TWO ESSAYS IN EMPIRICAL FINANCE

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Certificate of Originality

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__________________________ (Signed)

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Abstract

This thesis contains two essays in the area of empirical finance. The first essay tests and supports the hypothesis that short sales constraints reduce price informativeness by hindering negative information from being fully incorporated into price. The analysis is based on a unique regulatory setting in the Hong Kong market. By using two measures for price informativeness, I find that stock prices become more informative when restrictions on short sales are lifted and less informative when restrictions are re-imposed. The results are robust after controlling for the relevant firm characteristic variables which affect equilibrium level of information in stock price. Further analyses demonstrate that allowing short sales mitigates the downward drift following negative earnings surprises and enhances the ability of stock prices to forecast future earnings. The second essay investigates the cross-sectional pattern of the relation between stock returns and inflation. Previous studies have shown a negative relation between stock returns and both expected and unexpected inflation on the market level, which contradicts the Fisher's theory and the conventional wisdom. Two explanations have been suggested in the literature. The proxy effect hypothesis states that the negative relation is merely a proxy for the negative relation between expected future real economic activity and inflation, and the money illusion hypothesis assumes that investors erroneously discount real earnings by nominal discount rates. In this thesis, I support the rational explanation to the negative return-inflation relation by examining the cross-sectional pattern of return-inflation betas. I show that, consistent with the proxy effect hypothesis, there is much cross-sectional variation in return-inflation betas, and further the cross-sectional variation in return-inflation betas can be explained by the differential associations between firm fundamentals and inflation. I also examine the impacts of some observable firm characteristic variables on the return-inflation relation and the results are generally consistent with the prediction based on the proxy effect hypothesis.

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ESSAY I

Short Sales Constraints and Price Informativeness

Abstract

This essay tests and supports the hypothesis that short sales constraints reduce price informativeness by hindering negative information from being fully incorporated into price. The analysis is based on a unique regulatory setting in the Hong Kong market. By using two measures for price informativeness, I find that stock prices become more informative when restrictions on short sales are lifted and less informative when the restrictions are re-imposed. The results are robust after controlling for the relevant firm characteristic variables which affect the equilibrium level of information in stock price. Further analyses demonstrate that allowing short sales mitigates the downward drift following negative earnings surprises and enhances the ability of stock prices to forecast future earnings.

1. Introduction

Short sales 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 sales constraints. Second, there are measures for price informativeness which can capture the asymmetric impact of short sales 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 sales constraints.

To date, direct tests on this relation have been sparse. The major obstacles to empirical work are lack of clear measures or data for short sales constraints and lack of good proxies for price informativeness. Previous studies have used short interest, institutional ownership, option listing and rebate rate as measures for short sales constraints[1]. However, these measures are either indirect or confined to a limited sample period. In this study, we overcome this obstacle by focusing on a unique regulatory

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[1] Figlewski (1981) uses short interest, Figlewski and Web (1993) and Danielsen and Sorescu (2001) use option listing status, Asquith, Pathak and Ritter (2005) use institutional ownership as measures for short sale constraints. Jones and Lamont (2002) use rebate rate in the period of 1926 to 1933 and Saffi and Sigurdsson (2008) use rebate rate in a period of 2004 to 2006.

setting in the Hong Kong market where there is a list of designated securities eligible for short selling revised from time to time. Stocks not on the list are subject to the extreme form of short sales 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, the list provides a binary measure for short sales constraints, and a history of the revisions to the list identifies a series of addition and deletion events around which we can examine the changes in price informativeness for the underlying stocks. So far, we have not found such well-recorded and long-period data on short sales constraints in other markets, which partially explains why the sample is taken from the Hong Kong market.

In this research, we begin with two measures for price informativeness with respect to negative information: sell-minus-buy probability of information-based trading and downside-minus-upside price non-synchronicity. The first measure, sell-minus-buy probability of information-based trading (PIN_{s-b}) is based on the microstructure model developed by Easley, Kiefer, and O'Hara (1996, 1997a, 1997b). It is derived from the same set of parameters used to compute the PIN ratio. The second measure, downside-minus-upside price non-synchronicity (Ψ_{d-u}), which has been used by Bris, Goetzmann, and Zhu (2007) in a recent study on short sales, is a variation of the price non-synchronicity measure first proposed by Roll (1988) and recently developed by Morck, Yeung, and Yu (2000).

Our two measures aim to identify the effect of short sales 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. In contrast, short sales constraints, which only impede negative information incorporation, would cause changes in the two measures. By taking an event study, we find that the two measures increase for stocks added into the list (short sales restrictions repealed) and decrease for stocks deleted from the list (short sales restrictions imposed). This 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; Boehmer, Jones and Zhang, 2008; Christophe, Ferri, and Hsieh, 2010). Repealing short sales restrictions attracts more informed trading, and thus increases the information contents in price. On the contrary, deletions from the list result in changes in the opposite direction.

The results from the event study are robust after controlling for the firm characteristics that are likely to affect private information incorporation. We show this by using panel data regressions with the firm characteristics as control variables. It is worth noting that if the control variables affect price informativeness in a symmetric way, i.e., affect both positive and negative information incorporation to the same extent, they should have little correlation with $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$, and any significant changes in the two measures around events can only be attributed to the changes in short sales constraints. However, if their impacts are asymmetric, our regression analysis is able to capture these possible asymmetries by generating significant estimates of their coefficients.

Recent literature shows that PIN is not a pure proxy for informed trading. High PIN firms tend to be those with larger order imbalances which are also a common feature of illiquid firms. In light of this, Duarte and Young (2009) propose an adjusted PIN measure that isolates informed trading from illiquidity by considering the possibility of symmetric shocks to order flow process. Since stocks are selected into the list of shortable stocks based on a set of rules largely related to liquidity, Duarte and Young

(2009)'s adjusted PIN squarely fits our aim.[2] As a robustness check, we replicate the tests using the adjusted PIN model and the results are generally consistent. We show that $AdjPIN_{s\text{-}b}$, an alternative proxy for informed selling relative to buying, significantly increases when stocks are added into the list, and decreases when stocks are removed from the list. PSOS, a proxy for illiquidity, deceases around both addition and deletion events, which possibly represents a trend of enhanced liquidity over time. The adjusted model also allows for different arrival rates of informed buy orders and sell orders, which enables us to directly examine the impact of short sales constraints on informed selling relative to informed buying by looking at the two rates.

Next, we offer additional evidence to support the relation between stock price informativeness and short sales constraints by considering the impact of short sales constraints on return-earnings relation. One approach is to consider the effect of short sales constraints on the post earnings announcement drift (PEAD), one of the well known anomalies in accounting and finance. If short sales lead to more informative prices,

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[2] It is worth noting that our previous results are less likely to be affected by the component that proxies for illiquidity in the original PIN. According to the selection rules, large and more liquid stocks are more likely to be included into the list, and if the intensity of informed trading remains unchanged, the original PIN around addition events should decrease as liquidity increases. In contrast, our results show that the original PIN actually increases, which indicates that the component that proxies for informed trading in the original PIN must increase to an extent that overrides the decrease in PIN due to the increase in liquidity.

lifting restrictions on short sales will mitigate the PEAD anomaly. Further, we expect that short sales constraints will have different impacts on downward and upward drifts. The downward drift following negative earnings surprises can be partially attributed to short sales constraints, and the upward drift following positive shocks should not be related to the constraints. This is because when negative unexpected earnings are announced, the investors who are the most pessimistic about future fundamentals may be prohibited from selling by short sales constraints. If those investors process information rationally, we can observe a downward drift following the announcements when their opinions become gradually incorporated into price. In contrast, because short sales constraints do not impede optimistic investors from trading, they are not likely to be a cause of the under-reaction to positive earnings surprises. In our research setting, we hypothesize that shortable stocks have smaller downward drifts following negative earnings surprises than non-shortable stocks, and there is little difference between them in the upward drifts. To test this hypothesis, we calculate the CARs (Cumulative Abnormal Returns) associated with each annual earnings announcement in the 30, 90 and 120 trading days following the announcement date. The results support our prediction. For non-shortable stocks, the CARs of the most negative SUE

(Standardized Unexpected Earnings) quintile are significantly below zero, which forms a downward drift. However, for shortable stocks, we find that the CARs of the most negative SUE quintile are not significantly below zero (even slightly positive). The CARs of the most positive SUE quintile for non-shortable and shortable stocks are all significantly positive, and there is no significant difference between non-shortable and shortable stocks.

The other approach linking short sales constraints and return-earnings relation is to assess whether short sales constraints reduce the ability of stock prices to forecast future earnings. We use the idea of future earnings response coefficient (FERC) formulated by Collins, Kothari, Shanken, and Sloan (1994). FERC is defined as the estimated coefficients 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 sales constraints, by preventing some of the value-relevant information about future earnings being capitalized into current price, are negatively correlated with FERCs. We evaluate this hypothesis in an event study analysis and find supporting evidence. After stocks are added into the list and become shortable, their FERCs show positive changes.

Finally, we subject our results to a number of robustness checks. First, we change the length of the event window used in the study. We report the results using a one-year event window, but 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. Last, our results remain unchanged with respect to the use of returns of different frequencies in the estimation of $\Psi_{d\text{-}u}$. We report the results using bi-weekly return data.

The remainder of the first part of this thesis is organized as follows. Section 2 reviews the related literature. Section 3 introduces the regulatory framework on short sales in the Hong Kong market and constructs the sample from the revision history of the short sales list. Section 4 explains the two measures for price informativeness. Section 5 reports the empirical results on the relation between short sales constraints and price informativeness. We also discuss the possible self-selection bias in this section. Section 6 extends the analysis to examine the return-earnings relation for shortable and non-shortable stocks, which consists of the two tests on PEAD and FERC. The last Section concludes.

2. Literature

Theoretical models of both Miller (1977) and Diamond and Verrecchia (1987) suggest that short sales constraints hinder negative information from being fully reflected in stock prices. Miller (1977) argues that when both heterogeneous opinions and short sales constraints are present, stocks tend to be overpriced as short sales 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 sales 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 sales constraints still reduce price informativeness by decreasing the accuracy of information incorporation.

Prior empirical studies on the relation between short sales 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 sales constraints. Figlewski (1981) measures short sales 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 sales constraints when put options are introduced. Jones and Lamont (2002) measure short sales 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 designated securities eligible for short selling. Diamond and Verrecchia (1987) was first tested by Senchark Jr. 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 at moments immediately after execution, they are instantaneously treated as bad news.

This research takes a different approach to investigate the relation between short sales 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 for price informativeness with respect to negative information and examine the changes in the two measures as short sales restrictions are removed. Such an approach avoids 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 sales 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 sales 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 sales constraints and price informativeness are both correlated with the development of financial markets, which could cause a spurious relation between short sales 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 rate of informed orders. These parameters all shed lights on the trading process through which information is incorporated into price. Third, we examine the impact of short sales constraints on price informativeness in the context of return-earnings relation. We establish a link between short sales constraints and post-earnings announcement drift, and show that allowing short sales mitigates the downward drifts following negative earnings surprises. Since less anomalous return behavior indicates more information in price, our results support a negative relation between short sales constraints and price informativeness. We also consider the ability of current stock prices to forecast future earnings, and find that the prices of shortable stocks contain more value-relevant information than those of non-shortable stocks. By doing so, we offer further evidence on the claimed relation.

3. The List of Securities Eligible for Short Selling

Seventeen stocks were first added into the list of designated securities eligible for short selling when the Stock Exchange of Hong Kong launched a pilot scheme for regulated short selling in January 1994[3]. In our sample period from Jan. 1994 to Nov. 2002, the list was revised 18 times[4], and as of Nov. 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.[5]

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[3] The seventeen stocks are listed in the Appendix.

[4] 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.

[5] 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.

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 according to a set of criteria mainly based on market capitalization, turnover and Index membership:

1. All constituent stocks of indices which are the underlying indices of equity index products traded on the Exchange;
2. All constituent stocks of indices which are the underlying indices of equity index products traded on HKFE;
3. All underlying stocks of stock options traded on the Exchange;
4. All underlying stocks of Stock Futures Contracts traded on the Hong Kong Futures Exchange;
5. Stocks which maintain a public float capitalization of not less than HK$1 billion for either (i) a period of 60 consecutive trading days during which dealings in such stocks have not been suspended; or (ii) a period of no more than 70 consecutive trading days comprising 60 trading days during which dealings in such stocks have not been suspended;
6. Stocks with market capitalization of not less than HK$1 billion and

an aggregate turnover during the preceding 12 months to market capitalization ratio of not less than 40%;

7. Tracker Fund of Hong Kong and other Exchange Traded Funds approved by the Board in consultation with the Commission;
8. All securities traded under the Pilot Program (i.e., the 17 stocks that were allowed to be sold short on January 1994).

According to the criteria, large stocks and actively traded stocks are most likely to be included in the list. Hence, there could be a self-selection bias in our results. The favorable changes in $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$ when stocks are added into the list could be attributed to some factors that are positively correlated with the probability of being selected into the list. This endogeneity issue is discussed in Section 5.4 where we show that our measure construction method, regression analysis, and tests using adjusted PIN can refute the self-selection explanation to our results.

Table 1 summarizes the historical revisions to the list from Jan. 3, 1994 to Nov. 29, 2002. Column 1 reports the revision dates. Columns 2 and 3 report the number of stocks added into and deleted from the list on each revision date. The data on the revision history are provided by the Stock Exchange of Hong Kong. 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, respectively. 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 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 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 to 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.

It is noted that the addition and deletions events are clustered around some event dates. Figure 1 shows the distribution of the addition and deletion events around the event dates. Panel A shows that 35% of the addition events are on May 1, 1997, and 27% of the addition events are on Mar. 25, 1996. Panel B shows that 51% of the deletion events are on Nov. 9 1998, and 27% on Dec. 3, 2001. Given such clustered events, our results could be driven by the changes in informational environment around some specific event dates. Furthermore, since over half of the deletion events are on Nov., 9, 1998, when the Hong Kong market experienced a sharp downturn due to the Asian Financial Crisis, the changes in our price informativeness measures around that date could only be a result of a sudden change in market sentiment and trading behavior. However, clustered events are not likely an alternative explanation to our results. As shown by the following section, we construct our measures for price informativeness to eliminate the impact of changes in general market conditions. Put differently, changes in our asymmetric price informativeness measures only reflect changes in short sales constraints, but not changes in other general factors around some specific event dates. In addition, we discard the addition events on May 1, 1997 and deletion events on Nov., 9, 1998 and use the rest to replicate our main tests. The results are not quantitatively different.

4. Measures for Price Informativeness

4.1. Sell-minus-buy PIN (PIN_{s-b})

Our first measure for price informativeness with respect to negative information, $PIN_{s\text{-}b}$, 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 information-based 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 that a trade comes from informed investors.

PIN has been widely applied in both finance and accounting research to explain information-based regularities of stock prices. The literature has used this measure to study the relation between informed trading and post-earnings announcement drift (Vega, 2006), sensitivity of corporate investment to stock price (Chen, Goldstein, and Jiang, 2007), corporate governance policy (Ferreira and Laux, 2007), structure of corporate board (Ferreira, Ferreira, and Raposa, 2007), conference calls (Brown, Hillegiest, and Lo, 2004), earnings surprises (Brown, Hillegiest, and Lo, 2009), and Regulation Fair Disclosure (Duarte, Han, Harford, and Young, 2008). Our study adds to the above literature by investigating the impact of short sales constraints on PIN.

In Easley, Kiefer, and O'Hara's structural model of PIN, 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 $\varepsilon_b(\varepsilon_s)$ 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 bad (good) news occurs, informed investors execute sell (buy) orders at a daily rate μ. Given some history of trades, the estimates of the model's parameters can be used to construct the probability that orders are from informed traders as follows,

$$\text{PIN}=\frac{\alpha\mu}{\alpha\mu+\varepsilon_s+\varepsilon_b}$$

where $\alpha\mu+\varepsilon_s+\varepsilon_b$ 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 sales constraints, it is important to differentiate how bad and good news is responded by informed traders. We define PIN_{sell} and PIN_{buy} as,

$$\mathrm{PIN}_{\mathrm{sell}} = \frac{\alpha\delta\mu}{\alpha\mu + \varepsilon_s + \varepsilon_b}, \qquad \mathrm{PIN}_{\mathrm{buy}} = \frac{\alpha(1-\delta)\mu}{\alpha\mu + \varepsilon_s + \varepsilon_b}$$

where $\alpha\delta\mu$ is the arrival rate of information-based sell orders, and $\alpha(1-\delta)\mu$ is the arrival rate of information-based buy orders. $\mathrm{PIN}_{\mathrm{sell}}$ ($\mathrm{PIN}_{\mathrm{buy}}$) is then the probability that trades are information-based sell (buy) orders. A higher $\mathrm{PIN}_{\mathrm{sell}}$ ($\mathrm{PIN}_{\mathrm{buy}}$) indicates more negative (positive) private information is incorporated into price through the trading of informed investors. Thus, the difference between them,

$$\mathrm{PIN}_{\text{s-b}} = \mathrm{PIN}_{\mathrm{sell}} - \mathrm{PIN}_{\mathrm{buy}}$$

measures the amount of negative private information relative to positive private information in price. If short sales are prohibited, bad news cannot be effectively incorporated into price through informed trading, we expect to see a lower $\mathrm{PIN}_{\mathrm{sell}}$. In contrast, since short sales constraints do not affect the incorporation of positive private information, $\mathrm{PIN}_{\mathrm{buy}}$ should not change. Therefore $\mathrm{PIN}_{\text{s-b}}$ highlights the effect of short sales constraints on price informativeness with respect to negative information. A change in $\mathrm{PIN}_{\text{s-b}}$ is most likely caused by changes in short sales constraints. In our study, we focus on the change in $\mathrm{PIN}_{\text{s-b}}$ around addition and deletion events, and also examine the changes in $\mathrm{PIN}_{\mathrm{sell}}$ and $\mathrm{PIN}_{\mathrm{buy}}$ to know the source of the change in $\mathrm{PIN}_{\text{s-b}}$.

The set of parameters in the PIN model, $\theta = \{\alpha, \delta, \mu, \varepsilon_s, \varepsilon_b\}$, 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 specific 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 be submitted during the regular trading hours of the Stock Exchange of Hong Kong. Irregular trades are excluded in the estimation. For quotes, we eliminate those with bid-ask spreads that are greater than half of 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. The bid-ask data and the trade record data are provided by the

Stock Exchange of Hong Kong.

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

4.2. Downside-minus-upside Price Non-synchronicity

Our second measure, downside-minus-upside price non-synchronicity (Ψ_{d-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 price non-synchronicity) is indicative of either greater amount of private information or noise in price because systematic risk and public information seem to explain only a small portion of the return variation. Morck, Yeung and Yu (2000) support the informational view of R-square by showing 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 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; Fernandes and Ferreira, 2008). The key to our study is to extend the use of R-square to capturing the asymmetric impact of short sales constraints on the incorporation of negative and positive information into stock prices. Bris, Goetzmann, and Zhu (2007) propose downside-minus-upside R-square as such an extension. We follow their approach to define downside-minus-upside price non-synchronicity ($\Psi_{d\text{-}u}$) to measure price informativeness with respect to negative information.

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

$$r_t = \alpha^- + \beta^- r_{m,t}^- + \varepsilon_t^- , \qquad r_t = \alpha^+ + \beta^+ r_{m,t}^+ + \varepsilon_t^+$$

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. The return data are collected from the Pacific-Basin Capital Markets (PACAP) Research Database. We compute the R-squares for the two regressions, denoted by R_d^2 and R_u^2, respectively, and then do the following logarithm transformations,

$$\Psi_{\text{down}} = \log\left(\frac{1-R_d^2}{R_d^2}\right), \qquad \Psi_{\text{up}} = \log\left(\frac{1-R_u^2}{R_u^2}\right).$$

Downside-minus-upside price non-synchronicity, $\Psi_{\text{d-u}}$, is defined as the difference between Ψ_{d} and Ψ_{u},

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

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 price non-synchronicity 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 sales constraints, one must control for the change in equilibrium level of private information in price. If the factors other than short sales constraints have a symmetric effect on the equilibrium level of negative and positive information, a change in $\Psi_{d\text{-}u}$ can only be ascribed to changes in short sales constraints. In our research setting, we expect $\Psi_{d\text{-}u}$ to increase when stocks are added into the list and decrease when stocks are removed from the list.

In this study, we compute $\Psi_{d\text{-}u}$ 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 $\Psi_{d\text{-}u}$ is computed using the data from quarter *t-4* to *t-1*, and the post-addition $\Psi_{d\text{-}u}$ is computed using the data from quarter *t+1* to quarter *t+4*. Pre-deletion and post-deletion $\Psi_{d\text{-}u}$s are defined similarly. In the regression analysis, we compute calendar year $\Psi_{d\text{-}u}$ for all the stocks in the Hong Kong market, and then match the firm year $\Psi_{d\text{-}u}$ to a short sales dummy and the control variables. The results are not sensitive to the use of weekly return data in computing $\Psi_{d\text{-}u}$.

5. Short Sales Constraints and Price Informativeness

This section reports the empirical results on three groups of tests. First, we examine the changes in sell-minus-buy PIN and downside-minus-upside price non-synchronicity 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 designated 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 using the PIN and Ψ estimates for all Hong Kong firms. Third, we use Duarte and Young (2009)'s adjusted PIN model to separate information from liquidity. The results are consistent with our predictions. We discuss the possible self-selection bias in the last subsection. Although use of a control sample is natural in addressing our research question, for example, we could look at changes in the price informativeness measures around event dates relative to a sample of firms which have similar sizes but are not subject to changes in short sales regulations, we do not take such approach for three reasons. First, we cannot find firms with close market values to sample firms. Though on average the number of the sample firms is only one-fifth of the total number of firms in the Hong Kong market, the sample firms are all large firms and have an aggregate market value of over 80% of the total market value. Second, our measure construction method implicitly controls for the general changes in market conditions. In fact, we control for other factors by using PIN_b and Ψ_u of the same firms. Any changes other than short sales constraints will also affect PIN_b and Ψ_u and leave PIN_{s-b} and Ψ_{d-u} unchanged. Third, in the panel regressions, we are not confined to the sample firms and use all the firms in the Hong Kong market to construct the tests.

5.1. Event-study Analysis

5.1.1. PIN_{s-b} and Ψ_{d-u} around Addition Events

Table 2 summarizes the changes in PIN_{s-b} and Ψ_{d-u} around addition events. Figure 2 visualizes the results. Since we use a 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 4) 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 Nov. 29, 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 change and the last column reports the *t*-statistics of a paired *t*-test and Wilcoxon signed rank test.

As shown by Panel A, $PIN_{s\text{-}b}$ increases significantly around addition events. The mean of $PIN_{s\text{-}b}$ increases from -0.074 to -0.05 and the median increases from -0.08 to -0.05. Both changes are significant, as shown by the *t*-values 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 negative change of -0.008. Hence the change in $PIN_{s\text{-}b}$ is mainly driven by the change in PIN_{sell}, the probability of informed selling. This result supports our prediction that short sales 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 changes in the individual parameters from pre- to post-addition period 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 sales 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, the 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 sales constraints are removed. Last, though we do not make predictions about ε_b and ε_s, they are most likely to increase. It is because the introduction of the options and warrants following addition events will increase the trading for hedging purposes. This kind of trading is not information-based, and 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. In general, the results on PIN support our hypothesis that allowing short sales triggers more informed selling activity and thus conveys more private information into stock price.

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 the 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 Ψ_{d-u} when stocks are added into the list and become shortable. Around additions, the mean of Ψ_{d-u} changes from -0.348 to 0.502, and the median of Ψ_{d-u} changes from -0.223 to 0.557. The *t*-values of the paired *t*-test and the Wilcoxon test are all significant. Panel B shows that the increase in Ψ_{d-u} is mainly due to the increase in Ψ_{down}, which has a positive change of 0.905 or 50.3% in percentage terms. Ψ_{up} only shows an insignificant positive change of 2.5% in percentage terms. In general, our results on downside-minus-upside price non-synchronicity support Bris, Goetzmann, and Zhu (2007) on the individual stock level.

5.1.2. PIN_{s-b} and Ψ_{d-u} around Deletion Events

Table 3 presents the results on deletion events. Figure 3 visualizes the results. 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-b} and Ψ_{d-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 by Panel A, the mean and median of PIN_{s-b} show significant decreases around deletion events. The mean PIN_{s-b} in the pre-deletion period is -0.044 while the mean PIN_{s-b} in the post-deletion period is -0.075. The median changes from -0.051 to -0.077. The changes in mean and median are all significant. We also find that the decrease in PIN_{s-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 sales constraints reduce price informativeness by impeding informed selling. The individual parameters also show changes in the predicted directions. The probability of information arrival, the probability that the information is bad news, and the arrival rates of informed trading all decrease when short sales restrictions are re-imposed.

In Panel B, the downside-minus-upside price non-synchronicity 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, Ψ_{d-u}, reflects the effect of short sales constraints on price informativeness and it decreases around deletions. However, though Ψ_{d-u} shows a change in predicted direction, the change is not significant. In the regression analysis, we show that after controlling for firm characteristic variables, the relation becomes significant.

5.2. Regression Analysis

In this subsection, we investigate the relation between short sales constraints and price informativeness using panel regressions. This allows us to control for the other factors that can affect the equilibrium level of private information in price. We show that after controlling for those factors, shortable stocks still have a higher level of private information in their prices.

The methodology is as follows. First, we estimate quarterly PIN and yearly Ψ for all the stocks in the Hong Kong market, and form a panel dataset of all the estimates. Table 4 reports the summary statistics of PIN and Ψ for all the Hong Kong Firms. Second, we match firm characteristic variables to each estimate. Third, we match a dummy variable to each estimate based on the eligibility for short selling of the underlying stock in the estimation period. Last, we run panel regressions of the estimates on firm characteristics and the short sales dummy to see if the short sales dummy is significant or not. The previous event study mainly focuses on the time series change in price informativeness for the same stock when short sales restrictions are removed or re-imposed. In the regression framework, we are able to detect the cross-sectional difference in price informativeness between shortable and non-shortable stocks as well as the time series difference.

5.2.1. Regressions of PIN

We use the following model to test the relation between PIN and short sales constraints,

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

where $PINx_{i,t}$ denotes $PIN_{s\text{-}b}$, PIN_{sell} or PIN_{buy} of stock i in quarter t, $SSD_{i,t}$ is a dummy variable that takes value one if stock i is shortable throughout quarter t, and zero otherwise, $SSR_{i,t}$ is the average short sale ratio of stock i in quarter t where the short sale ratio is defined as daily dollar value of the shares sold short divided by daily dollar trading volume, $SIZE_{i,t}$ is the logarithm of market capitalization at the end of quarter $t-1$, $B/M_{i,t}$ is the logarithm of book to market ratio defined as book value of equity divided by market capitalization at the end of quarter t-1, $LEV_{i,t}$ is leverage ratio defined as long term debts divided by total assets at the end of quarter $t-1$, $ROE_{i,t}$ is return on equity defined as net income divided by lagged book value at the end of quarter *t-1*, $RET_{i,t}$ is the average monthly return over quarter *t-4* to *t-1*, $VRET_{i,t}$ is the standard deviation of the monthly return over quarter *t-4* to *t-1*, $TT_{i,t}$ is the average monthly turnover over quarter *t-4* to *t-1*, and $VTT_{i,t}$ is the standard deviation of the monthly turnover over quarter *t-4* to *t-1*. Accounting information in the latest financial report is used in constructing the variables. Heteroskedasticity and serial correlation robust *t*-statistic are reported in parentheses. The sample period is from 1993:Q1 to 2003:Q4 and we only use industrial firms in regressions with control variables. The accounting and market capitalization data are collected from the PACAP Database and the short sales ratio data are from the Stock Exchange of Hong Kong.

Basically we compute quarterly $PIN_{s\text{-}b}$, PIN_{sell} and PIN_{buy} for all the stocks listed in the Stock Exchange of Hong Kong, and determine the value of the short sales dummy for each firm quarter by referring to the list of designated securities eligible for short selling. In doing so, our analysis is not confined to the event firms in Section 5.1, and captures the cross-sectional as well as time series difference in the informativeness measures. If short sales constraints reduce price informativeness, we expect the coefficient on the short sales dummy (*SSD*) is positive.

We also use short sales ratio (*SSR*) as an alternative test variable to the short sales dummy (*SSD*). Previous studies have shown that short sales are most likely to be informed. This is not surprising given the high costs associated with short sales. Boehmer, Jones and Zhang (2008) partition short sales by account type and find that institutional non-program short sales are the most informative. Because in the Hong Kong market, almost all the short sales are conducted by the institutional investors,[6] high short sales ratio (*SSR*) is likely to indicate more value-relevant information in price. To capture the possible functional relation, we use *SSR* as an alternative test variable to *SSD* in some models.

Table 5 reports the regression results. For each dependent variable ($PIN_{s\text{-}b}$, PIN_{sell} and PIN_{buy}), we use four groups of independent variables: *SSD* only, *SSD* with control variables, *SSR* only and *SSR* with control variables. We also control for fixed firm effects in the regressions with only *SSD* or *SSR* as the independent variable, and control for fixed year effects in the regressions with the full set of control variables. Altogether, we have 3*4=12 different model specifications labeled as M1 to M12. In regressions M1 to M4 (The regressions with $PIN_{s\text{-}b}$ as the dependent variable), the coefficients on *SSD* and *SSR* are all significantly positive. As shown by the coefficient on *SSD* in M1, the average $PIN_{s\text{-}b}$ of shortable

[6] We consulted a local broker on this issue. Though there are no regulations banning short sales by individual investors, they seldom short because of the complicated procedures and rigid capital requirements.

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. 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 sales ratio is higher than that of stocks with low short sales ratio. In contrast, lifting short sales restrictions does not help enhance the informed buying. The results on regressions M9 to M12 (The regressions with PIN_{buy} as the dependent variable) actually record negative coefficients on *SSD* and *SSR*. In general, our results suggest that short sales enhance price informativeness by increasing the amount of negative private information built into stock prices.

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 $\text{PIN}_{\text{s-b}}$. 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 $\text{PIN}_{\text{s-b}}$. Return on equity (*ROE*) is negatively related to PIN_{sell}, but is not significantly related to PIN_{buy} or $\text{PIN}_{\text{s-b}}$. The insignificant coefficients in the regressions of $\text{PIN}_{\text{s-b}}$ show that most of the control variables have a symmetric impact on the incorporation of negative and positive information.

5.2.2. Regressions of Price Non-synchronicity

We use a similar model to test the relation between PIN and short sales constraints,

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

where $\Psi x_{i,t}$ denotes $\Psi_{\text{d-u}}$, Ψ_{down} or Ψ_{up} of stock i in year t, $SSD_{i,t}$ is a dummy variable that takes value one if stock i is shortable throughout year t, and zero otherwise, $SSR_{i,t}$ is the average short sale ratio of stock i in year t where the short sale ratio is defined as daily dollar value of the shares sold short divided by daily dollar trading volume, $SIZE_{i,t}$ is the logarithm of market capitalization at the end of year $t-1$, $B/M_{i,t}$ is the logarithm of book to market ratio defined as book value of equity divided by market capitalization at the end of year $t-1$, $LEV_{i,t}$ is leverage ratio defined as long term debts divided by total assets at the end of year $t-1$, $ROE_{i,t}$ is return on equity defined as net income divided by lagged book value at the end of year $t-1$, $RET_{i,t}$ is the average monthly return in year $t-1$, $VRET_{i,t}$ is the standard deviation of the monthly return in year $t-1$, $TT_{i,t}$ is the average monthly turnover in year $t-1$, and $VTT_{i,t}$ is the standard deviation of the monthly turnover in year *t-1*. Accounting information in the latest financial report is used in constructing the variables. Heteroskedasticity and serial correlation robust *t*-statistic are reported in parentheses. The sample period is from 1993:Q1 to 2003:Q4 and we only use industrial firms in regressions with control variables.

The testing framework is the same as that of the PIN ratios, except that we use yearly estimates of Ψ_{down} and Ψ_{up}, and make corresponding changes to the computation and matching of *SSD*, *SSR* and other control variables. Similarly, regressions M1 to M4 use $\Psi_{d\text{-}u}$, regressions M5 to M8 use Ψ_{down} and regressions M9 to M12 use Ψ_{up} as the dependent variable. Table 6 presents the results. We document positive coefficients on *SSD* and *SSR* in regressions M1 to M8, and negative coefficients on *SSD* in regressions M9 to M12. This is consistent with the results on PIN ratios. As shown by the coefficients on *SSD* in M1, M5 and M9, the average $\Psi_{d\text{-}u}$ 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 reduces the spread to 0.375. As for the control variables, firm size (SIZE) is negatively related to both Ψ_{down} and Ψ_{up}, and not related to $\Psi_{d\text{-}u}$. Book to Market (B/M) is also negatively correlated with Ψ_{down} and

Ψ_{up}, and not correlated with $\Psi_{d\text{-}u}$. Return on equity (ROE) has a positive relation with Ψ_{down}, a negative relation with Ψ_{up}, and hence a positive relation with $\Psi_{d\text{-}u}$. The results on price non-synchronicity generally conform to our prediction.

5.3. Robustness with Adjusted PIN Model

In this subsection, we replicate the previous tests using an adjusted PIN model developed by Duarte and Young (2009). Recent literature has argued that the original PIN is a biased measure of price informativeness, and the bias, to a large extent, is related to liquidity. This view is consistent with the observed fact that PIN is negatively related to firm size and turnover, which are all proxies for liquidity. In the original construction, stocks with low levels of trading in most of days and high imbalanced orders in some days will be identified as high PIN stocks. However, this order flow pattern is also common for illiquid stocks. Most likely PIN will have two components, one related to informed trading, and the other related to liquidity. The inability of the original PIN to isolate informed trading from illiquidity matters for our inference, because based on the selection rules, stocks are very likely to experience changes in liquidity around addition and deletion events. For instance, the documented increase in PIN around addition events could be driven by a decrease in liquidity rather than an increase in information-based trading. Although this is less likely the case because the inclusion into the list actually indicates an increase in liquidity, a measure that separates informed trading from liquidity should be more appropriate to address our question. Duarte and Young (2009)'s adjusted PIN model provides such a choice.

The basic structure of Duarte and Young (2009)'s adjusted PIN model is the same with that of the original one. However, they consider a new scenario in which both buy and sell orders increase in certain periods which are not explained by informed trading or liquidity trading. Such symmetric shocks to buy and sell order flows may be a result of disagreement on some value-relevant news among investors, or coordinated action of investors to reduce transaction costs. Duarte and Young (2009) find that this new model structure summarizes the order flow process more accurately and generate moments that are consistent with the observed order flow data, while the original set-up fails to correctly accommodate the large variances of buy and sell orders and the positive correlation between them. The insufficiency of the original model introduces a bias in its estimate of probability of informed trading. Specifically, those firms with higher probability or larger magnitude of symmetric order flow shocks are erroneously identified with high PINs, whereas they are more likely to be illiquid firms.

The adjusted PIN model is formed as follows. Similar to the original construction, an information event occurs with probability α, and the probability that the information is bad news is δ. When the information is good news, informed traders submit buy orders at rate μ_b, and submit sell orders at rate μ_s when the information is bad news. Uniformed investors submit buy (sell) orders at rate ε_b (ε_s) regardless of the occurrence of information event. The adjusted model allows for a symmetric order flow shock that happens with unconditional probability θ, and when it happens, buy orders increase by a rate of λ_b, and sell orders increase by a rate of λ_s. Similarly, the parameter set, $\{\alpha, \delta, \mu_b, \mu_s, \varepsilon_b, \varepsilon_s, \theta, \lambda_b, \lambda_s\}$, can be estimated by maximizing a likelihood function with six items, each corresponding to a branch of trading[7]. The adjusted probability of informed trading, AdjPIN is thus defined as,

$$\text{AdjPIN} = \frac{\alpha(\delta\mu_\text{s} + (1\text{-}\delta)\mu_\text{b})}{\alpha(\delta\mu_\text{s} + (1\text{-}\delta)\mu_\text{b}) + \theta(\lambda_\text{b} + \lambda_\text{s}) + \varepsilon_\text{b} + \varepsilon_\text{s}}.$$

The new item in the denominator, $\theta(\lambda_\text{b} + \lambda_\text{s})$, captures the impact of the symmetric order flow shock on order patterns. Duarte and Young

[7] To save space, we do not present the likelihood function here. Please refer to Duarte and Young (2009, p. 123) for the complete likelihood function.

(2009) further defines probability of order flow shock, PSOS, as,

$$\mathrm{PSOS} = \frac{\theta(\lambda_{\mathrm{b}}+\lambda_{\mathrm{s}})}{\alpha(\delta\mu_{\mathrm{s}}+(1\text{-}\delta)\mu_{\mathrm{b}})+\theta(\lambda_{\mathrm{b}}+\lambda_{\mathrm{s}})+\varepsilon_{\mathrm{b}}+\varepsilon_{\mathrm{s}}}.$$

The PSOS measure is the probability that a given trade is due to a symmetric order flow shock. Duarte and Young (2009) show that PSOS is positively related to average stock returns while AdjPIN is not. Given the fact that PSOS is positively related to other measures of illiquidity and illiquidity is a priced factor, they conclude that PSOS is a proxy for illiquidity extracted from trading process. Hence, AdjPIN is a cleaner measure of informed trading because high order flow imbalance caused by order flow shocks, which indicates illiquidity, should be captured by high PSOS, but not by AdjPIN.

To isolate the effect of short sale constraints on informed trading, we also define $\mathrm{AdjPIN}_{\mathrm{sell}}$, $\mathrm{AdjPIN}_{\mathrm{buy}}$ and $\mathrm{AdjPIN}_{\mathrm{s\text{-}b}}$ as,

$$\mathrm{AdjPIN}_{\mathrm{sell}} = \frac{\alpha\delta\mu_{\mathrm{s}}}{\alpha(\delta\mu_{\mathrm{s}}+(1\text{-}\delta)\mu_{\mathrm{b}})+\theta(\lambda_{\mathrm{b}}+\lambda_{\mathrm{s}})+\varepsilon_{\mathrm{b}}+\varepsilon_{\mathrm{s}}},$$

$$\mathrm{AdjPIN}_{\mathrm{buy}} = \frac{\alpha(1-\delta)\mu_{\mathrm{b}}}{\alpha(\delta\mu_{\mathrm{s}}+(1\text{-}\delta)\mu_{\mathrm{b}})+\theta(\lambda_{\mathrm{b}}+\lambda_{\mathrm{s}})+\varepsilon_{\mathrm{b}}+\varepsilon_{\mathrm{s}}},$$

$$\mathrm{AdjPIN}_{\mathrm{s\text{-}b}} = \mathrm{AdjPIN}_{\mathrm{sell}} - \mathrm{AdjPIN}_{\mathrm{buy}}.$$

Our predictions on the changes of the three measures around addition or deletion events correspond to those for the original PINs. We replicate the event study and the panel regressions using the adjusted measures. We also look at the changes in PSOS, though we do not make predictions on the change in PSOS.

It is worth noting that in the original model, the arrival rates of buy and sell orders are both equal to μ. In contrast, the adjusted model allows for different arrival rates of informed buy orders and sell orders. This adjustment is also relevant to our research. If inclusion into the list induces more informed short selling, we expect to see an increase in μ_s around addition events, and a decrease around deletion events. As short sales restrictions do not affect informed buying, we expect μ_b to remain relatively constant around events.

Table 7 reports the changes in AdjPIN measures around addition events. Consistent with our prediction, the average $\text{AdjPIN}_{\text{s-b}}$ increases from -0.019 to -0.007 around additions, and the change is mainly due to the increase in $\text{AdjPIN}_{\text{sell}}$. PSOS decreases around additions, which indicates enhanced liquidity. This finding is consistent with the selection rules that more liquid stocks are more likely to be included into the list. As for the individual parameters, μ_s shows a positive change, which implies increased informed short selling after additions; the informed buying, as shown by μ_b, shows only an insignificant change. In comparison, Table 8 gives the results on deletion events. As expected, $\text{AdjPIN}_{\text{s-b}}$ decreases from 0.003 to -0.02, which is caused by a decrease in $\text{AdjPIN}_{\text{sell}}$ and an increase in $\text{AdjPIN}_{\text{buy}}$. PSOS also shows a negative change, which is not surprising given the possibility of a general market enhancement in liquidity with time. However, μ_s shows an insignificant change around deletions. This finding does not contradict with our story either because μ_s measures the level of informed trading but we are more concerned with the fraction of informed sell orders to total orders. If we look at other estimates of trading intensity around deletions, like ε and λ, they all show significant decreases around deletions. These facts indicate a decrease in trading when stocks are removed from the list, but informed selling decreases to a larger extent. The liquidity enhances despite of the decreased trading, possibly because there is a decrease in the frequency of symmetric order flow shocks, as shown by a decreased θ.

Table 9 reports the panel regression results using the adjusted PINs. The results are consistent with those on the original measures. The coefficients on *SSD* in the regressions of $\text{AdjPIN}_{\text{s-b}}$ and $\text{AdjPIN}_{\text{sell}}$ are all significant except for M2, and $\text{AdjPIN}_{\text{buy}}$ does not show significant difference for shortable and non-shortable stocks.

It should be pointed out that using the AdjPIN is not without any problem. As the adjusted model adds a few new parameters to the original model, its estimation becomes extremely time-consuming. The AdjPIN does not look like an easily accepted measure in practice yet, to replace the original PIN. Thus, we take the analysis with the AdjPIN as a robustness check in this study.

5.4. Self-Selection Bias

According to the selection criteria of the exchange, large stocks and liquid stocks are most likely to be included in the list. This introduces a possible self-selection bias into our tests with PIN and Ψ. The enhancement in price informativeness could be a result of increased market capitalization, turnover, or inclusion into indices. Moreover, because the exchange did not publicize the selection criteria until February 2001, the selection before 2001 could be based on other factors governing the equilibrium level of information contained in price. However, we contend that self-selection bias is less likely an explanation to our results based on the following three facts. First, we have constructed the two measures to isolate the effect of short sales constraints on price informativeness. PIN_{s-b} (Ψ_{d-u}) is constructed as the difference between PIN_{sell} (Ψ_{down}) and PIN_{buy} (Ψ_{up}). If the quality of the overall informational environment enhances, both PIN_{sell} (Ψ_{down}) and PIN_{buy} (Ψ_{up}) will increase, and PIN_{s-b} (Ψ_{d-u}) should remain unchanged. The inclusion into the list implies a possible positive change in the overall informational environment, and should not be directly related to PIN_{s-b} (Ψ_{d-u}). Hence, our event study tests are immune to the self-selection bias. Second, as market size and turnover are the two most important factors considered by the exchange (index membership is also largely dependent on size and turnover), we explicitly control for them in the regressions. The results show that both market size and turnover are insignificant in the regressions with PIN_{s-b} and Ψ_{d-u} as the independent variable. This is not surprising given that variations in those two characteristics most likely reflect a change in the overall informational environment. Last, the results using the adjusted PIN model show that informed trading increase (decrease) around addition (deletion) events, after excluding the liquidity factor in the original PIN measure. As liquidity is an important index used by the regulators, the results indicate our conclusion is not induced by the change in liquidity around events.

6. Short Sales Constraints and Return-Earnings Relation

It is noted that our testing results obtained so far are conditional on the validity of the two measures for price informativeness. Therefore, it is indispensable to investigate our issue from tests independent of the two measures. This section conducts two of such tests, both on the relation between short sales constraints and return-earnings relation. First, we examine the post-earnings announcement drift for shortable and non-shortable stocks and show that shortable stocks have smaller drift following negative earnings surprises than non-shortable stocks. Then we look at the changes in future earnings response coefficient (FERC) as short sales restrictions are lifted. We find that FERCs increase as stocks are added into the list and become shortable.

6.1. Short Sales Constraints and PEAD

In this subsection, we look at the relation between short sales constraints and the post-earnings announcement drift (PEAD) anomaly. The post-earnings announcement drift is the tendency for stocks to earn positive (negative) abnormal returns in the three quarters subsequent to extreme positive (negative) earnings surprises. Since the seminal paper of

Ball and Brown (1968), numerous studies have documented this phenomenon. Early studies try to interpret PEAD in a rational expectation framework and have failed to fully account for the drift. Recent studies have turned to behavior finance and attribute the cause of PEAD to investors' under-reaction to earnings news (e.g., Bernard and Thomas, 1989, 1990; Ball and Bartov, 1996; Barberis, Shleifer and Vishny, 1998).

We hypothesize that short sales constraints partially cause the negative PEAD, but they do not affect the positive drift. The logic is as follows. Using the U.S. sample, Vega (2006) shows that high PIN firms have smaller PEAD following both positive and negative earnings surprises. This is interpreted by the fact that high PIN firms have more informative prices. Now put it into our research setting. If allowing short sales leads to more informative prices, in particular with respect to negative information, we then should expect that lifting restrictions on short sales mitigates the PEAD anomaly following negative earnings shocks, but not positive shocks. Theoretically, we argue that when negative unexpected earnings are announced, the investors, who are the most pessimistic about future fundamentals, may be prohibited from selling by short sales constraints. If those investors' view is correct, we can observe a downward drift following the announcements when their opinions become gradually incorporated into price. In contrast, because short sales constraints do not impede optimistic investors from trading, they are not likely a cause of the under-reaction to positive earnings surprises. Empirically, we predict that the magnitude of the drift following negative surprises is smaller for shortable stocks than for non-shortable stocks, and there is no difference in the positive drift.

However, it is hard to argue that if short sales mainly cause price manipulations or market panics, the negative PEAD should be mitigated following negative earnings shocks. To the contrary, we expect that manipulations or panics due to short sales would make the negative PEAD stay either increased or unchanged. The reason is that manipulations or panics would add more noises into prices, so as to make the stock prices less informative. Based on the findings by Vega (2006), less informative stock prices lead higher or conservatively unchanged PEAD.

Our methodology is as follows. From Jan. 01, 1992 to Dec. 31, 2004, we classify all the annual earnings announcements in the Hong Kong market into two groups based on the eligibility for short selling of the underlying stocks. A stock is identified as shortable if it is on the list of securities eligible for short selling. We then sort the announcements in each group into quintiles based on the standardized unexpected earnings

(SUE). We define SUE as (Actual Earnings -Mean Analyst Forecast) / (Std. Dev. of Analyst Forecasts) using the I/B/E/S data. We then calculate the average abnormal returns (CARs) of the quintiles of non-shortable group and shortable group. Abnormal returns are excess returns over size and B/M matched portfolios (3*3) formed on Jan. 1 and June 1 of each year.

Table 10 presents the results. We report average CARs of each quintile in 30 and 60 days before announcements, 3 days around announcements, and 60, 90 and 120 days after announcements. Panel A reports the results on non-shortable stocks and Panel B reports the results on shortable stocks. For the non-shortable group, there are significant negative drifts in 60, 90 and 120 days following extreme unexpected earnings. The average CAR (+2, +61), CAR (+2, +91) and CAR (+2, +121) of the extreme negative quintile are -1.32, -5.15 and -4.777, respectively. The CARs of quintile 5 (extreme positive quintile) also show a significant positive drift following announcements. For shortable stocks, most noticeably, the negative drift turns insignificant. The average CAR (+2, +61), CAR (+2, +91) and CAR (+2, +121) of the extreme negative quintile for the shortable group are 0.958, 0.771 and 0.632, respectively. All of them are insignificant. In contrast, there is still a positive drift for the shortable group as shown by the average CARs of quintile 5. In general, the results show that allowing short sales significantly reduces the drift following negative earnings surprises. Though we find no significant negative drift for shortable stocks, we do not conclude that short sales constraints fully account for the negative drift given a small sample size in our study. Apparently, our findings work against the prediction from the manipulation or panic story of short sales.

6.2. Short Sales Constraints and FERC

In this subsection, we evaluate whether short sales constraints reduce the ability of stock prices to forecast future earnings. This is analyzed by using the FERC, a measure capturing how well current stock prices predict future earnings. As interpreted by Durnev, Morck, Yeung, and Zarowin (2003), higher values of the measure indicate that current returns capitalize more information about future earnings. If removing restrictions on short sales means more informative stock prices, we anticipate finding higher FERCs for shortable stocks than for non-shortable stocks. Therefore, we hypothesize that FERCs increase as stocks are added into the list and become shortable. But the manipulation or panic story of short sales implies the opposite changes in FERCs. Manipulations or panics, if effective, mean more noises added into stock prices. Noises reduce rather than enhance the ability of stock prices to forecast future earnings.

Collins, Kothari, Shanken, and Sloan (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-1* to *t*, where the earnings are defined as the income available for common shares before extraordinary items deflated by the market value of equity three months after *t-1* fiscal year end. 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. b_0 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 also 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 $t+3$ 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 $\Psi_{d\text{-}u}$. 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. Ideally, we could also estimate downside-minus-upside FERC by separately considering negative and positive future earnings changes. However, given the rigid data requirements of the FERC model, it is not feasible to construct a difference measure like $PIN_{s\text{-}b}$ or $\Psi_{d\text{-}u}$. Thus we stick to the original FERCs in this subsection. The earnings and return data are collected from the PACAP Database.

The results are presented in Table 11. Panel A gives the results on the combined model. Panel B reports the results on the full model. Figure 4 visualizes results of 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 sales 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 $FERC_1$, $FERC_2$ and $FERC_3$ 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 $FERC_3$ 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 $FERC_1$, $FERC_2$ and $FERC_3$ 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,

$$
\begin{aligned}
R_{i,t} &= a_0 + b_0 \Delta E_{i,t} + b_1 \Delta E3_{i,t} + c_0 SSD_{i,t} + d_0 SSD_{i,t} * \Delta E3_{i,t} \\
&+ e_0 \mathrm{R}3_{i,t} + f_0 D_{i,t} * \mathrm{R}3_{i,t} + g_0 Control_{i,t} + h_0 Control_{i,t} * \Delta E3_{i,t} + \varepsilon_{i,t}
\end{aligned}
$$

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 12. 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. Overall, our results support the information story of short sales constraints; the manipulation or panic interpretation of short sales constraints is very unlikely to be true.

7. Conclusion

Short sales constraints have been a research topic in finance for centuries. However, the impact of imposing or lifting the constraints on stock prices remains controversial. Opposing views exist among academicians, practitioners and market regulators. Primarily, academicians and practitioners largely favor removing the constraints as otherwise equilibrium share prices might be distorted. Most regulators, however, hold the opposite view: they believe that short sales are likely to cause price manipulations and market panics, in particular during times of stock market tumbling. On basis of this concern, short sales are prohibited in many emerging markets; even in markets where short sales are allowed, they are often subject to heavy regulations and high costs. This study contributes to the literature by empirically examining this issue, based on unique short selling data in the Hong Kong market.

We find strong evidence to support the hypothesis that short sales constraints hinder negative information from being fully incorporated into stock price and thus make price less informative. Our analysis starts with two measures for price informativeness: the sell-minus-buy PIN and the downside-minus-upside price non-synchronicity. By construction, the higher the values of the two measures are, the more informative stock prices are. Preliminarily, we find that both measures increase when short sales restrictions are removed, and decrease when short sales restrictions are re-imposed. Next, we run panel regression analysis and find a strong negative relation between short sales constraints and the two measures. Finally, we offer consistent and supporting evidence from two additional analyses. One analysis is to link short sales constraints to the PEAD phenomenon. Our results show that PEADs become much smaller for stocks in the list, following negative earnings shocks. The other analysis finds that short sales constraints reduce the ability of stock price to forecast future earnings. Overall, our findings suggest that short sales constraints lead to less informative stock prices while the price manipulation or panic story of short sales does not seem to be true.

ESSAY II

Re-Examining Return-Inflation Relation: A Cross-Sectional Analysis

Abstract

This essay investigates the cross-sectional pattern of the relation between stock returns and inflation. Previous studies have shown a negative relation between stock returns and both expected and unexpected inflation on the market level, which contradicts the Fisher's theory and the conventional wisdom. Two explanations have been suggested in the literature. The proxy effect hypothesis states that the negative relation is merely a proxy for the negative relation between expected future real economic activity and inflation, and the money illusion hypothesis assumes that investors erroneously discount real earnings by nominal discount rates. In this thesis, I support the rational explanation to the negative return-inflation relation by examining the cross-sectional pattern of return-inflation betas. I show that, consistent with the proxy effect hypothesis, there is much cross-sectional variation in return-inflation betas, and further the cross-sectional variation in return-inflation betas can be explained by the differential associations between firm fundamentals and inflation. I also examine the impacts of some observable firm characteristic variables on the return-inflation relation and the results are generally consistent with the prediction based on the proxy effect hypothesis.

1. Literature

The relation between stock returns and inflation has been an important topic in finance for decades. Theoretically the expected nominal returns of common stocks should be equal to the equilibrium adjusted real returns plus expected inflation rate. This notion, generally known as the Fisher's hypothesis (Fisher, 1930), can be easily appreciated since in an efficient market no one would invest if they are not fully compensated for the erosion in purchasing power. However, there is no theory governing the relation between stock returns and unexpected inflation. As a shock to the overall economy, unexpected inflation can be related to future real economic activity and real discount rates, and thus has an ambiguous impact on stock valuations.

It is puzzling that the empirical literature has not supported Fisher's hypothesis in the U.S. market and in most of the overseas markets. In a comprehensive study on the relations between the returns of various classes of assets and inflation, Fama and Schwart (1977) show that, in the U.S. market, both expected and unexpected inflation are negatively associated with stock market returns[8]. Although inflation only explains a

[8] In their sample period, a one percent increase in expected inflation is expected to cause more than a five percent decrease in equally-weighted index level, and a

small portion of the variations in market returns, their results are puzzling enough given the Fisher's prediction that expected stock returns should vary in one-for-one correspondence with expected inflation. Similar results are also found in other countries. Gultekin (1983) studies the return-inflation relations in 26 countries and find that in most of the countries the relations are negative. Solnik (1983) uses a sample of nine countries and strongly reject a positive relation between stock returns and expected inflation. There are also a few studies that show positive relations. Firth (1979) provides supportive evidence for the Fisher's hypothesis using the British data. Boudoukh and Richardson (1993) show a positive relation between stock returns and inflation at long horizons. However, negative relations are more common in the literature.

There have been numerous studies that focus on the seemingly "anomalous" negative relation between stock returns and inflation, especially with expected inflation. Two explanations have been raised in the literature. The first one, proxy effect theory, assumes that investors process information rationally while the second one, money illusion theory, is based on a specific form of irrational behavior in which investors capitalize real earnings using nominal rates. The proponents of the proxy

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one percent increase in unexpected inflation is associated with more than a two percent drop in index price level. Please also see Bodie (1976), Jaffe and Mandelker (1976), and Nelson (1976) for more evidence on the U.S. market.

effect theory agree that the negative relation between stock returns and expected inflation is merely a proxy for the negative relation between expected future real economic activity and expected inflation, and is therefore spurious. However, they disagree on how expected real economic activity and expected inflation are negatively correlated. Fama (1981), who first formulated the proxy effect theory, interpret the relation between future real economic activity and expected inflation in the context of money demand theory and the quantity theory of money, while Benderly and Zwick (1985) interpret the relation in a real balance model of unemployment and output. Though using different macroeconomic models, both studies assume that the causality is from expected inflation to expected real economic output. In contrast, Geske and Roll (1983) propose a reverse causality model. They argue that a downward revision in expected future real economic output triggers inflationary policy adopted by the government to finance its potential budget deficit. Hence, when investors expect the future real economic output to decrease, they simultaneously adjust stock valuation downwards and adjust inflation expectation upwards. In this story, the causality is actually from expected future real economic activity to expected inflation. Kaul (1987) supports the reverse causality model by considering the pro-cyclical monetary policy adopted by the U.S. government in the 1930's and find an insignificant return-inflation relation in that period. Other studies use time series econometric models to examine the direction of the causality. James, Koreisha, and Partch (1985), using a VARMA model, investigate simultaneously the relations among stock returns, real activity, inflation and money supply changes, and show that there is a strong causal relation between stock returns, a proxy for future real activity, and the growth rate in monetary base, which supports Geske and Roll. Lee (1992), using a multivariate VAR approach, finds no causal relation between stock returns and money supply growth, which is more compatible with Fama (1981). Although the above studies disagree on the mechanism in which real output and inflation is related, they all contend that the observed negative return-inflation relation is a conjunction of two relations: 1) negative correlation between real output and inflation; 2) positive correlation between real output and stock returns. However, Ram and Spencer (1983) argue that the two relations should be reversed. Using a different inflation equation and different variables to represent real activity, they find that real activity and inflation is positively correlated and real activity and stock returns are negatively correlated, which is more compatible with the predictions of the Phillips curve hypothesis and the Mundell-Tobin effect.

Since both the two relations are reversed, combining the two still yields a negative return-inflation relation. Thus their study still falls in the category of the proxy effect theory. Finally, it is worth noting that proxy effect theory can explain the negative relations between stock returns with both expected and unexpected inflation. Intuitively, unexpected inflation is more likely to be negatively correlated with future real economic activity.

Besides the studies on the aggregate economy level, there is also supporting evidence for the proxy effect theory from cross-sectional studies. The key argument of the theory is that real economic activity is negatively associated with inflation. While empirical evidence has shown this is true on the aggregate level, one would expect this relation has much variation on the industry and firm level. Boudoukh, Richardson, and Whitelaw (1994) look at the cross-industry variations in inflation betas (defined as the slope coefficients in regressions of industry returns on expected and unexpected inflation) and find that the cyclical industries, as characterized by a high correlation between industrial output and aggregate output, generally have more negative inflation betas than non-cyclical industries. Given their findings that aggregate output and inflation are negatively correlated, they conclude that the cross-industry variation in inflation betas is caused by the variation in the relations between industry outputs and inflation.

The negative relation between stock returns and inflation can also be a result of market inefficiency. Modigliani and Cohn (1979) contend that the stock market suffers from a particular kind of irrationality called "money illusion", discounting real cash flows at nominal discount rates. As a result, an increase in inflation causes a drop in stock price. The Money illusion theory is based on two assumptions: 1) firm earnings move one-for-one with contemporaneous inflation; 2) inflation follows a persistent process and thus current inflation is a good forecast of future inflation. The theory can be understood as follows. In a rational world, when investors see a high inflation rate, under the persistence assumption, the expected future inflation rates are also high. If firm earnings move one-for-one with inflation, they should also expect future firm earnings to grow at the current high inflation rate. On the other hand, a high current inflation rate will also cause rational investors to capitalize future expected earnings at a higher rate to compensate for the erosion in purchasing power. As a result, the impacts of the adjustments in expected future earnings and discount rate on stock valuation offsets each other. However, the money illusion theory states that in the real world investors fail to adjust earnings expectations according to current inflation rate but do adjust discount rates upwards. In so doing, they effectively make a mistake by discounting real earnings by nominal discount rates, which induces the negative relation between inflation and stock prices. Though based on a strong assumption on investor's behavior, the theory is empirically appealing if we look at the recovery of the U.S. stock market from early 1980's, which can be partly viewed as a correction of stock prices from the underpricing in the previous high inflationary periods. Ritter and Warr (2002) explicitly test this conjecture using a ratio of intrinsic value to price (V/P ratio). As the name suggests, a high V/P ratio indicates undervaluation. In the period of 1978 to 1997, they find that the V/P ratio on the Dow 30 stocks is positively related to inflation, which supports the money illusion theory. Other tests of the money illusion theory generally look at the relation between stocks' yields and inflation. In an efficient market, yields like E/P and D/P should not be correlated with inflation. This can be seen in the simple Gordon growth model that represents D/P as the difference between nominal discount rate and earnings growth rate, which all move one-for-one with inflation. Therefore a change in inflation should have no impact on stocks' yields. In contrast, if investors behave as the money illusion theory describes, yields would increase with inflation. Along this line, Asness (2003) studies the famous Fed model which assumes a relation between yields and inflation. He argues that, though the model fails to be a theoretically sound valuation tool, investors seem to use it in valuation for a long time. Campbell and Vuolteenaho (2004), using the log-linear dynamic valuation framework, show that high inflation leads to stock market underpricing while expected dividend is actually positively related to inflation. Finally, Cohen, Polk, and Vuolteenaho (2005) find supporting evidence for the money illusion theory after controlling for the relation between inflation and risk.

2. Introduction

Previous studies have greatly enhanced our understanding of the return-inflation dynamics. This research adds to the literature by investigating two related questions: 1) what is the relation between stock returns and inflation on the firm level; 2) how can the cross-sectional pattern of the return-inflation relation help us differentiate between the two theories on the observed negative return-inflation relation? With respect to the first question, previous studies are only on the index level or industry level, and little is known about the relation on the firm level. Intuitively, there must be a rich cross-sectional pattern. Inflation can be bad news for some firms, and be neutral or even good news for some others. Boudoukh, Richardson, and Whitelaw (1994) have shown that there is much cross-industry variation in return-inflation betas. Non-cyclical industries, like Tobacco, food, and utilities industries, have a less negative or even positive correlation with inflation. We believe that, even within an industry, there is also significant variation which depends on firm characteristic variables like leverage, PPE, inventory valuation method, and some factors difficult to quantify like the negotiating power with suppliers and the ability to pass costs to customers. It is to some extent an empirical issue whether inflation is bad, neutral or good for a firm.

The cross-sectional evidence put us in a good position to answer the second question about whether the observed negative return-inflation relation is an outcome of rational behavior or not. The U.S. stock market history clearly shows that high valuations on the market level often coincide with low inflation rate. This fact is compatible with both the proxy effect theory and money illusion theory. It is difficult to tell which theory more accurately describes the investors' true valuation process by only looking at the data on the market level. Nonetheless, the two explanations have clearly different cross-sectional predictions. Money illusion theory predicts a uniform impact of inflation on stock prices. For instance, if current inflation is high, investors would undervalue all stocks. It is unlikely for them to confuse real and nominal numbers when valuing some stocks, but rationally set prices for other stocks. Put differently, if money illusion theory predicts a negative return-inflation relation, it would predict it for all individual stocks. Empirically, we should not find much variation in the return-inflation relation on the firm level. In contrast, the proxy effect theory allows much richer cross-sectional patterns. The theory predicts that the negative relation between market returns and inflation is a proxy for the negative relation between expected real economic output and inflation. On the firm level, the theory implies that the relation between individual stock returns and inflation could vary with a proxy for the relation between firm earnings and inflation. If the latter relation is positive, we expect the first relation to be also positive. Apparently using only market level data would miss a lot of cross-sectional information that is important in understanding the return-inflation dynamics.

In this study we provide cross-sectional evidence for the proxy effect theory by explicitly considering the relation between firm earnings and inflation, which can be viewed as a proxy for the relation between real economic output and inflation on the firm level. Specifically, we estimate two betas for each sample firm: the return-inflation beta, which is the slope coefficient in a regression of stock return on inflation, and the earnings-inflation beta, which is the slope coefficient in a regression of earnings growth rate on inflation. Our analysis first shows that there is much cross-sectional variation in the return-inflation betas. Though the price response to inflation on the market level is negative, the returns of a significant number of firms are positively associated with both expected and unexpected inflation. On average, in the period of 1973 to 2006, over 40% percent of the firms have positive return-inflation betas. If money illusion is the dominant factor in determining the return-inflation relation, we should not expect this large portion of firms with positive betas. In contrast, the rational story allows for such a pattern, because the effect of inflation on earnings can vary from firm to firm. Further analysis show this is the case. The estimates of the earnings-inflation betas have similar cross-sectional variations. In our sample period, around half of the firms have positive earnings-inflation betas. More importantly, if we form decile portfolios based on the earnings-inflation betas, the portfolio return-inflation betas show a monotonous trend. That is, a firm with a higher earnings-inflation beta tends to have a higher return-inflation beta, and vice versa. These findings are more consistent with the proxy effect theory than with the money illusion theory. The cross-sectional dependence of the two betas is also confirmed with panel regressions of returns on inflation with interaction terms between inflation and rankings of earnings-inflation betas, after controlling for industry effect. We also investigate the relation between ROE and inflation. Since a current increase in ROE to some extent reflects the improvement of managerial ability, it is more forward-looking and correlated with future firm performance. Our results show that return-inflation beta is also positively related to ROE-inflation beta.

It is worth noting that our analysis does not fully reject the money illusion theory. The cross-sectional variation in the return-inflation betas and the fact that the betas cross-sectionally depend on the earnings-inflation betas are still possible even if the market is undervalued during high inflationary periods and overvalued during low inflationary periods, as predicted by the money illusion theory. Some of our results support this mixed view. We find that, for some decile portfolios with positive earnings-inflation betas, the return-inflation betas are still negative. However, the empirical evidence in this research strongly indicates that the proxy effect theory plays a more important role in the real-world valuation process, and we soundly rule out the possibility that money illusion is the only factor that matters.

In this research we also consider the role of some observable firm characteristic variables in explaining the return-inflation relation. For instance, what firms are more likely to have positive inflation betas and hence are good hedges for inflation? The answer to this question is interesting to academicians as well as to practitioners. The cross-industry findings in Boudoukh, Richardson, and Whitelaw (1994) have been consistent with the common view that non-cyclical industries, like those producing necessities, are good inflation hedges. In this study, we further show that the return-inflation betas are cross-sectionally related to a set of observable firm characteristic variables like size, inventory, leverage and PPE etc., after controlling for industry effect. The interpretation of the results is still based on the framework of the proxy effect theory. The impact of a firm characteristic variable on return-inflation betas should depend on the variable's role in determining the relation between firm earnings and inflation. For example, if leverage is positively related to return-inflation betas, high leverage firms must have better earnings outlook when inflation rate is high. In this research we carefully analyze the interaction between each of the firm characteristic variables and the earnings-inflation relation to draw conclusions on the direction of the impact of the variable on the return-inflation relation. We also provide empirical evidence supporting our conclusions. However, our analysis on the role of the firm characteristic variables in the return-inflation dynamics only shows a small part of a large picture. Since many unobservable factors attribute to the cross-sectional variation in return-inflation betas, like bargaining position, pricing power and financing ability, etc., it is difficult to have a complete list. The bottom line is that as long as investors make rational decisions based on available information, the effects of some observable characteristic variables on return-inflation betas should be consistent with their impacts on firm earnings when inflation changes.

Our analysis with the firm characteristic variables is similar to the studies on the nominal contracting hypothesis. This strand of research focuses on the wealth redistributive effect of unexpected inflation through the revaluation of firms' nominal contracts. For example, a firm with a higher ratio of fixed-rate debts to assets would possibly benefit from high unexpected inflation as the real value of the corporate monetary obligation is actually reduced. The nominal contracting theory has been used in early literature to explain the negative relation between inflation and stock prices. Feldstein (1980) contends that the high inflation rate during the 1970's reduced the value of the corporate tax shield because of the historical cost depreciation method stipulated by the U.S. tax law, which induced a negative relation between inflation and stock prices. However, this conjecture was rejected by French, Ruback and Schwart (1983). Bernard (1986) and Pearce and Roley (1988) examine the effects of various nominal contracts on the relation between unexpected inflation and individual stock returns. They find that a few nominal contracts related to debt, labor and corporate tax play a role in the differential associations between return and unexpected inflation on the firm level. Obviously nominal contracting hypothesis is one of the rational stories and has direct cross-sectional implications. However, our analysis with the firm characteristic variables is different from the literature in that we also include expected inflation in the tests. Previous studies have looked at the impacts of some firm characteristic variables related to nominal contracts on the relation between stock returns and unexpected inflation. The underlying assumption is that the contracting parties can adjust the terms in their contracts immediately to eliminate the impact of a change in expected inflation. However, we believe that a change in expected inflation can also lead to revaluation of a firm's nominal contracts and thus revaluation of its stock in the short-run because the related parties may not be able to re-negotiate on the contracts, but this effect should diminish in the longer run.

The remainder of the second part of this thesis is organized as follows. Section 3 discusses the data, sample and the estimation of the inflation betas. Section 4 reports the empirical results. We first show that there is much cross-sectional variation in the inflation betas. Then we show that there is a positive relation between the return-inflation betas and the earnings-inflation betas by forming sorted decile portfolios and using multiple regressions. Finally, we analyze the role of firm characteristic variables in determining the return-inflation relation. Conclusions are offered in Section 5.

3. Data, Sample and Definition of Inflation Betas

Our sample consists of all the NYSE, AMEX and NASDAQ firms with return data available in the CRSP database and quarterly earnings data available in the CRSP-COMPUSTAT merged files for the period from 1973 to 2006. We focus only on domestic common stocks, and eliminate American Depositary Receipts, Real Estate Investment Trusts, and closed-end funds from the sample. The data on CPI and 3-month Treasury bill rate are also collected from CRSP. We exclude financial firms in the analysis with firm characteristic variables.

We estimate three betas for each sample firm: return-inflation beta, earnings-inflation beta, and ROE-inflation beta. For each type of beta, we further differentiate between expected inflation beta and unexpected inflation beta. Following Fama and Schwert (1977), return-inflation beta is defined as the slope coefficient of a regression of quarterly stock return on inflation,

$$\mathrm{R}_{i,t} = \alpha + \beta_{\mathrm{R}} INF_t + \varepsilon_{i,t},$$

where $R_{i,t}$ is the quarterly buy-and-hold return for firm i in quarter t, INF_t denotes expected or unexpected inflation in quarter t, β_{R} is the return-inflation beta for firm i in quarter t, and $\varepsilon_{i,t}$ is the disturbance term. Consistent with Fama and Schwert (1977), expected inflation is defined as the yield to maturity of the 3 month T-bill observed at the beginning of quarter t. Unexpected inflation is the difference between the rate of change in CPI and expected inflation. We use lagged unexpected inflation to ensure the news is known to the market in quarter t. Note that the cross-sectional average of the return-inflation betas should be equal to the beta in a regression of equally-weighted index return on inflation. Previous studies have shown that this index beta is mostly negative. Our goal is to show that there is much cross-sectional variation consistent with the prediction of the proxy effect theory even though the overall market return seems to be negatively associated to both expected and unexpected inflation.

To define an earnings-inflation beta, we need to have a reasonable measure of earnings growth rate. Since earnings can be negative, dividing the change in earnings by last period earnings could yield a meaningless number. We then define earnings growth rate as follows,

$$EGR_{i,t} = \frac{(E_{i,t} - E_{i,t-4})}{\sigma_{i,t}},$$

where $EGR_{i,t}$ is the earnings growth rate for firm i in quarter t, $E_{i,t}$ is the earnings for firm i in quarter t, $E_{i,t-4}$ is the earnings for firm i in $t-4$, and $\sigma_{i,t}$ is the standard deviation of $(E_{i,t} - E_{i,t-4})$ over the previous eight quarters. Our definition of earnings growth to some extent produces a normalized measure. It is noticeable that this measure is called "standardized unexpected earnings (SUE)" in the literature on the post earnings announcement drift (see, for instance, Bernard, 1990, Ball and Bartov, 1996). The name "standardized unexpected earnings" is based on the assumption that earnings follow a seasonal random walk process, and then $(E_{i,t} - E_{i,t-4})$ is the unexpected part of earnings change. However, in this research we do not make such an assumption. It is hard to believe that investors will use earnings four quarters ago as the best forecast of current earnings number. We think that this measure more appropriately captures the seasonally adjusted earnings growth that investors expect to be non-transitory and can persist into the future. As we try to evaluate the relation between a firm's expected future cash flows and inflation, this measure best serves our goal.

Given our definition of earnings growth rate, earnings-inflation beta can be estimated as the slope coefficient of a regression of earnings growth rate on inflation,

$$EGR_{i,t} = \alpha + \beta_{\mathrm{E}} INF_t + \varepsilon_{i,t}$$

where $EGR_{i,t}$ is the earning growth rate for firm i in quarter t, INF_t denotes expected or unexpected inflation in quarter t, β_{E} is the earnings-inflation beta for firm i in quarter t, and $\varepsilon_{i,t}$ is the disturbance term. The earnings-inflation beta, as defined in this way, measures the impact of inflation on contemporaneous firm earnings. This impact, however, is fairly persistent and has strong valuation effect cross-sectionally. Firms with high earnings-inflation betas are gainers in inflationary periods compared to firms with low earnings-inflation betas. We expect that their returns also respond more positively to inflation.

Investors may also look at profitability ratios to infer a firm's future performance. The most important one of these ratios is the return on equity (ROE). Since high inflation increases the book value of new inventory and fixed investments, both of which are items in the denominator when calculating ROE, an increase in ROE in high inflationary periods better indicate the ability of the management to pass the increased costs to customers. Hence, the impact of inflation on ROE can be more value-relevant than just using earnings numbers. To accommodate this possible effect, we estimate ROE-inflation beta as an alternative measure of the relation between firm fundamentals and inflation. We define ROE-inflation beta as,

$$ROE_{i,t} = \alpha + \beta_{\mathrm{ROE}} INF_t + \varepsilon_{i,t}$$

where $ROE_{i,t}$ is the seasonally-adjusted and de-trended[9] return on equity for firm i in quarter t, INF_t denotes expected or unexpected inflation in quarter t, β_{ROE} is the ROE-inflation beta for firm i in quarter t, and $\varepsilon_{i,t}$ is the disturbance term. The ROE-inflation beta is a variation of the earnings-inflation beta, and it is also supposed to represent the relation between firm fundamentals and inflation. We will sometimes refer to earnings-inflation beta and ROE-inflation beta as fundamental-inflation beta in this research. The two fundamental-inflation betas are expected to be positively correlated with return-inflation beta, if the proxy effect

[9] Seasonally-adjusted and de-trended ROE is the residual of a regression of the raw ROE on three quarter dummy variables and a trend variable.

dominates.

We use a common sample for all the three betas. That is, our sample includes all the firms that have relevant data for the estimation of the return-inflation, earnings-inflation and ROE-inflation betas, and the estimation intervals for the three betas should be same. This method ensures the comparability among the three betas. To minimize the impact of extreme values, we also exclude firms whose beta estimates lie beyond 1% and 99% percentiles.

4. Empirical Analysis

Our empirical analysis goes as follows. First, we show that there are much cross-sectional variations in the three inflation betas. Since the money illusion theory predicts a uniform undervaluation or overvaluation when inflation changes, our results are more consistent with the proxy effect theory. Second, we look at the relation between the three betas by sorting sample firms into decile groups based on the earnings-inflation or ROE-inflation betas. Consistent with the proxy effect theory, we find that firms with low fundamental-inflation betas also have low return-inflation betas. Third, we formally test the relation between the return-inflation betas and the fundamental-inflation betas using multiple regressions, and control for the industry effect. Last, we include firm characteristic variables in the regressions, and examine their impacts on the return-inflation relation. We show that most of them have impacts that are consistent with their joint impacts with inflation on firm earnings.

4.1. Cross-Sectional Variation of Inflation Betas

Panel A of Table 13 reports the summary statistics of the return-inflation, earnings-inflation and ROE-inflation betas estimated using expected inflation. Consistent with the previous studies, the return-inflation betas have a negative cross-sectional mean. However, the number is much smaller in absolute value compared to the beta of an equally-weighted index in Fama and Schwert (1977). We calculate a cross-sectional average of -2.427, while Fama and Schwert (1977) records -5.70 in their sample period. This difference suggests that stock returns vary less negatively with expected inflation in a more recent period. The distribution of the return-inflation betas has a standard deviation of 10.883, which indicates a large variation from firm to firm. The variation can also be seen from the minimum, 25%, median, 75%, and maximum of the return-inflation beta estimates. Finally there are 1916 firms out of 4672 firms that have positive return-inflation betas. That is a little more than 40% in percentage terms.

The rational story requires that the cross-sectional variation in return-inflation betas can be explained by the cross-sectional variation in fundamental-inflation betas. Consistent with our expectation, the two fundamental-inflation betas show large cross-sectional variances. However, both the means of the earnings-inflation betas and ROE-inflation betas are slightly positive (0.132 and 0.259 respectively), which is opposite to the sign of the mean of the return-inflation betas. It is not surprising because the correlation between fundamentals and inflation does not have a theoretically "correct" value. The key argument is that the return-inflation betas and the fundamental-inflation betas should be positively related. We are more concerned about the cross-sectional dependence between the return-inflation betas and the fundamental-inflation betas than the betas themselves given that the mechanism of how inflation impacts on firm fundamentals and valuation is rather complex.

Panel B of Table 13 presents the summary statistics of the return-inflation, earnings-inflation and ROE-inflation betas estimated using unexpected inflation. The mean of the return-inflation betas are slightly negative, a result inconsistent with Fama and Schwert (1977). Since there is no theory governing the relation between stock returns and unexpected inflation, the neutral reaction of stock returns to unexpected inflation in our sample period is not surprising. The means of the earnings-inflation and ROE-inflation betas are all positive, which suggests that unexpected inflation is on average good news for firm earnings, at least in our sample period. The variations in three betas are also large, as indicated by their standard deviations (7.996, 59.430, 4.581). Generally, the results in Table 13 show that there are much cross-sectional variations in the return-inflation betas and the fundamental-inflation betas.

4.2. Sorting Results

In this subsection, we show that the cross-sectional pattern of the return-inflation betas is more consistent with the prediction of the proxy effect theory, rather than with the prediction of the money illusion theory. The proxy effect theory implies a positive correlation between the return-inflation beta and the fundamental-inflation beta. That is, the firms which benefit from inflation, as shown by their high earnings-inflation betas, should have more positive, or less negative, price reaction to inflation. In contrast, the money illusion theory does not have such cross-sectional predictions. This subsection provides some preliminary evidence on the cross-sectional dependence of the two betas by sorting the sample firms into deciles based on one of the betas, and more rigorous regression tests are conducted in the next subsection.

In order to see whether the return-inflation beta and the fundamental-inflation beta are cross-sectionally associated, we sort all the sample firms into decile groups based on the estimates of the earnings-inflation betas or the ROE-inflation betas. The first group, D1, consists of the firms with the lowest fundamental-inflation betas and the last group, D10, is composed of the firms with the highest fundamental-inflation betas. We then compute the average return-inflation beta for each decile group. We expect that the mean return-inflation betas of the decile groups monotonically increase from D1 to D10.

The results are presented in Table 14. All the sample firms are sorted into decile groups based on the earnings-inflation beta and the ROE-inflation beta respectively. We report the averages of the return-inflation beta of each decile group, as well as that of the sorting betas. Panels A and B report the results for expected inflation and unexpected inflation respectively. A quick glance at the table shows that the ordering of the return-inflation betas is remarkably consistent with that of the earnings-inflation betas or the ROE-inflation betas, and this monotonic relation is found in both expected inflation betas and unexpected inflation betas. For example, the first two lines of Panel A present the average return-inflation betas of the decile groups sorted on the earnings-inflation betas. The average return-inflation beta of D1 is -8.791, and it increases to -2.109 in D5, and 2.871 in D10. The average return-inflation beta of the decile groups sorted on ROE-inflation also exhibits a clear monotonic trend. It increases from -6.276 in D1 to -0.933 in D9, though drops to -1.963 in D10. The results presented in Panel B for unexpected inflation are very similar to those for expected inflation. In general, the tests in this subsection support the view that the cross-sectional variation in the return-inflation beta is consistent with the cross-sectional variation in the fundamental-inflation beta. The direction and magnitude of the impact of inflation on firms' earnings is an important factor in determining the reaction of stock prices to inflation, and this fact is more consistent with the prediction of the proxy effect theory.

4.3. Regression Analysis

This subsection tests the cross-sectional correlation between the return-inflation beta and the fundamental-inflation beta using multiple regressions. These tests formalize the non-parametric results in last subsection, and most importantly enable us to control for the possible industry effect. Boudoukh, Richardson, and Whitelaw (1994) have shown that the differential industry return-inflation betas can be explained by the differential associations between industry output and aggregate output. They find that the cyclical industries, as characterized by a high correlation between industrial output and aggregate output, generally have more negative inflation betas than non-cyclical industries. Given their regression results that the aggregate output is negatively correlated with inflation, they attribute the cross-industry variation in return-inflation betas to the differential associations between industrial output and inflation. Our aim is to further show that a firm's return-inflation beta is to a large extent decided by the association between its earnings and inflation, and this effect even exists within a industry, because of the complexity of the process through which inflation impacts on firm fundamentals and then stock valuations.

We use the following panel model to test the relation between the return-inflation beta and the fundamental-inflation beta,

$$\begin{aligned} RET_{i,t} &= \alpha + \beta * INF_t + \theta * INF_t * RANK_i \\ &\quad + \gamma * RANK_i + \delta_j \sum_{j=1}^{n-1} INDU_j + \eta_j \sum_{j=1}^{n-1} INDU_j * INF_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where $RET_{i,t}$ is the return for firm i in quarter t, INF_t denotes expected inflation or unexpected inflation in quarter t, $RANK_i$ is the decile ranking for firm i based on the sorting on the earnings-inflation betas or the ROE-inflation betas, $INDU_j$ is a dummy variable that takes value one when firm i belongs to industry j, and n is the number of two-digit SIC industries. Specifically, we first rank all the sample firms based on the earnings-inflation beta or the ROE inflation beta, and assign each firm a rank number 1 to 10, denoted by $RANK_i$. Then we run a panel regression of stock returns on inflation and on the interaction terms between inflation and *RANK* and on the interaction terms between inflation and the industry dummy. In this construction, θ, the coefficient of the interaction term between inflation and *RANK*, measures the difference in return-inflation betas for two firms in the same industry but in two neighboring *RANK* groups. We expect this coefficient to be positive.

Table 15 reports the regression results of model 1. To save space, we do not include the coefficient estimates of the industry variables in the table. Consistent with our expectation, the coefficients of the interaction terms between inflation and rank are all significantly positive. This indicates that the firms with higher cross-sectional ranking in the fundamental-inflation betas also have higher return-inflation betas, even after controlling for industry. For instance, column 1 shows the results for expected inflation and for the *RANK* variable based the ranking of the earnings-inflation betas. The coefficient on *INF*RANK* is 0.517, which means that within a industry the average return-inflation beta increases 0.517 when we move from decile group *n* to decile group *n+1*. The results are similar for unexpected inflation and for ranks based on the ROE-inflation betas, as shown by the other columns.

We also use an alternative model to test the positive relation between the return-inflation beta and the fundamental inflation beta,

$$\begin{aligned} RET_{i,t} &= \alpha + \beta * INF_t + \sum_{i=2}^{5} \theta_i * QUIN_i * INF_t \\ &+ \sum_{i=2}^{5} \gamma_i * QUIN_i + \delta_j \sum_{j=1}^{n-1} INDU_j + \eta_j \sum_{j=1}^{n-1} INDU_j * INF_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where $RET_{i,t}$ is the return for firm *i* in quarter *t*, INF_t denotes expected inflation or unexpected inflation in quarter *t*, $QUIN_j$ is a dummy variable that takes value one if firm *i* belongs to quintile *j* based on the sorting on earnings-inflation beta or ROE-inflation beta, $INDU_j$ is a dummy variable that takes value one when firm *i* belongs to industry *j*, and *n* is the number of two-digit SIC industries. To estimate this model, we first sort all the sample firms into quintiles based on the earnings-inflation beta or the ROE-inflation beta, and then assign each firm a set of *QUIN* variable. For example, if a firm belongs to quintile 2, then the variables $QUIN_3$ to $QUIN_5$ are all set to be zero, and $QUIN_2$ is set to be one. Since we use quintile 1 as the reference group, $QUIN_2$ to $QUIN_5$ are all set to be zero for a firm in the first quintile. The interested coefficient is θ_j, which measures the difference in return-inflation betas between quintiles. We predict θ_j to be positive. This model specification is able to capture the possible non-linear differences in return-inflation betas across ranking groups. Because decile rankings would bring too many terms into the model, we use quintile rankings.

Table 16 summarizes the regression results of model 2. The coefficients of the interaction terms between inflation and $QUIN_j$ are all significant except for the coefficient in the regression using unexpected inflation and $QUIN_j$ based on ROE-inflation betas. In general, the results further confirm the positive relation between the return-inflation betas and the fundamental-inflation betas.

4.4. The Role of Firm Characteristic Variables

In this subsection we analyze the roles of some observable firm characteristic variables in explaining the return-inflation relation. The previous tests have shown that the differential return-inflation betas can be explained by the differential fundamental-inflation betas, and hence the effect of inflation on firm earnings or ROE is crucial in determining the reaction of stock price to inflation. It is natural to ask whether the effect of inflation on firm earnings or ROE is related to some observable firm characteristic variables. In other words, what firms are more likely to benefit from inflation and what firms are more likely to suffer? In this study, we identify some observable firm characteristic variables, mostly from the financial statement, and investigate their roles in explaining the cross-sectional variation in return-inflation betas. Our prediction for the roles of the variables on the return-inflation relation is still based on the proxy effect theory. That is, the impacts of the characteristic variables on the return-inflation relation should be consistent with their impacts on the earnings-inflation relation. We note that our list of the firm characteristic variables is far from complete, and there are numerous important unobservable factors like bargaining position, pricing power and financing ability, etc., and the issue is even more complex in today's highly globalized market.

Our list of the firm characteristic variables includes size, the ratio of inventory to total sales, inventory valuation method, the ratio of PPE to total assets, the ratio of intangible assets to total assets, and ratios of long-term debts to total assets. The test framework is similar to that in Section 4. Specifically, we estimate the following panel model,

$$\begin{aligned} RET_{i,t} &= \alpha + \beta * INF_t + \theta * INF_t * CRANK_i \\ &+ \gamma * CRANK_i + \delta_j \sum_{j=1}^{n-1} INDU_j + \eta_j \sum_{j=1}^{n-1} INDU_j * INF_t + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where $RET_{i,t}$ is the return for firm *i* in quarter *t*, INF_t denotes expected inflation or unexpected inflation in quarter *t*, $CRANK_i$ is the decile ranking for firm *i* based on sorting on one of the firm characteristic variables. $INDU_j$ is a dummy variable that takes value one when firm *i* belongs to industry *j*, and *n* is the number of two-digit SIC industries. The firm characteristic variables are as follows. $SIZE_i$ is the logarithm of market value for firm *i*, $INVENTORY_i$ is the ratio of inventory to total sales for firm *i*, $INVEN\_M_i$ is a dummy variable that takes value one if firm *i* use LIFO, PPE_i is the ratio of PPE to total assets for firm *i*, $INTAN_i$ is the ratio of intangible assets to total assets, $DEBTn_i$ is the ratio of long term debt due in *n* years to total assets and $PREFER_i$ is the ratio of the value of prefer stocks to total assets. All the characteristic variables are the averages over the sample period consistent with that of $RET_{i,t}$.

In this model, the characteristic variables themselves are not included in regression. Instead, we sort all the sample firms into deciles based on one of the firm characteristic variables, and then assign each firm a

CRANK number from 1 to 10. An interaction term between inflation and CRANK is then included in a panel regression of stock returns on inflation with control variables for industry effect. The coefficient of *INF*CRANK*, θ, measures the difference in the return-inflation betas for two firms in neighboring decile groups sorted on one of the firm characteristic variables. A positive effect of a characteristic variable on return-inflation beta is represented by a positive θ estimate in the regression, and vice versa.

Before presenting the empirical results, we first make some predictions for the relation between the characteristic variables and the return-inflation betas. In the analysis, it is important to differentiate between expected and unexpected inflation. A change in expected inflation is more persistent and can affect firm earnings in many periods. However, this long-term impact is neutralized by related parties adjusting their contracts. In contrast, unexpected inflation is transitory, but it is more likely to be negatively correlated with the aggregate economy. We then have the following predictions on the effects of the firm characteristic variables on return-inflation betas. 1) Size: Large firms are often in more advantageous positions when negotiating with customers and suppliers, and hence it is easier for them to benefit from an increase in expected inflation. In addition, they have wider business lines, and are more globalized, which makes them more flexible in operations when high inflation is anticipated. So we predict the effect of size on return-inflation relation is positive. On the other hand, high unexpected inflation is more of bad news to them because large firms' cash flows may be more correlated with the aggregate economy. Thus we predict that size has a negative valuation effect when unexpected inflation is high. 2) The ratio of inventory to total sales: Both expected and unexpected inflation is good for firms with high level of inventory. If sales increase at the rate of inflation, a large inventory means nominal gains to firms as the costs of production have been fixed. 3) Inventory valuation method: The choice of FIFO and LIFO influences the timing of corporate tax. In inflationary periods, firms with FIFO method will report higher corporate earnings than LIFO firms. As a result, they also pay higher corporate tax. So inflation is relatively advantageous to LIFO firms since they can postpone corporate taxes to later periods. As expected inflation is more persistent, we expect this effect to be more pronounced when expected inflation changes. For unexpected inflation, the effect is less pronounced. 4) The ratio of PPE to total assets : A change is expected inflation is relatively good news for firms with large ratios of PPE to total assets because these firms possibly have less need of fixed investments in the future. However, unexpected inflation is bad news for firms with high PPE ratios, because unexpected inflation is detrimental to the aggregate economy and firms with high PPE incur higher overhead costs during economic contractions. 5) The ratio of intangible assets to total assets: Firms with large ratios of intangible assets should benefit from an increase in expected inflation because the cash flows generated by some intangible assets increase with inflation, but there are no significant costs involved. Similarly, unexpected inflation should also be treated as good news for firms with large intangibles, but the effect is less significant. 6) The ratios of long-term debts to total assets – classified by maturity: High leverage firms benefit from unexpected inflation because unexpected inflation reduces those firms' monetary obligations in real terms. Further, the ratios of long-term debts with longer maturities should be more positively related to the return-inflation beta. In contrast, the relation is not so clear for expected inflation. When high inflation is anticipated, new corporate debts must be issued at higher discount rates. If operating income also increases one-for-one with expected inflation, the real net earnings will not be affected. However, if operating income does not move on a one-for-one basis, the final outcome is not clear. 7) Preferred stock to total assets: As another form of the corporate long term monetary obligations, we make the same predictions as we do for the long-term debts to total assets ratios.

Table 17 reports the regression results of model 3. The coefficients on the interaction term *INF*CRANK* are generally consistent with our predictions, though there are a few exceptions. In the regressions with expected inflation, *SIZE, INVEN_M, PPE* show the expected positive effects on return-inflation relation, *DEBT2-DEBT4*, and *PREFER* show negative effects, which is not to our surprise, but the effects of *INVENTORY* and *INTAN* seem to be inconsistent with our predictions. For the regressions with unexpected inflation, *SIZE*, *INVENTORY*, *DEBT2-DEBT5* show expected signs, but *INVEN_M, PPE and INTANGIBLE* show unexpected signs, or are insignificant. Considering the complexity of the issue, we do not try to be conclusive.

We also use an alternative model to allow for non-linear difference in return-inflation betas between different rank groups,

$$\begin{aligned} RET_{i,t} &= \alpha + \beta * INF_t + \sum_{i=2}^{5} \theta_i * CQUIN_i * INF_t \\ &+ \sum_{i=2}^{5} \gamma_i * CQUIN_i + \delta_j \sum_{j=1}^{n-1} INDU_j + \eta_j \sum_{j=1}^{n-1} INDU_j * INF_t + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where $RET_{i,t}$ is the return for firm i in quarter t, INF_t denotes expected inflation or unexpected inflation in quarter *t*, $CQUIN_j$ is a dummy variable that takes value one if firm *i* belongs to quintile *j* based on sorting on one of the firm characteristic variables. $INDU_j$ is a dummy variable that takes value one when firm *i* belongs to industry *j*, and *n* is the number of two-digit SIC industries. The firm characteristic variables used for ranking are the same with model 3.

This model is analogous to model 2. We first rank all the sample firms into quintiles based on one of the firm characteristic variables, and then assign each sample firm a set of *CQUIN* variables. For instance, if a firm belongs to quintile 3, its $CQUIN_3$ is set to be one, and $CQUIN_2$, $CQUIN_4$ and $CQUIN_5$ are all set to be zero. Since quintile 1 is the reference group, for a firm in quintile 1, all the *CQUIN* variables are set to be zero. The coefficient on the interaction variable between inflation and $CQUIN_j$, θ_i, measures the difference in return-inflation bets between a firm in quintile 1 and a firm in quintile *j*.

Table 18 provides the regression results of model 4. The results are largely consistent with those of model 3. In addition, the results show that the detected effects of the characteristic variables on return-inflation betas are not driven by the effects in some extreme rank groups. For most of the variables, the coefficients on $INF*QUIN_j$ increases in absolute value with *j*, and generally become significant when j is equal to or greater than 3.

5. Conclusion

Previous studies have documented negative relations between stock returns and both expected and unexpected inflation (See, e.g., Bodie, 1976, Jaffe and Mandelker, 1976, Nelson 1976, and Fama and Schwart, 1977 for the U.S. evidence; Gultekin, 1983 and Solnik, 1983 for the international evidence). This fact, especially for expected inflation, contradicts the Fisher's hypothesis that stock returns should move one-for-one with expected inflation, and the conventional wisdom that stocks, as claims to real assets, should be complete hedge for inflation.

Two explanations have been raised in the literature. The proxy effect theory, proposed by Fama (1981), attributes the negative relation between inflation and stock returns to a negative relation between inflation and expected future real cash flows. In contrast, the money illusion theory contends that the stock market suffers from a particular kind of irrationality called "money illusion", discounting real cash flows at nominal discount rates. Our research provides cross-sectional evidence that is more consistent the prediction of the proxy effect theory. We show that there is much cross-sectional variation in the return-inflation beta, which is not predicted by the money illusion theory. Further, the cross-sectional variation in the return-inflation beta can be explained by the differential associations between firm fundamentals and inflation. This finding supports the proxy effect theory which implies a positive correlation between the return-inflation beta and the fundamental-inflation beta. Finally, we study the roles of some observable firm characteristic variables in explaining the variation in return-inflation betas. The results are generally consistent with our predictions based on the proxy effect theory.

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Table 1

Historical Revisions to the List of Designated Securities Eligible for Short Selling

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

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 Jan. 03, 1994 to Nov. 29, 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 columns 2 to 4. In column 5, an addition event is defined as 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.

Table 2

Probability of Informed Trading and Price Non-synchronicity around Addition Events

Panel A: Probability of Informed Trading

		Pre-Addition	Post-Addition	Change	% Change	t-test /Wilcoxon test
$PIN_{s\text{-}b}$	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	19.83%	(4.43)
	Median	0.077	0.083	0.011	14.57%	(4.50)
PIN_{buy}	Mean	0.151	0.143	-0.008	-5.50%	(-2.58)
	Median	0.152	0.141	-0.005	-3.05%	(-2.22)
PIN	Mean	0.229	0.236	0.007	3.06%	(2.14)
	Median	0.233	0.228	0.009	4.01%	(2.82)
α	Mean	0.246	0.275	0.029	11.90%	(6.44)
	Median	0.231	0.277	0.035	14.98%	(7.10)
δ	Mean	0.342	0.392	0.051	14.87%	(4.48)
	Median	0.333	0.384	0.051	15.36%	(4.35)
μ	Mean	78.63	88.93	10.30	13.10%	(1.87)
	Median	44.61	63.81	12.13	27.18%	(4.12)
ε_s	Mean	42.79	48.57	5.78	13.51%	(1.59)
	Median	18.28	29.78	5.06	27.67%	(4.78)
ε_b	Mean	37.62	43.64	6.02	16.01%	(1.65)
	Median	13.76	21.42	3.62	26.31%	(4.74)

Panel B: Price Non-synchronicity

		Pre-Addition	Post-Addition	Change	% Change	t-test /Wilcoxon test
$\Psi_{d\text{-}u}$	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	50.29%	(3.91)
	Median	1.443	2.117	0.920	63.80%	(6.80)
Ψ_{up}	Mean	2.146	2.201	0.054	2.53%	(0.27)
	Median	1.725	1.758	0.398	23.09%	(1.19)

Panel A reports mean and median of the PIN estimates 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 change and the last column reports the t-statistics of a paired t-test and a 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-δ)*PIN. $PIN_{s\text{-}b}$ is defined as PIN_{sell}-PIN_{buy}. Panel B gives the results on price non-synchronicity. Ψ_{down} is defined as $\log((1\text{-}R^2_d)/R^2_d)$, where R^2_d is the R-square of a regression of bi-weekly individual 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. $\Psi_{d\text{-}u}$ is defined as Ψ_{down}-Ψ_{up}. For each addition event, we estimate 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. There are 360 addition events used in our study from Jan. 03, 1994 to Nov. 29, 2002.

Table 3

Probability of Informed Trading and Price Non-synchronicity around Deletion Events

Panel A: Probability of Informed Trading

		Pre-Deletion	Post-Deletion	Change	% Change	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	-16.79%	(-3.33)
	Median	0.097	0.079	-0.013	-13.18%	(-3.49)
PIN_{buy}	Mean	0.151	0.164	0.013	8.51%	(2.18)
	Median	0.152	0.164	0.017	11.34%	(1.96)
PIN	Mean	0.259	0.254	-0.005	-2.01%	(-0.98)
	Median	0.255	0.250	0.002	0.83%	(-0.88)
α	Mean	0.249	0.218	-0.032	-12.69%	(-4.59)
	Median	0.248	0.217	-0.041	-16.33%	(-5.15)
δ	Mean	0.410	0.359	-0.051	-12.44%	(-2.98)
	Median	0.395	0.341	-0.072	-18.30%	(-3.26)
μ	Mean	45.88	42.84	-3.04	-6.63%	(-0.87)
	Median	35.89	27.11	-3.51	-9.77%	(-1.79)
ε_s	Mean	19.55	15.01	-4.54	-23.23%	(-2.51)
	Median	11.59	8.30	-2.10	-18.14%	(-4.47)
ε_b	Mean	14.40	10.67	-3.73	-25.91%	(-2.82)
	Median	8.57	5.20	-1.63	-19.00%	(-5.30)

Panel B: Price Non-synchronicity

		Pre-Deletion	Post-Deletion	Change	% Change	t-test /Wilcoxon test
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	10.21%	(0.79)
	Median	1.768	1.784	0.152	8.58%	(0.61)
Ψ_{up}	Mean	2.569	3.279	0.710	27.65%	(2.01)
	Median	1.996	2.686	1.077	53.97%	(2.26)

Panel A reports mean and median of the PIN estimates 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. Columns 3 and 4 report the mean and median across events. Columns 5 and 6 report the change and the last column reports the t-statistics of a paired t-test and a 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 price non-synchronicity. 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 bi-weekly individual 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_{down} and Ψ_{up} in the four quarters before the event quarter, and post-deletion Ψ_{up} and Ψ_{down} in the four quarters after the event quarter. There are 207 deletion events used in our study from Mar. 25, 1996 to Nov. 29, 2002.

Table 4

Summary Statistics of PIN and Price Non-synchronicity for All Hong Kong Firms

	No. of Observations	Mean	Median	Min	Q1	Q3	Max	Std. Dev.
Panel A: Probability of Informed Trading (PIN) - Quarterly Estimates								
PIN_{s-b}	27073	-0.078	-0.075	-0.646	-0.187	0.003	0.622	0.177
PIN_{sell}	27073	0.114	0.092	0.000	0.046	0.153	0.630	0.095
PIN_{buy}	27073	0.181	0.168	0.000	0.109	0.240	0.651	0.102
PIN	27073	0.261	0.246	0.020	0.197	0.308	0.818	0.101
α	27073	0.246	0.228	0.016	0.143	0.322	0.963	0.141
δ	27073	0.408	0.378	0.000	0.201	0.580	0.999	0.248
μ	27073	47.242	17.225	1.148	5.987	52.242	624.506	74.411
ε_s	27073	21.981	5.034	0.000	1.771	19.328	448.980	43.463
ε_b	27073	19.417	3.715	0.000	1.364	15.792	402.439	39.904
Panel B: Price Non-synchronicity (Ψ) - Yearly Estimates								
Ψ_{d-u}	5346	-0.583	-0.516	-12.673	-2.319	1.177	12.117	3.181
Ψ_{down}	5346	2.180	1.764	-2.658	0.603	3.277	14.731	2.336
Ψ_{up}	5346	2.790	2.391	-1.755	1.184	3.810	15.427	2.283

Panel A reports the summary statistics of the quarterly PIN estimates for all HK firms. 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 summary statistics of the yearly price non-synchronicity estimates for all HK firms. 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 bi-weekly individual 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 $\Psi_{down}-\Psi_{up}$. The sample period is from 1993:Q1 to 2003:Q4.

Table 5

Regression of PIN on Short Sales Dummy, Short Sales Turnover and Control Variables

Independent Variables	Dependent Variables											
	$PIN_{s\text{-}b}$	$PIN_{s\text{-}b}$	$PIN_{s\text{-}b}$	$PIN_{s\text{-}b}$	PIN_{sell}	PIN_{sell}	PIN_{sell}	PIN_{sell}	PIN_{buy}	PIN_{buy}	PIN_{buy}	PIN_{buy}
	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)		
SSR			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)
TT		-0.004		0.011		-0.017		-0.014		-0.013		-0.025
		(-0.133)		(0.335)		(-1.124)		(-0.735)		(-0.803)		(-1.256)
VTT		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%

This table reports estimates of coefficients of the following regression,

$$PINx_{i,t} = c_0 + c_1SSD_{i,t} + c_2SSR_{i,t} + c_3SIZE_{i,t} + c_4B/M_{i,t} + c_5LEV_{i,t} + c_6ROE_{i,t} + c_7RET_{i,t} + c_8VRET_{i,t} + c_9TT_{i,t} + c_{10}VTT_{i,t} + \text{firm fixed effects (year fixed effects)} + \varepsilon_{i,t}$$

where $PINx_{i,t}$ denotes $PIN_{s\text{-}b}$, PIN_{sell} or PIN_{buy} of stock i in quarter t, $SSD_{i,t}$ is a dummy variable that takes value one if stock i is shortable throughout quarter t, and zero otherwise, $SSR_{i,t}$ is the average short sale ratio of stock i in quarter t where the short sale ratio is defined as daily dollar value of the shares sold short divided by daily dollar trading volume, $SIZE_{i,t}$ is the logarithm of market capitalization at the end of quarter t-1, $B/M_{i,t}$ is the logarithm of book to market ratio defined as book value of equity divided by market capitalization at the end of quarter t-1, $LEV_{i,t}$ is leverage ratio defined as long term debts divided by total assets at the end of quarter t-1, $ROE_{i,t}$ is return on equity defined as net income divided by lagged book value at the end of quarter t-1, $RET_{i,t}$ is the average monthly return over quarter t-4 to t-1, $VRET_{i,t}$ is the standard deviation of the monthly return over quarter t-4 to t-1, $TT_{i,t}$ is the average monthly turnover over quarter t-4 to t-1, and $VTT_{i,t}$ is the standard deviation of the monthly turnover over quarter t-4 to t-1. Accounting information in the latest financial report is used in constructing the variables. Heteroskedasticity and serial correlation robust t-statistic are reported in parentheses. The sample period is from 1993:Q1 to 2003:Q4 and we only use industrial firms in regressions with control variables.

Table 6

Regression of Price Non-synchronicity on Short Sales Dummy, Short Sales Turnover and Control Variables

Independent Variables	Dependent Variables											
	$\Psi_{d\text{-}u}$	$\Psi_{d\text{-}u}$	$\Psi_{d\text{-}u}$	$\Psi_{d\text{-}u}$	Ψ_{down}	Ψ_{down}	Ψ_{down}	Ψ_{down}	Ψ_{up}	Ψ_{up}	Ψ_{up}	Ψ_{up}
	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)		
SSR			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)
TT		0.204		-0.050		-0.080		-0.149		-0.284		-0.099
		(0.282)		(-0.057)		(-0.149)		(-0.225)		(-0.513)		(-0.150)
VTT		-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%

This table reports estimates of coefficients of the following regression,

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

where $\Psi x_{i,t}$ denotes $\Psi_{d\text{-}u}$, Ψ_{down} or Ψ_{up} of stock i in year t, $SSD_{i,t}$ is a dummy variable that takes value one if stock i is shortable throughout year t, and zero otherwise, $SSR_{i,t}$ is the average short sale ratio of stock i in year t where the short sale ratio is defined as daily dollar value of the shares sold short divided by daily dollar trading volume, $SIZE_{i,t}$ is the logarithm of market capitalization at the end of year t-1, $B/M_{i,t}$ is the logarithm of book to market ratio defined as book value of equity divided by market capitalization at the end of year t-1, $LEV_{i,t}$ is leverage ratio defined as long term debts divided by total assets at the end of year t-1, $ROE_{i,t}$ is return on equity defined as net income divided by lagged book value at the end of year t-1, $RET_{i,t}$ is the average monthly return in year t-1, $VRET_{i,t}$ is the standard deviation of the monthly return in year t-1, $TT_{i,t}$ is the average monthly turnover in year t-1, and $VTT_{i,t}$ is the standard deviation of the monthly turnover in year t-1. Accounting information in the latest financial report is used in constructing the variables. Heteroskedasticity and serial correlation robust t-statistic are reported in parentheses. The sample period is from 1993:Q1 to 2003:Q4 and we only use industrial firms in regressions with control variables.

Table 7

Adjusted Probability of Informed Trading (AdjPIN) around Addition Events

Panel A:AdjPIN and PSOS

		Pre-Addition	Post-Addition	Change	% Change	t-test /Wilcoxon test
$AdjPIN_{s-b}$	Mean	-0.019	-0.007	0.011		(2.52)
	Median	-0.015	-0.013	0.007		(2.18)
$AdjPIN_{sell}$	Mean	0.081	0.092	0.011	14.00%	(4.03)
	Median	0.081	0.082	0.009	11.55%	(3.85)
$AdjPIN_{buy}$	Mean	0.099	0.100	0.000	0.28%	(0.11)
	Median	0.097	0.095	0.002	1.76%	(0.24)
AdjPIN	Mean	0.180	0.192	0.012	6.43%	(3.67)
	Median	0.181	0.183	0.011	5.89%	(3.75)
PSOS	Mean	0.329	0.315	-0.013	-4.06%	(-2.62)
	Median	0.333	0.311	-0.016	-4.70%	(-2.64)

Panel B: Individual Parameters

	Pre-Addition	Post-Addition	Change	% Change	t-test /Wilcoxon test
α	0.403	0.427	0.024	5.95%	(3.22)
	0.390	0.435	0.030	7.74%	(3.70)
δ	0.504	0.505	0.001	0.18%	(0.08)
	0.516	0.495	0.009	1.81%	(0.15)
μ_s	41.222	52.882	11.660	28.29%	(3.24)
	25.025	36.009	6.735	26.91%	(5.07)
μ_b	57.203	60.772	3.569	6.24%	(0.91)
	34.444	49.038	5.128	14.89%	(3.53)
ε_s	25.283	31.004	5.720	22.62%	(2.59)
	10.166	16.722	3.155	31.03%	(4.88)
ε_b	23.784	29.097	5.313	22.34%	(2.56)
	9.800	14.903	2.477	25.28%	(4.42)
θ	0.253	0.261	0.008	3.25%	(1.36)
	0.233	0.271	0.005	2.29%	(1.39)
λ_s	65.390	65.764	0.374	0.57%	(0.08)
	40.003	49.337	4.257	10.64%	(2.38)
λ_b	63.770	68.705	4.935	7.74%	(1.14)
	42.007	53.650	7.721	18.38%	(3.00)

This table reports mean and median of the AdjPIN estimates 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. Panel A reports the changes in AdjPINs and PSOS. Panel B reports the changes in the individual parameters. α is the probability of information arrival, δ is the probability that the information is bad news, μ_b/μ_s is the arrival rate of informed buy/sell orders, θ is the probability of a symmetric order flow shock, $\varepsilon_b/\varepsilon_s$ is the arrival rate of uninformed buy/sell orders not due to the order flow shock, and λ_b/λ_s is the arrival rate of buy/sell orders due to the order flow shock. AdjPIN is the probability that a trade is information based, defined as $\alpha(\delta\mu_s+(1-\delta)\mu_b)/(\alpha(\delta\mu_s+(1-\delta)\mu_b)+\theta(\lambda_b+\lambda_s)+\varepsilon_b+\varepsilon_s)$. $AdjPIN_{sell}$ is the probability that a trade is information based sell, defined as $\alpha\delta\mu_s/(\alpha(\delta\mu_s+(1-\delta)\mu_b)+\theta(\lambda_b+\lambda_s)+\varepsilon_b+\varepsilon_s)$. $AdjPIN_{buy}$ is the probability that a trade is information based buy, defined as $\alpha(1-\delta)\mu_b/(\alpha(\delta\mu_s+(1-\delta)\mu_b)+\theta(\lambda_b+\lambda_s)+\varepsilon_b+\varepsilon_s)$. $AdjPIN_{s-b}$ is defined as $AdjPIN_{sell}$-$AdjPIN_{buy}$. PSOS is the probalility that a given trade is from a symmetric order flow shock, defined as $\theta(\lambda_b+\lambda_s)/(\alpha(\delta\mu_s+(1-\delta)\mu_b)+\theta(\lambda_b+\lambda_s)+\varepsilon_b+\varepsilon_s)$. There are 360 addition events used in our study from Jan. 03, 1994 to Nov. 29, 2002.

Table 8

Adjusted Probability of Informed Trading (AdjPIN) around Deletion Events

Panel A:AdjPIN and PSOS

		Pre-Deletion	Post-Deletion	Change	% Change	t-test /Wilcoxon test
$AdjPIN_{s\text{-}b}$	Mean	0.003	-0.020	-0.023		(-2.55)
	Median	0.000	-0.015	-0.014		(-2.23)
$AdjPIN_{sell}$	Mean	0.108	0.099	-0.009	-8.51%	(-1.58)
	Median	0.099	0.093	0.000	0.14%	(-0.95)
$AdjPIN_{buy}$	Mean	0.104	0.119	0.014	13.55%	(2.61)
	Median	0.102	0.107	0.008	8.32%	(2.32)
AdjPIN	Mean	0.212	0.217	0.005	2.35%	(0.76)
	Median	0.201	0.202	0.008	4.04%	(1.07)
PSOS	Mean	0.339	0.326	-0.013	-3.92%	(-1.36)
	Median	0.344	0.328	-0.012	-3.54%	(-1.62)

Panel B: Individual Parameters

	Pre-Deletion	Post-Deletion	Change	% Change	t-test /Wilcoxon test
α	0.410	0.385	-0.026	-6.22%	(-1.84)
	0.411	0.368	-0.032	-7.76%	(-1.92)
δ	0.541	0.521	-0.020	-3.74%	(-0.97)
	0.570	0.505	-0.035	-6.10%	(-1.03)
μ_s	24.674	21.015	-3.659	-14.83%	(-1.37)
	12.992	10.919	-0.958	-7.37%	(-1.86)
μ_b	34.341	29.494	-4.847	-14.11%	(-1.28)
	19.027	17.441	-1.199	-6.30%	(-1.51)
ε_s	9.980	6.211	-3.769	-37.77%	(-4.48)
	4.677	3.223	-0.856	-18.30%	(-5.40)
ε_b	9.052	5.392	-3.660	-40.43%	(-4.44)
	3.777	2.475	-0.557	-14.76%	(-4.68)
θ	0.234	0.203	-0.031	-13.12%	(-3.12)
	0.220	0.193	-0.040	-17.94%	(-3.81)
λ_s	38.998	30.632	-8.367	-21.45%	(-2.57)
	23.153	19.546	-1.911	-8.25%	(-2.34)
λ_b	37.959	31.061	-6.899	-18.17%	(-2.14)
	21.014	17.515	-1.346	-6.41%	(-1.96)

This table reports mean and median of the AdjPIN estimates 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-addition estimate is taken as the average of the four quarterly estimates after the event quarter. Panel A reports the changes in AdjPINs and PSOS. Panel B reports the changes in the individual parameters. α is the probability of information arrival, δ is the probability that the information is bad news, μ_b/μ_s is the arrival rate of informed buy/sell orders, θ is the probability of a symmetric order flow shock, $\varepsilon_b/\varepsilon_s$ is the arrival rate of uninformed buy/sell orders not due to the order flow shock, and λ_b/λ_s is the arrival rate of buy/sell orders due to the order flow shock. AdjPIN is the probability that a trade is information based, defined as $\alpha(\delta\mu_s+(1-\delta)\mu_b)/(\alpha(\delta\mu_s+(1-\delta)\mu_b)+\theta(\lambda_b+\lambda_s)+\varepsilon_b+\varepsilon_s)$. $AdjPIN_{sell}$ is the probability that a trade is information based sell, defined as $\alpha\delta\mu_s/(\alpha(\delta\mu_s+(1-\delta)\mu_b)+\theta(\lambda_b+\lambda_s)+\varepsilon_b+\varepsilon_s)$. $AdjPIN_{buy}$ is the probability that a trade is information based buy, defined as $\alpha(1-\delta)\mu_b/(\alpha(\delta\mu_s+(1-\delta)\mu_b)+\theta(\lambda_b+\lambda_s)+\varepsilon_b+\varepsilon_s)$. $AdjPIN_{s\text{-}b}$ is defined as $AdjPIN_{sell}$-$AdjPIN_{buy}$. PSOS is the probalility that a given trade is from a symmetric order flow shock, defined as $\theta(\lambda_b+\lambda_s)/(\alpha(\delta\mu_s+(1-\delta)\mu_b)+\theta(\lambda_b+\lambda_s)+\varepsilon_b+\varepsilon_s)$. There are 207 deletion events used in our study from Mar. 25, 1996 to Nov. 29, 2002.

Table 9

Regression of AdjPIN on Short Sales Dummy, Short Sales Turnover and Control Variables

Independent Variables	Dependent Variables											
	$AdjPIN_{s\text{-}b}$	$AdjPIN_{s\text{-}b}$	$AdjPIN_{s\text{-}b}$	$AdjPIN_{s\text{-}b}$	$AdjPIN_{sell}$	$AdjPIN_{sell}$	$AdjPIN_{sell}$	$AdjPIN_{sell}$	$AdjPIN_{buy}$	$AdjPIN_{buy}$	$AdjPIN_{buy}$	$AdjPIN_{buy}$
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
SSD	0.008	0.006			0.010	0.010			0.002	0.004		
	(2.595)	(1.711)			(5.328)	(4.395)			(1.228)	(1.736)		
SSR			-0.023	-0.019			0.105	0.142			0.128	0.161
			(-0.384)	(-0.307)			(2.534)	(3.342)			(2.392)	(3.104)
SIZE		-0.005		-0.006		-0.006		-0.007		-0.001		-0.001
		(-1.946)		(-2.301)		(-3.751)		(-4.156)		(-0.647)		(-0.507)
B/M		0.004		0.003		0.002		0.002		-0.001		-0.001
		(1.596)		(1.219)		(1.432)		(1.135)		(-0.803)		(-0.549)
LEV		-0.002		-0.004		0.012		0.015		0.013		0.018
		(-0.114)		(-0.219)		(1.207)		(1.332)		(1.303)		(1.544)
ROE		0.000		0.000		0.000		0.000		0.000		0.000
		(-0.415)		(-0.015)		(2.414)		(2.421)		(2.549)		(2.243)
RET		-0.001		-0.007		0.042		0.037		0.043		0.044
		(-0.034)		(-0.246)		(2.573)		(2.045)		(2.677)		(2.441)
VRET		0.002		0.004		-0.009		-0.007		-0.011		-0.011
		(0.287)		(0.548)		(-1.782)		(-1.240)		(-2.371)		(-2.171)
TT		-0.061		-0.057		-0.073		-0.064		-0.013		-0.008
		(-2.984)		(-2.559)		(-5.819)		(-4.584)		(-0.971)		(-0.544)
VTT		0.037		0.036		0.045		0.040		0.008		0.004
		(2.463)		(2.342)		(4.931)		(4.160)		(0.887)		(0.427)
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.	24302	18383	20465	15523	24302	18383	20465	15523	24302	18383	20465	15523
Adj. R^2	2.22%	2.16%	2.04%	1.86%	3.10%	3.35%	2.33%	2.38%	4.30%	3.55%	4.01%	3.17%

This table reports estimates of coefficients of the following regression,

$$AdjPINx_{i,t} = c_0 + c_1SSD_{i,t} + c_2SSR_{i,t} + c_3SIZE_{i,t} + c_4B/M_{i,t} + c_5LEV_{i,t} + c_6ROE_{i,t} + c_7RET_{i,t} + c_8VRET_{i,t} + c_9TT_{i,t} + c_{10}VTT_{i,t} + \text{firm fixed effects (year fixed effects)} + \varepsilon_{i,t}$$

where $AdjPINx_{i,t}$ denotes $AdjPIN_{s\text{-}b}$, $AdjPIN_{sell}$ or $AdjPIN_{buy}$ of stock i in quarter t, $SSD_{i,t}$ is a dummy variable that takes value one if stock i is shortable throughout quarter t, and zero otherwise, $SSR_{i,t}$ is the average short sale ratio of stock i in quarter t where the short sale ratio is defined as daily dollar value of the shares sold short divided by daily dollar trading volume, $SIZE_{i,t}$ is the logarithm of market capitalization at the end of quarter t-1, $B/M_{i,t}$ is the logarithm of book to market ratio defined as book value of equity divided by market capitalization at the end of quarter t-1, $LEV_{i,t}$ is leverage ratio defined as long term debts divided by total assets at the end of quarter t-1, $ROE_{i,t}$ is return on equity defined as net income divided by lagged book value at the end of quarter t-1, $RET_{i,t}$ is the average monthly return over quarter t-4 to t-1, $VRET_{i,t}$ is the standard deviation of the monthly return over quarter t-4 to t-1, $TT_{i,t}$ is the average monthly turnover over quarter t-4 to t-1, and $VTT_{i,t}$ is the standard deviation of the monthly turnover over quarter t-4 to t-1. Accounting information in the latest financial report is used in constructing the variables. Heteroskedasticity and serial correlation robust t-statistic are reported in parentheses. The sample period is from 1993:Q1 to 2003:Q4 and we only use industrial firms in regressions with control variables.

Table 10

Post Earnings Announcement Drift (PEAD) of Shortable and Non-Shortable Stocks

SUE Quintiles	SUE	CAR (-61, -2)	CAR (-31, -2)	CAR (-1, +1)	CAR (+2, +61)	CAR (+2, +91)	CAR (+2, +121)
Panel A: PEAD of Non-Shortable Stocks							
Quitile 1	-7.752	-5.047**	-4.185***	-3.881***	-1.320**	-5.150**	-4.777*
Quitile 2	-1.546	1.388	0.821	-0.938	-0.542	-0.083	0.225
Quitile 3	-0.558	6.090**	2.647	0.087	-0.053	-2.246	-4.003
Quitile 4	0.347	6.711	3.109**	-0.100	2.116	1.058	-0.066
Quitile 5	3.115	12.74***	6.512***	2.907***	4.307**	5.142**	5.021*
	Q5-Q1	17.787	10.697	6.788	5.627	10.292	9.798
Panel B: PEAD of Shortable Stocks							
Quitile 1	-4.982	-4.936**	-3.893**	-2.354***	0.958	0.771	0.632
Quitile 2	-1.305	0.645	-1.441	-0.653	0.831	0.951	0.708
Quitile 3	-0.441	2.535	1.176	-0.036	2.229	0.644	0.182
Quitile 4	0.215	2.877	0.758	0.857	3.054	2.440	4.029
Quitile 5	1.704	2.083	0.558	2.392***	3.345*	2.641*	3.247
	Q5-Q1	7.019	4.451	4.746	2.387	1.870	2.615

This table reports the post-earnings announcement drift for non-shortable and shortable stocks. From Jan. 01, 1992 to Dec. 31, 2004, we classify all the annual earnings announcements into two groups based on the eligibility for short selling of the underlying stocks. A stock is identified as shortable if it is on the list of securities eligible for short selling. Panel A reports the average CARs of quintiles sorted on standardized unexpected earnings (SUE) for non-shortable group and Panel B reports the CARs for shortable group. SUE is defined as (Actual Earnings -Mean Analyst Forecast)/(Std. Dev. of Analyst Forecasts) using the I/B/E/S data. Abnormal returns are excess returns over size and B/M matched portfolios (3*3) formed on Jan. 1 and June 1 of each year. The sample includes all the stocks with analyst forecast data in I/B/E/S and return and account data in PACAP. The significance of CAR is marked with "*", where "*" denotes significance at 10% level, "**" denotes significance at 5% level and "***" denotes significance at 1% level.

Table 11

Future Earnings Response Coefficients (FERCs) around 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)
	(2.38)	(4.91)		
Combined FERC	0.299	1.007	0.707	(1.84)
	(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)
	(2.62)	(3.69)		
$FERC_1$	0.201	0.414	0.213	(1.14)
	(1.82)	(2.83)		
$FERC_2$	0.137	0.289	0.152	(0.79)
	(1.55)	(1.57)		
$FERC_3$	0.063	0.240	0.177	(1.09)
	(0.90)	(1.50)		

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_o 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_o 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.

Table 12

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

	Control Variables							
	$SIZE_t$		$MTBV_t$		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)
ΔE3	-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*ΔE	0.365	(2.19)	0.396	(2.42)	0.302	(1.77)	0.435	(2.82)
SSD*ΔE3	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*ΔE3	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

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_o is the change in combined FERC from pre-addition to post-addition period.

Table 13

Summary Statistics of Return-Inflation Beta, Earnings-Inflation Beta and ROE-Inflation Beta

Panel A: Expected Inflation

	No. of Firms	Mean	Std. Dev.	Min	25%	50%	75%	Max	No. >=0	No. <= 0
Return-Inflation Beta	4672	-2.427	10.883	-51.149	-6.482	-1.222	2.225	38.945	1916	2756
Earnings-Inflation Beta	4672	0.132	114.328	-466.297	-51.111	-1.286	50.316	503.657	2295	2377
ROE-Inflation Beta	4672	0.259	10.857	-82.006	-0.850	0.194	1.435	87.213	2690	1982

Panel B: Unexpeced Inflation

	No. of Firms	Mean	Std. Dev.	Min	25%	50%	75%	Max	No. >=0	No. <= 0
Return-Inflation Beta	4656	-0.018	7.996	-23.866	-3.960	-1.034	3.254	35.272	1945	2711
Earnings-Inflation Beta	4656	10.627	59.430	-212.826	-19.990	9.579	41.260	257.599	2770	1886
ROE-Inflation Beta	4656	0.032	4.581	-38.033	-0.545	0.021	0.620	39.136	2389	2267

Note: Return-inflation beta is the slope coefficient of a regression of quarterly stock return on inflation. Earnings-inflation beta is the slope coefficient of a regression of quarterly earnings growth on inflation. ROE-Inflation beta is the slope coefficient of a regression of quarterly ROE on inflation. Panels A and B report the summary statistics of the three betas for the sample firms using expected inflation and unexpected inflation respectively. Our sample includes all the NYSE, AMEX and NASDAQ firms with at least 5-year return and accounting record in the period from 1973 to 2006. Earnings growth is defined as $(E_{i,t} - E_{i,t-4})/\sigma_{i,t}$, where $E_{i,t}$ represents the quarterly earnings for firm i in quarter t and $\sigma_{i,t}$ is the standard deviation of $(E_{i,t} - E_{i,t-4})$ over the previous eight quarters. ROE is defined as quarterly earnings over book value of equity at last quarter end, seasonally-adjusted and de-trended. Expected inflation is defined as the yield to maturity of the 3 month T-bill observed at the beginning of a quarter. Unexpected inflation is the difference between total inflation and expected inflation, and lagged for one period. In each panel, we trim the beta estimates at 1% and 99% percentiles and use a common sample for the three betas.

Table 14

Avergae Return-Inflation Beta of Decile Groups Sorted On Earnings-Inflation Beta and ROE-Inflation Beta

Panel A: Expeced Inflation

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Earnings-Inflation Beta (Sorting Variable)	-212.001	-90.580	-51.722	-27.812	-9.567	7.039	26.115	51.554	93.720	218.308
Return-Inflation Beta	-8.791	-6.409	-4.864	-2.615	-2.109	-1.902	-0.634	-0.298	0.574	2.871
ROE-Inflation Beta (Sorting Variable)	-17.368	-2.575	-0.889	-0.242	0.066	0.331	0.726	1.479	3.334	18.032
Return-Inflation Beta	-6.276	-5.899	-4.203	-1.207	-1.176	-1.014	-0.814	-0.773	-0.933	-1.963

Panel B: Unexpeced Inflation

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Earnings-Inflation Beta (Sorting Variable)	-99.066	-40.092	-20.304	-6.509	4.654	14.967	26.520	41.618	64.251	121.180
Return-Inflation Beta	-2.676	-1.370	-0.699	-0.312	-0.408	0.264	0.167	1.014	1.022	2.845
ROE-Inflation Beta (Sorting Variable)	-7.564	-1.333	-0.574	-0.265	-0.062	0.114	0.318	0.639	1.439	7.674
Return-Inflation Beta	1.430	-0.945	-1.444	-1.409	-1.486	-1.328	-1.150	0.607	1.343	4.242

Note: All the sample firms are sorted into deciles based on earnings-inflation/ROE-inflation beta. This table reports the mean of the return-inflation beta of each decile, as well as that of the sorting betas. Panels A and B report the results using expected inflation and unexpected inflation respectively. Decile1 (D1) has the smallest earnings-inflation/ROE-inflation beta and the Decile(D10) has the largest. Return-inflation beta is the slope coefficient of a regression of quarterly stock return on inflation. earnings-inflation beta is the slope coefficient of a regression of quarterly earnings growth on inflation. ROE-inflation beta is the slope coefficient of a regression of quarterly ROE on inflation. Our sample includes all the NYSE, AMEX and NASDAQ firms with at least 5-year return and accounting record in the period from 1973 to 2006. Earnings growth is defined as $(E_{i,t} - E_{i,t-4})/\sigma_{i,t}$, where $E_{i,t}$ represents the quarterly earnings for firm i in quarter t and $\sigma_{i,t}$ is the standard deviation of $(E_{i,t} - E_{i,t-4})$ over the previous eight quarters. ROE is defined as quarterly earnings over book value of equity at last quarter end, seasonally-adjusted and de-trended. Expected inflation is defined as the yield to maturity of the 3 month T-bill observed at the beginning of a quarter. Unexpected inflation is the difference between total inflation and expected inflation.

Table 15

Regression of Return on Inflation with Interaction Variables (Model 1)

INF denotes	Expected Inflation		Unexpected Inflation	
RANK based On	Earnings-beta	ROE-beta	Earnings-beta	ROE-beta
INTERCEPT	0.136	0.108	0.062	0.061
	(7.369)	(5.887)	(9.364)	(9.207)
INF	-4.434	-2.331	-2.713	-2.662
	(-5.237)	(-2.780)	(-4.112)	(-4.015)
*INF*RANK*	0.517	0.232	0.273	0.238
	(15.895)	(6.953)	(10.409)	(8.991)
RANK	-0.007	-0.003	0.001	0.001
	(-14.101)	(-6.298)	(4.145)	(4.683)
No. of Obs.	253148	253148	251749	251749
Adj. R-sqaure	0.353%	0.272%	0.371%	0.360%

Note: This table reports the regression results of the following panel model,

$$RET_{i,t} = \alpha + \beta * INF_t + \theta * INF_t * RANK_i + \gamma * RANK_i + \delta_j \sum_{j=1}^{n-1} INDU_j + \eta_j \sum_{j=1}^{n-1} INDU_j * INF_t + \varepsilon_{i,t}$$

where $RET_{i,t}$ is the return for firm i in quarter t, INF_t denotes expected inflation or unexpected inflation in quarter t, $RANK_i$ is the decile ranking for firm i based on sorting on earnings-inflation beta or ROE-inflation beta, where earnings-inflation beta is the slope coefficient of a regression of quarterly earnings growth on inflation and ROE-Inflation beta is the slope coefficient of a regression of quarterly ROE on inflation, $INDU_j$ is a dummy variable that takes value one when firm i belongs to industry j, and n is the number of two-digit SIC industries. Earnings growth is defined as $(E_{i,t} - E_{i,t-4})/\sigma_{i,t}$, where $E_{i,t}$ represents the quarterly earnings for firm i in quarter t and $\sigma_{i,t}$ is the standard deviation of $(E_{i,t} - E_{i,t-4})$ over the previous eight quarters. ROE is defined as quarterly earnings over book value of equity at last quarter end, seasonally-adjusted and de-trended. Expected inflation is defined as the yield to maturity of the 3 month T-bill observed at the beginning of a quarter. Unexpected inflation is the difference between total inflation and expected inflation. Heteroskedasticity and serial correlation robust t-statistics are reported in the parentheses.

Table 16

Regression of Return on Inflation with Interaction Variables (Model 2)

INF denotes	Expected Inflation		Unexpected Inflation	
QUIN based On	Earnings-beta	ROE-beta	Earnings-beta	ROE-beta
INTERCEPT	0.131	0.131	0.060	0.064
	(7.093)	(7.058)	(9.110)	(9.609)
INF	-4.248	-4.107	-2.436	-0.964
	(-4.988)	(-4.816)	(-3.671)	(-1.437)
*INF*QUIN2*	2.025	2.593	0.890	-0.959
	(7.173)	(9.129)	(3.813)	(-4.127)
*INF*QUIN3*	3.015	3.494	1.260	-0.972
	(10.898)	(12.576)	(5.419)	(-4.237)
*INF*QUIN4*	3.581	3.341	1.678	-0.135
	(12.675)	(11.727)	(7.236)	(-0.589)
*INF*QUIN5*	4.534	2.043	2.356	1.946
	(14.653)	(6.435)	(9.759)	(7.895)
No. of Obs.	253148	253148	251749	251749
Adj. R-sqaure	0.356%	0.329%	0.374%	0.417%

Note: This table reports the regression results of the following panel model,

$$RET_{i,t} = \alpha + \beta * INF_t + \sum_{i=2}^{5} \theta_i * QUIN_i * INF_t + \sum_{i=2}^{5} \gamma_i * QUIN_i + \delta_j \sum_{j=1}^{n-1} INDU_j + \eta_j \sum_{j=1}^{n-1} INDU_j * INF_t + \varepsilon_{i,t}$$

where $RET_{i,t}$ is the return for firm i in quarter t, INF_t denotes expected inflation or unexpected inflation in quarter t, $QUIN_j$ is a dummy variable that takes value one if firm i belongs to quintile j based on sorting by earnings-inflation beta or ROE-inflation beta, where earnings-inflation beta is the slope coefficient of a regression of quarterly earnings growth on inflation and ROE-Inflation beta is the slope coefficient of a regression of quarterly ROE on inflation, $INDU_j$ is a dummy variable that takes value one when firm i belongs to industry j, and n is the number of two-digit SIC industries. Earnings growth is defined as $(E_{i,t} - E_{i,t-4})/\sigma_{i,t}$, where $E_{i,t}$ represents the quarterly earnings for firm i in quarter t and $\sigma_{i,t}$ is the standard deviation of $(E_{i,t} - E_{i,t-4})$ over the previous eight quarters. ROE is defined as quarterly earnings over book value of equity at last quarter end, seasonally-adjusted and de-trended. Expected inflation is defined as the yield to maturity of the 3 month T-bill observed at the beginning of a quarter. Unexpected inflation is the difference between total inflation and expected inflation. Heteroskedasticity and serial correlation robust t-statistics are reported in the parentheses.

Table 17

Regression of Return on Inflation with Interaction Variables (Model 3)

Panel A: Expected Inflation

CRANK based on	$SIZE_i$	$INVENTORY_i$	$INVEN\_M_i$	PPE_i	$INTAN_i$	$DEBT2_i$	$DEBT3_i$	$DEBT4_i$	$DEBT5_i$	$PREFER_i$
INTERCEPT	0.106	0.109	0.152	0.109	0.097	0.124	0.124	0.128	0.134	0.090
	(5.751)	(5.588)	(5.023)	(5.938)	(4.623)	(5.011)	(5.026)	(5.191)	(5.429)	(4.880)
INF	-2.398	-1.478	-3.409	-1.980	-1.188	-1.564	-1.711	-2.066	-2.569	-0.862
	(-2.864)	(-1.646)	(-2.296)	(-2.373)	(-1.225)	(-1.333)	(-1.456)	(-1.756)	(-2.181)	(-1.030)
*INF*CRANK*	0.227	-0.023	0.120	0.215	-0.001	-0.150	-0.117	-0.058	0.027	-0.057
	(7.705)	(-0.533)	(3.431)	(5.108)	(-0.035)	(-4.581)	(-3.493)	(-1.685)	(0.763)	(-1.971)
CRANK	-0.002	-0.001	-0.002	-0.004	0.000	0.001	0.001	0.000	-0.001	0.001
	(-5.229)	(-1.688)	(-3.733)	(-6.569)	(0.494)	(2.568)	(2.113)	(0.767)	(-1.148)	(1.098)
No. of Obs.	253103	251434	165981	253036	242134	239027	238956	239019	238291	253125
Adj. R-sqaure	0.283%	0.265%	0.269%	0.272%	0.262%	0.279%	0.274%	0.269%	0.268%	0.256%

Panel B: Unexpected Inflation

CRANK based on	$SIZE_i$	$INVENTORY_i$	$INVEN\_M_i$	PPE_i	$INTAN_i$	$DEBT2_i$	$DEBT3_i$	$DEBT4_i$	$DEBT5_i$	$PREFER_i$
INTERCEPT	0.073	0.078	0.095	0.075	0.072	0.083	0.083	0.085	0.088	0.067
	(11.084)	(11.074)	(9.148)	(11.270)	(9.707)	(9.676)	(9.682)	(9.910)	(10.165)	(10.197)
INF	1.386	-1.386	1.051	-1.469	-0.864	-1.260	-0.946	-0.453	0.226	-1.471
	(2.102)	(-1.968)	(0.968)	(-2.218)	(-1.164)	(-1.440)	(-1.080)	(-0.516)	(0.257)	(-2.228)
*INF*CRANK*	-0.505	0.126	-0.102	0.050	-0.119	0.269	0.213	0.126	0.010	0.029
	(-20.017)	(3.455)	(-3.389)	(1.403)	(-4.075)	(9.554)	(7.454)	(4.330)	(0.358)	(1.163)
CRANK	-0.001	-0.001	-0.001	-0.002	0.000	0.000	0.000	0.000	-0.001	0.000
	(-3.518)	(-4.130)	(-3.099)	(-5.089)	(1.481)	(0.730)	(0.658)	(-0.797)	(-2.079)	(0.368)
No. of Obs.	251704	249979	164846	251617	240608	237945	237874	237937	237149	251726
Adj. R-sqaure	0.501%	0.348%	0.215%	0.345%	0.362%	0.381%	0.363%	0.346%	0.337%	0.329%

Note: This table reports the regression results of the following panel model,

$$RET_{i,t} = \alpha + \beta * INF_t + \theta * INF_t * CRANK_i + \gamma * CRANK_i + \delta_j \sum_{j=1}^{n-1} INDU_j + \eta_j \sum_{j=1}^{n-1} INDU_j * INF_t + \varepsilon_{i,t}$$

where $RET_{i,t}$ is the return for firm i in quarter t, INF_t denotes expected inflation or unexpected inflation in quarter t, $CRANK_i$ is the decile ranking for firm i based on sorting on one of the firm characteristic variables. $INDU_j$ is a dummy variable that takes value one when firm i belongs to industry j, and n is the number of two-digit SIC industries. The firm characteristic variables are as follows. $SIZE_i$ is the logarithm of market value for firm i, $INVENTORY_i$ is the ratio of inventory to total sales for firm i, $INVEN\_M_i$ is a dummy variable that takes value one if firm i use FIFO, PPE_i is the ratio of PPE to total assets for firm i, $INTAN_i$ is the ratio of intangible assets to total assets, $DEBTn_i$ is the ratio of long term debt due in n years to total assets and $PREFER_i$ is the ratio of the value of prefer stocks to total assets. All the characteristic variables are the averages over the sample period consistent with that of $RET_{i,t}$. Expected inflation is defined as the yield to maturity of the 3 month T-bill observed at the beginning of a quarter. Unexpected inflation is the difference between total inflation and expected inflation. Heteroskedasticity and serial correlation robust t-statistics are reported in the parentheses.

Table 18

Regression of Return on Inflation with Interaction Variables (Model 4)

Panel A: Expected Inflation

CQUIN based on	$SIZE_i$	$INVENTORY_i$	$INVEN\_M_i$	PPE_i	$INTAN_i$	$DEBT2_i$	$DEBT3_i$	$DEBT4_i$	$DEBT5_i$	$PREFER_i$
INTERCEPT	0.094	0.107	0.147	0.107	0.096	0.138	0.137	0.141	0.145	0.091
	(5.062)	(5.459)	(4.849)	(5.812)	(4.551)	(5.553)	(5.522)	(5.688)	(5.857)	(4.905)
INF	-1.784	-1.572	-3.165	-1.989	-1.104	-2.645	-2.582	-2.987	-3.321	-1.021
	(-2.105)	(-1.748)	(-2.124)	(-2.397)	(-1.134)	(-2.242)	(-2.180)	(-2.515)	(-2.790)	(-1.214)
*INF*CQUIN2 C*	-0.100	-0.080	0.214	1.680	-0.204	0.794	0.512	0.977	0.892	0.068
	(-0.352)	(-0.257)	(0.681)	(5.385)	(-0.783)	(2.761)	(1.741)	(3.134)	(2.714)	(0.272)
*INF*CQUIN3 C*	0.653	0.176	-2.087	1.915	0.023	0.692	0.730	0.844	1.258	-1.970
	(2.351)	(0.507)	(-4.619)	(6.203)	(0.084)	(2.406)	(2.491)	(2.734)	(3.955)	(-5.199)
*INF*CQUIN4 C*	1.211	0.027	0.203	1.789	-0.200	0.261	0.111	0.531	1.103	-0.351
	(4.425)	(0.075)	(0.646)	(5.512)	(-0.701)	(0.888)	(0.373)	(1.715)	(3.417)	(-1.402)
*INF*CQUIN5 C*	1.409	-0.136	1.212	2.097	0.069	-1.105	-0.826	-0.057	0.502	-0.254
	(5.284)	(-0.359)	(3.877)	(5.425)	(0.215)	(-3.508)	(-2.591)	(-0.174)	(1.482)	(-0.983)
No. of Obs.	253103	251434	165981	253036	242134	239027	238956	239019	238291	253125
Adj. R-sqaure	0.294%	0.265%	0.297%	0.279%	0.264%	0.296%	0.286%	0.278%	0.279%	0.269%

Panel B: Unexpected Inflation

CQUIN based on	$SIZE_i$	$INVENTORY_i$	$INVEN\_M_i$	PPE_i	$INTAN_i$	$DEBT2_i$	$DEBT3_i$	$DEBT4_i$	$DEBT5_i$	$PREFER_i$
INTERCEPT	0.066	0.074	0.091	0.075	0.073	0.089	0.090	0.092	0.094	0.066
	(9.958)	(10.566)	(8.768)	(11.400)	(9.753)	(10.343)	(10.431)	(10.568)	(10.775)	(9.861)
INF	0.402	-1.082	0.375	-1.093	-0.977	-0.074	-0.057	0.252	0.442	-1.669
	(0.602)	(-1.532)	(0.344)	(-1.664)	(-1.309)	(-0.085)	(-0.065)	(0.285)	(0.499)	(-2.515)
*INF*CQUIN2 C*	-0.329	0.109	0.624	-0.910	-0.371	-0.306	-0.165	-0.362	0.109	0.574
	(-1.346)	(0.409)	(2.314)	(-3.633)	(-1.645)	(-1.276)	(-0.675)	(-1.433)	(0.414)	(2.641)
*INF*CQUIN3 C*	-1.903	0.353	0.967	-0.882	-0.452	-0.188	-0.111	-0.304	-0.649	0.422
	(-7.994)	(1.204)	(3.068)	(-3.551)	(-1.923)	(-0.780)	(-0.454)	(-1.209)	(-2.548)	(1.680)
*INF*CQUIN4 C*	-3.102	0.347	-0.119	-0.134	-0.683	0.538	0.578	0.100	-0.350	0.279
	(-13.211)	(1.125)	(-0.441)	(-0.507)	(-2.789)	(2.194)	(2.330)	(0.398)	(-1.350)	(1.293)
*INF*CQUIN5 C*	-3.595	1.106	-0.690	0.238	-1.248	2.191	1.682	0.867	0.344	0.385
	(-15.763)	(3.456)	(-2.569)	(0.737)	(-4.726)	(8.297)	(6.325)	(3.207)	(1.259)	(1.734)
No. of Obs.	251704	249979	164846	251617	240608	237945	237874	237937	237149	251726
Adj. R-sqaure	0.513%	0.349%	0.240%	0.358%	0.365%	0.403%	0.379%	0.358%	0.356%	0.346%

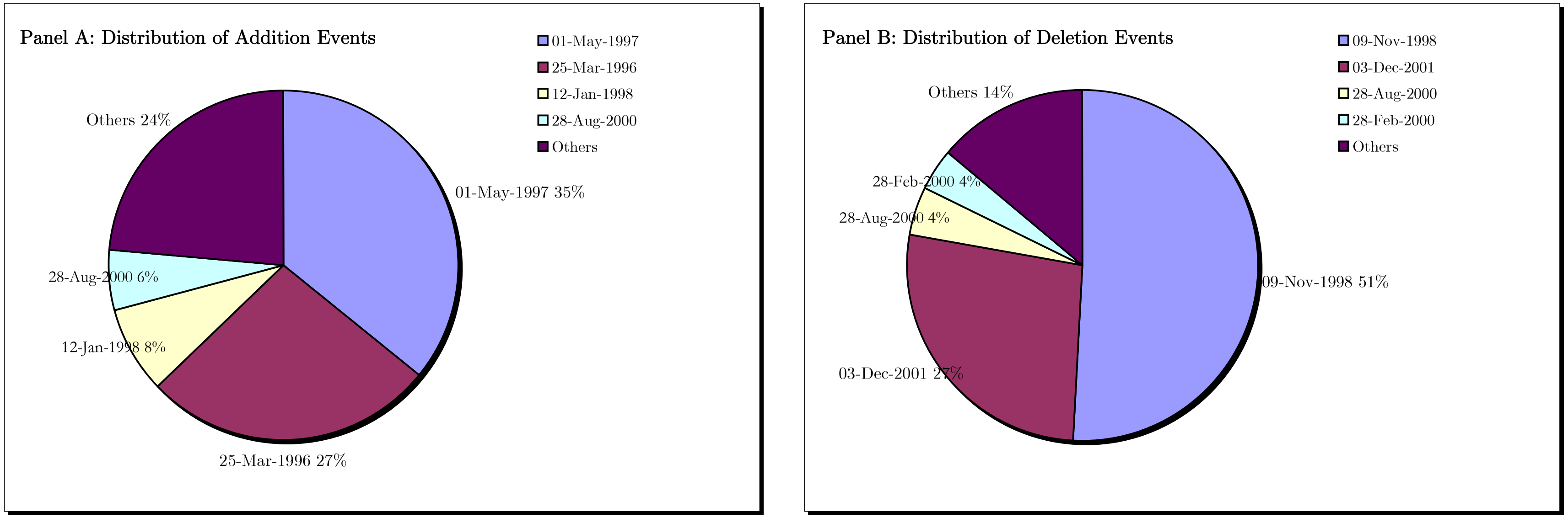
Note: This table reports the regression results of the following panel model,

$$RET_{i,t} = \alpha + \beta * INF_t + \sum_{i=2}^{5} \theta_i * CQUIN_i * INF_t + \sum_{i=2}^{5} \gamma_i * CQUIN_i + \delta_j \sum_{j=1}^{n-1} INDU_j + \eta_j \sum_{j=1}^{n-1} INDU_j * INF_t + \varepsilon_{i,t}$$

where $RET_{i,t}$ is the return for firm i in quarter t, INF_t denotes expected inflation or unexpected inflation in quarter t, $CQUIN_j$ is a dummy variable that takes value one if firm i belongs to quintile j based on sorting on one of the firm characteristic variables. $INDU_j$ is a dummy variable that takes value one when firm i belongs to industry j, and n is the number of two-digit SIC industries. The firm characteristic variables are as follows. $SIZE_i$ is the logarithm of market value for firm i, $INVENTORY_i$ is the ratio of inventory to total sales for firm i, $INVEN\_M_i$ is a dummy variable that takes value one if firm i use FIFO, PPE_i is the ratio of PPE to total assets for firm i, $INTAN_i$ is the ratio of intangible assets to total assets, $DEBTn_i$ is the ratio of long term debt due in n years to total assets and $PREFER_i$ is the ratio of the value of prefer stocks to total assets. All the characteristic variables are the averages over the sample period consistent with that of $RET_{i,t}$. Expected inflation is defined as the yield to maturity of the 3 month T-bill observed at the beginning of a quarter. Unexpected inflation is the difference between total inflation and expected inflation. Heteroskedasticity and serial correlation robust t-statistics are reported in the parentheses.

Figure 1

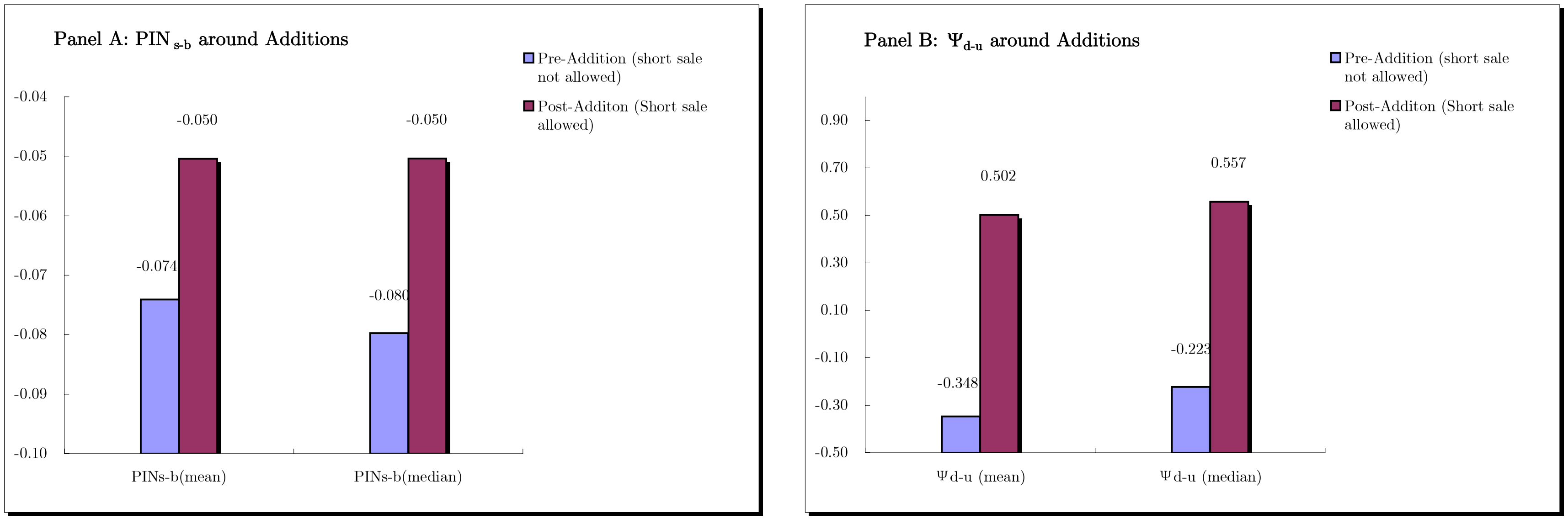
Distribution of Addition and Deletion Events around Event Dates



This figure shows the distribution of addition and deletion events around event dates. Panel A shows the distribution of addition events and Panel B shows the distribution of deletion events.

Figure 2

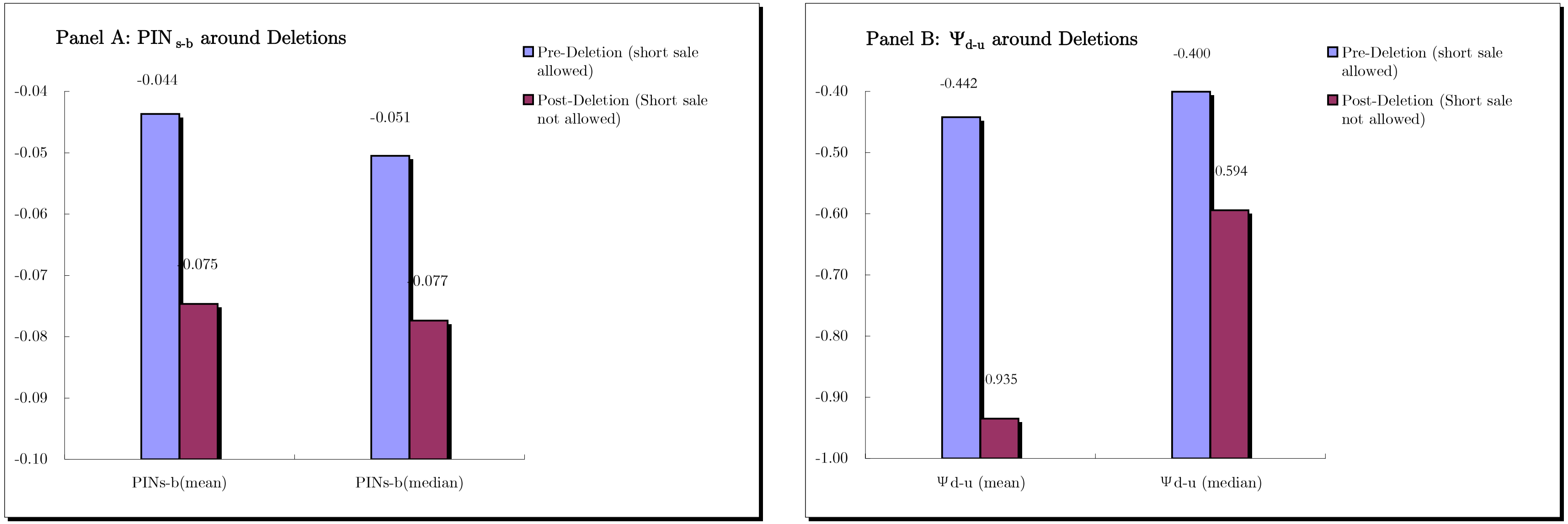
Probability of Informed Trading and Price Non-synchronicity around Addition Events



This figure shows mean and median of $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$ in the pre-addition and post-addition 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 $(1\text{-}\delta)$*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 $\log((1\text{-}R^2_u)/R^2_u)$, 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 Ψ_{down} is defined in a similar way when market return is negative.

Figure 3

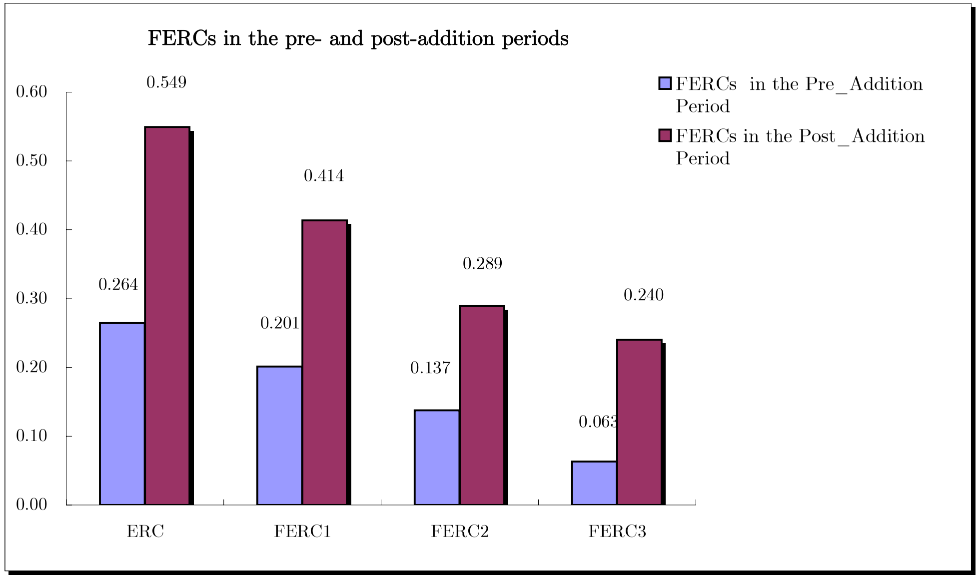
Probability of Informed Trading and Price Non-synchronicity around Deletion Events



This figure shows mean and median of $PIN_{s\text{-}b}$ and $\Psi_{d\text{-}u}$ in the pre-deletion and post-deletion 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 Ψ_{down} is defined in a similar way when market return is negative.

Figure 4

FERCs in the Pre- and Post-Addition Periods



This figure shows the ERC, FERCs estimated in the pre- and post-addition periods. FERCn is the estimated coefficient on the future earnings change n period ahead in a pooled regression of current annual returns on current earnings changes, three year future earnings changes, and three year annual future returns. ERC is the estimated coefficient on the current earnings change.

Appendix

The List of Securities Eligible for Short Selling on Jan. 3, 1994

Stock Code	Stock Name	股份簡稱
1	Cheung Kong (Holdings) Ltd.	長江實業
2	China Light & Power Co., Ltd.	中電控股
3	Hong Kong and China Gas Co. Ltd., The	香港中華煤氣
4	Wharf (Holdings) Ltd., The	九龍倉集團
5	HSBC Holdings plc	匯豐控股
6	Hongkong Electric Holdings Ltd.	香港電燈
7	Hongkong Land Holdings Ltd.	香港置地
8	Hong Kong Telecommunications Ltd.	香港電訊
11	Hang Seng Bank Ltd.	恆生銀行
12	Henderson Land Development Co. Ltd.	恆基地產
13	Hutchison Whampoa Ltd.	和記黃埔
15	Jardine Matheson Holdings Ltd.	怡和集團
16	Sun Hung Kai Properties Ltd.	新鴻基地產
17	New World Development Co., Ltd.	新世界發展
19	Swire Pacific Ltd. 'A'	太古股份公司 A
20	Wheelock and Co. Ltd.	會德豐
54	Hopewell Holdings Ltd.	合和實業