The Effectiveness of Price Limits When Investors Are Overconfident

Mei-Chen Lin Pin-Huang Chou *

October, 2002

Abstract

Price limits are useless in the absence of market imperfection and investor irrationality. However, numerous recent studies on behavioral finance suggest that human behavior displays systematic biases. Based on two well-known psychological biases, namely investor overconfidence and biased self-attribution as suggested by Daniel, Hirshleifer, and Subrahmanyam (1998), we find that, by lengthening the momentum phase, price limits are effective in attenuating overreaction and reducing excess volatility. Specifically, by not allowing prices to move beyond a certain range, price limits discourage overconfidence and force prices not to swing away from its fundamental value too much. This reduces unpredictable rapid movements and reduces risk to market participants. Thus, our evidence provides the most popular rationale for imposing price limits. However, while price limits reduce the risk to market participants, there is liquidity cost associated with their use. Therefore, it is in the public interest to discuss rationally the realignment of price limits. With the parameter values used, 5% limits are proper when traders are with 40% overconfidence level. As the confidence level reduces to 20%, 10% limits will be proper. Overall, we find that the higher the overconfidence level is, the tighter the price limit should be.

Key Words: overreaction, momentum, price limits, and overconfident

*Lin: Department of Finance, National Lien-Ho Institute of Technology, Miao Li 360, Taiwan. Fax: 886-3-7338380. E-mail Address: meclin@mail.nlhu.edu.tw.; Chou: Department of Finance, National Central University, Jung-Li 32001, Taiwan. Fax: 886-3-4252961. E-mail Address: choup@cc.ncu.edu.tw

The Effectiveness of Price Limits When Investors Are Overconfident

1 Introduction

The traditional economic paradigm assumes that individuals are rational, and the evidence of short-term underreaction and long-term overreaction are identified as two anomalous empirical patterns.[1] Though there exist various competing explanations for the above evidence of predictability, there remains disagreement over those interpretations.[2] A general criticism often raised about the previous research is that they lack integrated theory to explain the anomalies of short-term underreaction and long-term overreaction.

Several studies have suggested that investor overconfidence or changes in confidence offer a possible explanation for anomalies in securities markets (see Odean, 1998; Daniel, Hirshleifer, and Subrahmanyam (DHS), 1998, 2001). Daniel, Hirshleifer, and Subrahmanyam (1998) propose a theory of securities market under- and overreactions based on overconfidence and biased self-attribution. In Daniel, Hirshleifer, and Subrahmanyam (1998), overconfident investors overestimate the precision of his private information, which causes the stock price to overreact. As noisy public information arrives, the overconfident investors will update their confidence over time. Because of attribution bias, they will underweight information that lowers their self-esteem and overweight information that confirms their original valuation. As a result, their estimates of the precision of their valuations increase over time, which produces momentum phenomenon. Overall, Daniel, Hirshleifer, and Subrahmanyam (1998) show

[1]The underreaction evidence documents that news is incorporated slowly into prices, and this tends to exhibit positive serial correlation over 1-12 months (Jegadeesh and Titman, 1993; Chan, Jegadeesh, and Lakonishok, 1996; Daniel, 1996, and Rouwenhorst, 1998). The overreaction evidence shows that asset prices overreact to information released over longer intervals of perhaps 3-5 years, and this trend suggests that past winners (losers) tend to be future losers (winners) (see DeBondt and Thaler, 1985, 1987; Chopra, Lakonishok, and Ritter, 1992; Fama and French, 1996, 1998; Ball, Kothari, and Shanken, 1995; Poterba and summers, 1988; Richards, 1997; Kim, Nelson, and Startz, 1988; Carmel and Young, 1997; Daniel, 1996).

[2]For example, Hong, Lim, and Stein (2000) document that short-term price continuation is a consequence of the gradual diffusion of private information. On the other hand, Chan (1988) and Ball and Kothari (1989) argue that these reversals are due primarily to systematic changes in expected returns. Some studies have argued that the long-term price reversals can be attributed to size effect (see Fama and French, 1988, 1993; Zarowin, 1990). Conrad and Kaul (1993) and Ball, Kothari, and Shanken (1995) note that most of DeBondt and Thaler's (1985) long-term overreaction findings can be attributed to a combination of bid-ask spreads and price effect. However, Fama (1998) argues that market is efficient and these anomalies are chance deviations to expected value.

that, in the presence of investor's overconfidence and biased self-attribution, security price changes exhibit short-term momentum and long-term reversal, thereby causing excess volatility.

To prevent large price movements due to overreaction, price limits are imposed in many stock markets, such as Austria, Belgium, China, France, Greek, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, Spain, Switzerland, Taiwan, and Thailand. Several researchers have tried to examine the impact and effectiveness of price limits, either empirically or theoretically. Their impact on the operation of markets, however, is still under debate. Advocates and supporting evidence of price limits suggest that they provide a cool-off period in the events of overreaction, and the volatility following limits is substantially reduced (e.g., Anderson, 1984; Ma, Rao and Sears, 1989a, 1989b; Greenwald and Stein, 1991; and Arak and Cook, 1997). Opponents to price limits contend that the imposition of price limits, instead of stabilizing price changes, may impede the price discovery process by preventing the price from reaching its equilibrium level effectively. The view that price limits serve nothing, but merely slow down the price adjustment process has also many proponents and supporting evidence (e.g., Telser, 1981; Figlewski, 1984; Miller, Malkiel and Hawke, 1987; Lehmman, 1989; Fama, 1989; Meltzner, 1989; Kim and Rhee, 1997). It is also argued that price limits may impose additional risks on market participation because they prohibit mutually beneficial trades at prices outside the limits (e.g., Ackert and Hunter, 1994). A final argument against price limits is that they may have a "magnet effect" that acts to draw the price closer to a limit. This is because traders, for fear of losing liquidity and being locked in a position, would rush to protect themselves through active trading. As a result, when the price is close to a limit, the trading volume will be heavy and the price limit rule will serve as a magnet that further pulls the price even closer to the limit (e.g., Kuhn, Kuserk and Locke, 1989; Lee, Ready and Seguin, 1994; Subrahmanyam, 1994; and Harris, 1997).

Price limits, though reduce concurrent price volatility through limiting the prices from rising above or falling below the prespecified level, may cause volatility to spread out over a longer period of time (volatility spillover). Moreover, in the extent to which investors are biased self-attributed, the individual becomes more overconfident if he buys a security and an up limit is triggered (public signal confirms his trade), but his confidence falls by little if he buys but a down limit is hit (it disconfirms his trade). Then, as price limits are hit, despite updating based on an inconclusive public information, the traders will subsequently form expectations about the prices at next trading date. Then the effectiveness of price limits in reducing volatility when the investors are overconfident will be uncertain. If the momentum or overreaction effect induced by behavioral biases such as overconfidence and biased self-attribution can be attenuated with the imposition of price limits, then it appears that price limits can be said to be efficiency-improving. Therefore, this paper intends to examine the effectiveness of price limits in preventing excess volatility due to overconfidence and self-attribution theoretically. We find that when traders are overconfident, the imposition of price limits is effective in reducing average price volatility. This seems to support the argument that price limits provide a cool-off effect in the events of overreaction, as documented by Anderson (1984), Ma, Rao and Sears (1989a, 1989b), Greenwald and Stein (1991), and Arak and Cook (1997). In addition, with price limits, short-term momentum effect will exist even without the assumption of attribution bias. Since price will correct to its true value, long-term price reversal is also found whatever price limits are.

The remainder of the paper is organized as follows. Section 2 reviews the basic model of overconfidence proposed by Daniel, Hirshleifer, and Subrahmanyam (1998). Section 3 further derives the implications about stock price reactions to private information, price autocorrelations, and volatility when price limits are imposed. Section 4 provides simulation results and empirical implications. Section 5 concludes by summarizing our findings.

2 A Review of DHS Model

2.1 Constant Confidence

This section reviews Daniel, Hirshleifer, and Subrahmanyam (1998) model with static overconfidence. Investors differ in their skill at acquiring information through measures such as analyzing financial statement and interviewing management. An overconfident investor will overestimate the precision of his private signals and underestimate their forecast error. Those who receive the signal is referred to as the informed, I, and those who do not is referred to as the uninformed, U. Informed traders are assumed to be risk-neutral, and the uninformed traders are assumed to be risk-averse. There are four dates. At date 0, traders begin with identical prior beliefs. At date 1,

I investor receives a noisy private signal about underlying security value and trades with U. The underlying security value of θ is assumed to be normally distributed with mean 0 and variance σ_θ^2. The private signal received by I at date 1 is

$$s_1 = \theta + \epsilon, \tag{1}$$

where $\epsilon \sim N(0, \sigma_\epsilon^2)$. The overconfident investor underestimates the error variance ($\sigma_c^2 < \sigma_\epsilon^2$). At date 2, a noisy public signal arrives and a trade occurs again. The date 2 public signal is

$$s_2 = \theta + \eta, \tag{2}$$

where the error term $\eta \sim N(0, \sigma_p^2)$ is independent of θ and ϵ. At date 3, conclusive public information arrives, and the risky security generates a terminal value of θ.

2.1.1 Equilibrium Prices and Trades

Assuming that the informed traders are risk neutral, prices at each date satisfy

$$P_1 = E_c(\theta|\theta + \varepsilon), \tag{3}$$

$$P_2 = E_c(\theta|\theta + \varepsilon, \theta + \eta), \tag{4}$$

where the subscript c denotes the fact that the expectation operator is calculated based on the informed traders' confident beliefs. By definition, $P_0 = 0$, $P_3 = \theta$. By standard properties of normal variables,

$$P_1 = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_c^2}(\theta + \varepsilon), \tag{5}$$

$$P_2 = \frac{\sigma_\theta^2(\sigma_P^2 + \sigma_c^2)}{D}\theta + \frac{\sigma_\theta^2 \sigma_P^2}{D}\varepsilon + \frac{\sigma_\theta^2 \sigma_c^2}{D}\eta, \tag{6}$$

where $D = \sigma_\theta^2(\sigma_P^2 + \sigma_c^2) + \sigma_c^2 \sigma_P^2$.

2.1.2 Implications for Price Behavior

Overreaction and Underreaction

When the traders receive a positive private signal at date 1, overconfidence in the private signal $\theta + \epsilon$ causes the date 1 stock price to overreact to this new information. At date 2, when noisy public information signals arrive, the inefficient deviation of the price is partially corrected. This overreaction and correction imply that the covariance between the date 1 price change and the date 2 price change is negative ($cov(P_2 - P_1, P_1 - P_0) = \frac{\sigma_\theta^6 \sigma_c^2 (\sigma_c^2 - \sigma_\varepsilon^2)}{(\sigma_\theta^2 + \sigma_c^2)^2 D} < 0$). Furthermore, the overreaction to the private signal is partially corrected by the date 2 public signal, and fully corrected upon release of the date 3 public signal, so that $cov(P_3 - P_1, P_1 - P_0) = \frac{\sigma_\theta^4 (\sigma_c^2 - \sigma_\varepsilon^2)}{(\sigma_\theta^2 + \sigma_c^2)^2} < 0$. This suggests that if investors are overconfident, price moves resulting from private information arrival are on average partially reversed in the long run. Finally, $cov(P_3 - P_2, P_2 - P_1) = \frac{1}{D^2(\sigma_\theta^2 + \sigma_c^2)}[\sigma_\theta^6 \sigma_c^2 \sigma_P^2 (\sigma_\varepsilon^2 - \sigma_c^2)] > 0$. Therefore, the continuing correction in reaction to the arrival of public information causes price changes at the time of the public signal to be positively correlated with later price changes.

Unconditional serial correlations and volatility

$cov(P_2 - P_1, P_1 - P_0) < 0$ and $cov(P_3 - P_1, P_1 - P_0) < 0$ imply that if investors are overconfident, price changes are unconditionally negatively autocorrelated at both short and long lags. Thus, the constant-confidence model is accordance with long-run reversals (negative long-term autocorrelations), but not with short-term momentum (positive short-term autocorrelations).

When traders are overconfident, the date 1 price volatility, $var(P_1 - P_0) = \frac{\sigma_\theta^4 (\sigma_\theta^2 + \sigma_\varepsilon^2)}{(\sigma_\theta^2 + \sigma_c^2)^2}$, decreases with σ_c^2 (when informed agents are rational (subscripted by R), $var_R(P_1 - P_0) = \frac{\sigma_\theta^4}{\sigma_\theta^2 + \sigma_\varepsilon^2} < var(P_1 - P_0)$). Overconfidence causes prices moves away from fundamentals, and thereby causes excess price volatility around private signals. Overconfidence also causes the public signal to be under weighted, which tends to reduce the date 2 variance. Nevertheless, the date 1 swings away from fundamentals create a greater need for correction at dates 2 and 3. Therefore, greater overconfidence can either decrease or increase the volatility around public signals ($var(P_2 - P_1) = \frac{\sigma_c^4[\sigma_c^4 \sigma_\theta^6 + \sigma_\theta^8 \sigma_\varepsilon^2 + \sigma_\theta^4 \sigma_P^2 (\sigma_\theta^2 + \sigma_c^2)^2]}{(\sigma_\theta^2 + \sigma_c^2)^2 D^2}$ can either increase or decrease with σ_c^2). Furthermore, the unconditional volatility, defined as the average of $var(P_3 - P_2), var(P_2 - P_1)$, and $var(P_1 - P_0)$, is $\frac{1}{3}[\frac{\sigma_c^4 \sigma_P^4 \sigma_\theta^2 + \sigma_\theta^4 \sigma_P^4 \sigma_\varepsilon^2 + \sigma_\theta^4 \sigma_c^4 \sigma_P^2}{D^2} + \frac{\sigma_c^4[\sigma_c^4 \sigma_\theta^6 + \sigma_\theta^8 \sigma_\varepsilon^2 + \sigma_\theta^4 \sigma_P^2 (\sigma_\theta^2 + \sigma_c^2)^2]}{(\sigma_\theta^2 + \sigma_c^2)^2 D^2} + \frac{\sigma_\theta^4}{(\sigma_\theta^2 + \sigma_c^2)^2}(\sigma_\theta^2 + \sigma_\varepsilon^2)]$. When informed agents are rational, that is $\sigma_c^2 = \sigma_\varepsilon^2$, then the unconditional volatility reduces to $\frac{\sigma_\theta^2}{3}$, which is smaller as long as there exists overconfidence, $\sigma_c^2 < \sigma_\varepsilon^2$.

2.2 Outcome-Dependent Confidence

The implications discussed so far are based on a fixed confidence level. However, psychological evidence and theory suggest that actions and resulting outcomes affect confidence. In particular, when an investor receives public information that confirms his belief, his confidence rises; but his confidence decreases by little when receiving disconfirming information. This section considers this kind of psychological pattern.

Take into account an informed individual who buys or sells a security based on his private information. A public positive signal confirms his trade if they buy; a public negative signal confirms his trade if they sell. Assuming that the investor become more confident if the later public signal confirms his trade, and his confidence falls only modest if it disconfirms. This implies that public information adds to confidence, and as a result intensifying overreaction. The continuing overreaction leads to positive autocorrelation during the initial overreaction phase. As repeated public information arrival draws the price back toward its fundamental value, the initial overreaction is gradually reversed in the long run. The dynamic confidence is presented to capture the overreaction and correction phrase.

Assume that the public signal released at date 2 is discrete with s_2=1 or -1, and the precision assessed by the investors at date 2 about their earlier private signal depends on the public signal in the following way. If $sign(s_2) = sign(\theta+\varepsilon)$, confidence increases, and investors' assessment of noise variance decreases to $\sigma_c^2 - k$, $0 < k < \sigma_c^2$. If $sign(s_2) \neq sign(\theta + \varepsilon)$, confidence remains constant, so noise variance is still believed to be σ_c^2.

Given normal random variables, the date 1 price is

$$P_1 = E_c(\theta|\theta + \varepsilon) = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_c^2}(\theta + \varepsilon).$$

The date price $P_0 \equiv 0$. If $sign(s_2) \neq sign(\theta + \varepsilon)$, the price remains unchanged at date 2 since the public signal is uninformative. However, if $sign(s_2) = sign(\theta + \varepsilon)$, the new price, P_{2c}, is calculated using the new level of the assessed variance of ϵ.

$$P_{2c} = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_c^2 - k}(\theta + \varepsilon). \tag{7}$$

When overconfidence is not revised at date 2, the price at date $3'$ is given by equation (6). When overconfidence is revised at date 2, the price at date $3'$, denoted by $P_{3'c}$, is:

$$P_{3'c} = \frac{\sigma_\theta^2(\sigma_c^2 - k + \sigma_P^2)}{D'}\theta + \frac{\sigma_\theta^2\sigma_P^2}{D'}\varepsilon + \frac{\sigma_\theta^2(\sigma_c^2 - k)}{D'}\eta,$$

where $D' = \sigma_\theta^2(\sigma_c^2 - k + \sigma_P^2) + (\sigma_c^2 - k)\sigma_P^2$.

2.2.1 Implications

The probability of receiving a public signal +1 is assumed to be constant $\frac{1}{2}$. By the law of iterated expectations, it cab be shown that

$$cov(P_2 - P_1, P_1 - P_0) = \frac{k\sigma_\theta^4(\sigma_\theta^2 + \sigma_\varepsilon^2)}{2(\sigma_\theta^2 + \sigma_c^2)^2(\sigma_\theta^2 + \sigma_c^2 - k)} > 0.$$

Thus, the model shows that the overreaction phrase, not just the correction phrase, can contribute positively to short-term momentum. As a result,

$$cov(P_3 - P_1, P_1 - P_0) = -\frac{\sigma_\theta^4(\sigma_\varepsilon^2 - \sigma_c^2)}{(\sigma_\theta^2 + \sigma_c^2)^2} < 0;$$

$$cov(P_3 - P_2, P_2 - P_1) = -\frac{\sigma_\theta^2[k^2\sigma_\theta^2 + k(\sigma_\varepsilon^2 - \sigma_c^2)]}{2(\sigma_c^2 + \sigma_\theta^2)(\sigma_\theta^2 + \sigma_c^2 - k)^2} < 0,$$

since dates 1 and 2 overreactions must be reversed in the long run.

It is easy to show that all of the remaining single-period price-change autocorrelations are negative except for $cov(P_3 - P_{3'}, P_{3'} - P_2)$, which is positive. i.e.,

$$\begin{aligned} & cov(P_3 - P_3', P_3' - P_2) \\ = \ & \frac{\sigma_\theta^6}{2}[\frac{(\sigma_c^2 - k)(\sigma_\varepsilon^2 - \sigma_c^2 + k)}{D'(\sigma_\theta^2 + \sigma_c^2 - k)^2} + \frac{\sigma_c^2(\sigma_\varepsilon^2 - \sigma_c^2)}{(\sigma_\theta^2 + \sigma_c^2)[\sigma_\theta^2(\sigma_c^2 + \sigma_P^2) + \sigma_c^2\sigma_P^2}] > 0. \end{aligned}$$

Intuitively, date 2 is the extreme of the impulse response function. The single-period price-change single-lag autocorrelations that straddles the extreme is negative ($cov(P_3' - P_2, P_2 - P_1) < 0$), and the single-period price-change single-lag autocorrelation that that fall within either the overreaction phrase ($cov(P_2 - P_1, P_1 - P_0) > 0$) or within the correction phrase ($cov(P_3 - P_3', P_3' - P_2) > 0$) are positive. Thus, in empirical research, the calculated autocorrelations will be positive when the pairs of returns are drawn from overreaction or correction phase. In contrast, as longer-lag pairs of returns that straddle the extreme of the impulse response function are drawn, the calculated autocorrelations are negative. Therefore, the combination of overconfidence and biased self-attribution provide a joint explanation for both short-term momentum and long-term reversals.

In summary, in the basic model of fixed confidence, investors receive a private signal, and subsequently update their actions based on an noisy public signal. Thus, in the beginning, the market price overreacts to the signal. Eventually, the price corrects itself when the true state of the world resolves. The pattern of overreaction causes negative long run return autocorrelation. However, this approach does not capture the phenomenon of short-term continuation. If investor confidence changes because of biased self-attribution and the process of overreaction and correction is sufficiently smooth, then stock price changes exhibit short-run positive autocorrelation and long-term reversal. The patterns of price momentum and price reversal will causes excess price volatility in the financial markets. Since price limits have been argued by many research to moderate excess price volatility caused by an overreaction of traders to news (e.g., Anderson, 1984; Ma, Rao and Sears, 1989a, 1989b; Greenwald and Stein, 1991; and Arak and Cook, 1997), in the following section, we intend to investigate the effectiveness of price limits in the extent of overreaction resulting from trader's overconfidence.

3 With Price Limits

3.1 The Price Behavior under Price Limits

Under a price limit rule, the price during each trading day (period) cannot be above the previous *settlement price* plus an up limit, or below the previous settlement price minus a down limit. More formally, the *observed* price, Z_t, follows the relationship:

$$Z_t = \begin{cases} Z_{t-1} + L & \text{if } P_t \geq Z_{t-1} + L \\ P_t & \text{if } Z_{t-1} - L < P_t < Z_{t-1} + L \\ Z_{t-1} - L & \text{if } P_t \leq Z_{t-1} - L, \end{cases} \tag{8}$$

where P_t is the equilibrium price at time t and L is the maximum daily limit imposed on the absolute change in price in a trading day. Thus, the true price is observed (i.e., $Z_t = P_t$) only when it falls within the range, $(Z_{t-1} - L,\ Z_{t-1} + L)$; otherwise it is observed as equal to the limit price if it is outside the range. By subtracting Z_{t-1} from both sides of equation (8), we obtain:

$$z_t = \begin{cases} L & \text{if } P_t - Z_{t-1} \geq L \\ P_t - Z_{t-1} & \text{if } -L < P_t - Z_{t-1} < L \\ -L & \text{if } P_t - Z_{t-1} \leq -L, \end{cases} \tag{9}$$

where z_t is the observed daily price change at time t, i.e., $z_t = Z_t - Z_{t-1}$. Hence, the occurrence of a limit price depends on the magnitude of $Q_t \equiv P_t - Z_{t-1}$, rather than that of $r_t = P_t - P_{t-1}$, the true price change. We refer to Q_t as the *pseudo true price change*, and decompose it into two terms:

$$\begin{aligned} Q_t &= P_t - Z_{t-1} \\ &= (P_t - P_{t-1}) + (P_{t-1} - Z_{t-1}) \\ &= r_t + e_{t-1}, \end{aligned}$$

where $e_s = P_s - Z_s$ denotes a spillover term from trading day s, which can also be viewed as an unrealized residual shock being carried over to future trading days. Clearly, z_t is never equal to the true price change unless both t and $(t-1)$ are non-limit days.

3.2 Constant Overconfidence

In this paper, price limits are not imposed at date 3 because for most contracts, such as options and futures, price limits are removed so that the prices can converge to the so-called fundamental values. Removing the final-date price limits allows one to look at the effects of price limits on short and long-term price behavior. When investors with constant overconfidence receive a private signal, the *observed* price at date 1, Z_1, under price limits follows the relationship:

$$Z_1 = \begin{cases} L & \text{if } P_1 \geq L \\ P_1 = \frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_c^2}(\theta+\varepsilon) & \text{if } -L < P_1 < L \\ -L & \text{if } P_1 \leq -L, \end{cases} \tag{10}$$

Suppose that an up limit is hit at time 1, then potentially the price at time 2 is

$$\begin{aligned} P_2 &= E_c(\theta | P_1 > L, \theta+\eta) = E_c(\theta|\theta+\varepsilon > L', \theta+\eta) \\ &= \frac{\sigma_\theta^4(\sigma_P^2+\sigma_c^2)}{D\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2}}\lambda(\alpha_1) + \frac{\sigma_\theta^2\sigma_P^2\sigma_\varepsilon^2}{D\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2}}\lambda(\alpha_1) + \frac{\sigma_\theta^2\sigma_c^2}{D}\eta, \end{aligned}$$

with

$$\lambda(\alpha_1) = \frac{\phi(\alpha_1)}{1-\Phi(\alpha_1)}, \quad \alpha_1 = \frac{L'}{\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2}}, \quad L' = L\frac{\sigma_\theta^2+\sigma_c^2}{\sigma_\theta^2},$$

where $\phi(.)$ and $\Phi(.)$ denote the standard normal density and distribution functions, respectively. The *pseudo true price change* at date 2, Q_2, is

$$Q_2 = \frac{\sigma_\theta^4(\sigma_P^2+\sigma_c^2)}{D\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2}}\lambda(\alpha_1) + \frac{\sigma_\theta^2\sigma_P^2\sigma_\varepsilon^2}{D\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2}}\lambda(\alpha_1) + \frac{\sigma_\theta^2\sigma_c^2}{D}\eta - L.$$

Assume again that conclusive public information arrives at date 3 (the terminal date) and price limits are relaxed concurrently. If price limits are triggered at both dates 1 and 2, *the pseudo true price change* at date 3, Q_3, is

$$Q_3 = \begin{cases} \theta - 2L & \text{if } P_2 - Z_1 \geq L \\ \theta - P_2 & \text{if } -L < P_2 - Z_1 < L \\ \theta + 2L & \text{if } P_2 - Z_1 \leq -L, \end{cases} \tag{11}$$

Implication for Price Behavior

If an up limit is triggered at date 1, the expected price at date 1 is

$$E(P_1|P_1 > L) = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_c^2}\sqrt{\sigma_\theta^2 + \sigma_\varepsilon^2}\ \lambda(\alpha_1),$$

The variance of price change at date 1 given that price limits are hit is

$$var(P_1|P_1 > L) = \frac{\sigma_\theta^4(\sigma_\theta^2 + \sigma_\varepsilon^2)}{(\sigma_\theta^2 + \sigma_c^2)^2}(1 - \delta(\alpha_1)),$$

where $\delta(\alpha_1) = \lambda(\alpha_1)(\lambda(\alpha_1) - \alpha_1), 0 < \delta(\alpha_1) < 1$. We can find that

$$var(P_1 - P_0|P_1 > L) < var(P_1 - P_0) = \frac{\sigma_\theta^4(\sigma_\theta^2 + \sigma_\varepsilon^2)}{(\sigma_\theta^2 + \sigma_c^2)^2}.$$

This implies that the imposition of price limits decreases the price volatility around private signal releases.

The covariance between the date 1 and date 2 price changes given price limits hit at date 1, $cov(Q_1, Q_2|P_1 > L)$, is:

$$\begin{aligned} & cov(Q_1, Q_2|P_1 > L) \\ = \ & \frac{1}{D(\sigma_\theta^2 + \sigma_c^2)}[\sigma_\theta^6(\sigma_P^2 + \sigma_c^2)(1 - \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\epsilon^2}\delta(\alpha_1)) + \sigma_\theta^4\sigma_P^2\sigma_\varepsilon^2(1 - \frac{\sigma_\epsilon^2}{\sigma_\theta^2 + \sigma_\epsilon^2}\delta(\alpha_1))], \end{aligned}$$

which is positive. This indicates that price limits create positive autocorrelation around limit hits even when traders are rational ($\sigma_c^2 = \sigma_\epsilon^2$). The covariance between the date 2 and date 3 price changes given price limits hit at date 1, $cov(Q_2, Q_3|P_1 > L)$, is:

$$\begin{aligned} & cov(Q_2, Q_3|P_1 > L) \\ = \ & \frac{\sigma_\theta^4\sigma_c^2\sigma_P^2(\sigma_P^2 + \sigma_c^2)}{D^2}(1 - \delta(\alpha_1)) + \frac{\sigma_\theta^4\sigma_P^4\sigma_\varepsilon^2}{D^2}(1 - \delta(\alpha_1)) - \frac{\sigma_\theta^4\sigma_c^4\sigma_P^2}{D^2}, \end{aligned}$$

which may be positive or negative, depending on the overconfidence level, σ_c^2.

Figure 1 illustrates the average price path following a positive date 1 private signal shock with various price limits when traders are overconfident. Without price limits, overconfidence in private signal causes the price to overreact and it reaches the maximum in period 1. At date 2, the price declines due to the noisy public information arrivals, and eventually asymptotes to its terminal value. The price patterns accords with long-term price reversal, but not with short-term momentum. With price limits, the peak of the impulse-function shifts from date 1 to date 2 since they constrain the price change during a period and unrealized shocks will be carried over to next day. Thus, with price limits, short-term price momentum will occur even without consideration of biased self-attribution. Additionally, with the introduction of price limits, the price movement resulting from private information arrival will be smother and the excess volatility due to overconfidence will be reduced.

(Figure 1 about here)

3.3 Outcome-Dependent Confidence

If an investor's confidence rises when he receives a confirming public information, but falls by little when receiving disconfirming information, the story may be different. We first consider the case that when the noisy public information confirms the trader's trade, i.e., $sign(s_2) = sign(\theta+\varepsilon)$, and then the case when the trader receives disconfirming information, i.e., $sign(s_2) \neq sign(\theta+\varepsilon)$.

(1) $sign(s_2) = sign(\theta+\varepsilon)$

The conditional price of P_2 given price limits hit at date 1 is:

$$P_2 = E(\theta|P_1 > L, sign(s_2) = sign(\theta+\varepsilon)) = \frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_c^2-k}\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2}\ \lambda(\alpha_1),$$

and the conditional price of $P_{3'}$ given price limits hit at dates 1 and 2 is:

$$\begin{aligned} P_{3'} &= E(\theta|P_1 > L, P_2 > 2L, \theta+\eta, sign(s_2) = sign(\theta+\varepsilon)) \\ &= \frac{\sigma_\theta^4(\sigma_P^2+\sigma_c^2-k)}{D'(\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2})}\lambda(\alpha_2) + \frac{\sigma_\theta^2\sigma_P^2\sigma_\varepsilon^2}{D'(\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2})}\lambda(\alpha_2) + \frac{\sigma_\theta^2(\sigma_c^2-k)}{D'}\eta, \end{aligned}$$

where $\lambda(\alpha_2) = \frac{\phi(\alpha_2)}{1-\Phi(\alpha_2)}$, $\alpha_2 = \frac{L''}{\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2}}$, $L'' = \frac{2L(\sigma_\theta^2+\sigma_c^2-k)}{\sigma_\theta^2}$.

(2) $sign(s_2) \neq sign(\theta+\varepsilon)$

Along the same line, the conditional price of P_2 given price limits hit at date 1 is:

$$P_2 = E(\theta|P_1 > L, sign(s_2) \neq sign(\theta+\varepsilon)) = \frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_c^2}\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2}\ \lambda(\alpha_1),$$

and the conditional price of $P_{3'}$ given price limits hit at dates 1 and 2 is:

$$\begin{aligned} & P_{3'} = E(\theta|P_1 > L, P_2 > 2L, \theta+\eta, sign(s_2) \neq sign(\theta+\varepsilon)) \\ = & \frac{\sigma_\theta^4(\sigma_P^2+\sigma_c^2)}{D(\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2})}\lambda(\alpha_3) + \frac{\sigma_\theta^2\sigma_P^2\sigma_\varepsilon^2}{D(\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2})}\lambda(\alpha_3) + \frac{\sigma_\theta^2\sigma_c^2}{D}\eta, \end{aligned}$$

where $\lambda(\alpha_3) = \frac{\phi(\alpha_3)}{1-\Phi(\alpha_3)}, \alpha_3 = \frac{L'''}{\sqrt{\sigma_\theta^2+\sigma_\varepsilon^2}}, L''' = \frac{2L(\sigma_\theta^2+\sigma_c^2)}{\sigma_\theta^2}$.

Implication for Price Behavior

First, it can be shown that the price change between date 1 and 2 given price limits move at date 1 and $sign(s_2) = sign(\theta+\varepsilon)$, $cov(Q_2, Q_1|P_1 > L)$, is:

$$\begin{aligned} & cov(Q_2, Q_1|P_1 > L, sign(s_2) = sign(\theta+\varepsilon)) \\ = & cov(P_2 - L, P_1|P_1 > L, sign(s_2) = sign(\theta+\varepsilon)) \\ = & \frac{\sigma_\theta^4}{(\sigma_\theta^2+\sigma_c^2-k)(\sigma_\theta^2+\sigma_c^2)}[(\sigma_\theta^2+\sigma_\varepsilon^2)(1-\delta(\alpha_1))]. \end{aligned}$$

Second, if price limits are hit at date 1 and $sign(s_2) \neq sign(\theta+\varepsilon)$, then the price change between dates 1 and 2, $cov(Q_2, Q_1|P_1 > L, sign(s_2) \neq sign(\theta+\varepsilon))$, is:

$$\begin{aligned} & cov(Q_2, Q_1, |P_1 > L, sign(s_2) \neq sign(\theta+\varepsilon)) \\ = & \frac{\sigma_\theta^4}{(\sigma_\theta^2+\sigma_c^2)^2}[(\sigma_\theta^2+\sigma_\varepsilon^2)(1-\delta(\alpha_1))]. \end{aligned}$$

In sum, the price change between dates 1 and 2 when price limits are hit at date 1 is:

$$cov(Q_2, Q_1, |P_1 > L) = \frac{\sigma_\theta^4(2\sigma_\theta^2+2\sigma_c^2-k)[(\sigma_\theta^2+\sigma_\varepsilon^2)(1-\delta(\alpha_1))]}{2(\sigma_\theta^2+\sigma_c^2-k)(\sigma_\theta^2+\sigma_c^2)^2},$$

which is positive. The implies that the expected covariance for the price change between before and after price limits are positive even when investor displays biased self-attribution.

Further, if price limits are hit at both dates 1 and 2, the conditional covariance of $Q_{3'}$ and Q_2 when the public signal confirms the trader's trade is:

$$
\begin{aligned}
& cov(Q_{3'}, Q_2|P_1 > L, P_2 > 2L, sign(s_2) = sign(\theta + \varepsilon)) \\
= \; & \frac{\sigma_\theta^6(\sigma_P^2 + \sigma_c^2 - k)(1 - \frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_\epsilon^2}\delta(\alpha_2))}{D'(\sigma_\theta^2 + \sigma_c^2 - k)} + \frac{\sigma_\theta^4\sigma_P^2\sigma_\varepsilon^2(1 - \frac{\sigma_\epsilon^2}{\sigma_\theta^2+\sigma_\epsilon^2}\delta(\alpha_2))}{D'(\sigma_\theta^2 + \sigma_c^2 - k)},
\end{aligned}
$$

and, when the public signal disconfirms the trader's trade, it is:

$$
\begin{aligned}
& cov(Q_{3'}, Q_2|P_1 > L, P_2 > 2L, sign(s_2) \neq sign(\theta + \varepsilon)) \\
= \; & \frac{\sigma_\theta^6(\sigma_P^2 + \sigma_c^2)(1 - \frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_\epsilon^2}\delta(\alpha_2))}{D(\sigma_\theta^2 + \sigma_c^2)} + \frac{\sigma_\theta^4\sigma_P^2\sigma_\varepsilon^2(1 - \frac{\sigma_\epsilon^2}{\sigma_\theta^2+\sigma_\epsilon^2}\delta(\alpha_2))}{D(\sigma_\theta^2 + \sigma_c^2)},
\end{aligned}
$$

with $\delta(\alpha_2) = \lambda(\alpha_2)(\lambda(\alpha_2) - \alpha_2), 0 < \delta(\alpha_2) < 1$. In sum, if price limits are hit at both dates 1 and 2, then the price change between dates $3'$ and 2, $cov(Q_{3'}, Q_2|P_1 > L, P_2 > 2L)$, is:

$$
\begin{aligned}
& cov(Q_{3'}, Q_2|P_1 > L, P_2 > 2L) \\
= \; & \frac{\sigma_\theta^6(1 - \frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_\epsilon^2}\delta(\alpha_2))[D(\sigma_c^2 + \sigma_p^2 - k)(\sigma_\theta^2 + \sigma_c^2) + D'(\sigma_c^2 + \sigma_p^2)(\sigma_\theta^2 + \sigma_c^2 - k)]}{2DD'(\sigma_\theta^2 + \sigma_c^2)(\sigma_\theta + \sigma_c^2 - k)} \\
+ \; & \frac{\sigma_\theta^4\sigma_p^2(1 - \frac{\sigma_\epsilon^2}{\sigma_\theta^2+\sigma_\epsilon^2}\delta(\alpha_2))[D(\sigma_\theta^2 + \sigma_c^2) + D'(\sigma_\theta^2 + \sigma_c^2 - k)]}{2DD'(\sigma_\theta^2 + \sigma_c^2)(\sigma_\theta^2 + \sigma_c^2 - k)},
\end{aligned}
$$

which is positive. The implies that, when price limits are triggered twice, the covariance for price change between before and after price limits are positive even under outcome dependence model.

Figure 2 illustrates the average price path following a positive date 1 private signal shock with various price limits when traders are overconfident and biased self-attributed. Without price limits, the price initially jumps and continues moving up. It reaches the peak of the impulse-response function in period 2, then declines and eventually asymptotes to its terminal value. Thus, there is an initial overreaction phase where the price moves away from the true value as the investor's attribution bias causes him to place more weight on his private information. Eventually, the public information becomes precise enough that the investor revises his valuation of security downward. This is the correction phase. The analysis implies that patterns of security price-change are consistent with the short-term momentum and long-term price reversal phenomena in above section. With price limits, the average price jumps up at date 1, then reaches the maximum at date 3 and declines hereafter. In comparison, when traders are overconfident, the imposition of price limits is effective in reducing average price volatility by lengthening the momentum effect (The extreme shifts from date 2 to date 3'.). Overall, even with price limits, the short-lag price change autocorrelations are also positive and long-lag autocorrelations are also negative. Whereas, the short-term momentum effect will be extended to longer period when price limits are imposed strict.

(Figure 2 about here)

Above results are based on the fact that price limits are triggered. However, the pattern of price changes also depends on the probability of limit moves, therefore in the next section we use the simulation procedure to investigate the effect of price limits on subsequent price changes. Note that if the price change results from investor's overreacting, it will reverse to fundamental value as public information arrives. Therefore, if the price limit mechanism is useful in reducing excess volatility due to investor's overconfidence, it may reduce the risk to market participants.

4 Simulation Results

In this section we present numerical examples for normally distributed price changes to determine the effects of price limits on price behavior. We use the parameters P_0=100, σ_θ^2=σ_ϵ^2=25, $\sigma_\eta^2 = 187.5$, and k=5 for the simulation. Three various overconfidence levels, 10% ($\sigma_c^2 = 22.5$), 20% ($\sigma_c^2 = 20$), and 40% ($\sigma_c^2 = 15$), are used.[3] We perform this simulation 10,000 times, each time redrawing the value θ, the private signal $s_1 = \theta + \epsilon$, and the public information ϕ. Three different levels of the price limits are analyzed. They are 0.025, 0.05 and 0.1.

[3]The set of parameter values used in Daniel, Hirshleifer, and Subrahmanyam (1998) multiplied by 5 is the parameter values used in this paper.

4.1 Constant Overconfidence

Without Price Limits

Panel A of Table 1 presents the results for the simplest case for which there are no price limits and there is static confidence level. The results show that when traders are not overconfident and a price limit rule is not imposed, the covariance between any two dates is insignificantly different from zero. This implies that, when traders are rational, the price path following a positive or negative signal will be quite random. However, when traders are overconfident in their private signal, the date 1 price will overreact to the private signal shock. Further, the overreaction to the private price will be partially corrected when the date 2 public signal arrives. Our simulation results confirm the phenomenon because the correlation between date 1 price change and date 2 price change, ρ_{12}, is significantly negative. Finally, the overreaction will be fully corrected upon release of the date 3 public signal, so that $\rho(z_1, z_2 + z_3) < 0$. The correction phase staring from date 2 and ending at date 3 causes the price change at date 2 and date 3 is positively correlated ($\rho_{23} > 0$). Our simulation results also confirm these results. For example, when overconfidence level is 40%, ρ_{23} is 0.0725 with p-value 0.0001, and $\rho(z_1, z_2 + z_3)$ is -0.2350 with p-value 0.0001. Overall, if investors are overconfident, price changes are negatively autocorrelated at both short ($\rho_{12} < 0$)and long lags($\rho(z_1, z_2 + z_3) < 0$). The results are somewhat different for 10% and 20% overconfidence level. Specifically, ρ_{12} and ρ_{23} are not significantly different from zero, but $\rho(z_1, z_2 + z_3)$ and $\rho(z_1 + z_2, z_3)$ are significantly negative. As documented by Daniel, Hirshleifer, and Subrahmanyam (1998), this occurs if either the extra overreaction is small or the start of the correction is weak (or both).[4]

(Table 1 about here)

Panel A also shows that, without price limits, the volatility of private signal releases increases with overconfidence level. For example, the date 1 volatility rises from rational 12.534 to 13.620 with 10% overconfidence level, and further to 19.172 with 40% overconfidence level. This is because more overconfidence causes wider swings at

[4]The extra overreaction is small if confidence grows slightly when an investor's trade is confirmed by public information. Further, our simulation values of ρ_{13}, which are -0.0628 (p-value = 0.0001) for 10% overconfidence and -0.0374 (p-value = 0.0001) for 20% overconfidence, respectively, are pronouncedly different from zero. This implies that price adjusts relatively much more at the later correction phase.

date 1 away from fundamentals, and causes more excess volatility around private signal releases. In addition, the wider date 1 swings create a greater need to correct price movement at dates 2 and 3. But the overconfidence causes trader to underweight the public signal, which tends to reduce date 2 variance. Therefore, without price limits, greater overconfidence can either increase or decrease the volatility around public signals. Overall, our empirical results show that the price volatility at noisy public information releases, V_2, decreases with overconfidence level. But the average price volatility, V_T, rises with overconfidence level. Specifically, the more overconfident the investors are, the more increase in the average volatility will be.

With Price Limits

To prevent excessive price fluctuation and to foster an orderly market, the price limits are imposed in many markets. Panels B to D in Table 1 present the correlation between price change and price volatility around private signal and public signal releases with various price limits. First, it can be found that with 5% (10%) limits, the probability of limit moves increases from 7.74% (0.21%) with rational traders to 8.87% (0.34%) with 10% overconfidence, and further to 12.98% (1.03%) with 40% overconfidence. This indicates that the more overconfident the traders are, the larger the price diverge from the true values of securities, and the higher probability the limit will be triggered.[5]

A. Volatility

Recall that under a price limit rule, the price during each trading day (period) cannot be above the previous *settlement price* plus an up limit, or below the previous settlement price minus a down limit. Then there will be a spillover of unrealized residual shocks due to price limits. As a consequence, the price change following an up (down) limit move will also reflects unrealized residual shock from the previous trading day, then the volatility after an up (down) limit will increase. Our empirical result confirms the views by showing that the imposition of price limits reduces the price volatility around private signal release (at date 1). For example, with 40% overconfidence level, the date 1 volatility, V_1, reduces from 19.172 without price limits to

[5] Recall that, with price limits, the occurrence of a limit price depends on the magnitude of the pseudo true price change, rather than that of the true price change. Whereas, the volatility and the correlation is calculated based on the observed price.

18.375 with 10% price limits, and further to 11.483 with 5% price limits. Whereas, the price volatility around the public signal arrivals, V_2, increases. Specifically, the tighter the limits are, the more unrealized residual shocks due to price limits, and the greater volatility after a limits hit will be. For example, based on 40% overconfidence level, the volatility of date 2 price change increases from 0.460 without price limits to 0.508 with 10% price limits, and further to 1.599 with 5% price limits. Our results also show that, with a given overconfidence level, the volatility at date 3, V_3, and the average volatility, V_T, are lower than those without price limits.

The result also shows, within a given price limits, that the volatility of private signals, V_1, increases with overconfidence level. For example, with 5% price limits, the date 1 volatility rises from rational of 9.278 to 20% overconfidence of 10.376, and further to 40% overconfidence of 11.483. Despite that overreaction causes correcting price moves and under weighting public signals, the price volatility around public signals are also affected by the fact that the price limits move at date 1 creates a need to reflect unrealized price change and investors will form expectation about price at date2 conditional on limit move. It can be found that, within a tighter price limit such as 2.5% or 5%, the volatility around public signals, V_2, also increases with overconfidence level. For example, with 5% price limits, the date 2 volatility rise from rational of 1.180 to 20% overconfidence of 1.301, and further to 40% overconfidence of 1.599. However, as no price limits are imposed or they are put as wide as 10%, the price volatility around public signals decrease with overconfidence level. It is because the effect from greater overconfidence, which under weights the public signal and reduces date 2 variance, will cover the need to correction (Since the loose price limits (10%) does not constrain price movement too much, the unrealized shocks are relatively trivial.). Note that if the price change results from investor's overreacting, it will reverse to fundamental value as public information arrives. Therefore, if the price limit mechanism are useful in reducing excess volatility due to investor's overconfidence, it may reduce the risk to market participants. To examine this, we further calculate and the average price volatility, V_T, following the private signal shock. Indeed, the average price volatility without price limits is larger than those with price limits. Therefore, the price limits are effective in reducing the price volatility. .

In addition, we can find that, regardless of overconfidence level, the volatility decreases when a tighter limit is imposed. This seems to indicate that we should impose a very tighter limit for the purpose of reducing the volatility. However, as

Brennan (1986) points out, while price limits reduce the risk to market participants, there is liquidity cost associated with their use. The tighter the price limits, the more often the trading in the security markets is interrupted, thereby causing greater losses in liquidity to traders. Furthermore, if the price limits are imposed too tighter, they will impede the price discovery process by preventing the price from reaching its equilibrium level effectively. Therefore, it is in the public interest to discuss rationally the realignment of price limits. With the parameter values used in this paper, we find that the price volatility is 8.450 when traders are rational and no limits are imposed. With 2.5% limits, the volatility with limits is always lower than 8.450 regardless of the overconfidence level. Then 2.5% limit is too tight to reflect the true price change. With 40% overconfidence level, the proper limits are 5% because its corresponding volatility 8.866 is lower than that without limits 10.776, but a little higher than the reasonable price volatility 8.450. Along the same lines, as the confidence level reduces to 20%, 10% limits will be proper. As the overconfidence level is as low as 10%, wider limits will be needed. Overall, the higher the overconfidence level is, the tighter the price limit should be.

B. Serial Correlation, Momentum, and Overreaction

In addition, since price limits constraint a price movement and information is not fully reflected, then the following day's price movement would be influenced by the remaining information, the price in the following day will continue to increase. Then price limits will induce serial correlation at private signal arrivals even when the traders are rational. Our simulation results confirm the phenomenon because, for example, with rational traders and 5% limits, ρ_{12} is 0.3972, which is significantly positive .[6] That is, the extreme of the impulse response function shifts from date 1 to date 2. This implies that, with price limits, short-term momentum will exist even when traders are rational.[7]

When traders are overconfident, though the unrealized shocks will push price change forward and, conditional on a limit move, the traders will form expectation

[6] Whereas, with wider limits such as 10%, ρ_{12} with p-value 0.1376 is not significantly positive. Note that as limits are as loose as 10%, the probability of limit moves is only 0.21% when traders are rational. The low probability of limit moves can provide a reason why ρ_{12} is not significant when limits are imposed as 10%.

[7] Recall that when traders are overconfident and there is no price limits rule, the price change between private signals is also significantly positive.

about the price, the noisy public signal will cause the mispricing from overconfidence to be partially corrected. As a result, the correlations between private and public information arrivals will be conditional both on the overconfidence level and on the price limits.

We first consider the price changes at the time of and subsequently to the private signal (ρ_{12}). When 10% limits are imposed and the investor's overconfidence level is as moderate as 20% or less, there exhibits no significant evidence of serial correlation between date 1 and date 2 (e.g., ρ_{12} is 0.0128) with p-value 0.1994 for 10% overconfidence level). The reason is that the price is not far away from its true value and the wide limits do not constraint too much price movement during private signal release. Whereas, as overconfidence level increases to 40%, ρ_{12} becomes 0.0648 with p-value 0.0001. With tighter limits such as 2.5% and 5%, the correction power at noisy public information arrivals will be covered by the unrealized shocks. As a result, ρ_{12} will be positive.

The results for correlations between public signal release, ρ_{23}, are quite similar (but in different direction) to those between private signal release. Specifically, with a limit such as 2.5% or 5%, ρ_{23} is pronounced negative whatever the overconfidence level is. It is because the unrealized shocks cover the correction power from the release of public signal, thereby pulling the prices up at date 2, but the correction power at conclusive public information arrivals at date 3 will draw the price to its fundamental value. Therefore, the price changes at the time of and subsequently to the public signal is significantly negatively correlated (i.e., $\rho_{23} < 0$).[8] When price limits are put as wider as 10%, the correlations between public information arrivals will depends critically on the overconfidence level. Specifically, as investor's confidence level is as high as 40%, the greater overconfidence causes greater need for the mispricing is corrected, so that ρ_{23} is significantly negative (ρ_{23} = -0.0321 for 40% overconfidence). The moderate overconfidence levels of 10% and 20% will not push the price to swing away from fundamentals so much, therefore it can be found that the price-change correlation between dates 2 and 3 is not significantly different from zero (ρ_{23} = -0.0026 (0.7971) with p-value -0.0017 (0.2411) for 10% (20%) overconfidence level). Therefore, price will reverse itself significantly only when investor's overconfidence is

[8]To force the price to converge to its true value, we assume that price limits are abandoned at the final date. When a strict limit is imposed (e.g., 1%) and it is also imposed at terminal date, the correction power at conclusive public information arrivals will be covered by the unrealized shocks. As a result, ρ_{23} will be positive.

high enough so that the correction power will cover the unrealized shocks at date 2, thereby causing negative price change between dates 2 and 3 ($\rho_{23} < 0$).

Overall, $\rho_{12} > 0$ implies that, with price limits, momentum effect will exist even when traders are rational or it is only based on constant overconfidence model. The private signal is fully corrected upon release of date 3 private signal whatever price limits are, so that $\rho(z_{12}, z_3) < 0$ regardless of price limits. Therefore, long-term price reversal still occurs even when price limits are imposed. In addition, by not allowing prices to move beyond a certain range, price limits discourage overconfidence and forces price not to swing away from its fundamental value too much, thereby reducing unconditional volatility on average and prevents day-to-day wild swings in security prices. This provides the rationale for the use of price limits since it reduces unpredictable rapid movements and reduce risk to market participants.

4.2 Outcome Dependent Confidence

If a trader is biased self-attribution, his confidence will grow when public signal confirms his trade, but it decreases by little or remains constant when public signal contradicts his trade. This means that, on average, noisy public information can increase confidence, intensifying overreaction. The contiguous overreaction leads to positive autocorrelation during the initial overreaction phase. Later release of public information will draw the price back toward fundamentals, and the initial overreaction will be gradually be reversed in the long run. The process described above yields a hump-shaped impulse response function for a private signal. It indeed can be seen from our simulation results in Table 2 that, with outcome-dependent confidence, the pairs of returns drawn from the overreaction phase (ρ_{12}) and from the correction ($\rho_{3'3}$ are significantly positively correlated, whereas the pairs of returns that straddles the extreme of the impulse response function is significantly negatively correlated. For example, with no price limits and 40% overconfidence level (see Panel A in Table 2), $\rho_{1,2}$ and $\rho_{3'3}$ are 0.8532 (p = 0.0001) and 0.1532 (p = 0.0001), respectively. Along the same line, $\rho_{23'}$, $\rho(z_1, z_{23})$, $\rho(z_{12}, z_{3'3})$, and $\rho(z_{13'}, z_3)$, in which the pairs of price changes straddle the extreme, are significantly negative. That is, Date 2 is the extreme of the impulse response function, the price-change autocorrelations that fall entirely within either the overreaction phase and correction phase are positive correlated. These results are the same as those of Daniel, Hirshleifer, and Subrahmanyam (1998), which is obtained without consideration for the price limits.

(Table 2 about here)

To investigate the effects of the price limits, we also consider three various levels of price limits, which are 2.5%, 5% and 10%. The results are presented in Panel B to D of Table 2. As before, the noisy information arrivals at date $3'$ can cause the mispricing to be corrected, but the unrealized shock will push price forward. We find that, whatever the limits are, the unrealized shocks will be covered by the correction power from public information arrivals (There are two days to attenuate the overreaction, and the unrealized shocks will be trivial at date $3'$). As a result, $\rho_{23'}$ will be negative. That is, Date 2 is also the extreme of the impulse function, then the single-period price-changes straddling the extreme, $\rho_{23'}$ $\rho(z_{12}, z_{3'3})$, and $\rho(z_{13'}, z_3)$, are negative, whereas the autocorrelation within the overreaction phase, ρ_{12}, and the correction phase, $\rho_{3'3}$, are positive.

More specifically, the price continues moving up and reaches a maximum value in period 2. The average price then declines, and eventually asymptotes to its terminal value. Thus, there is an initial overreaction phase (It starts from date 0 and ends at date 2) where the price moves away from the true value as the investor's attribution bias causes him to place more weight on his private information. Eventually, the public information becomes precise enough that the investor revises his valuation of security downward. This is the correction phase (It starts from date 2 and ends at date3). This patterns of security price-change are consistent with the short-term momentum and long-term price reversal phenomena.

Finally, with price limits, we find that the average price volatility also decreases when investors are biased self-attributed. For example, with 40% overconfidence level, the average volatility decrease from 8.155 without price limits to 8.105 with 5% price limits. Therefore, the imposition of price limits seems to have desire effect to prevent large price movements due to investor's overconfidence.[9] In addition, as we note that while price limits reduce the risk to market participants, there is liquidity cost associated with their use. Under the model with biased self-attribution, from Panel E we find that the reasonable price volatility is 6.338 when traders are rational and no limits are imposed. When traders are overconfident and biased self-attribution, 2.5%

[9]It is worth to note that, though price limits reduce the volatility at private signal release and average volatility, the volatility following the private signal shock increases.

limit is too tight because the volatility with 2.5% limits is always lower than 8.450 regardless of the overconfidence level. With 40% overconfidence level, the 5% limits are more proper (than 2.5% and 10% limits) because its corresponding volatility 8.105 is lower than that without limits 8.155, but a little higher than the reasonable price volatility 6.338. Along the same lines, as the confidence level reduces to 20% and 10%, 10% limits will be proper. With biased self-attribution, we also find that the higher the overconfidence level is, the tighter the price limit should be.

Overall, the results are quite similar to those with constant overconfidence level. Specifically, price limits seems to have desire effect to prevent large price movements due to investor's overconfidence (the average volatility decreases); the combination of overconfidence and price limits adds to positive serial correlation between private signal releases ($\rho_{12} > 0$); the final correcting to the overreaction results in a negative correlation ($\rho(z_1 + z_2, z_{3'} + z_3) < 0$) in the long run. That is, there also exhibits the short-term momentum and long-term price reversal even with the imposition of price limits.

5 Conclusion

The price volatility unrelated to variation in fundamental values can increase the expected returns that investors require to hold security, which means higher cost of capital for firms. Therefore, price limits have been designed to serving as a price stabilization mechanism to reduce the price volatility. Several researchers have tried to examine the impact and effectiveness of price limits, either empirically or theoretically. Their impact on the operation of markets, however, is still under debate.

Daniel, Hirshleifer, and Subrahmanyam (1998) document that overconfident investor overestimate the precision of his private information, which causes the stock price to overreact. When noisy public information arrives and the overconfident investors update their confidence over time, the price moves closer to the fundamental value subsequently. This overreaction-correction pattern is consistent with long-term price reversals and unconditional excess volatility. Since the overreaction hypothesis is widely cited as the foundation for many of the existing regulation such as the price limits (Anderson, 1984; Greenward and Stein, 1988), this paper examines the effectiveness of price limits in reducing price volatility when traders are overconfident. If the overreaction effect induced by behavioral biases such as overconfidence can be attenuated with the imposition of price limits, therefore it appears that price limits can be said to be efficiency-improving. Our simulation results show that the imposition of price limits seems to have desire effect to prevent short-term overreaction and reduce the excess price volatility due to investor's overconfidence. Clearly price limits affect the price process, and the tighter the price limits are, the less the average volatility due to overreaction will be. Thus, this overreaction hypothesis provides the most popular rationale for imposing daily price limits. However, as Brennan (1986) points out, while price limits reduce the risk to market participants, there is liquidity cost associated with their use. Therefore, it is in the public interest to discuss rationally the realignment of price limits. With the parameter values used, 5% limits are proper when traders are with 40% overconfidence level. As the confidence level reduces to 20%, 10% limits will be proper. Overall, we find that the higher the overconfidence level is, the tighter the price limit should be.

We also evaluate the impact of price limits on short-term momentum and long-term price reversal phenomena. We find that not only self-attribution bias but also price limits will add to short-term momentum effect. Since price will correct to its true value, long-term price reversal is also found whatever price limits are. Finally, when traders are overconfident, the imposition of price limits is effective in reducing average price volatility by lengthening the momentum phase.

References

[1] Ackert, Lucy and William Hunter, 1994, Tests of a simple optimizing model of daily price limits on futures contracts, *Review of Financial Economics* 4, 93-108.

[2] Anderson, R. W., 1984, The industrial organization of futures markets: A survey; R. W., Anderson, ed., The Industrial Organization of Futures Markets.

[3] Arak, M. and R. E. Cook, 1997, Do daily price limits act as magnets? The case of treasury bond futures, *Journal of Financial Services Research* 12, 5-20.

[4] Ball, Ray, S. P. Kothari, and Jay Shanken, 1995, Problems in measuring portfolio performance: An application to contrarian investment strategies, *Journal of Financial Economics* 38, 79-107.

[5] Carmel, Jonathan Paul, and Martin Young, 1997, Long horizon mean reversion in the stock market: The postwar years, Working paper, University of Michigan Business School.

[6] Chan, K. C., 1988, On the contrarian investment strategy, *Journal of Business* 61, 147-163

[7] Chopra, Navin, Josef Lakonishok, and Jay R, Ritter, 1992, measuring abnormal performance: Do stocks overreact?, *Journal of Financial Economics* 31, 235-268.

[8] Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681-1713.

[9] Conrad, Jennifer S., and Gautam Kaul, 1993, Long-term market overreaction or biases in computed returns? *Journal of Finance* 48,39-64.

[10] Daniel, Kent D., 1996, The power and size of asset pricing tests, *Journal of Empirical Finance* 8, 493-535 .

[11] Daniel, K., D. Hirshleifer, and A.subrahmanyam,1998, Investor psychology and security market under-and overreactions, *Journal of Finance* 56, 921-965.

[12] Daniel, K., D. Hirshleifer, and A.subrahmanyam,1998, Mispricing, covariance risk, and the cross-section of security returns, *Journal of Finance* 53,1839-85.

[13] DeBondt, Werner F. M., and Richard H. Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793-808.

[14] DeBondt, Werner F. M., and Richard H. Thaler, 1987, Further evidence on investor overreaction and stock market seasonality, *Journal of Finance* 42, 557-581.

[15] Fama, Eugene F., 1989, "Perspectives on October 1987, or What Did We Learn from the Crash?" In: R. Kampuis, R. Kormendi, and J. Watson, eds., Black Monday and the Future of Financial Markets. Homewood, IL: Irwin, 71-82.

[16] Fama, E. F., 1998, Market efficiency, long-term rectums, and behavioral finance, *Journal of Financial Economics* 49,283-306.

[17] Fama, F. and K. R. French, 1988, Permanent and temporary components of stock prices, *Journal of Political Economy* 96, 246-273.

[18] Fama, E., and K. French, 1995, Size and Book-to-market Factors in Earnings and Returns, *Journal of Finance* 50, 131-155.

[19] Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51,55-84.

[20] Fama, Eugene F., and Kenneth R. French, 1998, Value versus growth: The international evidence, *Journal of Finance* 53,1975-1999.

[21] Figlewski, Stephen, 1984, Margins and market integrity: Margin setting for stock index futures and options, *Journal of Futures Markets* 4, 385-416.

[22] Greenwald, Bruce C. and Jeremy C. Stein, 1991, Transaction risk, market crashes, and the role of circuit breakers, *Journal of Business* 64, 443-462.

[23] Harris, Lawrence E., 1997, Circuit breakers and program trading limits: What have we learned?, working paper, University of Southern California.

[24] Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265-295.

[25] Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

[26] Johnson, Norman L. and Kotz, Samuel, 1982, Distributions in Statistics: Continuous Multivariate Distributions, New York: John Wiley and Sons.

[27] Kim, Kenneth A. and Rhee, S. Ghon, 1997, Price limit performance: Evidence from the Tokyo Stock Exchange, *Journal of Finance* 52, 885-901.

[28] Kuhn, Bestsey A., Gregory J. Kuserk, and Peter Locke, 1991, Do circuit breakers moderate volatility? *Review of Futures Markets* 7, 426-434.

[29] Lee, Charles M. C., Mark J. Ready, and Paul J. Seguin, 1994, Volume, volatility, and New York Stock Exchange trading halts, *Journal of Finance* 49, 183-214.

[30] Lehmann, Bruce N., 1989, Commentary : Volatility, price resolution, and the effectiveness of price limits, *Journal of Financial Services Research* 3, 205-209.

[31] Ma, C. K., R. P. Rao, and R. S. Sears, 1989a, Limit moves and price resolution: The case of the treasury bond futures market, *Journal of Futures Markets* 9, 321-335.

[32] Ma, C. K., R. P. Rao, and R. S. Sears, 1989b, Volatility, price Resolution, and the effectiveness of price limits, *Journal of Financial Services Research* 3, 165-199.

[33] Meltzer, A., 1989, "Overview." In: R. Kampuis, Jr., Kormendi, R., and Watson, J., eds.,*Black Monday and the Future of Financial Markets.* Homewood, IL: Irwin.

[34] Miller, M., Scholes, M., Malkiel, B. and Hawke, J., 1987, *Final Report of the Committee of Inquiry Appointed by the Chicago Mercantile Exchange to Examine the Events Surrounding October 1987.* December 1989.

[35] Odean, T., 1998, Are investors reluctant to realize their losses? *Journal of Finance 53*, 1775-1798.

[36] Telser, L. G., 1981, Margins and futures contracts, *Journal of Futures Markets* 2, 225-253.

[37] Zarowin, P., 1990, Size, seasonality, and stock market overreaction, *Journal of Financial and Quantitative Analysis* 25, 113-25.

[38] Kim, M. J., C. R. Nelson, and R. Startz, 1988, Mean reversion in stock prices? A reappraisal of the empirical evidence, *Review of Economic Studies* 58, 551-528.

[39] Poterba, J.M. and L.H. Summers, 1988, Mean-reversion in stock prices evidence and implications, *Journal of Financial Economics* 22, 27-59.

[40] Richards, Anthony J., 1997, Winner-loser reversals in national stock market indices: Can they be explained?, *Journal of Finance* 52, 2129-2144.

[41] Rouwenhorst, K. G., 1998, International Momentum strategies, *Journal of Finance* 53, 267-284.

Figure 1: Average price following a positive date 1 private signal with various limits when traders are overconfident

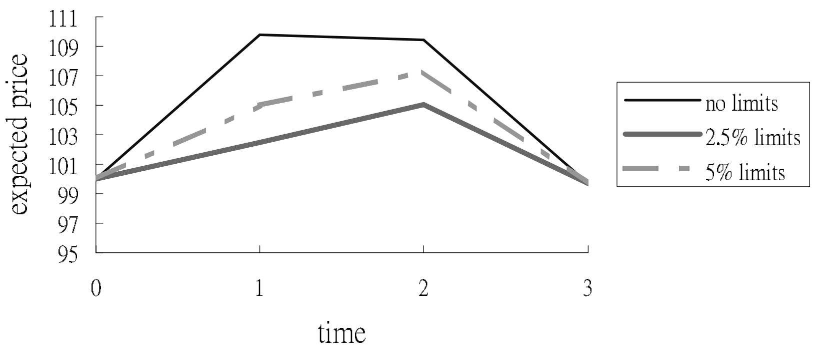

Figure 2: Average price following a positive date 1 private signal with various price limits when traders are overconfident and biased self-attributed

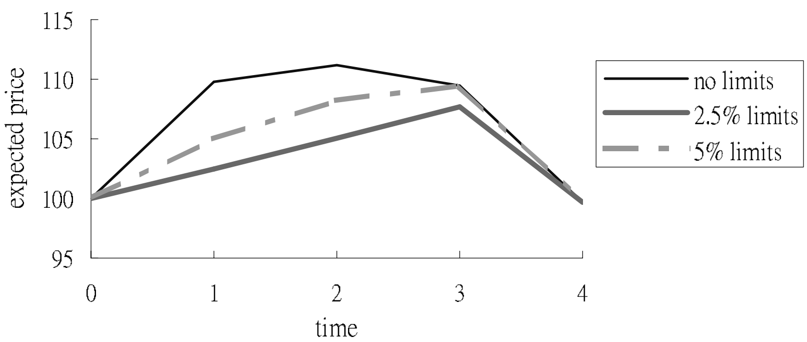

Table 1: Simulation Results with Various Price Limits and without Price Limits Based on a Fixed Confidence Level

We use the parameters P_0=100, σ_θ^2=σ_ϵ^2=25, $\sigma_\eta^2 = 187.5$, and k=5 for the simulation. We perform this simulation 10,000 times, each time redrawing the value θ, the private signal $s_1 = \theta + \epsilon$, and the public information ϕ. Prob is denoted as the probability of price limit triggered at date 1. V_1, V_2, and V_3 are the volatility of the observed price changes at date 1, 2, and 3, which are z_1, z_2, and z_3. V_T is the average volatility of z_1, z_2, and z_3. ρ_{12} is defined as the correlation of z_1 and z_2; ρ_{23} is the correlation of z_2 and z_3; $\rho(z_1, z_{23})$ is the correlation of z_1 and $z_2 + z_3$; $\rho(z_{12}, z_3)$ is the correlation of $z_1 + z_2$ and z_3.

Overconfidendce		volatility				correlation			
level	Prob(%)	V_1	V_2	V_3	V_T	ρ_{12}	ρ_{23}	$\rho(z_1, z_{23})$	$\rho(z_{12}, z_3)$
Panel A: No Limits									
NO	Na	12.534	0.783	12.033	8.450	0.0044	0.0103	-0.0090	-0.0076
						(0.6634)	(0.3037)	(0.3702)	(0.4454)
10%	Na	13.620	0.704	12.333	8.886	-0.0136	0.0068	-0.0641	-0.0599
						(0.1737)	(0.4973)	(0.0001)	(0.0001)
20%	Na	15.407	0.636	11.758	9.267	-0.0159	0.0138	-0.0400	-0.0335
						(0.1116)	(0.1693)	(0.0001)	(0.0008)
40%	Na	19.172	0.460	12.695	10.776	-0.0489	0.0725	-0.2350	-0.2208
						(0.0001)	(0.0001)	(0.0001)	(0.0001)
Panel B: Limits=2.5%									
NO	24.09	4.208	2.353	13.519	6.633	0.7525	-0.0026	0.3150	0.0151
						(0.0001)	(0.7947)	(0.0001)	(0.1301)
10%	24.54	4.116	2.553	13.738	6.802	0.7837	-0.0418	0.2984	-0.0300
						(0.0001)	(0.0001)	(0.0001)	(0.0027)
20%	26.10	4.280	2.668	14.067	7.032	0.7888	-0.0388	0.2990	-0.0315
						(0.0001)	(0.0001)	(0.0001)	(0.0017)
40%	28.99	4.415	3.351	14.659	7.475	0.8579	-0.1262	0.2615	-0.1358
						(0.0001)	(0.0001)	(0.0001)	(0.0001)
Panel C: Limits=5%									
NO	7.74	9.278	1.180	12.563	7.674	0.3972	-0.0340	0.1095	-0.0193
						(0.0001)	(0.0007)	(0.0001)	(0.0538)
10%	8.87	9.672	1.196	12.954	7.940	0.4369	-0.0581	0.0758	-0.0660
						(0.0001)	(0.0001)	(0.0001)	(0.0001)
20%	10.10	10.376	1.301	12.471	8.050	0.4430	-0.0517	0.0853	-0.0586
						(0.0001)	(0.0001)	(0.0001)	(0.0001)
40%	12.98	11.483	1.599	13.515	8.866	0.6206	-0.1674	-0.0083	-0.2262
						(0.0001)	(0.0001)	(0.0001)	(0.0001)
Panel D: Limits=10%									
NO	0.21	12.433	0.784	12.042	8.420	0.0209	-0.0090	-0.0051	-0.0082
						(0.1367)	(0.3684)	(0.6095)	(0.4135)
10%	0.34	13.410	0.716	12.350	8.825	0.0128	-0.0026	-0.0586	-0.0612
						(0.1994)	(0.7971)	(0.0001)	(0.0001)
20%	0.55	15.103	0.649	11.790	9.181	0.0065	-0.0117	-0.0348	-0.0338
						(0.5163)	(0.2411)	(0.0005)	(0.0007)
40%	1.03	18.375	0.508	12.741	10.541	0.0648	-0.0321	-0.2115	-0.2192
						(0.0001)	(0.0013)	(0.0001)	(0.0001)

Table 2: Simulation Results with Various Price Limits and without Price Limits When Traders are Overconfident and Biased Self-Attribution

We use the parameters P_0=100, σ_θ^2=σ_ϵ^2=25, $\sigma_\eta^2 = 187.5$, and k=5 for the simulation. We perform this simulation 10,000 times, each time redrawing the value θ, the private signal $s_1 = \theta + \epsilon$, and the public information ϕ. Prob is denoted as the probability of price limit triggered at date 1. V_1, V_2, and V_3 are the volatility of the observed price changes at date 1, 2, and 3, which are z_1, z_2, and z_3. V_T is the average volatility of z_1, z_2, $z_{3'}$, and z_3. ρ_{12} is defined as the correlation of z_1 and z_2; $\rho_{23'}$ is the correlation of z_2 and $z_{3'}$; $\rho_{3'3}$ is the correlation of $z_{3'}$ and z_3; $\rho(z_1, z_{23})$ is the correlation of z_1 and $z_2 + z_{3'} + z_3$; $\rho_{12,3'3}$ is the correlation of $z_1 + z_2$ and $z_{3'} + z_3$; and $\rho(z_{13'}, z_3)$ is the correlation of $z_1 + z_2 + z_{3'}$ and z_3.

Overconfidendce		volatility					correlation					
level	Prob(%)	V_1	V_2	$V_{3'}$	V_3	V_T	ρ_{12}	$\rho_{23'}$	$\rho_{3'3}$	$\rho(z_1, z_{23})$	$\rho(z_{12}, z_{3'3})$	$\rho(z_{13'}, z_3)$
Panel A: No limits												
10%	Na	13.620	0.065	0.776	12.333	6.699	0.8582	-0.3006	0.0205	-0.0641	-0.1263	-000599
							(0.0001)	(0.0001)	(0.0400)	(0.0001)	(0.0001)	(0.0001)
20%	Na	15.407	0.081	0.727	11.758	6.993	0.8562	-0.2930	0.0237	-0.0400	-0.1009	-0.0335
							(0.0001)	(0.0001)	(0.0178)	(0.0001)	(0.0001)	(0.0008)
40%	Na	19.172	0.136	0.619	12.695	8.155	0.8532	-0.4925	0.1532	-0.2350	-0.3125	-0.2208
							(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Panel B: Limits=2.5%												
10%	24.54	4.116	3.061	1.730	12.341	5.562	0.9057	-0.1969	0.0618	0.3115	-0.1036	-0.0117
							(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
20%	26.10	4.280	2.845	1.679	13.745	5.587	0.8519	-0.3582	0.0619	-0.1164	-0.1842	-0.1047
							(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
40%	28.99	4.415	2.696	1.758	15.134	6.001	0.9262	-0.0266	0.0408	0.2780	-0.1628	-0.1385
							(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Panel C: Limits=5%												
10%	8.87	9.672	1.177	1.305	12.455	6.152	0.8353	-0.3679	0.0175	0.0758	-0.1784	-0.0571
							(0.0001)	(0.0001)	(0.0806)	(0.0001)	(0.0001)	(0.0001)
0%	10.10	10.376	1.589	1.376	11.884	6.306	0.8235	-0.4587	0.0158	0.0853	-0.1798	-0.0313
							(0.0001)	(0.0001)	(0.1140)	(0.0001)	(0.0001)	(0.0017)
40%	12.98	15.122	2.738	1.737	12.821	8.105	0.8578	-0.5363	0.1004	0.0883	-0.3766	-0.2063
							(0.0001)	(0.0001)	(0.0008)	(0.0001)	(0.0001)	(0.0001)
Panel D: Limits=10%												
10%	0.34	13.410	0.222	0.913	12.333	6.720	0.9756	-0.4707	0.0337	-0.0586	-0.1857	-0.0599
							(0.0001)	(0.0001)	(0.0008)	(0.0001)	(0.0001)	(0.0001)
20%	0.55	15.103	0.293	0.914	11.758	7.017	0.9719	-0.4589	0.0298	-0.0348	-0.1594	-0.0335
							(0.0001)	(0.0001)	(0.0028)	(0.0005)	(0.0001)	(0.0001)
40%	1.03	18.375	0.568	0.951	12.695	8.147	0.9456	-0.6488	0.1950	-0.2115	-0.3817	-0.2208
							(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Panel E: No Limits, k=0												
No	Na	12.534	0	0.783	12.033	6.338	Na	Na	0.0703	-0.2474	-0.2474	-0.2330
							Na	Na	(0.0001)	(0.0001)	(0.0001)	(0.0001)