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Sentiment on cross-sectional stock returns and volatility

Abstract

This paper finds that the cross-section of future stock returns and volatility are conditional upon beginning-of-month sentiment. Specifically, small-sized, growth, and low dividend stocks are vulnerable to sentiment, and, when sentiment is high, extreme short-term losers and mid-term winners tend to earn significant low returns, but long-term losers earn positive returns in the subsequent month. An optimistic sentiment is followed by a downward change in conditional volatility for short-term winners, but an upward shift in conditional volatility for large stocks, extreme growth stocks, value stocks, higher cash flow/price stocks, higher earning/price stocks, long-term losers, and mid-term winners. On the contrary, a pessimistic sentiment leads to a downward volatility change for moderate cash flow/price and dividend-yield stocks, the highest earning/price stocks, long-term losers, and mid-term winners, but a higher volatility for larger stocks, lower cash flow/price stocks, moderate earning/price stocks, long-term winners, and stocks with short-term moderate performance. Above evidence reveals that stocks which are easy to arbitrage and attract rational speculation are not necessarily less volatile.

Keywords: sentiment, stock returns, volatility.
JEL Classification: G10, G11, G14.

Introduction

Conventional finance argues that when a market is efficient and rational, arbitrage will drive prices close to their fundamental values. However, continuing evidence of market anomalies, such as market under-reaction and overreaction, excess volatility, challenges efficient market theory. One reason is that arbitrage cannot eliminate the price divergence that comes from noise trader risk. Noise trader risk, an idea first introduced by De Long, Shleifer, Summers, and Waldmann (DSSW hereafter, 1990) and studied further by Shleifer and Vishny (1997), is the risk that the mis-pricing arbitrageurs try to exploit, worsens in the short run. In the DSSW (1990) model, the deviations in price from fundamental value created by investor sentiment are unpredictable. As asset prices deviate from intrinsic values and arbitrageurs bet against this mispricing, they run a risk, at least in the short run, because investor sentiment becomes more extreme and prices move even further away from their fundamental values. As a result, arbitrage is limited, mis-pricing cannot be eliminated completely, and investor sentiment affects security prices in equilibrium.

The noise trader model of DSSW has motivated a number of papers exploring the influences of noise trader risks on returns and volatility through their response to changes in sentiment regarding returns and volatility. In the context of the impacts of sentiment on returns, several studies have found the usefulness of sentiment index for explaining equity returns (e.g., Lee, Shleifer and Thaler, 1991; Kelly, 1997; Kothari and Shanken, 1997; Neal and Wheatley, 1998; Shiller, 1981; Shiller, 2000; Baker and Wurgler, 2000)[1]. In comparison, only a few papers have also investigated the relationship between sentiment and volatility. Brown (1999) showed that deviations from the mean level of sentiment are positively related to volatility during trading hours. Lee, Jiang, and Indro (2002) found that bullish (bearish) changes in sentiment lead to downward (upward) adjustments in volatility; Wang, Keswani, and Taylor (2006), contrarily, found that sentiment has limited forecasting ability power once returns are included as a forecasting variable.

Regarding cross-sectional returns, Lee, Shleifer and Thaler (1991) documented that investor sentiment affects the risk of common stocks and that firms with high sensitivity to this factor must be compensated for this extra risk. They also claimed that it affects the small-cap stock returns more. But they failed to point out which characteristics of stocks are strongly affected by investor sentiment. To complement this, Baker and Wurgler (2006) theoretically suggested that investor sentiment had significant effect on the cross-section of stock returns when sentiment-based demands or arbitrage constraints varied across stocks. Through these two channels, investor sentiment would be expected to have relatively more impact on newer, smaller and highly volatile stocks and firms in distress, with extreme growth potential and without dividends. A bunch of theoretical and empirical research has also

[1] However, not all related papers have come to these conclusions. Elton, Gruber and Busse (1998) showed that sentiment risk as defined by closed-end fund discount changes is uncorrelated with the time series of stock returns; Brown and Cliff (1999) found a weak relation between sentiment and short-term returns; both Brown and Cliff (2004) and Solt and Statman (1988) found stronger evidence that sentiment is caused by returns.

shown that, due to their high idiosyncratic risk and status as being more costly or impossible to trade, arbitrage was relatively risky and costly for newer, smaller and highly volatile and distressed, with extreme growth potential, firms (Wurgler and Zhuravskaya, 2002; Amihud and Mendelsohn, 1986; D'Avolio, 2002; Geczy, Musto, and Reed, 2002; Jones and Lamont, 2002; Duffie, Garleanu, and Pedersen, 2002).

One implication of the DSSW theory is that irrational investors acting coherently on noisy signal can cause systematic risk. If noise traders are sentimental, because noise trading not only affects prices and causes volatility but also the propensity of investors to speculate (Brown, 1999; Lee, Jiang, and Indro, 2002), sentiment should be correlated with volatility. Because stocks have different sensitivities to innovations in sentiment, sentiment has cross sectional effects on stock volatility. In addition, volatility is related to measures of risk, such as idiosyncratic risk, size, book-to-market, leverage, and earnings quality and accounting losses (Lui, Markov, Tamayo, 2007); then the cross sectional variation in risk leads to the cross-section of volatility. As noted, the volatility of firms whose value is judged much more subjectively and hard to arbitrage is more likely to be affected by shifts in investor sentiment. But in the DSSW model, rational arbitrage can increase volatility if arbitragers' early buying triggers positive feedback trading. To the best of my knowledge, no papers have investigated the relationship between a cross-section of stock volatility and investor sentiment[1]. In addition, changes in volatility induce changes in the investment opportunity set and asset risk (see Campbell and Hentschel, 1992; Glosten, Jagannathan, and Runkle, 1993), which in turn affect expected returns (De Long, Shleifer, Summers, and Waldmann, 1990; Bali and Cakici, 2006). Hence, stocks with different sensitivities to innovations in volatility should have different expected returns. Then it is in my interest to understand the impact of sentiment on stock returns and volatility.

On the other hand, Lee, Jiang, and Indro (2002) argued that because the DSSW (1990) model predicts that noise trader sentiment is relevant in asset pricing, empirical tests about the impact of sentiment either on the mean or variance of asset returns alone are mis-specified and somewhat incomplete. However, prior literature tests the impact of sentiment either on expected returns and variance alone (LST, 1991; Neal and Wheatley, 1998; Simon and Wiggons, 2001; Wang, 2001; Wang, Keswani, and Taylor, 2006) or ignores the lagged information (Lee, Jiang, and Indro, 2002). Additionally, though Lee, Jiang, and Indro (2002) contemporaneously tested the effects of expected returns and volatility for indices, they did not consider the cross-sectional effect of firm characteristics.

Therefore, this paper expands on the findings of prior work in two important ways. First, I extend Lee, Jiang, and Indro's (2002) work by examining portfolios sorted by: size, book-to-market equity, cash flow/price, and dividend/price, earnings/price, past five-year returns, past one-month returns, and past one-year returns to see if sentiment explanation ability is pervasive across different portfolios. I also include lagged returns to account for the limited forecasting ability of power of sentiment once returns are included as a forecasting variable[2] (Wang, Keswani, and Taylor, 2006). Second, I extend Baker and Wurgler's (2006) work by contemporaneously testing the impact of sentiment on the expected returns and volatility and investigating more firm-characteristic-based portfolios. Because cross-sectional patterns of sentiment-driven mis-pricing are hard to identify directly, I adopt investor sentiment of Baker and Wurgler (2006) to test whether or not there exists cross-sectional stock volatility.

I found strong evidence that investor sentiment influences future returns and volatility. In particular, when sentiment is high, extreme short-term losers and mid-term winners tend to earn significantly lower returns, but moderate cash flow stocks and long-term losers earn positive returns in the subsequent month. An optimistic sentiment is followed by an upward change in conditional volatility for large stocks, extreme growth stocks, value stocks, low and high cash flow/price stocks, moderate earning/price stocks, long-term losers, and mid-term winners. On the contrary, a pessimistic sentiment leads to a downward volatility change for moderate cash flow/price and dividend-yield stocks, high earning/price stocks, long-term losers, and mid-term winners.

The rest of this paper is organized as follows: section 1 discusses theoretical predictions, section 2 describes the empirical hypotheses and the data, and the empirical tests are presented in section 3, while the last section concludes the paper.

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[1] Ang, Hodrick, Xing, and Zhang (2006) investigated how aggregate volatility affects the cross-section of expected stock returns and found that stocks with high sensitivities to innovations in aggregate volatility have low average returns. Size, book-to-market, momentum, and liquidity effects cannot explain either the low average returns of stocks with high exposure to systematic volatility risk or the low average returns of stocks with high idiosyncratic volatility.

[2] Lee, Jiang, and Indro (2002) modified their model to include lagged excess return terms to remove the serial correlations (Dickey and Fuller, 1979; Balvers et al., 2000), and reduce the non-normality of the standardized residuals.

1. Theoretical effects of sentiment on the cross-section of returns and volatility

1.1. The cross-section of returns. Baker and Wurgler (2006) addressed the theoretical effects of sentiment on the cross-section of returns. They argued that investor sentiment might affect the cross-section of stock prices through two channels: sentiment-based demands and arbitrage constraints.

In the first channel, sentiment drives the relative demand for speculative investments, and so causes cross-sectional effects even if arbitrage constraints are the same across stocks. The more subjective their valuations are, the more vulnerable the stock is to shifts in the propensity to speculate. For instance, consider a firm whose lack of earnings histories is combined with apparently unlimited growth opportunities. Then its value contains much more subjectivity. It allows both unsophisticated investors and sophisticated investors to defend their decisions with a wide spectrum of valuations and even further argue for the high end of valuations. By contrast, much less subjective judgment is possible on the value of a firm with a long earnings history, tangible assets, and stable dividends. Therefore, it is likely to be less affected by fluctuations in the propensity to speculate. This channel suggests that investors demand stocks with some salient characteristics that are compatible with their sentiment. Investors have a low propensity to speculate on safe firms, like profitable, dividend-paying stocks. Likewise, salient characteristics such as, "no earnings", "young age", and "no dividends" contribute to the stocks being considered as speculative.

In the second channel, a body of theoretical and empirical research shows that arbitrage tends to be particularly risky and costly for young, small, unprofitable extreme-growth or distressed stocks (Wurgler and Zhuravskaya, 2002; Amihud and Mendelsohn, 1986; D'Avolio, 2002; Geczy, Musto, and Reed, 2002; Jones and Lamont, 2002; Duffie, Garleanu, and Pedersen, 2002; Lamont and Thaler, 2003; Mitchell, Pulvino, and Stafford, 2002; Brunnermeier and Pedersen, 2004). The same stocks that are the hardest to arbitrage also tend to be the most difficult to value (Baker and Wurgler, 2006). These two channels lead to quite similar predictions and have somewhat overlapping effects, which strengthens the predictions about what regions of the cross-section are most affected by sentiment. Along the same line of reasoning, stocks with prior extreme-performance have relatively subjective valuations and are relatively hard to arbitrage, and so they should be expected to be most affected by sentiment. Accordingly, hypothesis 1 is formed as follows:

Hypothesis 1: Young, small, low BE/ME, low dividend-paying, prior extreme-performing stocks are hard to value and arbitrage, therefore their expected returns are expected to be more affected by sentiment.

1.2. The cross-section of volatility. Intuitively, investor sentiment might also affect the cross-section of stock volatility through these two channels: sentiment-based demands and arbitrage constraints. There exist many supporting papers that investor sentiment will affect volatility through shocks from speculative demand. For example, Brown (1999) found that noise traders' sentiment was positively associated with stock volatility. Both Shiller (1981) and Leroy and Porter (1981) found stock market volatility to be far greater than could be justified by changes in dividends, which is usually named as "excess volatility" of stock prices. Black (1986) stated that the volatility of price will change over time for reasons like the rate of arrival of information about the firm, the firm's leverage, and changes of noise trading, etc. DDSW (1990) also modeled that unconditional price variance increases as investor sentiment persists. Then, stocks that are prone to be speculative objects will become more volatile.

From a theoretical standpoint, it is not clear whether arbitrage influences stock market volatility and cross sectional difference in volatility. Arbitrage is usually thought to restore the price equilibrium and lead to a less volatile market. However, there is much evidence that stock index futures failed to destabilize the market, and even increase cash market volatility (Maberly, Allen, and Gilbert, 1989; Brorsen, 1991; Harris, 1989; Lee and Ohk, 1992; Antoniou and Holmes, 1995). This raises a question as to whether arbitrageur activities increase instead of decrease price volatility. When rational speculators trade in an attempt to move prices in the direction of fundamentals, noise traders adopting positive feedback trading or trend chasing, rational speculation can be destabilizing to the markets. If arbitrageurs anticipate that their initial purchase (sell) will drive the price up (down) today and stimulate positive feedback trading tomorrow, they pay to trade ahead of noise traders. Tomorrow, positive feedback traders buy (sell) in response to today's price rise (fall) even when arbitrageurs sell out (buy in) and stabilize prices. As a result, arbitrageurs ride on the positive feedback trading and destabilize prices (De Long, Shleifer, Summers, and Waldmann, 1990). Therefore, stocks that are easy to arbitrage and attract rational speculation are not necessarily less volatile.

Overall, the difference in speculative demand and arbitrage costs would lead to cross section of expected returns and price volatilities. However, arbitrage does not necessary stabilize prices. Stocks that are easy to arbitrage are not necessarily less volatile than stocks that are hard to arbitrage. Accordingly, hypothesis 2 is formed as follows:

Hypothesis 2: Sentiment has cross sectional effects on stock volatility, but stocks that are easy to arbitrage are not necessarily less volatile than stocks that are hard to arbitrage.

2. Data and empirical methodology

2.1. Data. The firm-level data are from the merged CRSP-Compustat database. The data include all NYSE, AMEX, and NASDAQ common stocks that have market equity data for June of *t* and accounting data at the end of fiscal year *t*-1. The sample ranges from January, 1966 through to December, 2005. The size portfolios are constructed at the end of each June using price multiplied by the number of shares outstanding at the end of June, and are matched to monthly returns for July of year *t* to June of *t*+1. BE/ME portfolios are formed on BE/ME at the end of each June, where both BE and ME used in June of year *t* are the book equity and market equity for the last fiscal year end in *t*-1. Likewise, CF/P, E/P and D/P portfolios are formed on cash flow/price, earnings/price, and dividend yield at the end of each June, where the cash flow is total earnings before extraordinary items, plus equity's share of depreciation, plus deferred taxes (if available) for the last fiscal year end in *t*-1, earnings are total earnings before extraordinary items for the last fiscal year end in *t*-1, total dividends paid from July of *t*-1 to June of *t* per dollar of equity in June of *t*. Momentum portfolios are constructed monthly using NYSE prior two-to-twelve (2-12) month return, short-term reversal portfolios are constructed monthly using NYSE prior one-month return, and long-term reversal portfolios are constructed monthly using NYSE prior thirteen-to-sixty (13-60) month return[1].

Baker and Wurgler (2006) formed a composite index of sentiment that is based on the first principal component of six (standardized) sentiment proxies over 1962-2005 data, where each of the proxies has first been orthogonalized with respect to a set of macroeconomic conditions. The six underlying proxies for sentiment include the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. The closed-end fund discount, *CEFD*, is the average difference between the net asset values (NAV) of closed-end stock fund shares and their market prices. NYSE share turnover is based on the ratio of reported share volume to average shares. The number of IPOs, NIPO, and the average first-day returns, RIPO, are included since they are often viewed as sensitive to sentiment. The equity share is defined as gross equity issuance divided by gross equity plus gross long-term debt issuance. The dividend premium, *PD−ND*, is the log difference of the average market-to-book ratios of payers and nonpayers. The Baker and Wurgler's sentiment index was taken from Jeffrey Wurgler' website. Figure 1 presents the monthly sentiment index over the sample period.

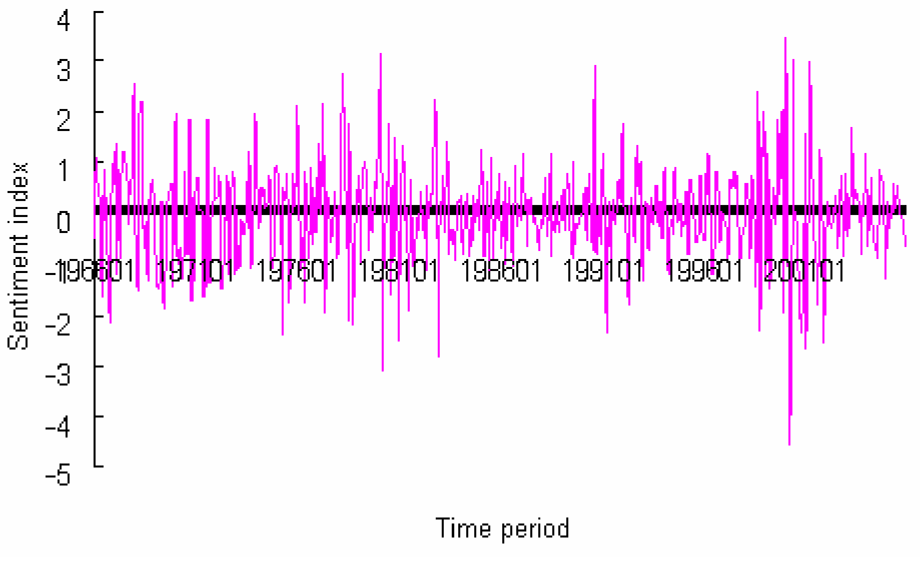

Fig. 1. Monthly sentiment index over 1966-2005

[1] The data were taken from Fama and French's website.

2.2. Empirical methodology. Lee, Jiag, and Indro (2002) argued that, in the DSSW model, the net result of sentiment changes on mean returns depends on the importance of the "price-pressure" relative to the "hold-more" effects. The "price-pressure" effect states that when the average sentiment of noise traders is bullish (bearish), the noise trading creates price pressure that leads to a purchase (sale) price higher (lower) than intrinsic value and thereby lowers expected returns. The "hold-more" effect refers to when noise traders' sentiment becomes bullish (bearish), their increased (decreased) holdings of risky assets raise (reduce) market risk and thereby result in higher (lower) expected returns. As a consequence, when noise traders' sentiment becomes more bullish, the returns will be higher only if the "hold-more" effects are larger than the "price-pressure" effect. However, when noise traders' sentiment becomes more bearish, both the "hold-more" and the "price-pressure" effects reinforce the probability that returns will be negative.

In the DSSW model, the magnitude of the changes in the noise traders' misperceptions about the asset risk also affects expected returns. Because noise traders usually buy (sell) just when other noise traders are buying (selling), their capital losses from poor market timing are larger and they increase with the magnitude of the changes in their misperceptions. Then, the changes in the noise traders' misperceptions about the asset risk result in lower expected returns. This is the so called "Friedman effect". On the other hand, the "create-space" effect implies that a rise in noise traders' misperceptions about the asset risk raises price uncertainty and crowds out risk-averse investors. This benefits noise traders. Overall, expected returns are higher when the "create-space" effect dominates the "Friedman effect" (Lee, Jiag, and Indro, 2002).

This section used AR(1)-EGARCH(1,1)-M model to examine the relationship between sentiment index and volatility. The GARCH model can capture whether the conditional volatility contemporaneously increased (decreased) with sentiment index. The GARCH-M model adds the heteroscedasticity term directly into the mean equation and the risk premium will be an increasing function of the conditional volatility of returns. In addition, though the GARCH and GARCH-M models assume that positive return shocks generate the same magnitude of volatility as negative return shocks do, they fail to capture the leverage effect that a negative return shock increases volatility more than a positive return shock does (Black, 1976). If the leverage effect really exists, the GARCH and GARCH-M models will underestimate the amount of volatility following negative return shocks and overestimate the amount of volatility following positive shocks. To complement this, Nelson's (1991) exponential GARCH (EGARCH) model has been used to estimate the asymmetric response to stock returns of conditional stock return volatility. Then the following AR(1)-EGARCH-M model was conducted to model the four effects of noise trading:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 h_t + \alpha_3 S_{t-1} + \eta_t,$$

$$\eta_t \sim \mathrm{N}(0, h_t) \tag{1}$$

$$h_t = \beta_0 + \beta_1 \frac{|\eta_{t-1}|}{\sqrt{h_{t-1}}} + \beta_2 \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} + \beta_3 h_{t-1} + \beta_4 R_{t-1} +$$

$$+ \beta_5 (S_{t-1})^2 D_{t-1} + \beta_6 (S_{t-1})^2 (1 - D_{t-1}), \tag{2}$$

where R_t is the monthly returns on the portfolio, h_t is the conditional volatility, and S_t is a measure of noise trader risk associated with the monthly sentiment, which is measured by sentiment index. The EGARCH-M model added the heteroscedasticity term (h_{it}) directly into the mean equation and the risk premium will be an increasing function of the conditional volatility of returns. If conditional volatility explains stock return, α_2 will be significantly different from zero. The positive (negative) estimate of α_2 implied that the stock returns contemporaneously increase (decrease) with conditional volatility. The asymmetry effect in the EGARCH model is captured by the volatility parameter β_2, which is expected to be negative if a negative shock is more likely to cause a larger upward revision of volatility than a positive shock of similar magnitude. Wang, Keswani and Taylor (2006) argued that the impact of sentiment on volatility became extremely weak when lagged return information was considered, therefore this equation also included prior market returns to avoid overestimating the role of sentiment in predicting volatility.

The measure of the noise trader risk is the sentiment index (S_t). $D_{t-1} = 0$ if $S_{t-1} \leq 0$ and $D_{t-1} = 1$ if $S_{t-1} > 0$. The hold-more and price-pressure effects are correlated with the direction of shifts in noise trader sentiment, and they directly influence returns. Therefore, the net effect of hold-more and price pressure effects on returns is reflected in the mean equation through the coefficients of α_3. The Friedman and create-space effects are related to the magnitude of shifts in noise trader sentiment, and they influence returns indirectly through changes in noise traders' misperceptions of the asset's risk. The coefficient α_2 reflects the net impact of the Friedman and the create-space effects on returns. The coefficients β_5 and β_6 in the conditional equation capture the effect of the magnitude of shifts in sentiment on volatility formation.

3. Empirical results

To distinguish between a common sentiment component and a common business cycle component, Baker and Wurgler (2006) formed an index by orthogonalizing to macro variables. In particular, they regressed each of the six raw proxies on growth in the industrial production index, growth in consumer durables, non-durables, and services, and a dummy variable for NBER recessions. The residuals from these regressions are thought to be cleaner proxies for investor sentiments. This section used Baker and Wurgler (2006) orthogonalized sentiment index to examine the cross sectional effects of investor sentiments.

Table 1 to Table 8 show the EGARCH-mean results for portfolios formed based on firm characteristics market value (ME), book-to-market value (BE/ME), cash flows over price (CF/P), dividend yield (D/P), earning over price (E/P), long-term reversal, short-term reversal, and mid-term momentum, respectively. Figures 2 to 5 show the results of sentiment on expected returns, on conditional volatility, volatility on expected returns, and asymmetric shock on volatility for Table 1 to Table 8 graphically. The "Up" and "Down" in Figure 3 represent high (optimistic) and low (pessimistic) sentiments. The following sections separately examine the relationship between sentiment and expected returns, sentiment and volatility, volatility and expected returns, and asymmetric shock on volatility.

3.1. Sentiment and expected returns (α_3). Table 1 shows that the coefficients of α_3 for all size portfolios were negative; this was consistent with the findings of Baker and Wurgler (2006) that subsequent returns across most of the cross section size portfolios tended to be higher when sentiment was low. Panel A of Figure 2 presented a stronger negative effect on small-size stocks, which confirmed with Lee, Shleifer and Thaler (1991) and Baker and Wurgler (2006) that sentiment had more effects on small-cap stocks[1].

From Table 2, six of the ten α_3 estimates for the book-to-market portfolios were negative, and only the eighth portfolios are statistically significantly negative. However, when attention was paid to the economic estimates, as shown on Panel B of Figure 2, the smallest BE/ME firms had the lowest negative coefficients and the sixth BE/ME firms have the biggest positive coefficients. This indicated that the effects of sentiment on expected returns varied with firms' BE/ME. In general, the negative values occurred in low BE/ME firms, which implied that growth firms appeared to have lower returns after a positive sentiment.

From Table 3, sentiments at the beginning of the month had positive effects on expected returns for six out of ten cash flow/price portfolios, and it was significant for the fourth, fifth, sixth, and eighth portfolios. This revealed that sentiment had greater positive effects on firms with moderate cash flows. When it turned to dividend yield portfolios (see Table 4), eight out of ten portfolios had positive α_3, but only the seventh portfolio was significantly positive at the 10% level. Furthermore, Panel D of Figure 2 revealed that the smaller dividend-paying companies were more vulnerable to sentiment shifts. Specifically, the positive coefficients indicated that the beginning positive (negative) sentiment would induce investors to buy low (high) -dividend companies, which pushed their prices up.

Table 5 shows that sentiments also had positive effects on six earning/price portfolios, but only the fourth, seventh, and tenth α_3 were significant at the 5% level. Panel E of Figure 2 confirms this pattern. Overall, this indicated that sentiment had more positive impacts on mid and high earning/price companies.

[1] Baker and Wurgler (2006) did not report the significance of each portfolio. Additionally, the findings that no coefficients were significant at the 5% level indicated that the size effect of Lee, Shleifer and Thaler (1991) could be assumed by macro economical factors.

Table 1. Size portfolios and investor sentiment

	1	p-value	2	p-value	3	p-value	4	p-value	5	p-value	6	p-value	7	p-value	8	p-value	9	p-value	10	p-value
α_0	-0.6100	(.4867)	-0.7301	(.4237)	-0.9590	(.3789)	-0.7941	(.4397)	0.8128	(.0095)	1.0452	(.0010)	0.9896	(.0017)	1.1107	(.0001)	1.1863	(.0000)	1.0831	(.0000)
α_1	0.2492	(.0000)	0.2839	(.0001)	0.2651	(.0013)	0.2681	(.0015)	0.1310	(.0122)	0.1278	(.0119)	0.0961	(.0679)	0.0837	(.1088)	0.0451	(.3853)	0.0459	(.3860)
α_2	0.0417	(.0509)	0.0381	(.0581)	0.0472	(.0667)	0.0448	(.0871)	0.0053	(.4579)	0.0016	(.8350)	0.0027	(.7537)	-0.0016	(.8470)	-0.0047	(.4917)	-0.0070	(.4147)
α_3	-0.4276	(.2702)	-0.4565	(.1873)	-0.2978	(.3608)	-0.3027	(.3222)	-0.4045	(.1206)	-0.3604	(.1717)	-0.2536	(.3254)	-0.2466	(.2602)	-0.1592	(.4777)	-0.1408	(.4382)
β_0	0.1075	(.6488)	0.6290	(.0406)	0.6700	(.0402)	0.7186	(.0305)	-0.1047	(.0393)	-0.1065	(.0392)	-0.1069	(.0392)	-0.0919	(.1002)	-0.0306	(.4488)	-0.0299	(.5450)
β_1	0.1394	(.1372)	0.1158	(.1259)	0.0407	(.5029)	0.0606	(.3525)	0.2079	(.0000)	0.2175	(.0000)	0.2092	(.0000)	0.2091	(.0000)	0.1287	(.0010)	0.1569	(.0031)
β_2	0.4791	(.0000)	-0.0526	(.7120)	-0.1540	(.2487)	-0.1742	(.1773)	-0.0537	(.3612)	-0.0099	(.8646)	0.0076	(.8916)	0.0093	(.8687)	0.0850	(.0739)	0.1362	(.0163)
β_3	0.9712	(.0000)	0.8067	(.0000)	0.8041	(.0000)	0.7824	(.0000)	0.9838	(.0000)	0.9824	(.0000)	0.9834	(.0000)	0.9797	(.0000)	0.9800	(.0000)	0.9752	(.0000)
β_4	-0.0778	(.0000)	-0.0308	(.1084)	-0.0180	(.3316)	-0.0171	(.3419)	-0.0073	(.3294)	-0.0104	(.1593)	-0.0121	(.1516)	-0.0162	(.0424)	-0.0271	(.0000)	-0.0363	(.0002)
β_5	0.0413	(.1452)	0.0187	(.5191)	0.0134	(.5337)	0.0085	(.7122)	0.0105	(.3958)	0.0122	(.3336)	0.0159	(.2283)	0.0165	(.1894)	0.0238	(.0298)	0.0219	(.1108)
β_6	-0.0149	(.2307)	0.0060	(.6720)	0.0087	(.5096)	0.0075	(.6056)	0.0164	(.1508)	0.0163	(.1479)	0.0187	(1382)	0.0180	(.1714)	0.0216	(.0045)	0.0131	(.1009)

Notes: The table reports the results of the following regression:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 h_t + \alpha_3 S_{t-1} + \eta_t, \quad \eta_t \sim N(0, h_t),$$

$$h_t = \beta_0 + \beta_1 \frac{|\eta_{t-1}|}{\sqrt{h_{t-1}}} + \beta_2 \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} + \beta_3 h_{t-1} + \beta_4 R_{t-1} + \beta_5 (S_{t-1})^2 D_{t-1} + \beta_6 (S_{t-1})^2 (1 - D_{t-1}),$$

where R_t is the monthly value-weighted returns for each market capitalization portfolio, h_t is the conditional volatility, and S_t is the monthly Baker and Wurgler (BW) sentiment index at the beginning of the month. BW Index is the monthly change of the Baker and Wurgler orthogonalized Sentiment Index which is the first principal component of the five orthogonalized sentiment proxies, the closed-end fund discount, the dividend premium, the number of IPOs, the average first day returns of IPOs, and the share of equity issues in total equity and debt issues. The portfolios are ranked in increasing orders. The first column reports the coefficients and the second column shows the p-values. The autocorrelations in the error terms are corrected using a Newey and West (1987) correction with 12 lags.

Table 2. Book-to-market value portfolios and investor sentiment

	1	p-value	2	p-value	3	p-value	4	p-value	5	p-value	6	p-value	7	p-value	8	p-value	9	p-value	10	p-value
α_0	0.6865	(.2573)	7.9027	(.0744)	-5.0469	(.2313)	3.6222	(.0723)	15.5099	(.1234)	-9.0068	(.0497)	1.8976	(.0225)	1.0515	(.3700)	0.2823	(.6306)	0.5624	(.4381)
α_1	0.0517	(.2055)	-0.3162	(.2046)	0.4193	(.1034)	-0.1057	(.3882)	-0.7153	(.0967)	0.5061	(.0073)	-0.0224	(.7186)	0.0550	(.0506)	0.1342	(.0393)	0.1817	(.0039)
α_2	-0.3948	(.1028)	-0.2514	(.5171)	0.1703	(.6902)	-0.1508	(.5991)	-0.2711	(.5339)	0.4846	(.0086)	-0.0322	(.8742)	-0.0448	(.0096)	0.1025	(.6538)	0.0505	(.8661)
α_3	0.0016	(.9446)	-0.2869	(.1232)	0.2414	(.1742)	-0.1102	(.2052)	-0.7146	(.1728)	0.5027	(.0462)	-0.0377	(.3737)	0.0025	(.0000)	0.0362	(.1313)	0.0187	(.4101)
β_0	0.4935	(.0541)	3.3063	(.0000)	2.9633	(.0000)	3.2048	(.0000)	3.2579	(.0000)	2.5520	(.0000)	2.3067	(.0000)	1.7741	(.0000)	1.0834	(.0004)	1.0388	(.0100)
β_1	0.1254	(.0077)	-0.0826	(.1259)	-0.1117	(.0752)	0.0110	(.9263)	-0.0826	(.0503)	-0.0452	(.0488)	-0.1664	(.1418)	-0.0918	(.3700)	0.0781	(.4057)	0.1121	(.1987)
β_2	0.5807	(.0000)	-0.1957	(.3064)	0.0093	(.9638)	-0.2307	(.5544)	-0.0838	(.3700)	-0.3396	(.0120)	-0.2475	(.4033)	-0.5930	(.0506)	-0.3612	(.0492)	-0.2238	(.3849)
β_3	0.8433	(.0000)	-0.0575	(.6485)	0.1000	(.4592)	-0.0764	(.7412)	-0.0860	(.2148)	0.1301	(.1697)	0.2131	(.2079)	0.3330	(.0096)	0.5941	(.0000)	0.6415	(.0000)
β_4	-0.1254	(.0000)	-0.0195	(.6147)	-0.0698	(.1028)	-0.0133	(.8547)	-0.0400	(.0357)	0.0217	(.3883)	-0.0406	(.5608)	0.0326	(.6301)	-0.0007	(.9839)	-0.0143	(.7396)
β_5	0.0475	(.0088)	0.0838	(.0790)	0.0156	(.7334)	0.1249	(.0883)	0.0397	(.1889)	0.0221	(.1860)	0.1606	(.0330)	0.1907	(.0019)	0.1042	(.0163)	0.1194	(.0257)
β_6	-0.0134	(.4494)	0.0320	(.2747)	-0.0639	(.0824)	0.0783	(.0617)	0.0112	(.5266)	-0.0389	(.1361)	0.0692	(.0558)	0.0591	(.1051)	0.0200	(.5147)	-0.0076	(.7888)

Notes: The table reports the results of the following regression:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 h_t + \alpha_3 S_{t-1} + \eta_t, \quad \eta_t \sim N(0, h_t),$$

$$h_t = \beta_0 + \beta_1 \frac{|\eta_{t-1}|}{\sqrt{h_{t-1}}} + \beta_2 \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} + \beta_3 h_{t-1} + \beta_4 R_{t-1} + \beta_5 (S_{t-1})^2 D_{t-1} + \beta_6 (S_{t-1})^2 (1 - D_{t-1}),$$

where R_t is the monthly value-weighted returns for each book-to-market ratio portfolio, h_t is the conditional volatility, and S_t is the monthly Baker and Wurgler (BW) sentiment index at the beginning of the month. BW Index is the monthly change of the Baker and Wurgler orthogonalized Sentiment Index which is the first principal component of the five orthogonalized sentiment proxies, the closed-end fund discount, the dividend premium, the number of IPOs, the average first day returns of IPOs, and the share of equity issues in total equity and debt issues. The portfolios are ranked in increasing orders. The first column reports the coefficients and the second column shows the p-values. The autocorrelations in the error terms are corrected using a Newey and West (1987) correction with 12 lags.

Table 3. Cash flow portfolios and investor sentiment

	1	p-value	2	p-value	3	p-value	4	p-value	5	p-value	6	p-value	7	p-value	8	p-value	9	p-value	10	p-value
α_0	0.7907	(.2891)	1.9269	(.0110)	-5.5810	(.0101)	-7.1236	(.0224)	-14.6926	(.1872)	-3.3394	(.0040)	5.0708	(.0320)	-6.6495	(.0160)	1.7818	(.0009)	2.1462	(.0369)
α_1	0.0104	(.8067)	0.0545	(.2702)	0.3502	(.0012)	0.3134	(.0238)	0.2962	(.1546)	0.3046	(.0001)	-0.1886	(.1165)	0.3171	(.0147)	-0.0689	(.0926)	-0.0525	(.4664)
α_2	-0.3863	(.1541)	0.0762	(.7308)	0.3470	(.0570)	0.6218	(.0172)	0.6158	(.0382)	0.3950	(.0047)	-0.1497	(.6590)	0.6779	(.0206)	-0.2228	(.2146)	-0.1761	(.4826)
α_3	0.0000	(.9998)	-0.0443	(.1540)	0.2817	(.0080)	0.3572	(.0137)	0.7409	(.1679)	0.2156	(.0017)	-0.1930	(.1142)	0.3782	(.0103)	-0.0267	(.3067)	-0.0302	(.4355)
β_0	0.5455	(.0717)	1.2229	(.0335)	2.0914	(.0000)	2.3705	(.0000)	2.0136	(.0010)	1.9400	(.0000)	3.4240	(.0000)	2.0731	(.0000)	1.4982	(.0004)	2.5958	(.0000)
β_1	0.1012	(.0409)	0.0518	(.4552)	0.0194	(.4965)	0.0230	(.4327)	0.0085	(.5499)	-0.0417	(.0995)	-0.0151	(.8321)	0.0010	(.9749)	-0.0069	(.9161)	-0.0758	(.4548)
β_2	0.6234	(.0005)	-1.1161	(.0003)	-0.4416	(.0002)	-0.3502	(.0053)	-0.1429	(.1013)	-0.6341	(.0000)	-0.2086	(.4647)	-0.3289	(.0090)	0.7903	(.0010)	-0.2653	(.2882)
β_3	0.8455	(.0000)	0.5136	(.0061)	0.3023	(.0060)	0.2131	(.0895)	0.3310	(.0786)	0.3129	(.0032)	-0.1951	(.3030)	0.2898	(.0406)	0.5700	(.0000)	0.1629	(.3571)
β_4	-0.1255	(.0000)	0.1736	(.0050)	0.0414	(.0599)	0.0332	(.1995)	0.0132	(.3334)	0.0752	(.0013)	-0.0111	(.8432)	0.0304	(.2303)	-0.2365	(.0000)	-0.0219	(.6465)
β_5	0.0358	(.0674)	0.1126	(.0188)	0.0124	(.3423)	0.0307	(.0654)	0.0121	(.2284)	0.0303	(.0918)	0.1425	(.0627)	0.0331	(.0390)	0.0649	(.0166)	0.2120	(.0085)
β_6	-0.0132	(.4590)	0.0838	(.0155)	-0.0445	(.0335)	-0.0612	(.0375)	-0.0245	(.2228)	-0.0515	(.0229)	0.0780	(.0950)	-0.0597	(.0393)	0.0003	(.9818)	0.0613	(.1485)

Notes: The table reports the results of the following regression:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 h_t + \alpha_3 S_{t-1} + \eta_t, \quad \eta_t \sim \mathrm{N}(0, h_t),$$

$$h_t = \beta_0 + \beta_1 \frac{|\eta_{t-1}|}{\sqrt{h_{t-1}}} + \beta_2 \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} + \beta_3 h_{t-1} + \beta_4 R_{t-1} + \beta_5 (S_{t-1})^2 D_{t-1} + \beta_6 (S_{t-1})^2 (1 - D_{t-1}),$$

where R_t is the monthly value-weighted returns for each cash flow portfolio, h_t is the conditional volatility, and S_t is the monthly Baker and Wurgler (BW) sentiment index at the beginning of the month. BW Index is the monthly change of the Baker and Wurgler orthogonalized Sentiment Index which is the first principal component of the five orthogonalized sentiment proxies, the closed-end fund discount, the dividend premium, the number of IPOs, the average first day returns of IPOs, and the share of equity issues in total equity and debt issues. The portfolios are ranked in increasing orders. The first column reports the coefficients and the second column shows the p-values. The autocorrelations in the error terms are corrected using a Newey and West (1987) correction with 12 lags.

Table 4. Dividend yield portfolios and investor sentiment

	1	p-value	2	p-value	3	p-value	4	p-value	5	p-value	6	p-value	7	p-value	8	p-value	9	p-value	10	p-value
α_0	13.0220	(.1118)	14.7866	(.1083)	1.3452	(.2086)	1.9637	(.1264)	0.4043	(.7255)	0.7021	(.4877)	-0.0053	(.9902)	-0.1867	(.7337)	6.6217	(.0963)	0.8164	(.0066)
α_1	-0.4836	(.1263)	-0.6386	(.0696)	0.0054	(.9405)	-0.0237	(.7883)	0.0574	(.5090)	0.0301	(.6736)	0.1155	(.0108)	0.1236	(.0141)	-0.3407	(.1212)	0.0263	(.5413)
α_2	0.3466	(.3566)	0.3931	(.2675)	0.1279	(.4911)	0.2036	(.2989)	0.2651	(.1672)	0.2708	(.1242)	0.2064	(.0661)	-0.0234	(.8443)	-0.1088	(.6869)	0.2150	(.1111)
α_3	-0.3657	(.1692)	-0.5314	(.1598)	-0.0103	(.8128)	-0.0375	(.4885)	0.0231	(.6541)	0.0160	(.7470)	0.0541	(.0351)	0.0751	(.0301)	-0.3320	(.1761)	0.0070	(.7368)
β_0	3.7205	(.0000)	3.2859	(.0000)	3.3305	(.0005)	3.5139	(.0000)	2.5997	(.0033)	3.3504	(.0000)	0.5047	(.0504)	0.9890	(.0020)	2.8984	(.0000)	0.2156	(.0236)
β_1	-0.0989	(.0753)	-0.0937	(.1007)	0.0367	(.7534)	-0.0116	(.9138)	-0.0406	(.7462)	-0.1657	(.0814)	0.1483	(.0001)	0.1154	(.0924)	-0.0060	(.9248)	0.0331	(.4632)
β_2	-0.1523	(.2266)	-0.1409	(.2119)	0.2708	(.4606)	-0.2592	(.3483)	-0.0329	(.9478)	0.0579	(.7926)	-0.7152	(.0000)	-0.8837	(.0000)	-0.0149	(.9219)	0.2136	(.0341)
β_3	-0.0593	(.4725)	0.0001	(.9992)	-0.0015	(.9959)	-0.1116	(.5997)	0.2013	(.4124)	-0.0357	(.8279)	0.7351	(.0000)	0.5412	(.0000)	-0.0489	(.6482)	0.9444	(.0000)
β_4	-0.0271	(.1633)	-0.0282	(.1326)	-0.1122	(.1116)	-0.0171	(.7700)	-0.0554	(.6393)	-0.1056	(.0299)	0.1392	(.0000)	0.1478	(.0000)	-0.0677	(.0741)	-0.0907	(.0006)
β_5	-0.0259	(.4715)	-0.0117	(.6257)	-0.1362	(.1121)	-0.0703	(.4222)	-0.0887	(.1989)	-0.1009	(.1206)	0.0152	(.4282)	0.0096	(.7196)	0.0472	(.2695)	-0.0119	(.1220)
β_6	-0.0190	(.5057)	-0.0160	(.4685)	-0.1289	(.0210)	-0.1539	(.0071)	-0.1351	(.0101)	-0.1445	(.0055)	-0.0466	(.0067)	0.0016	(.9267)	-0.0303	(.4144)	-0.0117	(.2108)

Notes: The table reports the results of the following regression:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 h_t + \alpha_3 S_{t-1} + \eta_t, \quad \eta_t \sim N(0, h_t),$$

$$h_t = \beta_0 + \beta_1 \frac{|\eta_{t-1}|}{\sqrt{h_{t-1}}} + \beta_2 \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} + \beta_3 h_{t-1} + \beta_4 R_{t-1} + \beta_5 (S_{t-1})^2 D_{t-1} + \beta_6 (S_{t-1})^2 (1 - D_{t-1}),$$

where R_t is the monthly value-weighted returns for each dividend yield portfolio, h_t is the conditional volatility, and S_t is the monthly Baker and Wurgler (BW) sentiment index at the beginning of the month. BW Index is the monthly change of the Baker and Wurgler orthogonalized Sentiment Index which is the first principal component of the five orthogonalized sentiment proxies, the closed-end fund discount, the dividend premium, the number of IPOs, the average first day returns of IPOs, and the share of equity issues in total equity and debt issues. The portfolios are ranked in increasing orders. The first column reports the coefficients and the second column shows the p-values. The autocorrelations in the error terms are corrected using a Newey and West (1987) correction with 12 lags.

Table 5. Earning-to-price portfolios and investor sentiment

	1	p-value	2	p-value	3	p-value	4	p-value	5	p-value	6	p-value	7	p-value	8	p-value	9	p-value	10	p-value
α_0	0.6228	(.3485)	2.5242	(.0068)	6.1327	(.1092)	-7.1732	(.0383)	1.3273	(.0794)	0.7487	(.3881)	-6.2579	(.0396)	454.47	(.0000)	1.0823	(.0505)	-4.1771	(.0208)
α_1	0.0213	(.6393)	-0.0681	(.3499)	-0.2143	(.3354)	0.2358	(.0493)	-0.0006	(.9924)	0.0593	(.4328)	0.4028	(.0050)	0.7687	(.1245)	0.0531	(.3453)	0.3426	(.0006)
α_2	-0.4488	(.0967)	0.0415	(.8656)	-0.2801	(.4505)	0.4859	(.0163)	0.1317	(.4948)	-0.0916	(.6767)	0.5552	(.0268)	0.2929	(.0956)	-0.1000	(.6592)	0.5828	(.0164)
α_3	0.0043	(.8331)	-0.0673	(.0758)	-0.2332	(.1808)	0.4158	(.0291)	-0.0194	(.5717)	0.0121	(.7585)	0.3616	(.0227)	-1.0342	(.0000)	0.0036	(.8762)	0.1837	(.0045)
β_0	0.3896	(.0758)	2.4245	(.0000)	3.3681	(.0000)	2.6371	(.0000)	2.0394	(.0003)	2.2804	(.0001)	2.4408	(.0000)	2.7457	(.0000)	1.3696	(.0000)	1.7533	(.0000)
β_1	0.1251	(.0158)	0.0010	(.9892)	-0.0406	(.5925)	0.0160	(.4808)	-0.0410	(.6894)	-0.0133	(.8780)	-0.0228	(.4422)	-0.0007	(.2828)	0.0156	(.8504)	-0.0903	(.0092)
β_2	0.4925	(.0053)	-1.0067	(.0028)	-0.1835	(.3950)	-0.4175	(.0100)	-0.8945	(.0133)	0.0944	(.7820)	-0.3663	(.0046)	0.0152	(.0000)	-0.1427	(.5080)	-0.4277	(.0000)
β_3	0.8795	(.0000)	0.1441	(.3817)	-0.1256	(.3856)	0.0814	(.5720)	0.2564	(.1652)	0.2321	(.2505)	0.1650	(.1025)	0.0724	(.0000)	0.5304	(.0000)	0.4747	(.0000)
β_4	-0.1022	(.0006)	0.1345	(.0620)	-0.0185	(.6832)	0.0599	(.0870)	0.1117	(.1199)	-0.1108	(.0999)	0.0232	(.3845)	-0.0002	(.9296)	-0.0552	(.1643)	0.0262	(.1360)
β_5	0.0345	(.0837)	0.0981	(.1269)	0.1147	(.0917)	0.0264	(.0824)	0.1239	(.0073)	0.1266	(.0714)	0.0338	(.1672)	-0.0007	(.1709)	0.1355	(.0111)	0.0347	(.0307)
β_6	-0.0128	(.4257)	0.0954	(.0103)	0.0479	(.2470)	-0.0570	(.0797)	0.0787	(.0478)	0.0298	(.3584)	-0.0575	(.0814)	0.0008	(.0588)	0.0269	(.3860)	-0.0408	(.0274)

Notes: The table reports the results of the following regression:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 h_t + \alpha_3 S_{t-1} + \eta_t, \quad \eta_t \sim \mathrm{N}(0, h_t),$$

$$h_t = \beta_0 + \beta_1 \frac{|\eta_{t-1}|}{\sqrt{h_{t-1}}} + \beta_2 \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} + \beta_3 h_{t-1} + \beta_4 R_{t-1} + \beta_5 (S_{t-1})^2 D_{t-1} + \beta_6 (S_{t-1})^2 (1 - D_{t-1}),$$

where R_t is the monthly value-weighted returns for each earning-to-price portfolio, h_t is the conditional volatility, and S_t is the monthly Baker and Wurgler (BW) sentiment index at the beginning of the month. BW Index is the monthly change of the Baker and Wurgler orthogonalized Sentiment Index which is the first principal component of the five orthogonalized sentiment proxies, the closed-end fund discount, the dividend premium, the number of IPOs, the average first day returns of IPOs, and the share of equity issues in total equity and debt issues. The portfolios are ranked in increasing orders. The first column reports the coefficients and the second column shows the p-values. The autocorrelations in the error terms are corrected using a Newey and West (1987) correction with 12 lags.

Table 6. Long-term reverse (5-year) portfolios and investor sentiment

	1	p-value	2	p-value	3	p-value	4	p-value	5	p-value	6	p-value	7	p-value	8	p-value	9	p-value	10	p-value
α_0	-4.0449	(.0000)	-7.1368	(.0096)	-9.3869	(.0079)	1.2246	(.1292)	1.3842	(.0504)	3.0559	(.0001)	5.4822	(.0060)	-3.3784	(.0140)	8.8185	(.0966)	6.2489	(.1277)
α_1	0.2562	(.0000)	0.3161	(.0015)	0.4022	(.0050)	0.0589	(.3786)	0.0130	(.8602)	-0.1177	(.0971)	-0.0773	(.1986)	0.1988	(.0076)	-0.3405	(.1897)	-0.1461	(.3552)
α_2	0.6623	(.0002)	0.8167	(.0152)	0.6895	(.0001)	-0.1427	(.5308)	-0.0263	(.9045)	-0.1862	(.4247)	-0.5939	(.0155)	0.2523	(.0799)	-0.3013	(.4243)	-0.0241	(.9502)
α_3	0.1286	(.0000)	0.3138	(.0036)	0.4717	(.0028)	-0.0102	(.7939)	-0.0142	(.6805)	-0.1009	(.0169)	-0.2199	(.0353)	0.2110	(.0055)	-0.3285	(.1468)	-0.1452	(.2024)
β_0	1.1687	(.0000)	1.8563	(.0000)	2.1132	(.0000)	2.0006	(.0012)	1.9501	(.0001)	2.3507	(.0000)	5.1943	(.0000)	1.9222	(.0000)	3.3551	(.0000)	3.3888	(.0000)
β_1	-0.0542	(.0023)	0.0035	(.8561)	-0.0268	(.0949)	0.0176	(.8277)	0.1519	(.2718)	-0.0138	(.8520)	0.1551	(.0038)	0.0846	(.0142)	-0.0698	(.1476)	-0.0067	(.9222)
β_2	-0.3850	(.0001)	-0.2981	(.0008)	-0.2861	(.0009)	-0.1036	(.7196)	-0.1368	(.7078)	-0.8644	(.0004)	0.0109	(.9224)	-0.6087	(.0000)	-0.1843	(.3180)	-0.0188	(.9372)
β_3	0.6814	(.0000)	0.4158	(.0019)	0.3055	(.0001)	0.2857	(.1679)	0.2536	(.1504)	0.0715	(.6703)	-0.8160	(.0000)	0.3024	(.0482)	-0.0806	(.5266)	0.0342	(.8585)
β_4	0.0241	(.0932)	0.0229	(.1545)	0.0194	(.1969)	-0.0505	(.3751)	-0.0479	(.5114)	0.1120	(.0487)	-0.0313	(.2391)	0.0947	(.0016)	-0.0182	(.5948)	-0.0374	(.3308)
β_5	0.0207	(.0000)	0.0296	(.0377)	0.0283	(.0040)	0.1868	(.0094)	0.1810	(.0219)	0.2259	(.0006)	0.1926	(.0017)	0.0109	(.4971)	0.0958	(.0832)	0.0620	(.3121)
β_6	-0.0415	(.0003)	-0.0554	(.0276)	-0.0376	(.0116)	0.0489	(.2048)	0.0664	(.0653)	0.0825	(.0486)	-0.0665	(.1376)	-0.0551	(.0324)	0.0407	(.2427)	0.0834	(.0387)

Notes: The table reports the results of the following regression:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 h_t + \alpha_3 S_{t-1} + \eta_t, \quad \eta_t \sim N(0, h_t),$$

$$h_t = \beta_0 + \beta_1 \frac{|\eta_{t-1}|}{\sqrt{h_{t-1}}} + \beta_2 \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} + \beta_3 h_{t-1} + \beta_4 R_{t-1} + \beta_5 (S_{t-1})^2 D_{t-1} + \beta_6 (S_{t-1})^2 (1 - D_{t-1}),$$

where R_t is the monthly value-weighted returns for each long-term reverse portfolio, h_t is the conditional volatility, and S_t is the monthly Baker and Wurgler (BW) sentiment index at the beginning of the month. BW Index is the monthly change of the Baker and Wurgler orthogonalized Sentiment Index which is the first principal component of the five orthogonalized sentiment proxies, the closed-end fund discount, the dividend premium, the number of IPOs, the average first day returns of IPOs, and the share of equity issues in total equity and debt issues. The portfolios are ranked in increasing orders. The first column reports the coefficients and the second column shows the p-values. The autocorrelations in the error terms are corrected using a Newey and West (1987) correction with 12 lags.

Table 7. Short-term reverse (1 month) portfolios and investor sentiment

	1	p-value	2	p-value	3	p-value	4	p-value	5	p-value	6	p-value	7	p-value	8	p-value	9	p-value	10	p-value
α_0	-0.8466	(.2722)	-0.4261	(.5768)	-0.3526	(.5819)	4.3391	(.0469)	4.9018	(.0355)	3.2887	(.0123)	5.0274	(.0662)	0.8192	(.0361)	18.9765	(.3142)	1.0787	(.1220)
α_1	0.1296	(.0025)	0.1701	(.0109)	0.2480	(.0003)	-0.1564	(.2596)	-0.2198	(.1224)	-0.0795	(.4426)	-0.1987	(.2765)	0.0191	(.6771)	-0.5729	(.2967)	0.0175	(.6963)
α_2	**-0.8938**	**(.0329)**	0.1135	(.6705)	0.3148	(.1154)	0.0573	(.8482)	0.0944	(.7397)	-0.0390	(.8735)	-0.1664	(.5698)	-0.3034	(.1750)	-0.0554	(.8952)	-0.2838	(.2850)
α_3	**0.0370**	**(.0223)**	**0.0448**	**(.0380)**	**0.0514**	**(.0382)**	-0.1390	(.1484)	-0.1849	(.1115)	**-0.1241**	**(.0670)**	-0.2180	(.1338)	0.0080	(.7035)	-0.7628	(.3429)	-0.0105	(.6633)
β_0	0.2160	(.2558)	1.6554	(.0000)	0.9386	(.0006)	2.5535	(.0000)	2.9637	(.0000)	2.7801	(.0000)	2.9615	(.0000)	0.0753	(.4380)	3.3877	(.0000)	0.2173	(.3872)
β_1	0.1596	(.0221)	0.0268	(.7216)	0.0932	(.1623)	-0.0926	(.3111)	-0.1171	(.0582)	-0.1027	(.1707)	-0.1075	(.1260)	0.2110	(.0002)	-0.0261	(.3510)	0.1446	(.0278)
β_2	0.2041	(.1409)	**-0.4071**	**(.0244)**	**-0.5826**	**(.0001)**	-0.3085	(.3341)	-0.1680	(.4876)	-0.3914	(.1811)	-0.1734	(.4692)	**0.2402**	**(.0767)**	0.0246	(.8094)	0.3380	(.1646)
β_3	0.9247	(.0000)	0.4881	(.0000)	0.6486	(.0000)	0.1566	(.3963)	0.0003	(.9980)	0.0045	(.9794)	-0.0297	(.8387)	0.9339	(.0000)	-0.0709	(.5113)	0.9136	(.0000)
β_4	-0.0593	(.0001)	-0.0114	(.7014)	0.0410	(.1127)	-0.0049	(.9362)	-0.0392	(.4461)	0.0140	(.8310)	-0.0321	(.5417)	-0.0603	(.0476)	-0.0380	(.1128)	-0.0579	(.1643)
β_5	**0.0336**	**(.0503)**	**0.0915**	**(.0149)**	**0.0483**	**(.0703)**	**0.1120**	**(.0850)**	**0.1035**	**(.0659)**	**0.1785**	**(.0030)**	**0.1336**	**(.0274)**	0.0208	(.1613)	0.0215	(.4618)	0.0211	(.2410)
β_6	-0.0092	(.5106)	0.0061	(.8109)	-0.0063	(.8057)	**0.0748**	**(.0146)**	**0.0814**	**(.0118)**	**0.0998**	**(.0045)**	0.0561	(.1418)	0.0050	(.6384)	0.0203	(.3596)	-0.0034	(.7602)

Notes: The table reports the results of the following regression:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 h_t + \alpha_3 S_{t-1} + \eta_t, \quad \eta_t \sim N(0, h_t),$$

$$h_t = \beta_0 + \beta_1 \frac{|\eta_{t-1}|}{\sqrt{h_{t-1}}} + \beta_2 \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} + \beta_3 h_{t-1} + \beta_4 R_{t-1} + \beta_5 (S_{t-1})^2 D_{t-1} + \beta_6 (S_{t-1})^2 (1 - D_{t-1}),$$

where R_t is the monthly value-weighted returns for each short-term reverse (1 month) portfolio, h_t is the conditional volatility, and S_t is the monthly Baker and Wurgler (BW) sentiment index at the beginning of the month. BW Index is the monthly change of the Baker and Wurgler orthogonalized Sentiment Index which is the first principal component of the five orthogonalized sentiment proxies, the closed-end fund discount, the dividend premium, the number of IPOs, the average first day returns of IPOs, and the share of equity issues in total equity and debt issues. The portfolios are ranked in increasing orders. The first column reports the coefficients and the second column shows the p-values. The autocorrelations in the error terms are corrected using a Newey and West (1987) correction with 12 lags.

Table 8. Mid-term momentum portfolios and investor sentiment

	1	p-value	2	p-value	3	p-value	4	p-value	5	p-value	6	p-value	7	p-value	8	p-value	9	p-value	10	p-value
α_0	-0.3138	(.4612)	0.2813	(.4988)	0.1371	(.7370)	-0.2311	(.6469)	0.5532	(.1834)	0.3977	(.5149)	12.0172	(.1206)	-4.4424	(.0036)	3.3350	(.0049)	3.1323	(.0012)
α_1	0.1222	(.0152)	0.0236	(.7105)	0.1079	(.0262)	0.1484	(.0073)	0.0875	(.0834)	0.1302	(.0558)	-0.6859	(.0266)	0.1502	(.0307)	-0.1162	(.0713)	-0.0965	(.0506)
α_2	-0.4139	(.1515)	0.3075	(.2030)	0.2150	(.2982)	0.4475	(.0110)	0.0911	(.6261)	0.0474	(.8099)	-0.2081	(.5934)	0.3656	(.0387)	-0.4564	(.0280)	-0.4847	(.0664)
α_3	0.0063	(.4841)	0.0121	(.3202)	0.0245	(.1441)	0.0438	(.0617)	0.0073	(.7447)	0.0198	(.4947)	-0.5387	(.1838)	0.2700	(.0014)	-0.0824	(.0881)	-0.0324	(.1690)
β_0	0.1840	(.0149)	0.1510	(.1959)	0.1707	(.1472)	0.4229	(.0286)	0.8584	(.0003)	1.4883	(.0001)	3.3406	(.0000)	2.8121	(.0000)	4.4133	(.0000)	3.8356	(.0000)
β_1	0.0736	(.1280)	0.1952	(.0573)	0.2185	(.0001)	0.0707	(.1026)	0.2035	(.0908)	0.1841	(.0485)	-0.0929	(.1495)	0.0482	(.0983)	-0.0180	(.8725)	0.1550	(.1016)
β_2	0.0941	(.3472)	-0.2559	(.0366)	-0.1738	(.1029)	-0.4622	(.0035)	-0.5323	(.0239)	-0.8512	(.0002)	-0.0512	(.5548)	-0.6475	(.0007)	0.8336	(.0049)	1.0861	(.0000)
β_3	0.9374	(.0000)	0.9029	(.0000)	0.8899	(.0000)	0.8228	(.0000)	0.6076	(.0000)	0.3859	(.0025)	-0.1163	(.1646)	0.0117	(.9542)	-0.3511	(.1776)	-0.0165	(.9457)
β_4	-0.0451	(.0006)	0.0041	(.8444)	-0.0124	(.5085)	0.0447	(.1700)	0.0276	(.5210)	0.1003	(.0244)	-0.0538	(.0426)	0.1104	(.0117)	-0.2113	(.0001)	-0.2009	(.0000)
β_5	-0.0110	(.2724)	0.0034	(.7903)	0.0024	(.8821)	0.0259	(.0284)	0.0839	(.0111)	0.0995	(.0279)	0.0584	(.1896)	0.0238	(.2140)	0.1703	(.0219)	0.1390	(.0113)
β_6	0.0009	(.9041)	0.0301	(.0861)	0.0054	(.6946)	-0.0021	(.8998)	0.0316	(.2557)	0.0481	(.2479)	0.0304	(.2015)	-0.1001	(.0083)	0.0105	(.7824)	0.0101	(.7690)

Notes: The table reports the results of the following regression:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 h_t + \alpha_3 S_{t-1} + \eta_t, \quad \eta_t \sim \mathrm{N}(0, h_t),$$

$$h_t = \beta_0 + \beta_1 \frac{|\eta_{t-1}|}{\sqrt{h_{t-1}}} + \beta_2 \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} + \beta_3 h_{t-1} + \beta_4 R_{t-1} + \beta_5 (S_{t-1})^2 D_{t-1} + \beta_6 (S_{t-1})^2 (1 - D_{t-1}),$$

where R_t is the monthly value-weighted returns for each mid-term momentum portfolio, h_t is the conditional volatility, and S_t is the monthly Baker and Wurgler (BW) sentiment index at the beginning o the month. BW Index is the monthly change of the Baker and Wurgler orthogonalized Sentiment Index which is the first principal component of the five orthogonalized sentiment proxies, the closed-end fun discount, the dividend premium, the number of IPOs, the average first day returns of IPOs, and the share of equity issues in total equity and debt issues. The portfolios are ranked in increasing orders. The firs column reports the coefficients and the second column shows the p-values. The autocorrelations in the error terms are corrected using a Newey and West (1987) correction with 12 lags.

Table 6 to Table 8 examined whether the effects of sentiment were related to stocks' past performance. Although there were no theoretical viewpoints about the difference in arbitrage costs of various-performing stocks, investors had high propensities to speculate on either past losers or past winners due to the long-term overreaction of De Bondt and Thaler (1985) and mid-term momentum of Jegadeesh and Titman (1993). α_3 in Table 6 revealed that initial sentiment had positive effects on past 5-year losers (the first, second, and third portfolios were significant), but negative effects on past 5-year winners (the seventh one was significant). The magnitude and direction shown on Panel F of Figure 2 also confirmed above findings, namely that long-term loser portfolios came into favor when sentiment was high, and the "hold-more" effects dominated the "price-pressure" effect, which caused positive returns. By contrast, the α_3 in Table 7 and Panel G of Figure 2 provided strong evidence that there was a negative effect of initial sentiment on extreme low (the first portfolio) past one-month returns. That is, for the extreme short-term losers, the "price-pressure" effect dominated the "hold-more" effects, which thereby lowered expected returns.

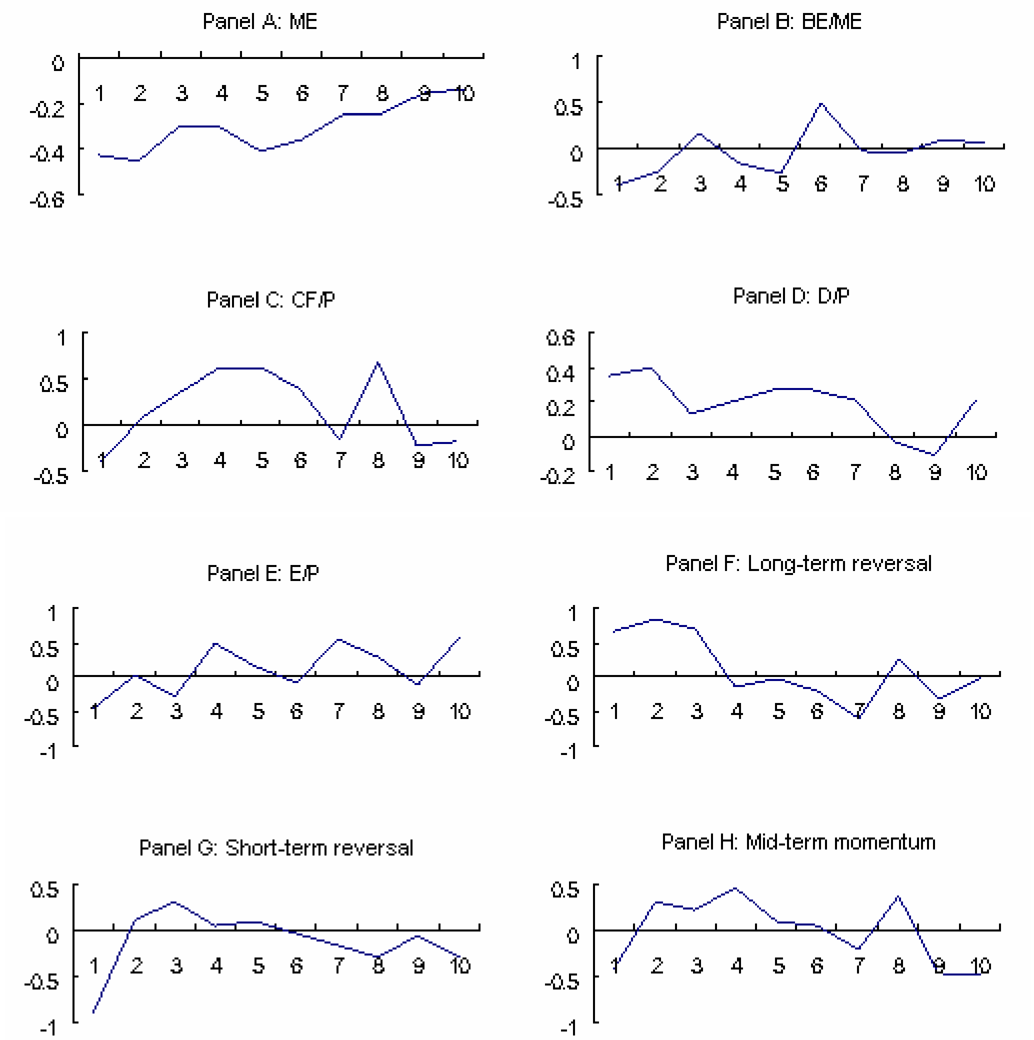

Fig. 2. Sentiments on expected returns for firm-characteristic portfolios

As for portfolios formed based upon past one-year returns, sentiment had positive effects on six out of ten momentum portfolios, in which two of them (the fourth and eighth ones) were significant. A closer look revealed that extreme losers (the first one) and extreme winners (the ninth and tenth ones) during past one-year displayed a negative sentiment effect. This implied that investors were averse to past one-year extreme losers and extreme winners when sentiment was high, but preferred moderately performing firms when sentiment was high.

Overall, sentiment had cross-sectional effects on expected returns of firms with different characteristics. There was some sort of size effects, with higher returns in low sentiment periods. The effects of noise trading on smaller stocks were stronger. It was confirmed by Lee, Shleifer and Thaler (1991) that small stocks were easily affected by sentiment. Higher sentiments also induced subsequent lower returns of growth stocks, but not of value stocks. Likewise, low dividend yield stocks would be speculative, hard to arbitrage, and then sensitive to investor sentiment. Consistent with the prediction, my results showed that low dividend yield stocks had higher returns after high sentiment periods. Investors appeared to demand long-term losers but were averse to short-term losers when *sentiment* was positive. They also kept off past mid-term extreme losers and extreme winners when initial sentiment was positive. Accordingly, when sentiment was optimistic, long-term losers earned positive returns, but short-term losers and mid-term winners had negative returns.

3.2. Sentiment and volatility (β_5 and β_6). The coefficients β_5 and β_6 in the conditional volatility equation captured the effect of the magnitude of shifts in optimistic and pessimistic sentiment on volatility formation, respectively. Table 1 showed that, for all portfolios except for the smallest-sized one, both bullish and bearish sentiments were related to greater return volatility. Among them, only the second to greatest one was significant. In comparison, shifts in sentiment had an asymmetric impact on conditional volatility of the smallest-sized portfolios (the first one), in which a bullish (bearish) sentiment was correlated with volatility increase (decrease). This provided a picture of the cross sectional effects of sentiment on size-sorted portfolios.

Likewise, sentiments also had an asymmetrical impact on conditional volatility for BE/ME-sorted portfolios (Table 2). The positive coefficients β_5 for all portfolios indicated that a positive sentiment was accompanied by a subsequent upward volatility, and it was statistically significant for the smallest and for the four greatest BE/ME portfolios. But there was no evidence for upward or downward adjustment in volatility after a negative sentiment at the 5% significance level.

As for portfolios sorted on cash flows to price (CF/P) reported in Table 3, when the sentiment became bullish, the stock volatilities in the greatest three portfolios increased significantly. As sentiment became bearish, there was a significant downward change in the volatility of stocks returns in the third, fourth, sixth, and eighth portfolios, but an upward change for the second portfolio. Overall, this indicated an upward shift in volatility for large-CF/P stocks after a positive sentiment and a downward shift in volatility for mid-CF/P stocks after a negative sentiment.

As far as dividend yield portfolios were considered (Table 4), neither upward nor downward changes in volatility were found after a positive sentiment, but moderate dividend yield groups (the third one to the seventh one) presented downward change in volatility after a negative sentiment. The effects of sentiment on cross sectional conditional volatility of earnings to price (E/P) portfolios were complicated. Basically, regardless of E/P, a positive sentiment caused a subsequent upward volatility, and it was significant at a 5% level for the fifth, ninth, and tenth portfolios (see Table 5). But, volatility shifts were either upward or downward after a pessimistic sentiment, depending on earnings to price level. Specifically, for the fifth portfolio, a pessimistic sentiment was followed by an increase in conditional volatility. But, the largest earning-to-price portfolio exhibited a decrease in volatility after a negative sentiment.

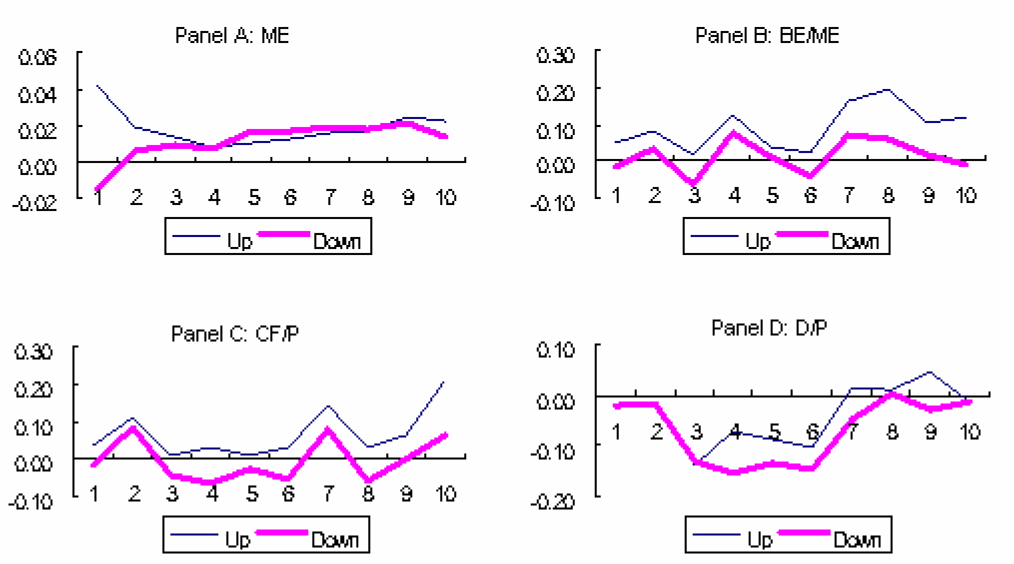

Fig. 3. Sentiments on conditional volatility for firm-characteristic portfolios

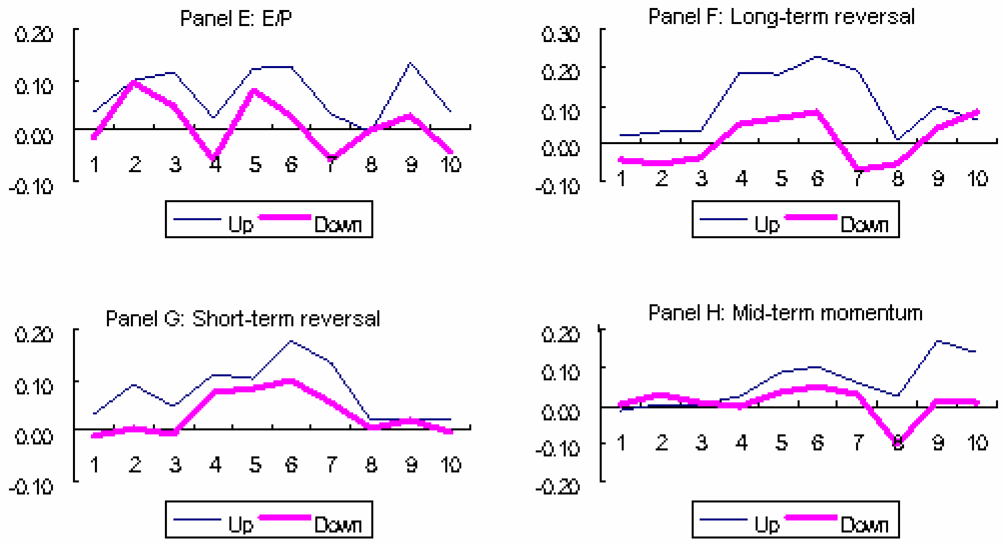

Fig. 3 (cont.). Sentiments on conditional volatility for firm-characteristic portfolios

From Table 6, bullish sentiments had the most impact on past five-year losers. In particular, bullish sentiment was correlated with an increase in conditional volatility of last losers (the first to the seventh portfolios). However, downward sentiment decreased the volatility of the three worst-performing portfolios, but increased the volatility of the past five-year extreme winners. When portfolios were formed based on past one-month performance (see Table 7), bullish sentiments resulted in a decrease in conditional volatility, respectively of past one-month returns (only the past three short-term winners were insignificant at the 10% level). The cross sectional effects of bearish sentiments on conditional volatility were relatively salient. In particular, volatilities of stocks with moderate past one-month returns (the fourth, fifth, and sixth portfolios) increased subsequent to a negative sentiment. However, a bearish sentiment was not associated with a subsequent decrease or increase in conditional volatility for past short-term winners or losers. The inverse of U-shaped pattern for long-term reversal and short-term reversal portfolios in Panels F and G in Figure 3 provided a more convincing picture that both the long-term and short-term moderate-performing portfolios were vulnerable to shifts in sentiment.

When portfolios were formed based on past one-year performance, both bull and bearish sentiments had positive effects on stock volatility for most portfolios (see Table 7). The exception was the eighth portfolio at the 5% level, in which bear sentiments were negatively correlated with its subsequent volatility. In addition, Panel H of Figure 3 provides a clearer outlook that the volatilities of past mid-term two extreme winners were the most sensitive to optimistic sentiment, and the third to best winners became more volatile subsequent to pessimistic sentiment.

Overall, my results showed that shifts in sentiment had a cross section of asymmetrical impact on conditional volatility. For portfolios formed on BE/ME and cash flow/price, the volatility of the larger ones was vulnerable to shifts in sentiments. But the volatility of moderate dividend yield stocks was more sensitive to change in sentiments. Sentiment had more effect on the volatility of the long-term and short-term moderate-performing portfolios, as well as the mid-term winners.

3.3. Volatility and expected returns (α_2). In the DSSW model, the magnitude of the changes in the noise traders' misperceptions about the asset risk also affects expected returns. Because noise traders usually buy (sell) just when other noise traders are buying (selling), their capital losses from poor market timing are larger and they increase with the magnitude of the changes in their misperceptions. Then, the changes in the noise traders' misperceptions about the asset risk result in lower expected returns. This is the so called the "Friedman effect". On the other hand, the "create-space" effect implies that a rise in noise traders' misperceptions about the asset risk raises price uncertainty and crowds out risk-averse investors. This benefits noise traders. Overall, expected returns are higher when the "create-space" effect dominates the "Friedman effect" (Lee, Jiag, and Indro, 2002).

The coefficients on h_t (α_2) presented the effects of volatility on expected returns. Roughly speaking, volatility was positively related to contemporaneously expected returns for the majority of characteristics-based portfolios (see Figure 4). For example, firms with smaller ME (the first, second, and fourth ones) and larger BE/ME ratio (the sixth and eighth portfolios) had pronouncedly positive relation between expected returns and conditional volatility. For four of CF/P portfolios (the third, fourth, sixth, and eighth ones), the relation between conditional volatility and expected returns was also significantly positive. Expected returns on half of the ten dividend yield portfolios were positively related to conditional volatility, and half were negatively related. But, among them, only two positive coefficients (the seventh and the eighth ones) were significant at the 5% level, and no negative coefficients were significant. At the 5% significance level, three earning/price portfolios (the fourth, the seventh, and the tenth portfolios) exhibited positive relationship between conditional volatility and returns. This implied that, for small firms, value stocks, and moderate cash flow/price, and high dividend yield stocks, the create-space effects dominated the Friedman effects, which led to higher expected returns from volatility. But the create-space effects and the Friedman effects did not pronouncedly dominate each other.

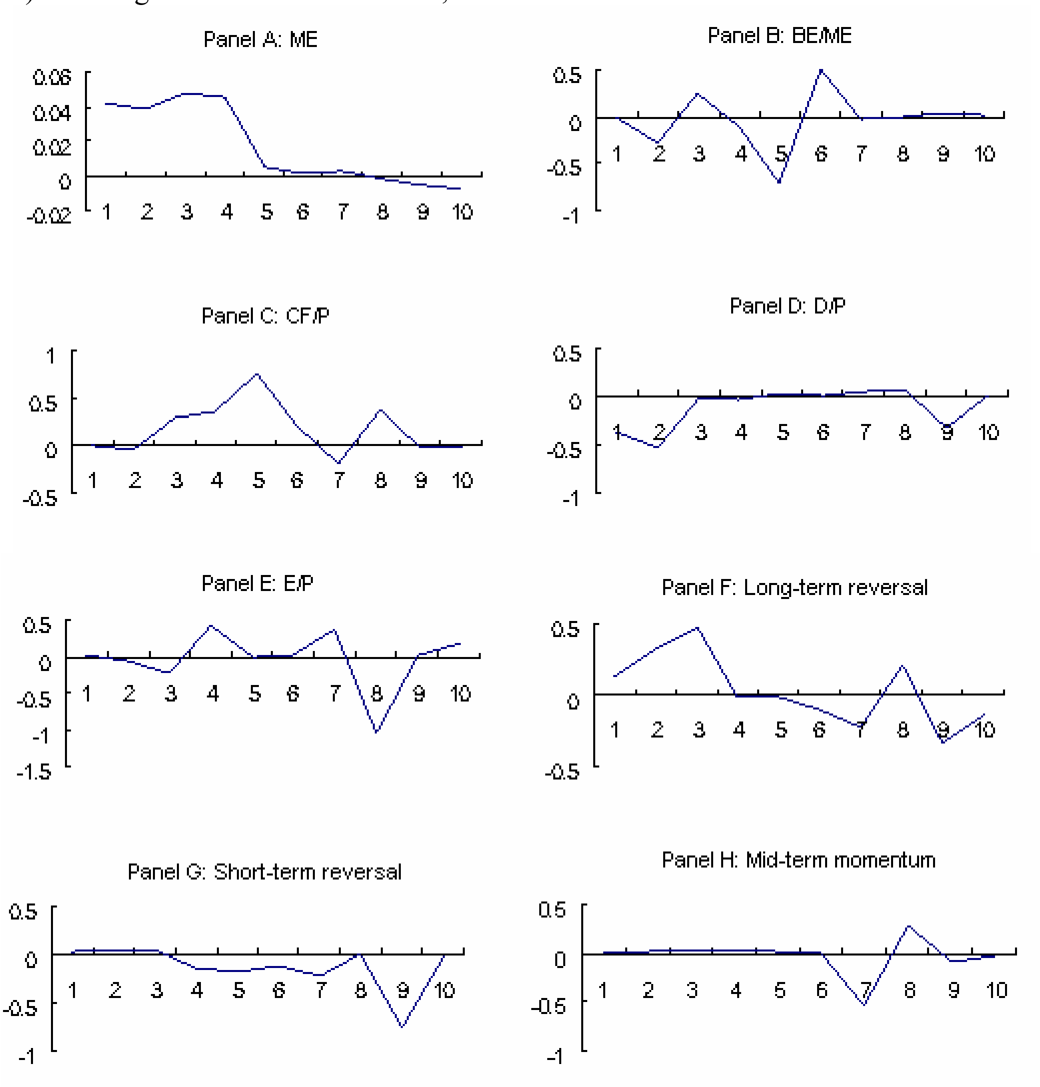

Fig. 4. Volatility on expected returns for firm-characteristic portfolios

The expected returns for three out of five long-term losers (the first, the second, and the third portfolios) were positively correlated with conditional volatility, while one out of winners (the eighth one) had significantly positive relations. Overall, long-term past losers had a relatively positive relation between the equity expected returns and conditional volatility than long-term winners. Similar to long-term reversal portfolios, three out of five short-term reversal portfolios (the first, the second and the third portfolios) had positive relation between expected returns and conditional volatility, but none out of short-term winners was significantly different from zero. Also, only in the eighth momentum portfolio, volatility had positive effects on excess volatility. This indicated that the positive relationship existed specifically in long-term losers, short-term losers, and mid-term winners.

Overall, there was a positive relation between the equity expected returns and conditional volatility, revealing that the create-space effects dominated the Friedman effects for most portfolios. These results were consistent with some economic theories that idiosyncratic volatility should be positively related to expected returns; for example, Malkiel and Xu (2002) and Jones and Rhodes-Kropf (2003) argued that if investors required compensation for not being able to diversify risk, they would demand a premium for holding stocks with high idiosyncratic volatility. Merton (1987) suggested that in an incomplete market, firms with larger firm-specific risk required higher returns to compensate investors for holding imperfectly diversified portfolios. Barberis and Huang (2001) also predicted that, due to loss aversion, higher idiosyncratic volatility stocks would require higher than expected returns. In addition, similar to Lintner (1965), Lehmann (1990), Tinic and West (1986), and Malkiel and Xu (2002), which worked with portfolios sorted on firm characteristics, my results were also similar to their findings either that portfolios with higher idiosyncratic volatility had higher returns or that there existed no statistically significant relation between idiosyncratic volatility and average returns[1].

3.4. Asymmetric shock on volatility (β_2). This section discussed if the asymmetric shock varied with *firm characteristics*. The coefficients on $\frac{\eta_{t-1}}{\sqrt{h_{t-1}}}(\beta_2)$ presented the asymmetric shock on volatility. If a negative shock is more likely to cause a larger upward revision of volatility then a positive shock of similar magnitude, β_2 will be negative.

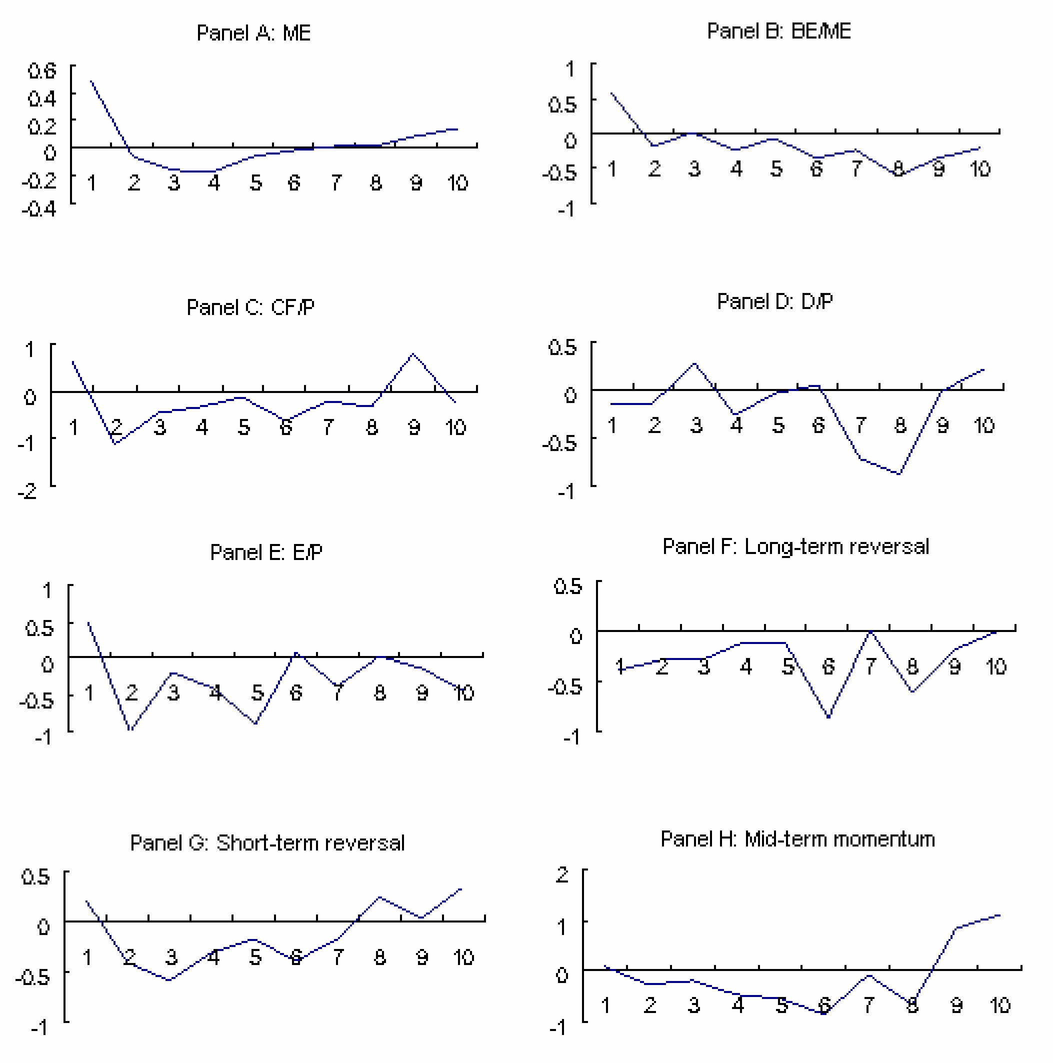

Fig. 5. Asymmetric shock on volatility for firm-characteristic portfolios

From Table 1 and Figure 5, the smallest and largest size portfolios had significantly positive β_2. This indicated that good news rather than bad news caused a greater magnitude of change in volatility of extremely large and small sized portfolios. The asymmetric effects of news on volatility occurred on larger book-to-market-value portfolios (the sixth, eighth, and ninth portfolios were significant) (see Table 2 and Figure 5) and moderate cash flow/price portfolio (the second, third, fourth, and eighth port-

[1] However, Ang, Hodrick, Xing, and Zhang (2006), by examining idiosyncratic volatility at the firm level and directly computing differences in average returns between stocks with low and high idiosyncratic volatilities, found that stocks with high idiosyncratic volatilities had low average returns.

folios were significant) (see Table 3 and Figure 5)[1]. Also, seven out of ten dividend yield portfolios (only the seventh and eight portfolios were significant) had this asymmetric effect, with the exception of the largest dividend yield one having significant positive β_2 (see Table 4 and Figure 5).

The asymmetric effects were relatively irregular for earning/price portfolios (see Table 5 and Figure 5). For example, good news had stronger shocks on the lowest and the eighth earning/price portfolios, but bad news caused large volatility for the five earning/price portfolios (the second, fourth, fifth, seventh, and tenth portfolios). Collectively evidence implied that good news can cause greater magnitude of the volatility change on extreme characteristics-based stocks, but bad news can lead to much larger volatility on moderate characteristics-based stocks.

As far as portfolios formed based on prior performance, bad news caused large volatility for nine out of ten long-term reversal portfolios (the first, second, third, sixth, and eighth portfolios are significant) (Table 6 and Figure 5) and six short-term reversal portfolios (the second and third portfolios are significant) (Table 7 and Figure 5). As for momentum portfolios, the second, fourth, fifth, sixth, and eighth portfolios had significantly negative β_2, but the ninth and tenth portfolios had significantly positive β_2. The above evidence showed that bad news had a greater impact on long-term losers, short-term losers and non-mid-term winners, but good news resulted in greater volatility of mid-term winners. Overall, the well-known asymmetric effect did not exist in all stocks, and its existence depended on firm characteristics.

Conclusion

This paper empirically tested the impact of noise trader risk on both conditional volatility and expected returns as suggested in DSSW (1990). In contrast to prior empirical studies where noise trader risk was measured by closed-end mutual fund discounts or Investors' Intelligence, a measure of investor sentiment compiled by Baker and Wurgler (2006) was used instead. Moreover, the issue of how the dynamics of volatility varied in the cross-section was as yet unexplored. To fill in this gap, this paper extended Baker and Wurgle'sr (2006) work by contemporaneously considering conditional volatility and expected returns.

The main empirical finding was that the cross-section of future stock returns was conditional upon beginning-of-month sentiment. As Baker and Wurgler (2006) noted, small-sized, growth, and low dividend stocks were vulnerable to sentiment since arbitrage tends to be particularly risky and costly to them. In addition, investors had high propensities to speculate on either past losers or past winners due to the long-term overreaction of De Bondt and Thaler (1985) and mid-term momentum of Jegadeesh and Titman (1993). When sentiment was high, extreme short-term losers and mid-term winners tended to earn significantly low returns, but long-term losers earned positive returns in the subsequent month. Nevertheless, these conditional cross-sectional patterns attenuated when conditional on a low sentiment.

With the exception of the cross sectional effects of sentiment on future stock returns, conditional volatilities also varied in the cross-section. An optimistic sentiment was followed by an upward change in conditional volatility for large stocks, extreme growth stocks, value stocks, low and high cash flow/price stocks, moderate earning/price stocks, long-term losers, and mid-term winners. On the contrary, a pessimistic sentiment led to a downward volatility change for moderate cash flow/price and dividend-yield stocks, high earning/price stocks, long-term losers, and mid-term winners. The above findings were consistent with Lee, Jiang, and Indro (2002) that bullish (bearish) changes in sentiment led to downward (upward) adjustments in volatility, and revealed that stocks easy to arbitrage and attract rational speculation were not necessarily less volatile.

The effects of conditional volatility on expected returns were also connected with firm characteristics. In particular, small, value, moderate cash flow/price, higher dividend-paying stocks, long-term losers and short-term losers have positive correlations. In comparison, there are fewer portfolios that have negative relations between conditional volatility on expected returns. These results were also consistent with earlier research that either found a significantly positive relation between volatility and average returns (e.g., Lintner, 1965; Lehmann, 1990; Tinic and West, 1986; and Malkiel and Xu, 2002), or that failed to find any statistically significant relation between volatility and average returns (Longstaff, 1989). The leverage effects also mainly occurred in value stocks, moderate cash flow/price stocks, non-extreme high dividend-paying stocks, long-term losers, short-term losers, non extreme mid-term winners. In summary, the effects of sentiment on expected returns and volatility, of volatility on expected returns, and the asymmetric effect did not exist in all stocks, and its existence depended on firm characteristics.

[1] But the coefficient on the lowest BE/ME portfolio was significantly positive at 5% level. Positive significances were also found on the lowest and eighth cash flow/price groups.

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