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The information content of trading halts

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Abstract

We investigate the impact of trading halts of NYSE-listed stocks on informationally related securities that continue to trade during the period of the halt. Informational relationships are established for companies in the same four-digit SIC industry based on the correlation of returns, volume, volatility, and the adverse selection components of spreads. We find a significant liquidity impact on informationally related securities with spreads and price impact of trades having substantial increases. However, we also find that quoted depths, the number of trades, and trade volume significantly increase. Our results are consistent with the trading halt model of Spiegel and Subrahmanyam [2000. Asymmetric information and news disclosure rules. Journal of Financial Intermediation 9, 363–403] and with the informed trading model of Tookes [2008. Information, trading, and product market interactions: cross-sectional implications of informed trading. Journal of Finance 63, 379–413]. In addition, our results indicate that there is a common liquidity response of informationally related securities to firm-specific trading halts.

JEL classifications: G14; G18; G19

Keywords: Trading halts; Microstructure; Market quality; Market liquidity

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0. Introduction

Under Rule 123D of the NYSE, the specialist, with the approval of a NYSE floor official, can suspend trading or delay the opening of a stock, to give investors time to assess new firm-specific information. These trading halts result from a variety of causes including order imbalances, news dissemination, or pending news relating to a specific company.[3] However, recent theoretical and empirical studies indicate that firm-specific trading halts have a market impact beyond that of the halted stock. Spiegel and Subrahmanyam (2000) (hereafter, SS) present a model based on information asymmetry that shows trading halts are a necessary component of markets. In their model, trading halts act as a signal that substantial information asymmetry exists for stocks that are related to the halted stock, such as stocks in the same industry.

Tookes (2008) develops a model based on Easley et al. (1998) in which industry effects on market microstructure measures are specifically considered. Restricting her analysis to a Cournot duopoly, she demonstrates that firm-specific news at the product market level impacts other related firms' trading. To illustrate how this might work for trading halts, assume that a company intends to announce FDA approval for a new drug that competes with drugs of several other firms. The company informs the exchange of its pending news announcement and trading is halted in the stock. As Tookes points out, insider trading laws limit any informed trading by principles of the announcing company in its own stock, but these laws have limited restrictions to trading in the stock of competitors. A trading halt is identical to the application of insider trading laws with perfect monitoring. Insiders are unable to trade in their own company's stock due to the halt and must seek other venues to obtain rents from their insider information. Under the SS model, the trading halt acts as an information asymmetry signal, implying a broad reduction in liquidity for informationally related securities. However, under the Tookes model, an informational event in one stock in an industry can instigate informed and insider trading in related stocks in that industry, implying an increase in trading. In this study, we investigate the information content of firm-specific trading halts on informationally related securities in the same industry.

To our knowledge, our paper is the first to focus on informationally related securities that continue to trade during the halt period. However, there is a related body of research dealing with trading halts. Madhavan (1992) shows that firm-specific trading halts are a natural response to excessive asymmetric information. Utilizing a Walrasian framework, Bhattacharya and Spiegel (1991) also demonstrate that trading halts arise when the degree of information asymmetry outweighs other motivations of trading. Edelen and Gervals (2003) propose a model that uses firm-specific trading halts as a method to limit specialist power. Empirically, Lee et al. (1994b) investigate the impact of trading halts on the trading characteristics of the halted stock after the halt is lifted. Christie et al. (2002) examine trading halts on the NASDAQ market and find that volatility, spreads, and volume increase after a halt. Corwin and Lipson (2000) explore the impact of intraday trading halts on the limit order book of the halted stock. More recently, Chakrabarty et al. (2007) evaluate informational content on the limited number of off-NYSE trades of the halted

[3]Under NYSE rule 80B, given specified market conditions, circuit breakers are activated and trading is suspended for the entire market. We do not investigate this type of trading halt.

stock, during the period of the NYSE trade suspension. All of these studies focus on the impact of the trading halt on the market characteristics of the halted company.

There is a growing body of literature (e.g., Chordia et al., 2000; Hasbrouck and Seppi, 2001) that documents commonality in order flow, returns and transaction costs for related stocks. The commonality literature coupled with the theoretical work of Spiegel and Subrahmanyam (2000) and Tookes (2008) indicate that a broader look at the impact of trading halts is relevant to the study of market liquidity and informed trading.

Our study adds to the literature in several ways. First, we contribute to the trading halts literature by showing that firm-specific trading halts have significant liquidity impacts on informationally related securities. Although we find that relative and absolute spreads increase significantly, we also find large increases in quoted depth, number of trades, and trading volume. Trades placed during the halt period are shown to have a larger price impact compared to a benchmark period. Our results directly support the implications of the SS model of trading halts and the informed trading model of Tookes (2008).

We show that a firm-specific trading halt is an informational event that impacts the market beyond that of the halted company. This finding also has potential regulatory implications. While current regulation limits insider trading in own-firm trades, there are relatively fewer restrictions on trading in competing firms' stocks. However, such trading may constitute an unfair informational advantage and may need to be closely monitored and even discouraged to bolster market integrity. Finally, we add to the commonality literature by evaluating the common liquidity impact of firms to firm-specific information. Previous papers such as Hasbrouck and Seppi (2001) assess commonality on a much broader scale. We find evidence of commonality in liquidity response to firm-specific stock risk factors for informationally related securities.

1. Hypotheses development

Spiegel and Subrahmanyam (2000) propose an asymmetric information model showing that without the option to halt trading, the level of asymmetric information in the market may become so large that trading will not occur. Ongoing trading without a halt signals low information asymmetry. A unique feature of the SS model is that the empirical implications are created not for the stock that is halted, but rather for informationally related stocks that continue trading. Proposition 10 in SS states that the ask (bid) pricing function of an informationally related security during the period of the trading halt will be greater (less) than the ask (bid) pricing function during a non-halt period, giving Hypothesis 1a:

Hypothesis 1a. When trading is halted for a stock, stocks in the same industry that are informationally related and continue to trade have reduced liquidity.

Under the SS model, a trading halt signals to the market that informational asymmetries exist for stocks that are informationally related to the halted security. Discretionary liquidity traders, in the sense of Admati and Pfleiderer (1988), observe the signal and withdraw from the market. The market-maker, observing the halt signal and the loss of liquidity, widens spreads and reduces quoted depths. Therefore, the SS model indicates that both the demand for and the supply of liquidity will decrease.

Tookes (2008) establishes a model of informed trading based on stock and industry-specific news events. Under the Tookes model, liquidity traders, discretionary or nondiscretionary, fail to understand and incorporate the halt signal and continue to trade. Based on Lemma 1 of her paper, 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. Because insiders are unable to trade their own stock due to the trading halt, a trading halt is equivalent to enforcement of insider trading laws with perfect monitoring. The market-maker and other liquidity suppliers observe the order flow and widen spreads. The wider spread compensates the market-maker for losses to informed traders, at the expense of liquidity traders. The implication is that trade-based measures of liquidity will increase because of the additional volume of informed traders while quote-based measures of liquidity will decrease. The implied market impact under the Tookes model is:

Hypothesis 1b. When trading is halted 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.

In addition to market liquidity measures, we also investigate the price impact of trades in informationally related stocks during the halt. Proposition 8 of the SS model indicates that the derivative of the pricing schedule with respect to quantity will increase for informationally related securities. On the other hand, the sequential trade model of Tookes is limited to a single trading period and does not present any direct evaluation of price impact. However, a larger price impact of trades during the halt is consistent with the increased informed trading of the Tookes model. Our final direct hypothesis is:

Hypothesis 2. When trading is halted for a stock, trades in stocks in the same industry that are informationally related and continue to trade will have larger price impact.[4]

We further investigate the impact of trading halts on market conditions of informationally related stocks by evaluating the determinants of identified liquidity impacts. Under the SS model, Proposition 7, companies with higher informational relatedness to the halted company should have a higher change in market liquidity during the trading halt. Lemma 2 of the Tookes model indicates that companies with lower market share simply lack the product market impact to affect the market liquidity of other stocks in the same industry. Therefore, the liquidity impact of a trading halt on related securities is increasing in the market share of the halted company and decreasing in the market share of the related security. This indicates that the net liquidity change is determined by the interaction between the market share of the halted company and that of the reference company. Tookes (2008, Eq. (4)) also indicates that smaller companies in the Reference Group (those traded during the halt period) should have the largest change in liquidity, implying that the liquidity impact is decreasing with increasing market capitalization. We test these implications using regression analysis. Beyond the implied liquidity determinants from these models, we also wish to investigate which parameters influence the choice of informed and insider traders' targets for trading.

[4]The specifics of this hypothesis are presented on page 384 of the SS paper.

2. Data and methods

2.1. Halt identification

Using TAQ data for the period January 2003, through December 2005, we identify trading halts for NYSE-listed securities though three condition codes—4, news dissemination; 7, order imbalance; and 11, news pending—for NYSE originated quotes. A trading halt begins with the first quote with a halt condition code and ends with the first quote with condition code 10, opening quote, or condition code 12, regular quote. We drop ADRs and when issued securities and require that a halted stock is included in the Compustat and CRSP databases. Because of our Reference Group methodology, we also drop all halts that occur on the same day in the same four-digit SIC industry.

In addition, Tookes separates single stock information events from industry-wide information events, which are likely to be associated with multiple simultaneous halts in a particular SIC industry. We drop multiple simultaneous halts from the liquidity analysis because of the complexity of measuring informational relatedness when there is more than one halted stock. But we identify the frequency of multiple halts and evaluate the causes of multiple halt events based on news announcements contained in Lexis-Nexis.

For each halted stock, we identify informationally related stocks in the same SIC Code. For each four-digit SIC Code, we begin with the top 15 companies based on market share and any other stocks with the same SIC code that were halted during our sample period. We also require an average price greater than five dollars for the year of the halt, listing in the TAQ database for the entire year in which the halt occurs, and a minimum market share of 0.5% based on Compustat sales data in the year before the halt.

2.2. Reference group formation

Our objective is to identify a Reference Group of stocks in the same SIC industry that have an informational relationship to the halted stock as the SIC grouping by itself is too coarse to be the sole criterion. While there are a number of microstructure trading models that are based on asymmetric information (e.g., Kyle, 1985; Easley and O'Hara, 1987; Admati and Pfleiderer, 1988), these models focus on a single security and the market impact of informed and uninformed trading on that security, rather than informational relationships between securities. However, Caballe and Krishnan (1994) present an information-based model of trading in a multi-trader multi-asset framework. They determine a pricing rule based on payoffs, noise trading, and private signals that establishes a relationship between order flows and prices. Their key assumption is that market-makers can observe all order flows, causing informed traders to determine their demand for securities jointly, rather than independently. This model implies that trading volume, returns, and the market-makers pricing schedule (i.e. spreads) represent market measures of the informational relation between securities.

Returns, volume, and spreads are also indicated as measures of informational relationships based on the commonality literature. Hasbrouck and Seppi (2001) document a commonality relationship between returns and volume, while Chordia et al. (2000) document commonality in spreads and other quote-based measures of liquidity. Also, the SS model of trading halts, based on Proposition 7, indicates that informationally related companies will have positively correlated volatilities. Based on these findings, we evaluate four dimensions of informational relationships: return, volume, volatility, and spread. These dimensions are not exhaustive and there are likely other dimensions of informational relationships that can be explored. However, we feel that these measures are reasonable for our assessment of trading halts. In evaluating additional dimensions of an informational relationship, we first recognize that a firm-specific trading halt is idiosyncratic. Where possible, we control for market-wide impact. We describe how we assess the informational relationship of stocks in the same SIC-defined industry in the next two sections.

2.2.1. Return reference group and volatility reference group

We extract daily return data from the CRSP database for each stock in the same SIC industry as the halted stock. For each stock in the industry, we obtain residuals from the market model and estimate a Pearson correlation between the residuals for the halted stock and each of our other candidate stocks in the same industry. We use a 10% significance level to accept or reject the hypothesis of informational relatedness. If no stock shows a statistically significant correlation with the halted stock, the halt is dropped from the sample. We estimate the correlations and form the Reference Groups for each year of the sample.

The daily volatility of each stock is estimated as the square of the residual from the market model. Stocks are included in a Reference Group if a stock's squared residual has a Pearson correlation with that of the halted stock at or above the 10% level. The volatility correlations are a trade-based proxy for the degree of co-movement in informed trading between the reference stock and the halted stock.

2.2.2. Volume reference group

We adopt the volume model of Ferris et al. (1988) to decouple industry- and firm-specific informational effects from macro economic effects impacting the market. We estimate $v_{i,t} = \alpha_I + \beta_i v_{m,t} + \gamma_{i,t}$, where $v_{i,t}$ is the daily trading volume divided by the shares outstanding for company i on day t, $v_{m,t}$ is the total market volume divided by the total number of shares outstanding for all securities on day t, and $\gamma_{i,t}$ is the residual of the regression. For each stock, the regression is estimated once for each sample year. Informationally related stocks are those that have a statistically significant correlation at the 10% level, based on the regression residual, with the halted stock. If no halted stock has a significant correlation with the reference stock, then the halt is dropped from the sample.

2.2.3. Adverse selection reference group

Our fourth dimension of informational relatedness is the correlation between the adverse selection components of the spread. We use the adverse selection component of spreads rather than total spread because other spread components, such as inventory and transaction cost, are not information based. We expect that the adverse selection component of spreads increases with increased informed trading. However, the adverse selection component of the spread represents a noisy transformation of trade-based information. In effect, the volatility correlation is a direct trade-based proxy of informed trading correlation while the adverse selection correlation represents the quote-based perception of the informed trading correlation. A positive correlation in the adverse selection component of spreads indicates that informed trading in the halted stock and the reference stock move together.

We use the method of Lin et al. (1995) to estimate the adverse selection component of spreads. The adverse selection component of spreads is estimated over 5-day increments for each year in the sample, producing roughly 50 adverse selection observations per year per stock. Stocks that have a statistically significant correlation with the halted stock in the adverse selection component of the spread are defined as informationally related.

2.2.4. Descriptive statistics for reference groups

Table 1, Panel A, shows statistics for trading halts. The number of trading halts that we are able to use varies by Reference Group. For brevity we only discuss the results of the Return Reference Group, which comprises 1314 halts—411 in 2003, 462 in 2004, and 441 in 2005—representing about half of all halts in the TAQ database. We have 1181 order imbalance halts, 11 news dissemination halts, and 122 news pending halts. Most halts are delayed openings. We further analyze the order imbalance trading halts to identify potential underlying causes. Using the Lexis-Nexis database, we evaluate news articles on the day before, of and after the halt event. Code 7 halts are identified as information based if we find a news-related article affecting the halted company and a confirming article identifying a market reaction to the news event. We find that 76% of order imbalance (code 7) halts are news related. There are only 83 intraday halts, which are halts occurring after the opening quote on the NYSE. Our halt durations are substantially shorter than those reported in pervious studies, with the average halt lasting 13.4 min. Our sample halts represent a large cross-section of industries, as shown in Table 1, Panel B, with 207 unique SIC industries representing 658 unique halted stocks. Our sample also includes a broad range of industry structures with Herfindahl index levels (defined as the sum of squared market shares) varying from a highly concentrated level of 0.89 to a small concentration level of 0.015. Market shares, calculated from sales data in the Compustat database for the year that the halt occurs, also have a good dispersion—the maximum is 94%, the minimum is 0.5%, and the average is 13.4%.

We also present descriptive statistics for the stocks in each Reference Group in Table 1, Panel C. For the Return Reference Group, we have 1353 unique Reference Group stocks. The median number of stocks that are informationally related to the halted stock per industry is 4, with a maximum number of 25. The average market share of the informationally related stocks is 8.8%, which is smaller than the average market share of the halted stocks.

Overall, each sample Reference Group contains a broad spectrum of industries and reference companies. Overlap between Reference Groups is measured relative to the Return Reference Group. While the Volatility Reference Group has 94% overlap with the Return Group, the Adverse Selection Group has only 80% overlap. Although there is overlap between the various Reference Groups, there are also a significant numbers of halts and reference stocks that are unique to each sample grouping.

3. Results

3.1. Multiple halts and market failure

A multiple stock halt event is when securities of two or more companies in the same SIC industry are halted simultaneously. Tookes (2008) shows that industry-wide news events

Table 1
Selected statistics for stock Reference Groups.

We examine stocks with the same four-digit SIC Code as the halted stock for possible inclusion in one or more Reference Groups. For the Volatility Group, we include a stock in this Reference Group if the coefficient of correlation between the volatility for the halted stock and the candidate stock is statistically significant. We repeat the procedure for volume (Volume Group), the adverse selection component of the spread (Adverse Selection Group), and squared abnormal returns (Volatility Group). The adverse selection component of the spread is estimated using the method of Lin et al. (1995). Panel A displays the characteristics of sample halts. Panel B shows characteristics of the halted stock and halted stock's industry. Panel C shows Reference Group characteristics.

	Volatility Group	Adverse Selection Group	Volume Group	Return Group
Panel A: Characteristics of sample halts				
Total number of halts	991	1160	1241	1314
2003	309	399	392	411
2004	350	299	444	462
2004	332	462	405	441
Halt by code				
Order Imbalance (code 7)	884	1031	1107	1181
News Dissemination (code 4)	8	12	11	11
News Pending (code 11)	99	117	123	122
Halt type				
Delay	924	1086	1,159	1231
Intraday	67	74	82	83
Halt duration (min)				
Mean	13.3	13.3	13.5	13.4
Min	4.3	4.3	4.3	4.3
Max	284.9	182.4	284.9	284.9
Median	11.7	11.7	11.7	11.7
Panel B: Industry characteristics of sample halts				
Unique SIC Codes in sample	177	203	199	207
Unique halted stocks in sample	516	604	623	658
Industry Herfindahl index				
Mean	0.229	0.237	0.243	0.248
Min	0.015	0.015	0.015	0.015
Max	0.845	0.889	0.892	0.889
Halted stock market share				
Mean	0.120	0.123	0.129	0.134
Min	0.005	0.005	0.005	0.005
Max	0.831	0.942	0.944	0.942
Panel C: Reference Group characteristics				
Unique reference stocks in sample	934	1308	1264	1353
% overlap with Return Group	94	80	84	–
Reference Group characteristics				
Mean companies per group	3.9	4.3	4.1	6.1
Min companies per group	1	1	1	1
Max companies per group	23	22	20	25
Median companies per group	2	3	3	4
Reference company market shares				
Mean	0.081	0.078	0.084	0.088
Min	0.005	0.005	0.005	0.005
Max	0.918	0.800	0.918	0.918

and firm-specific news events have different implications. Our focus is on firm-specific events and we leave a detailed analysis of multiple halt events to future research efforts. However, in this section, we briefly consider multiple simultaneous halts.

Table 2 presents the frequency of multiple halts and an analysis of the causes of multiple halts. Using Lexis-Nexis, we classify each halt according to one of six possible causes: Revenue Impact, Legal, Merger, Analyst Recommendation, Earnings, and Unclassified. Revenue Impact halts are due to news announcements that impact future sales revenue. Specifically, the two halts identified under this category are related to information regarding federal government contracts. Legal halts involve various types of legal cases and announcements. Merger halts are due to one or more stocks in the halted group having a relevant merger announcement. Analyst recommendation halts result from a change in analyst recommendation. Earnings halts relate to earnings announcements and warnings. To be classified in one of these segments, a minimum of two of the halted stocks must be referenced in the same article with the associated news event. We investigate news articles on the day before, the day of, and the day after the halt.

Multiple halt events are identified for groups of two, three, four, and six stocks within an SIC-defined industry (there are no instances of five simultaneous halts in our sample). Column 1 of Table 2 shows the classification when two stocks in the same industry are halted simultaneously. There are 43 such events representing ($43 \times 2 =$) 86 individual halts. We are unable to classify 18 of these events, meaning that we are unable to substantiate that the two (or more) halts are news related. We find that while simultaneous halts of two stocks are not uncommon, events that include more than two stocks are quite rare.

In total there are 56 multiple halt events identified in our sample, representing a total of 128 individual halts. Note that while specific and significant news incidents are identified

Table 2
Classification of multiple stock halts.

We identify simultaneous halts that involve multiple stocks in the same SIC industry.

We classify stocks using news articles from Lexis-Nexis. In each case, to be included in a particular classification, we require that at least two of the stocks be mentioned in a news article. Otherwise, we denote the halts as Unclassified. We base our classification on news articles on the day before, day of, and day after the halt. Revenue impact halts are due to news announcements that directly impact future sales revenue. Legal halts involve various types of legal cases. Merger halts are due to one or more stocks in the halted group having a merger announcement. Analyst recommendation halts results from a change in analyst recommendation. Earnings halts related to earnings announcements and warnings.

By type	Simultaneously halted stocks			
Reason for halt(s)	Number of 2 stock events	Number of 3 stock events	Number of 4 stock events	Number of 6 stock events
Revenue impact	1	1		
Legal	2	2	1	
Merger	4	1		
Analyst recommendation	7			1
Earnings	11	6		
Unclassified	18	1		
Total number of events	43	11	1	1
Total number of halts	86	33	4	5

for the majority of the multiple halt events, 116 of the 128 individual halt events are coded as caused by order imbalance, halt code 7, rather than the exchanged defined news events of code 4 and code 11 halts.

3.2. Liquidity impact of trading halts on informationally related securities

We continue our analysis by evaluating the liquidity impact of a trading halt on informationally related securities in the same SIC-defined industry. We select eight measures of market liquidity. There are four direct quote-based measures of liquidity: relative spread, absolute spread, quoted offer depth, and quoted bid depth. We also analyze a composite measure of quote-based liquidity: spread/total depth. Quote-based liquidity measures are evaluated only for quotes from the listing exchange. Trade-based liquidity measures include trade volume, the number of trades, and the number of D+ trades for informationally related stocks.[5] Quote-based measures of liquidity represent liquidity supply changes while trade-based measures of liquidity represent liquidity demand changes in the market.

To assess the liquidity impact of a trading halt on informationally related securities, the halt period is segmented into half minute increments. Quote-based measures of liquidity are time weighted over the half minute periods while trade-based measures are summed. We calculate the average of each liquidity measure, based on a window of 15 days before and 15 days after the day of the halt, for each informationally related reference stock, matching the time period of the halt. By matching the time periods, we control for possible intraday effects on liquidity. We then divide the liquidity measure of the halt period by the average calculated from the $\pm$15-day window. If a day in the reference period window contains an identified halt from the same SIC industry, the day is dropped from the average calculation. It should be noted that the TAQ database does not include trading halt information from NASDAQ. There is the potential to include a trading day in the reference window that contains a halt of a NASDAQ-listed security in the same SIC industry. However, given the implications of the SS and Tookes models, the inclusion of these days creates a more restrictive test of the theories. We conclude by averaging liquidity ratios for all reference stocks for each halt in the respective Reference Group to obtain a percentage change in the liquidity measure for each halt.

Table 3 shows the liquidity impact of a trading halt on informationally related stocks. We focus only on the Volatility Reference Group results for conciseness. Results are qualitatively similar for all of the informational groupings. For the Volatility Group, we find that relative spreads increase by a statistically significant 9.3%. We include absolute spread in our analysis to control for possible price changes in the related stock during the period of the halt, and find that this liquidity measure also increases by 8.8%. These results indicate a reduction of market liquidity. However, offer and bid depths also increase, though the increase is asymmetric, with offer depths increasing by 27.8% and bid depths increasing by 13.7%. For our composite measure of quote-based liquidity, we find that the composite measure spread/total depth also increases by a significant 6.8%, indicating that overall, quote-based liquidity is lower during the period of the halt. While the liquidity

[5] D+ orders are electronic limit orders submitted on the NYSE. For the sample period of this study, these orders were limited to a maximum number of share of 1099, and a 30-s delay was required between order submissions. These restrictions were removed when the NYSE moved to the hybrid market in September of 2006.

Table 3
Liquidity impact of trading halts on informationally related equities.

For a stock in the Volatility Group, we present the percentage increase (decrease) for each liquidity measure for four time periods: the entire halt period, and for the first, second, and third 5-min periods during the halt. Consider a stock that has a trading halt on day t for a duration of n half-minute periods. In addition, this stock has J informationally related equities. To asses the liquidity impact of the trading halt on the J informationally related equities, we proceed as follows. For a liquidity measure X, the average liquidity impact for informationally related equity k is then defined as $\alpha_k = 1/n\bar{x}_k\sum_{i=1}^{n}x_{k,i}$, where $\bar{x}_k$ represents the average value of the liquidity measure for that same intraday period of the halt calculated for a benchmark period spanning day $t-15$ through day $t+15$, excluding the day of the halt. If there is no change in liquidity of the informationally related stock, $\alpha_k = 1$. The average liquidity impact for the halt is defined as $A = 1/J\sum_{k=1}^{J}\alpha_k$. This process is repeated for each halt contained in a Reference Group. We then conduct a t-test to evaluate if the liquidity impact of the sample of halts is statistically different from 1. For quote-based measures of liquidity, time weighting is used, while for trade-based measures of liquidity, sums are used and aggregated for each half minute interval of the halt duration. We repeat this analysis for all the liquidity measures within each of the Reference Groups. A stock is selected for inclusion in one or more Reference Groups if it has the same four-digit SIC Code as the halted stock and has a statistically significant correlation with the halted stock on either squared abnormal return (Volatility Group) or adverse selection component of spreads (Adverse Selection Group).

	Full halt duration	First 5 min	Second 5 min	Third 5 min
Panel A: Volatility Group				
Number of halts	991	991	987	795
Relative spread (%)	9.3***	10.3***	8.3***	11.5***
Absolute spread	8.8***	9.9***	8.0***	11.2***
Offer depth (%)	27.8***	25.0***	22.4***	41.3***
Bid depth (%)	13.7***	11.6***	10.9***	24.0***
Spread/depth (%)	6.8***	10.6**	5.5**	4.2
Volume (%)	152.3***	170.2***	145.6***	128.1***
Number of trades (%)	71.0***	81.2***	70.0***	66.7***
Number of D+ trades (%)	61.6***	56.4***	60.3***	66.3***
Panel B: Adverse Selection Group				
Number of halts	1160	1143	1154	1154
Relative spread (%)	2.8**	2.6**	1.4	3.4***
Absolute spread (%)	2.8***	2.6**	1.4	3.5***
Offer depth (%)	19.5***	17.3***	20.0***	14.3***
Bid depth (%)	7.1***	3.6*	8.8***	8.9*
Spread/depth (%)	0.5	0.8	-0.9	3.0
Volume (%)	65.7***	72.8***	54.2***	56.7***
Number of trades (%)	30.6***	30.3***	27.0***	35.9***
Number of D+ trades (%)	33.8***	34.8***	30.4***	32.7***
Panel C: Volume Group				
Number of halts	1241	1226	1231	1231
Relative spread (%)	4.7***	5.6***	4.7***	4.4***
Absolute spread (%)	4.8***	5.7***	4.7***	4.4***
Offer depth (%)	24.0***	22.5***	22.2***	26.6***
Bid depth (%)	6.8***	3.5	6.4**	11.3***
Spread/depth (%)	4.5***	7.5**	4.1**	1.5
Volume (%)	115.1***	80.7***	81.7***	91.8***
Number of trades (%)	50.5***	38.2***	36.2***	50.0***
Number of D+ trades (%)	48.1***	28.2***	29.5***	39.9***

Table 3 (*continued*)

	Full halt duration	First 5 min	Second 5 min	Third 5 min
Panel D: Return Group				
Number of halts	1314	1301	1305	1305
Relative spread (%)	4.3***	4.0***	5.0***	5.0***
Absolute spread (%)	4.2***	3.9***	4.9***	4.9***
Offer depth (%)	21.9***	19.1***	22.7***	24.0***
Bid depth (%)	8.8***	3.1*	10.8***	14.3***
Spread/depth (%)	3.1**	3.3	3.2**	0.9
Volume (%)	80.0***	82.4***	78.1***	66.7***
Number of trades (%)	36.3***	41.1***	30.9***	38.6***
Number of D+ trades (%)	29.3***	23.7***	24.5***	33.3***

*Statistically significant at the 10% level.
**Statistically significant at the 5% level.
***Statistically significant at the 1% level.

impact of trading halts is mixed for quote-based measures of liquidity, trade-based measures of liquidity show dramatic increases. Volume increases by 152.3% and the number of trades and D+ trades increase by 71.0% and 61.6%, respectively. These results are only partially consistent with Hypothesis 1a.

To be fair, the SS model was motivated around the concept of news pending (code 11) halts. Hence, to explore these types of halts further, we limit our sample to news pending halts; our conclusions are qualitatively similar with increases in spread, quoted depth, and trade-based measures of liquidity. However, if the market is efficient, it is possible that the initial period of the halt conforms to the implications of the SS model, and that as informed traders reveal their information through trades, the efficient price is quickly established. We explore this possibility in the next section.

3.2.1. *Intra-halt liquidity*

We subdivide the halt period into three 5-min sections representing the first, second, and third 5-min of the halt and report the results in Table 3. Again, we focus only on the Volatility Group due to the strong similarity of the results across groups. For the Volatility Reference Group, shown in Table 3, Panel A, quote-based measures of liquidity, such as relative spread, widens over the entire halt duration. Relative spreads are 10.3% during the initial 5 min of the trading halt, decline during the second 5-min interval and increase to 11.5% for the third 5-min interval. Recall from Table 1 that the median duration of halts for all Reference Groups is 11.4 min. Thus, the sample size decreases as shorter duration halts terminate. The increase in trade volume, the number of trades, and the number of D+ electronic limit orders decrease during the halt duration. Initially, trade volume increases by 170.2%, but by the third 5-min period of the halt, the trade volume increase is only 128.1%. Intra-halt liquidity measures for the other Reference Groups also indicate that the liquidity change during the halt period is stable throughout the halt duration. All liquidity measures tend to be largest during the first 5-min of the halt period and then decrease. Overall, we find evidence indicating that quote-based liquidity measures are lower while trade-based liquidity measures are improved during the entire halt period, as predicted by Hypothesis 1b.

3.2.2. Discussion of results

The changes in liquidity during the halt period are not only statistically significant but also economically significant. To illustrate, we use the liquidity impact results from the Volatility Group. For the benchmark period, the global average absolute spread is roughly 9.0 cents. During the halt period, the spread increases by 8.8% or 0.8 cents. In addition, trading volume increases by 152%. For the benchmark period, the average volume per half minute of trading per stock is 2569 shares, but for the halt period the volume increases on average by 3905 shares per half minute of trading per stock in the Reference Group. From Table 1, Panel A, there are 991 trading halts in the sample, with an average halt duration of 13 min (26 0.5-min periods). From Table 1, Panel B, there are four informationally related companies per halt on average. Using these values, we estimate that for the total sample of halts in the Volatility Group, roughly an additional 400 million shares are traded ($3905 \times 26 \times 991 \times 4$). In total, for the halt period there are about 670 million shares traded at an increased half spread of 0.4 cents. Our estimation is that the transaction cost increase is up to about \$2.7 million over the sample period.

Our results differ from those of Lee et al. (1994a), who analyze liquidity impacts around earnings announcements using 1988 data and find that spreads widen, quoted depths decrease, and volume increases on earnings announcement days. We find that both spread and volume increase, but we also find that quoted depths increase. However, our analysis focuses on informationally related securities while Lee et al. (1994a) concentrate on stock liquidity measures. Still, the increase in quoted depth remains puzzling. We conjecture that the quoted depth increase reflects a shift in the sources of liquidity supply. Khandani and Lo (2007) note that over the last decade hedge funds and proprietary trading desks (HFPTDs) started competing with traditional market-makers, adding enormous amounts of liquidity to markets. These HFPTDs introduce three new issues into the supply and demand equilibrium of the market. First, they are executing orders that are part of wider investment strategies. In this sense, the execution of a given leg of the overall strategy can be more important than the specific execution price. The potential loss to the investment strategy because of failure to execute outweighs the potential loss to informed traders on a stock by stock basis. Second, HFPTD investments strategies may be time sensitive. Waiting for informational events to be fully impounded into market prices undercuts the statistical expectations and risk distribution of the overall investment strategy. Higher liquidity demand will allow for quicker execution for passive trading, resulting in higher quoted depths. Third, while as a group HFPTDs are large, individually they only offer limited liquidity supply. Once the limited liquidity supply is exhausted, individual liquidity sources withdraw from the market. The transient nature of the fragmented liquidity supply undercuts the Bayesian updating premise of sequential trading models because transient liquidity suppliers may observe only a limited number of trades before supply is withdrawn from the market. The extraction of information from the trade sequence will be limited and local. In effect, all markets, examined with a short enough time span look uninformed.

On the other hand, also based on 1988 data, Chung and Charoenwong (1998) find that there is no relationship between insider trading and spread. However, in their study the information event is hidden and the identification of informed trading is ex post. We find that the halt correctly signals an asymmetric information environment and that liquidity suppliers widen spreads in response to increased compensation for losses to informed traders. Later we also present evidence that price impact significantly increases for informationally related stocks during the period of the trading halt.

Our results show that the liquidity impact of trading halts on informationally related stocks are dramatic. There are statistically and economically significant increases in transaction costs as indicated by both relative and absolute spreads. While quoted depths increase, we feel this may be a response of liquidity suppliers to increased transaction demand from informed traders. This is consistent with our finding of extremely large increases in trading activity during the halt period. The large increase in trade-based measures of liquidity, coupled with a reduction in quote-based liquidity, clearly support Hypothesis 1b. In addition, in unreported results, we test our findings for robustness by dividing the sample and reevaluating the liquidity impact of the sub-period groups. With the exception of the spread measure for the Adverse Selection Reference Group in the first half of the sample, all results remain statistically significant and in the same qualitative and quantitative direction as the full sample.

3.3. Price impact of informationally related securities during the halt period

Spiegel and Subrahmanyam (2000) state, in Proposition 8, that during the halt period trades have a larger price impact than during a non-halt period. Hypothesis 2 addresses this implication. Our measure of price impact is based on Holthausen et al. (1987), who partition price impact into three components: temporary, permanent, and total. The total component of price impact is defined as $D_t \ln(P_t/P_{open})$, where P_t is the price at time t, P_{open} is the price at the open, and D_t is the inferred trade direction indicator with 1 for buyer-initiated trades and -1 for seller-initiated trades. The temporary component of price impact is defined as $D_t \ln(P_{close}/P_t)$. For opening and closing prices, we use the first and last trades in the TAQ database from the listing exchange of the security. Price impact is signed using the Lee and Ready (1991) trade inference algorithm. This measure of price impact has been used in microstructure-related research such as Keim and Madhavan (1996) to investigate the impact of large block trades on prices and liquidity measures.

The direction of the price impact depends on the underlying information. Price impact can be both more positive and more negative in that each trade on one side of the market creates a larger move in the price of the stock in the direction of the trade. We average the price impacts over the duration of the halt for the day of the halt and the benchmark period and then conduct a t-test to examine changes in the price impact of trades. We separate our analysis based on the market-adjusted return of the halted stock on the day of the halt, with a positive adjusted return, indicating a positive information event and a negative adjusted return implying a negative information event. Our analysis considers four categories: buyer-initiated trades, seller-initiated trades, buyer-initiated trades divided by number of lots, and seller-initiated trades divided by number of lots. Price impact is calculated for each half minute period of the halt and then averaged for each halt in the sample. Periods with no trades are dropped from the analysis. We report the mean of the differences over the duration of the halt. These results represent the average price impact per half minute of the halt duration.

The price impact results for the volatility and the adverse selection dimension of informational relationships are shown in Table 4. The results for the adverse selection Reference Group show that the total price impact of trades during the halt period is not statistically different from the benchmark period, regardless of the direction of the halt event. However, our expectation in forming the Adverse Selection Reference Group is that the adverse selection component of spreads increases with increased informed trading.

Table 4
Price impact of trading halts on informationally related equities.

Total price impact is $P_{i,total} = D\ln(P_t/P_{open})$ and temporary price impact is $P_{i,tmp} = D\ln(P_{close}/P_t)$, where D is 1 for buyer-initiated trades and -1 for seller-initiated trades. Before proceeding, we separate our halts into two groups, positive and negative, based on the abnormal return of the halted stock on the day of the halt. We consider four categories: buyer-initiated trades, seller-initiated trades, buyer-initiated trades divided by number of lots, and seller-initiated trades divided by number of lots. We report the mean of the differences over the duration of the halt. These results represent the average per half minute of the halt. A stock is selected for inclusion in one or more of the Reference Groups if it has the same four-digit SIC Code as the halted stock and has a statistically significant correlation with the halted stock for the liquidity measure for that Reference Group. The correlations for each Reference Group, in turn, are based on the squared abnormal return (Volatility Group), or the adverse selection component of spreads (Adverse Selection Group). If no trading occurs for the Reference Group during the halt the halt is dropped from consideration. All price impact values are in percent.

	Volatility Group		Adverse Selection Group	
	Positive event	Negative event	Positive event	Negative event
Number of halts	437	501	515	617
Panel A: Total price impact of trades				
Buyer-initiated	0.045	−0.150*	−0.106	−0.070
Seller-initiated	0.004	0.128	0.065	0.027
Buyer-initiated per lot	0.044	−0.090*	0.001	−0.021
Seller-initiated per lot	−0.026	0.087**	−0.031	−0.007
Panel B: Temporary price impact of trades				
Buyer-initiated	0.632***	−0.355***	0.415***	−0.277***
Seller-initiated	−0.547***	0.294***	−0.387***	0.249***
Buyer-initiated per lot	0.328***	−0.177***	0.162**	−0.185***
Seller-initiated per lot	−0.292***	0.160***	−0.162**	0.141**

*Statistically significant at the 10% level.
**Statistically significant at the 5% level.
***Statistically significant at the 1% level.

Informed trader models such as Admati and Pfleiderer (1988) show that informed traders attempt to hide their information from the market. If informed traders are successful in hiding their trades, the contemporaneous price impact relative to the open should be low. On the other hand, if informed traders are truly informed and have sufficient resources, the price impact of trades relative to the closing price, the temporary price impact, will be significant. This is exactly what we find for the Adverse Selection Reference Group. For a positive event on the halted stock, temporary price impacts of buyer-initiated trades show an increase of 0.415% while seller-initiated trades show a decrease in price impact of −0.387%. These results are mirrored for the negative event, with buyer-initiated trades having temporary price impacts of −0.277% and seller-initiated trades having a price impact of 0.249%.

The results for the Volatility Reference Group are qualitatively identical and quantitatively larger than the findings based on the Adverse Selection Group for temporary price impact measures. In addition, total price impacts for negative information events are statistically significant for buyer-initiated trades and both buyer- and seller-initiated trades per lot of shares traded. Nevertheless, total price impact measures are not statistically different from the benchmark period for positive information events. To summarize, we find some evidence that total price impact is greater during the period of the trading halt, but we find strong evidence that temporary price impact measures are significantly larger for trades during the halt period and that there are no reversals in price impact for informationally related stocks.

3.4. Listing exchange effects

In forming the portfolios of informationally related securities, we allow for securities to be listed on different exchanges. NASDAQ and the NYSE, which are both included in the sample, have significantly different market structures during our sample period—a specialist market for NYSE-listed securities and a competitive dealer market for NADSDAQ listed securities. Spiegel and Subrahmanyam (2000) tentatively investigate the impact of news discloser rules under a competing exchange structure. They show that exchanges attempt to maximize own exchange utility at the expense of cross-exchange interactions for informationally related securities. However, the implicit assumption that the competing exchanges have identical market trading structures limits any direct test of their assertion because of the inherent differences between the NYSE and NASDAQ markets. While we are unable to formulate a strictly rejectable hypothesis, we can condition our liquidity results based on the listing exchange of the reference company to see if the liquidity impact differs by exchange and if these results are consistent with the implication of SS.

Table 5 shows the liquidity impact results for the full duration of the halt conditioned by the listing exchange (NYSE only or NASDAQ only) of the reference company based on the Volatility and Adverse Selection Groups. If a halt has only NASDAQ (NYSE), listed stocks in the reference portfolio, the halt is dropped from the NYSE (NASDAQ). We find large differences in the quote-based measures of liquidity, but consistent increases in the trade-based measures of liquidity for each market center. Specifically, we find that the liquidity supply for NASDAQ-listed stocks improves during the duration of the halt with spreads remaining statistically unchanged or significantly decreasing in the case of the Adverse Selection Group. On the other hand, liquidity supply for NYSE-listed stocks shows an overall tightening during the period of the halt. Both exchanges show significant increases in the number of trades and trade volume, but NASDAQ's trade-based measures of liquidity uniformly increase more than for the NYSE. Still, the reaction of liquidity suppliers on the NASDAQ market is reasonable if there is limited evidence of informed trading on the market.

To add to the overall liquidity picture, we also present results of the price impact of trades conditioned on the listing exchange of the reference stock. In Table 6, Panel A, (Panel B) we show the price impact results for NYSE (NASDAQ)-listed companies. For NYSE-listed companies, the price impact results indicate that liquidity suppliers quickly react to the information content of the trading halt. All total price impact measures (price impact relative to the open) show statistically significant differences with the benchmark period with the expected sign. In addition, temporary price impacts (price impact relative to the close) show no reversals, indicating that earlier trades correctly indicate the closing return of the equity consistent with informed trading. On the other hand, most of the total price impact measures for NASDAQ-listed securities are not statistically significant or have the wrong sign based on segmentation of the halts into positive and negative information events. For example, for the Adverse Selection Group, if the halt reflects a

Table 5
Liquidity impact of trading halts on informationally related equities by exchange.

For each Reference Group, we present the percentage increase (decrease) for each liquidity measure for four time periods: the entire halt period, and for the first, second, and third 5-min periods during the halt. Consider a stock that has a trading halt on day t for a duration of n half-minute periods. In addition, this stock has J informationally related equities. To asses the liquidity impact of the trading halt on the J informationally related equities, we proceed as follows. Consider a liquidity measure X. The average liquidity impact for informationally related equity k is then defined as $\alpha_k = 1/n\bar{x}_k \sum_{i=1}^{n} x_{k,i}$, where $\bar{x}_k$ represents the average value of the liquidity measure for that same intraday period of the halt calculated for a benchmark period spanning day $t-15$ through day $t+15$, excluding the day of the halt. If there is no change in liquidity of the informationally related stock, $\alpha_k = 1$. The average liquidity impact for the halt is defined as $A = 1/J \sum_{k=1}^{J} \alpha_k$. This process is repeated for each halt contained in a Reference Group. We then conduct a t-test to evaluate if the liquidity impact of the sample of halts is statistically different from 1. For quote-based measures of liquidity, time weighting is used while for trade-based measures of liquidity, sums are used and aggregated for each half-minute interval of the halt duration. We repeat this analysis for all the liquidity measures within each of the Reference Groups. A stock is selected for inclusion in one or more Reference Groups if it has the same four-digit SIC Code as the halted stock and has a statistically significant correlation with the halted stock on either squared abnormal return (Volatility Group) or adverse selection component of spreads (Adverse Selection Group).

	Volatility Group		Adverse Selection Group	
	NYSE	NASDAQ	NYSE	NASDAQ
Number of halts	833	441	1058	581
Relative spread (%)	11.9***	4.3	5.3***	−3.4**
Offer depth (%)	36.7***	4.6	18.4***	18.2**
Bid depth (%)	18.4***	4.1	9.5***	−0.5
Spread/depth (%)	9.9***	3.3	3.4*	−5.2**
Volume (%)	140.3***	186.0***	55.3***	95.5***
Number of trades (%)	49.0***	127.9***	22.2***	52.4***

*Statistically significant at the 10% level.
**Statistically significant at the 5% level.
***Statistically significant at the 1% level.

positive information event, the total price impact for buyer-initiated trades is −0.725% and significant at the 10% level. However, the temporary price impact for the buyer-initiated trades is 0.915% and significant at the 1% level. This indicates that buy-initiated trades produce negative price reactions from liquidity suppliers during the halt period, but those reactions are completely reversed by the end of the day. In aggregate, we find that the NASDAQ market has a significantly lower contemporaneous reaction to the information content of trading halts, but information is compounded into the stock price by the close of the day.

When we examine the entire liquidity environment of the segmented markets—liquidity supply, liquidity demand, informed trading, and the price impact of trades—we find strong indications that the NYSE market is better at assessing the information content of firm-specific trading halts. While liquidity demand and the likelihood of informed trading increase on both markets, only the NYSE market shows a consistent reduction in liquidity supply and a pricing reaction fully consistent with the identified increase in informed trading. However, causality is difficult to assess. Under the SS model, the differing reaction of the markets could be caused by the trading halt rules established by the NYSE.

Table 6
Price impact of trading halts on informationally related equities by exchange.

Total price impact is $P_{i,total} = D\ln(P_t/P_{open})$ and temporary price impact is $P_{i,tmp} = D\ln(P_{close}/P_t)$, where D is 1 for buyer-initiated trades and -1 for seller-initiated trades. Before proceeding, we separate our halts into two groups, positive and negative, based on the abnormal return of the halted stock on the day of the halt. We report results for buyer-initiated trades and seller-initiated trades separately. We report the mean of the differences over the duration of the halt. These results represent the average for per half minute of the halt duration. A stock is selected for inclusion in one or more of the Reference Groups if it has the same four-digit SIC Code as the halted stock and has a statistically significant correlation with the halted stock on a given liquidity measure. The correlations for each Reference Group, in turn, are based on the squared abnormal return (Volatility Group), or the adverse selection component of spreads (Adverse Selection Group). If no trading occurs for the Reference Group during the halt, the halt is dropped. All price impact values are in percent. Results are segmented by the listing exchange of the reference stock.

	Volatility Group		Adverse Selection Group	
	Positive event	Negative event	Positive event	Negative event
Panel A: NYSE-listed reference stocks only				
Number of halts	374	426	459	571
Total price impact of trades				
Buyer-initiated	0.165***	−0.209***	0.098***	−0.166***
Seller-initiated	−0.147***	0.187***	−0.081**	0.118***
Temporary price impact of trades				
Buyer-initiated	0.494***	−0.239***	0.243***	−0.162***
Seller-initiated	−0.390***	0.207***	−0.233***	0.159***
Panel B: NASDAQ-listed reference stocks only				
Number of halts	184	205	225	282
Total price impact of trades				
Buyer-initiated	−0.094	−0.274	−0.725*	−0.037
Seller-initiated	0.218	0.227	0.508	−0.002
Temporary price impact of trades				
Buyer-initiated	0.892***	−0.578*	0.915**	−0.464*
Seller-initiated	−0.876**	0.523*	−0.873**	0.269

*Statistically significant at the 10% level.
**Statistically significant at the 5% level.
***Statistically significant at the 1% level.

Presumably, the NYSE would construct rules that specifically maximize the benefits of own stake holders at the expense of competitive exchanges. However, the liquidity differences could also reflect the alternative market structures of the two exchanges. Perhaps the more centralized liquidity supply of the specialist and NYSE floor are better positioned to process information events. In effect, the fragmented liquidity supply of the NASDAQ dealer market generates a myopic view of the market that slows the price discovery process. An analysis of trading halts in the post Regulation National Market System market, where the NYSE and NASDAQ market structures are more similar would be an interesting area for further research. We would also like to stress that the conditional analysis of the liquidity impact presented does not control for other variables such as price and market capitalization that are known to impact liquidity. We control for these and other variable in the regression results.

3.5. Determinants of the liquidity impact of trading halts on informationally related stocks

Previously, we have focused on the liquidity impact of trading halts on informationally related securities at the halt level. We now expand our analysis to evaluate and assess the determinants of the liquidity impact at the stock level. We examine relative spread, ask depth, bid depth, the number of trades, and trading volume. Absolute spread has a correlation with relative spread of 0.98 and adds little independent information to our investigation. D+ orders only exist for NYSE-listed companies and are also contained in the trade count metric. These measures are dropped from our regression analysis. The dependent variables of our analysis represent the percentage change in each liquidity measure relative to the benchmark period for the informationally related security. 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. Fig. 1 shows the frequency of trading halts intra-year for our sample period. While halts occur in each month, there is a pronounced tendency for trading halts to occur in the typical earnings announcement months of January, April, July, and October. Lee et al. (1994a) analyze changes in volume, spread, and quoted depth around earnings announcements and find significant changes in liquidity after the announcement is made. We add the dummy variable *Amnth* that is 1 if the halt is in a typical announcement month of January, April, July, or October, and 0 otherwise. Firm-specific characteristics have also been shown to impact market microstructure measures of liquidity (e.g., McInish and Wood, 1992). To control for these characteristics, we use CRSP 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 on the day before the halt.

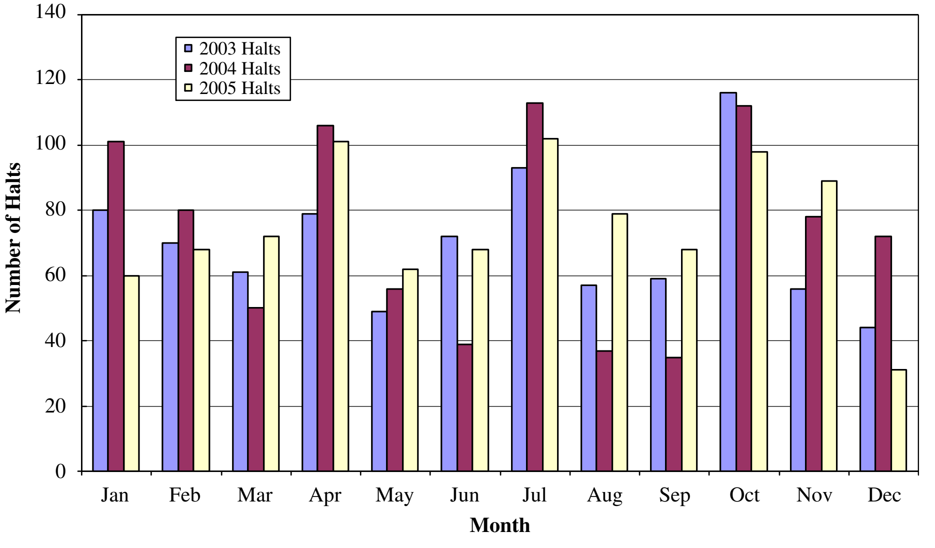

Fig. 1. The monthly distribution of halts for the sample period from January 2003 to December 2005.

Tookes (2008, p. 389) shows that higher market share of the halted stock (for the year the halt occurs), *Hmkt*, should increase the liquidity impact of the trading halt. Also, the greater the product of the market shares of the halted company and the reference company, *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 on the day before the halt, *LnRcap*, should result in a smaller liquidity impact as firm size increases. We include the market share of the reference company, *Rmkt*, to control for the relative effect between market share and market capitalization.

Under the SS model, the impact of the trading halt should be increasing as the strength of the informational relationship increases. To test this, *Vcor*, the correlation value is added to the regression.

To control for the listing exchange of the stock in the Reference Group, we introduce the variable *LST* that is 1 if the listing exchange is NASDAQ and 0 if the listing exchange is NYSE. Although our analysis from Table 3 indicates that the liquidity changes over the duration of the halt are stable, we include the variable *Hdur* (the duration of the halt as a percentage of the trading day) in our regression to control for the length of the halt.

While one can argue that any liquidity event such as a trading halt will be due to information, we wish to investigate the effects of trading halts that are clearly driven by news events. The majority of trading halts in our sample are order imbalance (code 7) halts. To collect information on code 7 halts, we examine Lexis-Nexis on the day before, day of, and day after the halt. We classify the halt as being based on news if we find both a news article relating to a significant event and another source indicating that the market reacted to the news. In addition, all news dissemination (code 4) and news pending (code 11) halts are considered to be news driven. We develop the dummy variable, *Info*, which equals 1 for the halts classified as news based and 0 otherwise.

We estimate the following regression:

$$\begin{aligned} LnLiqR_{i,k} = {} & \alpha + \beta_1 Amnth_k + \beta_2 Hmkt_k + \beta_3 Rmkt_{i,k} + \beta_4 Intrmkt_{i,k} + \beta_5 LnRcap_{i,k} \\ & + \beta_6 LnRvol_{i,k} + \beta_7 LnRprc_{i,k} + \beta_8 Vcor_{i,k} + \beta_9 Lst + \beta_{10} Hdur + \beta_{11} Info + \varepsilon_{i,k}. \end{aligned} \tag{1}$$

Table 7 shows the regression results for both volatility (Panel A) and the adverse selection Reference Group (Panel B). Coefficients have been standardized to assess the relative impact of each explanatory variable. For results reported in Panel A for the volatility Reference Group, we focus our discussion on the Number of Trades regression shown in Column 4 because we feel this regression best reflects the characteristics informed traders identify when selecting targets for trading. Our idea is that as the number of trades increase, so does informed trading. Consistent with the implication of the Tookes model, we find that the liquidity impact of a trading halt is increasing in the market share of the halted company and that traders tend to focus on smaller companies for trading. Specifically, the coefficient for *Hmkt* 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 related companies; *Rmkt* is positive and significant. While *IntrMkt* is not significant as an explanatory variable, it should be noted that 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.

Table 7
Determinants of halt liquidity impact.

The determinants of the liquidity impact of halts for each Reference Group are investigated. The dependent variable, *LnLiqR*, 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 halt. We estimate the following equation using linear regression:

$$LnLiqR_{i,k} = \alpha + \beta_1 Amnth_k + \beta_2 Hmkt_k + \beta_3 Rmkt_{i,k} + \beta_4 Intrmkt_{i,k} + \beta_5 LnRcap_{i,k} + \beta_6 LnRvol_{i,k} + \beta_7 LnRprc_{i,k} + \beta_8 Vcor_{i,k} + \beta_9 Lst + \beta_{10} Hdur + \beta_{11} Info + \varepsilon_{i,k}$$

Amnth is a dummy variable that is 1 if the halt occurs in a January, April, July, or October, and 0 otherwise. *Hmkt* and *Rmkt* are the market shares of the halted and reference stocks during the year of the halt. *IntrMkt* is the market share of the halted 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 before the halt. *Vcor* is the correlation coefficient between the reference stock and the halted stock. *Lst* is 0 if the listing exchange is the NYSE and 1 otherwise. *Hdur* is the duration of the halt as a percentage of the trading day, and *Info* is a dummy variable that is 1 if the halt is information based and 0 otherwise. *N* represents the number of observations in the sample, where one observation represents a single reference stock halt day. Because of the log transformation, if the specific liquidity ratio was 0 during the time of the halt, the observation is dropped. All coefficients are standardized.

	Log relative spread ratio	Log ask depth ratio	Log bid depth ratio	Log number of trades ratio	Log trade volume ratio
Panel A: Volatility grouping					
Intercept	0.000***	0.000***	0.000***	0.000	0.000***
Amnth	0.030*	0.016	0.014	0.029*	0.043***
Hmkt	0.054**	0.039	0.038	0.066**	0.050*
Rmkt	0.026	0.014	0.003	0.051**	0.034
IntrMkt	−0.014	0.023	−0.009	0.012	0.069**
LnRcap	−0.086***	−0.100***	−0.056*	−0.242***	−0.257***
LnRvol	0.006	0.109***	0.068***	0.060***	0.119***
LnRprc	0.162***	0.154***	0.115***	0.223***	0.302***
Vcor	0.051***	0.017	0.012	0.074***	0.073***
Lst	−0.078***	0.002	0.021	0.104***	0.043**
Hdur	0.062***	0.061***	0.055***	0.065***	0.058***
Info	0.008	−0.061***	−0.042**	0.051***	0.030*
Adj R^2 (%)	2.8	2.5	1.1	6.2	7.1
F-stat.	10.18	9.39	4.73	22.21	25.67
N	3548	3548	3548	3548	3548
Panel B: Adverse selection grouping					
Intercept	0.000	0.000***	0.000***	0.000	0.000***
Amnth	0.040***	−0.009	0.015	0.021	0.033**
Hmkt	−0.012	0.013	0.006	0.012	0.012
Rmkt	0.004	−0.040*	0.014	0.018	−0.010
IntrMkt	0.016	0.055**	0.003	0.036	0.068***
LnRcap	−0.045	−0.095***	−0.073**	−0.192***	−0.166***
LnRvol	0.039**	0.108***	0.103***	0.125***	0.168***
LnRprc	0.042*	0.157***	0.102***	0.168***	0.244***
Vcor	−0.015	−0.005	0.009	−0.032*	−0.007
Lst	−0.107***	0.025	−0.007	−0.093***	−0.048***
Hdur	−0.005	0.023*	0.021	−0.012	0.003
Info	−0.027*	−0.021	−0.011	0.009	−0.001

Table 7 (*continued*)

	Log relative spread ratio	Log ask depth ratio	Log bid depth ratio	Log number of trades ratio	Log trade volume ratio
Adj R^2 (%)	1.2	1.8	1.0	2.3	4.8
F-stat.	6.15	8.70	5.29	10.69	22.13
N	4576	4576	4576	4576	4576

*Statistically significant at the 10% level.
**Statistically significant at the 5% level.
***Statistically significant at the 1% level.

As indicated by the SS model, we find that traders also focus on firms that have the strongest relationship with the halted stock. *Vcor* is both positive and significant. Consistent with the univariate findings of Table 5, the coefficient for the listing exchange dummy, *Lst*, is significant and positive, showing a higher percentage increase in trading for NASDAQ-listed reference stocks. We find that *Hdur* and *Info* are also positive and significant, indicating that longer halts and those based on news events have a larger liquidity impact. The F-statistic for a joint test of significance to all explanatory variables is 22.2, which is significant at the 0.01 level.

We briefly comment on the results of our regressions for the other variables under the Volatility Reference Group. Comparing the trading volume regression and the trade 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 25.7. Given that jointly all variables are significant in both regressions, our conclusions and interpretations of the Volume Regression are identical to those of the Trade Regression. The results of the quote-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. Note that the *Lst* variable in the spreads regression is negative and significant at the 1% level, but not significant in either the ask or bid depth regressions. Earlier we conjectured that the finding that both spreads and depths increase results from fragmented liquidity supply, perhaps caused by hedge funds and proprietary trading desks. This result is consistent with our speculation because of the fragmented market structure of the NASDAQ dealer market compared with the specialist market of NYSE-listed firms. On the other hand, this result could be a function of the NYSE trading halt regulations in the sense of SS (2000, p. 387). A detailed analysis of this issue is beyond the scope of this paper and we leave this subject to further research.

Next, we turn to the results of the Adverse Selection Group. The primary focus of our paper is in analyzing the liquidity impact of trading halts on informationally related companies. However, we are also introducing a method for quantitatively assessing the informational relationship between companies by return, volume, volatility, and adverse selection correlations. As stated earlier, we identify the volatility correlation as a trade-based inference of the informational relationship and the adverse selection correlation as a quote-based inference of the informational relationship of companies. 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. Uniformly, the adjusted R^2 for the Adverse Selection Group results, shown in Table 7, Panel B, is lower than those for the Volatility Group, with the exception of the bid depth regression. This indicates that the trade-based measures of informational relatedness are stronger than quote-based measures.

Overall, the regression results for the Adverse Selection Group offer weaker support for the propositions of the SS model. However, their model is based on informationally related companies and, therefore, is conditioned by the effectiveness of the informational relationship estimate. We find that the Tookes-based explanatory variables have lower explanatory power compared to the volatility group results, although *LnRcap* is still significant and of the expected sign. By selecting the Volatility and Adverse Selection method to describe, we highlight the strongest and weakest findings for the four reference groups that we analyzed.

4. Conclusion

We analyze the market impact of trading halts on stocks that are informationally related to the halted stock but continue to trade during the duration of the halt. We find that informationally related stocks have statistically and economically significant increases in transaction costs during the period of the halt. Both relative spreads and the price impact of trades increases. However, we also find that quoted depths, the number of trades, and trade volume have large increases during the halt period. Analysis of a composite measure of quote-based liquidity, Spread/Total Depth, indicates that the increase in spreads dominates the increase in depths for the market. We find that the stronger the informational relationship is between the halted stock and the reference stock, the larger the liquidity impact. The liquidity impact tends to be stronger in smaller stocks, which are more susceptible to informed trading. In addition, the liquidity impact of a halt increases with the increasing market share of the halted stock.

We establish the informational relationship between a halted stock and a reference stock. Stocks must be in the same four-digit SIC-defined industry to be evaluated for an informational relationship with the halted stock. We establish an informational relationship through significant correlation in one or more of the following: returns, volatility, trading volume, and, the adverse selection component of the spread. We find that despite overlap between these four measures, each captures different aspects of the informational relationship. We find that trade-based measures of informational relationships are stronger than quote-based measures; our strongest results are for Reference Group formed based on correlations in volatility.

On the whole, our results are consistent with the trading halt model of Spiegel and Subrahmanyam (2000) and with the informed trader model of Tookes (2008). We show that, in response to the information event of a trading halt, informationally related securities experience significant changes in liquidity and price impact.

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