A Note on Intraday Event Studies

Ben R. Marshall*
Massey University
b.marshall@massey.ac.nz

Nhut H. Nguyen
Massey University
n.h.nguyen@massey.ac.nz

Nuttawat Visaltanachoti
Massey University
n.visaltanachoti@massey.ac.nz

Abstract

We investigate the specification and power of intraday event study test statistics. Both the mean and market models generate well-specified return results for 1-30 minute intervals. Moreover, they detect return shocks equivalent to one spread in one- and five-minute interval data and two or three spreads in longer intervals. Researchers using intraday return event studies can therefore be confident in the robustness of their results. However, while common volume and bid-ask spread event study approaches have reasonable power, they are not generally well specified.

JEL Classification Codes: G12, G14
Keywords: Intraday, Event Study

First Version: April 26, 2017
This Version: August 8, 2017

Acknowledgments:
We thank Andrea Bennett and Adrian Lee for valuable comments that have improved the paper. All errors are our own.

Corresponding author: Ben Marshall, School of Economics and Finance, Massey University, Private Bag 11-222, Palmerston North, New Zealand. Ph: 646 951 7033, Fax: 646 350 5651, Email: B.Marshall@Massey.ac.nz

A Note on Intraday Event Studies

Abstract

We investigate the specification and power of intraday event study test statistics. Both the mean and market models generate well-specified return results for 1-30 minute intervals. Moreover, they detect return shocks equivalent to one spread in one- and five-minute interval data and two or three spreads in longer intervals. Researchers using intraday return event studies can therefore be confident in the robustness of their results. However, while common volume and bid-ask spread event study approaches have reasonable power, they are not generally well specified.

JEL Classification Codes: G12, G14
Keywords: Intraday, Event Study

1. Introduction

We consider the effectiveness of event studies based on intraday data. Event studies, which were popularized by Fama, Fisher, Jensen, and Roll (1969) and Ball and Brown (1968), are widely used to measure how information around an event, such as a stock split, is reflected into stock returns.[1] The majority of papers focus on what we will define as "medium-term" horizons of days and months, and while potential statistical problems have, at times, been raised, the methods developed to address these, have gained acceptance in the literature or are easily implementable.[2] For instance, de Jong and Naumovska (2016) highlight how systematic confounding information can result in incorrect inferences being drawn, and emphasize the importance of considering and allowing for this when designing a study. Marks and Musumeci (2017) show the popular Patell (1976) test is not well specified when additional return variance is created by the event, but the Boehmer, Musumeci, and Poulsen (1991) test addresses this issue.

Long-horizon event studies are, in contrast, more controversial. While a large number of papers use event studies over monthly and annual horizons (see, Kothari and Warner, 1997), many papers document the difficulties that are faced in identifying a method that can be used to definitely conclude that abnormal performance exists.[3] In more recent times, applying events studies to intraday data has become more common. However, to the best of our knowledge, no papers have considered the performance of event studies in an intraday context. This is the focus of this paper.

The popularity of intraday event studies has increased over time, which is likely due to a number of reasons. First, linking an event to a particular time within the day and

[1] MacKinlay (1997) suggests event studies data back as far as Dolley (1933).
[2] See Binder (1998) and Corrado (2011) for excellent reviews.
[3] See for instance, Kothari and Warner (1997), Fama (1998), Lyon, Barber, and Tsai (1999), Brav (2000), Mitchell and Stafford (2000), Kothari and Warner (2004), Jegadeesh and Karceski (2009), and Viswanathan and Wei (2008).

considering the reaction of variables such as price, volume, and spread around that time reduces the risk of confounding events obscuring the impact of the event of interest. As McWilliams and Siegel (1997, p. 634) note "the longer the event window, the more difficult it is for researcher to claim they have controlled for confounding events." Second, there is evidence of markets becoming more efficient over time with information being impounded more quickly. For instance, Chorida, Roll, and Subrahmanyam (2005) note that serial dependence in returns is removed within 5-60 minutes. Third, rich intraday datasets covering a large number of instruments are now available. For example, the Thomson Reuters Tick History (TRTH) database includes over 5 million instruments including equities, bonds, currencies, and commodities (see Fong, Holden, and Trzcinka, 2017 and Hendershott and Riordan, 2013).

The use of intraday event studies to consider changes in return, volume, and bid-ask spread date back to the 1980s. Patell and Wolfson (1984) show that most of the stock price reaction to earnings and dividend announcements occurs within the first thirty minutes, while Lee (1992) measures abnormal intraday volumes in a study that documents differential trading intensity around earnings announcements between traders that trade in small and large quantities. Lee, Mucklow, and Ready (1993) study changes in spreads around earnings announcements. They use data for thirty-minute intervals and find spreads widen prior to announcements and are also wider following announcements although this effect dissipates once changes in volume are accounted for. However, the components of spread do not all increase around earnings announcements. Krinsky and Lee (1996) use thirty-minute data to show that while adverse selection costs increase, order processing and inventory holding costs decrease around announcements.

More recently, intraday event studies have been used to study the role analysts play in the price discovery process. Using returns over ten-minute intervals, Altinkilic and Hansen

(2009) and Altinkilic, Balashov, and Hansen (2010) conclude that analyst revisions often coincide with other events but are by themselves largely free of information that influences price. However, Bradley, Clark, Lee, and Ornthanalai (2014) suggest these findings are due to systematic delays in IBES timestamps. They show that newswire timestamps result in statistically significant 30-minute interval returns following both analyst upgrades and downgrades. A recent paper by Rogers, Skinner, and Zechman (2017) considers even finer windows. They show the release of SEC insider trading filings to paying subscribers of the SEC PDS feed results in an economically significant trading advantage that is revealed in prices, volumes, and spreads 30 seconds prior to the posting of information on the SEC website. Cross-country studies also use intraday data. For instance, Wongswon (2009) finds that equity markets in both developed and emerging markets impound information from U.S. monetary policy surprises within 15 minutes.

However, despite the benefits and growing popularity of intraday event studies, there is the possibility that microstructure bias has an impact on the results they generate. Papers such as Lease, Masulis, and Page (1991), Maloney and Mulherin (1992), and Conrad and Conroy (1994) show market microstructure issues such as bid-ask bounce can affect daily event studies. Moreover, it is clear that higher frequency data contains more microstructure frictions (e.g. Aït-Sahalia, Mykland, and Zhang (2005); Bandi and Russell (2006)). Understanding the specification and power of the test statistics generated from intraday data therefore seems particularly important. Our approach is similar to the simulation method used in Lyon, Barber, and Tsai (1999) for testing the performance of long-run event studies. We investigate intervals of one minute, five minutes, 15 minutes, and 30 minutes for a random selection of 50 U.S. stocks. We consider whether frequently used event study approaches for returns, bid-ask spreads, and volume and, following Chae (1999), turnover are a) well specified and b) have sufficient power. Our results indicate both mean-and market-adjusted event studies generate well-specified return results. Moreover, their power is sufficient to detect return shocks equivalent to the size of one spread one and five minute intervals and two to three spreads in 15 and 30 minute intervals. The mean-adjusted spread and volume and turnover event studies are, in contrast, not well-specified. However, they do display good power.

The rest of the paper is organised as follows: Section 2 contains a description of the data and method we adopt. The results are in Section 3 and our conclusions are in Section 4.

2. Data and Method

Our analysis is based on CRSP stocks for the post-decimalization 2002 – 2016 period. We calculate the average market capitalization of each stock over the entire period and then randomly select five stocks from each size decile. For each of the sample stocks, we randomly select 200 datetime events without replacement. We use returns in the same datetime of one trading year before an event as the estimation window. The estimation of abnormal returns is based on three different approaches. First is the mean return model, where the abnormal return is computed as the difference between the event return and the mean return over the estimation period. The second approach is the market model, where the market returns for the estimation period are drawn from the S&P500 interval returns and matched with the same datetime as the event series. The third approach is a market model with the market beta being assumed to be 1.

The specification test is then conducted to determine if the average of an abnormal return is significantly different from zero at the 5% level. The event randomization is repeated 1,000 times. The power test involves adding or subtracting a certain amount of returns, using basis points or spreads, and determining if the test can detect this. Abnormal spreads and abnormal volume and turnover are tested following the same process of randomization and estimation. However, these tests are limited to the mean-adjusted model.

3. Results

We present return specification and power tests for all stocks and by decile in Section 3.1. Section 3.2 contains spread specification and power test results while volume specification and power and results are in Section 3.3.

3.1. Return power and specification results

The return specification results in Table 1 indicate that all three models generate well-specified test statistics for the four intervals we consider. The null hypothesis that the power test proportion equals 5% cannot be rejected using the binomial test in any instance. There is no evidence of one model generating consistently superior results. The average proportion across the two return measures and four intervals is 0.0510, 0.0509, and 0.0509 for the mean model, market model with estimated betas, and the market model with the beta set at 1. There is little difference in the performance of the models depending on whether price or mid-point returns are used, with the exception of the 30-minute interval, where the average proportion is 0.0507 for price returns and 0.0577 for mid-point returns.

[Please Insert Table 1 Here]

In Table 2 we present power tests which involve measuring the proportion of times a test detects abnormal returns for various levels of induced abnormal returns. We add abnormal returns using two approaches. First, we vary the abnormal return by stock depending on its bid-ask spread. Here the induced abnormal returns vary from 50 – 400% of the spread. Second, the abnormal return is set at a fixed level for all stocks, ranging from 5 to 30 basis points.

The results indicate that all three models detect an abnormal return equivalent to the size of half a spread 95% of the time or more for intervals of one minute based on mid-point returns. When price returns are used the minimum abnormal return that is detected 95% of the time or more is one spread. Larger abnormal returns are required before detection is possible in 15-30 minutes, with abnormal returns equivalent to two – three spreads being detected 95% of the time or more.

Five basis point returns are detected in one-minute return intervals when mid-point returns are used, but ten basis points is the minimum required to be detected in both price and mid-point returns. These are detected in intervals of one, five, and occasionally 15 minutes. However, returns of 20 basis points or more are required before detection occurs 95% of the time or more in 30-minute interval data.

[Please Insert Table 2 Here]

Figures 1 and 2 plots the level of induced abnormal return, both negative and positive, that is associated with various levels of detection for the mean model. These show a pattern that is broadly symmetrical, indicating both negative and positive returns have similar levels of detection. The figures also indicate that the same return increment results in a higher chance of detection when the interval is shorter.

[Please Insert Figure 1 Here]

[Please Insert Figure 2 Here]

In Table 3 we investigate whether the tests specification varies by stock size. We report tests based on the mean model, but market model test results are qualitatively identical. The null hypothesis that the proportions equal 0.05 is unable to be rejected in every instance. Moreover, there is little evidence of material differences in the magnitude of the proportions across the different size deciles, particularly in the Panel A price return results. The average proportion is 0.051 in decile 1 and 0.050 in decile 10. The Panel B mid-point return results show slightly more variation with the average proportion being 0.056 in decile 1 compared to 0.051 in decile 10.

[Please Insert Table 3 Here]

The power test results in Table 4 indicate that an induced return of one spread is consistently detected 95% of the time or more across the four return intervals in the two smallest stock deciles. However, as the size of stocks increases the probability of the one spread return being detected starts to decline, particularly in longer return horizons. This is in contrast to the fixed return increments. A five basis point return is not detected 95% of the time in any return horizon for smaller stocks but is detected in shorter intervals for larger stocks. These differing results can be reconciled by larger spreads of small stocks.

Overall we conclude that return event studies are well specified and have good power. This is evident across one-, five-, 15-, and 30-miunte intervals and in the mean and two market models we test.

[Please Insert Table 4 Here]

3.2. Power and specification results for spreads and volume

In this section we present and discuss results for the effective spread and volume and turnover power and specification tests. The spread results in Table 5 involve two tests. Panel A relates to the mean-adjusted model and Panel B contains results for the standardized mean-adjusted model, where abnormal spreads are scaled by the standard deviation of spread. The Panel A results indicate the proportions are each further away from 0.05 than the equivalent return results, and the null hypothesis that they equal 0.05 is rejected with the binomial test in the 30-minute intervals. Mean-adjusted spread event studies are clearly less well specified than their return counterparts. Moreover, the standardized results do not lead to any improvement in test specification. Each of the proportions are further away from 0.05 than the Panel A results and the null hypothesis that they equal 0.05 is rejected in each instance.

However, while the spread power tests are not well specified, they do have strong power. In the mean-adjusted model a 100% increase in spreads is detected 95% of the time or more in intervals of one and five minutes. A spread increase of 200% is detected 95% of the time or more in intervals of 15 minutes, and a spread increase of 300% is detected 95% of the time or more in intervals of 30 minutes. The standardised results are even stronger with spread increments of 50% or more detected 95% of the time for all intervals.

[Please Insert Table 5 Here]

The volume[4] and turnover (volume scaled by shares outstanding) power and specification results are in Table 6. It is clear that these results, which are based on the mean model, are not well specified. The null hypothesis that these proportions equal 0.05 can be rejected at the 1% level based on the binomial test. However, as with spread, the volume and turnover tests do have high levels of power. Volume increases of 50% or more are detected 95% of the time in all intervals. Turnover increases of 50% or more are detected 95% of the time in intervals of five minutes or longer and turnover increases of 75% or more are detected 95% of the time in one-minute intervals.

[Please Insert Table 6 Here]

4. Conclusions

Intraday event studies have been used in the literature to consider changes in returns, spreads, and volumes. However, little is known about the power and specification of these tests. We address this issue in this paper. Our results indicate that both the mean and market models generate well-specified return results for 1-30 minute intervals. In addition, these models identify shocks in return equivalent to one spread in one- and five-minute interval data and two or three spreads in longer intervals. This indicates that researchers using intraday return event studies can take confidence in the robustness of their results. Moreover, standard volume, turnover, and bid-ask spread event study approaches have strong power, they are not generally well specified.

[4] Volume is measured as the natural logarithm of raw volume. See Bamber, Barron, and Stevens (2011) for an excellent discussion around volume measurement.

References

Aït-Sahalia, Yacine, Mykland, Per, and Zhang, Lan. (2005). How often to sample a continuious-time process in the presence of market microstructure noise. *Review of Financial Studies*, 18(2), 351-416.

Altinkilic, Oya, and Hansen, Robert. (2009). On the information role of stock recommendation revisions. *Journal of Accounting and Economics*, 48, 17-36.

Altinkilic, Oya, Balashov, Vadim., and Hansen, Robert. (2010). Evidence that analysts are not important information-intermediaries. SSRN Working Paper: http://ssrn.com/abstract=1364859

Binder, John. (1998). The event study methodology since 1969. *Review of Quantitative Finance and Accounting*, 11, 111-137.

Ball, Ray, and Brown, Philip. (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting Research*, 6, 159-178.

Bamber, Linda, Barron, Orie, and Stevens, Douglas. (2001). Trading volume around earnings announcements and other financial reports: Theory, research design, empirical evidence, and directions for future for research. *Contemporary Accounting Research*. 28(2), 431-471.

Bandi, Federico, and Russell, Jeffrey. (2006). Separating microstructure noise from volatility. *Journal of Financial Economics*, 79, 655-692.

Boehmer, Ekkehart, Musumeci, Jim, and Poulsen, Annette. (1990). Event-study methodology under conditions of event-induced variance. *Journal of Financial Economics*, 30, 245-256.

Bradley, Daniel, Clarke, Jonathan, Lee, Suzanne, and Ornthanalai, Chayawat. (2014). Are analysts' recommendation informative? Intraday evidence on the impact of time stamp delays. *Journal of Finance*, 69(2), 645-673.

Brav, Alon. (2000). Inference in long-horizon event studies: A Bayesian approach with application to initial public offerings. *Journal of Finance*, 55(5), 1979-2016.

Chae, Joon. (2005). Trading volume, information asymmetry, and timing information. *Journal of Finance*, 60(1), 413-442.

Chordia, Tarun, Roll, Richard, and Subramanyam, Avanidhar. (2005). Evidence on the speed of convergence to market efficiency. *Journal of Financial Economics*, 76, 271-292.

Conrad, Jennifer, and Conroy, Jennifer. (1994). Market microstructure and the ex-date return. *Journal of Finance*, 49(4), 1507-1519.

Corrado, Charles. (2011). Event studies: A methodology review. *Accounting and Finance*, 51, 207-234.

de Jong, Abe and Naumovska, Ivana. (2016). A note on event studies in finance and management research. *Review of Finance*, 1659-1672.

Dolley, James. (1933). Characteristics and procedure of common stock split-ups. *Harvard Business Review*, 11, 316-326.

Fama, Eugene. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, 49, 283-306.

Fama, Eugene, Fisher, Lawrence, Jensen, Michael, and Roll, Richard. (1969). The adjustment of stock prices to new information. *International Economic Review*, 10, 1-21.

Fong, Kingsley, Holden, Craig, and Trzcinka, Charles. (2017). What are the best liquidity proxies for global research? *Review of Finance* - Forthcoming.

Hendershott, Terrence, and Riordan, Ryan. (2013). Algorithmic trading and the market for liquidity. *Journal of Financial and Quantitative Analysis*, 48, 1001–1024.

Jegadeesh, Narasimhan and Karceski, Jason. (2009). Long-run performance evaluation: Correlation and heteroskedasticity-consistent tests. *Journal of Empirical Finance*, 16, 101-111.

Kothari, S.P, and Warner, Jerold. (1997). Measuring long-horizon security price performance. *Journal of Financial Economics*, 43, 301-339.

Kothari, S.P, and Warner, Jerold. (1997). Econometrics of event studies. SSRN Working Paper.

Krinsky, Itzhak, and Lee, Jason. (1996). Earnings announcements and the components of the bid-ask spread. *Journal of Finance*, 51(4), 1523-1534.

Lease, Ronald, Masulis, Ronald., and Page, John. (1991). An investigation of market microstructure impacts on event study returns. *Journal of Finance*, 66(4), 1523-1536.

Lee, Charles. (1992). Earnings news and small traders. *Journal of Accounting and Economics*, 15, 265-302.

Lee, Charles, Mucklow, Belinda., and Ready, Mark. (1993). Spreads, depths, and the impact of earnings information: An intraday analysis. *Review of Financial Studies*, 6(2), 345-374.

Lyon, John, Barber, Brad, and Tsai, Chih-Ling. (1999). Improved methods for tests of long-run abnormal stock returns. *Journal of Finance*, 54(1), 165-201.

MacKinlay, A. Craig. (1997). Event studies in economics and finance. *Journal of Economic Literature*, 35(1), 13-39.

Marks, Joseph and Musumeci, Jim. (2017). Misspecification in event studies. *Journal of Corporate Finance*, 45, 333-341.

McWilliams, Abagail., and Siegel, Donald. (1997). Event studies in management research: Theoretical and empirical issues. *The Academy of Management Journal*, 40(3), 626-657.

Maloney, Michael., and Mulherin, J. Harold. (1992). The effects of splitting on the ex: A microstructure reconciliation. *Financial Management*, 21(4), 44-59.

Mitchell, Mark, and Stafford, Erik. (2000). Managerial decisions and long-term stock performance. *Journal of Business*, 73(3), 287-329.

Patell, James. (1976). Corporate forecasts of earnings per share and stock price behaviour: Empirical test. *Journal of Accounting Research*, 14(2), 246-276.

Patell, James, and Wolfson, Mark. (1984). The intraday speed of adjustment of stock prices to earnings and dividend announcements. *Journal of Financial Economics*, 13, 223-252.

Rogers, Jonathan, Skinner, Douglas, and Zechman, Sarah. (2017). Run EDGAR run: SEC dissemination in a high-frequency world. *Journal of Accounting Research – forthcoming.*

Viswanathan, S, and Wei, Bin. (2008). Endogenous events and long-run returns. *Review of Financial Studies*, 21(2), 855-888.

Wongswon, Jon. (2009). The response of global equity indexes to U.S. monetary policy announcements. *Journal of International Money and Finance*, 28, 344-365.

Table 1
Return Specification Test

	Mean		Market		Market (β=1)	
Int	Price	Mid-Point	Price	Mid-Point	Price	Mid-Point
1	0.048	0.049	0.049	0.049	0.049	0.050
5	0.050	0.050	0.051	0.049	0.050	0.050
15	0.050	0.051	0.049	0.051	0.052	0.050
30	0.051	0.059	0.05	0.059	0.051	0.055

These results are based on CRSP data for the 2002 – 2016 period. We randomly select a total of 50 stocks (five for each decile) and randomly select 200 event dates for each stock. Excess returns are simulated 1,000 times using the mean model, the market model with dynamic betas, and a market model where beta is set to 1. This table reports the proportion of abnormal returns that are different to zero. Results are generated for intervals of 1-30 minutes for returns calculated based on prices and bid-ask mid points. A binomial test is used to test the null hypothesis that each statistic equals 0.05, with statistics that are different to 0.05 at the 10%, 5%, and 1% levels of statistical significance denoted by *, **, and *** respectively.

Table 2
Return Power Test

		Spread Increment					Basis Point Increment			
Int	Return	50%	100%	200%	300%	400%	5	10	20	30
					Panel A: Mean Model					
1	Price	0.941	0.997	0.999	1.000	1.000	0.887	0.975	1.000	1.000
5	Price	0.827	0.976	0.999	1.000	1.000	0.864	0.989	1.000	1.000
15	Price	0.589	0.896	0.987	0.998	1.000	0.664	0.961	1.000	1.000
30	Price	0.430	0.774	0.955	0.989	0.997	0.456	0.856	0.997	1.000
1	Mid-Point	0.984	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
5	Mid-Point	0.858	0.979	0.999	1.000	1.000	0.967	1.000	1.000	1.000
15	Mid-Point	0.597	0.889	0.987	0.998	1.000	0.681	0.978	1.000	1.000
30	Mid-Point	0.402	0.733	0.944	0.986	0.997	0.397	0.834	0.997	1.000
					Panel B: Market Model					
1	Price	0.920	0.992	0.997	0.998	0.998	0.864	0.950	0.997	1.000
5	Price	0.816	0.974	0.999	1.000	1.000	0.847	0.983	1.000	1.000
15	Price	0.585	0.892	0.986	0.998	1.000	0.652	0.956	1.000	1.000
30	Price	0.424	0.769	0.952	0.988	0.997	0.448	0.853	0.997	1.000
1	Mid-Point	0.984	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000
5	Mid-Point	0.856	0.979	0.999	1.000	1.000	0.950	1.000	1.000	1.000
15	Mid-Point	0.596	0.888	0.986	0.998	1.000	0.626	0.971	1.000	1.000
30	Mid-Point	0.395	0.728	0.943	0.985	0.996	0.363	0.809	0.996	1.000
					Panel C: Market Model β=1					
1	Price	0.906	0.993	0.998	0.998	0.998	0.865	0.955	0.998	1.000
5	Price	0.763	0.962	0.998	1.000	1.000	0.824	0.981	1.000	1.000
15	Price	0.531	0.853	0.978	0.996	0.999	0.584	0.943	1.000	1.000
30	Price	0.377	0.707	0.928	0.981	0.995	0.364	0.812	0.996	1.000
1	Mid-Point	0.974	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000
5	Mid-Point	0.816	0.968	0.999	1.000	1.000	0.950	1.000	1.000	1.000
15	Mid-Point	0.567	0.860	0.980	0.997	1.000	0.626	0.971	1.000	1.000
30	Mid-Point	0.392	0.703	0.928	0.980	0.994	0.363	0.809	0.996	1.000

These results are based on CRSP data for the 2002 – 2016 period. We randomly select a total of 50 stocks (five for each decile) and randomly select 200 event dates for each stock. Excess returns are simulated 1,000 times using the mean model, the market model with dynamic betas, and a market model where beta is set to 1. Abnormal returns increments are then included based on fixed amounts, ranging from 5-30 basis points, and relative amounts, ranging from 50-400% of the effective spread of the stock. The numbers reported are the percentage of samples where the null hypothesis of no abnormal returns is rejected. Results of 95% or more are highlighted in bold.

Table 3
Return Specification Test by Decile

	Decile									
INT	1	2	3	4	5	6	7	8	9	10
					Panel A: Price					
1	0.046	0.051	0.051	0.051	0.047	0.052	0.042	0.049	0.042	0.051
5	0.052	0.047	0.052	0.050	0.049	0.048	0.050	0.052	0.048	0.049
15	0.055	0.049	0.050	0.052	0.050	0.050	0.052	0.046	0.054	0.049
30	0.051	0.053	0.053	0.055	0.049	0.051	0.060	0.048	0.052	0.051
					Panel B: Mid-Point					
1	0.045	0.053	0.053	0.049	0.047	0.047	0.044	0.046	0.051	0.054
5	0.053	0.048	0.048	0.049	0.052	0.054	0.046	0.049	0.047	0.049
15	0.053	0.052	0.051	0.057	0.054	0.054	0.049	0.049	0.050	0.050
30	0.071	0.062	0.065	0.069	0.054	0.062	0.063	0.060	0.059	0.051

These results are based on CRSP data for the 2002 – 2016 period. We randomly select a total of 5 stocks from each decile and randomly select 200 event dates for each stock. Excess returns are simulated 1,000 times using the mean model, the market model with dynamic betas, and a market model where beta is set to 1. This table reports the proportion of abnormal returns that are different to zero. Results are generated for intervals of 1-30 minutes for returns calculated based on prices and bid-ask mid points. A binomial test is used to test the null hypothesis that each statistic equals 0.05, with statistics that are different to 0.05 at the 10%, 5%, and 1% levels of statistical significance denoted by *, **, and *** respectively.

Table 4
Return Power Test by Decile

Int	Return	Spread Increment 50%	100%	200%	300%	400%	Basis Point Increment 5	10	20	30
					Panel A: Decile 1					
1	Price	0.838	**0.975**	**0.994**	**0.996**	**0.996**	0.571	0.916	**0.999**	**1.000**
5	Price	**0.981**	**1.000**	**1.000**	**1.000**	**1.000**	0.642	**0.967**	**1.000**	**1.000**
15	Price	0.912	**1.000**	**1.000**	**1.000**	**1.000**	0.529	0.894	**1.000**	**1.000**
30	Price	0.798	**0.987**	**1.000**	**1.000**	**1.000**	0.396	0.732	**0.993**	**1.000**
					Panel B: Decile 2					
1	Price	0.893	**0.998**	**1.000**	**1.000**	**1.000**	0.451	0.858	**0.996**	**1.000**
5	Price	**0.987**	**1.000**	**1.000**	**1.000**	**1.000**	0.489	0.918	**1.000**	**1.000**
15	Price	**0.956**	**1.000**	**1.000**	**1.000**	**1.000**	0.344	0.844	**0.999**	**1.000**
30	Price	0.843	**1.000**	**1.000**	**1.000**	**1.000**	0.196	0.648	**0.989**	**1.000**
					Panel C: Decile 3					
1	Price	**0.963**	**0.999**	**1.000**	**1.000**	**1.000**	0.856	**0.973**	**1.000**	**1.000**
5	Price	**0.950**	**1.000**	**1.000**	**1.000**	**1.000**	0.776	**0.997**	**1.000**	**1.000**
15	Price	0.734	**0.996**	**1.000**	**1.000**	**1.000**	0.437	**0.958**	**1.000**	**1.000**
30	Price	0.522	0.930	**1.000**	**1.000**	**1.000**	0.248	0.747	**0.999**	**1.000**
					Panel D: Decile 4					
1	Price	**0.992**	**1.000**	**1.000**	**1.000**	**1.000**	**0.987**	**1.000**	**1.000**	**1.000**
5	Price	0.947	**1.000**	**1.000**	**1.000**	**1.000**	0.802	**0.998**	**1.000**	**1.000**
15	Price	0.691	**0.987**	**1.000**	**1.000**	**1.000**	0.419	0.900	**1.000**	**1.000**
30	Price	0.432	0.912	**0.999**	**1.000**	**1.000**	0.220	0.657	**0.991**	**1.000**
					Panel E: Decile 5					
1	Price	**0.979**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
5	Price	0.912	**1.000**	**1.000**	**1.000**	**1.000**	**0.959**	**1.000**	**1.000**	**1.000**
15	Price	0.675	**0.985**	**1.000**	**1.000**	**1.000**	0.725	**0.987**	**1.000**	**1.000**
30	Price	0.486	0.885	**0.998**	**1.000**	**1.000**	0.520	0.892	**0.999**	**1.000**
					Panel F: Decile 6					
1	Price	**0.981**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
5	Price	0.923	**1.000**	**1.000**	**1.000**	**1.000**	**0.989**	**1.000**	**1.000**	**1.000**
15	Price	0.602	**0.990**	**1.000**	**1.000**	**1.000**	0.752	**0.999**	**1.000**	**1.000**
30	Price	0.365	0.885	**1.000**	**1.000**	**1.000**	0.464	**0.964**	**1.000**	**1.000**

					Panel G: Decile 7					
1	Price	**0.978**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
5	Price	0.705	**0.997**	**1.000**	**1.000**	**1.000**	**0.980**	**1.000**	**1.000**	**1.000**
15	Price	0.324	0.841	**0.999**	**1.000**	**1.000**	0.716	**0.995**	**1.000**	**1.000**
30	Price	0.187	0.558	**0.973**	**0.999**	**1.000**	0.449	0.917	**1.000**	**1.000**
					Panel H: Decile 8					
1	Price	**0.985**	**1.000**	**1.000**	**1.000**	**1.000**	**0.993**	**1.000**	**1.000**	**1.000**
5	Price	0.829	**0.997**	**1.000**	**1.000**	**1.000**	**0.972**	**1.000**	**1.000**	**1.000**
15	Price	0.458	0.914	**0.999**	**1.000**	**1.000**	0.807	**0.993**	**1.000**	**1.000**
30	Price	0.264	0.731	**0.980**	**0.999**	**1.000**	0.542	0.941	**1.000**	**1.000**
					Panel I: Decile 9					
1	Price	**0.976**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
5	Price	0.662	**0.973**	**1.000**	**1.000**	**1.000**	**0.999**	**1.000**	**1.000**	**1.000**
15	Price	0.301	0.792	**0.989**	**1.000**	**1.000**	0.947	**1.000**	**1.000**	**1.000**
30	Price	0.179	0.541	0.929	**0.991**	**1.000**	0.757	**0.994**	**1.000**	**1.000**
					Panel J: Decile 10					
1	Price	0.820	**0.997**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
5	Price	0.337	0.792	**0.990**	**1.000**	**1.000**	**0.991**	**1.000**	**1.000**	**1.000**
15	Price	0.141	0.422	0.877	**0.977**	**0.996**	0.855	**0.997**	**1.000**	**1.000**
30	Price	0.091	0.233	0.645	0.890	**0.971**	0.601	**0.965**	**1.000**	**1.000**

These results are based on CRSP data for the 2002 – 2016 period. We randomly select a total of five stocks for each decile and randomly select 200 event dates for each stock. Excess returns are simulated 1,000 times using the mean model, the market model with dynamic betas, and a market model where beta is set to 1. Abnormal returns increments are then included based on fixed amounts, ranging from 5-30 basis points, and relative amounts, ranging from 50 – 400% of the effective spread of the stock. The numbers reported are the percentage of samples where the null hypothesis of no abnormal returns is rejected. Results of 95% or more are highlighted in bold.

Table 5
Effective Spread Specification and Power Test

Int	Specification Test	Power Test				
		Spread Increment				
		50%	100%	200%	300%	400%
		Panel A: Mean Model				
1	0.042	0.867	**0.967**	**0.989**	**0.993**	**0.995**
5	0.043	0.909	**0.973**	**0.989**	**0.992**	**0.994**
15	0.040	0.840	0.939	**0.974**	**0.983**	**0.987**
30	0.036**	0.704	0.861	0.939	**0.962**	**0.972**
		Panel B: Standardized Mean Model				
1	0.093	**0.982**	**0.995**	**0.997**	**0.998**	**0.998**
5	0.103	**0.986**	**0.992**	**0.995**	**0.995**	**0.995**
15	0.113	**0.981**	**0.989**	**0.992**	**0.993**	**0.993**
30	0.118	**0.974**	**0.985**	**0.989**	**0.990**	**0.991**

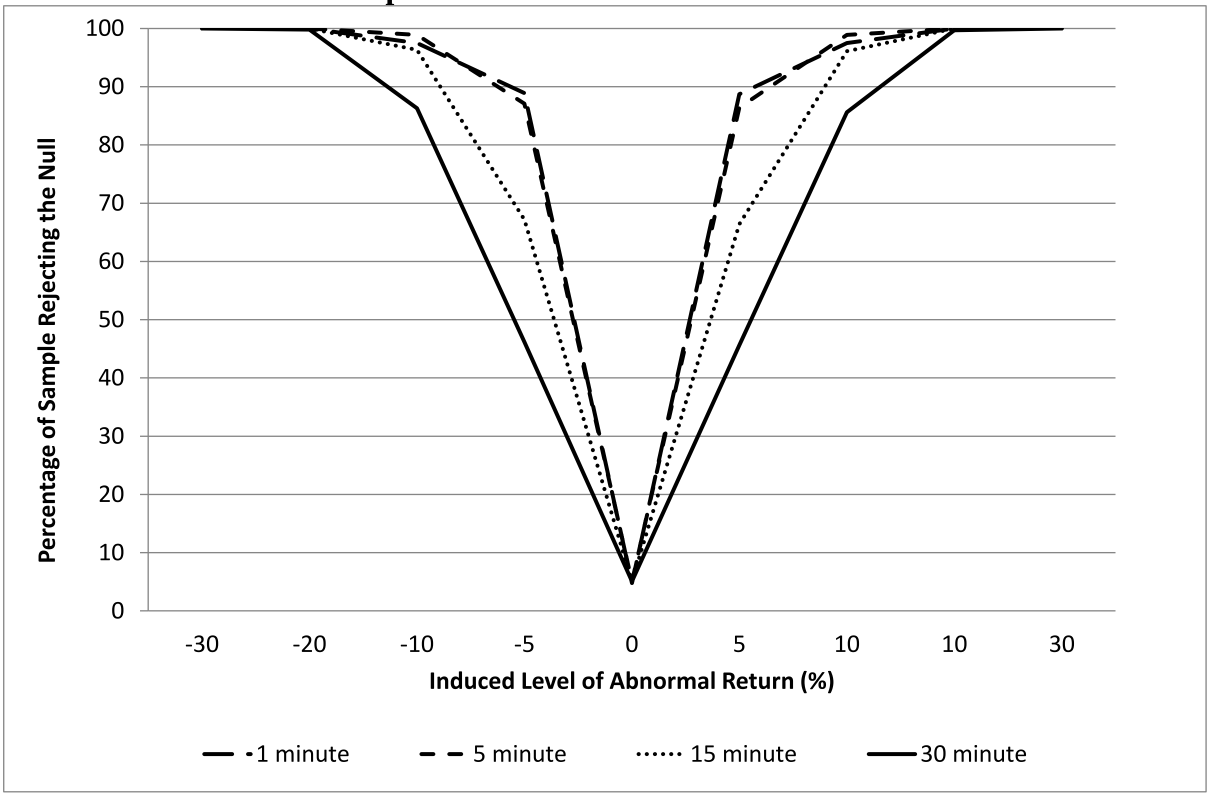
These results are based on CRSP data for the 2002 – 2016 period. We randomly select a total of 5 stocks from each decile and randomly select 200 event dates for each stock. Excess spreads are simulated 1,000 times using the mean model. This specification test is the proportion of abnormal spreads that are different to zero. Results are generated for intervals of 1-30 minutes A binomial test is used to test the null hypothesis that each statistic equals 0.05, with statistics that are different to 0.05 at the 10%, 5%, and 1% levels of statistical significance denoted by *, **, and *** respectively. In the power tests abnormal spread increments are then included based on relative amounts, ranging from 50 – 400% of the effective spread of the stock. The numbers reported are the percentage of samples where the null hypothesis of no abnormal spreads is rejected. Results of 95% or more are highlighted in bold.

Table 6
Volume and Turnover Specification and Power Test

	Specification Test	Power Test			
		Volume / Turnover Increase			
Int		25%	50%	75%	100%
Panel A: Volume					
1	0.098	0.658	**0.956**	**0.992**	**0.998**
5	0.127	0.778	**0.987**	**1.000**	**1.000**
15	0.154	0.815	**0.991**	**1.000**	**1.000**
30	0.172	0.832	**0.992**	**1.000**	**1.000**
Panel B: Turnover					
1	0.108	0.594	**0.948**	**0.990**	**0.997**
5	0.108	0.701	**0.967**	**0.984**	**0.986**
15	0.119	0.750	**0.972**	**0.987**	**0.991**
30	0.135	0.771	**0.975**	**0.990**	**0.995**

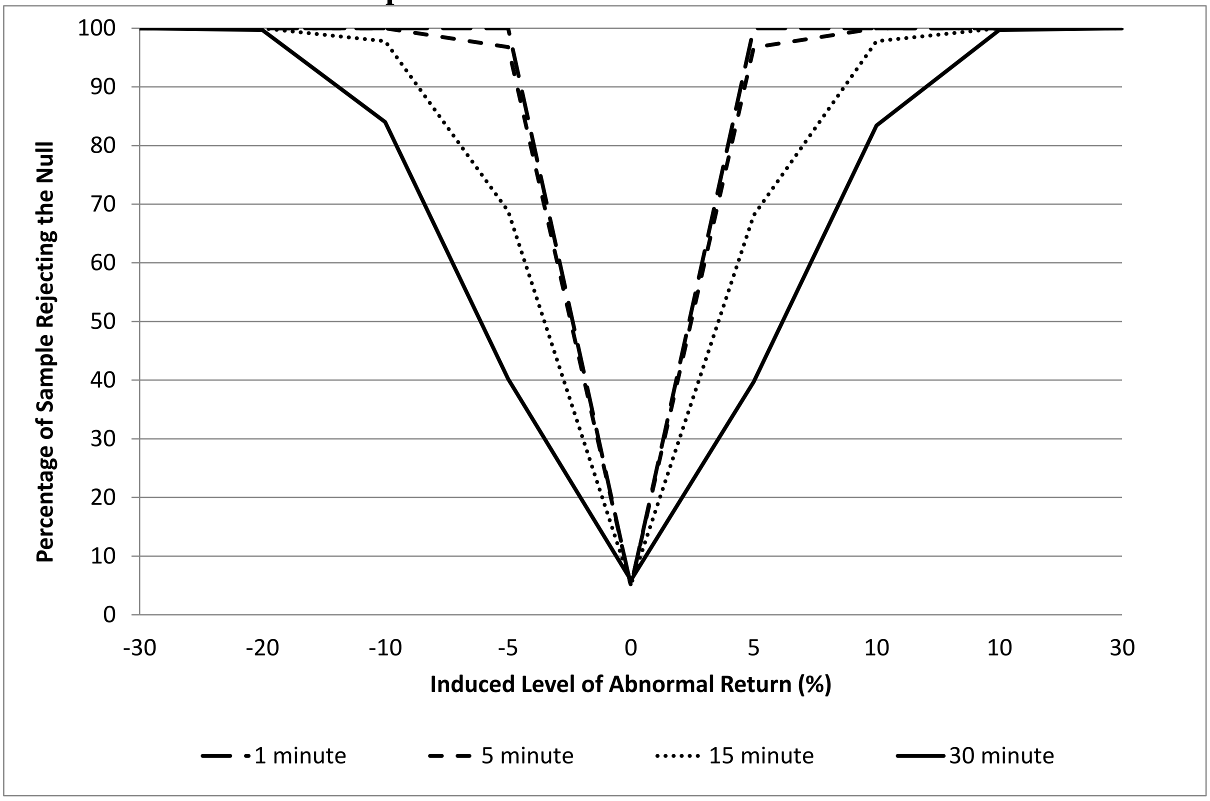
These results are based on CRSP data for the 2002 – 2016 period. We randomly select a total of 5 stocks from each decile and randomly select 200 event dates for each stock. Excess log volumes and turnover are simulated 1,000 times using the mean model. The specification tests are the proportion of abnormal log volume and turnover that is different to zero. Results are generated for intervals of 1-30 minutes A binomial test is used to test the null hypothesis that each statistic equals 0.05, with statistics that are different to 0.05 at the 10%, 5%, and 1% levels of statistical significance denoted by *, **, and *** respectively. In the power tests abnormal volume (turnover) increments are then included based on relative amounts, ranging from 25 – 100% of the volume (turnover) of the stock. The numbers reported are the percentage of samples where the null hypothesis of no abnormal volume (turnover) is rejected. Results of 95% or more are highlighted in bold.

Figure 1
Test Power in Random Samples Based on Price Returns



These results are based on CRSP data for the 2002 – 2016 period. We randomly select a total of 50 stocks (five for each decile) and randomly select 200 event dates for each stock. Excess returns are simulated 1,000 times using the mean model. Abnormal returns increments are then included based on fixed amounts, ranging from -30 to 30 basis points. These results, which are based on price returns, are the percentage of samples where the null hypothesis of no abnormal returns is rejected.

Figure 2
Test Power in Random Samples Based on Mid-Point Returns



These results are based on CRSP data for the 2002 – 2016 period. We randomly select a total of 50 stocks (five for each decile) and randomly select 200 event dates for each stock. Excess returns are simulated 1,000 times using the mean model. Abnormal returns increments are then included based on fixed amounts, ranging from -30 to 30 basis points. These results, which are based on mid-point returns, are the percentage of samples where the null hypothesis of no abnormal returns is rejected.