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Are Investment Strategies Exploiting Option Investor Sentiment Profitable? Evidence from Japan

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Abstract

This paper demonstrates that the put–call ratio (PCR), an index of option investor sentiment, is useful for equity investment. More specifically, we find that monthly market timing strategies for the Nikkei 225 using the PCRs of Nikkei 225 index options are profitable, even after considering transaction costs. This evidence suggests that the PCR operates as a useful contrarian indicator for the underlying asset in Japan. Our analysis also reveals that application of the multivariate GARCH model in Japan is effective in predicting changes in the Nikkei 225 using the level of PCR.

Keywords: Put–call ratio, Investor sentiment, Market timing, Multivariate GARCH, SETAR

1. Introduction

We generally view the put–call ratio (PCR) as a short-term, leading technical indicator of sentiment of the direction of future moves in the stock market. However, most contrarians use the PCR as a contrarian indicator because they believe that the less sophisticated public, not professionals, dominates options' trading. For this reason, they believe that public investors are generally wrong about the market, especially at significant turning points.

Analysts consequently use the PCR to identify the consensus on the 'herding' of public investors, and then execute trading strategies to bet on the opposite direction. For example, analysts consider that an increase in the volume of put options relative to the volume of call options indicates that public investors are predominately bearish. Therefore, contrarians interpret this PCR increase as a sign of future bullish movement in stock markets. In contrast, analysts believe that a decline in the volume of put options relative to call options suggests that public investors are predominately bullish about the equity market. Hence, contrarians view the optimism of public investors, who have little specialized information, as a future bearish market signal. As argued later, analysts advocate a variety of PCR values as buy and sell signals. They then use these signals to set up long or short positions in stock or option portfolios.

Several studies have analyzed the PCR in the US as a sentiment indicator of stock markets: see, for example, Billingsley and Chance (1988), Pan and Poteshman (2006), and Chang et al. (2009). (Note 1) However, in Japan, we are not aware of any prior research using the PCR. Hence, this paper is the first analysis of option investor sentiment using the PCR in Japan. Our second contribution is that we reveal the predictability of the PCR for the future stock market using a multivariate GARCH model. Our empirical analysis indicates a strong statistically significant nonlinear relation between the six-month lag of the PCR and current stock market dynamics. Our third contribution is that we clarify the effectiveness of the SETAR model for modeling option investor sentiment. We also confirm that when we use the derived thresholds from the SETAR model, we can construct a profitable trading strategy for equity investment even after considering transaction costs.

We note that our contribution is not only meaningful in a practical sense but also in the academic sense. Because our findings suggest that we can beat the market using the irrational herding behavior of public option investors, they also supply evidence of inefficient markets. The rest of this paper is organized as follows. Section 2 explains the data and the construction of the PCR. In Section 3, we describe the trading strategy, methodology, and empirical results. Section 4 models the PCRs with the SETAR model and documents the results of trading strategies using the derived thresholds. Section 5 investigates the predictability of PCRs for the stock market using the multivariate GARCH model. Section 6 supplies the discussions from our analysis, and Section 7 concludes the paper.

2. Construction of the put–call ratio

Option volume data for the Nikkei 225 option index used to construct the end-of-month PCRs are from the Osaka Securities Exchange. The formula for deriving the PCR at time t, PCR_t, is as follows: (Note 2)

$$PCR_t = \frac{1}{N}\sum_{i=1}^{N}\frac{[V_{P1,t+1-i} + V_{P2,t+1-i}]}{[V_{C1,t+1-i} + V_{C2,t+1-i}]} \times 100, \tag{1}$$

where $V_{P1,t+1-i}$ is the volume of put options of the near-maturity contract, $V_{P2,t+1-i}$ is the volume of put options of the second-nearest maturity contract, $V_{C1,t+1-i}$ is the volume of the call option of the near-maturity contract, $V_{C2,t+1-i}$ is the volume of the call option of the second-nearest maturity contract, and N denotes the number of business days at the end of each month. In this paper we set $N = 5$.

We also note that all options here are ‘out of the money’ options that are nearest to being ‘at the money’. Our sample period is January 1990 to February 2005. Figure 1 plots the Nikkei 225 and the PCR for this period. Table 1 provides descriptive statistics of the PCR in Japan. As shown, the PCR has positive skewness and slightly higher kurtosis than the normal distribution. We can also see that descriptive statistics are almost the same in the whole sample period and the two subsample periods.

3. Are investment strategies by the put–call ratio profitable?

Table 2 provides the percentile values of the PCR for the whole sample period and the subsample periods. In the three sample periods, these percentile values are generally stable; thus, we use the figures computed for our full sample period for the various market-timing strategies. In existing US studies, Billingsley and Chance (1988) used 100–60 and 70–40 strategies for the S&P 100 Index Option (OEX), and 70–40 and 65–40 strategies for the Chicago Board Options Exchange (CBOE) equity options. (Note 3) We also consider these settings.

3.1 Trading strategies without trading costs

Based on the above PCR percentile values and the settings in Billingsley and Chance (1988), we set up the following eight strategies; namely: 1) 100–60 strategy (Note 4), 2) 72.9–132.4 (10–90 percentile) strategy, 3) 81.0–128.0 (15–85 percentile) strategy, 4) 84.3–122.2 (20–80 percentile) strategy, 5) 87.4–120.1 (25–75 percentile) strategy, 6) 88.7–116.5 (30–70 percentile) strategy, 7) 93.5–112.4 (35–65 percentile) strategy, and 8) 96.7–109.7 (40–60 percentile) strategy. More specifically, when PCR values lie above the upper threshold, we buy the Nikkei 225, and when PCR values fall below the lower threshold, we sell the Nikkei 225. (Note 5) This is the actual trading rule using PCRs employed in this paper.

Table 3 provides the empirical results for the eight trading strategies, excluding transaction costs. The table shows the profit and loss for each transaction using the PCR. Table 3 shows that 1) the 100–60 strategy yields an average annual return of −0.577% and a gross percentage return of −8.757% for our full sample period with five transactions. Similarly, and in order, Table 3 shows 2) the 72.9–132.4 strategy yields an average annual return of 0.860% and a gross percentage return of 13.047% with 11 transactions, 3) the 81.0–128.0 strategy yields an average annual return of 1.465% and a gross percentage return of 22.227% with 15 transactions, 4) the 84.3–122.2 strategy yields an average annual return of 2.835% and a profit of gross percentage return of 43.003% with 23 transactions, 5) the 87.4–120.1 strategy yields an average annual return of 3.327% and a profit of gross percentage return of 50.455% with 33 transactions, 6) the 88.7–116.5 strategy yields an average annual return of 3.586% and a profit of gross percentage return of 54.382% with 39 transactions, 7) the 93.5–112.4 strategy yields an average annual return of 3.527% and a profit of gross percentage return of 53.491% with 45 transactions, and 8) the 96.7–109.7 strategy yields an average annual return of 3.080% and a profit of gross percentage return of 46.714% with 53 transactions.

3.2 Trading strategies considering trading costs

We next consider transaction costs. Following Stall and Whaley (1986) and Billingsley and Chance (1988), we use a value of 0.85% for our transaction costs. Table 4 displays the results of our empirical tests for the same eight trading strategies, including these transaction costs. As shown, the profit and loss for each transaction using the PCR is similar to that in Table 3. Expressed differently, Table 4 demonstrates that 1) the 100–60 strategy yields an average annual return of −0.687% and a gross percentage return of −10.417% in our full sample period with 5 transactions.

Similarly, and in order, Table 4 also shows that 2) the 72.9–132.4 strategy yields an average annual return of 0.740% and a gross percentage return of 11.230% with 11 transactions, 3) the 81.0–128.0 strategy yields an average annual return of 1.297% and a gross percentage return of 19.664% with 15 transactions, 4) the 84.3–122.2 strategy yields an average annual return of 2.428% and a gross percentage return of 36.819% with 23 transactions, 5) the 87.4–120.1 strategy yields an average annual return of 2.511% and a gross percentage return of 38.086% with 33 transactions, 6) the 88.7–116.5 strategy yields an average annual return of 2.518% and a gross percentage return of 38.182% with 39 transactions, 7) the 93.5–112.4 strategy yields an average annual return of 2.284% and a gross percentage return of 34.638% with 45 transactions, and 8) the 96.7–109.7 strategy yields an average annual return of 1.444% and a gross percentage return of 21.902% with 53 transactions.

As shown, the strategy that performs best is the 88.7–116.5 (30–70 percentile) strategy, yielding a gross percentage return of 38.182% for the period from January 1990 to February 2005, even if we consider transaction costs. Further, Figure 2 displays the loss and profit from each transaction for each strategy. As we have set up all of the strategies on a month-end basis, we conduct fewer transactions for each strategy in our sample period. We consider that this brings about profitable performance in all our strategies except the 100–60 strategy. Billingsley and Chance (1988), however, tested their trading strategies on a daily basis and concluded that they were not profitable. We suggest that their unprofitable results are due to too many transactions using a daily strategy setting.

4. Modeling option investor sentiment with the SETAR model: investment strategy by derived threshold values

4.1 Modeling PCR with the SETAR model

In the previous section, we tested eight strategies where two thresholds are set artificially and mechanically from the historical distributions of PCRs. In contrast to these simple procedures, this section attempts to model PCRs using modern econometric techniques. More specifically, we apply the self-exciting threshold autoregressive (SETAR) model, and attempt to obtain a more natural boundary for changes in the investor sentiment regime using data-driven thresholds from actual PCR data.

For this purpose, we first examine the Schwarz criterion (SC) for each lag order by applying the following standard linear AR(k) model in equation (2). Table 5 displays the results.

$$PCR_t = \gamma_0 + \sum_{i=1}^{k} \gamma_i PCR_{t-i} + \varepsilon_t \ . \tag{2}$$

According to the SC values in Table 5, the appropriate lag length k of model (2) is 1 because the SC is minimized when k = 1. Based on this information, we attempt to model the PCRs by applying the SETAR(1) model. In addition, following Brooks and Garrett (2002) we choose a one-period lag of the PCR as the state-determining variable.

To be specific, we estimate the following SETAR model, given by equation (3), using the nonlinear least squares (NLS) optimization procedure in Brooks and Garrett (2002):

$$PCR_t = \begin{cases} \gamma_{0,1} + \sum_{i=1}^{k} \gamma_{i,1} PCR_{t-i} + \varepsilon_{t,1} & \text{if } PCR_{t-1} < r_0 \\ \gamma_{0,2} + \sum_{i=1}^{k} \gamma_{i,2} PCR_{t-i} + \varepsilon_{t,2} & \text{if } r_0 \le PCR_{t-1} < r_1 \ , \\ \gamma_{0,3} + \sum_{i=1}^{k} \gamma_{i,3} PCR_{t-i} + \varepsilon_{t,3} & \text{if } PCR_{t-1} \ge r_1 \end{cases} \tag{3}$$

where we set k = 1. In determining the thresholds values of r_0 and r_1, we use a grid search procedure, also following Brooks and Garrett (2002). (Note 6)

Table 6 provides the estimation results of model (3). When we fit the SETAR(1) model, two sets of thresholds, namely r_0 = 93.5 and r_1 = 126.8 and r_0 = 72.0 and r_1 = 126.8, are derived. That is, the historical data imply that these thresholds divide option investor sentiment into three regimes. This is because when we use r_0 = 93.5 and r_1 = 126.8 or r_0 = 72.0 and r_1 = 126.8, the sum of the squared residuals becomes particularly small. The SETAR(1) model with r_0 = 72.0 and r_1 = 126.8 demonstrates better fit than the SETAR(1) model with r_0 = 93.5 and r_1 = 126.8 because the sum of squared residuals is smaller and the adjusted R-squared is larger in the former. Moreover, in the r_0 = 72.0 and r_1 = 126.8 SETAR(1) model, the γ_1s are statistically significant in all three regimes.

4.2 Trading strategies with trading costs using the thresholds derived from the SETAR model

This section examines two strategies using the boundaries derived from real data: namely, the 1) 93.5–126.8 strategy and 72.0–126.8 strategy. The results of our empirical tests for these two trading strategies are in Table 7 where transaction costs of 0.85% are considered. Table 7 demonstrates that 1) the 93.5–126.8 strategy yields an average annual return of 0.980% and a gross percentage return of 14.861% in our full sample period with 23 transactions. Table 7 also shows that the 72.0–126.8 strategy yields an average annual return of 0.740% and a gross percentage return of 11.230% with 11 transactions.

Clearly, the data-driven boundary value strategies do not necessarily produce more profitable results than the strategies using the artificially determined thresholds in Section 3. However, the SETAR model confirms that there exist at least three regimes in option investor sentiment, and by using the data-driven thresholds from options markets, we can construct profitable strategies for the Nikkei 225, the option's underlying asset.

5. Can the put–call ratio predict change in the Nikkei 225?

5.1 Linear prediction

We have demonstrated that we can construct profitable strategies for stock markets using the PCR in Japan. Moreover, the estimation results of the double threshold SETAR(1) model with boundary values of 72.0 and 126.8 in the lower part in Table 6 indicate that the dynamics of the PCRs are statistically significant and persistent in all three regimes. This implies that option investor sentiment continues in the bull, bear, or neutral phases for some periods. Accordingly, we expect we can use this characteristic to predict future stock market directions. Hence, using this conjecture and the estimated profitability of the PCR investment strategies for the underlying stock index, we can assume the forecastability of option investor sentiment for stock market dynamics in Japan.

Using the above arguments, this section tests the predictability of the PCR for change in the Nikkei 225. We begin by implementing the following simple linear regression:

$$\Delta NIKKEI_t = \tau + \xi PCR_{t-k} + \eta_t, \tag{4}$$

where $\Delta NIKKEI_t$ denotes the change in the Nikkei 225 from $t-1$ to t, and PCR_{t-k} is the kth lag of the PCR.

Table 8 presents the results for the linear relation. From this table, we can see that the first and sixth lags have predictability for the Nikkei 225 dynamics. Further, the relations are positive. This suggests that bear (bull) sentiment in the options markets predicts future stock price increases (decreases) over several months. This is consistent with the usage of PCRs by contrarian investors.

5.2 Time-varying relation between the Nikkei 225 change and the lagged put–call ratio: A nonlinear analysis using a multivariate GARCH model

The linear analysis in the previous section is rather simple. Hence, this section examines the nonlinear time-varying relations between PCRs and changes in the Nikkei 225. To evaluate the nonlinear time-varying intertemporal comovements, we employ the following multivariate BEKK GARCH model (Engle and Kroner (1995), Kroner and Ng (1998)). The BEKK model ensures that the H matrix is always positive definite, and is specified by:

$$\mathbf{H}_t = \mathbf{W} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{A}'\mathbf{\Xi}_{t-1}\mathbf{\Xi}'_{t-1}\mathbf{A}, \tag{5}$$

where **W**, **A**, and **B** are 2 × 2 matrices of parameters, and **W** is assumed to be symmetric and positive definite. For the purpose of clarity, in the case of two assets, we define the matrices as follows:

$$\mathbf{H}_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{12,t} & h_{22,t} \end{bmatrix},\ \mathbf{W} = \begin{bmatrix} w_{11} & w_{12} \\ w_{12} & w_{22} \end{bmatrix},\ \mathbf{A} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix},$$

$$\mathbf{B} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix},\ \mathbf{\Xi}_t = \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix}.$$

The model is then written in full as:

$$\begin{aligned} h_{11,t} &= w_{11} + a_{11}^2 u_{1,t-1}^2 + a_{21}^2 u_{2,t-1}^2 + 2a_{11}a_{21}u_{1,t-1}u_{2,t-1} + b_{11}^2 h_{11,t-1} + b_{21}^2 h_{22,t-1} + 2b_{11}b_{21}h_{12,t-1}, \\ h_{22,t} &= w_{22} + a_{12}^2 u_{1,t-1}^2 + a_{22}^2 u_{2,t-1}^2 + 2a_{12}a_{22}u_{1,t-1}u_{2,t-1} + b_{12}^2 h_{11,t-1} + b_{22}^2 h_{22,t-1} + 2b_{12}b_{22}h_{12,t-1}, \\ h_{12,t} &= w_{12} + a_{11}a_{12}u_{1,t-1}^2 + a_{21}a_{22}u_{2,t-1}^2 + (a_{12}a_{21} + a_{11}a_{22})u_{1,t-1}u_{2,t-1} \\ &\quad + b_{11}b_{12}h_{11,t-1} + b_{21}b_{22}h_{22,t-1} + (b_{11}b_{22} + b_{12}b_{21})h_{12,t-1}. \end{aligned}$$

Regarding the estimation of model (5), the parameters can be estimated by maximizing the log-likelihood function:

$$l(\theta) = -\frac{TN}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{T}(\log|\mathbf{H}_t| + \mathbf{\Xi}_t'\mathbf{H}_t^{-1}\mathbf{\Xi}_t),$$

where θ denotes unknown parameters to be estimated, N is the number of assets, T is the number of observations, and $\mathbf{H}_t$ and $\mathbf{\Xi}_t$ are as previously defined.

Table 9 provides the t tests on the correlation coefficients between change in the Nikkei 225 and the lagged PCRs derived via the multivariate GARCH model (5). Our null hypothesis H_0 of the t test is that the average values of the time-varying correlation coefficients between the lagged PCRs and the Nikkei 225 changes are zero. Our alternative hypothesis H_1 is that the average values of the time-varying correlation coefficients between the lagged PCRs and the Nikkei 225 changes are positive.

As shown, we can see that all lags from the first to the eighth lags (except for the first and third lags) statistically reject the null hypothesis, and support the alternative hypothesis. That is, in six of eight cases, the average values of the time-varying correlation coefficients between the lagged PCRs and the Nikkei 225 changes are statistically significantly positive at the 1% level. In particular, there is a stronger nonlinear relation between the sixth PCR lag and the Nikkei 225 changes as the corresponding *t* statistic is largest. Figure 3 displays the time-series trend of the time-varying correlation coefficients between the Nikkei 225 changes and the sixth PCR lag. Using this figure, we also confirm that the positive relation continues rather strongly throughout the full sample period.

6. Discussion

This section discusses our results and derives their implications. First, the results demonstrate the effectiveness of nonlinear models, such as the multivariate GARCH model used as in this study, for investigating the forecastability of sentiment variables for future stock market trends. This is highlighted by the difference in results between the simple linear model (4) and the nonlinear model (5). As shown in Table 8, the simple linear regression (4) cannot clearly present the relation between PCR and future Nikkei 225 changes, while the correlation coefficients between these variables derived from a multivariate GARCH model (5) demonstrates their strong relation in Table 9. Hence, although nonlinear models are not often used in existing studies analyzing investor sentiment, we recommend their use in related studies in the future.

Second, an important point concerns investor irrationalities. Our results in Table 9 indicate that after the option investors become bullish (bearish), the Nikkei 225 falls (rises) in a few months. Because of data unavailability, we cannot confirm whether smart money exists in Japanese options markets, and whether they judge the market turning points with accuracy. However, our evidence demonstrates overall that Japanese option investors are incorrect about market turning points. This means that smart money, even if it does exist, cannot correct the incorrect herding behavior of noisy investors in Japanese option markets.

Finally, an academically significant point concerns market efficiency. As we well know, the strong-form market efficient hypothesis (Fama 1970; 1991) means that prices reflect all information that can be acquired by painstaking analysis of companies, markets, and the economy, even insider information. In such a market, we should not be able to earn profits if we analyze the markets by collecting all available information. In contrast, our evidence shows that when we use past information on the PCR, we can obtain profits, even after deducting transaction costs. Thus, we suggest that our evidence is inconsistent with the strong-form efficient market hypothesis.

7. Conclusion

This paper has investigated the effectiveness of equity investment strategies using option investor sentiment in Japan. The three main findings of this paper are as follows.

- First, trading strategies using PCR are profitable when we consider several strategies on a monthly basis. We obtain rather successful results even if we take the effects of transaction costs into account. Our empirical analysis demonstrates that the best PCR strategy for the underlying asset, the Nikkei 225, is the 88.7–116.5 (30–70 percentile) strategy.
- Second, by modeling PCRs with the new econometric SETAR model, we find that there exist at least three regimes in PCR dynamics in Japan. We also examined two investment strategies by using the thresholds derived from the SETAR(1) model, and revealed that both strategies yield profitable results, even after considering the effects of transaction costs.
- Furthermore, we have also revealed that the Nikkei 225 is predictable using the lagged PCRs. In particular, our investigation into the nonlinear relation between lagged PCRs and the Nikkei 225 changes using a multivariate GARCH model clearly indicates that bull (bear) stock markets follow negative (positive) sentiment in the options markets in Japan. Our nonlinear analysis also suggests we can predict changes in the Nikkei 225 using the levels of past PCRs from the options markets.

The profits gained by the several trading strategies after deducting transaction costs may not be large; however, in an academic sense, the evidence is that we can beat the stock market by using the irrational herding behavior of public investors. This contradicts the strong-form of the efficient market hypothesis. To reveal further real world financial markets, we need to conduct research in different international markets using a similar context in the future.

References

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of Internet stock message boards. *Journal of Finance,* 59, 1259–1293.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance,* 61, 1645–1680.

Bandopadhyaya, A., & Jones, A. L. (2006). Measuring investor sentiment in equity markets. *Journal of Asset Management,* 7, 3–4.

Barberis, N., Shleifer, A., & Vishny, R. W. (1998). A model of investor sentiment. *Journal of Financial Economics,* 49, 307–343.

Barberis, N., Shleifer, A., & Wurgler, J. (2005). Comovement. *Journal of Financial Economics,* 75, 283–317.

Billingsley, R. S., & Chance, D. M. (1988). Put-call ratios and market timing effectiveness. *Financial Analysts Journal,* 15, 25–28.

Bodurtha, J. N., Kim, D., & Lee, C. M. C. (1995). Closed-end country funds and U.S. market sentiment. *Review of Financial Studies,* 8, 879–918.

Brooks, C., & Garrett, I. (2002). Can we explain the dynamics of the UK FTSE 100 stock and stock index futures markets? *Applied Financial Economics,* 12, 25–31.

Campbell, J. Y., Grossman, S. J., & Wang, J. (1993). Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics,* 108, 905–939.

Chang, C., Hsieh, P., & Lai, H. (2009). Do informed option investors predict stock returns? Evidence from the Taiwan Stock Exchange. *Journal of Banking & Finance*, forthcoming.

Cornelli, F., Goldreich, D., & Ljungqvist, A. (2006). Investor sentiment and pre-IPO markets. *Journal of Finance,* 61, 1187–1216.

Coval, J. D., & Shumway, T. (2001). Is sound just noise? *Journal of Finance,* 56, 1887–1910.

Daniel, K. D., Hirshleifer, D. A., & Subrahmanyam, A. (1998). Investor psychology and security market under- and over-reactions. *Journal of Finance,* 53, 1839–1886.

DeLong, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy,* 98, 703–738.

Edmans, A., García, D., & Norli, Ø. (2007). Sports sentiment and stock returns. *Journal of Finance,* 62, 1967–1998.

Engle R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. *Econometrics Theory,* 11, 122–50.

Fama, E. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, 25, 383–417

Fama, E. (1991). Efficient capital markets: II. *Journal of Finance*, 46, 1575–1617.

Fisher, K. L., & Statman, M. (2000). Investor sentiment and stock returns. *Financial Analysts Journal,* 56, 16–23.

Hirshleifer, D. (2001). Investor psychology and asset prices. *Journal of Finance,* 56, 1533–1597.

Kroner, K. F., & Ng, V. K. (1998). Modelling asymmetric comovement of assets returns. *Review of Financial Studies*, 11, 817–44.

Kumar, A., & Lee, C. M. C. (2006). Retail investor sentiment and return comovements. *Journal of Finance,* 61, 2451–2486.

Lee, C., Shleifer, A., & Thaler, R. H. (1991). Investor sentiment and the closed-end fund puzzle. *Journal of Finance,* 46, 75–109.

Neal, R., & Wheatley, S. M. (1998). Do measures of investor sentiment predict returns? *Journal of Financial and Quantitative Analysis,* 33, 523–547.

Pan, J., & Poteshman, A. M. (2006). The Information in option volume for future stock prices. *Review of Financial Studies,* 19, 871–908.

Shleifer, A. (2000). *Inefficient markets: An introduction to behavioral finance,* Oxford University Press.

Shleifer, A., & Summers, L. H. (1990). The noise trader approach to finance, *Journal of Economic Perspectives,* 4, 19–33.

Solt, M. E., & Statman, M. (1988). How useful is the sentiment index? *Financial Analysts Journal,* 44, 45–55.

Stoll, H., & Whaley, R. (1986). Expiration day effects of index options and futures. *Working Paper*, Vanderbilt University.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance,* 62, 1139–1168.

Notes

Note 1. There are several studies of investor sentiment in the US. These include Solt and Statman (1988), DeLong et al. (1990), Shleifer and Summers (1990), Lee et al. (1991), Campbell et al. (1993), Bodurtha et al. (1995), Barberis et al. (1998), Daniel et al. (1998), Neal and Wheatley (1998), Fisher and Statman (2000), Shleifer (2000), Coval and Shumway (2001), Hirshleifer (2001), Antweiler and Frank (2004), Barberis et al. (2005), Baker and Wurgler (2006), Bandopadhyaya and Jones (2006), Cornelli et al. (2006), Kumar and Lee (2006), Edmans et al. (2007), Tetlock (2007), amongst others. As none of these uses the PCR, comparable studies are limited, even internationally.

Note 2. Financial institutions and technical analysts appear to use several methods of deriving the PCR. However, there appears to be no significant difference in these formulas.

Note 3. For example, from the OEX options data, a PCR greater than 100 (70) is considered bullish, a ratio less than 60 (40) is considered bearish, and ratios in between are considered neutral. Hence, in the 100 (70)–60 (40) strategy, when the PCR is over 100 (70), it is a signal to buy, while when the PCR falls below 60 (40), it is a signal to sell.

Note 4. We also tried the 70–40 and 65–40 strategies; however, they did not work for the Nikkei 225 Index options.

Note 5. For example, in the 100–60 strategy, when the PCR is over 100, we buy the Nikkei 225, and when the PCR falls below 60, we sell the Nikkei 225.

Note 6. In the grid search procedure, following Brooks and Garrett (2002), we searched for the threshold value that minimizes the sum of squared residuals.

Table 1. Descriptive statistics of the put–call ratio in Japan

Statistic	Whole sample period Jan. 1990 to Feb. 2005	Subsample period Jan. 1990 to Dec. 1997	Subsample period Jan. 1998 to Feb. 2005
Mean	104.48	100.572	108.852
Median	103.03	96.863	109.143
Maximum	210.76	210.759	184.807
Minimum	49.17	49.165	66.904
Std. Dev.	25.42	28.261	21.148
Skewness	0.71	0.867	0.813
Kurtosis	4.46	4.415	4.565
Observations	182	96	86

Notes: 1. The full sample period is from January 1990 to February 2005.
2. Std. Dev. is the sample standard deviation.

Table 2. Percentile values of the put–call ratio in Japan

Percentile	Whole sample period Jan. 1990 to Feb. 2005	Subsample period Jan. 1990 to Dec. 1997	Subsample period Jan. 1998 to Feb. 2005
10%	72.90	67.630	82.573
90%	132.43	132.407	132.172
15%	80.95	70.852	87.556
85%	127.99	125.568	128.740
20%	84.27	75.546	89.266
80%	122.24	121.360	124.046
25%	87.41	81.686	94.361
75%	120.09	118.320	121.232
30%	88.66	85.336	97.273
70%	116.47	112.917	118.800
35%	93.45	87.451	100.182
65%	112.36	107.393	115.795
40%	96.65	88.658	102.475
60%	109.72	106.439	112.131

Notes: 1. The full sample period is from January 1990 to February 2005.
2. The figures in the table are the percentile values from the distribution of the PCR in Japan.

Table 3. Profits and losses from the market timing strategies using the put–call ratio

Strategy	Number of transactions	Average annual percentage return	Gross percentage return
100−60	5	−0.577	−8.757
72.9−132.4	11	0.860	13.047
81.0−128.0	15	1.465	22.227
84.3−122.2	23	2.835	43.003
87.4−120.1	33	3.327	50.455
88.7−116.5	39	3.586	54.382
93.5−112.4	45	3.527	53.491
96.7−109.7	53	3.080	46.714

Notes: 1. The sample period is from January 1990 to February 2005.

2. Average annual percentage return is from each strategy over the whole sample period.

3. Gross percentage return is from each strategy for the whole sample period.

Table 4. Profits and losses from the market timing strategies using the put–call ratio, including transaction costs

Strategy	Number of transactions	Average annual percentage return	Gross percentage return
100−60	5	−0.687	−10.417
72.9−132.4	11	0.740	11.230
81.0−128.0	15	1.297	19.664
84.3−122.2	23	2.428	36.819
87.4−120.1	33	2.511	38.086
88.7−116.5	39	2.518	38.182
93.5−112.4	45	2.284	34.638
96.7−109.7	53	1.444	21.902

Notes: 1. The sample period is from January 1990 to February 2005.

2. Average annual percentage return is from each strategy over the whole sample period.

3. Gross percentage return is from each strategy for the whole sample period.

Table 5. Schwarz criterion in autoregressive modeling of the put–call ratio in Japan

	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
SC	9.3130	9.3215	9.3195	9.3252	9.3510
	AR(6)	AR(7)	AR(8)	AR(9)	AR(10)
SC	9.3797	9.3867	9.4078	9.4440	9.4737

Notes: 1. Samples are monthly from January 1990 to February 2005.

2. SC denotes Schwarz criterion.

Table 6. Estimation results of the AR(1) model and the double threshold SETAR models for the put–call ratio in Japan

	AR(1) model	Double-threshold SETAR(1) model [93.5−126.8]		
		Beyond the lower threshold	Within the central bound	Beyond the upper threshold
γ_0	104.5973***	85.8128***	142.9388***	191.0295***
t statistic	40.2806	3.4381	4.8562	5.2312
p value	0.0000	0.0006	0.0000	0.0000
γ_1	0.2284**	0.0995	−0.3159	−0.5079**
t statistic	2.5294	0.3334	−1.1674	−2.0612
p value	0.0123	0.7388	0.2431	0.0393
r_0	−		93.5	
r_1	−		126.8	
Adjusted *R*-squared	0.0465		0.1467	
Sum of squared residuals	110875.2000		99777.3035	
		Double-threshold SETAR(1) model [72.0−126.8]		
		Beyond the lower threshold	Within the central bound	Beyond the upper threshold
γ_0		−98.8669**	68.8311***	191.0295***
t statistic		−2.1638	5.2966	5.2312
p value		0.0305	0.0000	0.0000
γ_1		3.0291***	0.3372**	−0.5079**
t statistic		4.3030	2.5532	−2.0612
p value		0.0000	0.0107	0.0393
r_0			72.0	
r_1			126.8	
Adjusted *R*-squared			0.1516	
Sum of squared residuals			99205.8815	

Notes: 1. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

2. Samples are monthly for the period January 1990 to February 2005.

3. γ_0 and γ_1 are model parameters and r_0 and r_1 are threshold values.

Table 7. Profits and losses from the market timing strategies using the threshold values from the SETAR model, including transaction costs

Strategy	The number of times of transactions	Average annual percentage return	Gross percentage return
93.5−126.8	23	0.980	14.861
72.0−126.8	11	0.740	11.230

Notes: 1. The sample period is from January 1990 to February 2005.

2. Average annual percentage return is from each strategy over the whole sample period.

3. Gross percentage return is from each strategy for the whole sample period.

Table 8. Forecasting power of lagged put–call ratio for the changes of Nikkei 225

	PCR(−1)	PCR(−2)	PCR(−3)	PCR(−4)	PCR(−5)
Constant	−767.406**	144.112	−398.535	−79.627	−401.449
p value	0.030	0.739	0.384	0.887	0.403
Coefficient	6.009*	−2.601	2.852	−0.198	2.701
p value	0.051	0.551	0.496	0.968	0.525
Adj. R^2	0.008	−0.003	−0.002	−0.006	−0.003
SE	1289.183	1287.006	1245.248	1250.690	1221.495
	PCR(−6)	PCR(−7)	PCR(−8)	PCR(−9)	PCR(−10)
Constant	−1136.587**	84.040	−191.339	−644.421	−322.281
p value	0.025	0.820	0.520	0.112	0.352
Coefficient	9.834**	−1.874	1.057	5.722	2.366
p value	0.032	0.588	0.689	0.130	0.485
Adj. R^2	0.037	−0.004	−0.005	0.011	−0.003
SE	1198.177	1225.372	1169.926	1102.096	1063.772

Notes: 1. Samples are monthly for the period from January 1990 to February 2005.

2. SE denotes the standard error of the regression.

3. * and ** denote statistical significance at the 10% and 5% levels, respectively.

4. Adj. R^2 is the Adjusted R-squared.

Table 9. The results of *t* tests on the time-varying correlation coefficients

	PCR(−1)	PCR(−2)	PCR(−3)	PCR(−4)
Correlation coefficients	−0.1000	0.1000	0.0126	0.0674
t statistic	−7.0690	8.9040***	1.0757	8.3137***
p value	−	0.0000	0.1418	0.0000
	PCR(−5)	PCR(−6)	PCR(−7)	PCR(−8)
Correlation coefficients	0.1101	0.1824	0.1100	0.1189
t statistic	10.5250***	19.8002***	8.5936***	7.2872***
p value	0.0000	0.0000	0.0000	0.0000

Notes: 1. Samples are monthly for the period from January 1990 to February 2005.

2. Correlation coefficients in the table are the average values of the time-varying correlation coefficients derived by the multivariate GARCH model.

3. *** denotes statistical significance that supports that the average values of the time-varying correlation coefficients are positive at the 1% level.

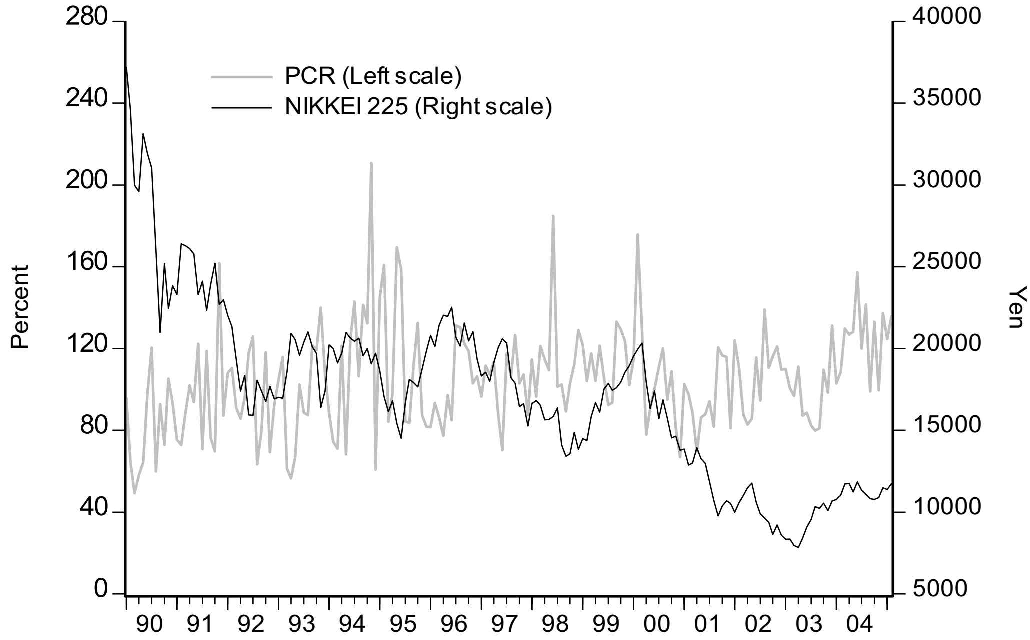
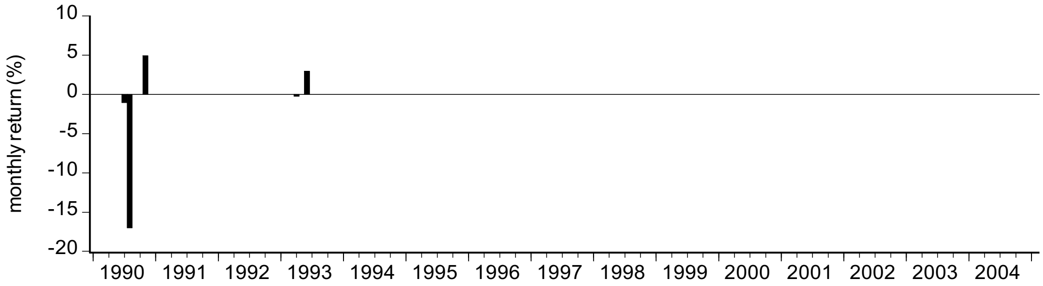
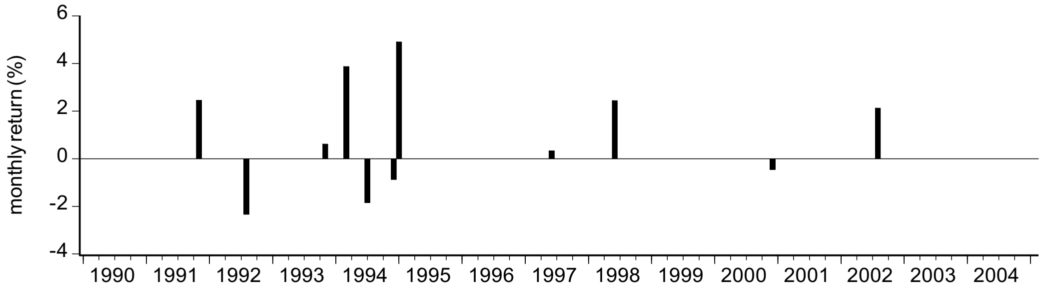


Figure 1. Trends in the Nikkei 225 and the put–call ratio

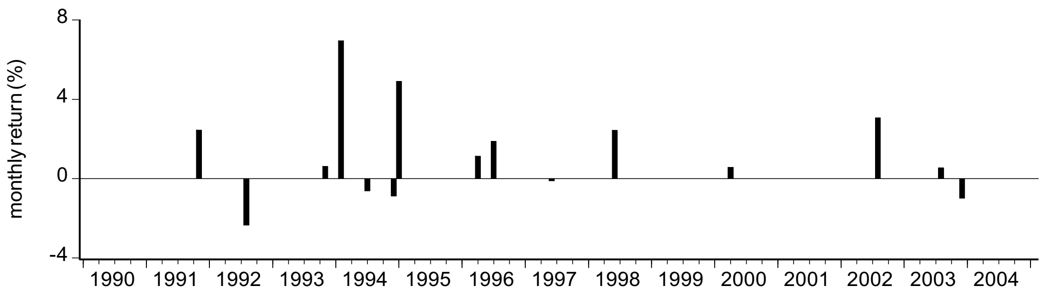
Panel A 100−60 strategy



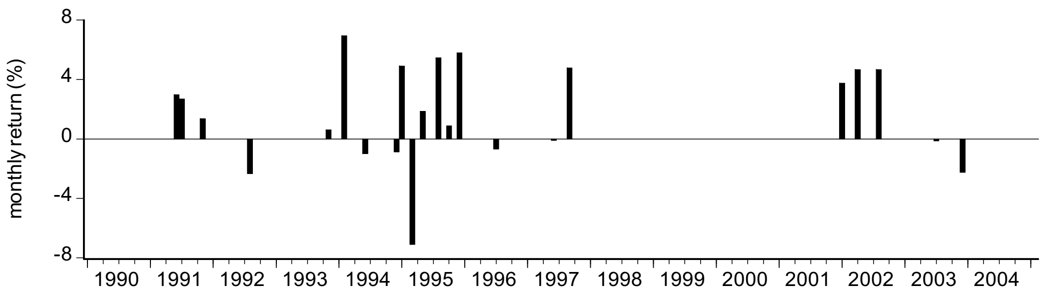
Panel B 72.9−132.4 strategy



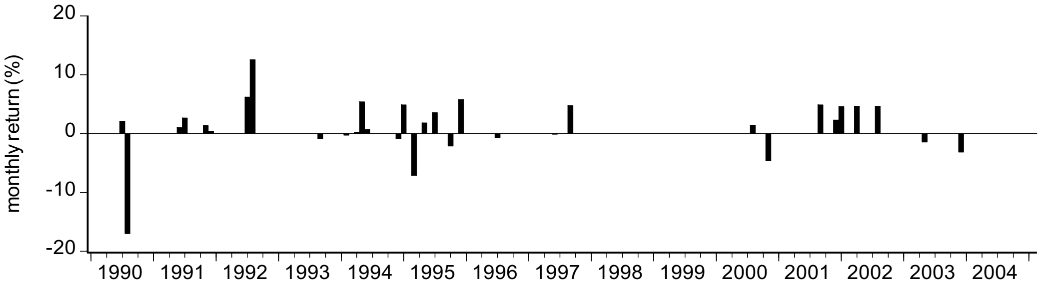
Panel C 81.0−128.0 strategy



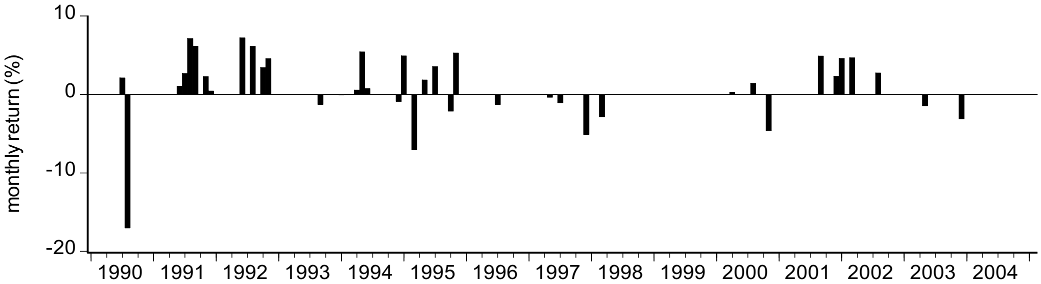
Panel D 84.3−122.2 strategy



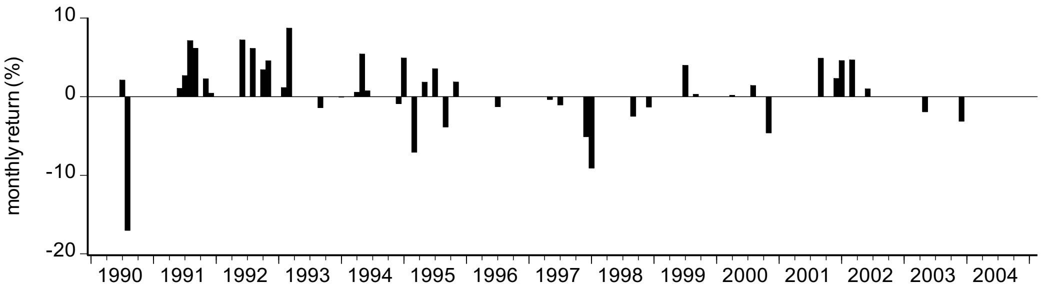
Panel E 87.4−120.1 strategy



Panel F 88.7−116.5 strategy



Panel G 93.5−112.4 strategy



Panel H 96.7−109.7 strategy

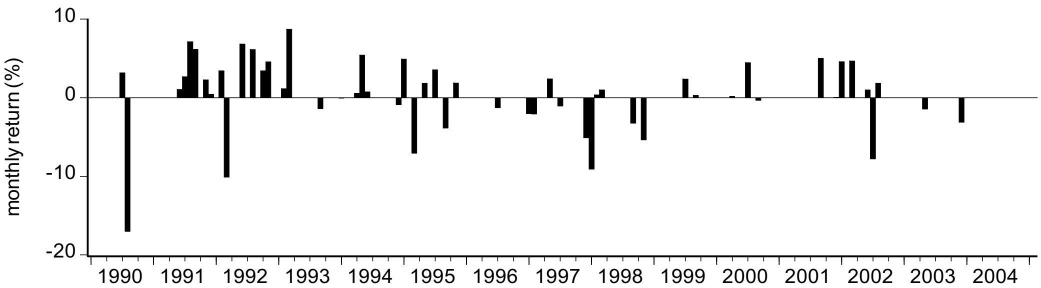


Figure 2. Profits and losses from the investment strategies using the put–call ratio, including transaction costs

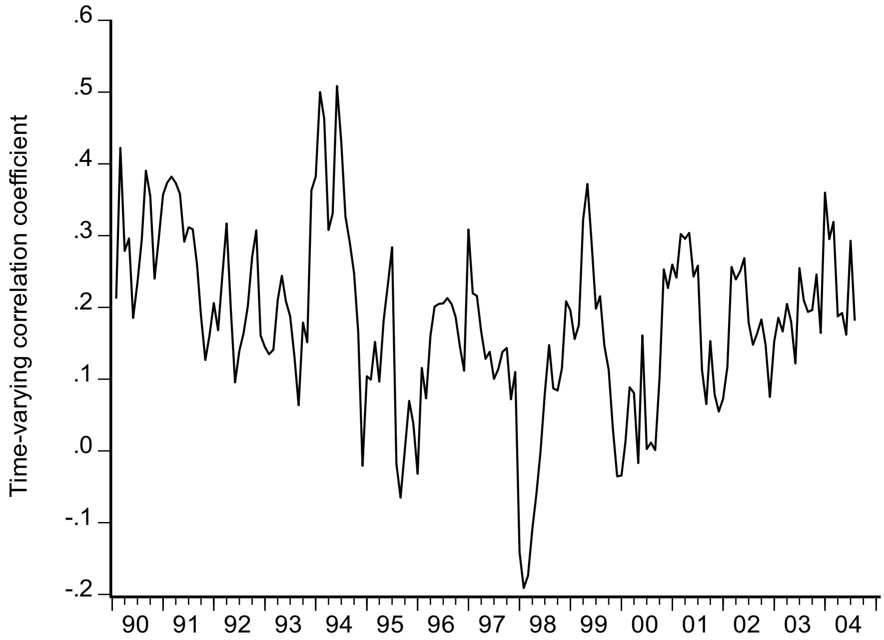


Figure 3. Time-varying correlation coefficients between changes in the Nikkei 225 and six-month lagged put–call ratio