Paper:
Koutmos, D. & Song, W. (2014). Speculative dynamics and price behavior in the Shanghai Stock Exchange. *Research in International Business and Finance, 31*, 74-86.

http://dx.doi.org/10.1016/j.ribaf.2013.11.006

SPECULATIVE DYNAMICS AND PRICE BEHAVIOR IN THE SHANGHAI STOCK EXCHANGE

MAY 2013

(For consideration at 'Research in International Business and Finance')

Abstract

This article examines the extent to which the trading behavior of heterogeneous investors manifests in stock price changes of asset portfolios which constitute the Shanghai Stock Exchange. There are three major findings that materialize. Firstly, reliable statistical evidence of a negative relation between the conditional first and second moments of the return distributions of stock prices lends support to the volatility feedback effect. Secondly, 'feedback,' or momentum-type investors, are not present in this market as is often detected from the daily price changes of other industrialized markets. Finally, trade volume as a proxy for 'information-driven' trading suggests that such investors play a statistically significant role in stock price movements. Parameter estimates from this latter group of investors imply that a rise in stock prices from a high volume trading day is more likely than a rise resulting from a low volume trading day.

Keywords: Shanghai Stock Exchange; heterogeneous investors; volatility feedback; range volatility; intertemporal capital asset pricing model; trade volume

1. Introduction

This article examines the extent to which the trading behavior of heterogeneous investors manifests in stock price changes of asset portfolios which constitute the Shanghai Stock Exchange. Using a range-based autoregressive asymmetric volatility model to capture the time-series dynamics of conditional market volatility, we provide an econometric framework to capture the possible impacts of 'rational' mean-variance optimizers, 'feedback' investors and 'information-driven' investors. Thus far inferences regarding the presence of such heterogeneous investors albeit inconclusive have been derived from industrialized and mature stock markets.

Broadly speaking, there are at least two predominant schools of thought on the statistical distribution of stock price movements. The number of followers for each school has shifted over the years whereby such shifts become ostensibly more pronounced during recessionary times and episodes of economic misfortune. The classical school of thought that has shaped much of the work in applied econometrics and asset pricing subscribes to the notion that stock price changes follow a random walk and are normal or Gaussian (Bachelier, 1900; Mandelbrot, 1963; Fama, 1965; Malkiel, 2003; inter alia). Consistent with this notion, it is believed information diffuses unrestrictedly to all market participants allowing them to compete fairly and equitably. This setting is the underpinning for the efficient market hypothesis and justifies the 'rational' practice of portfolio mean-variance optimization (Markowitz, 1952).

Rejecting the aforementioned, the second school of thought cites practical reasons why arbitrageurs are constrained in their ability to correct asset mispricing and argue heterogeneous investors impact stock price movements via the various technical, trend-chasing or portfolio insurance strategies that are actively in use by so many different types of investors (Cutler et al., 1990; De Long et al., 1990; Sentana and Wadhwani, 1992; Shleifer and Vishny, 1997; Abreu and Brunnermeier, 2003). Unlike the efficient market school of thought, there is a greater degree of opinion dispersion here as to the distributional dynamics of price changes. This is because heterogeneous investors, such as those mentioned earlier, drive stock prices in unpredictable ways. Investors trading on subjective criteria, rather than objective statistical measures such as mean and variance, reach investment decisions on the basis of unobservable and inherently unquantifiable parameters. Insomuch as information drives the behavior of investors and arrives to the market with varying degrees of proportion, one can justify the replacement of the classical

Gaussian distribution with the mixture of distributions hypothesis as an explanation of stock price changes (Clark, 1973; Epps and Epps, 1973; Tauchen and Pitts, 1983).

Behavioral explanations in academic literature have gained more acceptance and support especially in times of market upheaval. As Shiller (2000) indicates, we are experiencing today much more volatility which has little to do with shifts in stock market fundamentals. Likewise, many authors, some of whom are prominent psychologists, find that investors systematically make biases in their judgments, over-react to information instead of conducting careful deliberation, and make decisions on the basis of what their peers are doing (Tversky and Kahneman, 1974; inter alia). Koutmos (2012) argues that such behavioral explanations are receiving more scrutiny because it is becoming more self-evident that the classical asset pricing paradigm of portfolio formation on the basis of mean and variance is not sufficient in uncovering a statistical relation between risk and return on asset portfolios. This possibly stems from our fallacious tendency to overlook heterogeneous groups of investors especially in asset pricing paradigms that seek to describe variations in expected stock returns. The Merton (1980) intertemporal capital asset pricing model focuses exclusively on mean-variance optimizers as a source for stock price variation.

In light of the aforementioned, this article extends the intertemporal capital asset pricing to integrate the heterogeneous behavior of these rational mean-variance optimizers, feedback investors and information-driven investors. As already mentioned, and in accordance with the efficient market hypothesis, the first group of investors are 'rational' in the sense that they trade on the basis of mean and variance whereby their expected returns rise in the presence of greater market volatility (Merton, 1980).

The second group are feedback investors who buy and sell on the basis of past prices. If they are positive feedback investors they buy during price upswings and sell during price declines. Such behavior may manifest from bandwagon effects and herding, the use of stop-loss orders which induce selling after price declines, margin-call induced selling, or momentum-type technical strategies designed to catch incipient price trends. Conversely, negative feedback trading entails buying during price declines and selling during price appreciations.

Finally, the third group of investors are information-driven in the sense that their buying and selling investment decisions are based on an exogenous set of factors and not necessarily mean and variance considerations or previous price movements. Instead, they may be influenced by the arrival of news such as press releases and other corporate announcements. Trade volume thus varies through time along with the flow of pieces of news and the substantive nature of such news. It is therefore used to proxy for information-driven investors and is consistent with the notion that patterns in trade volume are closely linked with the flow and nature of information (Karpoff, 1987). Intuitively speaking, given news travels at different rates and with discrete weights, it is expected that stock prices exhibit varying distributional properties with different conditional variances across sampling periods thereby providing support for the mixture of distributions hypothesis.

This article focuses on various portfolios from the Shanghai Stock Exchange because this market is unexplored relative to other industrialized markets and has received little attention. It is arguably the fastest growing market by global standards and, as a result of its market-oriented reforms, has caught the attention of investors around the world (Chi and Young, 2007; Wan and Yuce, 2007; Fifield and Jetty, 2008; Loh, 2013). The proliferation of exchange traded funds which track various facets of the Chinese stock market is testament of this growing interest. Such interest has only expanded since the Chinese government in 2002 launched its ‘qualified foreign institutional investor’ scheme with the intention of making its stock markets more accessible to reputable foreign entities.

This article shows the interaction of these various groups of investors and shows, firstly, that a negative and significant relation emerges between risk and return. Secondly, feedback trading is not statistically present as is so often reported by other studies examining international markets. Finally, there is statistical evidence of the presence of information-driven investors whereby periods of high trade volume by such investors, more often than not, leads to rises in stock prices.

The remainder of this article is structured accordingly. Section 2 outlines the econometric framework that is used to model the impact of the aforementioned heterogeneous investors and the range-based autoregressive asymmetric volatility model used to estimate the conditional variance of each portfolio’s returns. Sections 3 and 4 provide a description of the data and the findings, respectively. Section 5 concludes.

2. Econometric framework

2.1. Measuring speculative dynamics

This article extends the intertemporal capital asset pricing model of Merton (1980) to integrate the trading impact of the aforementioned heterogeneous investors in order to decipher what impact they have on stock prices in the Shanghai Stock Exchange. An econometric framework proposed by Koutmos (2012) is used herein which nests the Sentana and Wadhwani (1992) and Cutler et al. (1990) models to provide a generalized framework for exploring the interaction between rational, feedback and information-driven investors to assess the impact of their trading behaviors on stock prices.

As mentioned, rational mean-variance optimizers base their investment decisions on the conditional first and second moments of assets' return distributions. Their demand for shares of stock is consistent with utility maximization theory and takes the following form:

$$\Upsilon_{1,t-1} = \frac{\left[E_{t-1}(R_t) - r_f\right]}{\theta\sigma_t^2};\ \theta > 0 \tag{1}$$

whereby $\Upsilon_{1,t-1}$ is the fraction of shares they hold at time $t-1$, $E_{t-1}(R_t)$ denotes the conditional expectation of the return given information that is available as of time $t-1$, r_f is the risk free rate, θ is the coefficient of relative risk aversion and σ_t^2 is the conditional variance at time t. The sign for θ is expected to have a positive sign consistent with the postulation that investors are rational and demand higher returns per unit of risk.

The equation in (1) collapses to the familiar intertemporal capital asset pricing model of Merton (1980) if *all* investors were in fact 'rational' (i.e. $\Upsilon_{1,t-1} = 1$), which can be expressed as $E_{t-1}(R_t) - r_f = \theta\sigma_t^2$. As mentioned however, there is evidence to suggest the presence of such heterogeneous investors that do not trade on the basis of mean and variance considerations.

The second group of investors considered here are feedback investors whose demand for underlying stock is based on past returns of that stock. Positive feedback investors' demand rises following price increases and falls following declines in price. This may result from overoptimism, the use of stop-loss orders or other forms of technical analysis. Shiller (1987) explains that the most important reason which caused individual and institutional investors to sell their positions on October 19, 1987 in the United States was the fact that prices had declined considerably and there was anxiety among investors that this would persist. The demand for such feedback investors is specified as follows:

$$\Upsilon_{2,t-1} = \delta\left(R_{t-1} - r_f\right);\ \delta > 0 \tag{2}$$

whereby $\Upsilon_{2,t-1}$ is the fraction of shares held by feedback traders and δ is the feedback parameter that is expected to have a positive sign if we assume that positive feedback traders outnumber and outweigh the impact of negative feedback traders.

Finally, information-driven investors trade on the basis of information flow, which we proxy for using trade volume (*TV*). Their demand can be specified as follows:

$$\Upsilon_{3,t-1} = \lambda(TV_t);\ \lambda > 0 \tag{3}$$

whereby $\Upsilon_{3,t-1}$ is the fraction of shares they hold at time $t-1$ and TV_t denotes trade volume at time t. Thus, information-driven investors' current demand is a function of news they receive in the current period as well as future news (e.g. imminent corporate announcements or unofficial announcements regarding merger activity). As is argued by He and Wang (1995), and consistent with equation (3), current volume is not only related to present information flow but also private information received previously. Moreover, it is possible that trade volume can reach its peak in future periods after the initial flow of private information to investors. A common example of this would be to not trade on inside information if you are an insider and instead wait until it is publicly announced.

Market equilibrium requires that all shares are held so that we have

$$\Upsilon_{1,t-1} + \Upsilon_{2,t-1} + \Upsilon_{3,t-1} = 1 \tag{4}$$

or, alternatively, we can express equation (4) as

$$\frac{\left[E_{t-1}(R_t) - r_f\right]}{\theta\sigma_t^2} + \delta\left(R_{t-1} - r_f\right) + \lambda(TV_t) = 1 \tag{5}$$

Equation (5) can be converted into a regression equation with a stochastic error by setting $R_t - r_f = r_t$ and $E_{t-1}(R_t) - r_f = r_t + \epsilon_t$. This gives us the following:

$$r_t = \theta\sigma_t^2 - \delta(\theta\sigma_t^2)(r_{t-1}) - \lambda(\theta\sigma_t^2)(TV_t) + \epsilon_t \tag{6}$$

whereby the term $-\delta(\theta\sigma_t^2)(r_{t-1})$ implies that positive feedback trading induces negative autocorrelation in stock returns. The higher the conditional variance, σ^2, the higher the degree of autocorrelation we ought to see.

The specification in (6) can be recast and expressed as follows:

$$r_t = \beta_0 + \beta_1\sigma_t^2 + \beta_2[(\sigma_t^2)(r_{t-1})] + \beta_3[(\sigma_t^2)(TV_t)] + \epsilon_t \tag{7}$$

whereby $\beta_0 = 0$, $\beta_1 = \theta$, $\beta_2 = -\delta\theta$ and $\beta_3 = -\lambda\theta$. The presence of rational mean-variance optimizers in the context of Merton (1980) is described by the coefficient β_1 and, consistent with theory, should have a statistically significant positive sign. The parameters β_2 and β_3 denote the presence of feedback and information-driven investors, respectively.

It should also be pointed out that the three types of investors interact in a way that they affect each others' demand function. For example, if feedback traders increase volatility this in turn will increase the required rate of return demanded by rational investors. If there is no change in their expected return, their demand for shares will likely decrease. Similarly, the higher volatility may be associated with bad news for information-driven investors and this will have an impact on their demand as well.

It is worth mentioning that β_1 , β_2 and β_3 are nonlinear functions of the original parameters θ, δ and λ. However, we can still get unique solutions for the restricted parameters because we have an exact identification (i.e., the number of restrictions, which are three in this case, is equal to the number of parameters to be estimated).

The model described in equations (1) through (7) nests both the Sentana and Wadhwani (1992) and Cutler et al. (1990) models. For example, if the conditional variance is constant over time, the model reduces to that of Cutler et al. (1990). Conceptually, it is impossible to capture the subjective expectations and attitudes of the so many different types of investors that are trading because undoubtedly there are classes of investors who do not fit into equation (7). Although no such general agreement can be reached on what constitutes a proxy for the demand of investors who neglect mean-variance optimization in portfolio allocation decisions, this article provides insights into how stock prices behave in the Shanghai Stock Exchange and, if trade volume serves as an accurate proxy for the flow of news, the extent to which information-driven investors push stock prices.

2.2. A range-based autoregressive asymmetric volatility model

In order to estimate (7) we need to define a volatility model and construct estimates for the conditional variance, σ^2. Under the classical assumption that the logarithm of a stock's price follows a stochastic process with stationary and independent increments, we can model its price P_t at time t according to a geometric Brownian motion

$$\mathrm{d}P_t = \mu P_t \mathrm{d}t + \sigma P_t \mathrm{d}B_t \tag{8}$$

whereby μ denotes the drift term and constant $\sigma > 0$ is the volatility parameter. Conventionally, the daily interval is normalized to unity to simplify the notation and so the ith interval on the trading day t, for $i = 1, 2, 3, \ldots, I$ with $I = 1/\Delta$ assumed to be integer (Martens and Dijk, 2007). Observing the last closing price in that interval for trading day t, $C_{t,i} = P_{t-1+i\Delta}$, the last high price, $H_{t,i} = \sup_{(i-1)\Delta<j<i\Delta} P_{t-1+j}$, and the low price, $L_{t,i} = \inf_{(i-1)\Delta<j<i\Delta} P_{t-1+j}$, and if we assume the drift μ^* is zero, it is possible to express an unbiased estimator of the variance, $\sigma^2\Delta$, during the specified sampling interval i as the squared return,

$$r_{t-1+i\Delta,\Delta}^2 = (\log C_{t,i} - \log C_{t,i-1})^2 \quad (9)$$

with a variance equivalent to $2\sigma^4\Delta^2$.

Martens and Dijk (2007) thoroughly demonstrate the aforementioned and indicate how the scaled high-low range variance estimator proposed by Parkinson (1980) theoretically yields a lower mean-squared error of the squared return in (9). Such range-based estimators possibly reveal more information of a stock's price volatility since, throughout any given trading day, a stock price whose value has diverged significantly until it achieves its final closing price naturally is considered more volatile. Readily obtainable high and low values of a stock price thus contain valuable economic information that is of use to investors and researchers (Mandelbrot, 1971; Nison, 1991; Tsay, 2010). Conventional parametric approaches to modelling volatility, such as the GARCH family of models, neglect to account for such potentially useful information. Therefore, from one trading day to another if there is no change in the closing price, the underlying stock return will be zero despite potentially exhibiting intraday volatility.

In light of this, the range-based variance estimator of Parkinson (1980) provides a scaled high-low range estimator for the variance, σ_{HL}^2,

$$\frac{\left(\log H_{t,i} - \log L_{t,i}\right)^2}{4 \log 2} \quad (10)$$

that is implicitly unbiased if there is no drift and μ^* is zero. Martens and Dijk (2007) show that variance of (10) is $\frac{9\zeta(3)}{(4\log 2)^2-1} * \sigma^4\Delta^2 \doteq 0.407\sigma^4\Delta^2$, where $\zeta(3) = \sum_{k=1}^{\infty} 1/k^3$ is defined as Riemann's zeta function.

A quick comparison of the variance from (10) with that of (9) provides useful insights. It seems the high-low estimator in (10) has a variance and mean-squared error of about five times less than that of the squared return in (9) and provides some justification for the use of range volatility models over conventional measures such as the realized variance. Alizadeh et al. (2002) and Shu and Zhang (2006) find support for the use of range variance estimators when benchmarked against realized variance and observe that such models do not exhibit significant biases in their estimates nor are influenced by microstructure errors such as the bid-ask spread. This argument is consistent with the notion that opening and closing prices may be induced by market microstructure effects while intraday high and low prices observed throughout the trading day are (more) free from such errors (Alizadeh et al., 2002).

As indicated in a recent article by Li and Hong (2011), despite the intuitive appeal of range variance estimators, they have not been able to capture the dynamic evolution of stock return volatility in practice. Hsieh (1991; 1993; 1995) has sought to provide an improvement in capturing the highly mean-reverting behavior of volatility and propose an autoregressive volatility model

$$r_t = \sigma_{HL,t} e_t \quad e_t \sim i.i.d.(0,1)$$
$$\log \sigma_{HL}^2 = \omega + \sum \psi_1 \log \sigma_{HL,t-i}^2 + v_t \quad v_t \sim i.i.d.(0, \sigma_v^t) \tag{11}$$

whereby σ_{HL}^2 is the range variance estimator from (10), while e_t and v_t, respectively, are i.i.d. with zero mean and finite variance and are assumed to be independent of each other.

Using the autoregressive parameterization in (11) can be accomplished using ordinary least squares (OLS) and, as Li and Hong (2011) demonstrate, can be augmented to incorporate other explanatory variables in order to account for the asymmetric impact of negative returns,

$$\log \sigma_{HL,t}^2 = \varphi_0 + \sum \psi_1 \log\ \sigma_{HL,t-i}^2 + \varphi_1 \left| \frac{r_{t-1}}{\sigma_{HL,t-1}} \right| + \varphi_2 \frac{r_{t-1}}{\sigma_{HL,t-1}} + v_t \quad v_t \sim i.i.d(0, \sigma_v^t) \tag{12}$$

whereby the parameters φ_1 and φ_2 are akin to the exponential GARCH of Nelson (1991) and, in this case, asymmetry is captured via φ_2. Thus, this parameterization can be considered an asymmetric autoregressive model and differs from the GARCH family of models in two respects. Firstly, it finds much less volatility persistence than its GARCH counterparts and this is important especially for multiday-ahead forecasts. Secondly, it requires no distributional assumptions regarding the behavior of the error term while GARCH models are conventionally estimated using maximum likelihood procedures and inevitably require such an assumption to be made.

Having estimated (12) for each of the sampled observations in this article, we extract estimates of the conditional variance of the respective asset prices and use them in (7) to examine the impact of heterogeneous investors on stock price movements.

3. Nature of data

3.1. Description of data sample

To provide insights into how the aforementioned heterogeneous investors drive stock prices, we examine stock prices of various portfolios that constitute the Shanghai Stock Exchange based on style, size and industry, as well as the major aggregate market indices. The data are collected from the Shanghai Stock Exchange's website (www.sse.com.cn) and the Bloomberg financial database. Table 1 describes the portfolios that are examined, their Bloomberg identifier code that can be used to access the data, the sample range and corresponding number of observations. The choice for the data ranges is determined by the availability of all data necessary to complete this study; namely, in addition to each of the prices of each of the portfolios, the risk-free rate and trade volume is necessary to estimate (7).

Each of the respective panels in table 1 considers portfolios based on some quality. For example, in panel A we have portfolios based on style allocation. The 'dividend' portfolio represents a portfolio of firms that have the highest dividend yields among all blue chip stocks. The 'high beta' and 'low beta' portfolios constitute, as their name suggests, firms with the highest betas and lowest betas, respectively, relative to all blue chip stocks.

Panel B contains portfolios based on market capitalization. A detailed description of each of these portfolios along with their constituent firms is provided by the China Securities Index Co., Ltd. (www.csindex.com.cn), a respected entity specializing in the creation and management of indices as well as index-related services. 'Small cap.' refers to stocks with the lowest market capitalization among Shanghai Stock Exchange-listed firms. 'Mid & small cap.' reflects an investor who wants a blended portfolio of mid and small capitalization stocks. 'Large, mid & small cap.' reflects an investor who wants a portfolio allocated proportionally among large, mid and small capitalization stocks.

Panel C describes ten industries that are vital to China's livelihood: Energy, materials, industrials, consumer discretionary, consumer staples, healthcare, financials, information technology, telecommunications, and utilities, respectively. According to the Shanghai Stock Exchange's website, which lists each of the constituent stocks that comprise each industry, the constituent companies are selected because they are the largest and most well-established companies within their respective industry. Therefore, fluctuations in the stock prices of these sectors provide useful economic information and reflect shifts in the market conditions of their respective industries.

Panel D lists the three major aggregate portfolio indices that comprise the Shanghai Stock Exchange and which are probably most familiar to outside foreign investors. The SSE 50 index contains the fifty largest and most liquid stocks. The SSE 180 and SSE 380 indices contain a broader spectrum of stocks which, according to the Shanghai Stock Exchange's website, possess good earnings records, reputations and reflect the performance of the blue chip stocks.

3.2. Time series dynamics of stock returns and volatility

The stock prices examined herein are of daily frequency and denominated in Renminbi. The distributional properties of the unconditional daily realized returns for each of the portfolios is shown in table 2. In panel A, the high beta portfolio has the highest daily mean return and standard deviation (*Std. dev.*) of 0.0549% and 2.2871%, respectively. This corresponds to an annualized mean return and standard deviation of approximately 13.8% and 36.3%, respectively. The coefficient of variation (*CV*) measures the degree of variation for each portfolio's returns and is expressed here as the annualized standard deviation divided by the annualized mean return. Another interpretation of this statistic is it computes how much volatility an investor is assuming compared to the expected returns of an underlying portfolio whereby a lower ratio generally reflects a better the risk-reward tradeoff for the investor. This ratio is lowest for the low beta portfolio, followed by the high beta and dividend portfolios.

For the style allocation portfolios, the small cap portfolio generally provides the most favorable risk-reward tradeoff while the large, mid & small cap provides the least favorable tradeoff. In panel C, the consumer staples industry portfolio provides the most favorable risk-reward tradeoff while the telecommunications portfolio fares the least favorable. Finally in panel D the SSE 380 index, which reflects the broad performance of the entire Shanghai Stock Exchange, provides the most favorable risk-reward tradeoff for the given sampling period considered here.

The skewness (*Skew.*) and kurtosis (*Kurt.*) statistics suggest that all the return series are negatively skewed and leptokurtic relative to a normal distribution. This is a commonly observed characteristic when working with financial time series and may result from the bursting of bubbles, which cause sizeable negative returns, or asymmetries in news disclosures to the public

(Mandelbrot, 1963; Fama, 1965; Blanchard and Watson, 1982; Campbell and Hentschel, 1992; Ekholm and Pasternack, 2005; inter alia). As mentioned before, and consistent with the mixture of distributions hypothesis, this may also reflect unevenness in the flow and dissemination of information to market participants. The Anderson-Darling (*A*-*D*) test statistic further confirms that all the respective portfolio returns to some extent depart from the general characteristics of a normal distribution.

Parameter estimates for the range-based autoregressive asymmetric volatility model in (12) are reported in table 3. The purpose of this specification is to produce estimates of the conditional variance, σ^2, and use them to estimate the heterogeneous model in (7) which extends the Merton (1980) intertemporal capital asset pricing model to account for the possible trading behaviors of the aforementioned investors.

As mentioned, this volatility specification is advantageous in that it accounts for valuable intraday price shifts which are neglected from the point of view of traditional GARCH-type specifications. The number of lags, ψ, is determined by the Schwarz criterion while the persistence of volatility is the sum of all the lags, $\sum\psi_i$. The two portfolios with the highest degree of persistence are the SSE 50 and SSE 380 indices while the portfolio with the lowest degree of persistence was the healthcare industry. In all cases, the persistence is less than 1 indicating that the log of volatility is a strictly stationary process. This finding is strikingly similar to what is reported by Li and Hong (2011) and further corroborates the view that this volatility specification shows much less volatility persistence that what is typically found when estimating GARCH-type models.

Finally, the asymmetry term, φ_2, is negative and significant in all cases and further confirms the view that negative shocks in returns lead to more volatility than positive shocks of equal magnitude. This has been the very motivation for asymmetric extensions of GARCH-type models and is rooted in the finding provided by behavioral economists and psychologists that down markets (i.e. negative shocks in the market) lead to (non-)proportionally more angst (i.e. more stock price volatility) among participants relative to the gratification garnered by up markets of equal magnitude (Tversky and Kahneman, 1974).

4. Evidence of speculative dynamics

Table 4 reports parameter estimates for (7) and is the crux of this article's objective; namely, to examine the extent to which the aforementioned heterogeneous investors drive stock prices in the Shanghai Stock Exchange. Having constructed estimates of volatility using (12), we estimate (7) and we seek to answer these three questions: firstly, is there a positive risk-return relation in the context of the Merton (1980) intertemporal capital asset pricing model? Secondly, are feedback, or momentum-type, investors present in this market? Thirdly, are information-driven investors present when we use trade volume as a proxy for the flow of news into the market?

The answer to the first question has been the source of much debate and controversy, as well as inspiration for the recent advancements in econometrics. Intuitively, we would expect a positive relation between risk and return as this corresponds to the notion that we are rational risk-averse investors who demand higher expected returns in the face of rising volatility. In terms of findings derived from industrialized markets, the results are very mixed and oftentimes statistically indistinguishable from zero.

The coefficient denoting such risk aversion is β_1 and, contra to intuition, is reliably negative across the cross-section of portfolios considered herein. This finding is not surprising from a qualitative perspective in comparison with the burgeoning literature on this topic that already reports weak findings for the risk-return relation inferred from stock prices in industrialized markets. It is interesting though from a quantitative perspective in the sense that *all* the portfolios consistently show such a negative and statistically significant relation.

This finding provides strong support for the volatility feedback hypothesis proposed by French et al. (1987) and further developed by Campbell and Hentschel (1992). This hypothesis posits that that if volatility is persistent, as was suggested even as early back as Mandelbrot (1963), then an increase in current volatility raises future expected volatility leading to an increase in the discount rate (i.e., required rate of return) investors use to discount future expected cash flows produced by the underlying firm. This leads to downward pressure on a stock's price as future expected cash flows are discounted at a higher rate. Assuming that earnings and dividends are not rising, it is obvious that prices will fall. In this case, we see that all the portfolios show a negative and statistically significant risk-return relation.

Looking at this from a different angle, this suggests that contrarian-type opportunities may exist in the Shanghai Stock Exchange. Specifically, if periods of high volatility are associated with declining prices as investors sell their positions, this may be an optimal time to buy. Conversely, periods of low volatility and rises in prices may be an appropriate time to sell.

The coefficient β_2 denotes the potential presence of feedback traders. As mentioned, positive feedback trading may result from overoptimism, the use of stop-loss orders or other forms of technical analysis. When looking at industrialized and developed markets, there is convincing evidence that positive feedback trading is present (Koutmos, 1997) albeit Koutmos (2012) suggests that this perhaps has to do with the frequency of the stock prices under consideration and, when considering monthly data, the impact of feedback traders dissipates potentially as a result of other heterogeneous investors that play a role in pushing prices back to fundamentals. Therefore, although it is common when using daily stock prices to find evidence of feedback trading among industrialized markets, there is no such evidence in the case of the Shanghai Stock Exchange. Only the healthcare and financials portfolios show evidence of such trading at the 5% and 10% level of significance, respectively.

Finally, the coefficient β_3 denotes the presence of information-driven investors when trade volume is used to proxy for the flow of information. There is consistent statistical evidence that such investors are present in this market. The sign of this coefficient is positive since $\beta_3 = -\lambda\theta$ and, as mentioned, θ is negative and significant across all the portfolios. This suggests that such information-driven investors are present in this market and whereby periods of rising stock prices are commonly associated with high volume trading days. Conversely, periods of declining stock prices are generally associated with low volume trading days.

5. Concluding remarks

This article examines the extent to which rational mean-variance optimizers, feedback investors and information-driven investors drive stock prices in the Shanghai Stock Exchange. Trade volume is used as a proxy for the flow of information. It is a stylized fact in empirical asset pricing that stock prices exhibit varying distributional properties with different conditional variances across sampling periods. This is consistent with the mixture of distributions which suggests that information travels at different rates and carries varying weights.

The econometric framework nests the Sentana and Wadhwani (1992) and Cutler et al. (1990) models to provide a generalized framework for exploring the interaction between the aforementioned heterogeneous investors. We utilize a range-based autoregressive asymmetric volatility model to capture intraday movements in stock prices which is used to produce estimates of the conditional variance for each of the various portfolios we consider and which constitute the Shanghai Stock Exchange. Namely, we present evidence from portfolios constructed on the basis of style, size, industry, as well as the aggregate market portfolios.

The Shanghai Stock Exchange is an unexplored stock market in relation to evidence derived from the United States and other major European stock markets. Interest in this market has expanded greatly since the Chinese government in 2002 launched its 'qualified foreign institutional investor' scheme in order to make its stock markets more accessible to reputable foreign entities.

The asset pricing implications of this paper are as follows. Firstly, there is consistent evidence of a statistically significant negative intertemporal relation between risk and return. This findings provides support for the volatility feedback effect proposed by French et al. (1987) and further developed by Campbell and Hentschel (1992). Secondly, unlike what is typically found in the United States and in European stock markets, there is no evidence of feedback trading in the Shanghai Stock Exchange. Finally, there is evidence of information-driven investors whereby rising stock prices are commonly associated with high volume trading days and periods of declining stock prices are generally associated with low volume trading days.

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Table 1. Description of data sample

	Bloomberg identifier	*Sample range*	*Number*
Panel A: Style allocation portfolio indices			
Dividend	SH000149 Index	Jan. 4, 2005 – Mar. 14, 2013	
High beta	SH000137 Index	Jan. 2, 2004 – Mar. 14, 2013	
Low beta	SH000138 Index	Jan. 2, 2004 – Mar. 14, 2013	
Panel B: Size allocation portfolio indices			
Small cap.	SH000045 Index	Jan. 4, 2005 – Mar. 14, 2013	
Mid & small cap.	SH000046 Index	Jan. 4, 2005 – Mar. 14, 2013	
Large, mid & small cap.	SH000047 Index	Jan. 4, 2005 – Mar. 14, 2013	
Panel C: Industry sector portfolio indices			
Energy	SH000032 Index	Jan. 4, 2005 – Mar. 14, 2013	
Materials	SH000033 Index	Jan. 4, 2005 – Mar. 14, 2013	
Industrials	SH000034 Index	Jan. 4, 2005 – Mar. 14, 2013	
Consumer discretionary	SH000035 Index	Jan. 4, 2005 – Mar. 14, 2013	
Consumer staples	SH000036 Index	Jan. 4, 2005 – Mar. 14, 2013	
Healthcare	SH000037 Index	Jan. 4, 2005 – Mar. 14, 2013	
Financials	SH000038 Index	Jan. 4, 2005 – Mar. 14, 2013	
Information technology	SH000039 Index	Jan. 4, 2005 – Mar. 14, 2013	
Telecommunications	SH000040 Index	Jan. 4, 2005 – Mar. 14, 2013	
Utilities	SH000041 Index	Jan. 4, 2005 – Mar. 14, 2013	
Panel D: Aggregate market portfolio indices			
SSE 50	SSE50 Index	Jan. 2, 2004 – Mar. 14, 2013	
SSE 180	SSE180 Index	Jun. 3, 2002 – Mar. 14, 2013	
SSE 380	SH000009 Index	Jan. 4, 2005 – Mar. 14, 2013	

Notes: This table describes the portfolios used herein and the corresponding Bloomberg identifiers that can be used to access the data. Panel A identifi allocation. Panel B identifies portfolios based on size. Panel C identifies portfolios that reflect the performance of the major industry sectors that co Exchange. Finally, panel D identifies the aggregate Shanghai stock market indices. Corresponding sample ranges and the resultant number of observat two columns. Daily stock prices are used to conduct subsequent empirical tests herein.

Table 2. Distributional properties of unconditional realized stock returns

	Mean	*Std. dev.*	*CV*	*Skew.*	*Kurt.*
Panel A: Style allocation portfolio indices					
Dividend	0.0456	2.0193	2.7896	-0.5535	5.8286
High beta	0.0549	2.2871	2.6243	-0.7184	5.3357
Low beta	0.0462	1.8362	2.5037	-0.5588	6.0795
Panel B: Size allocation portfolio indices					
Small cap.	0.0605	2.0681	2.1534	-0.6385	5.4921
Mid & small cap.	0.0559	2.0543	2.3150	-0.5927	5.4531
Large, mid & small cap.	0.0474	1.9119	2.5409	-0.4153	5.7556
Panel C: Industry sector portfolio indices					
Energy	0.0479	2.2458	2.9535	-0.1397	4.9768
Materials	0.0367	2.1941	3.7661	-0.3956	4.9567
Industrials	0.0229	1.9792	5.4444	-0.4341	5.8881
Consumer discretionary	0.0441	2.0898	2.9851	-0.5668	5.5412
Consumer staples	0.0859	1.9380	1.4212	-0.3368	5.4072
Healthcare	0.0819	2.0531	1.5792	-0.4811	5.5921
Financials	0.0715	2.1516	1.8956	-0.0811	5.2665
Information technology	0.0313	2.2805	4.5897	-0.5581	4.8312
Telecommunications	0.0259	2.3085	5.6147	-0.2352	5.8771
Utilities	0.0325	1.8732	3.6308	-0.5513	6.1914
Panel D: Aggregate market portfolio indices					
SSE 50	0.0240	1.8393	4.8277	-0.1511	5.9344
SSE 180	0.0186	1.7572	5.9512	-0.2443	6.2200
SSE 380	0.0656	2.0659	1.9838	-0.6479	5.5484

Notes: This table presents summary statistics for the daily realized stock returns of each portfolio in percentage terms along with the first fou
distributions. The coefficient of variation (CV) is computed as the annualized standard deviation divided by the annualized mean return. The Anderson
statistic (5% critical value is 0.752 / [1 + 0.75/T + 2.25/T^2], where T is the number of observations) tests the null that each of the return series are norm
A-D = $\sum_{i=1}^{n}\frac{1-2i}{n}\left\{\ln\left(F_0\left[Z_{(i)}\right]\right) + \ln\left(1 - F_0\left[Z_{(n+1-i)}\right]\right)\right\} - n$, where F_0 is the normal distribution with estimated parameters (μ , σ), n is the sample si
standardized sample value.† The null is rejected at the 10% level; * The null is rejected at the 5% level.

Table 3. Parameter estimates for range-based autoregressive asymmetric volatility model

	φ_0	ψ_1	ψ_2	ψ_3	ψ_4	ψ_5	φ_1
Panel A: Style allocation portfolio indices							
Dividend	-1.9776*	0.1928*	0.2346*	0.2034*	0.1496*		-0.0001
High beta	-2.7218*	0.2205*	0.1914*	0.1516*	0.1258*		0.0002
Low beta	-2.5802*	0.2273*	0.1881*	0.1705*	0.1339*		0.0001
Panel B: Size allocation portfolio indices							
Small cap.	-2.4823*	0.1957*	0.1802*	0.1626*	0.0946*	0.0920*	0.0536†
Mid & small cap.	-2.5851*	0.1933*	0.2206*	0.1805*	0.1158*		0.0002
Large, mid & small cap.	-2.2026*	0.1667*	0.2004*	0.1704*	0.1136*	0.1050*	0.0001
Panel C: Industry sector portfolio indices							
Energy	-2.5128*	0.1943*	0.1839*	0.1917*	0.1389*		0.0133
Materials	-1.9092*	0.2246*	0.1742*	0.1684*	0.0839*	0.1319*	0.0228
Industrials	-2.2587*	0.2216*	0.2367*	0.1908*	0.0983*		0.0005
Consumer discretionary	-4.0289*	0.2127*	0.1908*	0.1713*	0.1196*		0.0064†
Consumer staples	-2.4010*	0.2067*	0.1593*	0.1701*	0.0806*	0.1217*	0.0741*
Healthcare	-2.9533*	0.2603*	0.1669*	0.1492*	0.0945*		0.0473
Financials	-2.2295*	0.1869*	0.1813*	0.1584*	0.1363*	0.0904*	0.0664*
Information technology	-2.5500*	0.2210*	0.1633*	0.1462*	0.0912*	0.0875*	0.0602†
Telecommunications	-2.6503*	0.2474*	0.2030*	0.1486*	0.0973*		0.0601*
Utilities	-2.4107*	0.2424*	0.2037*	0.1580*	0.1366*		0.0604*
Panel D: Aggregate market portfolio indices							
SSE 50	-1.5161*	0.2137*	0.1869*	0.1553*	0.1420*	0.1127*	-0.0323
SSE 180	-1.7754*	0.2259*	0.2229*	0.1878*	0.1625*		-0.0496†
SSE 380	-1.6248*	0.2286*	0.2236*	0.1889*	0.1672*		-0.0386

Notes: This table presents parameter estimates for the asymmetric autoregressive volatility model in (12): $\log \sigma^2_{HL,t} = \varphi_0 + \sum \psi_1 \log\ \sigma^2_{HL,t-i} + \varphi_1 \left|\frac{r_{t-1}}{\sigma_{HL,t-1}}\right| + \varphi_2 \frac{r_{t-1}}{\sigma_{HL,t-1}} + \nu$ parameters φ_1 and φ_2 are akin to the exponential GARCH of Nelson (1991) whereby asymmetry is captured via φ_2. The number of lags, ψ, is determined by th persistence of volatility is the sum of all the lags, $\sum\psi_i$. Conditional variance estimates derived from (12) are used to proxy for volatility and to enable estimation of the het

† The null is rejected at the 10% level; * The null is rejected at the 5% level.

Table 4. Evidence of speculative traders

	β_0	β_1	β_2	
Panel A: Style allocation portfolio indices				
Dividend	0.5516 (0.3180)	-3.0359* (0.0212)	-0.0246 (0.5576)	0.3002*
High beta	-1.2223* (0.0348)	-2.5648* (0.0161)	-0.0189 (0.4110)	0.3321*
Low beta	-0.5185 (0.2894)	-3.2203* (0.0401)	-0.0607 (0.2412)	0.4202*
Panel B: Size allocation portfolio indices				
Small cap.	-0.2716† (0.0521)	-1.6217* (0.0008)	0.4978 (0.5103)	0.1674*
Mid & small cap.	-0.2429† (0.0822)	-1.8214* (0.0009)	0.0020 (0.8001)	0.1763*
Large, mid & small cap.	-0.1528 (0.2547)	-1.5944* (0.0118)	-0.0024 (0.7837)	0.1471*
Panel C: Industry sector portfolio indices				
Energy	0.3106† (0.0680)	-1.5612* (0.0000)	-0.0822 (0.8594)	0.4139*
Materials	0.1714 (0.2858)	-1.2628* (0.0001)	0.3361 (0.4552)	0.3072*
Industrials	-0.0892 (0.4764)	-1.5876* (0.0000)	-0.2458 (0.7335)	0.1741*
Consumer discretionary	-0.1586 (0.2302)	-0.8382* (0.0177)	0.7023 (0.2554)	0.1036*
Consumer staples	-0.0164 (0.8840)	-0.8687* (0.0031)	0.4725 (0.4819)	0.1121*
Healthcare	0.0604 (0.6748)	-0.9238* (0.0010)	1.8618* (0.0097)	0.1203*
Financials	0.1358 (0.2751)	-2.0229* (0.0000)	-1.1853† (0.0594)	0.2366*
Information technology	-0.0611 (0.6907)	-0.7517* (0.0042)	0.4893 (0.3304)	0.1023*
Telecommunications	-0.0489 (0.7727)	-0.9141* (0.0002)	-0.2820 (0.6493)	0.1231*
Utilities	0.0032 (0.9707)	-0.9587* (0.0060)	0.2844 (0.6878)	0.1181*
Panel D: Aggregate market portfolio indices				
SSE 50	0.1164 (0.1037)	-0.8672* (0.0372)	-0.4556 (0.1625)	0.1036*
SSE 180	0.0357 (0.5457)	-0.3202* (0.0052)	-0.3999 (0.1933)	0.0734*
SSE 380	0.1387† (0.0932)	-1.6537* (0.0001)	-0.0120 (0.3605)	0.4397*

Notes: This table presents parameter estimates for the heterogeneous model in (7): $r_t = \beta_0 + \beta_1\sigma_t^2 + \beta_2[(\sigma_t^2)(r_{t-1})] + \beta_3[(\sigma_t^2)(TV_t)] + \epsilon_t$. The pres

mean-variance optimizers in the context of Merton (1980) is described by the coefficient β_1. The parameters β_2 and β_3 denote the presence o

information-driven investors, respectively. The p-values are in parentheses.

† The null is rejected at the 10% level; * The null is rejected at the 5% level.