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Short Sale Constraints and Price Informativeness*

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Abstract

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JEL classification: G12, G14

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Abstract

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1. Introduction

Short sale constraints hinder negative information from being fully incorporated into stock price and thus make price less informative. A direct test of this hypothesis entails two conditions. First, there are measures for the level of short sale constraints. Second, there are measures for price informativeness which can capture the *asymmetric* impact of short sale constraints on the incorporation of negative and positive information. Given the two conditions, the hypothesis can be tested by examining the informativeness measures for stocks subject to different levels of short sale constraints.

To date, direct tests on the relation between short sale constraints and price informativeness have been sparse. The major obstacle to empirical work is the lack of a clear measure for short sale constraints. Previous studies have used short interest, institutional ownership, option listing and rebate rate as measures of short sale constraints[1]. However, they are either indirect measures or confined to an early sample. In this paper, we overcome this obstacle by focusing on a special regulatory setting in the Hong Kong market where there is a list of securities eligible for short selling revised from time to time. Stocks not on the list are subject to the extreme form of short sale constraints - prohibition of short sales. When the list is revised, stocks added into the list become shortable, and stocks deleted from the list become non-shortable. Thus, a history of the revisions to the list of securities eligible for short selling identifies a series of addition and deletion events, around which we can examine the changes in price informativeness for the underlying stocks.

We rely on two measures of price informativeness with respect to negative information, sell-minus-buy PIN and downside-minus-upside idiosyncratic volatility (methodology detailed in section 4). The first measure, sell-minus-buy PIN (PIN_{s-b}), comes from the work of Easley, Kiefer, and O'Hara (1996, 1997a, 1997b). It uses the information from the trading process. The second measure, downside-minus-upside idiosyncratic volatility (Ψ_{d-u}), which has been used by Bris, Goetzmann, and Zhu (2007) in a recent study on short sales, is a modified version of the price non-synchronicity measure first proposed by Roll (1988) and recently developed by Morck, Yeung,

[1] See, for instance, Figlewski (1981), Figlewski and Web (1993), Danielsen and Sorescu (2001), Asqiuth, Pathak and Ritter (2005) and Jones and Lamont (2002).

and Yu (2000).

Our two measures are aimed to isolate the effect of short sale constraints on price informativeness. By construction, they are proxies for the amount of negative private information relative to positive private information in price. Thus a change in the overall informational environment that symmetrically affects the incorporation of both negative and positive information has no effect on the two measures. By contrast, short sale constraints, by impeding only negative information incorporation, will cause changes in the two measures. In this study, increases in $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$ are predicted for stocks added into the list (short sale restrictions repealed), and decreases are predicted for stocks deleted from the list (short sale restrictions imposed).

The results on an event study analysis are consistent with our predictions. We find that when stocks are added into the list of securities eligible for short selling, their price informativeness as measured by $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$ significantly increases, and the increase is mainly driven by the increase in the amount of negative private information incorporated into the price. We also find that the probability of private information arrival, the probability that the private information is bad news and the arrival rate of informed orders all increase significantly. It is consistent with the previous results that short sales are most likely informed (e.g., Brent, Morse and Stice (1990), Dechow, Hutton Meulbroek and Sloan (2001) and Boehmer, Jones and Zhang (2008)). Repealing short sale restrictions attracts more informed trading, and thus increases the information contents in price. By contrast, deletions from the list result in changes in the opposite direction.

The observed negative relation between short sale constraints and price informativeness is robust after controlling for the firm characteristics that are likely to affect private information incorporation. We show this by using panel regressions with the firm characteristics as control variables and a dummy variable indicating eligibility for short selling. It is worth noting that if the control variables affect price informativeness in a symmetric way, i.e., affect positive information incorporation and negative information incorporation to the same extent, they should not be correlated with $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$. Any significant changes in the two measures around events can only be attributed to the changes in short sale constraints. However, if their impacts are asymmetric, our regression analysis should be able to accommodate these possible asymmetries.

We also assess whether short sale constraints reduce the ability of stock prices to forecast future real variables. Our two measures, PIN_{s-b} and Ψ_{d-u}, only use the information on the trading process and market prices. However, more informative prices should ultimately be reflected in their better ability to forecast future real variables, the most important one of which is future earnings. This is the idea of future earnings response coefficient (FERC), formulated by Collins, Kothari, Shanken, and Sloan (CKSS, 1994). FERC is defined as the estimated coefficient on future earnings in a regression of current return on current and future earnings, controlling for future returns. A higher FERC indicates a closer relation between current return and future earnings, and thus a more informative price with respect to information about future earnings. We argue that short sale constraints, by preventing some of the value-relevant information about future earnings being capitalized into current price, are negatively correlated with FERC. We evaluate this hypothesis in both an event study and regression analysis, and find supporting evidence. These tests supplement the tests on PIN_{s-b} and Ψ_{d-u} to consider the role of fundamental variables in determining the information contents in stock price. Durnev, Morck, Yeung and Zarowin (2003) have shown a positive relation between idiosyncratic volatility and FERC. Since we use both of them in this study, our results also lend supports to their work.

We also modify the PIN model to get separate estimates of the arrival rates of informed sell orders and buy orders. In the original construction, the arrival rates of informed sell orders and buy orders are assumed to be equal. This adjustment enables us to directly examine the change in the arrival rate of informed sell orders around events. If short sales convey information, we expect to see an increase in the arrival rate of informed selling when short sales are allowed, *ceteris paribus*. In this paper, we find consistent evidence that the estimated arrival rate of informed sell orders increases when stocks are added into the list, and decreases when stocks are deleted from the list. Short sale constraints do keep some of the informed traders with negative information out of the market. In addition, we repeat the event study and regression analysis using the PIN_{s-b} computed using the parameters in the adjusted model, and the results are similar.

Our results are robust to a number of tests. First, we change the length of the event window used in the study. We report the results using a one-year event window, and the results are similar when we use a two-year or three-year window. Second, we consider the effect of periods of abnormal trading activity on our results. It is well known that the Hong Kong government intervened heavily in the stock market during the 1997 Asian Financial Crisis. Our results are robust to the exclusion of that period. We also exclude the observations in the period of the outbreak of SARS, and our results remain intact. Last, our results are robust to the use of returns of different frequencies in the estimation of Ψ_{d-u}. We report the results using bi-weekly return data.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the two measures of price informativeness. Section 4 reviews the historical revisions to the list of securities eligible for short selling and describes the data source. Section 5 reports the empirical results. The last Section concludes.

2. Literature

Theoretical models of Miller (1977) and Diamond and Verrecchia (1987) all suggest that short sale constraints hinder negative information from being fully reflected in stock prices. Miller (1977) argues that when both heterogeneous opinions and short sale constraints are present, stocks tend to be overpriced as short sale constraints impede those investors who possess negative information but not in the long positions from selling. Diamond and Verrecchia (1987), however, do not suggest an overvaluation story. They argue that, if investors know there is negative information not incorporated into price because of short sale constraints, in a rational expectation framework, they will adjust their valuations based on their assessment of the suppressed negative information. As a result, stock prices are on average not too high or too low. Though Diamond and Verrechia's theory eliminates the possibility of systematic mispricing, short sale constraints still reduce price informativeness by decreasing the accuracy of information incorporation.

Prior empirical studies on the relation between short sale constraints and price informativeness are actually tests of the two models. The tests of the Miller theory generally focus on the negative abnormal returns generated when initially overvalued stocks revert to their fundamentals. They differ in the measures for short sale constraints. Figlewski (1981) measures short sale constraints by short interest and find that stocks with higher short interest yield lower subsequent returns. Danielsen and Sorescu (2001) argue that the negative abnormal returns around option introduction are due to the mitigation of short sale constraints when put options are introduced. Jones and Lamont (2002) measure short sale constraints by rebate rate, and also find supporting evidence for Miller. Chang, Cheng and Yu (2007) explore the special regulatory setting in the Hong Kong market, and report negative abnormal returns when stocks are added into the list of securities eligible for short selling. Diamond and Verrecchia (1987) was first tested by Senchark and Starks (1993) who report negative abnormal returns around announcements of unexpected high level of short interest. Their results are consistent with the idea that though investors cannot observe the pent-up negative information, they try to incorporate it into price by taking signals contained in short interest. Aitken, Frino, McCorry and Swan (1998) show that, in the Australian market where short sales are fully transparent moments after execution, they are instantaneously treated as bad news.

Our paper uses a different approach to investigate the relation between short sale constraints and price informativeness. Prior studies examine the relation by looking at the abnormal returns generated when pricing errors are corrected. In this study we directly construct two measures of price informativeness with respect to negative information and examine the changes in the two measures as short sale restrictions are removed. Such an approach can avoid the "joint hypothesis" problem in measuring abnormal returns, as in the tests of the Miller's model or the Diamond and Verrecchia's model.

A closely related study to ours is that of Bris, Goetzmann, and Zhu (2007) who explore the relation between short sale constraints and price informativeness in a cross-country setting. They use two measures for price informativeness, downside-minus-upside R-square and the cross-autocorrelation between individual stock return and one week lagged market return. They find that in countries where short sales are practiced, on average, prices are more informed than in countries where short sales are restricted. Short sales help facilitate more efficient price discovery at the country level. Our study is different from theirs and makes its own contributions in several respects. First, we examine the relation between short sale constraints and price informativeness in a within-country setting. It allows us to use more controls to isolate the interested relation. As noted by Bris, Goetzmann, and Zhu (2007), on the country level, short sale constraints and price informativeness are both correlated with the development of financial markets, which could cause a spurious relation between short sale constraints and price informativeness. Second, to the best of our knowledge, we are the first to use the PIN model to study short sales. PIN, the probability of informed trading, is a direct measure of price informativeness. Besides, the model also identifies a few important parameters, such as the probability of information arrival, the probability that information is bad news and the arrival rates of informed sell orders and buy orders. These parameters all shed lights on the trading process through which information is incorporated into price. Third, we consider the role of fundamental variables in the determination of price informativeness. Prior studies on short sale constraints are generally based on return data. In our study, in addition to the use of order-level data and market price data, we examine price informativeness in terms of the ability of current price to forecast future earnings. By doing so, we have a complete picture of the interested relation.

3. Measures for Price Informativeness

3.1 Sell-minus-buy PIN

Our first measure of price informativeness with respect to negative information, PINs-b, is based on a series of papers by Easley, Kiefer, and O'Hara (1996, 1997a, 1997b), who develop a model to estimate the probability of informed trading (PIN). Under the assumption that informed trading results in abnormal and unbalanced order flows, PIN is estimated from a structural market microstructure model by detecting the probability of a trade that comes from an informed investor..

In their model, trades are executed by two groups of investors: informed and uninformed investors. According to independent Poisson processes, uninformed investors submit their buy (sell) orders under a daily rate ε_b (ε_s) for the purpose of liquidity needs or noise trading, while informed investors utilize their private information advantage to perform informed trading. At the beginning of each trading day, a private information event occurs with the daily probability α, where the probability that bad news happens is δ and the probability that good news happens is 1-δ. If good (bad) news occurs, informed investors execute buy (sell) orders at a daily rate μ. Given some history of trades, the estimation of the model's parameters can be used to construct the probability that an order is from an informed trader as follows

$$PIN = \frac{a\mu}{a\mu + \varepsilon_s + \varepsilon_b}$$

, where $(a\mu + \varepsilon_s + \varepsilon_b)$ is the daily arrival rate of all orders and $\alpha\mu$ is the arrival rate of information based orders. Hence, PIN measures the fraction of orders that arise from informed traders relative to the overall order flow. PIN increases with either the frequency of private information events α or the average daily trading intensity of informed investors μ, while decreases with the average daily trading intensity of uninformed traders.

To understand the effect of short sale constraints, it is important to differentiate how bad and good news is responded by informed traders. We modify PIN into PIN_{Sell} and PIN_{Buy}. PIN_{Sell} (PIN_{Buy}) is the probability that a trade is informed based sell (buy), defined as δ*PIN ((1-δ)*PIN). Sell-minus-buy PIN is calculated as the difference between sell and buy PIN,

$$PIN_{s-b} = PIN_{\text{Sell}} - PIN_{\text{Buy}}.$$

If short sales are not allowed, bad news can not be effectively incorporated into stock price through informed trading, a lower PIN_{sell} is expected. However, since short sale constraints do not affect the incorporation of positive private information, PIN_{buy} is not expected to change. Thus the difference between them, PIN_{s-b}, highlights the effect of short sale constraints on price informativeness with respect to negative information. A change in PIN_{s-b} is most likely a result of a change in short sale constraints. In our study, we focus on the change in PIN_{s-b} around addition and deletion events, and also examine the changes in PIN_{sell} and PIN_{buy} to know the source of the change.

The set of parameters, $\theta = \{\alpha, \delta, \mu, \varepsilon_s, \varepsilon_b\}$, is estimated by maximizing the following likelihood function,

$$L(\theta, B, S) = \prod_{t=1}^{T} L(\theta, b_t, s_t),$$

where T denotes the number of trading days used in estimation, $b_t(s_t)$ denotes the number of buy (sell) orders on day t. For a typical day t, the likelihood function is

$$L(\theta \mid b_t, s_t) = (1-\alpha)e^{-\varepsilon_s}\frac{\varepsilon_s^{s_t}}{s_t}e^{-\varepsilon_b}\frac{\varepsilon_b^{b_t}}{b_t} + \alpha\delta e^{-(\varepsilon_s+\mu)}\frac{(\varepsilon_s+\mu)^{s_t}}{s_t}e^{-\varepsilon_b}\frac{\varepsilon_b^{b_t}}{b_t}$$
$$+\alpha(1-\delta)e^{-\varepsilon_s}\frac{\varepsilon_s^{s_t}}{s_t}e^{-(\varepsilon_b+\mu)}\frac{(\varepsilon_b+\mu)^{b_t}}{b_t}.$$

When estimating PIN, we require trades and quotes submitted during the regular trading hours of Hong Kong Stock Exchange. For quotes, we eliminate those with bid-ask spreads that are greater than half their mid-point quote prices. We employ the Lee and Ready (1991) algorithm to identify buy- or sell-initiated trades. Trades above the midpoint of the spread are classified as buys and those below the midpoint are classified as sells. Midpoints trades are classified using a tick test. Trades executed at higher prices than the previous trades are called buys and those at lower prices are called sells.

We estimate quarterly $PIN_{s\text{-}b}$ for all the stocks in the Hong Kong exchange. For an addition event in quarter *t*, the pre-addition $PIN_{s\text{-}b}$ is defined as the average of the four quarterly estimates of $PIN_{s\text{-}b}$ from quarter *t-4* to *t-1*, and the post-addition $PIN_{s\text{-}b}$ is defined as the average of the four quarterly estimates of $PIN_{s\text{-}b}$ from quarter *t+1* to *t+4*. Pre-deletion and post-deletion $PIN_{s\text{-}b}$ is defined similarly. In the regression analysis, we use the firm quarter $PIN_{s\text{-}b}$ for all the firms and match each $PIN_{s\text{-}b}$ to a short sale dummy and the control variables.

3.2 Downside-minus-upside Idiosyncratic Volatility

Our second measure, downside-minus-upside idiosyncratic volatility ($\Psi_{d\text{-}u}$), is constructed using the R-squares in regressions of individual stock return on market return. Roll (1988) suggests that a low R-square (Hence high idiosyncratic volatility, high firm-specific return variation or high price non-synchronicity) is indicative of either greater amount of private information in price or pricing noise, because systematic risk and public information seem to explain only a small portion of the return variation. Morck, Yeung and Yu (2000) support the information role of R-square in a cross country study. They find that in countries with weak investor property rights protection, stock returns have more synchronous movements as indicated by high R-squares. They argue that weak property rights protection impedes firm-specific information incorporation by making informed arbitrage unattractive. As a result, less firm-specific information is built into prices and we observe high R-squares. Durnev, Morck, and Yeung (2004) further show that both firms and industries with higher firm-specific return variation allocate capital more efficiently. Their results are consistent with the idea that the private information in price, possibly indicated by R-squares, enhances investment efficiency.

Recent literature has used R-square as a measure for price informativeness in addressing a wide range of empirical issues (e.g., Chen, Goldstein and Jiang (2007), Ferreira and Laux (2007), and Fernandes and Ferreira (2008)). The key to our study is to extend the use of R-square to capture the asymmetric impact of short sale constraints on the incorporation of negative and positive information. Bris, Goetzmann, and Zhu (2007) propose downside-minus-upside R-square as such an extension. We follow their approach to define downside-minus-upside idiosyncratic volatility, $\Psi_{d\text{-}u}$, to measure price informativeness with respect to negative information.

The measure is defined as follows. First, for each stock, we run two regressions,

$$R_t = \alpha^- + \beta^- R^-_{m,t} + \varepsilon^-_t$$
$$R_t = \alpha^+ + \beta^+ R^+_{m,t} + \varepsilon^+_t$$

where R_t is the individual stock return, $R^-_{m,t}$ is the market return when it is negative, and $R^+_{m,t}$ is the market return when it is either positive or zero. We compute the R-squares for the two regressions, denoted by R^2_d and R^2_u, respectively, and then do the following logarithm transformations,

$$\Psi_{down} = \log\left(\frac{1-R^2_d}{R^2_d}\right), \qquad \Psi_{up} = \log\left(\frac{1-R^2_u}{R^2_u}\right)$$

Downside-minus-upside idiosyncratic volatility, $\Psi_{d\text{-}u}$ is defined as the difference between Ψ_d and Ψ_u,

$$\Psi_{d\text{-}u} = \Psi_{down} - \Psi_{up}$$

Bris, Goetzmann, and Zhu (2007) suggest that this is a correct measure to study the impact of short sales on price informativeness. When short sales are restricted, only the price adjustment to bad news is constrained, and one would expect idiosyncratic volatility to be smaller when market return is negative, i.e., Ψ_{down} should be smaller. However, Ψ_{down} is also a function of a stock's informational characteristics. To highlight the role of short sale constraints, one must control for the change in equilibrium level of private information in price. If the other factors other than short sale constraints have a symmetric effect on the equilibrium level of negative and positive information, a change in Ψ_{d-u} can only be ascribed to a change in short sale constraints. In our research setting, we expect Ψ_{d-u} to increase when stocks are added into the list and decrease when stocks are removed from the list.

In this paper, we compute Ψ_{d-u} using the bi-weekly return data in the four calendar quarters before and after addition events. For example, if an addition event is in quarter *t*, then the pre-addition Ψ_{d-u} is computed using the data from quarter *t-4* to *t-1*, and the post-addition Ψ_{d-u} is computed using the data from quarter *t+1* to quarter *t+4*. Pre-deletion and post-deletion Ψd-u is defined similarly. In the regression analysis, we compute calendar year Ψ_{d-u} for all the stocks in the Hong Kong market, and then match the firm year Ψ_{d-u} to a short sale dummy and the control variables. The results are not sensitive to the use of weekly return data in computing Ψ_{d-u}.

4. Data and Descriptive Statistics

4.1 List of Securities Eligible for Short Selling

Seventeen stocks were first added into the list of securities eligible for short selling when the Stock Exchange of Hong Kong launched a pilot scheme for regulated short selling in January 1994. In our sample period from Jan. 1994 to Nov. 2002, the list was revised 18 times[2], and as of Oct. 29, 2002, there were 150 equity stocks on the list, out of 790 equity stocks listed on the main board and the growth enterprise market.[3]

Before 2001, the list was revised according to the discretion of the regulators reflecting the changing market conditions. From February 12, 2001, the list was revised on a quarterly basis

[2] There were another two revisions in which exchange traded funds and T-stocks were added into the list. These securities are not appropriate for our study and excluded from the sample.

[3] The growth enterprise market was launched in 1999 to help smaller firms which do not fulfill the profitability or track record requirements of the main board to raise capital.

according to a set of criteria based on market capitalization, turnover and Index membership. Table I summarizes the historical revisions to the list from Jan. 3, 1994 to Oct. 29, 2002. Column 1 reports the revision dates. Column 2 and 3 report the number of stocks added into or deleted from the list on each revision date, respectively. As shown by the table, during this period, the list was revised 18 times and there were altogether 495 stocks added into the list, and 345 stocks deleted from the list. The three largest additions took place on Mar. 25, 1996, May 1, 1997 and Jan. 12, 1998, and there were 97, 129, 69 stocks added into the list on these three dates. On Nov. 9, 1998, because of the outbreak of the Asian Financial Crisis, 148 stocks are removed from the list in the consideration to stabilize the market. After 2001, the list was revised on a quarterly basis and there were no large-scale additions or deletions.

Our initial sample for addition events consists of the 495 stocks that were added into the list during the sample period. However, a stock may be added into the list, and then deleted from the list on a later date. In our study, we use one year event-window to examine the changes in the price informativeness measures around events. So we refine the sample to ensure that short sales are not allowed throughout the pre-addition window, and are allowed throughout the post-addition window. An addition event is then defined as a one in which 1) a stock was added into the list, 2) the stock had not been in the list for at least 4 calendar quarters before it was added, and 3) the stock remained in the list for at least 4 calendar quarters after it was added. For example, if a stock was added into the list on Mar. 16, 1998 and then deleted from the list on Nov. 9, 1998, it will not be counted as an addition event, because after addition, it only remained shortable for approximately 8 months. Since we estimate the two measures for price informativeness in a one year window before and after addition events, 8 months are not enough for our estimation. Column 5 gives the number of the addition events on each revision date. The total number of addition events is 360, out of the initial 495 additions.

We define a deletion event as the opposite of an addition event. A deletion event is defined as a one in which 1) a stock was deleted from the list, 2) the stock had been in the list for at least 4 calendar quarters before it was deleted, and 3) the stock was not in the list for at least 4 calendar quarters after it was deleted. In contrast with an addition event, for a deletion event, short sales are allowed throughout the pre-deletion window, and are not allowed throughout the post-deletion window. Column 6 shows that there are 207 deletion events, out of the 345 initial deletions.

4.2 Descriptive Statistics

The early data on the historical revisions to the list of securities eligible for short selling are provided by the Hong Kong Stock Exchange. We hand-collect the data on later revisions by referring to the news archives on the Exchange's website. The bid and ask files and trading files used to estimate the PIN model are also from the Exchange. Return data and financial accounts data used in the computations of the R-squares, FERC and the regressions are from PACAP via WRDS.

5. Empirical Results

This section reports the empirical results on four groups of tests. First, we examine the changes in sell-minus-buy PIN and downside-minus-upside idiosyncratic volatility around addition and deletion events. We show that both $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$ increase as stocks are added into the list of securities eligible for short selling and decrease when they are removed from the list. Second, we investigate whether the informational characteristics of a stock can explain the changes in $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$ around events. This is done in a panel regression framework. Third, we look at the changes in future earnings response coefficient (FERC) as short sale restrictions are lifted. We also control for the variables possibly affecting FERC. Last, we adjust the PIN model and estimate separate arrival rates for informed sell orders and informed buy orders. The results are consistent with our predictions.

5.1 $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$ around Addition and Deletion Events

A. Addition Events

Table II summarizes the changes in $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$ around addition events. Since we use one-year event window, the pre-addition period is the 4 calendar quarters before addition, and the post-addition period is the 4 calendar quarters after addition. The methodology in defining addition events (see Section 3) ensures that throughout the pre-addition period, short sales are prohibited for the underlying stocks, and are allowed throughout the post-addition period. There are 360 addition events used in our study from Jan. 03, 1996 to Oct. 19, 2002. Our basic prediction is that price informativeness as measured by $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$ increase around addition events.

Panel A reports mean and median of parameter estimates of the PIN model in the pre-addition and post-addition periods, and the changes in the estimates around events. The pre-addition estimate is taken as the average of the four quarterly estimates before the event quarter, and the post-addition estimate is taken as the average of the four quarterly estimates after the event quarter. Columns 3 and 4 report the mean and median across events. Columns 5 and 6 report the changes and the last column reports the t-statistics of a paired t-test and Wilcoxon signed rank test.

As shown in Panel A, $PIN_{s\text{-}b}$ increases significantly around addition events. The mean of $PIN_{s\text{-}b}$ increases from -0.074 to -0.005 and the median increases from -0.008 to -0.005. Both changes are significant, as shown in the last column. The two components of $PIN_{s\text{-}b}$, PIN_{sell} and PIN_{buy}, change in different directions. The mean of PIN_{sell} shows a positive change of 0.015, while the mean of PIN_{buy} shows a smaller negative change of -0.008. Hence the change in $PIN_{s\text{-}b}$ is mainly driven by the increased probability of informed selling as indicated by PIN_{sell}, which supports our prediction that short sale constraints reduce price informativeness by limiting informed selling.

As for the individual parameters, the results are also revealing. Because $PIN_{s\text{-}b}$ is constructed using these parameter estimates, they deserve a closer look. We have the following predictions about the individual parameters based on the process through which information is transmitted from trading to price. First, when short sales are allowed, the investors who are not in the long position will gain the ability to sell when they receive a bad private signal. This will increase the percentage of the days with abnormal selling volume. In the PIN model, the percentage of days with abnormal trading volume (either buying or selling) identifies parameter α, the probability of information arrival, and when the number of days with abnormal selling volume increases, we get a higher α. Second, when the number of days with abnormal selling volume increases, the ratio of the number of days of abnormal selling volume to the number of days with abnormal buying volume also increases because the latter should not be affected by short sale constraints. As this ratio identifies the parameter δ, the probability that information is bad news, we expect a higher δ. Third, when short sales become feasible, investors in the long position (They are most likely to be the informed) are not constrained by their existing inventory. If one day they receive a very bad private signal, they will borrow to short sell, which increases the abnormal trading volume on that day. As abnormal trading volume is associated with the parameter μ, the arrival rate of informed selling, we expect it to increase when short sale constraints are removed. Last, though we do not make predictions about ε_b and ε_s, they are most likely to increase. It is possibly because the introduction of the options and warrants following addition events brings trading for hedging purposes. This trading is not information based, and it involves both buys and sells. The increased uninformed trading will identify a higher ε_b and ε_s in the PIN model.

The results on the individual parameters are consistent with our predictions. α increases about 11%, δ increases about 15% and μ increases about 13% around addition events. The changes are all significant. The results suggest that allowing short sales releases new private negative information to the market which increases informed selling.

Panel B presents the results on $\Psi_{d\text{-}u}$, Ψ_{down} and Ψ_{up}. For each addition event, we estimate the pre-addition Ψ_{down} and Ψ_{up} in the four quarters before the event quarter, and post-addition Ψ_{up} and Ψ_{down} in the four quarters after the event quarter. $\Psi_{d\text{-}u}$ is computed as Ψ_{down} minus Ψ_{up}. The results show a large improvement in price informativeness with respect to negative information as measured by $\Psi_{d\text{-}u}$ when stocks are added into the list and become shortable. The mean of $\Psi_{d\text{-}u}$ changes from -0.348 in the pre-addition period to 0.502 in the post addition period. The median of $\Psi_{d\text{-}u}$ has a similar pattern. The t-statistics of the paired t-test and the Wilcoxon test are all significant. Further results show that the increase in $\Psi_{d\text{-}u}$ is due to the increase in Ψ_{down}. The table reports a positive change of 0.905 for Ψ_{down}, or 50.3% in percentage terms. Ψ_{up} only shows an insignificant positive change of 2.5% in percentage terms. Our results on downside-minus-upside idiosyncratic volatility support Bris, Goetzmann, and Zhu (2007) on the individual stock level.

B. Deletion Events

Table III presents the results on deletion events. Similarly, the pre-deletion period is the 4 calendar quarters before deletion event, and the post-deletion period is the 4 calendar quarters after deletion event. We expect the changes in $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$ to be in the opposite direction to that of addition events. If a stock is deleted from the list and become non-shortable, its price informativeness should be reduced.

The results on the deletion events mainly conform to our prediction. As shown in Panel A, the mean and median of $PIN_{s\text{-}b}$ show significant decreases around deletion events. The average $PIN_{s\text{-}b}$ in the pre-deletion period is -0.044 while the average $PIN_{s\text{-}b}$ in the post-deletion period is -0.075. The median changes from -0.051 in the pre-deletion period to -0.077 in the post-deletion period. The changes in mean and median are all significant. We also find that the decrease in $PIN_{s\text{-}b}$ is caused by a significant decrease in PIN_{sell} and an insignificant increase in PIN_{buy}, which is consistent with our view that short sale constraints reduce price informativeness by impeding informed selling. The individual parameters also show changes in the predicted directions around deletion events. The probability of information arrival, the probability that the information is bad news and the arrival rate of informed trading all become smaller when short sale restrictions are imposed.

In Panel B, the downside-minus-upside idiosyncratic volatility moves in the predicted direction. Ψ_{down} and Ψ_{up} all increase, and Ψ_{up} has a larger increase (27.7%) than Ψ_{down} (10.2%). The fact that Ψ_{down} and Ψ_{up} all increase is not surprising because there could be other factors that affect Ψ_{down} and Ψ_{up} symmetrically. The difference between them, $\Psi_{d\text{-}u}$, reflects the effect of short sale constraints and is the relevant variable in our study. However, though $\Psi_{d\text{-}u}$ shows a change in predicted direction, the change is not significant as shown in the last column. We argue that it is possibly because the asymmetric effects of some firm characteristics on incorporation of negative and positive information. We control for them in the regression analysis in the next subsection.

5.2 Regression Analysis

In this subsection, we investigate the relation between short sale constraints and price informativeness in a panel regression framework. This allows us to control for the factors other than short sale constraints which are suggested by the literature to affect the equilibrium level of private information. We show that after controlling for those factors, shortable stocks still have a higher level of private information in their prices.

A. Regressions of PIN

For the PIN, we use the following model,

$$PINx_{i,t} = c_0 + c_1 SSD_{i,t} + c_2 SSI_{i,t} + c_3 SIZE_{i,t} + c_4 B/M_{i,t} + c_5 LEV_{i,t} + c_6 ROE_{i,t} + c_7 RET_{i,t} + c_8 VRET_{i,t} + c_9 TV_{i,t} + c_{10} VTV_{i,t} + \textit{firm fixed effects (year fixed effects)} + \varepsilon_{i,t}$$

where $PINx_{i,t}$ denotes $PIN_{s\text{-}b}$, PIN_{sell} or PIN_{buy} for stock *i* in quarter *t*, $SSD_{i,t}$ is a dummy that takes value one if stock *i* is shortable throughout quarter *t*, and zero otherwise, $SSI_{i,t}$ is the short interest ratio defined as the average of daily dollar value of shares short sold divided by market capitalization for stock *i* in quarter *t*, *SIZE* (omitting firm and time subscripts) is the logarithm of market capitalization at the last quarter end, *B/M* is the logarithm of the book to market ratio defined as book value of equity divided by market value at the last quarter end, *LEV* is the leverage ratio defined as long term debts divided by total assets, *ROE* is return on equity defined as net income divided by lagged book value, RET is the average monthly return over the last 4 quarters, *VRET* is the standard deviation of the monthly return over the last 4 quarters, *TV* is average monthly trading volume over the last 4 quarters defined as the number of shares traded divided by total shares outstanding, and *VTV* is the standard deviation of monthly trading volume over the last 4 quarters . Accounting data in the latest financial report are used in constructing quarterly variables. Heteroskedasticity and serial correlation robust t-statistic are reported in parentheses. The sample period is from 1996:Q1 to 2002:Q4. Our sample includes all industrial firms in the Hong Kong stock exchange.

Basically we compute quarterly $PIN_{s\text{-}b}$, PIN_{sell} and PIN_{buy} for all the stocks listed in the Hong Kong stock exchange, and determine the value of the short sale dummy for each firm quarter by referring to the list of securities eligible for short selling. In doing so, our analysis is not confined to the event firms in Section 6.1, and captures the cross-sectional as well as time series difference in the informativeness measures. If short sale constraints reduce price informativeness, we expect the coefficient on the short sale dummy (*SSD*) is positive.

We also use the short interest (*SSI*) as an alternative test variable to the short sale dummy (*SSD*). The idea is that if a stock has more pent-up negative information due to the restriction on short sales, more short selling volume is expected to transmit the information into the stock's price. This dictates a positive relation between short interest ratio and the improvement in price informativeness. In regressions, we expect a positive coefficient on *SSI*.

Table IV reports the regression results of the PINs. For each dependent variable (PIN_{s-b}, PIN_{sell} and PIN_{buy}), we use four groups of independent variables: *SSD* only, *SSD* with control variables, *SSI* only and *SSI* with control variables. We also control for fixed firm effects in the regressions with only *SSD* or *SSI* as the independent variables, and control for fixed year effects in the regressions with the full set of control variables. So altogether, we have *3*4=12* different model specifications labeled as M1 to M12. In regressions M1 to M4 (The regressions with PIN_{s-b} as the dependent variable), the coefficients on *SSD* and *SSI* are all significantly positive. As shown by the coefficient on *SSD* in M1, the average PIN_{s-b} of shortable stocks is higher than that of non-shortable stocks by 0.019. After controlling for other factors, shortable stocks still have a positive edge of 0.017 to non-shortable stocks, shown by M2. The results on regressions M5 to M8 show that the average PIN_{sell} of shortable stocks is significantly higher than that of non-shortable stocks, and the average PIN_{sell} of stocks with high short interest ratio is higher than that of stocks with low short interest ratio. By contrast, lifting short sale constraints does not help enhance the informed buying. The results on regressions M9 to M12 (The regressions with PIN_{buy} as the dependent variable) actually show negative coefficients on *SSD* and *SSI*. In general, our results suggest that short sales enhance price informativeness by increasing the amount of negative private information built into stock prices, and the enhancement is more pronounced for stocks with high short interest ratio.

The control variables show some explanatory power. Firm size (*SIZE*) is negatively correlated with both PIN_{sell} and PIN_{buy}, and is not significantly correlated with PIN_{s-b}. Book to Market (*B/M*) ratio has a positive relation with PIN_{sell} and an insignificant relation with PIN_{buy}. As a result it is positively correlated with PINs-b. Return on equity is negatively related to PIN_{sell}, but is not significantly related to PIN_{buy} or PIN_{s-b}. The opposite signs of the control variables in regressions of PIN_{buy} and PIN_{sell} suggest that some variables have an asymmetric impact on the incorporation of negative and positive information. However, as shown by the insignificant coefficients in the regressions of PIN_{s-b}, most of them have a symmetric impact.

B. Regressions of Idiosyncratic Volatility

We use a similar model for idiosyncratic volatility,

$$\Psi x_{i,t} = c_0 + c_1 SSD_{i,t} + c_2 SSI_{i,t} + c_3 SIZE_{i,t} + c_4 B/M_{i,t} + c_5 LEV_{i,t} + c_6 ROE_{i,t} + c_7 RET_{i,t} + c_8 VRET_{i,t} + c_9 TV_{i,t} + c_{10} VTV_{i,t} + \textit{firm fixed effects (year fixed effects)} + \varepsilon_{i,t}$$

where $\Psi x_{i,t}$ denotes $\Psi_{\text{d-u}}$, Ψ_{down} or Ψ_{up} for stock *i* in year *t*, $SSD_{i,t}$ is a dummy that takes value one if stock *i* is shortable throughout year *t*, and zero otherwise, $SSI_{i,t}$ is the short interest ratio defined as the average of daily dollar value of shares short sold divided by market capitalization for stock *i* in year *t*, *SIZE* (omitting firm and time subscripts) is the logarithm of market capitalization at the last year end, *B/M* is the logarithm of the book to market ratio defined as book value of equity divided by market value at the last year end, *LEV* is the leverage ratio defined as long term debts divided by total assets, *ROE* is return on equity defined as net income divided by lagged book value, *RET* is the average monthly return over the last year, *VRET* is the standard deviation of the monthly return over the last year, *TV* is average monthly trading volume over the last year defined as the number of shares traded divided by total shares outstanding, and *VTV* is the standard deviation of monthly trading volume over the last year. Heteroskedasticity and serial correlation robust t-statistic are reported in parentheses. The sample period is from 1994:Q1 to 2002:Q4. Our sample includes all industrial firms in the Hong Kong stock exchange.

The testing framework is the same with that of the PINs, except that we use yearly estimates of Ψ_{down} and Ψ_{up}, and make corresponding changes to the computation and matching of *SSD*, *SSI* and other control variables. Similarly, regressions M1 to M4 use $\Psi_{\text{d-u}}$, regressions M5 to M8 use Ψ_{down} and regressions M9 to M12 use Ψ_{up} as the dependent variable. Table V presents the results. We document positive coefficients on *SSD* and *SSI* in regressions M1 to M8, and negative coefficients on *SSD* in regressions M9 to M12. This is consistent with the results for the PINs. As shown by the coefficients on *SSD* in M1, M5 and M9, the average $\Psi_{\text{d-u}}$ for shortable stocks is higher than that of non-shortable stocks by 0.39, and this spread is due to a positive spread of 0.247 in Ψ_{down} and a negative spread of -0.143 in Ψ_{up}. As shown by M2, adding the control variables only slightly reduce the spread to 0.375. As for the control variables, firm size (*SIZE*) is negatively related to both Ψ_{down} and Ψ_{up}. Book to Market (*B/M*) is also negatively correlated with Ψ_{down} and Ψ_{up}, and not correlated with Ψ_{d-u}. Return on equity has a positive relation with Ψ_{down}, and a negative relation with Ψ_{up}. As a result, it has a positive relation with Ψ_{d-u}. The results on idiosyncratic volatility generally conform to our prediction.

5.3 Short Sale Constraints and FERC

In this subsection, we evaluate whether short sale constraints reduce the ability of the price to forecast future earnings. We hypothesize that FERC increases as stocks are added into the list and become shortable. CKSS (1994) define FERC in a model that links current period's returns to current period's unexpected earnings and revisions in expectations of future earnings,

$$R_{i,t} = a_0 + b_0 \Delta E_{i,t} + \sum_{k=1}^{n} b_k \Delta E_{i,t+k} + \sum_{k=1}^{n} c_k R_{i,t+k} + \varepsilon_{i,t}$$

where R_t (omitting firm subscript i) is the return measured over a 12-month period ending three months after t fiscal year end. ΔE_t is the earnings change from fiscal year $t\text{-}1$ to t, where the earnings are defined as the income available for common before extraordinary items deflated by the market value of equity three months after $t\text{-}1$ fiscal year end. ΔE_{t+k} is the earnings change from fiscal year $t+k\text{-}1$ to $t+k$, deflated by the market value of equity three months after $t+k\text{-}1$ fiscal year end. R_{t+k} is the return measured over a 12-month period ending three months after $t+k$ fiscal year end. b_o is the earnings response coefficient (ERC). b_k is the future earnings response coefficient for earnings k period ahead ($FERC_k$).

Lundholm and Myers (2002) use the averages of future earnings and future returns to estimate FERC. They argue that average earnings contain less noise. Following them, we estimate a combined version of the FERC model,

$$R_{i,t} = a_0 + b_0 \Delta E_{i,t} + b_1 \Delta E3_{i,t} + c_0 R3_{i,t} + \varepsilon_{i,t}$$

where R_t and ΔE_t are as previously defined. $\Delta E3_t$ is the average of ΔE_t for the three fiscal years following fiscal year *t*. $R3_t$ is the average annual return for the three-year period ending three months after *t+2* fiscal year end. In this model, b_0 is the earnings response coefficient (ERC) and b_1 is the combined future earnings response coefficient (combined FERC) for three years' future earnings.

A natural way to test the changes in FERCs around additions is to estimate the FERCs for each firm in the pre-addition period and post-addition period, keep and estimates, and do the same tests as those for $PIN_{s\text{-}b}$ and Ψ_{down}. However, to get time series estimates of FERCs for each firm, we need continuous return and earnings data for at least 9 years before and after the addition events. Such requirement leaves us insufficient number of stocks. So we estimate the pre-addition FERCs in a panel regression using the data for the three fiscal years before the addition events, and the post-addition FERCs in a panel regression using the data for the three fiscal years after the addition events. We estimate both the full model and the combined model.

The results are presented in Table VI. Panel A gives the results on the combined model. Panel B reports the results on the full model. The significance of change is the t-statistic of an interaction term between $\Delta E3_t$ (or ΔE_t) and a short sale dummy (equal to one if fiscal year *t* is in post-addition period) in a regression pooling all the observations before and after the addition events. We also report the estimates of ERC for reference. Panel A shows that the combined FERC changes from 0.299 to 1.007 around addition events, and the change is significant at 5% level, one-tailed. Panel B shows that FERC1, FERC2 and FERC3 all increase around addition events. The $FERC_1$ estimated in the pre-addition period is 0.201, compared to 0.414 in the post-addition period. $FERC_2$ and $FERC_3$ also show an increase of 0.152 and 0.177 respectively. The decreasing trend as we move from $FERC_1$ to $FERC_3$ is also consistent with the literature. However, the changes in $FERC_1$ to $FERC_3$ around addition events are not significant. Easton, Harris and Ohlson (1992) find that the aggregate earnings reduce the measurement error in earnings and better explain the security returns. In our case, the average future earnings seem to contain much less noise and better explain the variation in current returns.

We then examine the change in combined FERC around addition events controlling for other factors. Specifically we estimate the following regressions,

$$R_{i,t} = a_0 + b_0 \Delta E_{i,t} + b_1 \Delta E3_{i,t} + c_0 SSD_{i,t}$$
$$+ d_0 SSD_{i,t} * \Delta E3_{i,t} + e_0 R3_{i,t} + f_0 D_{i,t} * R3_{i,t} + g_0 Control_{i,t} + h_0 Control_{i,t} * \Delta E3_{i,t} + \varepsilon_{i,t}$$

where R_t, ΔE, $\Delta E3_t$ and $R3_t$ are as previously defined. SSD_t is a dummy set equal to one if fiscal year *t* is in the pre-addition period and zero otherwise. $Control_t$ refers to one of the four control variables: $SIZE_t$ is the natural logarithm of the market value of equity three months after *t-1* fiscal year end. $MTBV_t$ is the market-to-book ratio defined as the market value of equity three months after *t-1* fiscal year end divided by the book value of equity at *t-1* fiscal year end. SD_E_t is the standard deviation of the earnings from fiscal year *t+1* to year *t+3*, deflated by the market value of equity three months after *t-1* fiscal year end. $LOSS_t$ is a dummy set equal to 1 if the earnings in fiscal year *t* are negative.

We report the regression results in Table VII. The regression uses the data for the three fiscal years before and after addition events. In this construction, b_1 is the combined future earnings response coefficient (combined FERC) for three years' future earnings in the pre-addition period, and the coefficient on $SSD*\Delta E3$ (d_0) is the change in combined FERC from pre-addition to post-addition period. We predict d_o to be significantly positive. The results show that after controlling for other variables, the combined FERC still show a significant increase around addition events. The coefficients on $SSD*\Delta E3$ are all significantly positive in the four regressions with different control variables.

5.4 Adjusted PIN Model

In this subsection, we adjust the PIN model to estimate separate arrival rates for informed sell orders and informed buy orders. In the original PIN model, μ is the arrival rate of either informed sell orders or buy orders. In the adjusted model, we replace μ by μ_s and μ_b, which are the arrival rates of informed sell orders and the arrival rate of informed buy orders, respectively. In doing so, we can directly examine whether short sale constraints have effect on the arrival rate of informed selling (μ_s) relative to informed buying (μ_b). In addition, we also repeat the event study and regression analysis on $PIN\_ADJ_{s\text{-}b}$ as a robustness check.

The adjusted model is,

$$L(\theta \mid b_t, s_t) = (1-\alpha)e^{-\varepsilon_s}\frac{\varepsilon_s^{s_t}}{s_t}e^{-\varepsilon_b}\frac{\varepsilon_b^{b_t}}{b_t} + \alpha\delta e^{-(\varepsilon_s+\mu_s)}\frac{(\varepsilon_s+\mu_s)^{s_t}}{s_t}e^{-\varepsilon_b}\frac{\varepsilon_b^{b_t}}{b_t}$$
$$+\alpha(1-\delta)e^{-\varepsilon_s}\frac{\varepsilon_s^{s_t}}{s_t}e^{-(\varepsilon_b+\mu_b)}\frac{(\varepsilon_b+\mu_b)^{b_t}}{b_t}$$

where all the other parameters are as previously defined. μ_s is the arrival rate of informed sell orders and μ_b is the arrival rate of the informed buy orders. Table VIII reports the estimates using the adjusted model in the pre-event and post-event period. Panel A reports the results on addition events and Panel B gives the results on deletion events. As shown by Panel A, the average arrival rate of informed selling, μ_s, is 51.04 in the pre-addition period, and is 66.05 in the post-addition period. This is a 29.4% change in percentage terms. The average arrival rate of informed buy orders, μ_b, also increases. However, it increases to a lesser extent. The arrival rate of informed sell orders increase around addition events relative to the arrival rate of informed buy orders, which is consistent with our prediction. By contrast, Panel B shows an opposite pattern for μ_s and μ_b. After stocks are removed from the list, the arrival rates of informed buy orders and informed sell orders both decrease, and the arrival rate of informed sell orders show a steeper decrease. The changes in $PIN\_ADJ_{s\text{-}b}$, PIN_ADJ_{sell} and PIN_ADJ_{buy} around addition and deletion events are consistent with the previous results.

Table IX reports the regression results using the adjusted PINs. Specifically, we substitute $PIN\_ADJ_{s\text{-}b}$, PIN_ADJ_{sell} and PIN_ADJ_{buy} for $PIN_{s\text{-}b}$, PIN_{sell} and PIN_{buy} in the regressions. Other settings remain unchanged. The results are not significantly different.

6. Conclusions

Academic studies show that short sale constraints hinder negative information from being incorporated into stock price and thus reduce price informativeness. Another view, often held by regulators, states that short sales are likely to destabilize the markets by causing price manipulations and market panics. Based on such considerations, short sales are prohibited in many of the emerging markets, and even in the markets where short sales are allowed, they are subject to heavy regulations and the costs associated with short sales are generally high.

In this paper we directly investigate the relation between short sale constraints and price informativeness by examining the changes in some measures for price informativeness around events in which short sales constraints are changed. We find that short sale constraints are negatively correlated with both of the two measures. The sell-mius-buy PIN and the downside-minus-upside idiosyncratic volatility increase as short sale restrictions are removed, and decrease as short sale restrictions are imposed. Further analysis shows that short sale constraints reduce the ability of the price to forecast future earnings, as measured by future earnings response coefficient. Our results support the first view that short sale constraints impair price informativeness. However, we admit that the conclusion is conditional on the validity of our measures for price informativeness.

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Table I

Historical Revisions to the List of Securities Eligible for Short Selling

This table summarizes the historical revisions to the list of designated securities for short selling in the Hong Kong Stock Exchange. Exchange traded funds and T-stocks are excluded from the summary. From 03-Jan-1994 to 29-Oct-2002, there were altogether 18 revisions. The number of stocks on the list, the number of stocks added into the list and the number of stocks deleted from the list on each revision date are reported in column 2 to 4. In column 5, an addition event is defined as a one in which 1) a stock was added into the list, 2) the stock had not been in the list for at least 4 calendar quarters before it was added, and 3) the stock remained in the list for at least 4 calendar quarters after it was added. Thus the addition events are a subset of the firms added into the list on each revision date. In column 6, a deletion event is defined as the opposite of an addition event.

Rivision Dates	**No. of Stocks on the List**	**No. of Stocks Added**	**No. of Stocks Deleted**	**No. of Addition Events**	**No. of Deletion Events**
03-Jan-1994	17	17	0	17	0
25-Mar-1996	112	97	2	97	2
01-May-1997	240	129	1	129	1
12-Jan-1998	309	69	0	29	0
16-Mar-1998	323	15	1	11	1
09-Nov-1998	194	19	148	13	105
01-Mar-1999	194	7	7	2	3
20-Sep-1999	180	3	17	0	6
28-Feb-2000	192	24	12	14	8
28-Aug-2000	208	32	16	20	9
12-Feb-2001	208	12	12	4	6
14-May-2001	212	5	1	2	1
20-Aug-2001	207	6	11	2	2
03-Dec-2001	139	12	80	6	56
25-Feb-2002	132	7	14	1	5
21-May-2002	137	11	6	2	2
29-Jul-2002	159	25	3	7	0
29-Nov-2002	150	5	14	4	0
	Total:	495	345	360	207

Table II

Probability of Informed Trading, Relative Idiosyncratic Volatility aound Addition Events

Panel A reports mean and median of parameter estimates of the PIN model in the pre-addition and post-addition periods, and the changes in the estimates around events. The pre-addition estimate is taken as the average of the four quarterly estimates before the event quarter, and the post-addition estimate is taken as the average of the four quarterly estimates after the event quarter. Column 3 and 4 report the mean and median across events. Column 5 and 6 report the change and the last column reports the t-statistics of a paired t-test and Wilcoxon signed rank test. α is the probability of information arrival, δ is the probability that the information is bad news, μ is the arrival rate of informed orders, ε_s is the arrival rate of uninformed sell orders and ε_b is the arrival rate of uninformed buy orders. PIN is the probability that a trade is information based, defined as $\alpha*\mu/(\alpha*\mu+\varepsilon_b+\varepsilon_s)$. PIN_{sell} is the probability that a trade is information based sell, defined as δ*PIN. PIN_{buy} is the probability that a trade is information based buy, defined as $(1-\delta)$*PIN. PIN_{s-b} is defined as PIN_{sell}-PIN_{buy}. **Panel B** gives the results on log transformed relative idiosyncratic volatility. Ψ_{total} is defined as $\log((1-R^2)/R^2)$ where R^2 is the R-square of a regression of stock return on market return using bi-weekly data. Ψ_{down} is defined as $\log((1-R^2_d)/R^2_d)$, where R^2_d is the R-square of a regression of stock return on market return when market return is negative. Ψ_{up} is defined in a similar way when market return is positive or zero. Ψ_{d-u} is defined as $\Psi_{down}-\Psi_{up}$. For each addition event, we estimate pre-addition Ψ_{total}, Ψ_{down} and Ψ_{up} in the four quarters before the event quarter, and post-addition Ψ_{total}, Ψ_{up} and Ψ_{down} in the four quarters after the event quarter. There are 360 addition events used in our study from 03-Jan-94 to 29-Nov-02.

Panel A: Probability of Informed Trading

Parameters		Pre-Addition **(Not Shortable)**	Post-Addition **(Shortable)**	Change (Post minus Pre)	Change in Percentage	Paired t-test /Wilcoxon test
PIN_{s-b}	*Mean*	-0.074	-0.050	0.024		(4.07)
	Median	-0.080	-0.050	0.023		(3.92)
PIN_{sell}	*Mean*	0.077	0.093	0.015	19.8%	(4.43)
	Median	0.077	0.083	0.011	14.6%	(4.50)
PIN_{buy}	*Mean*	0.151	0.143	-0.008	-5.5%	(-2.58)
	Median	0.152	0.141	-0.005	-3.0%	(-2.22)
PIN	*Mean*	0.229	0.236	0.007	3.1%	(2.14)
	Median	0.233	0.228	0.009	4.0%	(2.82)
α	*Mean*	0.246	0.275	0.029	11.9%	(6.44)
	Median	0.231	0.277	0.035	15.0%	(7.10)
δ	*Mean*	0.342	0.392	0.051	14.9%	(4.48)
	Median	0.333	0.384	0.051	15.4%	(4.35)
μ	*Mean*	78.63	88.93	10.30	13.1%	(1.87)
	Median	44.61	63.81	12.13	27.2%	(4.12)
ε_s	*Mean*	42.79	48.57	5.78	13.5%	(1.59)
	Median	18.28	29.78	5.06	27.7%	(4.78)
ε_b	*Mean*	37.62	43.64	6.02	16.0%	(1.65)
	Median	13.76	21.42	3.62	26.3%	(4.74)

Panel B: Relative Idiosyncratic Volatility

Ψ_{d-u}	*Mean*	-0.348	0.502	0.850		(2.89)
	Median	-0.223	0.557	0.699		(4.07)
Ψ_{down}	*Mean*	1.799	2.703	0.905	50.3%	(3.91)
	Median	1.443	2.117	0.920	63.8%	(6.80)
Ψ_{up}	*Mean*	2.146	2.201	0.054	2.5%	(0.27)
	Median	1.725	1.758	0.398	23.1%	(1.19)

Table III

Probability of Informed Trading, Relative Idiosyncratic Volatility around Deletion Events

Panel A reports mean and median of parameter estimates of the PIN model in the pre-deletion and post-deletion periods, and the changes in the estimates around events. The pre-deletion estimate is taken as the average of the four quarterly estimates before the event quarter, and the post-deletion estimate is taken as the average of the four quarterly estimates after the event quarter. Column 3 and 4 report the mean and median across events. Column 5 and 6 report the change and the last column reports the t-statistics of a paired t-test and Wilcoxon signed rank test. α is the probability of information arrival, δ is the probability that the information is bad news, μ is the arrival rate of informed orders, ε_s is the arrival rate of uninformed sell orders and ε_b is the arrival rate of uninformed buy orders. PIN is the probability that a trade is information based, defined as $\alpha*\mu/(\alpha*\mu+\varepsilon_b+\varepsilon_s)$. PIN_{sell} is the probability that a trade is information based sell, defined as δ*PIN. PIN_{buy} is the probability that a trade is information based buy, defined as $(1-\delta)$*PIN. PIN_{s-b} is defined as PIN_{sell}-PIN_{buy}. **Panel B** gives the results on log transformed relative idiosyncratic volatility. Ψ_{total} is defined as $\log((1-R^2)/R^2)$ where R^2 is the R-square of a regression of stock return on market return using bi-weekly data. Ψ_{down} is defined as $\log((1-R^2_d)/R^2_d)$, where R^2_d is the R-square of a regression of stock return on market return when market return is negative. Ψ_{up} is defined in a similar way when market return is positive or zero. Ψ_{d-u} is defined as Ψ_{down}-Ψ_{up}. For each deletion event, we estimate pre-deletion Ψ_{total}, Ψ_{down} and Ψ_{up} in the four quarters before the event quarter, and post-deletion Ψ_{total}, Ψ_{up} and Ψ_{down} in the four quarters after the event quarter. There are 207 deletion events used in our study from 03-Jan-94 to 29-Nov-02.

Panel A: Probability of Informed Trading

Parameters		Pre-Deletion **(Shortable)**	Post-Deletion **(Not Shortable)**	Change (Post minus Pre)	Change in Percentage	Paired t-test /Wilcoxon test
PIN_{s-b}	*Mean*	-0.044	-0.075	-0.031		(-3.09)
	Median	-0.051	-0.077	-0.033		(-3.04)
PIN_{sell}	*Mean*	0.108	0.090	-0.018	-16.8%	(-3.33)
	Median	0.097	0.079	-0.013	-13.2%	(-3.49)
PIN_{buy}	*Mean*	0.151	0.164	0.013	8.5%	(-2.18)
	Median	0.152	0.164	0.017	11.3%	(-1.96)
PIN	*Mean*	0.259	0.254	-0.005	-2.0%	(-0.98)
	Median	0.255	0.250	0.002	0.8%	(-0.88)
α	*Mean*	0.249	0.218	-0.032	-12.7%	(-4.59)
	Median	0.248	0.217	-0.041	-16.3%	(-5.15)
δ	*Mean*	0.410	0.359	-0.051	-12.4%	(-2.98)
	Median	0.395	0.341	-0.072	-18.3%	(-3.26)
μ	*Mean*	45.88	42.84	-3.04	-6.6%	(-0.87)
	Median	35.89	27.11	-3.51	-9.8%	(-1.79)
ε_s	*Mean*	19.55	15.01	-4.54	-23.2%	(-2.51)
	Median	11.59	8.30	-2.10	-18.1%	(-4.47)
ε_b	*Mean*	14.40	10.67	-3.73	-25.9%	(-2.82)
	Median	8.57	5.20	-1.63	-19.0%	(-5.30)

Panel B: Relative Idiosyncratic Volatility

Ψ_{d-u}	*Mean*	-0.442	-0.935	-0.493		(-1.13)
	Median	-0.400	-0.594	-0.591		(-1.45)
Ψ_{down}	*Mean*	2.127	2.344	0.217	10.2%	(0.79)
	Median	1.768	1.784	0.152	8.6%	(0.61)
Ψ_{up}	*Mean*	2.569	3.279	0.710	27.7%	(2.01)
	Median	1.996	2.686	1.077	54.0%	(2.26)

Table IV

Regression of PIN Ratios on Short Sale Dummy, Short Interest and Control Variables

This table reports estimates of coefficients of the following regression,

$$PINx_{i,t} = c_0 + c_1 SSD_{i,t} + c_2 SSI_{i,t} + c_3 SIZE_{i,t} + c_4 B/M_{i,t} + c_5 LEV_{i,t} + c_6 ROE_{i,t} + c_7 RET_{i,t} + c_8 VRET_{i,t} + c_9 TV_{i,t} + c_{10} VTV_{i,t} + \textit{firm fixed effects (year fixed effects)} + \varepsilon_{i,t}$$

where $PINx_{i,t}$ denotes $PIN_{s\text{-}b}$, PIN_{sell} or PIN_{buy} for stock *i* in quarter *t*, $SSD_{i,t}$ is a dummy that takes value one if stock *i* is shortable throughout quarter *t*, and zero otherwise, $SSI_{i,t}$ is the short interest ratio defined as the average of daily dollar value of shares short sold divided by market capitalization for stock *i* in quarter *t*, *SIZE* (omitting firm and time subscripts) is the logarithm of market capitalization at the last quarter end, *B/M* is the logarithm of the book to market ratio defined as book value of equity divided by market value at the last quarter end, *LEV* is the leverage ratio defined as long term debts divided by total assets, *ROE* is return on equity defined as net income divided by lagged book value, *RET* is the average monthly return over the last 4 quarters, *VRET* is the standard deviation of the monthly return over the last 4 quarters, *TV* is average monthly trading volume over the last 4 quarters defined as the number of shares traded divided by total shares outstanding, and *VTV* is the standard deviation of monthly trading volume over the last 4 quarters . Accounting data in the latest financial report are used in constructing quarterly variables. Heteroskedasticity and serial correlation robust *t*-statistic are reported in parentheses. The sample period is from 1996:Q1 to 2002:Q4. Our sample includes all industrial firms in the Hong Kong stock exchange.

	Dependent Variable =											
	$PIN_{s\text{-}b}$	$PIN_{s\text{-}b}$	$PIN_{s\text{-}b}$	$PIN_{s\text{-}b}$	PIN_{sell}	PIN_{sell}	PIN_{sell}	PIN_{sell}	PIN_{buy}	PIN_{buy}	PIN_{buy}	PIN_{buy}
Independent Var.	*M1*	*M2*	*M3*	*M4*	*M5*	*M6*	*M7*	*M8*	*M9*	*M10*	*M11*	*M12*
SSD	0.019	0.017			0.015	0.017			-0.004	-0.001		
	(5.208)	(3.908)			(7.272)	(6.784)			(-1.993)	(-0.287)		
SSI			0.387	0.364			0.188	0.212			-0.199	-0.152
			(4.236)	(3.886)			(3.973)	(4.597)			(-2.544)	(-1.870)
SIZE		0.001		-0.001		-0.005		-0.005		-0.005		-0.004
		(0.238)		(-0.281)		(-2.466)		(-2.502)		(-2.195)		(-1.451)
B/M		0.008		0.006		0.005		0.005		-0.003		-0.002
		(2.305)		(1.855)		(2.797)		(2.714)		(-1.288)		(-0.634)
LEV		-0.008		-0.014		0.010		0.008		0.018		0.022
		(-0.420)		(-0.671)		(0.946)		(0.610)		(1.535)		(1.617)
ROE		-0.001		-0.001		-0.001		-0.001		0.000		0.000
		(-1.095)		(-0.943)		(-2.276)		(-2.242)		(-0.335)		(-0.556)
RET		0.034		0.028		0.015		0.016		-0.019		-0.012
		(1.183)		(0.891)		(0.973)		(0.931)		(-0.982)		(-0.559)
VRET		-0.008		-0.006		-0.001		0.000		0.008		0.006
		(-0.865)		(-0.542)		(-0.123)		(0.024)		(1.216)		(0.812)
TV		-0.004		0.011		-0.017		-0.014		-0.013		-0.025
		(-0.133)		(0.335)		(-1.124)		(-0.735)		(-0.803)		(-1.256)
VTV		0.000		-0.011		0.009		0.007		0.008		0.017
		(0.019)		(-0.481)		(0.868)		(0.520)		(0.720)		(1.275)
Other Controls	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year
No. of Obs.	27073	19288	22928	16117	27073	19288	22928	16117	27073	19288	22928	16117
Adj. R^2	3.51%	3.28%	3.31%	3.65%	2.97%	5.03%	2.62%	5.14%	7.90%	3.23%	7.52%	3.39%

Table V

Regression of Idiosyncratic Volatility on Short Sale Dummy, Short Interest and Control Variables

This table reports estimates of coefficients of the following regression,

$$\Psi x_{i,t} = c_0 + c_1 SSD_{i,t} + c_2 SSI_{i,t} + c_3 SIZE_{i,t} + c_4 B/M_{i,t} + c_5 LEV_{i,t} + c_6 ROE_{i,t} + c_7 RET_{i,t} + c_8 VRET_{i,t} + c_9 TV_{i,t} + c_{10} VTV_{i,t} + \textit{firm fixed effects (year fixed effects)} + \varepsilon_{i,t}$$

where $\Psi x_{i,t}$ denotes $\Psi_{d\text{-}u}$, Ψ_{down} or Ψ_{up} for stock *i* in year *t*, $SSD_{i,t}$ is a dummy that takes value one if stock *i* is shortable throughout year *t*, and zero otherwise, $SSI_{i,t}$ is the short interest ratio defined as the average of daily dollar value of shares short sold divided by market capitalization for stock *i* in year *t*, *SIZE* (omitting firm and time subscripts) is the logarithm of market capitalization at the last year end, *B/M* is the logarithm of the book to market ratio defined as book value of equity divided by market value at the last year end, *LEV* is the leverage ratio defined as long term debts divided by total assets, *ROE* is return on equity defined as net income divided by lagged book value, *RET* is the average monthly return over the last year, *VRET* is the standard deviation of the monthly return over the last year, *TV* is average monthly trading volume over the last year defined as the number of shares traded divided by total shares outstanding, and *VTV* is the standard deviation of monthly trading volume over the last year. Heteroskedasticity and serial correlation robust *t*-statistic are reported in parentheses. The sample period is from 1994:Q1 to 2002:Q4. Our sample includes all industrial firms in the Hong Kong

	Dependent Variable =											
	$\Psi_{d\text{-}u}$	$\Psi_{d\text{-}u}$	$\Psi_{d\text{-}u}$	$\Psi_{d\text{-}u}$	Ψ_{down}	Ψ_{down}	Ψ_{down}	Ψ_{down}	Ψ_{up}	Ψ_{up}	Ψ_{up}	Ψ_{up}
Independent Var.	*M1*	*M2*	*M3*	*M4*	*M5*	*M6*	*M7*	*M8*	*M9*	*M10*	*M11*	*M12*
SSD	0.390	0.375			0.247	0.389			-0.143	0.014		
	(2.444)	(2.403)			(2.132)	(3.321)			(-1.350)	(0.137)		
SSI			6.904	3.348			4.725	4.391			-2.179	1.042
			(1.247)	(0.692)			(1.204)	(1.296)			(-0.509)	(0.313)
SIZE		-0.025		-0.013		-0.314		-0.235		-0.289		-0.222
		(-0.614)		(-0.272)		(-9.229)		(-6.773)		(-8.325)		(-6.087)
B/M		0.007		-0.001		-0.149		-0.139		-0.156		-0.137
		(0.153)		(-0.021)		(-3.879)		(-3.243)		(-4.118)		(-3.270)
LEV		-0.546		-0.559		0.094		0.126		0.641		0.685
		(-1.192)		(-1.053)		(0.283)		(0.341)		(1.840)		(1.761)
ROE		0.002		0.002		0.001		0.001		-0.001		-0.001
		(10.496)		(9.080)		(7.010)		(5.523)		(-5.618)		(-5.737)
RET		0.617		1.191		1.003		1.504		0.386		0.313
		(0.573)		(1.031)		(1.418)		(2.069)		(0.474)		(0.356)
VRET		-0.062		-0.230		-0.252		-0.388		-0.190		-0.158
		(-0.153)		(-0.544)		(-0.839)		(-1.257)		(-0.765)		(-0.594)
TV		0.204		-0.050		-0.080		-0.149		-0.284		-0.099
		(0.282)		(-0.057)		(-0.149)		(-0.225)		(-0.513)		(-0.150)
VTV		-0.241		-0.079		-0.117		-0.045		0.124		0.035
		(-0.486)		(-0.133)		(-0.321)		(-0.099)		(0.331)		(0.080)
Other Controls	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year
No. of Obs.	5436	4064	4605	3443	5436	4064	4605	3443	5436	4064	4605	3443
Adj. R^2	1.05%	2.53%	0.84%	1.89%	5.90%	5.66%	4.29%	3.96%	4.81%	5.62%	3.25%	3.94%

Table VI
Change in Future Earnings Response Coefficients around Addition Events

Panel A reports the change in combined FERC around addition events as estimated in the following regression,

$$R_{i,t} = a_0 + b_0\Delta E_{i,t} + b_1\Delta E3_{i,t} + c_0 R3_{i,t} + \varepsilon_{i,t}$$

where R_t (omitting firm subscript *i*) is the return measured over a 12-month period ending three months after *t* fiscal year end. ΔE_t is the earnings change from fiscal year *t-1* to *t*, where the earnings are defined as the income available for common before extraordinary items deflated by the market value of equity three months after *t-1* fiscal year end. $\Delta E3_t$ is the average of ΔE_t for the three fiscal years following fiscal year *t*. $R3_t$ is the average annual return for the three-year period ending three months after *t+2* fiscal year end. In this model, b_0 is the earnings response coefficient (ERC) and b_1 is the combined future earnings response coefficient (combined FERC) for three years' future earnings. The pre-addition FERC is estimated in a panel regression using the data for the three fiscal years before the addition events, and the post-addition FERC is estimated using the data for the three fiscal years after the addition events. The significance of change is the t-statistic of an interaction term between $\Delta E3_t$ (or ΔE_t) and a short sale dummy (equal to one if fiscal year *t* is in post-addition period) in a regression pooling all the observations before and after the addition events.

Panel B reports the changes in 1, 2 and 3-year FERCs around addition events as estimated in the following regression,

$$R_{i,t} = a_0 + b_0\Delta E_{i,t} + \sum_{k=1}^{n} b_k \Delta E_{i,t+k} + \sum_{k=1}^{n} c_k R_{i,t+k} + \varepsilon_{i,t}$$

where R_t and ΔE_t are as previously defined. ΔE_{t+k} is the earnings change from fiscal year *t+k-1* to *t+k*, deflated by the market value of equity three months after *t+k-1* fiscal year end. R_{t+k} is the return measured over a 12-month period ending three months after *t+k* fiscal year end. In this model, b_0 is the earnings response coefficient (ERC) and b_k is the future earnings response coefficient for earnings *k* period ahead ($FERC_k$). The pre-addition FERCs is estimated in a panel regression using the data for the three fiscal years before the addition events, and the post-addition FERCs is estimated using the data for the three fiscal years after the addition events. The significance of change is the t-statistic of an interaction term between ΔE_{t+k} (or ΔE_t) and a short sale dummy (equal to one if fiscal year *t* is in post-addition period) in a regression pooling all the observations before and after the addition events.

Panel A: Combined FERC Model Estimates

	Pre-Addition	Post-Addition	Change	Signifcance of Change
ERC	0.232	0.616	0.384	(2.36)
t-stat.	(2.38)	(4.91)		
Combined FERC	0.299	1.007	0.707	(1.84)
t-stat.	(1.72)	(2.73)		

Panel B: Full Model Estimates

	Pre-Addition	Post-Addition	Change	Signifcance of Change
ERC	0.264	0.549	0.285	(1.59)
t-stat.	(2.62)	(3.69)		
$FERC_1$	0.201	0.414	0.213	(1.14)
t-stat.	(1.82)	(2.83)		
$FERC_2$	0.137	0.289	0.152	(0.79)
t-stat.	(1.55)	(1.57)		
$FERC_3$	0.063	0.240	0.177	(1.09)
t-stat.	(0.90)	(1.50)		

Table VII

Regression of Current Return on Combined Future Earnings and Interaction with Short Sale Dummy

This table reports estimates of coefficients of the following regression,

$$R_{i,t} = a_0 + b_0 \Delta E_{i,t} + b_1 \Delta E3_{i,t} + c_0 SSD_{i,t} + d_0 SSD_{i,t} * \Delta E3_{i,t} + e_0 R3_{i,t} + f_0 D_{i,t} * R3_{i,t} + g_0 Control_{i,t} + h_0 Control_{i,t} * \Delta E3_{i,t} + \varepsilon_{i,t}$$

where R_t is the return measured over a 12-month period ending three months after *t* fiscal year end. ΔE_t is the earnings change from fiscal year *t-1* to *t*, where the earnings are defined as the income available for common before extraordinary items deflated by the market value of equity three months after *t-1* fiscal year end. $\Delta E3_t$ is the average of ΔE_t for the three fiscal years following fiscal year *t*. $R3_t$ is the average annual return for the three-year period ending three months after *t+2* fiscal year end. SSD_t is a dummy set equal to one if fiscal year *t* is in the pre-addition period and zero otherwise. $Control_t$ refers to one of the four control variables: $SIZE_t$ is the natural logarithm of the market value of equity three months after t-1 fiscal year end. $MTBV_t$ is the market-to-book ratio defined as the market value of equity three months after t-1 fiscal year end divided by the book value of equity at t-1 fiscal year end. SD_E_t is the standard deviation of the earnings from fiscal year *t+1* to year *t+3*, deflated by the market value of equity three months after *t-1* fiscal year end. $LOSS_t$ is a dummy set equal to 1 if the earnings in fiscal year *t* is negative. The regression is run using the data for the three fiscal years before and after addition events. In this construction, b_1 is the combined future earnings response coefficient (combined FERC) for three years' future earnings in the pre-addition period, and d_0 is the change in combined FERC from pre-addition to post-addition period.

	Control Variable =							
	$SIZE_t$		$MTBV_t$		SD_E_t		$LOSS_t$	
	Coefs.	t-stat.	Coefs.	t-stat.	Coefs.	t-stat.	Coefs.	t-stat.
Constant	0.163	(1.67)	0.201	(5.35)	0.230	(6.98)	0.235	(7.57)
ΔE	0.229	(1.87)	0.230	(1.89)	0.234	(1.93)	0.264	(2.24)
$\Delta E3$	-0.704	(-0.72)	0.343	(1.16)	0.721	(2.41)	0.272	(1.32)
R3	-0.096	(-0.69)	-0.061	(-0.43)	-0.134	(-0.95)	-0.056	(-0.43)
$SSD*\Delta E$	0.365	(2.19)	0.396	(2.42)	0.302	(1.77)	0.435	(2.82)
$SSD*\Delta E3$	0.814	(2.05)	0.689	(1.76)	0.918	(2.27)	1.119	(2.69)
*SSD*R3*	-0.081	(-0.44)	-0.086	(-0.46)	-0.017	(-0.09)	-0.185	(-1.06)
Control	0.007	(0.60)	0.014	(1.38)	-0.158	(-1.26)	-0.372	(-5.31)
$Control*\Delta E3$	0.133	(1.06)	-0.021	(-0.09)	-1.497	(-1.83)	0.097	(0.17)
SSD	-0.250	(-5.06)	-0.253	(-5.27)	-0.248	(-5.21)	-0.206	(-4.49)
Adj. R2		27.12%		27.04%		28.02%		34.61%
No. of obs.		276		276		276		276

Table VIII

Change in Adjusted PIN Ratios around Addition and Deletion Events

This table reports mean and median of parameter estimates of the adjusted PIN model in the pre-event and post-event periods, and the changes in the estimates around events. The pre-event estimate is taken as the average of the four quarterly estimates before the event quarter, and the post-event estimate is taken as the average of the four quarterly estimates after the event quarter. Column 3 and 4 report the mean and median across events. Column 5 and 6 report the change from pre-event to post-event, and the last column reports the t-statistics of a paired t-test and Wilcoxon signed rank test. α is the probability of information arrival, δ is the probability that the information is bad news, μ_s is the arrival rate of informed sell orders, μ_b is the arrival rate of informed buy orders, ε_s is the arrival rate of uninformed sell orders and ε_b is the arrival rate of uninformed buy orders. PIN_ADJ is the probability that a trade is information based, defined as $(\alpha\delta\mu_s+\alpha(1-\delta)\mu_b)/(\alpha\delta\mu_s+\alpha(1-\delta)\mu_b+\varepsilon_b+\varepsilon_s)$. PIN_ADJ_{sell} is the probability that a trade is informed sell, defined as $\alpha\delta\mu_s/(\alpha\delta\mu_s+\alpha(1-\delta)\mu_b+\varepsilon_b+\varepsilon_s)$. PIN_ADJ_{buy} is the probability that a trade is informed buy, defined as $\alpha(1-\delta)\mu_b/(\alpha\delta\mu_s+\alpha(1-\delta)\mu_b+\varepsilon_b+\varepsilon_s)$. PIN_ADJ_{s-b} is defined as PIN_ADJ_{sell}-PIN_ADJ_{buy}. Panel A gives the results on addition events and Panel B gives the results on deletion events. There are 343 addition events and 207 deletion events used in our study from 25-Mar-96 to 19-Oct-02.

Panel A: Change around Addition Events

Parameters		Pre-Addition **(Not Shortable)**	Post-Addition **(Shortable)**	Change (Post minus Pre)	Change in Percentage	Paired t-test /Wilcoxon test
PIN_ADJ_{s-b}	*Mean*	-0.075	-0.057	0.018		(2.90)
	Median	-0.085	-0.057	0.020		(3.39)
PIN_ADJ_{sell}	*Mean*	0.083	0.093	0.010	12.3%	(2.70)
	Median	0.081	0.081	0.009	11.6%	(2.85)
PIN_ADJ_{buy}	*Mean*	0.158	0.150	-0.008	-4.8%	(-2.27)
	Median	0.161	0.144	-0.005	-3.2%	(-2.53)
PIN_ADJ	*Mean*	0.240	0.243	0.003	1.1%	(0.71)
	Median	0.245	0.231	0.003	1.2%	(0.94)
α	*Mean*	0.328	0.337	0.008	2.6%	(1.31)
	Median	0.324	0.331	0.000	0.0%	(0.96)
δ	*Mean*	0.412	0.429	0.017	4.2%	(1.56)
	Median	0.408	0.421	0.001	0.4%	(1.45)
μ_s	*Mean*	51.04	66.05	15.01	29.4%	(3.35)
	Median	25.19	42.14	6.85	27.2%	(5.34)
μ_b	*Mean*	69.51	83.45	13.93	20.0%	(2.86)
	Median	42.25	64.04	12.19	28.8%	(4.86)
ε_s	*Mean*	39.81	47.43	7.62	19.1%	(2.38)
	Median	17.98	29.50	5.65	31.4%	(4.81)
ε_b	*Mean*	34.07	42.03	7.96	23.4%	(2.67)
	Median	13.44	21.12	3.56	26.5%	(5.00)

Panel B: Change around Deletion Events

Parameters		Pre-Deletion **(Shortable)**	Post-Deletion **(Not Shortable)**	Change (Post minus Pre)	Change in Percentage	Paired t-test /Wilcoxon test
PIN_ADJ_{s-b}	*Mean*	-0.050	-0.083	-0.033		(-2.50)
	Median	-0.059	-0.091	-0.033		(-2.96)
PIN_ADJ_{sell}	*Mean*	0.112	0.097	-0.015	-13.6%	(-1.91)
	Median	0.102	0.084	-0.018	-17.4%	(-2.54)
PIN_ADJ_{buy}	*Mean*	0.162	0.180	0.018	11.1%	(2.46)
	Median	0.160	0.176	0.017	10.4%	(2.89)
PIN_ADJ	*Mean*	0.274	0.276	0.003	1.0%	(0.35)
	Median	0.261	0.268	0.007	2.5%	(0.32)
α	*Mean*	0.325	0.291	-0.034	-10.5%	(-2.59)
	Median	0.302	0.271	-0.031	-10.4%	(-2.56)
δ	*Mean*	0.457	0.417	-0.041	-8.9%	(-1.99)
	Median	0.470	0.416	-0.055	-11.6%	(-2.10)
μ_s	*Mean*	29.35	23.35	-6.00	-20.4%	(-2.44)
	Median	17.65	13.02	-4.63	-26.2%	(-2.44)
μ_b	*Mean*	43.39	37.22	-6.17	-14.2%	(-1.76)
	Median	27.35	23.67	-3.68	-13.5%	(-1.78)
ε_s	*Mean*	17.96	11.65	-6.31	-35.1%	(-4.09)
	Median	10.42	6.92	-3.49	-33.5%	(-4.50)
ε_b	*Mean*	13.58	8.15	-5.43	-40.0%	(-4.57)
	Median	6.38	4.53	-1.84	-28.9%	(-5.48)

Table IX

Regression of Adjusted PIN Ratios on Short Sale Dummy, Short Sale Turnover and Control Variables

This table reports estimates of coefficients of the following regression,

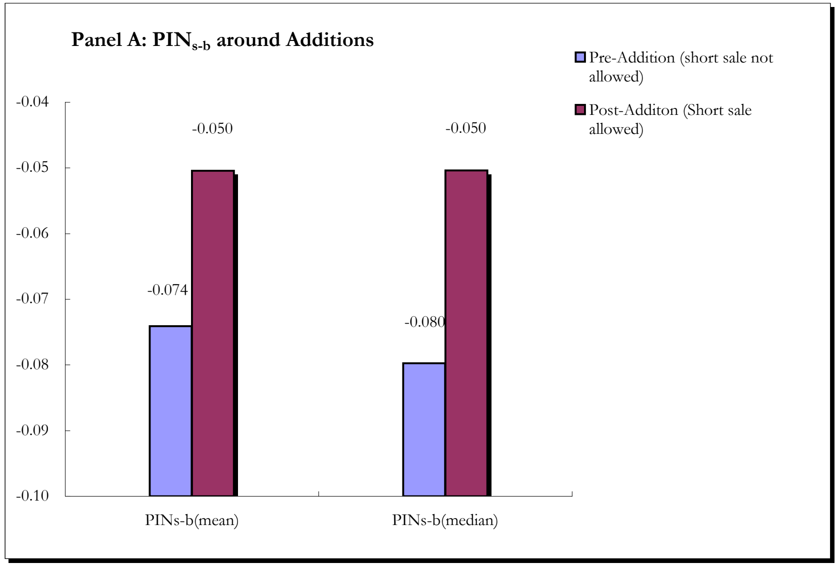
$$PIN\_ADJx_{i,t} = c_0 + c_1 SSD_{i,t} + c_2 SSI_{i,t} + c_3 SIZE_{i,t} + c_4 B/M_{i,t} + c_5 LEV_{i,t} + c_6 ROE_{i,t} + c_7 RET_{i,t} + c_8 VRET_{i,t} + c_9 TV_{i,t} + c_{10} VTV_{i,t} + \textit{firm fixed effects (year fixed effects)} + \varepsilon_{i,t}$$

where $PIN\_ADJx_{i,t}$ denotes $PIN\_ADJ_{s\text{-}b}$, PIN_ADJ_{sell} or PIN_ADJ_{buy} for stock i in quarter t, $SSD_{i,t}$ is a dummy that takes value one if stock i is shortable throughout quarter t, and zero otherwise, $SSI_{i,t}$ is the short interest ratio defined as the average of daily dollar value of shares short sold divided by market capitalization for stock i in quarter t, *SIZE* is the logarithm of market capitalization at the last quarter end, *B/M* is the logarithm of the book to market ratio defined as book value of equity divided by market value at the last quarter end, *LEV* is the leverage ratio defined as long term debts divided by total assets, *ROE* is return on equity defined as net income divided by lagged book value, *RET* is the average monthly return over the last 4 quarters, *VRET* is the standard deviation of the monthly return over the last 4 quarters, *TV* is average monthly trading volume over the last 4 quarters defined as the number of shares traded divided by total shares outstanding, and *VTV* is the standard deviation of monthly trading volume over the last 4 quarters . Accounting data in the latest financial report are used in constructing quarterly variables. Heteroskedasticity and serial correlation robust t-statistic are reported in parentheses. The sample period is from 1994:Q1 to 2002:Q4. Our sample includes all industrial firms in the Hong Kong stock exchange.

	Dependent Variable =											
	$PIN\_ADJ_{s\text{-}b}$	$PIN\_ADJ_{s\text{-}b}$	$PIN\_ADJ_{s\text{-}b}$	$PIN\_ADJ_{s\text{-}b}$	PIN_ADJ_{sell}	PIN_ADJ_{sell}	PIN_ADJ_{sell}	PIN_ADJ_{sell}	PIN_ADJ_{buy}	PIN_ADJ_{buy}	PIN_ADJ_{buy}	PIN_ADJ_{buy}
Independent Var.	*M1*	*M2*	*M3*	*M4*	*M5*	*M6*	*M7*	*M8*	*M9*	*M10*	*M11*	*M12*
SSD	0.008	0.004			0.007	0.009			-0.001	0.005		
	(1.960)	(0.884)			(3.051)	(2.984)			(-0.278)	(1.642)		
SSI			0.374	0.295			0.190	0.206			-0.184	-0.089
			(3.624)	(2.816)			(3.101)	(3.238)			(-2.160)	(-1.139)
SIZE		0.006		0.003		-0.002		-0.004		-0.008		-0.006
		(1.466)		(0.659)		(-1.161)		(-1.623)		(-3.389)		(-2.490)
B/M		0.010		0.008		0.006		0.006		-0.003		-0.002
		(2.707)		(2.174)		(3.226)		(3.021)		(-1.506)		(-0.780)
LEV		-0.003		-0.017		0.017		0.013		0.020		0.030
		(-0.185)		(-0.786)		(1.444)		(0.943)		(1.794)		(2.322)
ROE		0.000		0.000		-0.001		-0.001		-0.001		-0.001
		(-0.360)		(-0.128)		(-1.759)		(-1.726)		(-0.991)		(-1.228)
RET		0.008		0.011		0.007		0.011		0.000		0.000
		(0.245)		(0.308)		(0.422)		(0.535)		(-0.011)		(0.001)
VRET		0.002		0.003		0.002		0.003		0.000		0.000
		(0.169)		(0.274)		(0.357)		(0.396)		(0.070)		(-0.053)
TV		0.001		0.025		-0.027		-0.019		-0.028		-0.044
		(0.024)		(0.617)		(-1.485)		(-0.813)		(-1.591)		(-2.072)
VTV		-0.003		-0.021		0.014		0.009		0.017		0.030
		(-0.124)		(-0.785)		(1.151)		(0.556)		(1.410)		(2.115)
Other Controls	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year	Fixed Firm	Fixed Year
No. of Obs.	26752	19064	22638	15915	26752	19064	22638	15915	26752	19064	22638	15915
Adj. R^2	3.10%	2.71%	2.86%	2.95%	3.03%	4.01%	2.54%	4.07%	5.82%	3.10%	5.36%	2.92%

Figure 1: Changes in PINs-b and $\Psi_{d\text{-}u}$ around Events

This figure shows mean and median of $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$ in the pre-event and post-event periods. $PIN_{s\text{-}b}$ is defined as PIN_{sell}-PIN_{buy} where PIN_{buy} is the probability that a buy order is information based, defined as (1-δ)*PIN. PIN_{sell} is the probability that a sell order is information based, defined as δ*PIN. $\Psi_{d\text{-}u}$ is defined as Ψ_{down}-Ψ_{up}, in which Ψ_{up} is defined as $\log((1-R^2_u)/R^2_u)$, where R^2_u is the R-square of a regression of stock return on market return when market return is zero or positive and Ψdown is defined in a similar way when market return is negative.



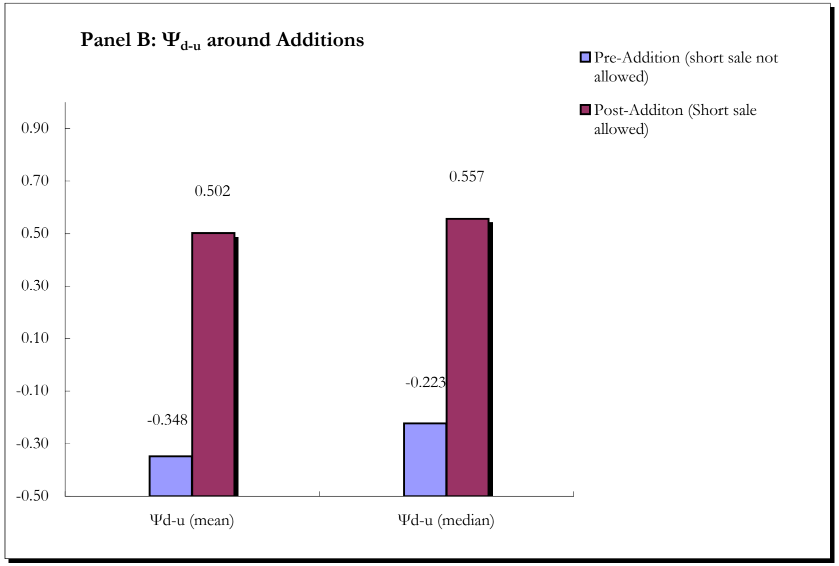


Figure 1: Changes in PINs-b and Ψ_{d-u} around Events (continued)