20)	(4.00)	(3.66)
ϕ_2		−0.025	−0.034	−0.041	−0.041		0.003	−0.005	−0.034	−0.039
		(−2.02)	(−3.10)	(−3.90)	(−3.92)		(0.00)	(−0.44)	(−3.22)	(−3.72)
ϕ_3			−0.000	−0.003	−0.002			0.027	0.006	0.001
			(−0.00)	(−0.31)	(−0.17)			(2.45)	(0.58)	(0.13)
ϕ_4				0.044	0.046				0.047	0.046
				(4.12)	(4.35)				(4.48)	(4.39)
ϕ_5					0.013					0.016
					(1.27)					(1.55)
c_1 (×100)	0.091	0.093	0.175	0.125	0.252	−0.086	−0.143	−0.436	−0.118	−0.028
	(2.61)	(2.32)	(3.03)	(1.40)	(1.96)	(−2.43)	(−3.15)	(−6.34)	(−5.39)	(−0.15)
ρ_1	0.082	0.025	−0.041	0.016	0.006	−0.087	−0.052	−0.146	−0.057	0.041
	(3.09)	(0.79)	(−0.79)	(0.19)	(0.05)	(−3.28)	(−1.68)	(−3.22)	(−0.78)	(0.37)
ρ_2		−0.138	−0.179	−0.118	−0.069		−0.228	−0.332	−0.174	0.077
		(−4.40)	(−3.76)	(−1.22)	(−0.46)		(−7.06)	(−7.49)	(−2.25)	(0.71)
ρ_3			0.007	−0.039	−0.058			−0.224	−0.371	−0.129
			(0.14)	(−0.47)	(−0.40)			(−4.26)	(−4.26)	(−1.05)
ρ_4				−0.024	−0.346				0.064	−0.108
				(−0.30)	(−2.53)				(0.75)	(−0.77)
ρ_5					−0.005					−0.323
					(−0.04)					(−2.38)
F-STAT	9.59	9.03	11.20	2.10	6.84	10.74	52.96	134.36	21.62	6.07
(p-value)	(0.00)	(0.00)	(0.00)	(0.15)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
ψ_0	0.082	−0.113	−0.213	−0.165	−0.472	−0.087	−0.280	−0.702	−0.538	−0.442
ψ_1	0.053	−0.099	−0.208	−0.130	−0.421	−0.030	−0.211	−0.611	−0.476	−0.380
μ_1	0.032	0.102	0.159	0.127	0.191	−0.061	−0.122	−0.273	−0.072	−0.011

Panel 2: Second sub-period (01/17/62–12/31/98)

Panel 2A. Holding period return patterns (01/17/62–12/31/98)

c_0 (×100)	−0.061	−0.086	−0.064	−0.063	−0.072	0.046	0.063	0.056	0.048	0.050
	(−3.42)	(−4.62)	(−3.34)	(−3.21)	(−3.66)	(2.60)	(3.45)	(3.04)	(2.56)	(2.66)
ϕ_1	0.006	0.045	0.056	0.072	0.087	0.127	0.099	0.116	0.111	0.093
	(0.30)	(2.68)	(3.53)	(4.65)	(5.73)	(6.13)	(5.42)	(6.53)	(6.42)	(5.44)
ϕ_2		−0.139	−0.135	−0.124	−0.121		−0.019	0.008	0.015	0.011
		(−7.86)	(−8.15)	(−7.82)	(−7.78)		(−1.09)	(0.49)	(0.86)	(0.63)
ϕ_3			−0.007	0.012	−0.011			−0.052	−0.065	−0.041
			(−0.41)	(0.70)	(−0.72)			(−3.17)	(−3.91)	(−2.43)
ϕ_4				−0.098	−0.098				0.021	0.019
				(−5.87)	(−6.06)				(1.28)	(1.18)
ϕ_5					−0.021					0.003
					(−1.28)					(0.17)
c_1 (×100)	0.108	0.149	0.101	0.111	0.122	−0.109	−0.149	−0.101	−0.111	−0.122
	(4.27)	(5.71)	(4.52)	(4.09)	(4.48)	(−4.30)	(−5.72)	(−4.52)	(−4.09)	(−4.48)
ρ_1	0.120	0.054	0.060	0.039	0.005	−0.122	−0.054	−0.060	−0.039	−0.005
	(4.23)	(2.15)	(2.51)	(1.67)	(0.24)	(−4.30)	(−2.15)	(−2.51)	(−1.67)	(−0.24)
ρ_2		0.120	0.144	0.139	0.132		−0.120	−0.144	−0.139	−0.132
		(4.77)	(6.00)	(5.92)	(5.72)		(−4.77)	(−6.00)	(−5.92)	(−5.72)
ρ_3			−0.045	−0.076	−0.029			0.045	0.076	0.029
			(−1.88)	(−3.26)	(−1.26)			(1.88)	(3.26)	(1.26)
ρ_4				0.119	0.117				−0.119	−0.117
				(5.12)	(5.12)				(−5.12)	(−5.12)
ρ_5					0.024					−0.024
					(1.05)					(−1.05)
F-STAT	17.86	19.35	10.49	14.81	14.83	18.46	19.36	10.49	14.81	14.83
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ψ_0	0.120	0.174	0.159	0.221	0.249	−0.122	−0.174	−0.159	−0.221	−0.249
ψ_1	0.126	0.080	0.073	0.083	0.085	0.005	−0.094	−0.087	−0.139	−0.164
μ_1	0.054	0.068	0.040	0.052	0.055	−0.063	−0.079	−0.041	−0.055	−0.062

Panel 2B. Consecutive return patterns (01/17/62–12/31/98)

c_0 (×100)	−0.061	0.014	0.032	0.034	0.033	0.046	0.043	0.036	0.028	0.032
	(−3.42)	(1.21)	(3.17)	(3.56)	(3.53)	(2.60)	(3.63)	(3.53)	(2.95)	(3.43)

Table 4 (*continued*)

	Case PC-m					Case NC-m				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
ϕ_1	0.006	0.099	0.111	0.112	0.110	0.127	0.136	0.140	0.153	0.114
	(0.30)	(7.80)	(9.84)	(10.5)	(10.5)	(6.13)	(10.0)	(11.6)	(13.6)	(10.7)
ϕ_2		−0.052	−0.038	−0.038	−0.038		−0.048	−0.042	−0.033	−0.038
		(−4.08)	(−3.36)	(−3.52)	(−3.57)		(−3.92)	(−3.74)	(−3.10)	(−3.55)
ϕ_3			−0.004	0.002	−0.001			−0.009	0.003	−0.003
			(−0.32)	(0.20)	(−0.10)			(−0.85)	(0.27)	(−0.28)
ϕ_4				−0.012	−0.018				−0.010	−0.015
				(−1.11)	(−1.66)				(−0.94)	(−1.45)
ϕ_5					0.012					0.014
					(1.09)					(1.37)
c_1 (×100)	0.108	0.071	0.023	0.077	0.029	−0.109	−0.001	−0.106	−0.258	−0.168
	(4.27)	(2.36)	(0.54)	(1.28)	(0.34)	(−4.30)	(−4.55)	(−2.25)	(−3.55)	(−1.46)
ρ_1	0.120	−0.014	−0.014	−0.019	−0.014	−0.122	−0.193	−0.269	−0.399	−0.120
	(4.23)	(−0.44)	(−0.34)	(−0.31)	(−0.14)	(−4.30)	(−6.90)	(−8.55)	(−10.9)	(−1.55)
ρ_2		0.004	−0.005	0.022	−0.040		0.052	0.037	−0.023	−0.015
		(0.11)	(−0.11)	(0.38)	(−0.48)		(1.47)	(0.77)	(−0.36)	(−0.17)
ρ_3			−0.015	−0.095	−0.073			0.166	0.026	−0.126
			(−0.38)	(−1.71)	(−0.90)			(3.30)	(0.38)	(−1.29)
ρ_4				−0.066	0.011				0.020	−0.132
				(−1.24)	(0.14)				(0.28)	(−1.40)
ρ_5					0.054					−0.123
					(0.72)					(−1.19)
F-STAT	17.86	0.06	0.31	3.16	0.21	18.46	12.01	1.14	15.42	3.04
(p-value)	(0.00)	(0.80)	(0.58)	(0.08)	(0.65)	(0.00)	(0.00)	(0.29)	(0.00)	(0.08)
ψ_0	0.120	−0.010	−0.034	−0.158	−0.062	−0.122	−0.141	−0.066	−0.376	−0.516
ψ_1	0.126	0.037	0.035	−0.094	0.003	0.005	−0.053	0.023	−0.263	−0.444
μ_1	0.054	0.088	0.057	0.101	0.062	−0.063	−0.055	−0.072	−0.182	−0.094

ψ_0 is the sum of asymmetry autocorrelation coefficients, i.e., $\psi_0 = \sum_{i=1}^{m} \rho_i$. F-STAT denotes the F-statistics for the null of $\psi_0 = 0$ for each corresponding model. ψ_1 is the sum of autocorrelation coefficients when $m_t = 1$, and is calculated as $\psi_1 = \sum_{i=1}^{m} \phi_i + \sum_{i=1}^{m} \rho_i$. μ_1 denotes the unconditional mean return when $m_t = 1$, and is calculated as $\mu_1 = (c_0 + c_1)/(1 - \psi_1)$.

$\mu_1 < 0$. Thus, there is a positive unconditional mean return for a prior positive return and a negative unconditional mean return for a prior negative return.

In sum, there are several notable findings: (a) Daily returns exhibit a strong asymmetric pattern with positive returns persisting longer than negative returns. (b) The asymmetric reverting pattern is better identified with a positive or negative prior m-day holding-period return pattern than with a prior positive or negative m-consecutive daily return pattern. (c) The unconditional mean return implied from the asymmetric nonlinear autoregressive models is positive under a prior positive return and negative under a prior negative return. Finding (c) provides an important clue about the profitability of our trading strategies. The result indicates that taking a long position after a recent positive price change is likely to yield a greater profit before transaction costs than taking a short position after a recent negative price change. This finding is consistent with the results reported in Table 6, which show a positive return for buy signals and a negative return for sell signals.

3.3. *Out-of-sample test*

Predictive performance of the nonlinear AR(m) model is examined out of sample. Following the method by Gençay (1998b), we perform out-of-sample tests on 19 sub-samples. Each of the first 18 sub-samples contains 1000 observations, and the 19th one includes 612 observations. [9] For each sub-sample, the forecast horizons are 10 days, 20 days and 30 days.

Root mean square prediction errors (RMSPE) of each nonlinear AR(m) model are compared with RMSPE of the corresponding benchmark model. The benchmark model is simply the linear AR(m) model. We compute the ratio of RMSPE of the nonlinear AR(m) to the RMSPE of the linear AR(m) to measure the out-of-sample performance between the nonlinear and linear models. A ratio of less than one indicates the nonlinear model outperforms the linear model, providing more accurate predictions in the out-of-sample forecast. Similarly, a ratio greater than one indicates the nonlinear model provides less accurate predictions than the benchmark linear model.

Table 5 reports the ratios for the 19 sub-samples. Panel A shows the ratios of the PC-m Cases and NC-m Cases for the 10-day forecast horizon. [10] Panels B and C show the ratios for the 20- and 30-day forecast horizons, respectively. Panel A reports Model 1's ratio is the smallest of the five models for both cases. The average ratio for the PC-m Cases is 0.696 and for the NC-m Cases is 0.729. This indicates that the asymmetric, nonlinear AR(1) model yields an average forecast improvement of 30.4% for the PC-m Case and 27.1% for the NC-m Case, respectively. The asymmetric, nonlinear AR(1) model also outperforms the linear AR(1) model for 20- and 30-day forecast horizons. The forecast improvements of the asymmetric, nonlinear

[9] The sum of all the sub-sample observations is 18,612, which is the total number of observations for the entire period of 01/03/29–12/31/98.

[10] We found similar results for the cases with the prior holding-period return patterns.

Table 5
Out of sample test

	Case PC-*m*					Case NC-*m*				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A. 10 Days										
Period 1	0.754	0.967	0.988	0.994	0.996	0.744	0.954	0.986	1.011	0.988
Period 2	0.967	0.896	0.890	0.929	0.992	0.881	0.677	0.813	0.937	0.979
Period 3	0.596	0.824	1.027	0.920	0.995	0.576	1.032	1.036	0.915	0.983
Period 4	0.541	0.847	0.922	0.934	0.964	0.534	0.820	0.952	0.985	0.989
Period 5	0.639	0.850	0.959	0.976	0.989	0.580	0.854	0.984	1.007	1.002
Period 6	1.265	1.151	1.044	1.052	1.002	1.246	1.432	1.313	1.137	0.999
Period 7	0.646	1.039	1.079	1.023	1.019	0.651	0.807	0.949	0.979	0.992
Period 8	0.484	0.841	0.916	0.963	0.993	0.468	0.867	1.022	1.053	1.041
Period 9	0.533	0.620	0.674	0.747	0.822	0.540	0.859	0.967	0.989	0.995
Period 10	0.776	0.805	0.799	0.971	0.980	1.630	1.426	1.171	1.088	1.044
Period 11	0.530	0.608	0.678	0.833	0.917	0.533	0.790	0.885	0.951	0.977
Period 12	0.651	0.838	0.839	0.865	1.033	0.639	0.781	0.899	0.934	0.962
Period 13	0.551	0.909	0.910	0.987	0.994	0.548	0.973	0.949	0.999	0.999
Period 14	0.619	1.007	0.982	0.996	0.985	0.619	0.966	0.963	1.005	0.997
Period 15	0.676	0.783	0.849	0.946	0.973	0.674	0.614	0.864	0.937	1.017
Period 16	0.713	1.004	1.058	0.993	0.961	0.711	1.037	0.996	0.988	1.007
Period 17	0.918	1.153	1.176	1.023	1.012	0.915	0.670	1.063	1.026	1.006
Period 18	0.711	0.969	0.937	1.018	1.025	0.710	1.041	1.005	1.019	1.018
Period 19	0.644	0.924	0.933	0.916	0.912	0.645	0.887	0.974	0.984	0.985
Avg. ratio	0.696	0.897	0.930	0.952	0.977	0.729	0.920	0.989	0.997	0.999
No. of periods for ratio <1.0	18	14	14	15	14	17	14	13	11	12
Panel B. 20 Days										
Period 1	0.753	0.951	0.981	0.999	0.999	0.757	0.924	0.980	0.989	0.978
Period 2	1.026	0.933	0.957	0.961	1.001	0.983	0.826	0.839	0.951	0.983
Period 3	0.649	0.863	0.943	0.996	0.998	0.639	0.883	0.902	0.994	0.992
Period 4	0.609	0.793	0.865	0.865	0.985	0.591	0.801	0.925	0.930	0.997
Period 5	0.662	0.793	0.974	0.988	1.003	0.669	0.896	0.994	0.988	0.999
Period 6	0.983	1.175	1.127	1.019	1.160	1.005	1.067	1.090	1.106	1.011
Period 7	0.718	1.007	1.047	1.044	1.020	0.825	0.866	0.935	0.971	0.987
Period 8	0.598	0.883	0.985	1.002	1.004	0.600	0.890	0.992	1.010	1.009
Period 9	0.535	0.652	0.971	0.818	0.873	0.544	0.825	0.894	0.985	0.987
Period 10	1.188	0.830	0.802	0.869	0.940	1.119	1.081	1.052	1.019	1.006
Period 11	0.617	0.736	0.770	0.871	0.939	0.623	0.894	0.988	0.959	0.979
Period 12	0.652	0.791	0.811	0.861	0.983	0.640	0.811	0.906	0.937	0.964
Period 13	0.581	0.906	0.933	0.950	0.997	0.578	0.927	0.988	0.979	0.990
Period 14	0.644	0.900	0.965	0.998	0.993	0.642	0.960	0.176	1.004	0.983
Period 15	0.690	0.919	0.900	0.977	0.999	0.690	0.790	0.941	0.970	0.997
Period 16	0.941	0.933	1.060	1.006	0.983	0.944	0.949	1.176	0.989	0.974
Period 17	0.730	0.981	1.024	1.012	1.006	0.729	0.538	1.012	0.928	0.982
Period 18	0.570	0.955	0.961	0.997	0.983	0.569	0.773	0.950	1.015	1.009
Period 19	0.643	0.930	0.940	0.968	0.962	0.644	0.930	0.951	0.987	0.915

Table 5 (*continued*)

	Case PC-*m*					Case NC-*m*				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Avg. ratio	0.726	0.891	0.948	0.958	0.991	0.726	0.875	0.931	0.987	0.988
No. of periods for ratio <1.0	17	17	15	14	13	17	17	15	14	15
Panel C. 30 Days										
Period 1	0.758	0.937	0.982	0.998	0.999	0.758	0.948	0.987	0.963	0.971
Period 2	1.050	0.925	0.989	0.978	1.002	1.029	0.795	0.851	0.961	0.987
Period 3	0.695	0.856	0.966	0.985	0.991	0.689	0.994	0.995	0.992	0.991
Period 4	0.621	0.835	0.868	0.918	1.035	0.595	0.830	0.932	0.949	0.995
Period 5	0.658	0.813	0.981	1.008	1.003	0.671	0.889	0.995	0.998	0.999
Period 6	0.925	1.088	1.068	0.994	1.009	0.964	1.047	1.065	1.120	1.011
Period 7	0.728	0.893	0.931	0.983	1.011	0.749	0.936	0.974	0.986	0.994
Period 8	0.619	0.913	0.984	0.999	1.002	0.618	0.857	0.977	1.011	1.009
Period 9	0.600	0.689	0.807	0.842	0.931	0.608	0.843	0.943	0.986	0.994
Period 10	0.755	0.803	0.888	0.861	0.965	0.724	0.722	0.710	0.957	1.218
Period 11	0.687	0.801	0.882	0.930	0.968	0.681	0.972	1.058	1.033	1.020
Period 12	0.663	0.821	0.870	0.910	0.980	0.658	0.958	0.990	0.989	0.992
Period 13	0.584	0.932	0.981	0.972	0.971	0.581	0.924	0.976	0.973	0.986
Period 14	0.650	0.837	0.871	0.923	0.961	0.651	0.939	0.987	0.993	0.995
Period 15	0.681	0.974	0.937	0.986	0.996	0.682	0.811	0.968	0.977	0.997
Period 16	0.744	0.914	0.947	0.999	0.999	0.746	0.936	1.033	0.989	0.998
Period 17	0.596	0.944	0.976	0.994	0.996	0.669	0.822	1.010	1.013	0.982
Period 18	0.613	0.860	0.754	0.925	0.945	0.613	0.857	0.966	0.985	0.997
Period 19	0.638	1.002	0.932	0.943	0.937	0.638	0.951	0.991	0.995	0.986
Avg. ratio	0.698	0.886	0.927	0.955	0.984	0.701	0.896	0.969	0.993	1.006
No. of periods for ratio <1.0	18	17	18	18	13	18	18	15	15	15

AR(1) model are confirmed by the number of periods with ratios less than one. Panel A shows that 18 of the 19 sub-samples show a forecast improvement for the PC-*m* Cases and 17 of the 19 for the NC-*m* Cases. The results for the 20- and 30-day forecast horizons also show similar forecast improvements.

4. Trading strategies and profitability

The asymmetric reverting patterns of return dynamics can be used to generate profitable trading rules. Cases PH-*m* and PC-*m* initiate long position signals, and Cases NH-*m* and NC-*m* generate short position signals. These trading rules exploit the observed asymmetry in the estimated unconditional mean returns.

Two trading rules for detecting buy and sell signals are controlled by a prior *m*-day holding-period return pattern and a prior *m*-day consecutive return pattern.

Table 6
Standard test results for the implied trading strategies over the full-period of 01/03/29–12/31/98

Test	*N* (Buy)	*N* (Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy–Sell
Strategies under the rule controlled by prior holding-period return patterns							
$m = 1$	9630	8555	0.000999	−0.000513	0.556179	0.475862	0.001512
			(5.121634)	(−5.334412)			(11.472765)
$m = 2$	10106	8485	0.000790	−0.000342	0.533149	0.498763	0.001132
			(3.706267)	(−4.162625)			(8.668774)
$m = 3$	10259	8347	0.000758	−0.000321	0.529779	0.502216	0.001079
			(3.487770)	(−4.000718)			(8.250833)
$m = 4$	10430	8177	0.000700	−0.000268	0.529243	0.502385	0.000968
			(3.087619)	(−3.618999)			(7.388990)
$m = 5$	10512	8095	0.000744	−0.000334	0.533486	0.496726	0.001077
			(3.414194)	(−4.040411)			(8.212652)
Average			0.000798	−0.000356	0.536367	0.495190	0.001154
Strategies under the rule controlled by prior consecutive daily return patterns							
$m = 1$	9630	8555	0.000999	−0.000513	0.556179	0.475862	0.001512
			(5.121634)	(−5.334412)			(11.472765)
$m = 2$	5355	4311	0.000699	−0.000158	0.533794	0.498028	0.000856
			(2.428696)	(−2.259829)			(4.716823)
$m = 3$	2859	2089	0.000561	0.000202	0.526768	0.507899	0.000359
			(1.268156)	(0.273730)			(1.405234)
$m = 4$	1506	990	0.000536	0.000359	0.529880	0.507071	0.000177
			(0.869172)	(0.231891)			(0.488898)
$m = 5$	798	476	0.000388	0.000917	0.522556	0.529412	−0.000529
			(0.280885)	(1.229104)			(−1.229104)
Average			0.000637	0.000161	0.533835	0.503654	0.000475

Under the rule controlled by a prior holding-period return pattern, PH-m Cases generate buy signals, and NH-m Cases generate sell signals. Likewise, under the rule controlled by a prior consecutive return pattern, PC-m Cases generate buy signals, and NC-m Cases generate sell signals. For each rule, there are five trading strategies that can be implemented along with a value of m. [11] Under the rule with the prior holding-period return pattern, for example, the strategy of $m = 2$ initiates a buy signal when the prior 2-day holding period return is positive and a sell signal when the prior 2-day holding period return is negative. Under the rule with the prior consecutive return pattern, the strategy of $m = 2$ initiates a buy (sell) signal when the prior 2-consecutive daily returns are positive (negative). It should be noted that the strategy with $m = 1$ is identical under both rules.

In order to evaluate the profitability of each trading strategy, we apply the analysis of Brock et al. (1992). Table 6 presents the standard test results for the trading strategies of the two trading rules using daily return data on the S&P 500 index. Column 1 represents the different strategies defined by the value of m under each rule. Columns 2 and 3 refer to the number of buy and sell signals for the different strategies, and Columns 4 and 5 show the mean daily returns during buy and sell periods with corresponding t-statistics (in parenthesis below) testing the difference of mean buy and mean sell from the unconditional 1-day mean. Columns 6 and 7 show the fraction of buy and sell returns greater than zero, and the last column shows the buy–sell spread, which is the average daily buy return minus the average daily sell return.

A strategy is successful when there is a significant positive return for each signal and a positive spread between the buy and sell signals. The results in Table 6 shows that buy signals in general generate statistically significant positive returns and sell signals generate negative returns. For strategies under the rule controlled by a prior holding period return pattern, the buy returns are all positive with an average daily return of 0.0798% (20.75% annualized). This result compares with the unconditional mean daily return of 0.0275% (7.15% annualized). The sell returns are negative with an average daily return of −0.0356% (−9.26% annualized). The t-tests for the five strategies reject the null hypothesis that the buy and sell returns are insignificantly different from the unconditional daily mean return at the 1% level using a two-tailed test. The spread between buy and sell returns across all strategies is positive and statistically significant at the 1% level, with an average daily spread of 0.1154%. Also, 53.6% of buy signals generate positive returns and 50.5% of sell signals generate negative returns.

For the strategies under the rule controlled by prior consecutive daily return patterns, only strategies with $m = 1$ and 2 have statistical significance at the 5% level. For the two strategies, the table shows positive buy signals, negative sell signals, and positive buy–sell spreads. Partial success of strategies based upon the prior consecutive return patterns might be directly associated with the finding that the

[11] Each strategy with a value of m corresponds to Model m in each case. For example, the strategy of $m = 3$ under the Case PH-m exploits the asymmetry identified with Model 3 under the PH-m Case.

asymmetric reverting pattern is better identified with a positive or negative pattern of a prior m-day holding-period return as a control variable than with the pattern of a prior m-daily consecutive return.

Table 7 reports the same standard test results for the two sub-periods. Panels 1 and 2 present the test results for the first and second sub-period samples, respectively. For the first sub-period, strategies based upon the prior holding period return pattern generate positive buy returns, negative sell returns, and positive buy–sell spreads that are all statistical significant. The results are consistent with those for the full-period samples. The buy returns are all positive with an average daily return of 0.0694% (18.04% annualized), and the sell returns are all negative with an average daily return of −0.0402% (−10.45% annualized). However, the test for the strategies based upon prior consecutive return patterns generates somewhat inconsistent results. While the buy signals generate a positive return for all strategies, the sell signals generate mixed results.

Panel 2 presents the test results for the second sub-period sample. All the strategies based upon the prior holding-period return patterns generate positive buy returns, negative sell returns, and positive buy–sell spreads, with statistical significance at the 1% level. The panel also shows that buy signals consistently generate more positive returns (54.73%) than do sell signals (49.67%). However, not all strategies under the rule controlled by the prior consecutive return pattern are successful. Only the strategies $m = 1$ and 2 generate a statistically significant positive return, and the strategies $m = 1$–3 generate a statistically significant negative return and a positive buy–sell spread. In general, the results for the two sub-period samples are consistent with those for the full-period sample; positive buy returns, negative sell returns, and positive buy–sell spreads.

A number of studies have investigated the movement of stock prices after an extreme return shock. [12] For example, Brown et al. (1988) document that extreme price changes, either positive or negative, are followed by significant positive returns. Atkins and Dyl (1990) and Bremer and Sweeney (1991) find that stocks that experience extreme 1-day price declines earn significant abnormal returns. [13] Hudson et al. (2001) investigate the pattern of returns after extreme 1-day return changes of various sizes. They find that returns exhibit persistence after a large 1-day price change. Thus, it is meaningful to test whether the magnitude effect of extreme 1-day price changes is exploitable for the profitability of technical trading strategies.

We check the profitability on the implied strategies based upon the prior return pattern with a one standard deviation return change. [14] Even with a long series of data, consecutive extreme return shocks are quite infrequent, thus we only consider

[12] The authors are indebted to an anonymous referee on this point.

[13] While Cox and Peterson (1994) attribute the reversal to bid–ask bounce, Park (1995) notes that much of the reversal can be attributed to market structure.

[14] Estimation results of all five models based upon the one standard deviation return change also show statistically significant asymmetry in return dynamics.

Table 7
Standard test results for the implied trading strategies over the two sub-periods

Test	*N* (Buy)	*N* (Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy–Sell
Panel 1: First sub-period (01/03/29–01/16/62)							
Strategies under the rule controlled by prior holding-period return patterns							
$m = 1$	4752	4751	0.000741	−0.000365	0.543350	0.476816	0.001106
			(2.516399)	(−2.480457)			(3.931064)
$m = 2$	5076	4210	0.000592	−0.000277	0.533149	0.501188	0.000870
			(1.877871)	(−2.097841)			(3.143972)
$m = 3$	5130	4170	0.000695	−0.000413	0.529779	0.500480	0.001108
			(2.374996)	(−2.688716)			(4.005522)
$m = 4$	5218	4083	0.000690	−0.000428	0.529243	0.497918	0.001118
			(2.369642)	(−2.729952)			(4.034464)
$m = 5$	5283	4018	0.000753	−0.000525	0.533486	0.491538	0.001277
			(2.681995)	(−3.131049)			(4.599377)
Average			0.000694	−0.000402	0.533801	0.493588	0.001096
Strategies under the rule controlled by prior consecutive daily return patterns							
$m = 1$	4752	4751	0.000741	−0.000365	0.543350	0.476816	0.001106
			(2.516399)	(−2.480457)			(3.931064)
$m = 2$	2582	2038	0.000297	0.000387	0.510070	0.508832	−0.000090
			(0.354226)	(0.610526)			(−0.307257)
$m = 3$	1317	937	0.000353	0.001247	0.509491	0.519744	−0.000894
			(0.409941)	(2.361474)			(−2.062384)
$m = 4$	671	414	0.000565	0.001131	0.514158	0.524155	−0.000566
			(0.704490)	(1.415084)			(−0.867481)
$m = 5$	345	185	0.000160	0.002514	0.481159	0.583784	−0.002353
			(0.052347)	(2.362088)			(−2.412485)
Average			0.000423	0.000983	0.511646	0.522666	−0.000559

Table 7 (*continued*)

Test	*N* (Buy)	*N* (Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy–Sell
Panel 2: Second sub-period (01/17/62–12/31/98)							
Strategies under the rule controlled by prior holding-period return patterns							
$m = 1$	4878	4370	0.001251	−0.000652	0.568676	0.475057	0.001903
			(6.320317)	(−6.713341)			(10.298835)
$m = 2$	5030	4273	0.000990	−0.000403	0.547714	0.496373	0.001394
			(4.547008)	(−5.001652)			(7.551338)
$m = 3$	5129	4174	0.000820	−0.000228	0.540651	0.503833	0.001049
			(3.367888)	(−3.801915)			(5.671381)
$m = 4$	5211	4091	0.000711	−0.000111	0.537901	0.506478	0.000822
			(2.604964)	(−3.003518)			(4.437309)
$m = 5$	5229	4072	0.000735	−0.000143	0.541595	0.501719	0.000877
			(2.775880)	(−3.204039)			(4.730962)
Average			0.000901	−0.000307	0.547307	0.496692	0.001209
Strategies under the rule controlled by prior consecutive daily return patterns							
$m = 1$	4878	4370	0.001251	−0.000652	0.568676	0.475057	0.001903
			(6.320317)	(−6.713341)			(10.298835)
$m = 2$	2774	2271	0.001073	−0.000642	0.555876	0.488331	0.001715
			(4.007667)	(−5.026881)			(6.830691)
$m = 3$	1542	1151	0.000739	−0.000649	0.541505	0.497828	0.001388
			(1.657193)	(−3.704686)			(4.016116)
$m = 4$	835	576	0.000513	−0.000196	0.542515	0.494792	0.000709
			(0.522544)	(−1.452706)			(1.475958)
$m = 5$	453	291	0.000562	−0.000097	0.554084	0.494845	0.000659
			(0.504008)	(−0.852097)			(0.989092)
Average			0.000828	−0.000447	0.552531	0.490171	0.001275

the strategies under the rule controlled by a prior holding-period return pattern. [15] In this case, each strategy generates a buy (sell) signal when the prior m-day holding-period return is greater than (less than) one standard deviation.

Table 8 presents the standard test results for profitability of the strategies based upon a one standard deviation change. The table shows consistent test results across all three samples. For the full-period sample, all five strategies generate profitable buy and sell signals, with strong statistical significance. The buy returns are all positive with an average return of 0.1154% (30% annualized), and the sell returns are all negative with an average daily return of −0.0484% (−12.58% annualized). The average buy–sell spread is 0.1639% (42.6% annualized). These numbers are greater than those in Table 6, [16] implying that strategies based upon a one standard deviation return change are more profitable. Tests for the two sub-periods also show similar results; statistically significant positive returns for buy signals, negative returns for sell signals, and positive buy–sell spreads.

In sum, the standard tests indicate that the strategies exploiting asymmetric reverting patterns are profitable. Standard tests show that most strategies considered generate positive returns for buy signals, negative returns for sell signals, and positive spreads. The source of the positive (negative) return for buy (sell) signals is the positive (negative) unconditional mean of return dynamics, which is induced from the asymmetrical evolution of the return process identified under the prior return pattern. The asymmetry is better captured by the cases controlled by the prior holding-period return pattern. The strategies based upon the prior holding-period return pattern yield more reliable and consistent standard test results than under the rule controlled by the prior consecutive daily return pattern. [17]

Based on empirical results we conclude that the observed asymmetry in return dynamics is exploitable and profitable.

5. Concluding remarks

This paper explores a possible link between an asymmetric dynamic process of stock returns and profitable technical trading rules. Using daily returns on the S&P 500 market index, we have identified an asymmetry in return dynamics. This

[15] For example, there are only 66 cases observed for the three consecutive realizations of an extreme negative shock, with one standard deviation return change for the entire sample period.

[16] Buy (sell) signals generate 20.75% (−9.26%) annualized, and the buy–sell spread generates 30% at an annual rate of return.

[17] It should be noted that, even though daily index returns exhibit a strong reverting pattern under negative price changes, our results show that trading rules exploiting the reverting pattern, i.e., negative feedback trading rules are not profitable (yielding a negative return). This negative return of the negative feedback trading rules is due to a negative unconditional mean return under a prior negative price change. In other words, although a negative return tends to revert quickly, its reverting magnitude is not sufficient enough to generate a positive unconditional mean return, such that it is not exploitable for the profitability of negative feedback trading rules. Obviously, persisting magnitude is greater than reverting magnitude of a negative return, thereby yielding a negative unconditional mean return.

Table 8
Standard test results for the implied trading strategies with one standard deviation return change

Test	N (Buy)	N (Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy–Sell
Full-period (01/03/29–12/31/98)							
$m = 1$	1712	1629	0.001740	−0.000410	0.539720	0.478821	0.002149
			(5.143375)	(−2.343985)			(5.502798)
$m = 2$	3313	2981	0.001166	−0.000391	0.531542	0.498826	0.001557
			(4.195080)	(−2.985193)			(5.466322)
$m = 3$	4386	3713	0.000949	−0.000528	0.544624	0.493132	0.001477
			(3.567722)	(−3.952028)			(5.870468)
$m = 4$	5218	4202	0.000977	−0.000603	0.530820	0.488101	0.001581
			(3.981879)	(−4.548718)			(6.757410)
$m = 5$	5844	4576	0.000940	−0.000489	0.530459	0.493881	0.001429
			(3.938128)	(−4.093874)			(6.413627)
Average			0.001154	−0.000484	0.535433	0.490552	0.001639
First sub-period (01/03/29–01/16/62)							
$m = 1$	793	817	0.001195	0.000465	0.494325	0.495716	0.000730
			(2.072470)	(0.563120)			(1.103675)
$m = 2$	1437	1406	0.000866	0.000131	0.498260	0.514225	0.000734
			(1.838551)	(0.181251)			(1.475569)
$m = 3$	1971	1734	0.000790	−0.000533	0.505838	0.489043	0.001323
			(1.885363)	(−2.192770)			(3.028575)
$m = 4$	2341	2001	0.000968	−0.000841	0.510038	0.481759	0.001809
			(2.647572)	(−3.326823)			(4.477759)
$m = 5$	2670	2205	0.001057	−0.000727	0.521348	0.484807	0.001784
			(3.130169)	(−3.094324)			(4.692945)
Average			0.000975	−0.000301	0.505962	0.493110	0.001276

Second sub-period (01/17/62–12/31/98)							
$m = 1$	1097	1000	0.002407	−0.001830	0.590702	0.431000	0.004237
			(7.468772)	(−7.566645)			(10.925321)
$m = 2$	2033	1734	0.001496	−0.000677	0.556321	0.486159	0.002173
			(5.534736)	(−4.607463)			(7.493852)
$m = 3$	2613	2109	0.001007	−0.000442	0.539992	0.496444	0.001448
			(3.548741)	(−3.879640)			(5.577798)
$m = 4$	2998	2366	0.000958	−0.000292	0.545364	0.499155	0.001250
			(3.485724)	(−3.313942)			(5.124798)
$m = 5$	3299	2519	0.000715	−0.000243	0.532889	0.500595	0.000958
			(2.181045)	(−3.146660)			(4.081881)
Average			0.001317	−0.000697	0.553053	0.482671	0.002013

asymmetrical evolution of return generating processes induces a positive (negative) unconditional mean return under a prior positive (negative) return pattern for daily index returns.

We have shown that the asymmetry in return dynamics can be exploited by generating profitable buy and sell signals for various technical trading strategies. When a buy signal occurs, a long position is taken in the index for one day. Similarly, when a sell signal occurs, a short position is taken in the index for one day. Our results show that the asymmetry is the main source of profitability for the implied strategies; the positive (negative) unconditional mean is consistent with a subsequent positive (negative) return.

Our results also indicate that trading strategies for buy and sell signals based upon prior *m*-day holding-period return patterns yield greater predictive power and profitability than those based upon prior *m*-daily consecutive return patterns. [18] In conclusion, viewed from the fact that the observed asymmetry of return dynamics is the main source of profitability for the implied trading strategies, it is difficult to negate the usefulness of technical trading strategies in stock market investments.

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Appendix A

Model 1

Case PH-1 and PC-1: $m_t = 1$ only if $R_{t-1} > 0$;
Case NH-1 and NC-1: $m_t = 1$ only if $R_{t-1} < 0$.

Model 2

Case PH-2: $m_t = 1$ only if $R_{t-1} + R_{t-2} > 0$;
Case PC-2: $m_t = 1$ only if $R_{t-1} > 0$ and $R_{t-2} > 0$;

[18] We have performed the same standard test for each strategy by changing the holding period up to five days before closing the transaction position. The tests show a consistent result that a one day holding period leads to the best outcome for all strategies. We also have performed the same test on weekly return series and 10-day return series. Surprisingly, most of the strategies do not yield significant profitability before transaction costs. In addition, we have extended our analysis by changing *m* to 10, 20, 30, 40, and 50 days for identifying a prior holding-period return. The results are very similar to those found in Table 6, a positive return for buy signals, a negative return for sell signals, and a positive spread, with strong statistical significance.

Case NH-2: $m_t = 1$ only if $R_{t-1} + R_{t-2} < 0$;
Case NC-2: $m_t = 1$ only if $R_{t-1} < 0$ and $R_{t-2} < 0$.

Model 3

Case PH-3: $m_t = 1$ only if $R_{t-1} + R_{t-2} + R_{t-3} > 0$;
Case PC-3: $m_t = 1$ only if $R_{t-1} > 0$, $R_{t-2} > 0$, and $R_{t-3} > 0$;
Case NH-3: $m_t = 1$ only if $R_{t-1} + R_{t-2} + R_{t-3} < 0$;
Case NC-3: $m_t = 1$ only if $R_{t-1} < 0$, $R_{t-2} < 0$, and $R_{t-3} < 0$.

Model 4

Case PH-4: $m_t = 1$ only if $R_{t-1} + R_{t-2} + R_{t-3} + R_{t-4} > 0$;
Case PC-4: $m_t = 1$ only if $R_{t-1} > 0$, $R_{t-2} > 0$, $R_{t-3} > 0$, and $R_{t-4} > 0$;
Case NH-4: $m_t = 1$ only if $R_{t-1} + R_{t-2} + R_{t-3} + R_{t-4} < 0$;
Case NC-4: $m_t = 1$ only if $R_{t-1} < 0$, $R_{t-2} < 0$, $R_{t-3} < 0$, and $R_{t-4} < 0$.

Model 5

Case PH-5: $m_t = 1$ only if $R_{t-1} + R_{t-2} + R_{t-3} + R_{t-4} + R_{t-5} > 0$;
Case PC-5: $m_t = 1$ only if $R_{t-1} > 0$, $R_{t-2} > 0$, $R_{t-3} > 0$, $R_{t-4} > 0$, and $R_{t-5} > 0$;
Case NH-5: $m_t = 1$ only if $R_{t-1} + R_{t-2} + R_{t-3} + R_{t-4} + R_{t-5} < 0$;
Case NC-5: $m_t = 1$ only if $R_{t-1} < 0$, $R_{t-2} < 0$, $R_{t-3} < 0$, $R_{t-4} < 0$, and $R_{t-5} < 0$.

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