Limit Hits and Connected Stocks

Jia-Hau Guo*, Lung-Fu Chang**, and Mao-Wei Hung***

ABSTRACT

We extend the trading-halt analysis of Jiang et al. (2009) by studying price limits and connected stocks. We employ an identification strategy of propensity score matching to achieve a better specification of the connected firms across industries. We find a significant liquidity impact on connected stocks and price impact of trades having substantial increases. We find that informed traders may trade connected stocks as a substitution of the hitting stock and connected stocks seem to provide alternatives for traders to reverse their earlier suboptimal trades even prior to the hit. We find liquidity impacts of informative limit hits are weaker than those of uninformative limit hits. In addition, our results indicate that there is a common liquidity response of connected stocks to firm-specific limit hits.

JEL Classification: G14, G18, G19

Keywords：Price Limit; Liquidity Impact; Price Impact; Propensity Score Match; Asymmetry Information; Order Imbalance Reversal

---

* Guo is from the Department of Information Management and Finance, College of Management, National Chiao Tung University, Hsinchu, Taiwan. ** Chang is from the Department of Finance, National Taipei University of Business, Taipei, Taiwan. *** Hung is from the College of Management, National Taiwan University, Taipei, Taiwan. Address correspondence to: Associate Professor Jia-Hau Guo, College of Management, National Chiao Tung University, No. 1001, Ta-Hsueh Road, Hsinchu 300, Taiwan. Tel:+886-3-5712121#57078 Fax:+886-3-5733260 E-mail:jiahau@faculty.nctu.edu.tw

0. Introduction

Recently, Jiang et al. (2009) investigate the information content of trading halts of NYSE-listed stocks on informationally related securities that continue to trade during the period of the halt. We extend Jiang et al. (2009) by studying price limits. Such an extension is important because most stock markets around the world use price limits (e.g., Kim and Park (2010) point out that 23 out of 43 of the most important world markets use price limits).[1] Price limits are believed to mitigate excessive price volatility, mitigate panic behavior, and/or minimize price manipulation.[2] Despite their significant presence, however, these price limit mechanisms are not still known enough and there are many unanswered questions to make informed decisions regarding market regulation because of the lack of appropriate study samples using U.S. data.[3] In this paper, we as well as Kim and Limpaphayom (2000) and Kim (2001) look to the Taiwan Stock Exchange (TWSE) where price limits are systematically imposed and regularly used.[4]

---

[1] We acknowledge our anonymous referees for pointing this out to us.
[2] See Kim and Rhee (1997), Kim (2001), Kim and Yang (2004), and Kim and Park (2010).
[3] See France et al. (1994), Harris (1998), and Chan et al. (2005).
[4] Kim and Limpaphayom (2000) find the TWSE to be a very useful market to test price limit effects because their price limits have been historically narrow enough to have had a significant impact on stock prices. Kim (2001) also justifies the use of Taiwan data for similar reasons.

Although price limits and trading halts are both circuit breakers to reduce information asymmetry,[5] they differ in several ways. First, price limits are artificial boundaries imposed on markets to confine the daily movements of securities within a predetermined range, whereas trading halts represent a temporary interruption in the trading of an individual security to disseminate information. Therefore, trading is still permissible in the case of price limits as long as it remains within the preset trading range, whereas trading halts indicate a complete cessation of trading activity. Second, price limits are typically specified by a percent based on the previous day's closing price but trading halts do not included limitations on price movements. Third, the activation of price limits depends solely on the price movement (rule-based price limits) but trading halts are subjectively imposed in certain circumstances by officials or regulators (discretionary trading halts). Therefore, price limits are easier for traders to observe and predict than trading halts. Fourth, during news pending halts, firms are often required to release information related to the cause of the halt, which may reduce the degree of information asymmetry among market participants. However, when

[5] The activation of circuit breakers attempts to provide investors with more time to evaluate new information and make rational decisions. For example, investors are forced to cool off and digest new information when trading is suspended. On the basis of this cooling-off argument, regulators expect that price limit and trading halts cause stock prices to become more informative, reduce uncertainty, and protect uninformed investors from excessive price movements. See Kim et al. (2008).

a stock hits its price limit, there is no special announcement; instead, this information is simply posted on the exchange's trading screens.[6]

Consequently, there remain questions about limit hits that are not applicable to trading halts. Two instances are as follows: (1) the fact that limit prices are known in advance and (2) the fact that limit-hitting stocks can continue to trade (either at the limit price or away from the limit price). In the first instance, we might expect there to be anticipatory changes in the market that precede the limit hit, which could be addressed in the empirical work. The second fact suggests that the empirical work should also account for the post-limit hit environment, since presumably, some stocks that hit the limit continue to trade actively while others may not trade at all. In fact, Kim et al. (2008) conduct a daily analysis to compare relative performance of trading halts and price limits using data from Spanish Stock Exchange, and find some different liquidity results for trading halts and limit hits. This further sheds light in the importance of our extension of Jiang et al. (2009) from trading halts to limit hits.[7]

---

[6] Firm characteristics of trading halt firms may be different from those of limit hitting firms. For example, Kim and Limpaphayom (2000) find that small market capitalization stocks hit price limits more often, and Bhattacharya and Spiegel (1998) find that larger capitalization stocks are suspended more often on the NYSE.

[7] Because both mechanisms had been used in the Continuous Spanish Stock Market (SIBE) prior to May 2001, it provides a natural setting to study the performance of trading halts and price limits. During the study period of Kim et al. (2008) from January 1998 to April 2001, there are 66 trading halts (49 good-news, 17 bad-news) and 160 limit hits (106 upper-hit, 53 lower-hit) in the sample. One of their reasons for conducting daily analyses instead of intraday analyses is the problem of their already small sample size. The daily price limit set

Previous studies usually treat trading halts and limit hits as signals to investors that substantial asymmetric information may exist in the market. For instance, Bhattacharya and Spiegel (1991) indicate that trading halts arise when the degree of information asymmetry outweighs other motivations for trading, and Shen and Wang (1998) show that informed traders' private information will become public information in the process of trading. What kind of impact does a trading halt or limit hit have on the stock market? These issues have been studied over the last two decades; however, most researches have investigated the impact of trading halts or limit hits on the halted or limit-hitting stock itself.[8] Instead of examining direct impact on limit-hitting stocks, this paper investigates the information

---

by SIBE was 15% during the study period. Their study focuses on trading halt stocks and limit hitting stocks themselves.

[8] Previous studies have focused on the overreaction hypothesis and investigate the price reversals based on abnormal returns. See Ma et al. (1989a, 1989b) in U.S. future markets; Huang (1998) and Huang et al. (2001) in TWSE; and Diacogiannis et al. (2005) in the Athens Stock Exchange. In addition, Kim and Rhee (1997) summarize three negative effects of price limits—the delayed price discovery hypothesis, the volatility spillover hypothesis, and the trading interference hypothesis—and conclude the ineffectiveness of the price limit mechanism. Based on a similar approach, Bildik and Gulay (2006) show consistent results in the Istanbul Stock Exchange, as do Henke and Voronkova (2005) in the Warsaw Stock Exchange. Chen et al. (2005) and Kim et al. (2013) both study the regulatory price limits imposed in China's stock markets and find evidence of volatility reduction of the price limit mechanism for A shares in China. Li et al. (2014) test three hypotheses (delayed price discovery hypothesis, volatility spillover hypothesis, and trading interference hypothesis) using daily data of cross-listed stocks and analyze the shares of the same company stocks across different markets when price limits are hit in the A share market. Yeh and Yang (2013) use a different approach: they test the same three hypotheses based on an artificial stock market composed of bounded rational and heterogeneous traders. Recent research has used intraday data to investigate the effect of price limits, such as Kim and Yang (2008), and Lee and Chou (2004).

content of price limit hits through informational relationships with other securities.[9] It is an extension of Jiang et al. (2009), who study the same topic but focus on trading halts instead of limit hits.

Measuring the cross-firm information relationship is a concern in the literature. For example, Caballe and Krishnan (1994) provide a model to measure the information relationship between securities from their trading volumes, returns, and spreads in the market. Lo and Wang (2000) show that a factor structure of trading volume can be implied from portfolio rebalancing and liquidation under certain assumptions. Hasbrouck and Seppi (2001) find that there are common factors in cross-firm returns, order flows, and market liquidity. Spiegel and Subrahmanyam (2000) propose a model in which informationally related equities have a positive correlation in their volatilities; they show that the mechanism giving investors more time to reassess new information is a necessary component of markets. The cessation of trading is regarded as a signal of asymmetric information, and there is a reduction in liquidity for informationally related stocks as a result. Tookes (2008) demonstrates that an

[9] Although most informational related stocks are in the same industry, we acknowledge our referee for pointing out that informational related stocks are not necessary in the same industry. Hence, we take this possibility into account and conduct an informational related group of stocks across industries by propensity score matching.

informational event in one stock in an industry can trigger informed trading in informationally related stocks in the same industry, which implies an increase in trading.

Jiang et al. (2009) establish the informational relationships between halted stocks and non-halted stocks in the same industry by return, volatility, volume, and adverse selection correlations separately, and then conduct analyses on both the liquidity and price impacts of trading halts on informationally related equities.[10] However, in evaluating the relative strength of the informational relationship inference method, the quote-based measure (adverse selection correlation) of informational relatedness is shown to be weaker than the trade-based measures (return, volatility, and volume correlations).[11] Therefore, only trade-based measures of informational relatedness are considered in this paper to extend the analysis framework of Jiang et al. (2009) from trading halts to limit hits with the aid of TWSE market data. However, many industries within the TWSE marketplace seem to be related to one another and the number of firms in an industry can be very small. For example, the word "electronic" appears in more than one industry name and there are only four firms in

---

[10] For example, in the work of Jiang et al. (2009) for return reference groups, residuals from the market model are first obtained for each stock in the industry, and then a Pearson correlation between the residuals for the halted stock and each of other candidate stocks in the same industry is estimated. A 10% significance level is used to accept or reject the hypothesis of informational relatedness.

[11] The overall model fit result of the adjusted R^2 measure is used in Jiang et al. (2009) for the evaluation.

the glass industry in 2013. Consequently, we also employ an identification strategy of propensity score matching that combines the information from the correlations of all three variables (return, volatility, and volume) in order to achieve a better specification of the connected firms across industries to show the robust methodology for categorizing a firm as informationally connected, instead of using a 10% significance level for the correlation each time.[12] A stock is regarded as a limit-hitting stock if it reached its daily price limit within one day. For each limit-hitting stock, its informationally related stocks are identified by four reference groups (return, volatility, volume, and propensity score).

This paper examines the informational relationship of the stocks listed on TWSE from the aspects of liquidity and the price impacts of limit hits on informationally related stocks. It is noteworthy that limit hits can be distinguished lower limit hits from upper limit hits and they may have different impacts on informationally related stocks. Besides investigating the liquidity impact during the whole period of limit hits, the liquidity impact in the post-limit hit environment is further examined by classifying the whole period of limit hits into two sub-periods: the continually trading period and the trading cessation period. We also explore the impact of imminent limit hits on informational related stocks since traders may

[12] We are deeply indebted to our anonymous referees for providing these detailed comments, guidance, and important insights.

sub-optimally advance their trades in anticipation of an impending price limit hit.[13] In addition to investigating the impact of limit hits on informationally related securities at the hit level, we also expand our analysis to evaluate and assess the determinants of the impact at the stock level. We follow Jiang et al. (2009) to conduct a multivariate analysis investigating the characteristics explaining the impact of limit hits on informationally related stocks.

The remainder of the paper is organized as follows: Section 2 describes our hypotheses, Section 3 introduces the data and defines informationally related stocks, Section 4 presents the methodology to test the hypotheses, Section 5 discusses empirical results, and Section 6 concludes.

1. Institutional background

At the end of 2013, there were 838 stocks listed on TWSE with a total market capitalization of NT$2.45 $\times 10^{13}$ (819 billion USD).[14] In that year, the trading volume is 543,162 million shares which amount to 633 billion USD and the percentage of trades executed by domestic individuals is 59.2%.[15] Trading on the TWSE begins at 9:00 a.m. and ends at 1:30 p.m., Monday through Friday, holidays excluded. Orders can be submitted one

[13] See Subrahmanyam (1994).

[14] Stocks of foreign companies are included but Taiwan depositary receipts (TDR), ETFs, and other securities are excluded. US$1=NT$29.93 on December 31, 2013.

[15] The percentage is derived from trading value. Resource: TWSE.

half-hour prior to the market opening. The opening price is the one that maximizes trading volume.

TWSE is a purely order-driven market with no market makers or specialists. Traders submit orders specifying price, sign, and quantity, and then all trades are carried out by automated computers. With regard to the trade price, the price priority principle must be satisfied first, followed by the time priority principle. The best five bid and ask prices and corresponding volumes of the limit order book are continuously disclosed. The minimum price variation (tick size) varies with the market price of stock. Normally, the TWSE sets its daily price limit for each stock at 7%, which is based on the previous day's closing price of each stock. However, daily price limits have been temporarily adjusted to 3.5% to stabilize stock markets when unusual events occurred, such as the 921 Earthquake of 1999, the September 11 attacks, and the 2008 credit crunch. Since June 1 in 2015, TWSE reset its daily price limit for each stock to 10%. Because there is no market makers exist in the Taiwan market, a critical question then is who provides liquidity in an order-driven market in the absence of market makers. Lee et al. (2004) report based on TWSE's call market-based transaction data that all trader types are successful de facto market makers, with large domestic investors conducting the most informed trades and large individuals serving as noise or liquidity traders (see Chan et al. 2005). Moreover, limit order traders are assumed to provide liquidity implicit in a lot of literature on spread components.

2. Hypotheses development

Under the Tookes (2008) model of informed trading based on stock and industry-specific news events, discretionary or nondiscretionary liquidity traders fail to understand and incorporate the halt signal and continue to trade. Nevertheless, Lemma 1 of Tookes (2008) indicates that insiders of the halted company and their proxies enter the market and use their superior knowledge of the industry to place informed trades in informationally related securities. Trading halts can be view as signals of information asymmetry. Liquidity suppliers observe signals and widen spreads to compensate for losses to informed traders. The implication is that quote-based measures of liquidity will decrease, and trade-based measures of liquidity will increase because of the additional transactions of informed traders. Jiang et al. (2009) find empirical evidence that clearly support the model prediction of Tookes (2008) for the liquidity impact of trading halts on informationally related stocks listed on NYSE.

Price limits and trading halts are both circuit breakers and the activation of circuit breakers attempts to provider market participants with more time to evaluate new information and make rational decisions during the cooling-off period. Regulators expect that circuit breakers cause stock prices to become more informative, reduce uncertainty, and protect uninformed investors from excessive price movements. Typically, price limits and trading halts are viewed as trying to achieve either directly or indirectly the same objective, which is to reduce information asymmetry (e.g., see Kim et al. 2008).[16] Therefore, the similarity between these two market mechanisms gives a similar hypothesis for limit hits as Hypothesis 1b of Jiang et al. (2009) for trading halts.

Hypothesis 1. When the price limit is hit for a stock, stocks in the same industry that are informationally related and continue to trade have higher trade-based liquidity and lower quote-based liquidity. □

However, why do stocks have to be in the same industry to be informationally related? Many industries within the TWSE marketplace seem to be related to one another. For

[16] Wong et al. (2009) use transactions and quotes data within the TWSE marketplace and find that, due to information asymmetry, investors trade aggressively for fear of position lock and illiquidity when stock prices approach limit bounds. Their findings are consistent with the theoretical model of Subrahmanyam (1994).

example, the word "electronic" appears in more than one industry name. Consequently, we believe that the liquidity-impacts of limit hits on informationally related stocks do not depend on whether connected stocks are in the same industry or not:

Hypothesis 2. Liquidity-impacts of limit hits on informationally related stocks across industries are qualitatively similar to those on connected stocks in the same industry. □

As mentioned in the introduction, firms are often required to release information related to the cause of the news pending halt, which may reduce the degree of information asymmetry among market participants. No such requirement exists for price limits. However, it is possible for firms to publicly announce material information that cause their stocks to hit the price limits. Oftentimes, information asymmetry would decrease when firms release information publicly. Therefore, if the liquidity impact of limit hits is caused by information asymmetry, the liquidity impact of limit hits accompanied with the release of material information by firms (so-called "informative limit hits") on informationally related stocks would be weaker than those of limits hits without the release of material information (so-call "uninformative limit hits").

Hypothesis 3. Liquidity-impacts of informative limit hits on informationally related stocks are weaker than those of uninformative limit hits. □

Aside from the market liquidity measures, we also investigate the price impact of trades in connected stocks during the limit hit. Proposition 8 of Spiegel and Subrahmanyam (2008) shows that the derivative of the pricing schedule with respect to quantity will increase for informationally related securities. Although the sequential trade model of Tookes (2008) does not provide any direct evaluation of price impact, a larger price impact of trades during the halt is consistent with the increased informed trading of the Tookes model. Jiang et al. (2009) also use NYSE-listed stocks to provide evidence that trades in stocks in the same industry that are informationally related and continue to trade will have larger price impact. Because of the similarity between price limits and trading halts and the above-mentioned assertion that stocks are not necessary in the same industry to be informationally related, Hypothesis 2 of Jiang et al. (2009) for trading halts is modified to give a more generalized price-impact hypothesis for limit hits:

Hypothesis 4. When the price limit is hit for a stock, trades in stocks that are informationally related and continue to trade will have larger price impact. □

We follow Jiang et al. (2009) to investigation the impact of limits hits on market conditions of informationally related stocks by evaluating the determinants of identified liquidity impacts. For example, Proposition 7 of Spiegel and Subrahmanyam (2008) suggest that firms with higher informational relatedness to the halted firm should have a higher change in market liquidity during the trading halt. In addition, Lemma 2 of Tookes (2008) also shows that firms with lower market share frankly have less the product market impact to affect the market liquidity of other stocks in the same industry. Hence, a reasonable deduction is that the liquidity impact of a trading halt on connected stocks is increasing in the market share of the halt firm and decreasing in the market share of the connected firms. It implies that the net liquidity change is determined by the interaction between the market share of the halt firm and that of the connected firm. Because Tookes (2008) also points out that smaller firms in the Reference Group should have the largest change in liquidity, the liquidity impact is decreasing with increasing market capitalization. Because of the similarity between price limits and trading halts, we test these implications using regression analysis in accordance with Jiang et al. (2009). In fact, empirical studies of price limits also indicate some determinants of limit hits. For example, Kim and Limpaphayom (2000) find that volatile stocks, actively traded stocks, and small market capitalization stocks hit price limits more often than other stocks. We also wish to investigate which parameters influence the choice of informed and insider traders' targets for trading when the price limit is hit.

3. Data and methodology

3.1 Data

In order to examine how limit hits affect market liquidity and the informationally related stocks, Taiwan Economic Journal Database (TEJ) is used to obtain our sample data of common stocks listed on TWSE (which normally employs a 7% price limit) between 2004/1/1 and 2013/12/31 (about 2,475 business days). New industry categories of TWSE-listed common stocks are shown in Table 1 along with the industry number and the number of our sample stocks in each industry. Stocks of foreign companies, TDRs, ETFs, and other securities are excluded from our sample data.

[Table 1 is about here.]

Table 2 shows the numbers of trading days, stocks, and limit hits in each year. Because there is one day missing data in 2005, only the data from the remaining 246 days is used for analysis. In addition, we excluded 10 extra trading days from 2008/10/13 to 2008/10/24 due to a temporary adjustment of lower price limits from 7% to 3.5%. There are 2,475 trading days remaining for analysis. If a stock hits its upper limit and lower limit on the same day, limit hits of this stock on this day are not included in our analysis samples.

[Table 2 is about here.]

The descriptive statistics of limit hits are shown in Table 3. Mean durations of lower limit hits and upper limit hits are 1,141.43 (sec.) and 1,742.67 (sec.), respectively. We define trading cessation periods as time periods during which the bid depth of the lower limit-hitting stock is equal to zero or the offer depth of the upper limit-hitting stock is equal to zero. Different from the complete cessation of trading activity in trading halts, trading is still permissible as long as it is within the pre-set trading range in the case of price limits. We observe that the mean percentage of the trading period at lower limits is 26% and at upper limits is 37%. The mean of the trading period at lower limits is 246.71 (sec.) and at upper limits is 159.70 (sec.). The mean of the trading volume at limit prices before the cessation of trading is 547.69 thousand shares per five minutes for lower limit hits and 912.87 thousand shares per five minutes for upper limit hits.

[Table 3 is about here.]

In addition, we classify limit hits into informative limit hits and uninformative limit hits with the aid of the "material information" data from the Market Observation Post System (MOPS) maintained by TWSE.[17] If a TWSE-listed firm either announces news or clarifies rumors, the "material information" data will keep a record containing its stock ticker, firm

[17] MOPS website: http://emops.twse.com.tw/emops_all.htm

name, announcement date and time, subject of material information, and its detail. TWSE-listed firms are required to announce their material information on MOPS to the public in order to mitigate the information asymmetry.

3.2 Reference group clarification

We first follow Jiang et al. (2009) to determine the informational relationship between stocks in the same industry from their correlations of trading volumes, volatilities, and returns. The informational relationship between securities in each year depends on trading data in the previous year. It is determined from their correlations of trading volumes, volatilities, and returns in the previous year. Then, we also employ an identification strategy of propensity score matching that combines the information from the correlations of all three variables (return, volatility, and volume) in order to achieve a better specification of the connected firms across industries to show the robust methodology for categorizing a firm as informationally connected, instead of using a 10% significance level for the correlation each time. A stock is regarded as a limit-hitting stock if it reached its daily price limit within one day. For each limit-hitting stock, its informationally related stocks are identified by four reference groups (volume, return, volatility, and propensity score).

3.2.1 Volume reference group

To separate the industry- and firm-specific informational effects from macroeconomic effects, the volume reference group is formatted by running the volume model of Ferris et al. (1988):

$$V_{i,D} = \alpha_i + \beta_i V_{m,D} + \varepsilon_{i,D} \tag{1}$$

where

$V_{i,D}$ = the turnover for stock i on day D,

$$= \frac{\text{the number of shares of stock } i \text{ traded on day } D}{\text{the number of shares of stock } i \text{ outstanding on day } D},$$

$$V_{m,D} = \frac{\text{the number of shares of all stocks traded on day } D}{\text{the number of shares of all stocks outstanding on day } D}, \text{and}$$

$\varepsilon_{i,D}$ = the abnormal turnover for stock i on day D.

Intraday trading volume for stocks in the TWSE is obtained from intraday data on the TEJ database. For each stock, the regression is estimated once for each sample year. Informationally related stocks are those that have a statistically significant Pearson correlation at the 10% level, based on the regression residual, with the limit-hitting stock in the same industry. If no limit-hitting stock has a significant correlation with the reference stock, then the limit hit is dropped from the sample.

3.2.2 Return reference group and volatility reference group

Similarly, the market model is adopted to separate the macroeconomic effects from each stock's adjusted return for return reference groups:

$$R_{i,D} = \alpha_i + \beta_i \, R_{m,D} + \varepsilon_{i,D} \tag{2}$$

where

$R_{i,D}$ = the adjusted return of stock i on day D,

$R_{m,D}$ = the adjusted return of TWSE's total return index on day D, and

$\varepsilon_{i,D}$ = the abnormal return for stock i on day D.

For each stock, a Pearson correlation between the abnormal returns of the limit-hitting stock and that of the remaining stocks in the same industry is estimated; then, the hypothesis of informational relatedness is accepted or rejected with a 10% significance level.

As for the volatility reference group, the square of the residual from the market model (i.e., $\varepsilon_{i,D}^2$) is regarded as the daily volatility of the stock. Based on the correlation of $\varepsilon_{i,D}^2$, a stock is included in the volatility reference group of the limit-hitting stock if it is significantly correlated with the limit-hitting stock.

3.2.3 Propensity reference group

Recently, propensity score matching (PSM) methodologies are developed and employed to overcome the selectivity problem. Rosenbaum and Rubin (1983) first introduce PSM methodology based on the strongly ignorable treatment assignment assumption (conditional-independence assumption). PSM methods focus on the comparability of the treatment and nonexperimental comparison groups in terms of preintervention variables. The propensity score is defined as the probability of assignment to treatment conditional on covariates, summarizes the preintervention variables, and controls for differences between the treatment and nonexperimental comparison groups.

For each limit-hitting stock, stocks in the same industry are viewed as the treatment group and other stocks are taken as the nonexperimental comparison group. The correlations of all three variables (volume, return, and volatility) between the limit-hitting stock and other stocks are calculated, and then regarded as covariates.[18] We follow Dehejia and Wahba (1999) to use a logistic probability model.[19] We employ the standard tool of PSM in Stata called "pscore" with a significance level of 1% to estimate the propensity scores of all stocks for each limit-hitting stock. Once the propensity scores of stocks across industries are estimated, informationally related stocks can be identified by matching their propensity scores. However, the probability of observing two stocks with exactly the same value of the propensity score is in principle zero. Various methods have been proposed in the literature to overcome this problem and two of the most widely used are the nearest neighbor matching and the radius matching. These matching methods are also employed to form our propensity reference group for each limit-hitting stock. Stocks whose propensity score falls within a pre-specified range

[18] Other stocks are not necessary in the same industry as the limit-hitting stock.
[19] Dehejia and Wahba (1999) assert that other standard models yield similar results.

of neighborhood of the propensity score of the limit-hitting stock are chosen to form the propensity reference group. However, if the range of the neighborhood, i.e. the radius, is set to be very small, it is possible that there is no stock in the propensity reference group and this limit-hitting stock is dropped from the sample. To reduce this probability, stocks are sorted from lowest to highest absolute propensity score difference from the limit-hitting stock, and then top five stocks whose three correlation coefficients (volume, return, and volatility) are at least one 10% significant are also classified into the propensity reference group.[20] Our pre-specified range is 1% of the propensity score of the limit hitting stock and our matching method is a hybrid of the nearest neighbor matching and the radius matching. Table 4 reports the descriptive statistics for the four groups.

[Table 4 is about here.]

3.3 Methodology

This section explains how to measure the impact of the limit hits on informationally related stocks. Section 3.3.1 describes the liquidity measures and the details of the analysis process of liquidity impact. The analysis process of price impact is shown in Section 3.3.2.

3.3.1. Liquidity impacts of limit hits on informationally related stocks

[20] Mean companies per group in Jiang et al. (2009): 3.9 for volatility grouping, 4.3 for adverse selection grouping, 4.1 for volume grouping, and 6.1 for return grouping.

Many studies use liquidity measures to study the liquidity of the market, such as Chan and Pinder (2000) and Elyasiani et al. (2000). Six quote-based market liquidity measures of different aspects are used in liquidity impact analysis. The relative spread, absolute spread, offer depth, bid depth, and total depth obtained from the TEJ intraday database belong to directly quote-based liquidity measures. In addition, Fernandez (2000) emphasizes the need to use different liquidity measures to capture different aspects of liquidity. Hence, the quote slope measure, such as the spread/depth presented by Hasbrouck and Seppi (2001), is also used.[21] These six liquidity measures are classified by three aspects—tightness (relative spread and absolute spread), depth (offer depth, bid depth, and total depth), and quote slope. Depth has the same direction as market liquidity change; for example, depth increases when market liquidity increases. However, tightness and quote slope decrease when market liquidity increases. Any changes in these quote-based liquidity measures, such as spreads, may reveal the change of information asymmetry in the market.

While quote-based liquidity measures represent the liquidity supply changes; trade-based liquidity measures represent the liquidity demand changes. Informed traders may take their advantage of private information to trade informationally related stocks especially

[21] We use spread/depth to denote the relative spread divided by total depth.

during the trading cessation period of the limit-hitting stock. Consequently, a limit hit arising from information asymmetry may incur the substitution effect and result in an increase in trade-based liquidity measure of informationally related stocks. For trade-based measures of liquidity, the volume, value, and number of trades are used to analyze the liquidity impact of limit hits on informationally related stocks. The empirical findings will be presented in Section 4.

The entire limit-hitting interval is further divided into two sub-periods (trading and trading cessation) for the assessment of the liquidity impact on informationally related stocks. The liquidity impact is investigated by comparing the short-term liquidity measure (during day *D* that a limit hit takes place) to the liquidity measure of the benchmark period (the benchmark period of the window between day *D*-5 to day *D*-1).[22] Alternatively, we also consider to just use day *D*-5 as the benchmark period because of the concern that the day immediately before the limit-hit day may not be a clean benchmark day.[23] However, results are qualitatively similar, and are not tabulated in a table for the sake of space but available

[22] The following day windows are also considered as the benchmark period for the robustness check: day *D*±15 excluding day *D*, day *D*±10 excluding day *D*, day *D*±5 excluding day *D*, day *D*-15 to day *D*-1, and day *D*-10 to day *D*-1. Results are qualitatively similar and are not reported for the sake of space, but available from the authors upon request.

[23] We acknowledge our anonymous referees for kindly reminding to confirm the results remain qualitatively similar for the robustness check.

from the authors upon request. If investors observe an impending limit hit, the signal effect of information-asymmetry may quickly spread around the market and we will observe changes of the liquidity measures of informationally related stocks. Consequently, the short-term liquidity measures of informationally related stocks should be significantly different from those of the benchmark period.

Quote-based liquidity measures are evaluated by using the TEJ intraday database. At the time of limit hitting, quote-based liquidity measures are calculated by their time-weighted average over the period. A time-weighted average liquidity impact that a limit-hitting stock k has on an informationally related stock k_j is defined as follows:

$$x_{k_j} = \frac{1}{\sum_{i=1}^{m_j} \Delta t_i} \sum_{i=1}^{m_j} x_{k_j,i} \times \Delta t_i \tag{3}$$

where

$k_j =$ the j-th informationally related stock with the limit-hitting stock k,

$x_{k_j} =$ the liquidity measure of stock k_j,

$m_j =$ the number of trade records for stock k_j during the limit-hitting period of stock k,

$\Delta t_i =$ the time interval between the i-th trade record and the $(i+1)$-th trade record for stock k_j, and

$x_{k_j,i} =$ the liquidity measure of stock k_j at the i-th trade record.

In addition, trade-based liquidity measures during the day *D* that a limit hit occurs are also evaluated by using the TEJ intraday database. These short-term liquidity measures are estimated by the aggregation of trade-based liquidity impacts per five minutes. However, trade-based liquidity measures of the benchmark period are calculated based on the TEJ daily market data and are further transformed into the liquidity measure per five minutes for comparison.

To assess liquidity impact, we consider that a stock on day *D*, denoted by stock k, which hits its price limit boundary, has J informationally related stocks. For a liquidity measure x, the liquidity impact of the limit hit of stock k on an informationally related stock k_j is defined as follows:

$$\alpha_{k_j}^{x} = x_{k_j} / \bar{x}_{k_j} \tag{4}$$

where

$x_{k_j} =$ the short-term liquidity measure of the j-th connected stock k_j during the limit-hitting period of stock k, and

$\bar{x}_{k_j} =$ the liquidity measure of stock k_j during the benchmark period.

After assessing all $\alpha_{k_j}^{x}$ for $j = 1, \cdots, J$, the liquidity impact of the limit hit of stock k on its J informationally related stocks is defined as follows:

$$\alpha_{k}^{x} = \frac{1}{J}\sum_{j=1}^{J} \alpha_{k_j}^{x}. \tag{5}$$

These processes are repeated for each limit hit; then, a *t*-test is conducted to evaluate whether the liquidity impact of the sample of limit hits is statistically significantly different from the value 1. This analysis is repeated for all liquidity measures of stocks within each reference group.

3.3.2. Price impacts of limit hits on informationally related stocks

Spiegel and Subrahmanyam (2000) show that trades have a larger price impact during a trading halt period compared to a period of continuous trading. As well as Jiang et al. (2009), we employ two price impact measures (temporary price impact and total price impact) proposed by Holthausen et al. (1987) to analyze the price impact of limit hits on trades of informationally related stocks.[24] These two price impact measures are defined by

$$P_{t,total} = D_t \ln\left(\frac{P_t}{P_{open}}\right) \tag{6}$$

and

$$P_{t,temp} = D_t \ln\left(\frac{P_{close}}{P_t}\right) \tag{7}$$

where

$P_t =$ the price at time t,

$P_{open} =$ the price at the opening,

$P_{close} =$ the price at the closing, and

[24] Keim and Madhavan (1996) used these price impact measures to investigate the impact of large block trades on price and liquidity measures.

$D_t = 1$ if the trade is buyer-initiated and -1 if the trade is seller-initiated.

The usually buy/sell classification scheme by Lee and Ready (1991) is not readily applicable to the call market method since all orders are batched for execution at a single price. In the call market environment, we follow Chan et al. (2005) to examine whether the price chang is an increase or a decrease from the immediately preceding executed price rather than sorting executed trades into buyer- or seller-initiated trades. In a tick test, if the trade price is larger than or equal to the preceding trade price (uptick or zero uptick), the trade is buyer-initiated; if the trade price is lower than or equal to the preceding trade price (downtick or zero downtick), the trade is seller-initiated. For opening and closing prices, we use the first and last trades in the TEJ database from the listing exchange of the stock. We note that Kim et al. (2008) find no evidence to support the information leak prior to the event day of limit hits.[25] However, Wong et al. (2009) find that there is strong evidence that magnet effects are caused by uninformed individuals when limit hits are imminent. The findings of Wong et al. (2009) justify that the limit hits can be highly anticipated before the event actually happens during the event day of limit hits. Hence, we just use day *D*-1 as the benchmark period and exclude

[25] Kim et al. (2008) show that there is no significant CAAR (Cumulative Average Abnormal Returns) during the five-day period (the window between day *D*-5 to day *D*-1) for upper limit hits and therefore no apparent information leak prior to the event day of upper limit hits. In addition, their Table 5 also shows that there is no significant CAAR during the five-day period for lower limit hits and therefore no apparent information leak prior to the event day of lower limit hits.

all trades before the limit hit on day D.[26] Both $P_{t,total}$ and $P_{t,temp}$ are calculated once a trade is completed in the market during the limit hit period on day D and during the benchmark period; then, a t-test is conducted to examine the difference of their averages between the limit hit period and the benchmark period.

The private information itself decides the direction of price impact on each trade. Based on Hypothesis 2, informed traders may enter into the market to trade informationally related stocks according their private information when the price limit of the stock is hit. Consequently, the price impact measures on trades of these informationally related stocks during the time period of limit hits can be significantly different from those during the benchmark period. Oftentimes, positive information may cause upper limit hits, whereas negative information may result in lower limit hits. Hence, the analysis of price impact is partitioned into four aspects: buyer-initiated positive information events, seller-initiated positive information events, buyer-initiated negative information events, and seller-initiated negative information events. The empirical results of price impacts of limit hits on trades of informationally related stocks are shown in Section 4.

4. Empirical Results

[26] We acknowledge our anonymous referees for kindly reminding to address this problem in detail.

4.1 Liquidity impact of limit hits on informationally related stocks

Table 5 shows the liquidity impact of informative limit hits on informationally related stocks in the same industry and across industries. There are several interesting findings. First, the liquidity impacts of limit hits on informationally related stocks do not seem to depend on whether these stocks are in the same industry or not. Table 5 shows that they are qualitatively similar among all groupings including return, volatility, and volume reference groups for connected stocks in the same industry and propensity reference group for connected stocks across industries. Therefore, Table 5 provides evidence to support Hypothesis 2.

[Table 5 is about here.]

Second, we find that the relative spreads increase significantly during the entirely lower limit-hitting period, whereas they significantly decrease during the entirely upper limit-hitting period. Because results are qualitatively similar for all the informational groupings, we focus only on the Propensity Reference Group results for conciseness. For the Propensity Group, we find that the relative spreads increase by a statistically significant 13.44% at lower limit hits. We include absolute spread in our analysis to control for possible price changes in the connected stock during the period of the limit hit, and find that this liquidity measure also increases by 7.66%. These results indicate that lower limit hits incur a reduction of market liquidity. Nevertheless, we identify an asymmetry in the impact of limit hits on liquidity demand: an increase in spreads for lower limit hits and a decrease in spreads for upper limit hits. We find the relative spreads decrease by a statistically significant 5.75% at upper limit hits. We also include absolute spread in our analysis to control for possible price changes in the connected stock during the period of the limit hit, and find that this liquidity measure also decreases by 4.26%. These results indicate that upper limit hits improve the market liquidity. Our results seem to be partially consistent with Kim et al. (2008). They conduct daily analysis to study the liquidity impact of limit hits on the limit-hitting stock itself and find a significant increase in the spread measure only after lower limit hits.

Third, total depth significantly increases for both lower and upper limit hits. Total depth increases 20.45% for lower limit hits and 20.59% for upper limit hits. For our composite measure of quote-based liquidity, we find an asymmetry that the composite measure spread/total depth increases by a significant 16.52% for lower limit hits, whereas it decreases a significant 8.58% for upper limit hits. Our finding indicates that overall, quote-based liquidity is lower during the period of lower limit hits but is higher during the period of upper limit hits. The asymmetry in the impact of limit hits on liquidity demand arises from the asymmetry in the spread of limit hits.

Fourth, while the liquidity impact of limit hits is mixed for quote-based measures of liquidity, trade-based measures of liquidity show significant increases. This significant increase in trading activity may occur because price limits constrain investors from directly trading the limit-hitting stock until new price limits are established on the following day. Therefore, informed traders may take their advantage of information to trade connected stocks as a substitution of the limit hitting stock. Consequently, trade-based measures of liquidity will increase because of the additional transactions of informed traders. For lower limit hits, trade volume increases by 30.33% and the trade value and number of trades increase by 21.87% and 9.37%, respectively. For upper limit hits, trade volume increases by 25.46% and the trade value and number of trades increase by 27.73% and 8.50%, respectively. Overall, we find evidence indicating that quote-based liquidity measures are lower while trade-based liquidity measures are improved during the entire period of lower limit hits, as predicted by Hypothesis 1. However, during the entire period of upper limit hits, the market liquidity is significantly improved in both the quote-based liquidity measure and the trade-based liquidity measure.

Fifth, the duration of limit hits is further classified into the trading sub-period and the trading cessation sub-period to study the intra-hit liquidity and the results are reported in

Table 5. Again, we focus only on the Propensity Group due to the strong similarity of the results across groups. For the Propensity Group, shown in Table 5, Panel D, quote-based measures of liquidity, such as relative spread, widens over the entire duration of lower limit hits. Relative spreads are 13.52% during the trading sub-period and decline to 0.81% for the trading cessation sub-period. We include absolute spread in our analysis to control for possible price changes in the connected stock during the period of limit hits, and find that this liquidity measure also increases by 7.96% during the trading sub-period but decreases by 4.42% during the trading cessation sub-period. Hence, the increase in the relative spread during the trading cessation sub-period may cause by the falling prices of connected stocks. Our results indicate that the spread liquidity is lower during the trading sub-period but the spread liquidity is improved during the trading cessation sub-period. As for upper limit hits, our results indicate that the spread liquidity is further improved during the trading-cessation sub-period. In addition, the total depth increases by 17.25% during the trading sub-period and also increases by 7.01% during the trading cessation sub-period. Overall, we find evidence to support that the quote-based liquidity of connected stocks is improved during the trading cessation sub-period of both limit hits and only has a reduction during the trading sub-period of lower limit hits. Our results are qualitatively similar across groups.

Sixth, we find that trade-based liquidity of connected stocks significantly increases especially during the trading sub-period of limit hits. One possible reason is that informed traders with private information may be unable or unwilling to reveal their information when price limits are hit simply because prices are not allowed to move beyond their limits (Chan et al. 2005; Kim and Rhee, 1997). Hence, they may trade connected stocks instead of the limit hitting stock itself and the additional transactions of informed traders increase the trade-based liquidity of connected stocks. Chan et al. (2005) show that price limits postpone the arrival of informed traders because some informed traders have to wait for the resumption of trading to incorporate their private information into stock prices. However, our results show that connected stocks seem to provide alternatives for informed traders to incorporate their private information into stock prices.

Seventh, we identify that there are order imbalance reversals in the impact of limit hits on connected stocks. For the Propensity Reference Group, the bid depth significantly increases by 49.22% and the offer depth significantly decrease by 10.64% during the whole period of lower limit hits; instead, only the offer depth significantly increases by 41.93% during the whole period of upper limit hits. Our findings show that connected stocks seem to provide alternatives for traders try to reverse their earlier suboptimal trades.[27] However, it is interesting why investors do not directly choose the limit-hitting stock itself to reverse their earlier suboptimal trades. One possible reason is that it might be difficult for trader to recognize their irrational trade directly.

Hypothesis 3 predicts that if limit hits are connected to information released by firms, due to less information asymmetry, their liquidity impacts on informationally related stocks will be weaker than those of uninformative limit hits. Table 6 shows the liquidity impacts of uninformative limit hits on connected stocks. We compare Table 6 with Table 5, and find that the liquidity impacts of uninformative limit hits are actually almost stronger than those of informative limit hits. Again, we focus only on the Propensity Group due to the strong similarity of the results across groups. For example, for the Propensity Reference Group, the increase of relative spread is 17.60% for uninformative lower limit hits, whereas it is 13.44% for informative lower limit hits. Results are qualitatively similar for all of the informational groupings. Consequently, our findings provide evidence to support Hypothesis 3.

[27] Chan et al. (2005) show that if traders know that trading will be stopped when prices reach their upper (lower) limits, they will then buy (sell) frantically before the circuit breaker is triggered. They find that the order imbalance prior to the limit hit suggest a magnet effect (i.e., where suboptimal trades are being made in anticipation of a limit-hit), and the subsequent order imbalance reversal after the limit hit lends further support that a magnet effect did take place during the prehit period.

Table 7 shows the liquidity impact of all impending limit hits on connected stocks. Again, we focus only on the Propensity Group due to the strong similarity of the results across groups. We find that the more a limit hit impends, the more the order imbalance revere. For example, the bid depth increases by 14.29% whereas the offer depth decreases by 18.18% when the stock price falls between 5.5% and 6%, the bid depth increases by 17.00% whereas the offer depth decreases by 20.19% when the stock price falls between 6% and 6.5%, and the bid depth increases by 21.22% whereas the offer depth decreases by 21.37% when the stock price falls between 6.5% and 7%. Our findings provide evidence that, prior to the hit of price limits, connected stocks seem to already provide alternatives for traders to reverse their suboptimal trades incurred by the anticipation of a limit-hit. We find strong evidence that the quote-based liquidity is improved in anticipation of an impending upper limit hit and only find partial evidence in anticipation of an impending lower limit hit. This finding seems consistent to Cho et al. (2003) who find only weak evidence of magnet at the floor. In addition, we find that the trade-based liquidity of connected stocks is consistently reduced when traders anticipate impending limit hits.

Due to the strong similarity of results among groupings mentioned above, we focus on the Propensity Group to investigate the liquidity impact of all limit hits on connected stocks in limit hit order. Table 8 shows that the order imbalance reversal increases with the limit hit order. For example, for lower limit hits, the bid depth increases by 23.77%, whereas the offer depth decreases by 14.40% during the first limit hit period, the bid depth increases by 36.73%, whereas the offer depth decreases by 15.96% during the second limit hit period, and the bid depth increases by 46.32%, whereas the offer depth decreases by 16.49% during the first limit hit period. We also find that the quote-based liquidity increases with the limit hit order, whereas the trade-based liquidity decreases with the limit hit order.

Table 9 shows the price impacts of all limit hits on informationally related stocks. Again, due to the strong similarity of results among groupings, we focus on the Propensity Group. We find strong evidence that total price impact is greater during the period of the limit hits and the temporary price impact measures are significantly larger for trades during the limit hit period and there are reversals in price impact for connected stocks. For example, for upper limit hits, the temporary price impacts of buyer-initiated trades show a decrease in price impact of 0.25% while the seller-initiated trades show an increase of 0.26%. These results are mirrored for lower limit hits, with buyer-initiated trades having temporary price impact of 1.09% and seller-initiated trades having a price impact of -0.30%. These results provide evidence that there are price reversals. In addition, for upper limit hits, the total price impacts of buyer-initiated trades show an increase in price impact of 1.20% while the seller-initiated trades show a decrease of 0.33%. These results are mirrored for lower limit hits, with buyer-initiated trades having total price impact of -0.07% and seller-initiated trades having a price impact of 1.94%. These results provide evidence that the private information is quickly incorporate into stock prices. Therefore, Hypothesis 4 is supported by our findings.

Previously, we have focused on the liquidity impact of limit hits on informationally related stocks at the hit level. We now expand our analysis to evaluate and assess the determinants of the liquidity impact at the stock level. We examine relative spread, bid depth, the number of trades, and trade volume for lower limit hits and relative spread, ask depth, the number of trades, and trade volume for upper limit hits. The dependent variables of our analysis represent the percentage change in each liquidity measure relative to the benchmark period for the informationally related stock. This metric is log transformed to remove nonlinearities.

In selecting determinants of the liquidity change to include in our regression analysis, we control for temporal patterns that could affect the degree of change in each liquidity measure. We add the dummy variable Amnth that is 1 if the hit is in a typical announcement month of January, April, July, and October, and 0 otherwise. Firm specific characteristics have also been shown to impact market microstructure measures of liquidity. To control for these characteristics, we use TEJ data to calculate three variables, *LnRcap*, *LnRvol*, and *LnRprc*, which are respectively, the log transformations of the market capitalization, volume, and closing price of the reference stock. As Tookes (2008) shows that the higher market share of the halted stock, *LHmkt*, should increase the liquidity impact of the halt. Also, the greater the product of the market shares of the halted firm and the reference firm, *IntrMkt*, the greater the impact on liquidity. She also shows that trading halts affect smaller firms more than larger firms so that the log of the market capitalization of the reference stock, *LnRcap*, should result in a smaller liquidity impact as firm size increases. Due to the circuit-breaker similarity of price limits to trading halts, we also adopt these arguments in verifying determinants of limit hits. The market share of the reference firm, *Rmkt*, is also included to control for the relative effect between market share and market capitalization.

Moreover, the model of Spiegel and Subrahmanyam (2000) indicates that the impact of the trading halt should be increasing as the strength of the informational relationship increases. To test this, Vcor, the correlation value for volatility, volume, and return groups or the degree of propensity matching for the propensity group is added to the regression. We define the degree of propensity matching as one minus the absolute propensity score difference between the limit-hitting firm and its reference firm. We also include variables *LHTdur* (the trading sub-period duration of the limit hit), *LHCdur* (the trading cessation sub-period duration of the limit hit), and *LHSeq* (the limit hit order) in our regression to control for the length of the trading sub-period of the limit hit, the length of the trading cessation sub-period of the limit hit, and the hit-sequence of the limit hit. While one can argue the any liquidity event such as a limit hit will be due to information, we wish to investigate the effects of limit hits that are connected to the announcement of material information. The majority of limit hits in our sample are uninformative.[28] We develop the dummy variable, *Annc*, which counts the number of announcements released on the day of the limit hit. We estimate the following regression:

$$\begin{aligned} LnLiqR_{i,k} = {} & \alpha + \beta_1 Amnth_k + \beta_2 LHmkt_k + \beta_3 Rmkt_{i,k} + \beta_4 Intrmkt_{i,k} + \beta_5 LnRcap_{i,k} \\ & + \beta_6 LnRvol_{i,k} + \beta_7 LnRprc_{i,k} + \beta_8 Vcor_{i,k} + \beta_9 LHTdur_{i,k} + \beta_{10} LHCdur_{i,k} \\ & + \beta_{11} Annc_k + \beta_{12} LHSeq_k + \varepsilon_{i,k} \end{aligned} \tag{8}$$

Table 10 show the regression results for both Volatility Reference Group (Panel A) and Propensity Reference Group (Panel B). For results reported in Panel B for the Propensity Reference Group, we focus our discussion on the Number of Trades regression shown in

[28] For Propensity Group, our sample of uninformative limit hits consists of 418215 records of matched hit and its reference stock and the sample of informative limit hits consists of 53635 records of matched hit and its reference stock.

Column 7 for upper limit hits because we feel that this regression best reflects the characteristics informed traders identify when selecting targets for trading. The idea is that as the number of trades increases, so does informed trading. Consistent with the trading halt implication of Tookes (2008), we find that the liquidity impact of a limit hit is increasing in the market share of the halted company and traders tend to focus on smaller companies for trading. Specifically, the coefficient for *LHmkt* is positive and significant while the coefficient for *LnRcap* is negative and significant. However, rather than simplistically focusing on the smallest companies, informed traders appear to balance the choice variables of firm size and firm market share for the connected firms; *Rmkt* is positive and significant. While *IntrMkt* is significant and negative, it contradicts the prediction of Tookes (2008) and it may be reasonable because the Tookes model is motivated by a simple Cournot industry structure, which is not representative of the more complex industry structures considered in our analysis.

As the indication of Spiegel and Subrahmanyam (2000), we find that traders also focus on firms that have the strongest relationship with the limit-hitting stock. *Vcor* is both positive and significant. We find that *LHTdur*, *LHCdur*, and *Annc* are both negative and significant, indicating that longer limit hits and those connected to material information announcements have a smaller liquidity impact. The *F*-statistic for a joint test of significance to all explanatory variables is 1.01e+3, which is significant at the 1% level. As for lower limit hits, we find that the coefficient of *Vcor* becomes negative and significant while the coefficient of *Annc* is still negative but becomes insignificant. These results imply that informed traders do not seem to take their advantage of private information to trade stock with the strongest informational relationship. Other results of lower limit hits are qualitatively similar to those of upper limit hits.

We brief comment on the results of our regressions for the other variables under the Propensity Reference Group. Comparing the trading volume regression and the trade number regression, there is strong alignment between the signs, magnitudes, and significance levels. We find no statistically significant sign reversals of any explanatory variable contained in the model and the joint test of variable significance results in an *F*-statistic of 3.04e+3. Given that jointly all variables are significant in both regressions, our conclusions and interpretations of the Volatility Regression are identical to those of the Trade Number Regression. The results of the quite-based liquidity measures-spread, ask depth, and bid depth- are more varied. However, the joint significance test for each regression shows that all variables are significant at the 1% level.

Next, we turn to the results of the Volatility Reference Group. The results are qualitatively similar to the Propensity Reference Group. In fact, the results of the other two reference groups (Volume Group and Return Group) are also qualitatively similar to those of Propensity Group and not presented for the sake of space, but available from the authors upon request. In evaluating the relative strength of the informational relationship inference method, we look to the overall model fit result of the adjusted R^2 measure. Propensity Group, in which connected stocks are across industries, seems to perform as well as Volatility Group, in which connected stocks are in the same industry.

5. Conclusion

We extend the trading-halt analysis of Jiang et al. (2009) by studying price limits and connected stocks. Such an extension is important because most stock markets around the world use price limits. We also employ an identification strategy of propensity score matching that combines the information from the correlations of all three variables (return, volatility, and volume) in order to achieve a better specification of the connected firms across industries and find that liquidity impacts of limit hits on connected stocks across industries are qualitatively similar to those in the same industry.

We identify that quote-based liquidity is lower during the period of lower limit hits but is higher during the period of upper limit hits. The asymmetry in the impact of limit hits on liquidity demand arises from the asymmetry in the spread: an increase in spreads for lower limit hits and a decrease in spreads for upper limit hits. In addition, significant increases in trade-based measures of liquidity are found to support that informed traders may take their advantage of information to trade connected stocks as a substitution of the limit hitting stock. After dividing the duration of limit hits into the trading sub-period and the trading cessation sub-period to study the intra-hit liquidity, we find that the quote-based liquidity of connected stocks is improved during the trading cessation sub-period of both limit hits and only has a reduction during the trading sub-period of lower limit hits. Our results show that connected stocks seem to provide alternatives for informed traders to incorporate their private information into stock prices because the trade-based liquidity of connected stocks is found to significantly increase especially during the trading sub-period of limit hits. Our findings show that connected stocks seem to provide alternatives for traders try to reverse their earlier suboptimal trades because there are order imbalance reversals in the impact of limit hits on connected stocks. Our results are qualitatively similar across groups.

After classifying limit hits according to news announcements, we find that if limit hits are connected to material information released by firms, due to less information asymmetry, their liquidity impacts on informationally related stocks will be weaker than those of uninformative limit hits. Our findings in quote-based liquidity of impending limit hits provide evidence that, prior to the hit of price limits, connected stocks seem to already provide alternatives for traders to reverse their suboptimal trades incurred by the anticipation of a limit-hit. We find strong evidence that the quote-based liquidity is improved in anticipation of an impending upper limit hit and only find partial evidence in anticipation of an impending lower limit hit. We also find that the quote-based liquidity increases with the limit hit order, whereas the trade-based liquidity decreases with the limit hit order. Moreover, we find strong evidence that total price impact is greater during the period of the limit hit and the temporary price impact measures are significantly larger for trades during the limit hit period and there are reversals in price impact for connected stocks.

We find that the stronger the informational relationship is between the limit hitting stock and the reference stock, the larger the liquidity impact of upper limit hits on connected stocks. However, the trade-based liquidity of lower limit hits is found to decrease with the informational relationship is between the limit hitting stock and the reference stock. The liquidity impact tends to be stronger in smaller connected stocks, which are more susceptible to informed trading. In addition, the liquidity impact of a hit increases with the increasing market share of the limit hitting stock.

References

Admati, A., and P. Pfleiderer, 1988, A theory of intraday patterns: volume and price variability, *Review of Financial Studies* **1**, 3–40.

Baker, M., and J. Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* **21**, 129–151.

Bhattacharya, U., and M. Spiegel, 1991, Insiders, outsiders, and market breakdowns, *Review of Financial Studies* **4**, 255–282.

Bhattacharya, U., and M. Spiegel, 1998, Anatomy of a market failure: NYSE trading suspensions (1974–1988), *Journal of Business and Economic Statistics* **16(2)**, 216–226.

Bildik, R., and G. Gulay, 2006, Are price limits effective? Evidence from the Istanbul Stock Exchange, *Journal of Financial Research* **29**, 383–403.

Brady, N.F. et al., 1988, *Report of the Presidential Task Force on market mechanisms* (Government Printing Office, Washington D.C.).

Caballe, J., and M. Krishnan, 1994, Imperfect competition in a multi-security market with risk neutrality, *Journal of Econometric Society* **62**, 695–704.

Chan, H. W., and S. M. Pinder, 2000, The value of liquidity: Evidence from the derivatives market, *Pacific-Basin Finance Journal* **8**, 483–503.

Chan, S. H., K. A. Kim, and S. G. Rhee, 2005, Price limit performance: evidence from transactions data and the limit order book, *Journal of Empirical Finance* **12**, 269-290.

Chen, G. M., O. M. Rui, and S. S. Wang, 2005, The effectiveness of price limits and stock characteristics: evidence from the Shanghai and Shenzhen Stock Exchanges, *Review of Quantitative Finance and Accounting* **25**, 159–182.

Cho, D., J. Russell, T. George, and R. Tsay, 2003, The magnet effects of price limits: evidence from high-frequency data on Taiwan stock exchange, *Journal of Empirical Finance* **10**, 133-168.

Dehejia, R. H., and S. Wahba, 1999, Causal effects in nonexperimental studies: reevaluating the evaluation of training programs, *Journal of the American Statistical Association* **94**(**448**), 1053-1062.

Diacogiannis, G. P., N. Patsalis, N. V. Tsangarakis, and E. D. Tsiritakis, 2005, Price limits and overreaction in the Athens Stock Exchange, *Applied Financial Economics* **15**, 53–61.

Elyasiani, E., S. Hauser, and B. Lauterbach, 2000, Market response to liquidity improvements: evidence from exchange listings, *Finance Review* **35**, 1–14.

Fernandez, F. A., 1999, Liquidity risk, working paper, SIA.

Ferris, S. P., R. A. Haugen, and A. K. Makhija, 1988, Predicting contemporary volume with historic volume at differential price levels: evidence supporting the disposition effect, *Journal of Finance* **43**, 677–697.

France, V. G., L. E. Kodres, and J. T. Moser, 1994, A review of regulatory mechanisms to control the volatility of prices, Federal Reserve Bank of Chicago. *Economic Perspectives* **18**, 15–26.

Harris, L., 1998, Circuit breakers and program trading limits: what have we learned? In: Litan, R. R., Santomero, A. M. (Eds.), *Brookings-Wharton Papers on Financial Services*. Brookings Institutions Press, Washington D. C., 17–63.

Hasbrouck, J., and D. J. Seppi, 2001, Common factors in prices, order flows, and liquidity, *Journal of Financial Economics* **53**, 383–11.

Henke, H., and S. Voronkova, 2005, Price limits on a call auction market: evidence from the Warsaw Stock Exchange, *International Review of Economics & Finance* **14**, 439–453.

Holthausen, R. W., R. W. Leftwich, and D. Mayers, 1987, The effect of large block transactions on security prices: a cross-sectional analysis, *Journal of Financial Economics* **19**, 237–267.

Huang, Y. S., 1998, Stock price reaction to daily limit moves: evidence from the Taiwan Stock Exchange, *Journal of Business Finance and Accounting* **25**, 469–483.

Huang, Y. S., T. W. Fu, and M. C. Ke, 2001, Daily price limits and stock price behavior: evidence from the Taiwan Stock Exchange, *International Review of Economics and Finance* **10**, 263–288.

Jiang, C., T. McInish, and J. Upson, 2009, The information content of trading halts, *Journal of Financial Markets* **12**, 703–726.

Keim, D. B., and A. Madhavan, 1996, The upstairs market for large-block transactions: Analysis and measurement of price effects, *Review of Financial Studies* **9**, 1–36.

Kim, K. A., 2001, Price Limits and stock market volatility, *Economics Letters* **71**, 131–136.

Kim, K. A., H. Liu, and J. J. Yang, 2013, Reconsidering price limit effectiveness, *Journal of Financial Research* **36**, 493–517.

Kim, K. A., and P. Limpaphayom, 2000, Characteristics of stocks that frequently hit price limits: empirical evidence from Taiwan and Thailand, *Journal of Financial Markets* **3**, 315–332.

Kim, K. A., and J. Park, 2010, Why do price limits exist in stock markets? A manipulation-based explanation, *European Financial Management* **16**, 296–318.

Kim, K. A., and S. G. Rhee, 1997, Price limit performance: Evidence from the Tokyo Stock Exchange, *Journal of Finance* **52**, 885–901.

Kim, O., and R. Verrecchia, 1991, Market liquidity and volume around earnings announcements, working paper, University of California at Los Angeles and University of Pennsylvania.

Kim, Y. H., and J. J. Yang, 2004, What makes circuit breakers attractive to financial markets? A survey, *Financial Markets, Institutions, and Instruments* **13**, 109–146.

Kim, Y. H., and J. J. Yang, 2008, The effect of price limits on intraday volatility and information asymmetry, *Pacific-Basin Finance Journal* **16**, 522–538.

Kim, Y. H., J. Yagüe, and J. J. Yang, 2008, Relative performance between trading halts and price limits: evidence from the Spanish Stock Exchange, *International Review of Economics and Finance* **17**, 197–215.

Lee, C. M., B. Mucklow, and M. J. Ready, 1993, Spreads, depths, and the impact of earnings information: an intraday analysis, *Review of Financial Studies* **6**, 345–374.

Lee, C. M., and M. J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* **46**, 733–746.

Lee, J. H., and R. K. Chou, 2004, The intraday stock return characteristics surrounding price limit hits, *Journal of Multinational Financial Management* **14**, 485–501.

Li, H., D. Zheng, and J. Chen, 2014, Effectiveness, cause and impact of price limit-evidence from China's cross-listed stocks, *Journal of International Financial Markets*, *Institutions*, *and Money* **29**, 217–247.

Lo, A. W., and J. W. Wang, 2000, Trading volume: Definitions, data analysis, and implications of portfolio theory, *Review of Financial Studies* **13**, 257–300.

Ma, C. K., R. P. Rao, and R. S. Sears, 1989a, Volatility, price resolution, and the effectiveness of price limits, *Journal of Financial Services Research* **3**, 165–99.

Ma, C. K., R. P. Rao, and R. S. Sears, 1989b, Limit moves and price resolution: The case of the Treasury bond futures market, *Journal of Futures Market* **9**, 321–35.

Rourke, T., 2009, The information content of the supply and demand for liquidity in stock and option markets, *Financial Management Association Conference* (Reno, Nevada).

Rosenbaum, P., and D. B. Rubin, 1983, The central role of the propensity score in observational studies for causal effects, *Biometrica* **70**, 41-55.

Shen, C. H., and L. R. Wang, 1998, Daily serial correlation, trading volume and price limits: evidence from the Taiwan Stock Market, *Pacific-Basin Financial Journal* **6**, 251–273.

Spiegel, M., and A. Subrahmanyam, 2000, Asymmetric information and news disclosure rules, *Journal of Financial Intermediation* **9**, 363–403.

Subrahmanyam, A., 1994, Circuit breakers and market volatility: a theoretical perspective, *Journal of Finance* **49**, 237-254.

Tookes, H. E., 2008, Information, trading, and product market interactions: Cross-sectional implications of informed trading, *Journal of Finance* **63**, 379–413.

Wong, W. K., M. C. Chang, and A. H. Tu, 2009, Are magnet effects caused by uninformed traders? Evidence from Taiwan Stock Exchange, *Pacific-Basin Finance Journal* **17**, 28-40.

Yeh, C. H., and C. Y. Yang, 2013, Do price limits hurt the market? *Journal of Economic Interaction and Coordination* **8**, 125–153.

Tables

Table 1. Industrial Classification of TWSE-listed Common Stocks in Our Sample Data

No.	Industry Name	Firms	No.	Industry Name	Firms
01	Cement Industry	7	17	Financial and Insurance Industry	42
02	Food Industry	24	18	Trading and Consumers' Goods Industry	12
03	Plastic Industry	23	20	Others Industry	41
04	Textile Industry	47	21	Chemical Industry	24
05	Electric Machinery Industry	39	22	Biotechnology and Medical Care Industry	20
06	Electrical and Cable Industry	17	23	Gas and Electricity Industry	8
08	Glass and Ceramic Industry	4	24	Semiconductor Industry	70
09	Paper and Pulp Industry	7	25	Computer and Peripheral Equipment Industry	61
10	Iron and Steel Industry	29	26	Optoelectronic Industry	78
11	Rubber Industry	10	27	Communications and Internet Industry	43
12	Automobile Industry	5	28	Electronic Parts and Components Industry	86
14	Building Material and Construction Industry	46	29	Electronic Products Distribution Industry	27
15	Shipping and Transportation Industry	19	30	Information Service Industry	17
16	Tourism Industry	8	31	Other Electronic Industry	35

Resource: Taiwan Economic Data Center website and TWSE

New industry categories of TWSE-listed common stocks are shown in the table along with the industry number and the number of our sample stocks in each industry.[29] The sample period is from 1/1/2004 to 12/31/2013. Our sample data includes common stocks listed on TWSE during the sample period but excludes stocks of foreign companies, TDR, ETF, and other securities.

[29] TWSE revised its industrial classification system on July 2nd, 2007. According with the TWSE new industry classification, the chemical industry (No. 7) was split into two new industries, namely chemical industry and biotechnology and medical care industry; the electronics industry (No. 13) was split into eight new industries, namely semiconductor industry, computer and peripheral equipment industry, optoelectronic industry, communications and internet industry, electronic parts and components industry, electronic products distribution industry, information service industry, and other electronic industry; Since the one and only firm (Ticker No. 9801) in the general industry (No. 19) was reclassified as one of firms in the trading and consumers' goods industry on July 5th in 2006, there has been no firms existing in the general industry. Hence, the general industry is omitted in Table 1.

Table 2. Trading Days, Stocks, and Limit Hits in Each Year

Year	Number of Trading Days	Number of Analysis Stocks	Number of Limit Hits (7%)		
			Up	Down	Up & Down
2004	250	606	8,432	7,916	307
2005	247	619	5,167	3,086	172
2006	248	641	7,614	3,606	167
2007	247	637	8,332	6,080	153
2008	249	650	11,364	1,3762	295
2009	251	684	13,252	5,424	214
2010	251	714	6,378	3,769	84
2011	247	728	5,165	6,127	55
2012	250	746	4,829	2,477	45
2013	246	769	4,385	1,518	38

Because there is one day missing data in 2005, only the data from the remaining 246 days is used for analysis. In addition, we excluded 10 extra trading days from 2008/10/13 to 2008/10/24 due to a temporary adjustment of lower price limits from 7% to 3.5%.[30] Consequently, there are 2,475 trading days remaining for analysis. The number of limit hits in the case of Up & Down will increase one if a stock hits its upper limit and lower limit on the same day. Limit hits in the case of Up & Down are also excluded from the analysis samples.

[30] There are 3,781 lower limit hits from 2008/10/13 to 2008/10/24.

Table 3. Limit-Hit Descriptive Statistics

	Lower Limit Hits		Upper Limit Hits	
	Mean	Std. Dev.	Mean	Std. Dev.
Whole Period of Limit Hits (sec)	1,141.43	2,905.01	1,742.67	3,800.14
Trading Sub-Period (sec)	246.71	788.38	159.70	528.47
Trading Cessation Sub-Period (sec)	894.72	2,770.77	1,582.97	3,767.27
Percentage of Trading	0.26	0.39	0.37	0.43
Percentage of Trading Cessation	0.74	0.39	0.63	0.43
Trading Volume (1000 shares/5 mins)	547.69	3,068.39	912.87	4,791.15

The duration of limit hits can be further subdivided into two sub-periods: trading and trading cessation. The trading cessation sub-period is defined by the time during which the quoted bid depth of a lower limit-hitting stock is equal to zero or when the quoted offer depth of an upper limit-hitting stock is equal to zero.

Table 4. Descriptive Statistics for Stock Reference Group

	Across-Industry	In-the-Same-Industry		
	PSM Group	Volatility Group	Volume Group	Return Group
Unique Reference Stocks in Sample	846	846	846	846
% Overlap with Return Group	37.82	98.91	94.96	—
Mean Firms per Group	5.09	13.33	18.41	32.14
Min Firms per Group	5	1	1	1
Max Firms per Group	34	54	63	78
Median Firms per Group	5	11	17	32

We examine stocks for possible inclusion in one or more Reference Groups. Reference Groups are classified into two categories: Across-Industry Reference Group (PSM Group) and In-the-Same-Industry Group (Volatility Group, Volume Group, and Return Group). For the Return Group, we include a stock in the same industry into this Reference Group if the coefficient of correlation between the abnormal return for the limit-hitting stock and the candidate stock is statistically significant. We repeat the procedure for volume (Volume Group) and squared abnormal returns (Volatility Group). For the PSM Group, we include a stock across industries into this Reference Group if its propensity score is matched with the propensity score of the limit-hitting stock.

Table 5. Liquidity Impact of Informative Limit Hits on Informationally Related Stocks. (NewliquidityImpactData T>=600)

	Lower Limit Hits			Upper Limit Hits		
	Whole Period	Trading Period	Trading Cessation Period	Whole Period	Trading Period	Trading Cessation Period
Panel A: Return Reference Group						
Relative Spread (%)	13.74***	13.94***	0.95	-7.22***	-3.85***	-11.40***
Absolute Spread (%)	7.44***	7.51***	-4.56***	-4.83***	-1.89***	-9.09***
Bid Depth (%)	40.59***	35.02***	23.78***	4.02**	-1.64***	-0.25***
Offer Depth (%)	-12.04***	-13.24***	-22.96***	34.70***	25.55***	28.81***
Total Depth (%)	15.80***	12.26***	1.70***	17.10***	9.96**	12.23***
Spread/Total Depth (%)	17.41***	18.43***	4.31	-8.68***	-3.33***	-12.76***
Trade Volume (%)	26.34***	33.79***	15.48***	19.51***	50.10***	16.61***
Trade Value (%)	17.49***	25.76***	6.94***	19.72***	51.70***	16.86***
Number of Trades (%)	8.40***	13.84***	-3.43***	7.97***	16.69***	3.41***
Panel B: Volatility Reference Group						
Relative Spread (%)	14.78***	14.81***	2.13	-6.80***	-3.37***	-10.74***
Absolute Spread (%)	8.41***	8.53***	-3.72***	-4.82***	-1.81***	-8.75***
Bid Depth (%)	43.12***	36.66***	26.37***	3.42**	-1.85***	-0.71***
Offer Depth (%)	-11.67***	-13.35***	-21.87***	36.31***	26.35***	30.70***
Total Depth (%)	17.28***	13.21***	3.54*	17.44***	10.15***	12.72***
Spread/Total Depth (%)	17.45***	18.34***	4.71	-9.53***	-3.87***	-13.45***
Trade Volume (%)	30.08***	36.56***	19.21***	22.71***	59.84***	20.09***
Trade Value (%)	21.27***	28.26***	10.99***	23.81***	63.23***	21.35***
Number of Trades (%)	9.07***	14.98***	-2.44***	9.07***	19.87***	4.52***

Table 5 (continued). Liquidity Impact of Informative Limit Hits on Informationally Related Stocks. (NewliquidityImpactData T>=600)

	Lower Limit Hits			Upper Limit Hits		
	Whole Period	Trading Period	Trading Cessation Period	Whole Period	Trading Period	Trading Cessation Period
Panel C: Volume Reference Group						
Relative Spread (%)	13.96***	14.19***	0.98	-6.63***	-3.45***	-10.83***
Absolute Spread (%)	7.48***	7.58***	-4.63***	-4.56***	-1.84***	-8.77***
Bid Depth (%)	42.10***	35.30***	25.24***	3.50*	-2.16***	-0.87***
Offer Depth (%)	-11.08***	-11.82***	-22.10***	37.35***	28.39***	31.74***
Total Depth (%)	16.81***	12.90***	2.77**	18.05***	10.92***	13.22***
Spread/Total Depth (%)	17.03***	18.10***	3.63	-9.27***	-3.77***	-13.41***
Trade Volume (%)	27.12***	33.95***	16.00***	21.99***	53.89***	18.86***
Trade Value (%)	18.02***	25.59***	7.54***	23.14***	55.95***	20.03***
Number of Trades (%)	8.76***	14.01***	-3.02***	8.49***	17.74***	3.94***
Panel D: Propensity Reference Group						
Relative Spread (%)	13.44***	13.52***	0.81***	-5.75***	-2.76***	-9.69***
Absolute Spread (%)	7.66***	7.96***	-4.42***	-4.26***	-1.54**	-8.28***
Bid Depth (%)	49.22***	43.16***	32.90***	4.77	-1.02***	0.55**
Offer Depth (%)	-10.64***	-11.36***	-20.66***	41.93***	32.57***	37.07***
Total Depth (%)	20.45***	17.25***	7.01	20.59***	13.39***	16.22***
Spread/Total Depth (%)	16.52***	17.02***	3.51***	-8.58***	-3.75***	-12.53***
Trade Volume (%)	30.33***	39.33***	19.10***	25.46***	67.13***	21.99***
Trade Value (%)	21.87***	30.16***	10.92***	27.73***	71.32***	24.31***
Number of Trades (%)	9.37***	15.52***	-2.72***	8.50***	18.37***	4.07***

Table 6. Liquidity Impact of Uninformative Limit Hits on Informationally Related Stocks. (NewliquidityImpactData T>=600)

	Lower Limit Hits			Upper Limit Hits		
	Whole Period	Trading Period	Trading Cessation Period	Whole Period	Trading Period	Trading Cessation Period
Panel A: Return Reference Group						
Relative Spread (%)	16.61***	16.58***	1.68***	-8.00***	-5.04***	-12.07***
Absolute Spread (%)	9.97***	9.85***	-4.24***	-5.65***	-3.10***	-9.77***
Bid Depth (%)	43.53***	38.29***	24.96***	4.74	-0.51***	0.15***
Offer Depth (%)	-16.24***	-16.91***	-27.90***	36.22***	28.33***	29.47***
Total Depth (%)	15.18***	12.00***	-0.13***	18.06***	11.71***	12.58***
Spread/Total Depth (%)	19.20***	19.65***	4.08**	-10.65***	-5.78***	-14.73***
Trade Volume (%)	25.98***	31.27***	14.09***	22.12***	50.78***	18.82***
Trade Value (%)	16.44***	21.96***	4.95***	22.13***	50.27***	18.66***
Number of Trades (%)	9.72***	15.07***	-3.73***	9.96***	19.10***	5.33***
Panel B: Volatility Reference Group						
Relative Spread (%)	17.35***	17.25***	2.17***	-7.79***	-4.93***	-11.85***
Absolute Spread (%)	10.39***	10.27***	-4.04***	-5.64***	-3.15***	-9.71***
Bid Depth (%)	48.12***	41.76***	29.04***	5.65	0.60***	1.13***
Offer Depth (%)	-14.94***	-15.97***	-26.74***	39.38***	31.37***	32.62***
Total Depth (%)	18.05***	14.15***	2.42***	19.92***	13.61***	14.47***
Spread/Total Depth (%)	20.49***	20.94***	5.10**	-10.91***	-6.04***	-14.85***
Trade Volume (%)	29.30***	36.25***	16.94***	27.46***	59.67***	24.31***
Trade Value (%)	19.46***	26.79***	7.83***	28.35***	60.12***	25.08***
Number of Trades (%)	11.02***	16.82***	-2.55***	11.77***	21.46***	7.20***

Table 6 (continued). Liquidity Impact of Uninformative Limit Hits on Informationally Related Stocks. (NewliquidityImpactData T>=600)

	Lower Limit Hits			Upper Limit Hits		
	Whole Period	Trading Period	Trading Cessation Period	Whole Period	Trading Period	Trading Cessation Period
Panel C: Volume Reference Group						
Relative Spread (%)	17.05***	16.86***	2.09***	-7.86***	-5.02***	-11.91***
Absolute Spread (%)	10.20***	9.95***	-4.02***	-5.57***	-3.10***	-9.66***
Bid Depth (%)	44.94***	39.66***	26.85***	5.06	-0.23***	0.48***
Offer Depth (%)	-15.70***	-16.34***	-27.28***	37.51***	29.55***	30.84***
Total Depth (%)	16.01***	12.86***	1.03***	18.77***	12.35***	13.34***
Spread/Total Depth (%)	20.35***	20.65***	5.10	-10.79***	-5.92***	-14.78***
Trade Volume (%)	27.28***	33.11***	15.40***	24.76***	55.85***	21.43***
Trade Value (%)	17.55***	23.66***	6.04***	25.19***	55.67***	21.73***
Number of Trades (%)	10.12***	15.69***	-3.25***	10.92***	20.45***	6.30***
Panel D: Propensity Reference Group						
Relative Spread (%)	17.60***	17.56***	2.38***	-7.24***	-4.63***	-11.25***
Absolute Spread (%)	11.40***	11.35***	-3.13***	-5.23***	-2.91***	-9.31***
Bid Depth (%)	52.63***	47.94***	33.22***	6.53***	1.33**	2.05
Offer Depth (%)	-13.07***	-13.85***	-24.78***	40.80***	32.47***	34.61***
Total Depth (%)	21.07***	18.21***	5.29***	20.88***	14.34***	15.73***
Spread/Total Depth (%)	21.09***	21.22***	5.47***	-10.54***	-5.98***	-14.48***
Trade Volume (%)	34.22***	40.05***	23.10***	29.68***	69.20***	26.40***
Trade Value (%)	24.49***	30.22***	13.98***	32.47***	73.60***	28.96***
Number of Trades (%)	12.76***	18.71***	-0.87***	11.66***	21.76***	7.06***

For each reference group, we present the percentage increase (decrease) for each liquidity measure for three time periods: the whole period of limit hits, trading sub-period, and trading cessation sub-period. The liquidity impact is investigated by comparing the short-term liquidity measure (during the day *D* that the limit hit takes place) to the liquidity measure of the benchmark period (the benchmark period of *D*-5 to *D*-1 day window, excluding day *D*). Only trade-based liquidity measures of the benchmark period are calculated based on the daily market data of the TEJ. Asterisks (***, **, *) denote that coefficient is significant at 1%, 5%, and 10% respectively. (T>=600s)

Table 7. Liquidity Impact around All Limit Hits: Anticipatory Changes (NewliquidityImpactData T>=600)

	Price Down			Price Up		
	6.5%~7%	6%~6.5%	5.5%~6%	6.5%~7%	6%~6.5%	5.5%~6%
Panel A: Return Reference Group						
Relative Spread (%)	-1.95***	-1.60***	-0.31***	-20.82***	-19.31***	-18.33***
Absolute Spread (%)	-3.97***	-2.39***	-1.11***	-17.12***	-15.38***	-14.32***
Bid Depth (%)	16.94***	13.59***	11.32***	-7.19***	-4.23***	-3.54***
Offer Depth (%)	-22.31***	-20.94***	-19.17***	33.37***	28.80***	26.01***
Total Depth (%)	-1.95***	-3.14***	-3.59***	9.26***	9.53***	8.84***
Spread/Total Depth (%)	1.12***	2.12***	3.21***	-22.52***	-21.89***	-20.70***
Trade Volume (%)	-8.95***	-9.40***	-11.01***	-8.55***	-7.97***	-7.25***
Trade Value (%)	-14.33***	-13.47***	-14.44***	-7.37***	-7.28***	-6.18***
Number of Trades (%)	-6.90***	-6.43***	-5.45***	-4.90***	-4.06***	-3.44***
Panel B: Volatility Reference Group						
Relative Spread (%)	0.58***	1.32***	2.30***	-20.24***	-18.46***	-17.54***
Absolute Spread (%)	-3.29***	-2.72***	-2.91***	-17.77***	-15.87***	-14.89***
Bid Depth (%)	19.26***	15.84***	11.72***	-7.48***	-4.16***	-3.88***
Offer Depth (%)	-21.61***	-19.98***	-18.85***	35.78***	29.02***	25.80***
Total Depth (%)	-0.41***	-1.62***	-3.38***	9.92***	9.52***	8.50***
Spread/Total Depth (%)	3.29***	3.85***	5.12***	-23.18***	-21.85***	-20.67***
Trade Volume (%)	-7.45***	-7.73***	-9.74***	-4.59***	-6.63***	-3.78***
Trade Value (%)	-13.16***	-12.31***	-13.48***	-3.09***	-5.39***	-2.16***
Number of Trades (%)	-6.98***	-6.29***	-5.45***	-4.12***	-4.08***	-2.49***

Table 7 (continued). Liquidity Impact of All Impending Limit Hits: Anticipatory Changes (NewliquidityImpactData T>=600)

	Price Down			Price Up		
	6.5%~7%	6%~6.5%	5.5%~6%	6.5%~7%	6%~6.5%	5.5%~6%
Panel C: Volume Reference Group						
Relative Spread (%)	0.46***	1.20***	2.29***	-19.46***	-17.90***	-17.22***
Absolute Spread (%)	-3.15***	-1.81***	-0.34***	-17.00***	-15.21***	-13.52***
Bid Depth (%)	18.10***	15.68***	12.31***	-6.55***	-4.26***	-3.12***
Offer Depth (%)	-21.52***	-20.12***	-18.44***	34.96***	30.21***	27.15***
Total Depth (%)	-1.00***	-1.78***	-2.80***	9.98***	10.06***	9.50***
Spread/Total Depth (%)	2.68***	3.31***	4.94***	-22.36***	-21.03***	-20.18***
Trade Volume (%)	-6.93***	-7.42***	-10.26***	-6.37***	-6.49***	-4.99***
Trade Value (%)	-12.67***	-12.02***	-13.93***	-5.37***	-5.19***	-3.66***
Number of Trades (%)	-6.58***	-6.19***	-5.33***	-4.81***	-3.60***	-2.90***
Panel D: Propensity Reference Group						
Relative Spread (%)	1.98**	2.63**	3.83	-19.55***	-17.88***	-16.69***
Absolute Spread (%)	-2.68***	-0.89***	0.14***	-17.67***	-15.95***	-15.01***
Bid Depth (%)	21.22***	17.00***	14.29***	-6.48***	-5.09***	-3.17***
Offer Depth (%)	-21.37***	-20.19***	-18.18***	34.76***	27.28***	25.66***
Total Depth (%)	0.50***	-1.30***	-1.87***	9.93***	8.23***	8.64***
Spread/Total Depth (%)	4.73	5.32*	6.77	-22.31***	-21.10***	-19.78***
Trade Volume (%)	-5.88***	-7.12***	-8.33***	-5.10***	-4.53***	-4.47***
Trade Value (%)	-11.36***	-12.36***	-12.50***	-3.69***	-3.48***	-2.71***
Number of Trades (%)	-6.81***	-6.26***	-5.23***	-5.28***	-3.44***	-3.39***

For each reference group, we present the percentage increase (decrease) for each liquidity measure for the specified price-range period before the limit hitting. The liquidity impact is investigated by comparing the short-term liquidity measure (during the day *D* that the limit hit takes place) to the liquidity measure of the benchmark period (the benchmark period of *D*-5 to *D*-1 day window, excluding day *D*). Only trade-based liquidity measures of the benchmark period are calculated based on daily market data of the TEJ. Asterisks (***, **, *) denote that coefficient is significant at 1%, 5%, and 10% respectively.

Table 8. Liquidity Impact of All Limit Hits in Limit Hit Order (NewliquidityImpactData T>=600)

Propensity Reference Group	Lower Limit Hits			Upper Limit Hits		
	Whole Period	Trading Period	Trading Cessation Period	Whole Period	Trading Period	Trading Cessation Period
Panel A: First Limit Hit Period						
Relative Spread (%)	21.90***	20.15***	4.87***	-5.36***	-0.27***	-8.90***
Absolute Spread (%)	15.38***	13.92***	-1.07	-3.14***	1.47***	-6.71***
Bid Depth (%)	23.77***	18.85***	4.69	1.84	-6.12***	-1.75***
Offer Depth (%)	-14.40***	-14.13***	-29.34***	25.05***	17.38***	20.81***
Total Depth (%)	5.54***	2.95***	-11.59***	11.88***	4.18***	8.10***
Spread/Total Depth (%)	27.14***	25.70***	9.79***	-6.84***	0.98***	-10.39***
Trade Volume (%)	52.86***	49.48***	41.07***	39.50***	99.80***	36.98***
Trade Value (%)	42.31***	41.87***	30.55***	39.30***	98.81***	36.54***
Number of Trades (%)	16.91***	20.43***	0.75**	14.23***	26.71***	10.45***
Panel B: Second Limit Hit Period						
Relative Spread (%)	16.51***	17.95***	-2.66***	-7.04***	-2.95***	-10.66***
Absolute Spread (%)	10.25***	11.53***	-7.91***	-4.85***	-1.25***	-8.57***
Bid Depth (%)	36.76***	31.96***	13.40**	3.39	-3.61***	-0.61***
Offer Depth (%)	-15.96***	-17.63***	-30.29***	28.94***	19.28***	23.22***
Total Depth (%)	11.87**	8.52	-7.32***	14.05***	5.99	9.35***
Spread/Total Depth (%)	19.14***	21.53***	-0.15***	-8.75***	-2.30***	-12.83***
Trade Volume (%)	22.94***	35.84***	6.32**	21.60***	51.11***	17.94***
Trade Value (%)	14.25***	26.80***	-1.60	21.37***	50.26***	17.84***
Number of Trades (%)	10.90***	16.95***	-5.78***	10.59***	21.32***	6.40***

Table 8 (continued). Liquidity Impact of All Limit Hits in Limit Hit Order (NewliquidityImpactData T>=600)

PSM	Lower Limit Hits			Upper Limit Hits		
Reference Group	Whole Period	Trading Period	Trading Cessation Period	Whole Period	Trading Period	Trading Cessation Period
Panel C: Third Limit Hit Period						
Relative Spread (%)	16.04***	16.55***	-0.16***	-8.93***	-6.78***	-13.57***
Absolute Spread (%)	9.39***	9.70***	-5.94***	-6.66***	-4.96***	-11.34***
Bid Depth (%)	46.32***	41.35***	26.02***	5.38	0.82***	-0.10***
Offer Depth (%)	-16.49***	-17.35***	-29.09***	38.02***	29.25***	30.30***
Total Depth (%)	16.81***	13.73***	0.10***	19.00***	12.63***	12.57***
Spread/Total Depth (%)	18.39***	19.51***	1.89***	-12.15***	-8.48***	-16.60***
Trade Volume (%)	20.46***	30.36***	6.25	15.22***	29.22***	10.35***
Trade Value (%)	10.67***	19.51***	-2.60***	15.19***	28.92***	10.15***
Number of Trades (%)	9.57***	15.73***	-4.85***	8.98***	16.54***	3.64***

For each reference group, we present the percentage increase (decrease) for each liquidity measure for three time periods: the whole limit hit period, the trading period, and the trading cessation period during the limit hitting. The liquidity impact is investigated by comparing the short-term liquidity measure (during the day *D* that the limit hit takes place) to the liquidity measure of the benchmark period (the benchmark period of *D*-5 to *D*-1 day window, excluding day *D*). Only trade-based liquidity measures of the benchmark period are calculated based on daily market data of the TEJ. Asterisks (***, **, *) denote that coefficient is significant at 1%, 5%, and 10% respectively.

Table 9. Price Impact of All Limit Hits on Informationally Related Stocks (T>=600s)

	Lower Limit Hits				Upper Limit Hits			
Reference Group	Return	Volatility	Volume	Propensity	Return	Volatility	Volume	Propensity
Total Price Impact								
Buyer-Initiated	-1.00***	-0.35***	-0.83***	-0.07***	1.04***	1.22***	1.10***	1.20***
Seller-Initiated	1.73***	1.89***	1.80***	1.94***	-0.51***	-0.38***	-0.48***	-0.33***
Temporary Price Impact								
Buyer-Initiated	0.03***	0.75***	0.25***	1.09***	-0.27***	-0.19***	-0.23***	-0.25***
Seller-Initiated	-0.35***	-0.27***	-0.32 ***	-0.30***	-0.06***	0.17***	0.03***	0.26***

The total price impact is measured by $P_{t,total} = D_t \ ln(P_t/P_{open})$; the temporary price impact is measured by $P_{t,temp} = D_t \ ln(P_{close}/P_t)$, where D_t is 1 for buyer-initiated and -1 for seller-initiated. All trades occurring during day *D*-1 are treated as the benchmark. We report the mean of price impacts over the period of limit hits. All price impact values are in percent. Asterisks (***, **, *) denote that coefficient is significant at 1%, 5%, and 10% respectively.

Table 10 Determinants of Limit Hit Liquidity Impact (T>=600s)

	Lower Limit Hits				Upper Limit Hits			
	Log relative Spread ratio	Log bid depth ratio	Log number of trades ratio	Log trade volume ratio	Log relative Spread ratio	Log ask depth ratio	Log number of trades ratio	Log trade volume ratio
Panel A: Volatility grouping								
Intercept	0.121***	-0.201***	0.703***	0.442***	-0.465***	-0.469***	0.615***	0.039***
Amnth	-0.008***	-0.020***	-0.021***	-0.054***	0.008***	0.033***	-0.006***	-0.010***
LHmkt	-0.000	0.347***	0.243***	0.680***	-0.286***	0.996***	0.722***	1.328***
Rmkt	-0.012	-0.134***	0.213***	0.403***	-0.067***	-0.046*	0.413***	0.477***
IntrMkt	0.222	2.787***	-0.666**	-0.755	0.895***	-0.017	-2.163***	-0.766**
LnRcap	-0.036***	-0.087***	-0.057***	-0.066***	0.026***	-0.050***	-0.097***	-0.148***
LnRvol	0.021***	0.086***	0.006***	0.046***	0.014***	0.080***	0.045***	0.144***
LnRprc	0.047***	0.051***	0.012***	0.008***	0.010***	0.017***	0.011***	0.033***
Vcor	0.063***	0.272***	-0.157***	-0.124***	-0.043***	0.299***	0.139***	0.416***
LHTdur	-0.342***	0.229***	-0.788***	-1.050***	0.033***	0.464***	-0.644***	-0.814***
LHCdur	-0.063***	0.369***	-0.405***	-0.411***	-0.001	0.317***	-0.180***	-0.168***
Annc	-0.011***	-0.058***	-0.001	-0.016***	0.010***	-0.025***	-0.011***	-0.028***
LHSeq	-0.005***	0.008***	-0.009***	-0.015***	-0.003***	0.004***	-0.008***	-0.016***
Adj R^2(%)	1.4	2.5	6.9	3.0	3.3	3.8	6.9	6.7
F-stat.	362	625	1.84e+3	768	1.48e+3	1.68e+3	3.18e+3	3.04e+3
N	298651	298651	298651	298651	511254	511254	511254	511254
Panel B: Propensity grouping								
Intercept	0.111***	-0.223***	0.644***	0.431***	-0.433***	-0.546***	0.511***	-0.097***
Amnth	-0.023***	-0.016***	-0.033***	-0.074***	0.014***	0.008**	-0.010***	-0.021***

LHmkt	0.090***	0.297***	0.186***	0.417***	-0.164***	0.600***	0.446***	0.871***
Rmkt	0.042*	-0.079*	0.143***	0.214***	-0.041***	-0.005	0.298***	0.405***
IntrMkt	-0.432*	1.337***	-0.307	-0.346	0.226*	1.126***	-0.781***	0.592*
LnRcap	-0.037***	-0.076***	-0.049***	-0.053***	0.027***	-0.049***	-0.099***	-0.150***
LnRvol	0.021***	0.081***	0.001	0.036***	0.011***	0.087***	0.055***	0.156***
LnRprc	0.053***	0.042***	0.015***	0.007	0.006***	0.02***	0.018***	0.042***
Vcor	0.018***	0.094***	-0.025***	-0.027**	-0.021***	0.147***	0.103***	0.273***
LHTdur	-0.322***	0.183***	-0.728***	-0.980***	0.041***	0.370***	-0.579***	-0.716***
LHCdur	-0.064***	0.347***	-0.405***	-0.413***	-0.000	0.302***	-0.192***	-0.192***
Annc	-0.021***	-0.033***	-0.002	-0.009	0.011***	-0.021***	-0.006*	-0.016**
LHSeq	-0.005***	0.008***	-0.009***	-0.016***	-0.003***	0.004***	-0.008***	-0.017***
Adj R^2(%)	1.6	2.2	6.6	3.0	2.6	4.1	6.7	7.4
F-stat.	136	187	602	264	373	595	1.01e+3	1.12e+3
N	101714	101714	101714	101714	168786	168786	168786	168786

The determinants of the liquidity impact of limit hits for each Reference Group are investigated. The dependent variable, $LnLiqR_{i,k}$, is the log of each liquidity measure ratio, in turn. Each observation in the sample represents the average liquidity impact on each reference stock for the limit hit. We estimate the following equation using linear regression:

$$LnLiqR_{i,k} = \alpha + \beta_1 Amnth_k + \beta_2 LHmkt_k + \beta_3 Rmkt_{i,k} + \beta_4 Intrmkt_{i,k} + \beta_5 LnRcap_{i,k} + \beta_6 LnRvol_{i,k} + \beta_7 LnRprc_{i,k} + \beta_8 Vcor_{i,k} + \beta_9 LHTdur_{i,k} + \beta_{10} LHCdur_{i,k} + \beta_{11} Annc_k + \beta_{12} LHSeq_k + \varepsilon_{i,k}$$

Amnth is dummy variable that is 1 if the limit hit occurs in a January, April, July, or October, and 0 otherwise. *LHmkt* and *Rmkt* are the market shares of the limit hit and reference stocks during the previous year of the limit hit. *IntrMkt* is the market share of the limit hit stock multiplied by the market share of the reference stock. *LnRcap*, *LnRvol*, and *LnRprc* are the logs of the market capitalization, volume, and closing price, respectively, for the reference stock on the day of the limit hit. *Vcor* is the correlation coefficient between the reference stock and the limit hit stock for Return Grouping, Volatility Grouping, and Volume Grouping, and is replaced by the matched propensity variable *PSM* for PSM Grouping. *PSM* is defined by one minus the absolute value of the propensity score difference between the limit hit stock and its reference stock. *LHTdur* and *LHCdur* are the trading and trading cessation durations of the limit hit, respectively, as percentages of the trading day. *Annc* is the number of material information announcements about the limit hit stock on the day of the limit hit. *LHseq* is the sequence of the limit hit for the limit hit stock on the day of the limit hit. N represents the number of observations in the sample, where one observation represents a matched set of the limit hit and a single reference stock. Because of the log transformation, if the specific liquidity ratio was 0 during the time of the limit hit, the observation is dropped. Asterisks (***, **, *) denote that coefficient is significant at 1%, 5%, and 10% respectively.

For Robust Test: Table 5A. Liquidity Impact of Informative Limit Hits on Informationally Related Stocks. (NewliquidityImpactData T>=600)

	Lower Limit Hits			Upper Limit Hits		
	Whole Period	Trading Period	Trading Cessation Period	Whole Period	Trading Period	Trading Cessation Period
Panel A: Return Reference Group						
Relative Spread (%)	17.27***	17.48***	4.08	-4.88***	-1.41***	-9.23***
Absolute Spread (%)	8.96***	9.03***	-3.20***	-3.45***	-0.45***	-7.80***
Bid Depth (%)	47.84***	41.68***	30.71***	7.93***	2.06***	3.52***
Offer Depth (%)	-11.19***	-12.49***	-22.34***	42.46***	32.60***	36.41***
Total Depth (%)	18.31***	14.64	3.99***	21.67**	14.15	16.73
Spread/Total Depth (%)	22.20***	23.46***	8.45	-6.04***	-0.45***	-10.36***
Trade Volume (%)	32.68***	41.32***	21.34***	34.07***	69.93***	31.15***
Trade Value (%)	22.58***	31.69***	11.23***	35.38***	73.02***	32.49***
Number of Trades (%)	8.83***	14.17***	-2.94***	11.56***	20.73***	6.77***
Panel B: Volatility Reference Group						
Relative Spread (%)	19.14***	19.20***	5.92	-4.39***	-0.82***	-8.50***
Absolute Spread (%)	10.94***	11.08***	-1.50***	-2.93***	0.13*	-6.96***
Bid Depth (%)	53.72***	46.09***	36.54***	8.91***	3.50***	4.55***
Offer Depth (%)	-8.15***	-10.06***	-19.15***	47.49***	36.03***	41.55***
Total Depth (%)	21.99***	17.62*	7.94***	23.91***	15.89	18.95**
Spread/Total Depth (%)	24.70***	25.70***	10.98	-5.47***	0.52***	-9.64***
Trade Volume (%)	40.99***	48.72***	29.32***	42.49***	89.04***	40.15***
Trade Value (%)	31.20***	39.66***	19.59***	45.77***	96.16***	43.47***
Number of Trades (%)	10.78***	16.65***	-0.68***	13.98***	25.52***	9.17***

Table 5A (continued). Liquidity Impact of Informative Limit Hits on Informationally Related Stocks. (NewliquidityImpactData T>=600)

	Lower Limit Hits			Upper Limit Hits		
	Whole Period	Trading Period	Trading Cessation Period	Whole Period	Trading Period	Trading Cessation Period
Panel C: Volume Reference Group						
Relative Spread (%)	17.70***	17.92***	4.34	-4.42***	-1.14***	-8.80***
Absolute Spread (%)	9.36***	9.47***	-2.91***	-3.10***	-0.32***	-7.42***
Bid Depth (%)	50.93***	43.92***	34.03***	8.86**	2.88***	4.24***
Offer Depth (%)	-9.10***	-9.95***	-20.49***	47.28***	37.44***	41.52***
Total Depth (%)	20.33***	16.50*	6.15***	24.02***	16.46	19.00***
Spread/Total Depth (%)	23.56***	24.77***	9.34	-5.68***	0.06***	-10.07***
Trade Volume (%)	35.80***	44.16***	23.66***	40.66***	78.96***	36.98***
Trade Value (%)	25.19***	33.69***	13.57***	42.88***	82.79***	39.15***
Number of Trades (%)	9.90***	15.22***	-1.99***	13.16***	23.09***	8.27***
Panel D: Propensity Reference Group						
Relative Spread (%)	18.74***	18.71***	5.40	-3.08***	0.08***	-7.23***
Absolute Spread (%)	10.75***	11.02***	-1.74***	-1.87***	0.92	-6.06***
Bid Depth (%)	63.16***	57.17***	45.92***	12.38*	6.28***	7.92**
Offer Depth (%)	-4.84***	-5.46***	-16.49***	57.90***	46.80***	53.04***
Total Depth (%)	26.85***	24.01***	12.56***	29.15***	21.48***	24.70***
Spread/Total Depth (%)	24.76***	25.27***	10.73	-4.31***	0.81***	-8.58***
Trade Volume (%)	45.26***	54.50***	33.19***	48.39***	103.29***	43.88***
Trade Value (%)	34.97***	43.16***	23.36***	53.49***	111.69***	48.79***
Number of Trades (%)	11.46***	17.54***	-0.68***	14.02***	24.52***	9.24***

Table 6A. Liquidity Impact of Uninformative Limit Hits on Informationally Related Stocks. (NewliquidityImpactData T>=600)

	Lower Limit Hits			Upper Limit Hits		
	Whole Period	Trading Period	Trading Cessation Period	Whole Period	Trading Period	Trading Cessation Period
Panel A: Return Reference Group						
Relative Spread (%)	21.49***	21.47***	6.01***	-6.39***	-3.37***	-10.62***
Absolute Spread (%)	12.64***	12.52***	-1.88***	-4.53***	-1.96***	-8.74***
Bid Depth (%)	50.40***	44.79***	31.05***	9.89***	4.43***	5.06***
Offer Depth (%)	-15.54***	-16.27***	-27.42***	46.60***	37.75***	39.66***
Total Depth (%)	17.08***	13.82	1.49***	24.35***	17.54***	18.66***
Spread/Total Depth (%)	26.69***	27.19***	10.66***	-8.07***	-3.07***	-12.27***
Trade Volume (%)	32.88***	38.75***	20.16***	37.94***	72.22***	34.29***
Trade Value (%)	21.97***	27.84***	9.76***	38.71***	72.49***	34.97***
Number of Trades (%)	10.44***	15.79***	-3.18***	14.19***	23.80***	9.40***
Panel B: Volatility Reference Group						
Relative Spread (%)	22.93***	22.83***	7.11**	-5.88***	-2.92***	-10.09***
Absolute Spread (%)	13.81***	13.71***	-1.00***	-4.06***	-1.50***	-8.24***
Bid Depth (%)	59.25***	52.42***	38.73***	12.31***	6.96***	7.40***
Offer Depth (%)	-12.21***	-13.24***	-24.60***	52.05***	43.13***	44.98***
Total Depth (%)	22.59***	18.60**	6.24***	27.61***	20.81***	21.85***
Spread/Total Depth (%)	29.39***	29.89***	12.99***	-7.50***	-2.40***	-11.66***
Trade Volume (%)	40.69***	48.27***	26.92***	49.30***	89.23***	45.67***
Trade Value (%)	29.55***	37.47***	16.57***	52.24***	92.13***	48.47***
Number of Trades (%)	12.90***	18.72***	-0.89***	17.70***	28.13***	12.82***

Table 6A (continued). Liquidity Impact of Uninformative Limit Hits on Informationally Related Stocks. (NewliquidityImpactData T>=600)

	Lower Limit Hits			Upper Limit Hits		
	Whole Period	Trading Period	Trading Cessation Period	Whole Period	Trading Period	Trading Cessation Period
Panel C: Volume Reference Group						
Relative Spread (%)	22.17***	21.97***	6.62***	-6.06***	-3.15***	-10.28***
Absolute Spread (%)	13.19***	12.94***	-1.37***	-4.21***	-1.71***	-8.41***
Bid Depth (%)	54.31***	48.61***	35.15***	11.19***	5.65***	6.32***
Offer Depth (%)	-13.98***	-14.61***	-25.94***	49.52***	40.72***	42.63***
Total Depth (%)	19.47***	16.23	4.04***	25.94***	19.09***	20.28***
Spread/Total Depth (%)	28.46***	28.81***	12.24***	-7.76***	-2.73***	-12.00***
Trade Volume (%)	36.63***	43.06***	23.56***	43.63***	81.79***	39.94***
Trade Value (%)	25.64***	32.10***	12.98***	45.45***	83.11***	41.69***
Number of Trades (%)	11.36***	16.94***	-2.23***	15.96***	26.05***	11.12***
Panel D: Propensity Reference Group						
Relative Spread (%)	23.80***	23.75***	7.89**	-4.87***	-2.17***	-9.10***
Absolute Spread (%)	15.38***	15.35***	0.42***	-3.16***	-0.79***	-7.40***
Bid Depth (%)	66.20***	61.02***	45.13***	14.90***	9.42**	9.98
Offer Depth (%)	-8.74***	-9.49***	-21.31***	56.70***	47.60***	50.12***
Total Depth (%)	26.67***	23.74***	10.09***	30.07***	23.09***	24.62***
Spread/Total Depth (%)	31.10***	31.22***	14.32*	-6.62***	-1.86***	-10.90***
Trade Volume (%)	49.36***	56.02***	36.47***	55.23***	104.28***	51.50***
Trade Value (%)	38.24***	44.73***	26.01***	61.84***	114.00***	57.79***
Number of Trades (%)	15.68***	21.79***	1.55***	18.09***	28.88***	13.26***

For each reference group, we present the percentage increase (decrease) for each liquidity measure for three time periods: the whole period of limit hits, trading sub-period, and trading cessation sub-period. The liquidity impact is investigated by comparing the short-term liquidity measure (during the day *D* that the limit hit takes place) to the liquidity measure of the benchmark period (during the day *D*-5). Only trade-based liquidity measures of the benchmark period are calculated based on the daily market data of the TEJ. Asterisks (***, **, *) denote that coefficient is significant at 1%, 5%, and 10% respectively.