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Why Do Traders Split Orders?

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Appendix

Order Splitting Variable Correlations

In Table 1A, we report the Pearson correlation coefficients between the order splitting variables (discussed on pages 16-17). The magnitudes and relations between variables vary. Overall, there are 19 positive and 16 negative correlation coefficients. The negative correlations between market capitalization and order size, quoted depth, and turnover are somewhat surprising. The negative correlation between order size and market capitalization may, in part, be driven by the tendency of larger stocks to trade in a wider variety of sizes. This presents greater incentive (opportunity) for the DMA traders to trade in smaller sizes to disguise their strategies. And, a negative correlation between order size and market capitalization can exist. One might also initially expect the correlation between market capitalization and quoted depth (turnover) to be positive. When quoted depth (turnover) is low on large capitalization stocks, these unusual market conditions may attract DMA traders. And, a negative correlation between market capitalization and quoted depth (turnover) can exist. For example, lower depth (turnover) on large capitalization stocks can provide greater profit opportunities for liquidity supplying strategies. Overall, the DMA traders are net suppliers of liquidity.

Execution Time and Split (Single) Order Separate Regressions

In Table 2A, we examine the relation between information and execution time for spilt and non-split orders in two separate regressions (rather than use a split order dummy in Table

3). The dependent variable in each ordinary least squares regression is the price change associated with an order execution; and, the main independent variable is the order time to execution. The standard control variables are included. The order execution time variable is negative and highly significant in all regressions, indicating that for both split and non-split orders, a shorter time to execution is a key determinant of information-based trading.

Robustness Tests

We conduct three sets of robustness tests on the main regression results shown in Table 3. First, we focus on the 100, 500, and 1000 most active traders and re-examine the relation between split (single) orders, execution time, and information. The regression results are reported in Table 3A. Similar to prior results, there is a strong negative correlation between time to execution and information. For example, for the 100, 500, and 1000 most active traders, the coefficient (t-stat) for the order execution time variable with both order types is -0.038 (-4.33), -0.072 (-4.30), and -0.024 (-5.20). The split order dummy variable is positive in each regression and statistically significant at the 1% level in two of the three regressions. For example, for the 100, 500, and 1000 most active traders, the coefficient (t-stat) for the order splitting variable with both order types is 0.013 (0.92), 0.031 (2.86), and 0.040 (3.98). Sorting the results for marketable and non-marketable limit orders separately provides a similar result with execution time while the significance of the order splitting variable is less.

For the second robustness test, we examine regression results in Table 3 using trader and stock fixed effects. In Table 4A we confine results to the 100 most active traders and stocks for computational feasibility. For all orders, marketable orders, and non-marketable limit orders, the order execution time variable is negative and statistically significant at the 1% or 5% level. The order splitting dummy is positive in each regression and significant at the 5% level for all orders, 10% level for marketable orders, and 1% level for non-marketable limit orders. When both order types are included in the same regression, the coefficient (*t*-stat) for order execution time is -0.024 (-6.92) and the split order dummy coefficient is 0.030 (2.26).

Finally, we re-examine Table 3 results using an alternative order splitting measure. Instead of using a dummy variable to identify a split order execution, we use the log number of order executions per split order. Table 5A shows the results. The log number of orders coefficient is positive and significant at the 1% level in two of the three regressions while the log order execution time coefficient is negative and significant at the 1% level in all three regressions. Consider the results using both order types. The coefficient (*t*-stat) for the number of orders is 0.061 (3.58) and for order execution time -0.025 (-5.37).

Table 1A
Correlations

The table results highlight Pearson correlation coefficients between the order splitting variables. See Table 1 caption for a description of the variables.

	Split Order	Log order size	Buy-sell indicator	Bid-ask spread	Log quoted depth	Log half-hour volume	Half-hour price volatility	Log market cap.	1 / stock price	Stock turnover
Split Order	1									
Log order size	0.267	1								
Buy-sell indicator	0.007	0.008	1							
Bid-ask spread	-0.017	0.216	-0.003	1						
Log quoted depth	-0.056	0.506	-0.021	0.214	1					
Log half-hour volume	-0.006	-0.157	0.000	-0.039	-0.206	1				
Half-hour price volatility	-0.003	-0.042	0.001	0.004	-0.052	0.176	1			
Log market capitalization	-0.002	-0.338	-0.000	-0.518	-0.241	0.140	0.022	1		
1 / stock price	-0.032	0.010	0.000	0.730	0.331	-0.087	-0.009	-0.570	1	
Stock turnover	0.025	0.018	-0.003	-0.010	-0.010	-0.062	-0.011	-0.178	0.010	1

Table 2A

Split Orders-Execution Time Separate Regressions

Orders are segregated into single and split order executions. A split order is one in which a trader executes a string of multiple orders in the same stock, in the same direction, and on the same day. The dependent variable in each ordinary least squares regression is the price change associated with a single (split) order execution. For each buy order, price change is the NBBO quote midpoint five minutes after the (initial) order submission of a single (split) order minus the NBBO quote midpoint at the time of order submission, divided by the NBBO quote midpoint at the time of order submission. For each sell order, price change is the NBBO quote midpoint at the time of order submission minus the NBBO quote midpoint five minutes later, divided by the order submission NBBO quote midpoint. The main independent variable is the log share-weighted order execution time. Execution time is measured from order submission to execution. For split order executions, execution time is share-weighted across order executions. Control variables (see Table 1) are included in the regression. Marketable orders consist of market orders and limit orders with a buy (sell) price greater (less) than or equal to the national best offer (bid) at the time a trader submits an order. Non-marketable limit orders consist of limit orders with a buy (sell) price less (greater) than the national best offer (bid) at the time a trader submits an order. Split orders are classified as either marketable or non-marketable based on if a majority of the order (share-basis) is marketable or non-marketable. Sequential orders that are split evenly between both order types are classified as marketable. The *t*-statistics (in parentheses) are calculated using clustered standard errors (as in Petersen, 2009), where the cluster is defined at the trader and day level.

Single order executions

	All orders		Marketable orders		Non-marketable orders	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	-0.040	(-0.70)	0.353***	(3.98)	-0.823***	(-8.42)
Log order execution time	-0.032***	(-3.50)	-0.004***	(-3.99)	-0.040***	(-6.62)
Log order size	0.034***	(11.81)	0.051***	(13.36)	0.018***	(6.61)
Buy-sell indicator	0.060***	(7.71)	0.067***	(7.93)	0.057***	(7.58)
Bid-ask spread	-0.036***	(-3.81)	0.170***	(9.57)	-0.052***	(-3.02)
Log quoted depth	-0.048***	(-16.54)	-0.037***	(-14.37)	-0.039***	(-10.29)
Log half-hour volume	-0.000	(-0.60)	-0.003***	(-5.49)	0.002***	(3.88)
Half-hour price volatility	-0.018	(-0.88)	-0.130	(-1.54)	0.004	(0.13)
Log market capitalization	-0.002	(-0.77)	-0.036***	(-11.08)	0.041***	(11.27)
1 / stock price	-0.031***	(-3.69)	0.005	(0.50)	-0.100***	(-6.44)
Stock turnover	0.002	(0.46)	0.000	(0.06)	0.004	(0.55)
Year fixed effects	Yes		Yes		Yes	
Market center fixed effects	Yes		Yes		Yes	
No. of obs. (000,000's)	3.3		1.3		1.9	
Adjusted R^2	2.5%		3.7%		5.1%	

Split order executions

	All orders		Marketable orders		Non-marketable orders	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	-0.153	(-1.46)	0.533***	(3.47)	-1.478***	(-9.67)
Log order execution time	-0.045***	(-5.04)	-0.031***	(-12.84)	-0.047***	(-6.77)
Log order size	0.067***	(11.98)	0.083***	(14.47)	0.029***	(4.40)
Buy-sell indicator	0.041***	(4.56)	0.052***	(6.53)	-0.002	(-0.24)
Bid-ask spread	0.072***	(4.56)	0.171***	(7.48)	0.000	(0.00)
Log quoted depth	-0.050***	(-15.41)	-0.047***	(-11.17)	-0.014***	(-2.87)
Log half-hour volume	-0.000	(-0.36)	-0.004***	(-6.98)	0.006***	(9.00)
Half-hour price volatility	0.037	(1.03)	0.031	(0.62)	0.026	(0.52)
Log market capitalization	-0.013***	(-4.06)	-0.052***	(-11.12)	0.050***	(8.90)
1 / stock price	-0.005	(-0.43)	-0.008	(-0.52)	-0.029	(-1.40)
Stock turnover	-0.016	(-2.79)	-0.020**	(-2.30)	-0.009	(-0.91)
Year fixed effects	Yes		Yes		Yes	
Market center fixed effects	Yes		Yes		Yes	
No. of obs. (000,000's)	0.9		0.5		0.4	
Adjusted R^2	2.9%		4.9%		1.8%	

***,** indicate significance at the 0.01 and 0.05 level, respectively.

Table 3A
Active Trader Robustness Results

Robustness tests are conducted on Table 3 results for the 100, 500, and 1000 most active traders (control variables are not reported for brevity). The *t*-statistics (in parentheses) are calculated using clustered standard errors (as in Petersen, 2009), where the cluster is defined at the trader and day level.

100 most active traders

	All orders		Marketable orders		Non-marketable orders	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	-0.172*	(-1.82)	0.300**	(2.06)	-0.893***	(-5.41)
Log order execution time	-0.038***	(-4.33)	-0.044**	(-2.37)	-0.069***	(-7.96)
Split order dummy	0.013	(0.92)	0.041**	(2.34)	0.162***	(9.30)
No. of obs. (000,000's)	2.2		0.9		1.3	
Adjusted R^2	2.5%		5.4%		5.7%	

500 most active traders

	All orders		Marketable orders		Non-marketable orders	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	0.003	(0.04)	0.420***	(4.02)	-0.827***	(-6.91)
Log order execution time	-0.072***	(-4.30)	-0.012***	(-3.73)	-0.050***	(-7.51)
Split order dummy	0.031***	(2.86)	0.017	(1.49)	0.145***	(10.80)
No. of obs. (000,000's)	3.4		1.5		1.9	
Adjusted R^2	2.6%		4.5%		5.1%	

1000 most active traders

	All orders		Marketable orders		Non-marketable orders	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	0.009	(0.15)	0.417***	(4.39)	-0.827***	(-7.96)
Log order execution time	-0.024***	(-5.20)	-0.011***	(-3.82)	-0.042***	(-6.96)
Split order dummy	0.040***	(3.98)	0.017	(1.62)	0.132***	(10.76)
No. of obs. (000,000's)	3.9		1.7		2.2	
Adjusted R^2	2.5%		4.2%		4.7%	

***,**,* indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

Table 4A

Trader-Stock Fixed Effects Robustness Results

Robustness tests are conducted on Table 3 results using a subsample of the 100 most active traders and 100 most actively traded stocks. Trader and stock fixed effects regressions are reported for the most active traders and stocks (control variables are not reported for brevity). The *t*-statistics (in parentheses) are calculated using clustered standard errors (as in Petersen, 2009), where the cluster is defined at the trader and day level.

	All orders		Marketable orders		Non-marketable orders	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	0.226	(2.54)	0.729***	(2.73)	-0.849**	(-2.47)
Log order execution time	-0.024***	(-6.92)	-0.039**	(-2.29)	-0.062***	(-9.07)
Split order dummy	0.030**	(2.26)	0.027*	(1.80)	0.145***	(9.82)
No. of obs. (000,000's)	2.2		0.9		1.2	
Adjusted R^2	3.0%		6.2%		6.6%	

***,**,* indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

Table 5A
Alternative Order Splitting Robustness Results

Robustness tests are conducted on Table 3 results using an alternative order splitting measure (control variables are not reported for brevity). The log number of executions in the split order is used as the main independent variable. The *t*-statistics (in parentheses) are calculated using clustered standard errors (as in Petersen, 2009), where the cluster is defined at the trader and day level.

	All orders		Marketable orders		Non-marketable orders	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	-0.052	(-0.97)	0.439***	(4.99)	-0.717***	(-7.39)
Log order execution time	-0.025***	(-5.37)	-0.014***	(-5.34)	-0.038***	(-6.60)
Log number of executions	0.061***	(3.58)	0.020	(1.11)	0.195***	(9.18)
No. of obs. (000,000's)	4.2		1.9		2.3	
Adjusted R^2	2.4%		4.0%		4.4%	

*** indicate significance at the 0.01 level.

Why Do Traders Split Orders?

Ryan Garvey, Tao Huang, Fei Wu*

Abstract

We examine factors that influence decisions by U.S. equity traders to execute a string of orders, in the same stock, in the same direction, around the same time. Order splitting is more likely to occur when traders submit larger-size orders and when market depth and trading activity are lower. Order splitters demand liquidity more and pay higher trading costs, but their overall performance is better. When controlling for execution time, split orders are more informative than single orders. Our results suggest that order splitting arises from a variety of factors, including informational differences, order and trader characteristics, and market conditions.

1. Introduction

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U.S. equity markets are constantly changing, yet traders in today's marketplace continue to face some of the same underlying challenges that they have always faced (Angel, Harris, and Spatt, 2011, 2015). A classic trading problem is that large traders cannot widely display their interests because it will drive up their trading costs. They often respond by slicing their orders into smaller pieces, and with continued advances in trading technology, such strategies have become increasingly common. Although order splitting strategies are widespread in securities markets, there has been little research into the practice using trader order-level data, most likely because of data constraints. For example, O'Hara (2015) notes that publicly available transaction-level data are less useful for understanding trader order submission decisions in highly automated markets. The objective of our study is to provide a sound first step to a better understanding of order splitting in electronically driven markets by using order-level data on proprietary firms and individuals who trade through a U.S. broker-dealer.[1] We seek to provide some insight toward answering the fundamental question, "*Why do traders split orders?*"

One reason traders may split an order is to lower their cost of trading. If large traders expose their trading interests, the potential exists to drive up trading costs (e.g., higher price impact) because it will scare away counterparties and attract front runners and others who seek to profit at the expense of the large trader. Regardless of whether or not a large trader is informed, splitting an order into smaller parts can become an attractive strategy for minimizing trading costs (Angel, Harris, and Spatt, 2011, 2015). A second reason traders may split an order is to hide their informational advantage. Better informed traders will naturally want to trade in

[1] O'Hara (2015) examines how the parent orders of large buy-side institutions are split into numerous child trades using broker-dealer data from ITG. The traders we study are not large buy-side institutions but a mix of proprietary trading desks and retail clients. Large buy-side institutions typically do not have the choice to trade their orders in a single execution while our traders may. Therefore, readers should have caution generalizing our findings to large buy-side institutions.

large amounts to maximize their profits. They may split orders into smaller sizes, or "stealth trade," because transacting in a smaller size can enable them to conceal their information advantage more effectively (e.g., Barclay and Warner, 1993; Chakravarty, 2001; Alexander and Peterson, 2007).[2] Absent the ability to split, an informed trader may not be willing to trade (bring information to the market) at all because the cost of transacting may outweigh their informational advantage. One disadvantage of order splitting is that it can often result in execution delay if smaller orders originating from the initial order are not executed simultaneously. In highly competitive securities markets, execution delay is critical because market conditions and informational advantages change rapidly. Thus, a large trader is often confronted with a trade-off between executing quickly and potentially paying higher trading costs versus delaying the execution which may result in missed trading opportunities.

To conduct our study, we obtained proprietary order-level data from a U.S. direct market access (DMA) broker and examined more than six million order execution decisions made by more than three thousand equity traders over eight calendar years. DMA brokerage data are advantageous for studying order splitting because clients of these brokers manage all aspects of the trading process, including how or if their orders are split. If traders execute multiple orders in the same stock, in the same direction, and on the same day, we identify the occurrence as a split order and aggregate the sequential order executions accordingly.

Traders slice orders to lower their trading costs. When there is less depth or trading activity in the market, traders may be forced to split orders to find liquidity at multiple price

[2] The stealth trading hypothesis indicates that informed trading occurs through medium size trades (e.g., 500-9,999 shares). However, more recent research in electronically-driven markets (e.g., Choe and Hansch, 2005; O'Hara, Yao, and Ye, 2014) suggests that small size trades are most informative (e.g., 100 shares or less).

levels and/or across multiple market participants. We find that order splitting is more likely to occur when traders submit larger-size orders and when market depth and trading activity are lower. Order splitting strategies may also be more prevalent among larger-size traders who are susceptible to higher trading costs (e.g., Angel, Harris, and Spatt, 2011, 2015). Consistent with this, we find that traders who engage in order splitting more often are more active and are larger-size traders. They trade on more days, use more order types and execution venues, and demand liquidity more often. Trading cost measures such as effective spread and price impact are higher for traders who split more, but overall performance is better. Trading performance is measured from the share-weighted execution price to future market prices.

Traders also slice orders to conceal their information. This suggests that a relationship will exist between order splitting, time to execution, and information. First, on average, time to execution should be longer for split- rather than single-order executions. And, orders that take longer to execute should, on average, be less informative about future prices. Therefore, split and single orders that execute quickly will be more informed. This reasoning is broadly consistent with studies in the financial literature that document a link between trading speed and information through various settings. For example, the common assumption in the financial literature is that informed traders use market orders rather than limit orders because they execute faster (e.g., Kyle, 1985; Glosten, 1994; Garvey and Wu, 2012);[3] Barclay, Hendershott, and McCormick (2003) and Boehmer (2005) find that trading is more informative on faster – and anonymous – execution venues; Garvey and Wu (2009) find that trading is more

[3] Several papers also suggest that informed traders actively submit limit orders (see, for example, Bloomfield, O'Hara, and Saar, 2005; Kaniel and Liu, 2006; Rosu, 2009; O'Hara, 2015).

informative at times of day when order execution is faster; and Hendershott and Moulton (2011) find that prices are more informative when trading speed increases in the marketplace.

Our findings indicate that order splitting is not a clear indicator of information-based trading. However, split orders that execute quickly are more informative about future prices. Or, when traders slice large buy orders into smaller sizes and execute the parts quickly, market prices tend to rise in the future. When they chop large sell orders into smaller pieces and execute quickly, market prices tend to fall in the future. When we control for time to execution, split orders are more informative than single orders. Our findings may also be linked to research on the order type decision that infers limit orders tend to be more informative than market orders. For example, Kaniel and Lu (2006) and Bloomfield, O'Hara, and Saar (2005) conjecture that informed traders use both market orders and limit orders, but that limit orders tend to convey more information than market orders. A trader is more likely to execute quickly (slowly) with a market (limit) order when their information horizon is shorter (longer), as in Kaniel and Lu (2006), or when their information value is higher (lower), as in Bloomfield, O'Hara, and Saar (2005). Similarly, informed traders may or may not choose to split their orders. We find that split orders do not convey information. From a trader perspective, the decision to split or not is driven by optimizing various trade-offs with respect to price impact, information revelation, and the costs of missed trading opportunities. However, the information signal is likely to be stronger when a split order executes quickly because there is a greater likelihood that the trader behind the order has a shorter information horizon or a higher information value.

To the best of our knowledge, our study is the first to examine determinants of order splitting using data on individual traders. For example, O'Hara (2015) examines order splitting practices using broker-dealer data, but she does not examine determinants of order splitting. Furthermore, the brokerage data used in O'Hara (2015) is for large buy-side institutions. In contrast, we study DMA brokerage-level data on proprietary firms and individuals who execute their own orders. Many studies document a relation between smaller size trading and information (i.e., stealth trading literature), but these studies tend to analyze market-center level data sources which are limited and do not consider time to execution. Our results suggest that order execution time is an important factor upon which split orders are informed.

The remainder of our study is as follows. In Section 2, we describe the data. Section 3 reports the main empirical results. First, we examine when split order execution is more likely to occur. Then we analyze the information content of orders, focusing on whether an order is split and time to execution. Lastly, we analyze the relation between trader characteristics and order splitting in Section 4. Section 5 provides concluding remarks.

2. Data

The primary data we use in the study originates from a U.S. broker-dealer. The broker-dealer firm has multiple trading operations which includes a market making desk. Also, they own and operate alternative trading systems. Our focus is on the brokerage operation, which specializes in providing capabilities for direct market access for trading in U.S. equities. DMA brokers attract a wide variety of clients with different trading strategies and objectives. In general, though, DMA traders tend to be fairly active and possess larger capital amounts because of the sophisticated trading tools and services that are provided. The brokerage data consists of 3,014 traders. These traders execute 6.2 million orders (9.3 million trades) and 12.1 billion shares (dollar value of $104 billion) on 4,599 NASDAQ-listed stocks over an approximate six and one-half year sample period that begins in October 1999 and ends in May 2006. The data represents approximately 0.41% of overall NASDAQ-listed share volume (the focus market) and 1.0% of share volume on those days on which traders are active in sample stocks.

The DMA traders are part of an overall market group that is estimated (at times during the sample period) to consist of about 30,000 traders who represent approximately 40% of U.S. equity volume (Goldberg and Luperico, 2004). The sample data may initially seem small when compared to the Goldberg and Luperico (2004) trader-volume numbers. However, there are differences in the terminology used and while we study 3,000 DMA users overall, traders enter and exit the sample over the eight calendar years.[4] The DMA market is bifurcated between proprietary firms and individuals with each group representing approximately half of the overall volume. The proprietary trader risks firm capital to trade on behalf of the firm. In contrast, the individual trader works on their own behalf and risks their own capital. Similar to the overall DMA market, our sample broker caters to both groups of traders and our data includes both groups of traders. We conduct separate analyses on the two trader types and find qualitatively similar results.

The sample traders are geographically dispersed from the East Coast (New York) to the West Coast (California) of America and manage all aspects of the trading process, including how

[4] For example, the 30,000 DMA trader number is based on the most active DMA traders or those who trade more than 25 times per day. We study all DMA traders at a sample firm and do not exclude less active accounts. The average sample trader is active (trades) on 86 trading days and executes a total of more than 2,000 orders (3,000 trades) and 4,000,000 shares on 55 stocks.

or if orders are split and where they are routed for execution. All of the analyzed trading is automated. The human traders enter order instructions into the DMA firm's electronic trading platform. Algorithms execute orders according to pre-programmed instructions by traders. These instructions may include factors relating to size, price, timing, venue, etc. Overall, traders use 27 different trading systems in 18 market venues.[5]

In addition to the trader order-level data obtained from the U.S. broker-dealer, we use two public data sources to enhance the overall analysis. First, the Thomson Reuters Tick History database is used to examine market conditions when order splitting occurs. The tick data are also useful for measuring the information content behind split orders. For example, our proxy of order information is based on the change in the National Best Bid and Offer (NBBO) quote midpoint from initial order submission to five minutes later. This information can be obtained from the tick database. The matching analysis entails sifting through billions of intraday market pricing observations (on thousands of stocks) over eight calendar years in order to match millions of order executions from the broker data. The second data source used in conjunction with the trader data is the Center for Research in Security Prices (CRSP) database. CRSP is useful because it allows us to examine various characteristics of the stocks traded, which can also affect the trading process on the stock.

Before conducting analyses, we filter the original data obtained from the DMA broker. First, we eliminate trading on stocks for which we are unable to retrieve matching market data

[5] The 18 market venues in order of market share are: Island ECN, NASDAQ, Attain ECN, Knight Capital Group (market maker dark pool), Archipelago ECN, Instinet ECN, Direct Edge ECN, Redibook ECN, Track ECN, Brass Utility ECN, Bloomberg Tradebook ECN, Strike Technologies ECN, Noci ECN, NexTrade ECN, Market XT ECN, American Stock Exchange, Chicago Stock Exchange, and sample broker-dealer internal execution. Some market venues have multiple execution systems across the sample. For example, NASDAQ execution systems include SOES (Small Order Execution System), SelectNet, SuperSOES, ACES (Advanced Computer Execution System), and NMCES (NASDAQ Market Center Execution System).

from the two public data sources (Thomson Reuters and CRSP). Without the matching market data, we are unable to compute our proxy of order information and other key variables. We eliminate trading that occurs outside the normal market opening hours because trading before the open or after the close occurs in a very different manner which could bias analysis of order splitting determinants in a number of different ways. During our sample period, we focus only on NASDAQ-listed stock trading because different trading protocols exist between NYSE- and NASDAQ-listed stocks. Trading on NASDAQ stocks occurs over multiple electronic markets and traders have the ability to split their orders across numerous markets. The primary benefit of using a DMA broker is the ability to access liquidity quickly and directly across the multiple electronic markets. By contrast, order splitting is much less common on NYSE-listed stocks. Trading in these stocks is mainly confined to a single physical trading floor during the sample period (NYSE), is much slower (often manual), and automated trading is heavily restricted. Consequently, during the sample period, most order executions through DMA brokers (including the firm under analysis) occur on NASDAQ-listed stocks.[6] These three filters do not significantly limit the overall data very much. On the whole, we analyze more than 90% of the trading activity originating from the firm's brokerage operation.

2.1. Data Limitations

Examining brokerage-level data is important to our study for a number of reasons, including the ability to identify traders through an identification number and trace their trading activity over time. Each trade execution is linked to a single order through a numeric identifier

[6] The NYSE launched its Hybrid Market model at the end of 2006, which dramatically increased automated trading and execution speed (see Hendershott and Moulton, 2011).

and information on the order submission (e.g., original order size) and the trade execution (e.g., trade execution size) is revealed. This information allows us to identify likely occurrences of order splitting. It is not obtainable in public transaction databases obtained at the market center level.[7] There are, of course, limitations with the sample brokerage data and potential endogeneity concerns. For example, the data consist of (partial) order executions and do not contain orders that are 100% cancelled. This could result in a selection bias and misspecification of observed variables. For example, a limit order execution that appears to be a single order execution may actually be the last order in a string of cancelled orders. If so, our measure of order execution time (derived from the single order submission to execution) will be understated and not reflective of the true time it takes to execute the order. Measures of information will also be misstated. Goldstein, Shkilko, Van Ness, and Van Ness (2008) find that around 50% of all NASDAQ orders are cancelled around the middle of our sample period, raising concern about the potential size of this misspecification. However, even if we could identify orders submitted and fully cancelled, it is not clear if aggregating these orders with a subsequent order submission and execution would always be appropriate. Trader preferences and order characteristics often change over time with changing market conditions. For example, suppose a trader submits and cancels a buy order for 2,000 shares of Apple stock. Market conditions subsequently change and the trader re-evaluates their desire to purchase Apple. The trader submits and ultimately executes an order for 1,000 shares of Apple stock. Although an underlying link exists between the two sequential orders, trader preferences and

[7] See Bessembinder (2003) for some of the limitations with transaction-level data.

order chacterisitcs differ between the two orders. It is not clear if or how these orders should be combined for computing measures of interest (e.g., order execution time).

A second potential problem is that we examine trading through a single broker and do not know if an order is part of a larger overall order being worked by a trader through multiple brokers. While traders certainly have the ability to split an order across multiple brokers, this may be less likely to occur in our setting. Large buy side traders often split their orders across brokers to hide their trading intentions. However, DMA traders execute their own orders and have access to an array of sophisticated trading tools and services for hiding their trading intentions within the single broker.

Finally, it is possible that a client account at the DMA broker processes activities of several sister funds belonging to the same family. For example, what we view as order splitting by a single trader could in reality be activities of several independent trading desks. Similar to before, we suspect this occurrence is less likely in our setting. For instance, proprietary clients can open up multiple accounts with their different activities for more efficient record keeping purposes. While a user identification code in the data allows us to trace activity to each brokerage account, we are unable to identify the actual trader behind each account or the affiliations and motivations of the trader.

3. Empirical Results

3.1. Order Splitting Identification

Our empirical focus is on examining determinants of order splitting. Each (parent) order execution may consist of multiple (child) trades. An identifier code in the data links each trade execution to a single order. One way to identify a split order is if a single order execution consists of multiple trades.[8] However, this approach is susceptible to measurement error because traders may execute large orders using separate smaller order executions over time (and each distinct order execution may consist of multiple trades). Assume that a trader wants to execute 5,000 shares of Microsoft. The trader may begin by submitting an initial order into the firm's electronic trading platform to execute 1,000 shares. Suppose that 400 shares execute through two separate 200-share trades. The trader evaluates the situation and continues to execute a string of separate orders until the 5,000-share order is completely filled. Although the sequential order executions are distinct, they should be considered one split order because they are part of a larger overall order being worked by the trader.

While we are unable to identify trader intentions, we are able to observe the complete order execution records for each individual trader. Therefore, we identify a split order as one where a trader executes a string of multiple orders in the same stock, in the same direction, and on the same day. For example, assume that a trader executes four orders during the day on Microsoft: a buy order at 10:30 a.m., a buy order at 10:35 a.m., a buy order at 10:38 a.m., and a sell order at 3:30 p.m. The three buy orders would constitute one split order. Approximately 42% of the 6.2 million order executions in the sample are split orders and 58% single orders.[9] In terms of overall shares traded, split orders account for 37% and single orders 63% (see Figure 1).

[8] We conduct all of our results using this alternative approach, and the main findings do not change. The results are omitted for brevity and may be obtained by contacting the authors.

[9] Single orders can walk the book with multiple price executions which may cause concern with their non-split classification. There are 692,615 market orders that walk the book and 387,080 of these orders execute within five seconds (e.g., a short time period). We eliminate all orders that walk the book and all orders that walk the book within five seconds, determine single and split orders using the approach described, and rerun our main regression results. The results are qualitatively similar and omitted for brevity.

A concern with aggregating sequential order executions is whether each order execution is independent. For example, if traders are engaging in intraday trading strategies, they may be reacting to changing information during the day. And each execution, even if it is part of a string of multiple orders in the same stock, in the same direction, and on the same day, could result from multiple independent decisions. We examine the sample data and find that there is a sell (buy) order execution on the same day a trader has a split buy (sell) order 22.7% of the time. Unfortunately, we lack data on trader intentions, and it is not clear if sequential order executions on these (other) trader days are truly independent.

A final issue arises with order type. Trader decision to submit a marketable (i.e., immediately executable) or non-marketable limit order will have an impact on their resulting time to execution, which is a focus variable in our study. Splitting decisions may also differ based on trader order type preference. Therefore, we attempt to report results separately (in addition to aggregating all orders) for the two main order types. Marketable orders consist of market orders and limit orders with a buy (sell) price greater (less) than or equal to the national best offer (bid) at the time a trader submits an order. Non-marketable limit orders consist of orders with a buy (sell) price less (greater) than the national best offer (bid) at the time a trader submits an order. One difficulty with examining results by order type is that split orders may consist of marketable orders and non-marketable limit orders. For example, there are 348,488 split orders (8% of order observations) comprised of both order types. Therefore, we classify split orders as either marketable or non-marketable based on if a majority of the order (on a share-basis) is marketable or non-marketable. A small number of sequential orders are split evenly between both order types (88,476 occurrences or 2% of order observations) and these are classified as marketable. If we remove multi-order type split orders from the analyses, results remain qualitatively similar.

3.2. When Order Splitting Occurs

We first examine when order splitting is more likely to occur. There are a number of different order characteristics, market conditions, stock characteristics, etc., that could contribute to whether an order is split. Our assumption is that order splitting is more likely to occur when trader liquidity demands are higher and market liquidity supply is lower. At these times, traders will have greater incentive to split in order to reduce their market impact costs. For example, if a trader is looking to fill a larger order and there is less depth available at quoted market prices, then order splitting would seem more likely. Other factors such as trading volume, order direction, etc., could also matter. For example, prior studies find that differences in execution performance and trader behavior exist between buy and sell orders (e.g., Keim and Madhavan 1995; Harris and Hasbrouck, 1996). To understand key determinants of order splitting, a logit model is estimated. The dependent variable is set equal to one (zero) if a split order execution occurs. A number of independent variables are selected, including:[10]

Two order characteristic variables:

- the log submitted order size;
- an order direction dummy variable that takes the value of 1 or, otherwise, 0, if the order is a buy;

Four market condition variables:

[10] Some independent variables are positively skewed and, as such, are converted to logs to improve model fit.

- the quoted national best bid and offer percentage spread [100*(ask price–bid price)/midpoint price] at the time a trader submits a single order or an initial order of a split sequence;
- the log quoted (consolidated) NBBO depth at the time a trader submits a single order or an initial order of a split sequence (inside offer depth for buy orders and inside bid depth for sell orders);
- log total trading volume on the stock within the half-hour interval when a trader submits a single order or an initial order of a split sequence;
- the price volatility on the stock within the half-hour interval when a trader submits a single order or an initial order of a split sequence, which is computed by subtracting the minimum execution trade price from the maximum execution trade price and dividing the difference by the average trade execution price;[11]

Three stock characteristic variables:

- the prior month-end log market capitalization for the stock;
- 1 divided by the prior month-end price for the stock;
- the prior year average monthly turnover (volume/shares outstanding) for the stock;

Table 1 results highlight summary statistics for the order splitting variables. Table 2 shows the logit regressions for both order types and for marketable and non-marketable limit orders separately. In addition to the logit model results, we report the marginal effects dy/dx (x is an independent variable) evaluated at the means of all variables and corresponding z-

[11] A volatility measure similar to Foucault and Menkveld (2008) is used. We also experiment with realized volatility measures (e.g., standard deviation of NBBO midpoint returns) and find similar results.

statistics. All regressions include year- and market-center fixed effects, and the regression *z*-statistics are calculated using the clustered standard error approach in Petersen (2009), where the cluster is defined at the trader and day level.[12]

The results indicate that various factors increase the likelihood of order splitting. For example, consider the logit regression for both order types. The order size coefficient of 1.386 is positive and highly significant (e.g., *z*-stat of 27.92), indicating that there is a higher probability of order splitting with larger-sized orders. The order size marginal effects coefficient is 0.177 and standard deviation is 1.233 (Table 1). Therefore, a one standard increase of order size will result in the odds of a trader splitting an order increasing by approximately 21.8% (0.177*1.233).

The market depth and volume coefficients are both negative and statistically significant at the 1% level. When there is less depth and/or trading activity in the marketplace, traders will be forced to split orders to access liquidity across multiple price levels and/or market participants. Volatility is positively correlated with order splitting. Higher variation in prices results in greater trading risks. Under these conditions, traders may seek to transact in smaller sizes to help mitigate those risks. The initial results also indicate that there is a higher probability of order splitting on larger, higher-priced, and more actively traded stocks. Because trading in bigger (smaller) and more actively traded companies occurs over a wider (smaller) range of trade sizes, this may spur more order splitting opportunities for traders.

3.3. Split Orders, Execution Time and Information

[12] For robustness, the *z*-statistics are also calculated using clustered standard errors where the cluster is defined at the stock and day level (as in Thomson, 2011). These results are similar and are omitted for brevity.

Traders may also split a large order into smaller parts to hide information and engage in stealth trading practices (Barclay and Warner, 1993). The problem with such strategies is that they often result in execution delay if the parts are not executed simultaneously. In highly competitive securities markets, execution delay is critical because informational advantages erode rapidly. The apparent tradeoff raises a natural question, "Do informed traders have a preference for order splitting or single order execution?" To provide some insight for answering this question, we first compute measures of execution time and information.

Each time a trader clicks their mouse to submit a distinct order and when a subsequent execution occurs, the time is recorded in the data. Execution time is then measured from the order submission time to the last trade execution time. For split orders, execution time is share-weighted across the multiple order executions. As expected, split orders take significantly longer to execute than single orders. The average execution time for split (single) order executions is 1,080 (146) seconds. The results are consistent with the notion that while order splitting strategies may allow for concealment of information, on average, they also result in execution delay. Of course, some single order executions in the data wait longer to execute and can be considered more patient than certain split orders that execute more quickly.

Identifying the information content behind an order is less straightforward. Barclay and Warner (1993) and others use the cumulative price impact as a proxy to identify information-based trading. This measure is less useful in our setting because we are not analyzing complete transaction-level data over time. Instead, our setting is based on trader order-level submissions and executions at various points in time (in different stocks). In order to identify the information content behind an order (both single and split) in our sample data, we examine changes in the market price after a trader submits an order. We assume that if, on average, the market price rises (falls) following a buy (sell) order submission, the order is more likely to be submitted by an informed trader. On the other hand, if, on average, the market price falls (rises) after a buy (sell) order submission, the order is more likely to be submitted by an uninformed trader. Theoretical and empirical research assumes that U.S. equity traders' informational horizons are relatively short because of competitive market forces. A five-minute time horizon is often used in the financial literature. Thus, we consider a five-minute NBBO quote midpoint price change (i.e., price impact) measure as a proxy for informed trading.[13] For each buy order, price change is the NBBO quote midpoint five minutes after the (initial) order submission of a single (split) order minus the NBBO quote midpoint at the time of order submission, divided by the NBBO quote midpoint at the time of order submission.[14] For each sell order, price change is the NBBO quote midpoint at the time of order submission minus the NBBO quote midpoint five minutes later, divided by the order submission NBBO quote midpoint.[15]

3.4. Regression results

We are interested in examining differences between split orders and single orders with respect to execution time and information. There are many factors that might influence a price change following order execution, and it is important to control for some of these factors using

[13] We also consider a one-hour, end-of-day, and end-of-following-trading day NBBO quote midpoint price change measure as a proxy for informed trading and find qualitatively similar results. The results are omitted for brevity and may be obtained by contacting the authors.

[14] The results are qualitatively similar if the dollar price change is used rather than dividing by the NBBO quote midpoint. The results are omitted for brevity and may be obtained by contacting the authors.

[15] We also compare the initial order submission quote midpoint with the quote midpoint after the first (last) trade execution. The results are qualitatively similar and omitted for brevity.

regression analysis. Consistent with the financial literature, our underlying assumption is that time to execution will be an important factor behind information-based trading. A split order occurrence in and of itself may not be a clear indicator of information-based trading. As indicated, larger size traders may split their orders to lower their trading costs but this need not imply that they are informed about future price direction. Further, split orders take longer to execute, on average, than single orders. Faster trading is often associated with informed trading. If we control for time to execution, we expect to find that split orders will be more reflective of information-based trading. And both split (single) orders that execute quickly (slowly) should be informed (uninformed) about future price direction.

In Table 3, we examine the information content of U.S. equity trader orders with a focus on whether an order is split and its time to execution. The dependent variable in each ordinary least squares regression is the price change associated with an order execution. The main independent variables are a dummy variable that takes the value of 1 or, otherwise, 0, if a string of order executions is executed by the same trader, in the same stock, in the same direction, on the same date; and, the log share-weighted order execution time. The control variables are the same independent variables used in the logit regression.

We estimate three sets of ordinary least-squares regressions. For each regression set, results are estimated for all orders, marketable orders, and non-marketable limit orders. We exclude execution time from the first regression set, and focus on the split order dummy. The dummy variable representing a split order is negative and statistically significant at the 1% level in all three regressions, indicating that split orders are less informative than single orders. The initial result suggests that split orders are more often motivated by trader desire to reduce their trading costs rather than information.

For the second regression set, we exclude the split order dummy and focus on order execution time. The execution time coefficient is negative and statistically significant at the 1% level in all three regressions, indicating that orders that execute more quickly are more informative. For the regression with all orders, the order execution time variable coefficient is -0.021 (*t*-stat -5.84). Thus, a one standard deviation increase of the log order execution time variable results in a 2.7% decrease of price change [(2.239*-0.021)/1.746].[16] In highly competitive securities markets, prices react quickly to information and speed is an important indicator of information based trading.

When we include both the split order dummy and order execution time in the same regression, the execution time coefficient remains negative and highly significant. However, the split order dummy variable turns positive and highly significant. For the regression with all orders, the split order dummy is 0.044 (*t*-stat 4.63). The results highlight the importance of time in determining which split orders are informed versus which are uninformed and likely motivated to reduce trading costs. When time to execution is (not) controlled for split order executions are more (less) informative about future prices than single order executions.

The regression results indicate that a number of (other) variables are correlated with price change when all else is held equal. For example, larger orders are more likely to indicate a future price change. For all regressions, the order size coefficient is positive and statistically

[16] The regression variable coefficients are interpreted in terms of a one standard deviation increase on price change [(std. dev. of execution time variable*coefficient)/std. dev. of price change]. The standard deviation of price change and the log order execution time variable are 1.746 and 2.239, respectively. See Table 1 for all other regression variable standard deviations.

significant at the 1% level. For example, for the regression with all orders that includes both order execution time and split order dummy, the order size variable coefficient is 0.040 (*t*-stat 13.63). Thus, a one standard deviation increase of the log order size variable results in a 2.8% increase of price change [(1.233*0.040)/1.746]. Larger order sizes would seem more likely to create a supply-demand imbalance and subsequent price change.

In Figure 2, we examine the relationship between order splitting, execution time, and information in a non-regression format. Order executions are double sorted based on if they are split or not and then into quintiles based on time to execution. The average price change is reported for each execution time quintile. Split and non-split orders with the shortest (longest) time to execution are most (least) informative, and orders are increasingly more informative about future prices as time to execution decreases.

4. Trader Characteristics and Order Splitting

An advantage of using brokerage-level data is that we are able to match executions to individual traders. This is not possible in many datasets because the data typically originate at the market center level. We use the unique features of our data to study the trading characteristics of those who are more (less) likely to split orders. Traders are sorted into quintiles based on their percentage of order splitting (i.e., the total number of split shares executed divided by the total number of shares executed). A number of trading measures are computed for each individual trader and then averaged across traders in each group. The trading measures are:

- Total number of shares executed per trader;

- Total number of orders executed per trader;
- Average order submission size (shares) per trader;
- Total number of days a trader is active;
- Market venue concentration which, for each trader, is the sum of the squared percentage of trading activity occurring in each trading venue;
- Order type concentration which, for each trader, is the sum of the squared percentage of trading activity occurring in each order type;
- The average performance per trader, which, for buy (sell) orders, is the NBBO quote midpoint five minutes after execution (share-weighted execution price) minus the share-weighted order execution price (NBBO quote midpoint five minutes after execution). The performance difference is then divided by the share-weighted order execution price;
- The average percentage of marketable orders per trader, which is the number of marketable orders executed divided by all orders executed (both marketable and non-marketable limit orders);
- The average effective spread percentage per trader, which, for buy (sell) orders, is twice the difference between the share-weighted order execution price (NBBO quote midpoint) and the NBBO quote midpoint (share-weighted order execution price) at the time of order submission divided by the share-weighted order execution price (marketable orders only);
- The average price impact percentage per trader, which, for buy (sell) orders, is the NBBO quote midpoint five minutes after the initial order submission (NBBO

quote midpoint at the time of initial order submission) minus the NBBO quote midpoint at the time of initial order submission (NBBO quote midpoint five minutes after the initial order submission), divided by the initial order submission NBBO quote midpoint (marketable orders only).

- The average fill rate per trader which is the order execution size divided by the average order submission size. Results are reported for marketable and non-marketable limit orders separately;
- The average ex-post cost percentage per trader, which, for buy (sell) orders, is the execution price (national best offer quote five minutes after execution) minus the national best bid quote five minutes after execution (execution price), divided by the execution price (non-marketable limit orders only).

In Table 4, we report average differences between traders in the highest and lowest order splitting groups, along with *t*-statistics, which indicate whether the mean differences are significantly different from zero. Overall, the results indicate that large differences exist between traders who use split order execution, the most versus the least. Those who have the highest percentage of order splitting are significantly more active and are larger size traders. On average, they execute 10.3 million shares and 5,597 orders. The average submission size of an executed order is 1,155 shares. By contrast, traders with the lowest percentage of order splitting execute, on average, 1.1 million shares and 883 orders. The average submission size of an executed order is 692 shares. The total number of days traded for those who use order splitting the most (least) is 154 (75).

Traders who use order splitting the most exhibit greater trading diversity. For example, they use more trading venues and order types. On the other hand, traders with the lowest percentage of order splitting use fewer trading venues and order types. For traders with the highest (lowest) percentage of order splitting, the market venue and order type concentration measures are 0.4721 (0.5530) and 0.3248 (0.3573), respectively.

Performance differences seem to exist between traders who use order splitting the most and the least. In order to proxy for trading performance, fixed ex-post order execution prices are analyzed relative to the execution price. The intuition is that, if the market price rises (declines) in relation to the buy (sell) order execution price, traders are subsequently performing well. On the other hand, if the market price declines (rises) following the buy (sell) order execution price, traders are subsequently not performing well. For example, for traders with the highest (lowest) percentage of order splitting, the five-minute performance measure is 0.0007 (-0.0002). As with the other mean differences, the mean performance differences vary statistically from zero at the 1% level.

Finally, order splitters demand liquidity more and pay an overall higher cost to trade. The percentage of marketable orders for traders with the highest percentage of order splitting is 53.45%. In contrast, the percentage of marketable orders for traders with the lowest percentage of order splitting is 39.78%. For marketable order trading costs, traders who engage in order splitting the most have a higher effective spread and price impact and a lower fill rate than traders who engage in order splitting the least. The mean trading cost differences are all highly significant. For non-marketable limit orders, traders who engage in order splitting the most have a lower fill rate. Non-marketable limit order executions are exposed to adverse selection costs. We provide an estimate of this using a similar approach to Peterson and Sirri (2003), Harris and Hasbrouck (1996), and others. The ex post cost for traders who engage in order splitting the most is higher, although the mean difference between the highest-lowest order splitters is not statistically significant.

5. Conclusion

In financial markets, traders often slice large orders into smaller ones. The decision to split or not to split is important, as it can have direct implications for both market liquidity and price discovery. In our paper, we seek to provide some insight into the key determinants of order splitting. In order to do so, we obtain proprietary data from a U.S direct market access brokerage firm and study trader order (submission) execution decisions. We identify a split order as one in which a trader executes a string of multiple orders in the same stock, in the same direction, and on the same day.

We find that, among other things, split order execution is more likely to occur when: trader liquidity demands rise relative to the market supply or when traders submit larger-size orders; and, when market depth and trading activity are lower. At the individual trader-level, large differences exist between traders who use split order execution the most versus the least. In general, we find that order splitters are more active and engage in strategies that demand liquidity more. Trading cost measures are also higher for traders who split more, but overall performance is better.

Order execution times are significantly longer for split orders. Given that trading speed is critical to the informed trader, this suggests an execution tradeoff. For example, informed traders can transact in a single execution quickly, but this will reveal information to the market immediately. Alternatively, informed traders may split orders to hide information, but this is likely to result in slower order execution. Delayed execution can result in information leakage and other trading risks because market conditions change continually. We find when controlling for a host of factors (e.g., order characteristics, market conditions, stock characteristics, etc.) excluding execution time, split order executions are less informative about future prices than single order executions. However, when execution time is also controlled for, split orders are more informative than single orders. This suggests that trading speed is an important factor in whether or not split orders are informed. We find that orders with the shortest (longest) time to execution are most (least) informative about future prices.

While order splitting strategies may allow informed traders to hide more effectively in the marketplace, there are other ways for traders to conceal their informational advantage, such as trading at different times of day or in different locations. For example, financial theory posits that informed traders have a preference for trading around the morning and opening hours of trading when there is more trading activity, which enables them to hide more efficiently (Admati and Pfleiderer, 1988). Moreover, trading venues are considered either "lit" or "dark." In lit (dark) markets, the trading interests of market participants are (not) displayed prior to execution. Zhu (2014) conjectures that dark markets are less attractive to informed traders because execution risk is greater in these venues. Thus, it would be interesting to examine how order splitting vs. execution speed tradeoffs might vary by time of day, in certain trading venues, or in other types of settings where variations in trader information are more pronounced.

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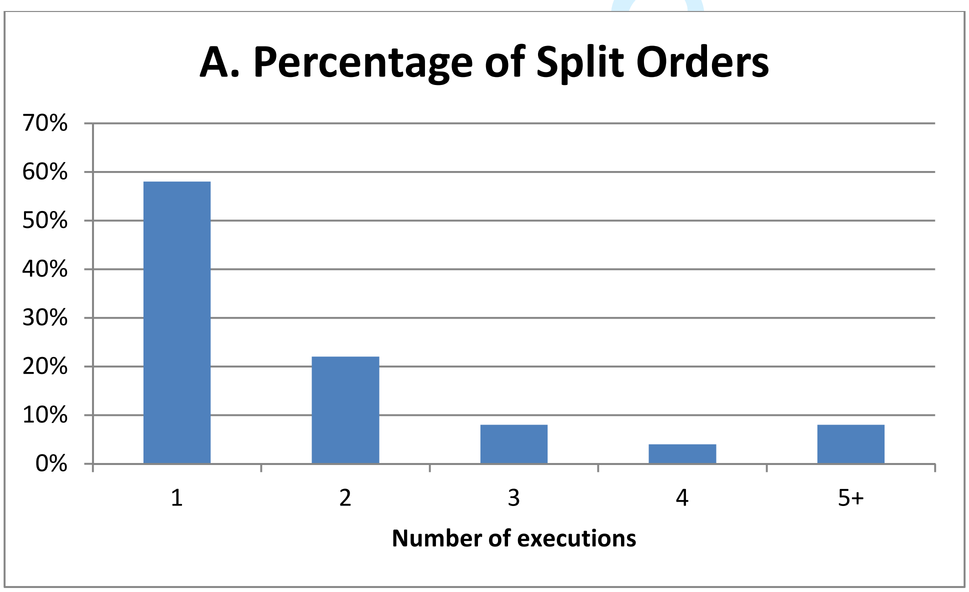


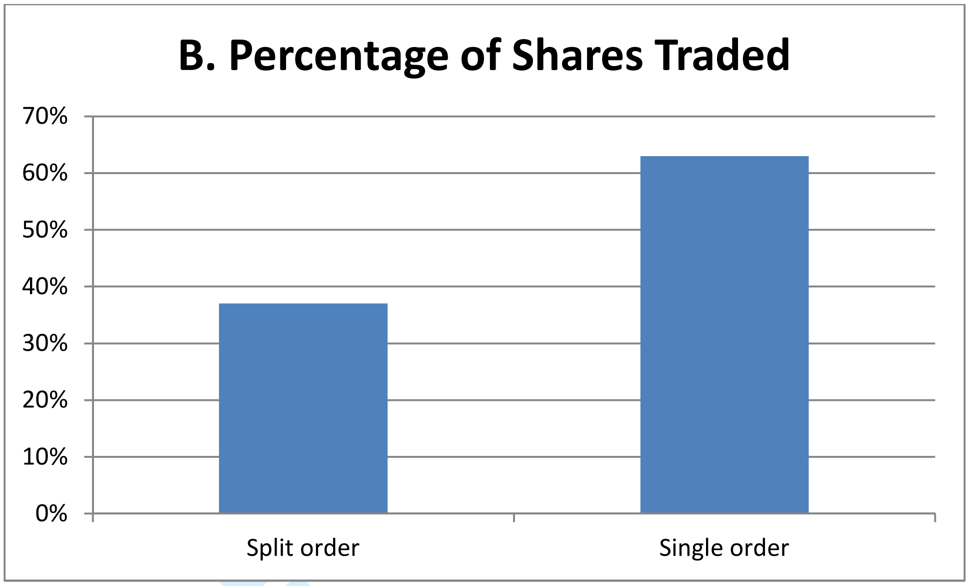
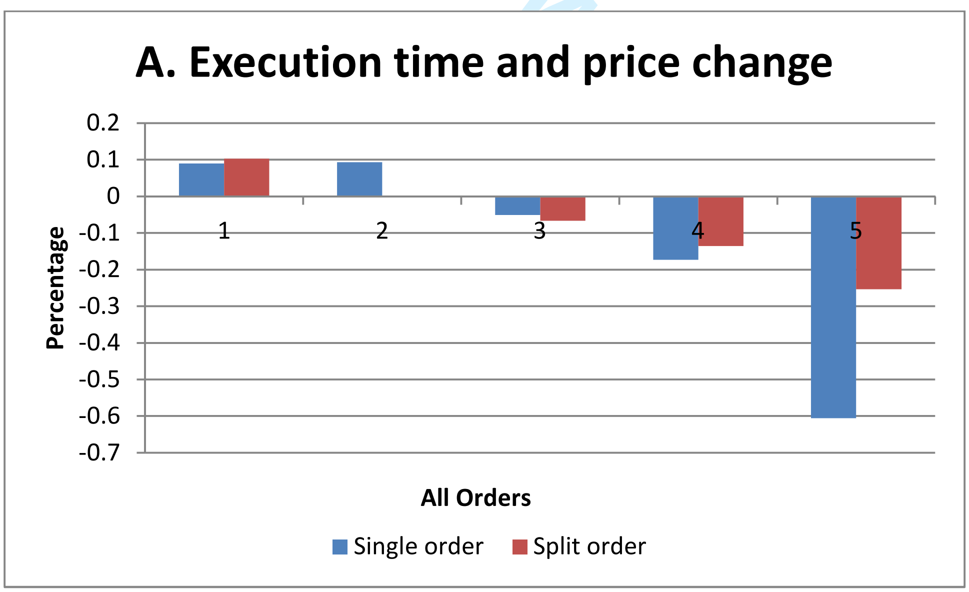
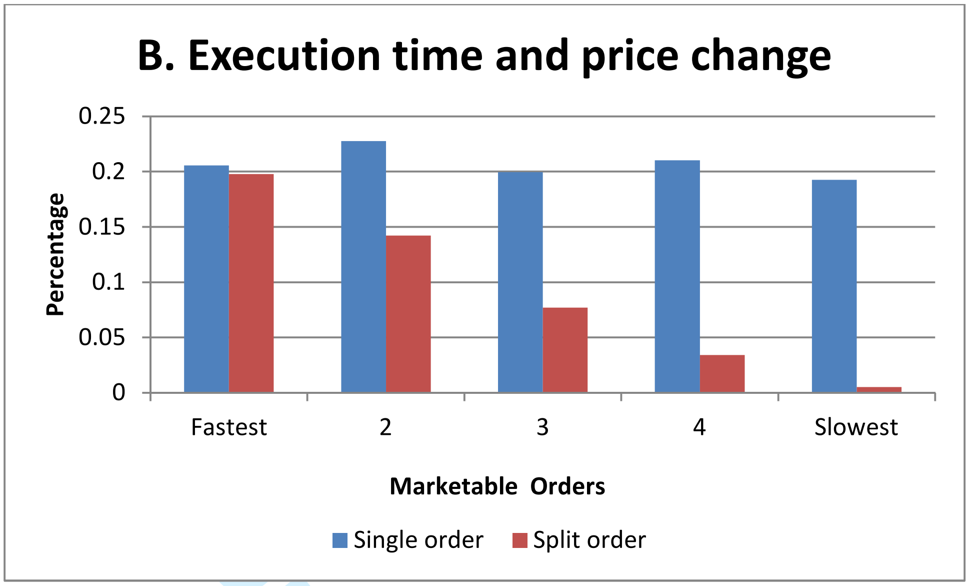


Figure 1
Order Splitting Frequency

Figure A depicts the percentage of single (1) and split (2 - 5+) order executions. Figure B depicts the percentage of overall shares traded for single and split orders. A split order is one in which a trader executes a string of multiple orders in the same stock, in the same direction, and on the same day.





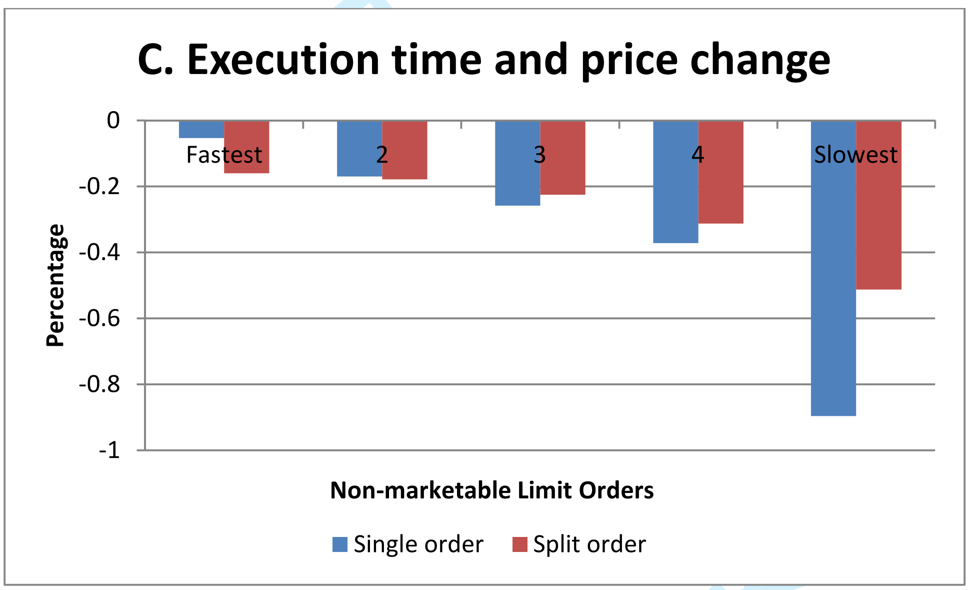


Figure 2
Execution Time-Price Change

Order executions are double sorted based on if they are single or split and then into quintiles based on time-to-execution. A split order is one in which a trader executes a string of multiple orders in the same stock, in the same direction, and on the same day. Execution time is measured from order submission to final execution. For split orders, execution time is share-weighted across order executions. The average price change is reported for each execution time quintile. For each buy order, price change is the NBBO quote midpoint five minutes after the (initial) order submission of a single (split) order minus the NBBO quote midpoint at the time of order submission, divided by the NBBO quote midpoint at the time of order submission. For each sell order, price change is the NBBO quote midpoint at the time of order submission minus the NBBO quote midpoint five minutes later, divided by the order submission NBBO quote midpoint. Marketable orders consist of market orders and limit orders with a buy (sell) price greater (less) than or equal to the national best offer (bid) at the time a trader submits an order. Non-marketable limit orders consist of orders with a buy (sell) price less (greater) than the national best offer (bid) at the time a trader submits an order. Split orders are classified as marketable or non-marketable based on if a majority of the order (share-basis) is marketable or non-marketable. Sequential orders that are split evenly between both order types are classified as marketable.

Table 1

Order Splitting Variable Summary Statistics

The table results highlight summary statistics for the order splitting variables. A split order is one in which a trader executes a string of multiple orders in the same stock, in the same direction, and on the same day. The variables include a split order dummy variable that takes the value of 1 or, otherwise, 0, if a split order execution occurs; the log order submission size; an order direction dummy variable that takes the value of 1 or, otherwise, 0, if the order is a buy; the quoted NBBO percentage spread [100*(ask price–bid price)/midpoint price] at the time a trader submits a single order or an initial order of a split sequence; the log quoted NBBO depth at the time a trader submits a single order or an initial order of a split sequence (inside offer depth for buy orders and inside bid depth for sell orders); log total trading volume on the stock within the half-hour interval when a trader submits a single order or an initial order of a split sequence; price volatility on the stock within the half-hour interval when a trader submits a single order or an initial order of a split sequence which is computed by subtracting the minimum execution trade price from the maximum execution trade price and dividing the difference by the average trade execution price; the prior month-end log market capitalization for the stock; 1 divided by the prior month-end price for the stock; the prior month average daily turnover (volume/shares outstanding) for the stock.

	Mean	**Standard Deviation**
Split order dummy	0.216	0.412
Log order size	7.320	1.233
Buy-sell indicator	0.496	0.500
Bid-ask spread	0.701	1.931
Log quoted depth	3.614	2.029
Log half-hour volume	6.861	5.648
Half-hour price volatility	0.023	0.052
Log market capitalization	22.073	2.431

1 / stock price	0.526	1.311
Stock turnover	0.571	0.561

Table 2

When Split Order Executions Occur

The table results highlight when order splitting is more likely to occur with a logit regression. The dependent variable is set equal to one (zero) if a split order execution occurs. A split order is one in which a trader executes a string of multiple orders in the same stock, in the same direction, and on the same day. Marketable orders consist of market orders and limit orders with a buy (sell) price greater (less) than or equal to the national best offer (bid) at the time a trader submits an order. Non-marketable limit orders consist of orders with a buy (sell) price less (greater) than the national best offer (bid) at the time a trader submits an order. Split orders are classified as marketable or non-marketable based on if a majority of the order (share-basis) is marketable or non-marketable. Sequential orders that are split evenly between both order types are classified as marketable. See Table 1 caption for descriptions of the variables. The regressions also include year and market center fixed effects. In addition to the logit model results, the table reports the first stage marginal effects dy/dx (x is an independent variable) evaluated at the means of all variables and corresponding z-statistics. The *z*-statistics (in parentheses) are calculated using clustered standard errors (as in Petersen, 2009), where the cluster is defined at the trader and day level.

Logit regression

	All orders		**Marketable orders**		**Non-marketable limit orders**	
	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic
Constant	-10.131***	(-18.53)	-10.697***	(-21.52)	-9.718***	(-14.37)
Log order size	1.386***	(27.92)	1.500***	(30.92)	1.251***	(20.75)
Buy-sell indicator	0.014	(0.64)	-0.083***	(-2.98)	0.025	(1.12)
Bid-ask spread	-0.010	(-1.08)	0.115***	(7.14)	-0.052***	(-3.10)
Log quoted depth	-0.237***	(-14.13)	-0.214***	(-15.55)	-0.207***	(-7.94)
Log half-hour volume	-0.006***	(-3.49)	0.001	(0.41)	-0.009***	(-4.40)
Half-hour price volatility	0.243***	(2.82)	0.249***	(2.66)	0.233**	(2.08)
Log market capitalization	0.042***	(2.72)	0.068***	(3.16)	0.068***	(3.16)

1 / stock price	-0.179***	(-7.25)	-0.273***	(-9.49)	-0.140***	(-4.04)
Stock turnover	0.067***	(3.20)	0.074***	(3.74)	0.055	(1.64)
Year fixed effects	Yes		Yes		Yes	
Market center fixed effects	Yes		Yes		Yes	
No. of obs. (000,000's)	4.2		1.9		2.3	
Pseudo R^2	17.46%		18.35%		16.72%	

Marginal effects

	All orders		Marketable orders		Non-marketable limit orders	
	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic
Log order size	0.177***	(31.24)	0.242***	(32.11)	0.125***	(23.28)
Buy-sell indicator	0.002	(0.65)	-0.013***	(-3.06)	0.002	(1.13)
Bid-ask spread	-0.001	(-1.22)	0.019***	(9.13)	-0.005***	(-3.28)
Log quoted depth	-0.030***	(-16.45)	-0.035***	(-15.85)	-0.021***	(-9.35)
Log half-hour volume	-0.001***	(-3.91)	0.000	(0.47)	-0.001***	(-4.66)
Half-hour price volatility	0.031***	(3.24)	0.040***	(3.48)	0.023**	(2.24)
Log market capitalization	0.005***	(2.78)	0.003	(1.26)	0.007***	(3.19)
1 / stock price	-0.023***	(-7.12)	-0.044***	(-10.36)	-0.014***	(-3.79)
Stock turnover	0.009***	(3.34)	0.012***	(4.14)	0.006*	(1.66)

***,**,* indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

Table 3

Split Orders-Execution Time: Baseline Regression Results

The dependent variable in each ordinary least squares regression is the price change associated with a single (split) order. For each buy order, price change is the NBBO quote midpoint five minutes after the (initial) order submission of a single (split) order minus the NBBO quote midpoint at the time of order submission, divided by the NBBO quote midpoint at the time of order submission. For each sell order, price change is the NBBO quote midpoint at the time of order submission minus the NBBO quote midpoint five minutes later, divided by the order submission NBBO quote midpoint. The main independent variables are a split order dummy variable and a log share-weighted order execution time. A split order is one in which a trader executes a string of multiple orders in the same stock, in the same direction, and on the same day. Execution time is measured from order submission to execution. For split order executions, execution time is share-weighted across order executions. See Tables 1 and 2 captions for descriptions of the other variables. The *t*-statistics (in parentheses) are calculated using clustered standard errors (as in Petersen, 2009), where the cluster is defined at the trader and day level.

Split order dummy

	All orders		Marketable orders		Non-marketable limit orders	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	-0.031	(-0.59)	0.380***	(4.30)	-0.615***	(-5.48)
Split order dummy	-0.029***	(-5.12)	-0.052***	(-7.98)	-0.028***	(-3.35)
Log order size	0.040***	(13.42)	0.059***	(17.34)	0.023***	(7.91)
Buy-sell indicator	0.053***	(7.28)	0.062***	(8.14)	0.046***	(6.94)
Bid-ask spread	-0.020**	(-2.06)	0.169***	(10.15)	-0.044***	(-2.62)
Log quoted depth	-0.048***	(-18.19)	-0.040***	(-15.46)	-0.036***	(-8.61)
Log half-hour volume	-0.000	(-0.55)	-0.003***	(-6.85)	0.003***	(6.92)
Half-hour price volatility	-0.010	(-0.61)	-0.075	(-1.17)	0.001	(-1.17)

Log market capitalization	-0.005**	(-2.33)	-0.040***	(-12.83)	0.032***	(7.15)
1 / stock price	-0.029***	(-3.51)	0.002	(0.24)	-0.092***	(-6.08)
Stock turnover	-0.002	(-0.41)	-0.004	(-0.76)	-0.008	(-0.88)
Year fixed effects	Yes		Yes		Yes	
Market center fixed effects	Yes		Yes		Yes	
No. of obs. (000,000's)	4.2		1.9		2.3	
Adjusted R^2	2.4%		4.0%		4.1%	

Table 3 continued

Order execution time

	All orders		**Marketable orders**		**Non-marketable limit orders**	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	-0.051	(-0.96)	0.439***	(5.01)	-0.729***	(-7.65)
Log order execution time	-0.021***	(-5.84)	-0.012***	(-6.38)	-0.029***	(-5.61)
Log order size	0.053***	(7.24)	0.057***	(16.06)	0.008***	(2.58)
Buy-sell indicator	0.039***	(4.16)	0.061***	(8.08)	0.046***	(6.94)
Bid-ask spread	-0.020**	(-2.06)	0.169***	(10.13)	-0.046***	(-2.79)
Log quoted depth	-0.049***	(-18.90)	-0.040***	(-15.37)	-0.034***	(-9.15)
Log half-hour volume	-0.000	(-0.65)	-0.003***	(-7.00)	0.003***	(6.51)
Half-hour price volatility	-0.009	(-0.55)	-0.077	(-1.20)	0.001	(0.03)
Log market capitalization	-0.005**	(-2.36)	-0.041***	(-13.25)	0.038***	(10.25)
1 / stock price	-0.029***	(-3.58)	0.004	(0.40)	-0.091***	(-6.19)
Stock turnover	-0.002	(-0.38)	-0.005	(-0.90)	-0.001	(-0.17)
Year fixed effects	Yes		Yes		Yes	
Market center fixed effects	Yes		Yes		Yes	
No. of obs. (000,000's)	4.2		1.9		2.3	
Adjusted R^2	2.4%		4.0%		4.3%	

Order execution time and split order dummy

	All orders		**Marketable orders**		**Non-marketable limit orders**	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	-0.004	(-0.08)	0.417***	(4.72)	-0.846***	(-8.93)

Log order execution time	-0.025***	(-4.62)	-0.010***	(-3.56)	-0.039***	(-6.73)
Split order dummy	0.044***	(4.63)	0.021**	(2.10)	0.124***	(10.63)
Log order size	0.040***	(13.63)	0.060***	(17.23)	0.019***	(6.49)
Buy-sell indicator	0.053***	(7.22)	0.061***	(8.08)	0.047***	(6.97)
Bid-ask spread	-0.019**	(-2.02)	0.169***	(10.12)	-0.048***	(-2.88)
Log quoted depth	-0.048***	(-18.00)	-0.040***	(-15.49)	-0.035***	(-9.30)
Log half-hour volume	0.000	(-0.47)	-0.003***	(-6.98)	0.002***	(6.02)
Half-hour price volatility	-0.010	(-0.64)	-0.076	(-1.19)	0.004	(0.16)
Log market capitalization	-0.006***	(-2.78)	-0.040***	(-13.09)	0.041***	(11.26)
1 / stock price	-0.029***	(-3.50)	0.003	(0.33)	-0.092***	(-6.23)
Stock turnover	-0.003	(-0.62)	-0.005	(-0.85)	0.002	(0.29)
Year fixed effects	Yes		Yes		Yes	
Market center fixed effects	Yes		Yes		Yes	
No. of obs. (000,000's)	4.2		1.9		2.3	
Adjusted R^2	2.4%		4.0%		4.4%	

***,** indicate significance at the 0.01 and 0.05 level, respectively.

Table 4

Trader behavior differences

Traders are sorted into quintiles based on their percentage of split orders (number of split shares executed divided by total shares executed) and average differences between traders in the highest (lowest) groups are reported. Trading activity measures include total number of shares (orders) executed. Average submission size is the average submitted size (shares) of executed orders. Trading days is the total number of days a trader is active. Market venue concentration is the sum of the squared percentage of trading activity occurring in each trading venue for each trader. Order type concentration is the sum of the squared percentage of trading activity occurring in each order type for each trader. For each trader buy order (the reverse calculation is done for sell orders), performance is computed as the NBBO quote midpoint five minutes after execution minus the share-weighted order execution price, divided by the share-weighted order execution price. Marketable order is the number of marketable orders executed divided by all orders executed (marketable orders and non-marketable limit orders). Trading cost measures are computed for marketable orders and non-marketable limit orders separately. Marketable orders consist of market orders and limit orders with a buy (sell) price greater (less) than or equal to the national best offer (bid) at the time a trader submits an order. Non-marketable limit orders consist of orders with a buy (sell) price less (greater) than the national best offer (bid) at the time a trader submits an order. The effective spread for buy (sell) orders is twice the difference between the share-weighted order execution price (NBBO quote midpoint) and the NBBO quote midpoint (share-weighted order execution price) at the time of order submission, divided by the share-weighted order execution price. Price impact for buy (sell) orders is the NBBO quote midpoint five minutes after the initial order submission (NBBO quote midpoint at the time of initial order submission) minus the NBBO quote midpoint at the time of initial order submission (NBBO quote midpoint five minutes after the initial order submission), divided by the initial order submission NBBO quote midpoint. Fill rate is the number of shares executed per order divided by the number of shares submitted. The ex post cost percentage for buy (sell) orders is the execution price (national best offer quote five minutes after execution) minus the national best bid quote five minutes after execution (execution price), divided by the execution price. The *t*-statistics indicate whether the mean differences are statistically different from zero.

Trader Order Splitting Frequency	Highest	2	3	4	Lowest	Average Difference	*t*-stat
Number of shares (000s)	10,287	7,565	6,253	3,778	1,149	9,138***	(3.86)
Number of orders	5,597	3,370	2,836	2,061	883	4,714***	(5.18)
Avg. submission size	1,155	1,106	1,059	862	692	463***	(6.40)
Trading days	154	140	122	102	75	79***	(-10.03)
Market venue concentration	0.4721	0.5323	0.4968	0.5323	0.5530	0.0809***	(6.01)
Order type concentration	0.3248	0.2939	0.2967	0.3099	0.3573	0.0326***	(3.19)
Performance %	0.0007	0.0006	0.0000	-0.0002	-0.0002	-0.0002***	(2.64)
Marketable order	0.5345	0.4857	0.4612	0.4042	0.3978	0.1367***	(8.26)
Trading costs (marketable orders)							
Effective spread %	0.7425	0.5283	0.4616	0.4701	0.4832	0.2593**	(1.96)
Price impact %	0.2882	0.2046	0.1655	0.1624	0.1523	0.1425***	(9.76)
Fill rate	0.8753	0.8942	0.9046	0.9263	0.9535	0.0782***	(18.94)
Trading costs (non-marketable orders)							
Ex post cost %	0.1996	0.1611	0.1712	0.2124	0.1742	0.0254	(1.27)
Fill rate	0.9303	0.9372	0.9439	0.9544	0.9695	0.0392***	(15.07)

***,** indicate significance at the 0.01 and 0.05 level, respectively.