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Excess volatility and the cross-section of stock returns

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ABSTRACT

We document a reliable positive relation between excess volatility and the cross-section of stock returns over the sample period of 1963 to 2010. Significantly positive differentials have been found between the two decile portfolios with the largest and the least excess volatility, under all the situations we have examined. Size, value, and momentum effects cannot explain our empirical results. Likewise they cannot be explained by liquidity, bid-ask bounce, and risk-aversion-related inventory effects.

1. Introduction

The excess volatility puzzle, identified by Shiller (1981) and LeRoy and Porter (1981), has gained much attention over the past three decades. Surprisingly, unlike other financial anomalies in the

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literature,[2] few papers have attempted to explore profitable trading rules implied by excess volatility. Dumas (2003) makes the following remark:

> "If there is excessive volatility, one can argue that this is evidence of financial market inefficiency. In that case, one should be able to develop some 'volatility arbitrage' that would reap profits. In particular, if the reason for excess volatility is irrationality of one or several categories of traders, one should be able to find a way for rational traders to take advantage of their behavior [.]"

But Dumas (2003) immediately points out that "[t]hat is not easy to conceive". In this article, we will provide such an effort and investigate the relation between excess volatility and the cross-section of stock returns.[3]

Shiller (1981) defines excess volatility as the volatility of the equity market that cannot be justified by variation in subsequent dividends. Since the information that investors use to forecast future dividends is unobservable in nature, researchers often examine the excess volatility puzzle by comparing the realized stock price volatility to the volatility bounds. These bounds are formalized based on the ex-post present values derived from some discount-rate models. However, the empirical methodologies employed in the volatility test literature have been under extensive critiques ever since Shiller (1981). For example, Cochrane (1991) criticizes that the volatility tests are only tests of specific discount-rate models; they do not have any advantage over other empirical methods such as return-forecasting regressions or Euler equations and cannot tell much about the market efficiency or inefficiency.

This issue of unobservable information becomes even more disturbing when we try to identify profitable opportunities implied by excess volatility. We cannot use any ex-post information—such as ex-post dividend distributions, which are often utilized in the volatility test literature—to quantify excess volatility. Thus, some innovative method must be attempted in order to accomplish the challenging task that is posited by Dumas (2003).

We go back to the literature for possible clues to quantify excess volatility. First, Shiller (1981) states that the short-term stock market volatility is too excessive to be explained by the subsequent variation in the economic fundamentals. In the longer horizon, however, the extra volatility should fade away as more real information about economic growth, corporate earnings, and changes in the business condition are factored into the stock price. Second, French and Roll (1986) propose that if trading noises are the source that causes excess volatility in daily returns, the variance of long-horizon returns should be less than the cumulated variance of daily returns. They find that mispricing can be responsible for 4–12% of the variance in daily returns on average. Third, Fama (1990) and Schwert (1990) provide abundant empirical evidence that the fluctuation in stock returns over longer holding horizons can be explained more by variation in the subsequent real activities. They argue that since economic information is usually spread over many previous periods, the cumulative economic information can be better captured by the longer-term stock returns.

Although the classical studies listed above have various research aims on their own, they share the same view that the economic fundamentals are more correctly reflected by longer-horizon stock returns. Thus, the difference between the volatility of short- and long-horizon returns can be very informative for quantifying excess volatility.

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[2] For example, Lehmann (1990) and Lo and MacKinlay (1990) identify profitable trading rules implied by the reversals in short-term stock returns. Their contrarian investment portfolios are constructed by selling winners and buying losers in previous week(s) and make significantly positive profits over short holding periods. In contrast, Jegadeesh and Titman (1993, 2001) provide a variety of profitable strategies based on the continuation of past returns. They document that the momentum strategies formed by selling losers and buying winners of the past 3–12 months can earn superior returns over short to intermediate holding periods. More recently, Ang, Hodrick, Xing, and Zhang (2006, 2009) investigate the relation between idiosyncratic volatility and the cross-section of stock returns for the U.S. and international markets. They find that "stocks with high idiosyncratic volatility relative to the Fama and French (1993) model have abysmally low average returns". They provide an investment strategy accordingly that earns superior returns. These reversal, momentum and idiosyncratic volatility effects cannot be easily accommodated by the efficient market hypothesis of Jensen (1978).

[3] See Subrahmanyam (2010) for a late review on many other predictors of the cross-sectional stock returns.

We employ the variance difference (VD) as a proxy for excess volatility. Our definition of VD is adapted from the definition of the variance difference in Lo and MacKinlay (1988).[4] That is, VD of q-period returns is given by the difference between q of the variance of one-period return and the variance of q-period return. The economic intuition of VD of q-period returns (VD(q)) is that the volatility that cannot be justified by the economic fundamentals impounded in the stock market from one period to q periods should partially, if not completely, die out in the volatility of q-period returns, with q substantially greater than one. Since daily returns are more likely contaminated by the misinterpretation of information, which may be smoothed out in the weekly or monthly data, we define VD(q) based on daily return data in order to better capture excess volatility caused by trading noises, mispricing or other sources.

Following Jegadeesh and Titman (1993, 2001), we first use a portfolio approach to identify possible profitable opportunities and document the relation between excess volatility and cross-sectional stock returns. Our ten equally weighted decile portfolios are ranked from P1 to P10 with ascending VD(q). That is, portfolio P1 has the least VD(q) while portfolio P10 has the greatest VD(q). We find that portfolios with excess volatility tend to have a significant abnormal monthly return. Moreover, portfolio P10 significantly outperforms P1, under all scenarios we have examined. Over the sample period of 1963–2010, the investment portfolio formed by buying the greatest VD(22) decile portfolio and selling the least VD(22) decile portfolio, with formation and holding periods of 12 months, can make a monthly return of 0.99%. We show that the abnormal returns cannot be explained by the CAPM and the Fama–French–Carhart 4-factor Model. Likewise, they cannot be explained by bid-ask bounce, trading volume and the risk-aversion-related inventory effect. Second, the reliable positive relation between excess volatility and cross-sectional stock returns is confirmed to be robust by the Fama–MacBeth (1973) regressions. The average slope from the monthly Fama–MacBeth regression of returns on VD alone equals 16.7%, with a t-statistic of 3.68 (see Panel a in Table 8). The average slopes remain significantly positive with addition of other explanatory variables of size, value, liquidity, momentum and others.

The remainder of the paper is organized as follows. Section 2 describes the data, definitions, and trading strategies. Section 3 reports the performances of the excess volatility investment portfolios. Section 4 examines alternative explanations of our empirical results. Section 5 concludes.

2. Data, definitions, and trading strategies

2.1. Data

We include all the NYSE/AMEX/NASDAQ common stocks (share code 10 or 11) in our research. The sample period is from January 1963 to December 2010.[5] All the stock transaction data are downloaded from daily stock prices file or monthly stock prices file in the Center for Research in Securities Prices (CRSP).

2.2. Variance difference and variance ratio

Let P_k be the logarithmic stock price on the k-th day for $k = 0, 1, 2, \ldots$. Following Lo and MacKinlay (1988), we define VD of q-day returns as follows.

$$\mathrm{VD}(q) = q\hat{\sigma}_1^2 - \hat{\sigma}_q^2 = q\sum_{k=1}^{n}\frac{(P_k - P_{k-1} - \hat{\mu})^2}{n-1} - \sum_{k=q}^{n}\frac{(P_k - P_{k-q} - q\hat{\mu})^2}{m} \quad (1)$$

[4] Notice that the variance difference defined by Lo and MacKinlay (1988) is mainly used for testing if the market follows a random walk. Our definition of VD is used to detect excess volatility and investigate how VD is related to the cross-section of stock returns. In particular, we use it to examine if there are portfolios that can earn abnormal stock returns.

[5] The sample period in this article refers to the observation period for the raw data. The observation period for the VD and VR or other variables may differ from the sample period. For example, if we need 12-month formation period to calculate VD, then the actual observation period for VD is from December 1963 to December 2010 over the sample period of January 1963–December 2010.

where

$$\hat{\mu} = \sum_{k=1}^{n} \frac{P_k - P_{k-1}}{n}$$

is the mean estimator of daily log stock returns,

$$\hat{\sigma}_1^2 = \sum_{k=1}^{n} \frac{(P_k - P_{k-1} - \hat{\mu})^2}{n-1}$$

and

$$\hat{\sigma}_q^2 = \sum_{k=q}^{n} \frac{(P_k - P_{k-q} - q\hat{\mu})^2}{m}$$

are the unbiased variance estimators of daily and q-day log stock returns, respectively. Note that

$m = (n - q + 1)\left(1 - \frac{q}{n}\right)$ is used to accommodate for the overlapping observations so that $\hat{\sigma}_q^2$ is an unbiased estimator. Also note that the variance difference defined in Lo and MacKinlay (1988) equals $-\text{VD}(q)/q$. The economic intuition of VD(q) is that the volatility of daily logarithmic returns that cannot be justified by the economic information impounded in the stock market from one day to q days should partially, if not completely, die out in the volatility of q-day logarithmic returns, with q substantially greater than one.

Since the excess volatility defined in this article is expected to be characterized with overreaction or mean reversion in short-horizon returns, we also report the variance ratio (VR), a measure of autocorrelation, for all the investment portfolios. Following Lo and MacKinlay (1988), we define VR of q-day returns as follows.

$$\text{VR}(q) = \frac{\hat{\sigma}_q^2}{q\hat{\sigma}_1^2} = (n-1)\sum_{k=q}^{n} \frac{(P_k - P_{k-q} - q\hat{\mu})^2}{qm\sum_{k=1}^{n}(P_k - P_{k-1} - \hat{\mu})^2} \tag{2}$$

where $\hat{\sigma}_q^2$ and $\hat{\sigma}_q^1$ are the unbiased variance estimators defined above. Cochrane (1988) and Lo and MacKinlay (1988, 1989) have shown that VR can also be approximately estimated by

$$\text{VR}(q) = 1 + 2\sum_{k=1}^{q-1} \frac{(q-k)\rho_k}{q} \tag{3}$$

where ρ_k is the estimated kth lag autocorrelation coefficient of stock returns. This means that variance ratio is actually a linear combination of the first $q-1$ autocorrelation coefficient estimators of stock returns with arithmetically declining weights. VR that is greater (less) than unity indicates that the return series is positively (negatively) autocorrelated. Since the overreacted returns can be negatively autocorrelated up to arbitrary lag(s), VR may be a more comprehensive measure for overreaction in stock returns (Kaul & Nimalendran, 1990). Note that VR equals unity if and only if VD equals zero. It is not surprising to find out in Table 1 that VD ascends while VR descends across all three periods of 1963–2010, 1963–1989, and 1989–2010. In fact, VD can be derived from VR by

$$\text{VD}(q) = q{\sigma_1}^2(1 - \text{VR}(q)) \tag{4}$$

2.3. Trading strategies

We examine the cross-sectional returns pattern by sorting stocks on individual VD(q). Our trading strategies follow those described in Jegadeesh and Titman (1993, 2001) closely, with a formation period of M months and a holding period of N months. We implement our investment strategies $M/N/q$ as follows. At the beginning of each month t, we employ Eq. (1) to calculate the individual VD(q) based on the past M month stock returns. Then, we sort all the stocks into ten deciles with

Table 1
Performances of the investment portfolios ranked on variance difference of 22-, 44- and 66-day returns.

q=	22						44						66					
Portfolio	AR	*t*-stat	VD	V(1)*22	V(22)	VR	AR	*t*-stat	VD	V(1)*44	V(44)	VR	AR	*t*-stat	VD	V(1)*66	V(66)	VR
P1	1.10	3.29	−1.95	4.14	6.09	1.59	1.07	3.18	−5.48	8.37	13.85	1.82	1.07	3.21	−10.06	12.54	22.60	2.00
P2	1.14	4.56	−0.43	1.85	2.28	1.37	1.15	4.65	−1.13	3.79	4.92	1.47	1.18	4.80	−1.94	5.66	7.61	1.53
P3	1.18	5.61	−0.14	1.29	1.43	1.17	1.19	5.75	−0.33	2.59	2.92	1.19	1.18	5.75	−0.50	3.84	4.35	1.18
P4	1.20	6.06	0.03	1.21	1.18	0.99	1.19	6.12	0.10	2.35	2.25	0.95	1.19	6.28	0.25	3.43	3.18	0.90
P5	1.20	6.03	0.19	1.35	1.16	0.85	1.19	6.07	0.48	2.61	2.13	0.77	1.21	6.23	0.88	3.84	2.96	0.71
P6	1.23	5.75	0.39	1.69	1.30	0.73	1.23	5.82	0.94	3.30	2.37	0.65	1.25	5.83	1.63	4.92	3.29	0.59
P7	1.27	5.34	0.67	2.24	1.57	0.65	1.29	5.38	1.59	4.44	2.84	0.58	1.29	5.35	2.71	6.67	3.96	0.52
P8	1.34	4.95	1.15	3.12	1.96	0.59	1.34	4.90	2.69	6.21	3.52	0.52	1.34	4.84	4.49	9.40	4.91	0.47
P9	1.47	4.64	2.19	4.80	2.62	0.53	1.48	4.61	4.97	9.65	4.69	0.46	1.45	4.49	8.10	14.53	6.42	0.41
P10	2.09	5.37	7.82	12.19	4.37	0.41	2.09	5.29	16.87	24.51	7.63	0.35	2.07	5.19	26.41	36.90	10.50	0.32
P10–P1	0.99	5.17	9.77	8.05	−1.72	−1.18	1.02	5.35	22.35	16.14	−6.22	−1.46	1.00	5.30	36.47	24.36	−12.10	−1.68

Note: This table reports the performances of the investment portfolios ranked on variance difference of q-day returns ($q = 22$, 44 and 66), with a 12-month forming period and 12-month holding period. The column AR is the average monthly return for each portfolio. V(1) is the average variance estimator for daily return of stocks constituting each portfolio. We multiply it by q so that it can be comparable to the average q-day return variance estimator (V(q)). VD is the average variance difference of stocks constituting each portfolio. VR is the average variance ratio of stocks constituting each portfolio. AR, VD, V(1)*q and V(q) are reported in percentage. The sample period is from January 1963 to December 2010.

ascending VD(q). Finally, we construct our excess volatility investment portfolios (P1, P2, . . ., P10) at the beginning of each month by equally including all the stocks ranked in the same VD(q) decile in any of the latest N ranking months. For example, the investment portfolio P1 at month t consists of 1/Nth of the lowest equally weighted VD(q) decile ranked at the beginning of month t, 1/Nth of the lowest equally weighted VD(q) decile ranked at the beginning of month $t-1$, . . ., and 1/Nth of the lowest equally weighted VD(q) decile ranked at the beginning of month $t-N+1$. Similarly, the investment portfolio P10 at month t consists of 1/Nth of the largest equally weighted VD(q) decile ranked at the beginning of month t, 1/Nth of the largest equally weighted VD(q) decile ranked at the beginning of month $t-1$, . . ., and 1/Nth of the largest equally weighted VD(q) decile ranked at the beginning of month $t-N+1$. The investment strategy or portfolio P10–P1 is implemented by buying the decile portfolio with the largest VD(q), P10, and selling the decile portfolio with the smallest VD(q), P1, every month.

We examine the performances of the ten equally weighted investment portfolios P1, P2, . . ., P10 and pay special attention to the profitability of the investment portfolio P10–P1.

3. Performances of the excess volatility investment portfolios

This section reports the performances of the investment portfolios formed based on the methodology described in Section 2. Table 1 reports the performances of the ten portfolios generated by the strategies 12/12/q for q = 22, 44, 66. As shown in Table 1, the average monthly return (AR) is an increasing sequence along ascending VD(q) across the ten portfolios P1, P2, . . ., P10 for each q. The portfolio P10 significantly outperforms the portfolio P1 by an average monthly return of 0.99% (t-statistic = 5.17) over the sample period of 1963–2010 for q = 22. The same portfolios P10–P1 generate average monthly returns of 1.02% and 1% when q increases from 22 to 44 and 66 days, respectively. Thus, little benefits to AR have been observed empirically when q goes beyond 22 days.[6]

Notice that the excess volatility identified by VD is characterized with mean reversion in daily returns. For example, VR of the largest VD(22) decile portfolio P10 is 0.41, which indicates rapid mean reversion in returns of stocks constituting portfolio P10. Since negatively autocorrelated returns can be a consequence of investors' overreaction (Daniel, Hirshleifer, & Subrahmanyam, 1998; De Bondt & Thaler, 1985; Kaul & Nimalendran, 1990; Lo & MacKinlay, 1990), the overreaction may play a crucial role in determining the relation between excess volatility and average stock returns. Dumas, Kurshev, and Uppal (2009) state that some investors overreact to the signal and introduce an additional risk causing stock prices to be excessively volatile. As the sentiment risk is difficult to be overcome, risk-averse investors would be more conservative in investing those stocks. They may exclude or underweight in their portfolios the stocks with excess volatility. Consequently, those stocks with excess volatility can be undervalued relative to other stocks. However, as the excess volatility would be corrected in longer term, the stocks with excess volatility would be held by more investors relative to the past. As a result, the stocks with excess volatility outperform other stocks over longer horizons.

Table 2 reports the profitability of the investment portfolio P10–P1 with alternative formation and holding period combinations. All the investment portfolios in Table 2 are ranked on VD(22). We vary both the formation and holding periods among 6, 12, 24, and 36 months. This gives us 16 investment strategies in total. The results presented in Table 2 are consistent with the profitability of the investment portfolios P10–P1 described in Table 1. The most profitable portfolio is the one with a 6-month formation period and a 12-month holding period, which makes an average monthly return of 1% (t-statistic = 4.92). The least profitable portfolio is the one with a 36-month formation period and a 36-month holding period, which makes an average monthly return of 0.64% (t-statistic = 3.39). Since the empirical results are robust to the variation in q, M and N, we will henceforth simply concentrate on the investment strategy 12/12/22, unless otherwise specified.

[6] One interesting feature that should be noted is that VR(q) is descending while VD(q) is ascending along the ten portfolios. But both V(1)*q and V(q) form a big "smile" shape with the minimum point reached around the portfolio(s) with VD(q) close to zero, across all three sample periods and the three values of q. That is, V(1)*q and V(q) start to decline at the portfolio P1 and continue to do so along the portfolios with negative VD(q). The two curves start to increase around the portfolio(s) where VD(q) is close to zero.

Table 2
Performances of P10–P1 with various formation and holding period combinations.

M	*N*	6	12	24	36
6	P10	1.89	2.07	2.14	2.00
	t-stat	4.65	5.22	5.39	5.05
	P1	1.01	1.07	1.17	1.12
	t-stat	3.07	3.12	3.43	3.35
	P10–P1	0.88	1.00	0.97	0.88
	t-stat	4.55	4.92	4.49	3.95
12	P10	1.96	2.09	2.10	1.95
	t-stat	4.98	5.37	5.41	5.05
	P1	1.07	1.10	1.15	1.12
	t-stat	3.26	3.29	3.46	3.43
	P10–P1	0.89	0.99	0.96	0.83
	t-stat	5.17	5.17	4.68	3.91
24	P10	1.94	2.01	1.99	1.86
	t-stat	5.08	5.31	5.26	4.96
	P1	1.17	1.16	1.19	1.17
	t-stat	3.68	3.62	3.72	3.70
	P10–P1	0.77	0.85	0.80	0.69
	t-stat	4.80	4.81	4.20	3.48
36	P10	1.88	1.93	1.91	1.82
	t-stat	5.07	5.26	5.20	4.96
	P1	1.22	1.21	1.22	1.18
	t-stat	3.92	3.86	3.91	3.82
	P10–P1	0.65	0.72	0.69	0.64
	t-stat	4.46	4.44	3.86	3.39

Note: This table reports the average monthly return and its *t*-statistics on the investment portfolio P10–P1 with a formation period of *M* months and a holding period of *N* months. The average monthly returns on P10–P1 are reported in percentages and their *t*-statistics are also included. The sample period is from January 1963 to December 2010.

Table 3 reports the empirical results of the investment strategy 12/12/22 for the two subperiods of 1963–1989 and 1990–2010. The costless portfolio P10–P1 yields average monthly returns of 0.64% and 1.42%, respectively, for the two subperiods. Notice that the abnormal return earned by the investment portfolio P10–P1 over 1990–2010 is much higher than that over 1963–2010. This empirical finding corroborates the evidence provided by Fig. 1. As illustrated in Fig. 1, the time-varying abnormal returns exhibit high volatility across the whole sample period. The investment portfolio P10–P1 can make positive or negative abnormal returns across both recessions and expansions. The large volatility of the abnormal returns across time reflects high holding costs for arbitrageur documented in Shleifer and Vishny (1997) and hence reinforce the argument made in Dumas et al. (2009) that it takes a fairly long time for rational investors to overcome the irrationality caused by overconfident investors.

Table 3
Results obtained for two subperiods.

	1963–1989						1990–2010					
	AR	*t*-stat	VD	V(1)*22	V(22)	VR	AR	*t*-stat	VD	V(1)*22	V(22)	VR
P1	1.07	2.66	−1.68	2.91	4.58	1.69	1.14	2.03	−2.29	5.67	7.95	1.46
P2	1.18	3.47	−0.51	1.49	2.00	1.49	1.09	2.96	−0.33	2.30	2.63	1.21
P3	1.24	4.14	−0.25	1.12	1.37	1.33	1.11	3.81	0.00	1.50	1.50	0.97
P4	1.28	4.60	−0.10	0.97	1.08	1.16	1.10	3.94	0.20	1.50	1.30	0.78
P5	1.30	4.79	0.01	0.94	0.93	0.99	1.08	3.67	0.41	1.86	1.45	0.67
P6	1.30	4.58	0.12	1.07	0.95	0.83	1.14	3.51	0.71	2.45	1.74	0.61
P7	1.33	4.18	0.28	1.41	1.13	0.74	1.20	3.32	1.16	3.27	2.12	0.55
P8	1.38	3.79	0.54	1.98	1.45	0.67	1.30	3.18	1.91	4.52	2.60	0.50
P9	1.37	3.23	1.08	3.00	1.92	0.60	1.60	3.34	3.55	7.03	3.48	0.45
P10	1.71	3.37	4.07	7.13	3.05	0.46	2.56	4.24	12.46	18.47	6.01	0.36
P10–P1	0.64	2.97	5.75	4.22	−1.53	−1.24	1.42	4.26	14.74	12.80	−1.94	−1.11

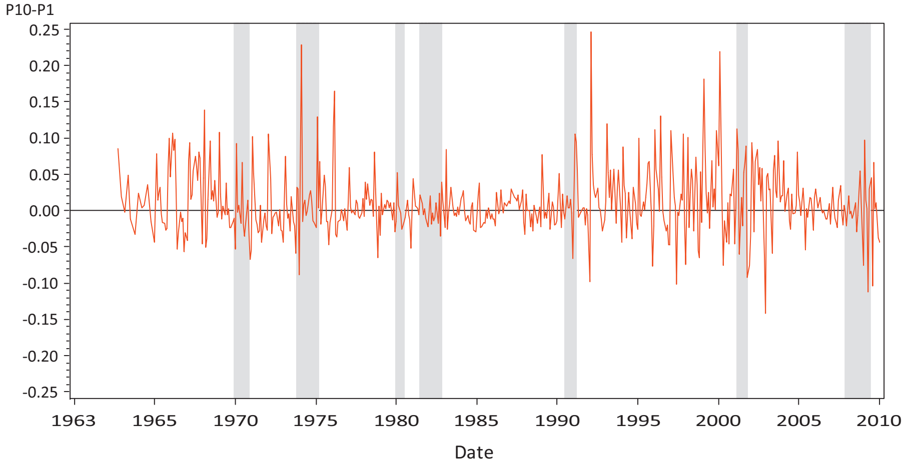

Fig. 1. The monthly returns of the investment portfolio P10–P1 over the whole sample period. *Note*: This figure illustrates the monthly returns earned by the portfolio P10–P1generated by the investment strategy 12/12/22 over the sample period of 1963–2010. The shaded areas are the recession periods identified by NBER.

Finally, as shown in both Tables 1 and 3, VR is less sensitive to changes in V(1). This is why VD has been chosen to provide a rank of investment portfolios because our target is to identify excess volatility in V(1), not just the mean reversion or persistence in daily returns. The marginal difference in VR across the ten portfolios is about the same, but the marginal differences of VD and AR are quite different across the ten portfolios. Consider the sample period of 1963–2010. VD increases from P9 to P10 by 5.63% and VR decreases just by −0.12%, with AR increasing substantially by 0.62%. When VR changes little, change in VD is dominated by the variation in V(1), as shown by Eq. (5), which is obtained by taking differentials on both sides of Eq. (4),

$$d(\mathrm{VD}(q)) = \frac{2q\mathrm{VD}(q)}{\sigma_1} d(\sigma_1) - q\sigma_1^2 d(\mathrm{VR}(q)) \tag{5}$$

Consequently, if a change in sentiments or other factors changes V(1) substantially while has little impact on VR(q), then such a change will be immediately captured by VD(q) but not by VR(q).

4. Alternative explanations and considerations

4.1. Can classical risk-based asset pricing models explain the profitability?

This subsection examines if the abnormal returns earned by the excess volatility investment portfolios can be explained by the CAPM and the Fama–French three-factor Model (Fama & French, 1993, 1996) augmented with a momentum factor (Carhart, 1997; henceforth, Fama–French–Carhart 4-factor Model). We obtain the data on the Fama–French three factors and the momentum factor from the Fama file in the CRSP database.[7]

As shown in Table 4, the two sequences of alphas are basically increasing, with only one exception at P2 for the Fama–French–Carhart 4-factor Model. Notice that VD and AR are two ascending sequences as well, as shown in Table 1. The levels of the t-statistics are significant for majority alphas. To be more

[7] We include the momentum factor in the Fama–French three-factor Model to test if the excess volatility effect is robust to the momentum effect and check if the profitability of the excess volatility investment strategy can be explained by the momentum. We also include a liquidity factor from Pastor and Stambaugh (2003) into Fama–French–Carhart 4-factor Model. Since the Pastor and Stambaugh (2003) liquidity factor is available beginning 1968, which is different from the sample period of Table 4, we do not report it in this article. Empirical results are available upon request. Our conclusions reported in this subsection remain the same as the inclusion of liquidity factor.

Table 4
Regression Results of the CAPM and the Fama–French–Carhart 4-factor Model.

Portfolio	CAPM		Fama–French–Carhart 4-factor model				
	Alpha	MF	Alpha	MF	HMF	SMF	MOMF
P1	0.03 (0.17)	1.42 (32.95)	0.10 (0.80)	1.14 (39.81)	1.13 (28.83)	0.02 (0.42)	−0.37 (−13.50)
P2	0.19 (1.62)	1.16 (45.72)	0.05 (0.85)	1.04 (74.14)	0.72 (37.08)	0.29 (13.79)	−0.19 (−13.54)
P3	0.30 (3.31)	1.00 (50.18)	0.12 (2.36)	0.94 (76.65)	0.51 (30.32)	0.33 (17.91)	−0.11 (−9.03)
P4	0.34 (4.18)	0.95 (52.88)	0.16 (3.54)	0.90 (83.41)	0.47 (31.85)	0.31 (19.13)	−0.08 (−7.78)
P5	0.34 (4.10)	0.95 (51.91)	0.18 (4.34)	0.88 (89.40)	0.52 (38.28)	0.28 (18.69)	−0.10 (−10.21)
P6	0.35 (3.58)	1.00 (46.94)	0.20 (4.75)	0.89 (89.16)	0.65 (46.96)	0.25 (16.51)	−0.13 (−13.53)
P7	0.35 (2.95)	1.08 (41.24)	0.22 (4.24)	0.92 (76.67)	0.83 (50.14)	0.19 (10.43)	−0.15 (−12.84)
P8	0.39 (2.48)	1.17 (33.94)	0.26 (3.35)	0.94 (52.88)	1.06 (43.16)	0.15 (5.72)	−0.19 (−10.80)
P9	0.48 (2.27)	1.24 (26.76)	0.32 (2.56)	0.96 (32.66)	1.33 (32.98)	0.17 (3.85)	−0.23 (−8.09)
P10	1.09 (3.54)	1.26 (18.71)	0.82 (3.58)	0.93 (17.52)	1.67 (22.85)	0.30 (3.74)	−0.25 (−4.80)
P10–P1	1.06 (5.57)	−0.16 (−3.84)	0.72 (3.96)	−0.20 (−4.83)	0.54 (9.25)	0.28 (4.41)	0.13 (3.07)

Note: This table presents the estimated coefficients and relevant *t*-statistics (in parentheses) obtained by regressing the monthly abnormal returns, earned by the investment strategy 12/12/22, on the market factor (MF), the value factor (HMF), the size factor (SMF), and the momentum factor (MOMF). The CAPM regression is as follows: $R_{st} - R_{ft} = \alpha + \beta MF_t + \varepsilon_t$ and the Fama–French–Carhart 4-factor model regression is as follows: $R_{st} - R_{ft} = \alpha + \beta_1 MF_t + \beta_2 HMF_t + \beta_3 SMF_t + \beta_4 MOMF_t + \varepsilon_t$, where R_{st}, R_{ft} and ε_t are respectively the average monthly return on the investment strategy 12/12/22, the monthly return on the 1-month treasury bill and white noise. The sample period is from January 1963 to December 2010.

specific, the portfolio P10, which has the greatest VD, has an alpha of 1.09% with a *t*-statistic of 3.54 and the portfolio P1, which has the least VD, has an alpha of 0.03% with an insignificant *t*-statistic of 0.17 in the CAPM. In the Fama–French–Carhart 4-factor Model, the alpha of portfolio P10 equals 0.82% with a *t*-statistic of 3.58 and the alpha of portfolio P1 equals 0.10% with an insignificant *t*-statistic of 0.8. As expected, the alpha of portfolio P10–P1 equals 1.05% with a *t*-statistic of 5.57 in the CAPM. Likewise the alpha of portfolio P10–P1 equals 0.72% with a *t*-statistic of 3.96 in the Fama–French–Carhart 4-factor Model. These results reveal that the profitability of the investment portfolios documented in Tables 1–3 cannot be explained by size, value, and momentum effects.[8]

4.2. *Bid-ask errors, risk-aversion-related inventory effect or overreaction?*

As documented in Tables 1 and 3, the profitability of the excess volatility investment portfolios P1–P10 is closely related to the mean-reversion in daily stock returns. Overreaction is one source that contributes to the negatively autocorrelation or the mean-reversion in returns. But it may not be the only source. Kaul and Nimalendran (1990), Conrad, Kaul, and Nimalendran (1991) and Jegadeesh and Titman (1995), among others, argue that the negatively autocorrelated returns may be caused by the bid-ask bounce. Kaul and Nimalendran (1990) find that stock returns, which are negatively autocorrelated, become positively autocorrelated, after the transaction return data is replaced by the bid return data. The latter is free of bid-ask errors. Moreover, they find that almost half of the variances of daily stock returns are related to the bid-ask bounce.

Reversals in short-term returns may also be a consequence of the risk-aversion-related inventory effect. Campbell, Grossman, and Wang (1993) show that risk-averse investors who are akin to the "market makers" may require higher returns than the liquidity traders. They demonstrate that price changes accompanied by high volume caused by the "non-informational demands for immediacy" (Avramov, Chordia, & Goyal, 2006) tend to be reversed but price changes on days with low volume

[8] It is quite amazing to find out in Table 4 that the value factor in the Fama–French–Carhart 4-factor model regression also has a "smile" shape with the minimum point reached right at the portfolio P4. The momentum factor, on the other hand, has an upside down "smile" with the maximum point reached at the portfolio P4. The size factor is slightly more complicated. But the upside down "smile" can still be observed with a few exceptions. Interestingly, the alphas of the two regressions do not form a "smile" shape. Instead, they are basically ascending, with one exception at P2 in the Fama–French–Carhart 4-factor model regression. These "smile" shapes we have just illustrated are novel empirical observations. They should be closely related to the facts that both V(1)*22 and V(22) "smile" as well. But we have not established a theory to make a link among them. Such a theory should be interesting and will be left for future study.

Table 5
Performances of the investment strategy 12/12/22 based on bid returns and transaction returns.

	Bid returns						Transaction returns					
	AR	*t*-stat	VD	V(1)*22	V(22)	VR	AR	*t*-stat	VD	V(1)*22	V(22)	VR
P1	1.09	1.96	−2.53	4.52	7.06	1.72	1.07	1.99	−1.83	4.05	5.87	1.54
P2	1.16	2.73	−0.50	1.98	2.48	1.36	1.15	2.81	−0.38	1.84	2.23	1.31
P3	1.08	3.16	−0.17	1.37	1.54	1.17	1.06	3.24	−0.12	1.28	1.40	1.13
P4	1.05	3.42	−0.01	1.08	1.09	0.99	1.05	3.42	0.02	1.06	1.04	0.95
P5	1.01	3.31	0.10	1.03	0.93	0.84	1.05	3.44	0.12	1.06	0.94	0.82
P6	1.05	3.31	0.20	1.14	0.94	0.74	1.05	3.27	0.23	1.21	0.98	0.73
P7	1.07	3.12	0.33	1.41	1.08	0.68	1.07	3.05	0.36	1.48	1.12	0.68
P8	1.13	3.03	0.52	1.84	1.31	0.64	1.10	2.88	0.57	1.98	1.41	0.64
P9	1.17	2.74	0.93	2.81	1.87	0.59	1.17	2.64	1.04	3.06	2.02	0.59
P10	1.80	3.16	7.51	12.26	4.75	0.51	1.87	3.12	5.07	9.63	4.56	0.49
P10–P1	0.71	2.80	10.04	7.74	−2.30	−1.21	0.80	2.54	6.89	5.58	−1.31	−1.05

Note: This table reports the performances of the investment portfolios generated by the strategy 12/12/22 based on bid returns data and transaction returns data. Because a continuous series of bid return data for NYSE and AMEX stocks are only available beginning December 1992 and the bid return data for the NASDAQ have a different definition from those for the NYSE and AMEX stocks, we only include the NYSE and AMEX stocks over the period of January 1993–December 2010 in this table. The included firms should have sufficient observations available to estimate the ranking variable VD.

may not. Conrad, Hameed, and Niden (1994) and Avramov et al. (2006) find evidence in support to the risk-aversion-related inventory effect. In contrast, Cooper (1999) and Subrahmanyam (2005) provide empirical evidence that is against it. They find that the predictability of monthly returns is mainly driven by overreaction.

The divergences in the literature invite some interesting concerns about our empirical results. One may wonder if our results are driven by volatility purely induced by bid-ask errors or the risk-aversion-related inventory effect. To address these concerns, we follow Kaul and Nimalendran (1990) to use the bid return data to duplicate the investment strategy 12/12/22. We also study how the daily dollar trading volume and turnover ratio are related to our ten portfolios.

If the source of excess volatility and the profitability of the portfolio P10–P1 come from the bid-ask errors, then we should be able to observe substantial differences between the returns of the ten portfolios using the two sets of data. If the reversals in the short-term returns mainly come from the risk-aversion-related inventory effect, the portfolio with the greatest VD should have high trading activities.

Table 5 reports the empirical results with the bid return data and the transaction return data. The two AR sequences are almost identical. Over the sample period of 1993–2010, the investment portfolio P10–P1 earns a monthly return of 0.80% with a *t*-statistic of 2.54 with the transaction return data. The same portfolio earns a monthly return of 0.71% with a *t*-statistic of 2.8 with the bid return data. The two sequences of VRs are almost identical too, with slightly sizable difference at P1 only. In particular, the decile portfolio P10 has VR that equals 0.51 and 0.49 for the two different datasets. According to Lo and MacKinlay (1988), the variance ratio that is substantially lower than unity represents that stock returns are negatively autocorrelated. Our results show that the bid-ask errors may somehow affect the returns but their impacts are too small. We can conclude that the profitability of the investment portfolio P10–P1 is unlikely driven by the bid-ask errors.

To address the risk-aversion-related inventory effect, we examine the average daily dollar trading volume (DVOL) and turnover ratio (TURN) of the ten portfolios P1–P10 over the 12-month formation period. Table 6 reports the empirical results. It is of interest to note that the portfolios that have VD close to zero have the highest DVOL with low TURN. The portfolio P10, which is negatively autocorrelated and has rapid mean-reversion, has the lowest DVOL and TURN. In contrast, the polar portfolio P1, positively autocorrelated in returns, has the second lowest DVOL but the highest TURN. Our study, though limited in its content, shows that abnormal returns associated with excess volatility are unlikely caused by the risk-aversion-related inventory effect.

The relation between the trading volume and cross-section of stock returns has been extensively studied in the literature, see, e.g., Brennan, Chordia, and Subrahmanyam (1998) and Chordia,

Table 6
Trading volume and excess volatility.

	AR	*t*-stat	VD	VR	DVOL	TURN
P1	1.10	3.62	−1.30	1.57	5.27	0.44
P2	1.18	4.85	−0.34	1.34	8.82	0.32
P3	1.17	5.61	−0.13	1.16	11.63	0.28
P4	1.18	6.01	−0.01	0.99	13.71	0.26
P5	1.20	6.15	0.09	0.85	14.61	0.26
P6	1.24	5.96	0.19	0.76	13.66	0.28
P7	1.27	5.50	0.32	0.69	12.37	0.30
P8	1.31	5.04	0.55	0.65	10.37	0.32
P9	1.32	4.31	1.08	0.59	6.93	0.32
P10	1.95	4.82	5.20	0.46	2.44	0.26
P10–P1	0.86	3.82	6.50	−1.11	−2.84	−0.18

Note: This table reports the characteristics of trading volume on the investment portfolios generated by the strategy 12/12/22. The DVOL and TURN are the average daily dollar trading volume and turnover ratio (the number of shares traded divided by the number of shares outstanding) over the 12-month formation period, respectively. DVOL is reported in millions and TURN is reported in percentage. AR, *t*-stat, and VD are defined in Table 1. The sample period is from 1963 to 2010. The sample only includes NYSE and AMEX stocks.

Subrahmanyam, and Anshuman (2001). A typical conclusion is that trading volume is negatively related to stock returns. Such a relation may not hold among our ten portfolios. Portfolio P5 has the highest DVOL, which is almost three times as large as the DVOL of portfolio P1. Yet portfolio P5 has a higher monthly return than P1. Portfolios P10 and P5 have the same TURN, but the return differential between P10 and P5 equals a sizable 0.75% per month. These results suggest the profitability of the portfolio P10–P1 may not be explained by the trading volume effect. A comprehensive analysis of how excess volatility affects the trading volume effect will be left for future study.

4.3. Does size matter?

If excess volatility is caused by irrational behavior due to presence of overconfident investors and the associated risk limits rational investors from doing arbitrage (Dumas et al., 2009), then the excess volatility effect should be much weaker for large firms, since large firms have more rational investors and lower excess volatility. How does size affect the excess volatility investment strategy?

Following Jegadeesh and Titman (2001), we divide all the common stocks into small or large stocks by comparing an individual stock's market value with the median market value of all the NYSE stocks at the end of the formation period. A firm whose market value is smaller (bigger) than the median value is considered as a small (large) firm. Then, we duplicate the investment strategy 12/12/22 for the small and large firms respectively. The empirical results are reported in Table 7.

As shown in Table 7, the profitability of the investment strategy 12/12/22 for the large firms is much weaker than that for the small firms. To be more specific, the large firms have a much smaller marginal difference in the average monthly returns along the ten portfolios, even though those investment portfolios with positive VD still have significantly positive alphas estimated from the Fama–French–Carhart 4-factor model regression. The low monthly return of the investment portfolio P10–P1 for the large firms, 0.18% (t-statistic = 2.05), may just compensate for transaction costs in trading or arbitrage. In contrast, the two alpha sequences for the small firms are ascending along with the ascending VD. The average monthly return of the investment portfolio P10–P1 for the small firms is 1.06%, with a high t-statistic of 5.27.

Ang et al. (2006) investigate how aggregate volatility affects the cross-section of stock returns. They find that stocks with high idiosyncratic volatility relative to the Fama and French (1993) model have awfully low average returns. Following Ang et al. (2006), we also present the idiosyncratic volatility for each of our investment portfolios in Table 7. As shown in Table 7, excess volatility and idiosyncratic volatility for the large firms are much less than those for the small firms. The VD gap between P10 and P1 for the small firms is 10.89%, which is about six times as big as the same gap, 1.75%, for the large firms. The average monthly idiosyncratic volatility for the stocks in the investment portfolio P10–P1 for the small firms equals 5.57%, which is twice as much as 2.46% for the large firms. The empirical

Table 7
Performances on the investment strategy 12/12/22 for small firms and large firms.

(a) Small firms

Portfolio	AR	*t*1	Alpha1	*t*2	Alpha2	*t*3	VD	V(1)*22	V(22)	VR	IV
P1	1.15	3.32	0.08	0.37	0.14	1.05	−2.09	4.44	6.53	1.58	3.90
P2	1.21	4.56	0.25	1.76	0.08	1.20	−0.47	2.14	2.61	1.34	2.64
P3	1.27	5.59	0.38	3.21	0.15	2.56	−0.12	1.59	1.71	1.14	2.26
P4	1.27	5.86	0.40	3.52	0.17	3.30	0.10	1.54	1.44	0.96	2.24
P5	1.31	5.91	0.43	3.63	0.21	4.12	0.31	1.73	1.42	0.82	2.39
P6	1.35	5.69	0.45	3.40	0.25	4.46	0.56	2.13	1.57	0.71	2.70
P7	1.39	5.28	0.46	2.93	0.27	3.76	0.91	2.76	1.85	0.63	3.14
P8	1.44	4.89	0.47	2.50	0.28	2.83	1.49	3.72	2.23	0.57	3.72
P9	1.58	4.72	0.59	2.48	0.39	2.59	2.69	5.56	2.87	0.51	4.64
P10	2.21	5.50	1.22	3.74	0.93	3.75	8.81	13.41	4.60	0.39	7.24
P10–P1	1.06	5.27	1.14	5.70	0.78	4.03	10.89	8.97	−1.92	−1.19	5.57

(b) Large firms

Portfolio	Return	*t*1	Alpha1	*t*2	Alpha2	*t*3	VD	V(1)*22	V(22)	VR	IV
P1	0.88	3.05	−0.18	−1.63	−0.02	−0.21	−0.86	1.96	2.83	1.56	2.32
P2	1.03	4.66	0.10	1.50	0.08	1.41	−0.26	1.04	1.30	1.35	1.72
P3	1.05	5.24	0.17	2.65	0.10	1.76	−0.12	0.84	0.96	1.18	1.56
P4	1.05	5.52	0.20	3.07	0.11	1.90	−0.03	0.76	0.79	1.04	1.48
P5	1.07	5.72	0.22	3.50	0.12	2.21	0.04	0.75	0.71	0.93	1.47
P6	1.05	5.68	0.21	3.41	0.13	2.46	0.10	0.78	0.67	0.83	1.50
P7	1.07	5.68	0.22	3.97	0.15	3.36	0.17	0.86	0.69	0.76	1.58
P8	1.07	5.25	0.17	3.26	0.16	3.46	0.26	1.04	0.78	0.70	1.74
P9	1.01	4.35	0.05	0.84	0.12	2.35	0.41	1.38	0.97	0.65	1.99
P10	1.07	3.58	0.00	0.01	0.19	2.08	0.88	2.34	1.46	0.59	2.60
P10–P1	0.18	2.05	0.18	1.98	0.21	2.35	1.75	0.38	−1.37	−0.97	2.46

Note: This table reports the performances on the investment strategy 12/12/22 described in Table 1 for small firms and large firms. *t*1 is the *t*-statistics for AR. The alpha1 and alpha2 are obtained from the CAPM regression and Fama–French–Carhart 4-factor model regression described in Table 4, respectively. Following Ang et al. (2006), the idiosyncratic volatility (IV) is calculated as the standard variance of residuals estimated from Fama–French three-factor model regression for an individual stock with a 12-month formation period. All AR, alpha1, alpha2, VD, V(1)*22, V(22) and IV are presented in percentage. *t*2 and *t*3 are the *t*-statistics for alpha1 and alpha2, respectively. The sample period is from January 1963 to December 2010.

results in Table 7 corroborate the theories proposed in Shleifer and Vishny (1997) and Dumas et al. (2009), both of which claim that high volatility can stop rational investors from doing arbitrage.

Notice that our VD is ascending from P1 to P10. But the idiosyncratic volatility for both small and large firms forms “smile” shapes as shown in Table 7 (Panels a and b). This shows that the excess volatility effect identified in this paper is not contained by the idiosyncratic volatility effect documented in Ang et al. (2006, 2009). For example, P1 and P8 for the small firms in Table 7 (Panel a) have almost identical idiosyncratic volatility, 3.9% versus 3.72%. So these two portfolios may be sorted as one in Ang et al. (2006). But they are two portfolios that perform quite differently in our paper.

Also notice that the empirical results documented in Table 7 suggest again that VD is superior to VR to identify profitable strategies against the market efficient hypothesis set forth by Jensen (1978). The incremental difference of VR between P10 and P1 for the small firms equals −1.19, which is very close to that for the large firms, −0.97. However, the average monthly return of the portfolio P10–P1 for the small firms is 1.06%, which is about five times as much as that for the large firms, 0.18%. Such a performance difference can be better understood by the fact that the VD gap between P10 and P1 for the small firms is six times more than that for the large firms.

4.4. Fama–MacBeth regression analysis

As a robustness check for the above empirical results obtained by portfolio approach, this subsection performs month-by-month Fama–MacBeth (1973, hereafter FM) regressions of cross-sectional stock

Table 8
Results of Fama–MacBeth regressions.

Panel a

Name	M1	M2	M3	M4	M5	M6
VR	−0.005 (−3.91)					
VD		0.167 (3.68)	0.103 (3.08)	0.125 (3.55)	0.241 (6.48)	0.232 (6.29)
Log(SIZE)			−0.002 (−3.49)	−0.002 (−3.98)	−0.003 (−6.89)	−0.002 (−5.01)
CR6				0.009 (4.16)	0.009 (3.98)	0.010 (5.20)
IV					−0.311 (−7.93)	−0.288 (−7.97)
Log(MB)						−0.004 (−5.02)
ADJRSQ	0.004	0.010	0.023	0.033	0.040	0.046

Panel b

Name	M1	M2	M3	M4	M5	M6	M7
VR	−0.003 (−2.34)						
VD		0.156 (3.25)	0.092 (2.49)	0.115 (3.02)	0.112 (2.94)	0.230 (5.93)	0.224 (5.84)
Log(SIZE)			−0.001 (−3.28)	−0.002 (−3.64)	−0.002 (−3.54)	−0.002 (−5.81)	−0.002 (−4.58)
CR6				0.009 (3.59)	0.011 (4.44)	0.010 (4.43)	0.012 (5.55)
Log(TURN)					−0.001 (−2.17)	−0.001 (−1.01)	−0.001 (−0.96)
IV						−0.288 (−8.33)	−0.274 (−8.30)
Log(MB)							−0.003 (−4.42)
ADJRSQ	0.004	0.012	0.026	0.036	0.047	0.052	0.057

Note: The monthly Fama–MacBeth regression is defined as follows: $R_{i,t} = \alpha_0 + \alpha_1 X_{i,t-1} + \varepsilon_t$. The dependent variable $R_{i,t}$ is the monthly return of individual stock i over a given month t. The explanatory variables $X_{i,t-1}$ include the variance ratio (VR), the variance difference (VD), the natural logarithm of firm market value (log(SIZE)), the cumulative stock return over the month $t-2$ to $t-7$ (CR6), the natural logarithm of turnover ratio in month $t-2$ (Log(TURN)), the idiosyncratic volatility (IV) over the month $t-1$ and the natural logarithm of Market-to-Book ratio (Log(MB)). The VD and VR are estimated over the month $t-1$ to $t-12$. The Log(size) and Log(MB) are calculated at the end of month $t-1$. The t-statistics reported in parentheses are adjusted for overlap with the method of Newey and West (1987). The last row reports the average adjusted R^2 for the cross-sectional regressions. The results in Panel a are based on all the NYSE/AMEX//NASDAQ stocks. But the results in Panel b are only based on NYSE/AMEX stocks for the inclusion of Log(TURN). The sample period is from 1963 to 2010.

returns on excess volatility and other predictive variables. Specifically, the dependent variable is the monthly return over a given month t. The explanatory variables include the variance ratio (VR), the variance difference (VD), the natural logarithm of firm market value (log(SIZE)), the cumulative stock return over the month $t-2$ to $t-7$ (CR6), the natural logarithm of turnover ratio in month $t-2$ (Log(TURN)), the idiosyncratic volatility (IV) over the month $t-1$ and the natural logarithm of Market-to-Book ratio (Log(MB)). The VD and VR are estimated over the month $t-1$ to $t-12$. The Log(size) and Log(MB) are calculated at the end of month $t-1$.

The time-series averages of the slopes from the monthly FM regressions are reported in Table 8. The t-statistics reported in parentheses are adjusted for overlap with the method of Newey and West (1987). Consistent with the previous empirical results, the regressions in Table 8 show that both VD and VR have the explanatory power over the variation in cross-sectional stock returns. The average slope from the monthly regressions of returns on VR alone (M1 in Panel a) is −0.5%, with a t-statistic of −3.91 and an adjusted R^2 of 0.4%. In contrast, the average slope from the monthly regressions of returns on VD alone (M2 in Panel a) is 16.7%, with a t-statistic of 3.68 and an adjusted R^2 of 1%. More importantly, the reliable positive relation between VD and the cross-section of stock returns has not been changed with each addition of other explanatory variables in the regressions from M2 to M6 in Panel a and from M2 to M7 in Panel b, although the magnitude of slopes is somehow affected, as expected.

Table 8 shows that the three factors of size (Log(SIZE)), idiosyncratic volatility (IV), and value (Log(MB)) are negatively related to the cross-sectional stock returns at a significant level, a result consistent with those of FM regressions reported in Fama and French (1992), Ang et al. (2009), Fu (2009), and many others. In contrast, the momentum factor (CR6) has a significantly positive relation with the cross-sectional stock returns. However, the negative coefficient of Log(TURN) is no longer significant with the inclusion of IV as shown in M6 and M7 in Panel b.

5. Conclusions

We have used the difference between the volatility of short- and long-horizon returns as a proxy for excess volatility and empirically examined its relation to the cross-section of stock returns. A positive relation has been found with both the portfolio approach and the Fama–MacBeth regressions. The importance of our research can be seen from several aspects.

First, we complement the excess volatility literature by empirically relating excess volatility to the cross-sectional stock returns. Our empirical work has shown that over the sample period of 1963–2010, the portfolio that has the largest VD significantly outperforms the portfolio that has the least VD, under all the situations we have examined.

Second, although we document that excess volatility measured with VD is driven by overreaction, we believe that VD is not an approximation of overreaction. It is more likely to be an approximation of the fluctuation of overreaction. Or it may act as a new proxy for sentiment risk. If that is true, the factor VD should be incorporated into the noted Fama–French–Carhart 4-factor Model by subsequent researches, under the assumption that sentiment risk cannot be easily arbitraged away by investors. In addition, as the forecasting of volatility has been attracting more and more researchers' attention recently (Asai and Brugal, 2013; Chang, Jimenez-Martin, Mcaleer, & Amaral, 2013; Chuang, Huang, & Lin, 2013), it is of interest to study the impact of excess volatility to the predictability of volatility.

Notice that VD is just one measure that captures some aspect of excess volatility. Other measures are equally important. It is a challenge task how to incorporate these measures into a single framework to study the relation between excess volatility and the stock returns.

Third, although VR has been proven to be the optimal test for the random walk hypothesis (Lo & MacKinlay, 1989; Faust, 1992), VD may be superior to VR to identify profitable strategies against the market efficient hypothesis set forth by Jensen (1978). Because the VD is more sensitive to the variation in cross-sectional returns, the profitability of the investment portfolios ranked on VD would be more significant than those ranked on VR. However, as the high volatility of abnormal returns is obtained by excess volatility investment portfolios (see Fig. 1.), it is not easy to determine if the market is efficient. We leave this important issue to future researches.

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