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Asymmetric temporary and permanent stock-price innovations

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Abstract

This paper estimates a nonlinear, structural bivariate threshold model in order to identify independent temporary and permanent stock-price innovations in positive-return and negative-return regimes. The model finds that temporary innovations account for as much as 68% of the innovations after negative returns and less than 4% of the innovations after positive returns. This paper shows that the negative-return regime is also the high-volatility regime, a result that links the excess-volatility and asymmetric-volatility literatures. This link provides evidence that temporary stock-price innovations are due primarily to time-varying expected returns in an efficient market and not to a market inefficiency.

JEL classification: G12; C32
Keywords: Nonlinear structural model; Threshold vector autoregression; Temporary–permanent decomposition; Asymmetric volatility; Excess volatility

1. Introduction

There are at least two distinct literatures in finance that analyze the volatility of stock prices. One literature documents and seeks to explain asymmetric volatility in which stock returns and the conditional variance of next period's return are negatively correlated. A separate literature documents and seeks to explain the excess volatility in stock prices relative to the volatility of the underlying stream of dividend cash flows. This paper shows that excess volatility and asymmetric volatility represent two sides of the same phenomenon, and it uses this link to show that

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temporary stock-price innovations are due primarily to time-varying expected returns in an efficient market and not a market inefficiency.

Asymmetric volatility in stock prices was first documented by Black (1976), Christie (1982), and Cox and Ross (1976). There are two competing explanations for asymmetric volatility: a "leverage effect" in which decreasing stock prices increase financial leverage, which increases risk and the volatility of stock prices, and a "volatility-feedback effect" in which expected returns time vary in anticipation of changing volatility, which causes current stock prices to adjust inversely with anticipated changes in volatility. The two explanations imply opposite causality. The lever-age effect implies that changing stock prices cause volatility to change, whereas the volatility-feedback effect implies that anticipated changes in volatility cause current stock prices to change. Black (1976) and Christie (1982) find evidence in favor of the leverage effect, whereas Campbell and Hentschel (1992), French et al. (1987), and Pindyck (1984) find evidence in favor of the volatility-feedback effect. Schwert (1989) finds that the leverage effect is not large enough to explain the degree of asymmetric volatility found in stock prices, and the more recent studies of Bekaert and Wu (2000) and Wu (2001) find that the volatility-feedback effect dominates the leverage effect.

A large literature on excess volatility has grown out of the relationship between stock prices and their underlying fundamental value. Using a standard dividend-discount model to determine fundamental value, Shiller (1981, 1984) and LeRoy and Porter (1981) show that stock prices are much more volatile than the underlying stream of dividend cash flows would suggest. In addition to a generally accepted permanent component in stock prices such as a random walk, Summers (1986) hypothesizes that the "excess" volatility in stock prices is due to a slowly mean-reverting component with temporary innovations. Subsequently, the univariate linear studies of Fama and French (1988), Kim et al. (1991), Lo and MacKinlay (1988), Mankiw et al. (1985, 1991), Poterba and Summers (1988), Richardson (1993), and Shively (2000), and the multivariate linear studies of Cochrane (1994), Gallagher and Taylor (2000), Hess and Lee (1999), Lee (1995), and Shively (2003) all find evidence in favor of temporary stock-price innovations.

There is a recent and growing literature that addresses whether stock prices are consistent with a nonlinear data-generating process. Chaotic nonlinearity is the most common type of nonlinearity modeled in stock prices, but the empirical evidence from chaos models is mixed at best. Abhyankar et al. (1997), Kohers et al. (1997), Mayer-Foulkes and Feliz (1996), Pandey et al. (1998), Scheinkman and LeBaron (1989), and Willey (1992) find little or no evidence of nonlinear chaotic dynamics, whereas Atchison and White (1996) find evidence in favor of chaotic nonlinearity. Other types of nonlinearities have been modeled in stock prices with more success. Kanas (2001) and Qi (1999) find evidence supporting neural-network models; Evans (1998), Schaller and van Norden (1997), and Turner et al. (1989) find evidence supporting Hamilton's (1989) Markov-switching model; and Sarantis (2001) finds evidence supporting smooth transition autoregressive models.

This paper evaluates the existence, size, and dynamic effect of temporary and permanent stock-price innovations in two independent stock-market regimes using a nonlinear, structural bivariate threshold model. This model exploits the joint behavior of real stock prices (returns) and real interest rates, which are related through the dividend-discount model, and it identifies independent temporary and permanent stock-price innovations using covariance restrictions and the Blanchard and Quah (1989) restriction on the long-run multiplier of the temporary stock-price innovation. The threshold variable used to partition the regimes is the stock return lagged one period. Therefore, variation in the stock return last period determines the stochastic process of the model this period. Consequently, this is a model in which investors learn from period to period, like the two-regime Markov-switching models of Evans (1998) and Turner et al. (1989), which incorporate short-term learning dynamics, and the models in Barsky and De Long (1993) and

Timmermann (1994), in which investors periodically update their long-term expectations of future dividends.

After applying Tsay's (1998) chi-squared test to show that real stock prices (returns) and real interest rates are highly nonlinear in the one-period lagged return, this paper partitions the data into two regimes based on whether the return last period was positive or negative. This partition is supported by the asymmetric-volatility literature, which finds that stock volatility behaves differently after positive and negative returns, as well as Tsay's (1998) multivariate threshold modeling technique. The model finds that temporary innovations account for as much as 68% of the innovations to stock prices in the negative-return regime and less than 4% of the innovations in the positive-return regime. Consequently, the model finds that stock prices follow an asymmetric nonlinear threshold process in which the temporary innovations are concentrated in, and dominate, the negative-return regime. When the two regimes are looked at in terms of their volatility, the standard deviation of stock returns is over 43% higher in the negative-return regime than in the positive-return regime, a result that is consistent with the asymmetric-volatility literature. Consequently, the temporary innovations are concentrated in the high-volatility regime, which links the excess-volatility and asymmetric-volatility literatures.

There has been a substantial debate in the excess-volatility literature about whether temporary stock-price innovations are due to time-varying expected returns in an efficient market or to a predictable component in an inefficient market. The link identified here between excess volatility and asymmetric volatility provides insight into this issue. The fact that temporary innovations are concentrated in the negative-return high-volatility regime, combined with the evidence from previous studies in favor of the volatility-feedback effect as the source of asymmetric volatility, is evidence that the source of the temporary stock-price innovations is primarily time-varying expected returns in an efficient market.

The remainder of this paper is organized as follows: Section 2 describes the model, Section 3 describes the data, Section 4 tests for threshold nonlinearity, Section 5 presents empirical results, Section 6 presents robustness checks, and Section 7 concludes.

2. The structural bivariate threshold model

Let s_t be the natural logarithm of the stock price at time t, $\tilde{r}_t = s_t - s_{t-1}$ be the nominal stock return from $t-1$ to t, $\tilde{i}_t$ be the nominal interest rate from $t-1$ to t, p_t be the natural logarithm of the time t consumer price index, and $\pi_t = p_t - p_{t-1}$ be the inflation rate from $t-1$ to t. Then the real stock return is $r_t = \tilde{r}_t - \pi_t$ and the real interest rate is $i_t = \tilde{i}_t - \pi_t$. Let $X_t = (r_t, i_t)'$; then the nonlinear threshold vector autoregression under consideration is

$$X_t = c_j + \sum_{i=1}^{p_j} \phi_i^{(j)} X_{t-i} + \varepsilon_t^{(j)} \text{ for } \tau_{j-1} < r_{t-d} \leq \tau_j \tag{1}$$

where $j = \{1, 2\}$ indexes the two stock-market regimes, c_j is a constant vector, $p_j > 0$, $\phi_i^{(j)}$ is a (2×2) parameter matrix, and $\epsilon_t^{(j)} = (\epsilon_t^{r_j}, \epsilon_t^{i_j})'$ is a mean zero vector of innovations with covariance structure $\sum_j$. The stationary threshold variable used to partition the regimes is r_{t-d}, the stock return delayed d periods where the delay indicates the speed of adjustment to the long-run mean. The threshold return values are $-\infty = \tau_0 < \tau_1 < \tau_2 = \infty$, where τ_1 is the single nontrivial threshold value that partitions the two stock-market regimes.

Threshold models are linear within a regime but nonlinear across regimes since the parameters, lag lengths, and innovation covariance structure differ across regimes. They can be estimated in each regime by least squares conditional on the threshold variable, the number of regimes, and the lag lengths. Based on a nonrestrictive set of assumptions, Tsay (1998) shows that the least-squares estimates are strongly consistent as the regime sample sizes go to infinity.

The model in Eq. (1) can be rewritten as

$$\Phi_j(L)X_t = \varepsilon_t^{(j)} \text{ for } \tau_{j-1}<r_{t-d}\leq\tau_j \tag{2}$$

where $\Phi_j(L)$ has the appropriate lags p_j and the constant vector c_j is suppressed. This model assumes that real stock returns and real interest rates are stationary. Therefore, Eq. (2) can be inverted and represented by the infinite-order moving-average model

$$X_t = C_j(L)\varepsilon_t^{(j)} \text{ for } \tau_{j-1}<r_{t-d}\leq\tau_j \tag{3}$$

where $C_j(L)=\Phi_j(L)^{-1}$ and the contemporaneous effect of $\epsilon_t^{(j)}$ on X_t is the identity matrix.

The structural bivariate threshold model that identifies the independent temporary and permanent stock-price innovations in each regime is

$$X_t = A_j(L)\eta_t^{(j)} \text{ for } \tau_{j-1}<r_{t-d}\leq\tau_j \tag{4}$$

where $\eta_t^{(j)}=(\eta_t^{T_j}, \eta_t^{P_j})'$ is a mean zero vector of orthogonalized innovations with a covariance structure normalized to the identity matrix. The structural model is identified in each regime by comparing Eqs. (3) and (4) and observing that $\epsilon_t^{(j)}=A_j(0)\eta_t^{(j)}$ and $A_j(k)=C_j(k)A_j(0)$, where $A_j(0)$ is the contemporaneous effect of $\eta_t^{(j)}$ on X_t in regime j. Therefore, the four elements of $A_j(0)$ just identify the structural model in each regime. Covariance restrictions establish three of the four restrictions necessary to identify $A_j(0)$ since $\sum_j=A_j(0)A_j(0)'$. The fourth restriction is the Blanchard and Quah (1989) identifying restriction that the long-run dynamic response of the stock price to the structural innovation $\eta_t^{T_j}$ is zero, or $\sum_{k=1}^{\infty}a_{1,1}^{(j)}(k)=0$. These four restrictions just identify the four elements of $A_j(0)$ in each regime. The last restriction identifies $\eta_t^{T_j}$ as the temporary stock-price innovation and $\eta_t^{P_j}$ as the permanent stock-price innovation in the structural model.

3. Data

The data are end-of-month observations from January 1955 through December 2003 of the Standard & Poor's (S&P) 500 composite stock index, the Federal Funds interest rate from the Federal Reserve Board, and the consumer price index (for all urban consumers) from the Bureau of Labor Statistics. The Federal Funds rate is used in order to emphasize the link between the financial markets and Federal Reserve monetary policy.[1]

The model in Section 2 assumes that stock prices are nonstationary and that real stock returns and real interest rates are mean-stationary. The Dickey-Fuller unit-root t test finds that the S&P 500 index does not reject the unit-root null hypothesis in favor of the trend-stationary alternative, whereas the real S&P 500 index return and the real Federal Funds rate reject the unit-root null hypothesis at the 0.001 level in favor of the mean-stationary alternative. Fig. 1 presents time plots

[1] Conover et al. (1999) and Jensen et al. (1996) discuss the link between stock index returns and monetary conditions.

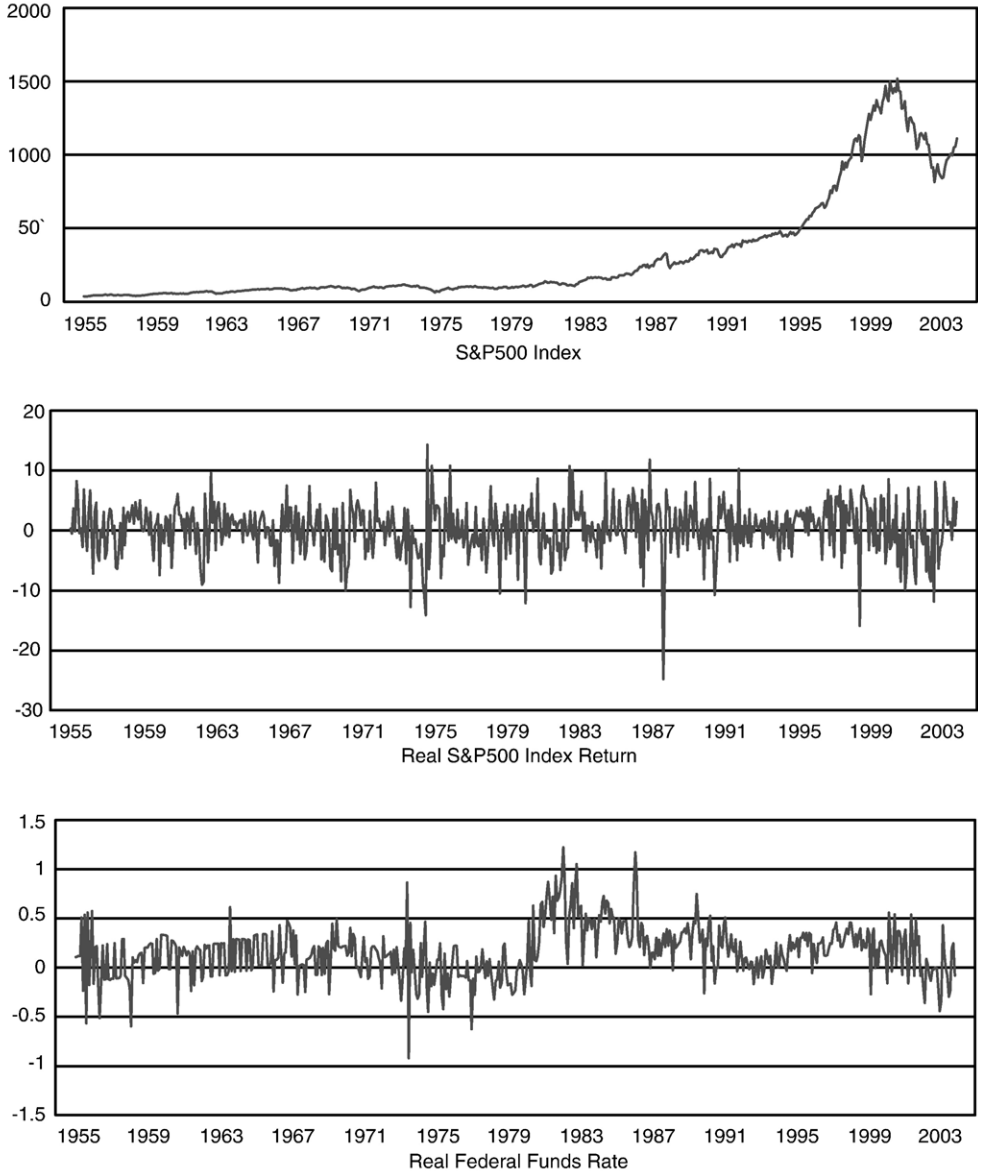

Fig. 1. Time plots of the S&P 500 index, the real S&P 500 index return, and the real Federal Funds rate.

of the S&P 500 index, the real S&P 500 index return, and the real Federal Funds rates. It shows that the S&P 500 index drifts upward without bound and that the real S&P 500 index return and real Federal Funds rate both fluctuate around a fixed mean.

4. Bivariate threshold nonlinearity

This section applies Tsay's (1998) chi-squared test for multivariate threshold nonlinearity to show that real stock prices (returns) and real interest rates are highly consistent with bivariate

Table 1
Tsay's (1998) chi-squared test for multivariate threshold nonlinearity

Delay $d=$	1	2	3	4	5	6	7	8	9	10	11	12
Chi-squared test statistic	85.8	50.5	52.3	59.7	47.2	74.8	49.9	55.3	49.6	59.8	55.0	35.7

This test statistic has an asymptotic chi-squared distribution with 50 degrees of freedom. The 0.05, 0.025, 0.01, and 0.001 level critical values are 67.5, 71.4, 76.2, and 86.7, respectively.

threshold nonlinearity. This test performs well in finite samples, it does not have problems with undefined parameters under the null hypothesis, it does not depend on the alternative model, and it is robust to heteroskedasticity. The test detects bivariate threshold nonlinearity in the model

$$\Phi(L)X_t = \varepsilon_t$$

by first reordering the data by the threshold variable and then computing predictive residuals using recursive least squares. If the null hypothesis of one regime is correct, then the predictive residuals are independent of the regressor and are white noise. If the alternative hypothesis of threshold nonlinearity is correct, then the predictive residuals are no longer white noise since they are correlated with the regressor, and the least-squares estimates are biased. The test statistic is asymptotically chi-squared distributed with $2(2p+1)$ degrees of freedom, where p is the number lags in the estimated model.

Table 1 lists values of the chi-squared test statistic using 100 observations for the start-up period of the recursive least squares estimates, $p=12$ lags, and delays $d \leq p$ for the threshold variable. Twelve lags are used in order to capture annual variation in the monthly data and to be consistent with the structural model estimated in Section 5. The maximum value of the chi-squared test statistic is 85.8 at the delay $d=1$ for the threshold variable. With 50 degrees of freedom, this test statistic is highly significant at the 0.01 level and decisively rejects the null hypothesis of one regime in favor of bivariate threshold nonlinearity.

5. Empirical results

This section presents forecast-error variance decompositions and impulse response functions from the model in Section 2 for real stock prices in order to identify the existence, size, and dynamic effect of independent temporary and permanent stock-price innovations in the two stock-market regimes.[2] The model is estimated with 12 lags in order to capture annual variation in the monthly data. The variance decompositions are normalized such that the forecast-error variances of the two structural innovations sum to 100%. Therefore, only the percentage of the forecast-error variance that is due to the temporary stock-price innovation is presented. The impulse response functions are generated by one-unit temporary or permanent innovations. The forecast-error variance decompositions and impulse response functions both include one-standard error confidence intervals, which are bootstrapped with 400 repetitions of the model.

[2] Forecast-error variance decompositions and impulse response functions are not presented for the real interest rate since its purpose here is to identify the independent temporary and permanent stock-price innovations. Briefly, the variance decompositions show that the innovation which has a temporary impact on stock prices accounts for about 50% of the Federal Funds forecast-error variance in the negative-return regime and about 75% of the forecast-error variance in the positive-return regime. The impulse response functions show that both innovations have only a small dynamic impact on the real interest rate.

Table 2
Number of regime changes

Regime at time t	Regime at time $t-1$	
	Negative	Positive
Negative	114	139
Positive	140	182

Tsay's (1998) multivariate threshold modeling technique selects the delay for the threshold variable based on the maximum value of the chi-squared test statistic. The maximum value of 85.8 in Table 1 selects a delay of $d=1$ for the threshold variable. Therefore, variation in the stock return last month determines the stochastic process of the model this month. The two stock-market regimes are partitioned based on whether the 1-month lagged stock return is positive or negative. Consequently, the single nontrivial threshold return value τ_1 is set at 0. This data partition is supported by the asymmetric-volatility literature, which finds that stock volatility behaves differently after positive and negative returns. There are 254 (44.2%) observations in the regime defined by lagged negative returns and 321 (55.8%) observations in the regime defined by lagged positive returns. Table 2 lists the number of times that the model changes from one regime to another. Of the 254 observations in the negative-return regime, the model stays in this regime 114 (44.9%) times and switches to the positive-return regime 140 (55.1%) times. Of the 321 observations in the positive-return regime, the model stays in this regime 182 (56.7%) times and switches to the negative-return regime 139 (43.3%) times.

Table 3 presents forecast-error variance decompositions. They show that temporary innovations dominate stock prices at short-run and medium-run horizons in the negative-return regime with a maximum impact of 68.5% at the 6-month horizon and an impact of over 50%

Table 3
Forecast-error variance decompositions

Forecast horizon (months)	No regimes (575 obs.)	(S.E.)	Negative regime (254 obs.)	(S.E.)	Positive regime (321 obs.)	(S.E.)
Percentage of the variance due to temporary stock-price innovations:						
1	17.2	(17.3)	60.3	(31.1)	4.0	(11.2)
2	17.3	(17.3)	64.4	(31.5)	2.7	(10.2)
3	18.0	(17.6)	67.0	(31.5)	2.6	(10.0)
4	17.3	(17.3)	66.8	(31.5)	2.4	(9.7)
5	17.5	(17.4)	67.6	(31.5)	2.4	(9.5)
6	18.6	(17.7)	68.5	(31.6)	3.0	(9.4)
9	18.6	(17.5)	67.3	(31.4)	3.6	(8.9)
12	17.1	(16.3)	61.9	(30.4)	3.6	(8.2)
24	12.6	(12.0)	51.4	(27.0)	2.4	(5.4)
36	9.4	(8.8)	41.4	(22.6)	1.8	(3.8)
48	7.3	(6.7)	33.1	(18.6)	1.3	(2.9)
60	5.8	(5.2)	26.7	(15.2)	1.1	(2.3)
72	4.8	(4.2)	21.7	(12.6)	0.9	(1.9)
84	4.1	(3.5)	18.0	(10.5)	0.8	(1.6)
96	3.5	(3.0)	15.2	(8.9)	0.7	(1.4)
108	3.1	(2.6)	13.0	(7.7)	0.6	(1.2)
120	2.7	(2.2)	11.3	(6.7)	0.5	(1.1)

Standard errors are listed in parentheses. They are bootstrapped with 400 repetitions of the model.

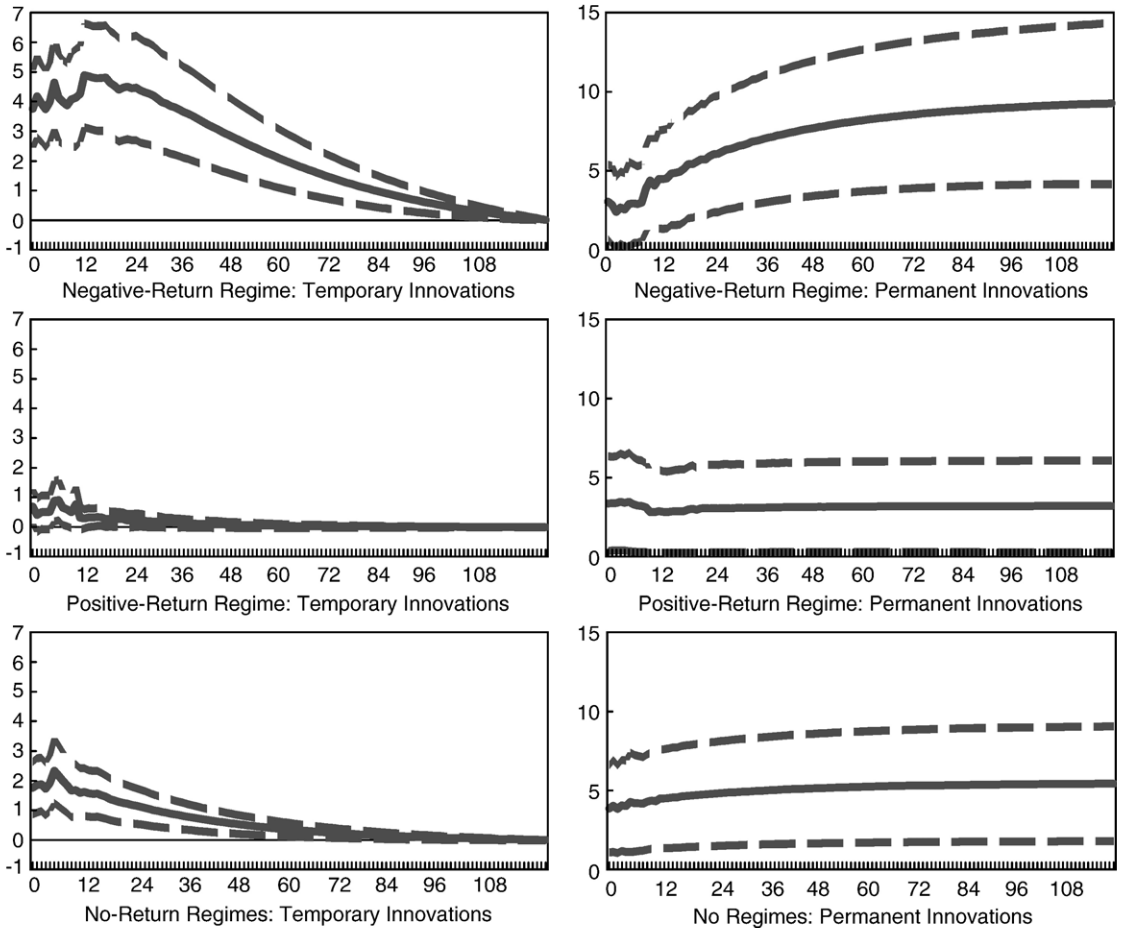

Fig. 2. Impulse response functions to one-unit temporary or permanent stock-price innovations. Standard-error bands are bootstrapped with 400 repetitions of the model.

through the 25-month horizon. In contrast, temporary innovations account for less than 4% of the forecast-error variance in the positive-return regime after the first month.

Fig. 2 presents impulse response functions. They show that temporary innovations have a large dynamic effect in the negative-return regime with an initial impact of 3.8, a maximum impact of 4.9 at the 13-month horizon, and a response that is over 1.0 through the 80-month horizon. In contrast, temporary innovations in the positive-return regime have an impact that is less than 1.0 at all forecast horizons. Permanent innovations also have a much larger long-run impact of 9.6 in the negative-return regime relative to the long-run impact of 3.2 in the positive-return regime.

6. Robustness checks

This section considers several robustness checks to the specification of the model above. The model is estimated without regimes, Tsay's (1998) multivariate threshold modeling technique is used to partition the two regimes, and the model is estimated after replacing four potential outliers with an average of the two surrounding months. The summaries here show that the empirical results presented above are robust to these specification changes.

When the model is estimated without regimes, then it finds evidence consistent with previous studies. The variance decompositions in Table 3 show that temporary stock-price innovations account for 15% to 19% of the forecast-error variance through the 17-month horizon and over 10% through the 33-month horizon. The impulse response functions in Fig. 2 show that temporary innovations have a maximum impact of 2.3 at the 6-month horizon and a response of over 1.0 through the 29-month horizon. Permanent innovations have an initial impact of 3.7 and a long-run impact of 5.4.

Tsay's (1998) multivariate threshold modeling technique selects the threshold return value τ_1 based on the minimum value of the Akaiki information criterion (AIC) in a grid search across the empirical range of the threshold variable. Conducting the grid search across $\tau_1 \in [-5.0\%, 5.0\%]$ with 500 points in the interval, the minimum AIC of 6413.9 selects $\tau_1 = 0.269\%$ and essentially partitions the sample into negative-return and positive-return regimes. There are 266 (46.3%) observations in the (essentially) negative-return regime ($\tau_{t-1} \leq 0.269$) and 309 (53.7%) observations in the (essentially) positive-return regime ($\tau_{t-1} > 0.269$). Consequently, only 12 (2.1%) observations switch regimes and the empirical results mirror those above. In the (essentially) negative-return regime, temporary innovations have a maximum impact on the forecast-error variance of 59.0% at the 6-month horizon and an impact of over 40% through the 25-month horizon. In the (essentially) positive-return regime, temporary innovations account for less than 8% of the forecast-error variance at all horizons.

The model is estimated after replacing four observations for which the stock return was over ±3 standard deviations from zero with an average of the two nearest monthly observations in order to eliminate the impact of potential outliers. Three observations are affected in the negative-return regime and 1 observation is affected in the positive-return regime. The empirical results after this change are similar to, yet more pronounced than, the results above. In the negative-return regime, temporary innovations have a maximum impact on the forecast-error variance of 86.0% at the 6-month horizon and an impact of over 50% through the 39-month horizon. In the positive-return regime, temporary innovations account for less than 2.4% of the forecast-error variance at all horizons.

7. Conclusion

This paper estimates a nonlinear, structural bivariate threshold model which partitions the data into positive-return and negative-return regimes based on whether the one-month lagged return is positive or negative. The model finds that temporary innovations account for as much as 68% of the innovations to stock prices in the negative-return regime and less than 4% of the innovations in the positive-return regime. When the two regimes are looked at in terms of their volatility, the standard deviation of monthly stock returns of 5.1% in the negative-return regime is over 43% higher than the standard deviation of 3.6% in the positive-return regime, a result that is consistent with the asymmetric-volatility literature. Consequently, the temporary innovations are concentrated in the negative-return high-volatility regime, which is evidence that excess volatility and asymmetric volatility are separate realizations of the same phenomenon. When combined with the evidence that the volatility-feedback effect is the primary source of asymmetric volatility, this is evidence that the primary source of the temporary stock-price innovations is time-varying expected returns in an efficient market rather than a predictable component in an inefficient market.

References

Abhyankar, A., Copeland, L., Wong, W., 1997. Uncovering nonlinear structure in real-time stock-market indexes: the S&P 500, the DAX, the Nikkei 225, and the FTSE-100. Journal of Business & Economic Statistics 15, 1–14.

Atchison, M., White, M., 1996. Disappearing evidence of chaos in security returns: a simulation. Quarterly Journal of Business and Economics 35, 21–37.

Barsky, R., De Long, J., 1993. Why does the stock market fluctuate? Quarterly Journal of Economics 108, 291–311.

Bekaert, G., Wu, G., 2000. Asymmetric volatility and risk in equity markets. Review of Financial Studies 13, 1–42.

Black, F., 1976. Studies of stock price volatility changes. Proceedings of the 1976 Meetings of the Business and Economic Statistics Section, American Statistical Association, pp. 177–181.

Blanchard, O., Quah, D., 1989. The dynamic effects of aggregate demand and supply disturbances. American Economic Review 79, 665–673.

Campbell, J., Hentschel, L., 1992. No news is good news: an asymmetric model of changing volatility in stock returns. Journal of Financial Economics 31, 281–318.

Christie, A., 1982. The stochastic behavior of common stock variances: value, leverage, and interest rate effects. Journal of Financial Economics 10, 407–432.

Cochrane, J., 1994. Permanent and transitory components of GNP and stock prices. Quarterly Journal of Economics 109, 241–265.

Conover, C., Jensen, G., Johnson, R., 1999. Monetary environment and international stock returns. Journal of Banking and Finance 23, 1357–1381.

Cox, J., Ross, S., 1976. The valuation of options for alternative stochastic processes. Journal of Financial Economics 3, 145–166.

Evans, M., 1998. Dividend variability and stock market swings. Review of Economic Studies 65, 711–740.

Fama, E., French, K., 1988. Permanent and temporary components of stock prices. Journal of Political Economy 96, 246–273.

French, K., Schwert, G., Stambaugh, R., 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 3–29.

Gallagher, L., Taylor, M., 2000. Measuring the temporary component of stock prices: robust multivariate analysis. Economics Letters 67, 193–200.

Hamilton, J., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica 57, 357–384.

Hess, P., Lee, B., 1999. Stock returns and inflation with supply and demand disturbances. The Review of Financial Studies 12, 1203–1218.

Jensen, G., Mercer, J., Johnson, R., 1996. Business conditions, monetary policy, and expected security returns. Journal of Financial Economics 40, 213–237.

Kanas, A., 2001. Neural network linear forecasts for stock returns. International Journal of Finance and Economics 6, 245–254.

Kim, M., Nelson, C., Startz, R., 1991. Mean reversion in stock prices? A reappraisal of the empirical evidence. Review of Economic Studies 58, 515–528.

Kohers, T., Pandey, V., Kohers, G., 1997. Using nonlinear dynamics to test for market efficiency among the major U.S. stock exchanges. Quarterly Review of Economics and Finance 37, 523–545.

Lee, B., 1995. The response of stock prices to permanent and temporary shocks to dividends. Journal of Financial and Quantitative Analysis 30, 1–22.

LeRoy, S., Porter, R., 1981. The present-value relation: tests based on implied variance bounds. Econometrica 49, 555–574.

Lo, A., Mackinlay, A., 1988. Stock market prices do not follow random walks: evidence from a simple specification test. Review of Financial Studies 1, 41–66.
Mankiw, N., Romer, D., Shapiro, M., 1985. An unbiased reexamination of stock market volatility. Journal of Finance 40, 677–687.
Mankiw, N., Romer, D., Shapiro, M., 1991. Stock market forecastability and volatility: a statistical appraisal. Review of Economic Studies 58, 455–477.
Mayer-Foulkes, D., Feliz, R., 1996. Nonlinear dynamics in the stock exchange. Revista de Analisis Economico 11, 3–21.
Pandey, V., Kohers, T., Kohers, G., 1998. Deterministic nonlinearity in the stock returns of major European equity markets and the united states. Financial Review 33, 45–63.
Pindyck, R., 1984. Risk, inflation, and the stock market. American Economic Review 74, 335–351.
Poterba, J., Summers, L., 1988. Mean reversion in stock prices: evidence and implications. Journal of Financial Economics 22, 27–59.
Qi, M., 1999. Nonlinear predictability of stock returns using financial and economic variables. Journal of Business & Economic Statistics 17, 419–429.
Richardson, M., 1993. Temporary components of stock prices: a skeptic's view. Journal of Business & Economic Statistics 11, 199–207.
Sarantis, N., 2001. Nonlinearities, cyclical behavior and predictability in stock markets: international evidence. International Journal of Forecasting 17, 459–482.
Scheinkman, J., LeBaron, B., 1989. Nonlinear dynamics and stock returns. Journal of Business 62, 311–337.
Schwert, G., 1989. Why does stock market volatility change over time. Journal of Finance 44, 1115–1153.
Schaller, H., van Norden, S., 1997. Regime switching in stock market returns. Applied Financial Economics 7, 177–191.
Shiller, R., 1981. Do stock prices move too much to be justified by subsequent dividends? American Economic Review 71, 421–436.
Shiller, R., 1984. Stock prices and social dynamics. Brookings Papers on Economic Activity 2, 457–510.
Shively, P., 2000. Stationary components in stock prices: an exact pointwise most powerful invariant test. Journal of Business & Economic Statistics 18, 489–496.
Shively, P., 2003. International evidence of temporary and permanent stock-price innovations: a multivariate approach. Applied Economics Letters 10, 499–503.
Summers, L., 1986. Does the stock market rationally reflect fundamental values? Journal of Finance 43, 591–601.
Timmermann, A., 1994. Can agents learn to form rational expectations? Some results on convergence and stability of learning in the UK stock market. Economic Journal 104, 777–797.
Tsay, R., 1998. Testing and modeling multivariate threshold models. Journal of the American Statistical Association 93, 1188–1202.
Turner, C., Startz, R., Nelson, C., 1989. A Markov model of heteroskedasticity, risk, and learning in the stock market. Journal of Financial Economics 25, 3–22.
Willey, T., 1992. Testing for nonlinear dependence in daily stock indices. Journal of Economics and Business 44, 63–74.
Wu, G., 2001. The determinants of asymmetric volatility. Review of Financial Studies 14, 837–859.