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When is inter-transaction time informative? ☆

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Abstract

This paper estimates the role of inter-transaction time in price discovery for 100 NYSE-listed firms between 1993 and 2003. We find faster arriving trades move prices more than slower arriving trades across stocks and across time. We further document that the information content of inter-transaction time varies with trading activity, and is weakest for the most actively traded stocks. We then distinguish trades in the same direction as the previous trade from trades in the reverse direction. Our empirical findings document that inter-transaction time is informative for both types of trades, but in opposite directions. Faster arriving trades in the same direction are more informative, whereas faster arriving trades in opposite directions are less informative.
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Previous research has generally found trades arriving quicker move prices more than trades arriving slower. However, these studies have generally analyzed a relatively small number of stocks or a small time period of trading. In this study, we investigate the role of inter-transaction time in price discovery on a sample of 100 NYSE-listed stocks over the period 1993 to 2003. This large panel dataset allows for a deeper examination of how the information content of inter-transaction time varies across stocks and over time.

We focus on two aspects of inter-transaction time. First, we explore whether the information content of the time between trades is related to the typical trading activity of a given stock. To motivate, suppose a particular stock is traded each 6.5 h day by 250 uninformed traders. If an

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information event occurs, an additional 50 "informed" traders will transact. This implies trades occur approximately every 93 s when there is no information and every 78 s when there is. Suppose this 16% reduction in average inter-transaction time is sufficient to inform a market maker that a new information event has occurred. Now assume "uninformed" trading in another stock is 750 trades per day, but the number of potential informed traders remains at 50.[1] Market makers would then see an average inter-transaction time of 31 s when there is no information and 29 s when there is. Given the variability of inter-transaction times around their mean, it is conceivable that this difference is insufficient to convey information. More generally, as average inter-transaction times fall, one might believe the information conveyed by variation in the time between trades declines. This paper explores whether the information content of inter-transaction time is related to a stock's trading volume.

The second aspect of inter-transaction time on which we focus is whether or not the direction of trading relates to the information content of the time between trades. A number of fast-arriving buy orders may convey a significant probability of an information event suggesting a need for a higher price. Fast-arriving trades that are both orders to sell and orders to buy, however, need not convey anything more than a large presence of liquidity traders. Thus, the information contained in fast arrival may vary according to whether trades are of the same type (e.g. all buy orders) or of different type (e.g. a mixture of buys and sells).

We document the following results new to the microstructure literature. First, we find the information content of inter-transaction time is negatively related to a stock's average trading intensity. This is consistent with the hypothesis that rapid rates of typical trade arrival mask the information contained in the variation of these arrival rates. Second, we find the information content of inter-transaction time depends on whether a trade is in the same direction as the previous trade or in the reverse direction. In particular, fast arrival moves prices more for same-direction trades but less for reverse-direction trades. This is consistent with similar-direction trades having a greater likelihood of signaling an information event.

The paper is organized as follows. Section 1 reviews the microstructure literature related to the information content of the time between trades. Section 2 describes the data used in the study. Section 3 reviews the Dufour and Engle (2000) model of price discovery implemented in the paper. Section 4 presents empirical results for Disney stock (ticker DIS), which is illustrative for the remainder of the paper. Section 5 presents results from the full sample of 100 NYSE-listed companies and documents the relationship between typical trading activity and the information content of inter-transaction time. Section 6 documents the significance of trade direction. Section 7 concludes.

1. Related literature

The time between trades falls as the number of trades increases. Thus, the information content of fast trade arrival depends on whether the increase in the number of trades reflects the arrival of predominantly uninformed investors, as modeled by Admati and Pfleiderer (1988), or informed investors, analyzed by Easley and O'Hara (1992). Moreover, the likelihood of informed trade arrival may relate to the average trading volume of a particular stock (Easley et al., 1996) or whether informed traders wish to buy or sell (Diamond and Verrecchia, 1987).

Empirical tests of the above theories have discovered the relationship between inter-transaction time and price impact depends on the market being examined. In foreign exchange markets, Lyons

[1] Evidence of this relative frequency of "uninformed" traders is supported by Easley et al. (2001).

(1996) documents that trades are less informative when they occur quickly, a finding consistent with the theoretical result of Admati and Pfleiderer (1988). Dufour and Engle (2000), however, study a set of actively traded stocks and find the opposite empirical relationship. In their sample, shorter inter-transaction times correlate with greater price impact. That is, faster arriving trades contain more information. Spierdijk et al. (2004) examine 10 infrequently traded stocks and document that the information content of inter-transaction time is greater for illiquid stocks than for the actively traded stocks examined in Dufour and Engle (2000). In a further empirical study, Spierdijk (2004) estimates that the endogenous response of inter-transaction time to past trading and past stock returns has little affect on the author's estimate of the price impact of a trade.

2. The data

The transaction data come from the NYSE TAQ (Trades and Quotes) database. The sample period covers the 2765 trading days beginning January 4, 1993 and ending on December 31, 2003. We began with a sample of firms whose stock data was available in the TAQ data and also recorded in the CRSP daily stock files over the same period. To abstract from potential differences in the price impact of trading across different exchanges, only firms listed on the NYSE and trading under the same ticker symbol for the entire sample were considered. Following Hasbrouck (1991), we also impose a minimum price requirement on each company's stock. We require each stock to be trading for at least \$5, on average, throughout the sample period. Also following Hasbrouck (1991), we require a minimum level of trading activity. We eliminated, therefore, stocks that over the sample were in the least traded quartile of activity.[2,3] Of the remaining firms, we then selected 100 at random.

The data are then adjusted according to procedures common in the microstructure literature. We drop quotes with obviously erroneous data, such as quotes with bid or ask prices equal to zero or quotes with bid–ask spreads dramatically different from the previous and subsequent quote. Following Hasbrouck (1991), we keep only New York quotes and consider multiple trades on a regional exchange for the same stock at the same price and time to be one trade. Then, the trade data (for each company and day) are sorted by time, with the prevailing quote at transaction t defined to be the last quote posted at least 5 s before the transaction (Lee and Ready, 1991).[4]

For much of the analysis, we report results separately across three different subperiods to reflect the previous literature that has emphasized the potential important relationship between minimum tick size and stock liquidity.[5] The first covers a minimum tick size of 1/8 (i.e. 12.5 cents) and extends from the start of the sample until June 23, 1997. The second period examines trading with a minimum tick size of 1/16 (i.e. 6.25 cents) and runs from June 26, 1997 until January 26, 2001. The

[2] Hasbrouck (1991) chose a threshold of approximately 8 trades a day for data in 1989. Eight trades per day is roughly the 25th percentile of trading activity at the beginning of our sample period in January 1993.

[3] Thus, our sample excludes the least actively traded stocks analyzed by Spierdijk et al. (2004).

[4] Peterson and Sirri (2003), using data from 1997, find higher success rates of matching trades and quotes occurs when no time delay is imposed between trades and quotes. Thus, the 5 s proposed by Lee and Ready (1991) may not necessarily be the best approach for the entire sample period. Peterson and Sirri (2003), however, report results indicating the difference in matching success is very similar quantitatively when comparing lags of zero and 5 s. As a robustness check, the analysis below was repeated without implementing any delay for the second two sub-samples. Results were not noticeably changed. For additional discussion of the appropriate trade-quote matching algorithm, see Ellis et al. (2000), Peterson and Sirri (2003), Piwowar and Wei (2003).

[5] Goldstein and Kavajecz (2000) analyze how the reduction from eighths to sixteenths affected spreads and liquidity. See Furfine (2003) and the references listed therein for evidence on the impact of decimalization.

Table 1
Trading frequencies for sample stocks

	Tick size 1/8: Jan 4, 1993–Jun 23, 1997				Tick size 1/16: Jun 26, 1997–Jan 26, 2001				Tick size 1/100: Jan 29, 2001–Dec 31, 2003			
		Time between trades				Time between trades				Time between trades		
	Trades/day	Fast	Typical	Slow	Trades/day	Fast	Typical	Slow	Trades/day	Fast	Typical	Slow
ACG	61.7	248.0	372.8	528.2	57.8	266.5	389.7	551.8	328.5	44.7	66.8	94.8
ACV	34.2	428.7	617.9	862.2	89.4	151.8	241.8	375.2	536.5	23.6	38.6	61.0
ADM	447.1	31.0	48.6	71.4	564.4	24.6	38.3	56.2	1212.3	11.4	17.7	26.3
ALA	53.7	284.6	405.6	571.1	500.4	26.5	42.1	64.6	800.0	15.4	25.4	40.8
ALK	71.0	200.7	307.7	441.4	303.8	39.8	68.3	109.7	511.3	23.7	39.9	65.4
AMD	700.1	16.3	29.2	48.2	2275.0	5.2	8.9	14.6	3905.0	3.3	5.3	8.4
ASA	108.7	117.2	195.6	315.0	70.1	194.7	314.9	484.6	263.0	40.0	73.4	132.5
ATO	17.4	879.2	1103.2	1318.1	57.5	249.6	381.4	568.2	276.4	45.2	76.7	122.4
AXP	579.7	22.9	37.0	56.1	1537.6	8.6	13.4	20.7	3974.1	3.6	5.3	7.8
BDG	33.7	454.2	641.2	866.6	54.2	252.5	397.1	602.7	148.3	80.8	142.0	239.2
BEC	35.0	446.5	636.7	868.7	148.7	83.4	139.4	222.4	670.1	18.3	30.7	49.3
BGG	66.4	209.1	323.1	487.7	131.2	96.5	159.8	254.6	350.1	33.3	58.2	96.7
BJS	53.9	236.6	352.9	524.6	545.9	21.5	36.3	60.7	2037.5	6.0	10.0	16.0
BLS	457.0	31.1	47.6	69.4	1134.5	12.7	19.0	27.4	2681.1	5.4	8.0	11.6
BMY	1050.9	13.3	20.6	30.1	1830.2	7.8	11.7	16.9	4030.7	3.6	5.3	7.7
BOW	73.1	193.4	293.0	435.8	227.7	51.5	88.4	147.2	772.7	15.3	25.9	42.7
BPT	51.4	306.1	432.6	592.0	72.5	197.6	300.7	436.7	200.8	63.8	105.6	166.9
BR	168.3	81.3	128.0	191.2	473.9	28.6	44.5	66.8	1545.4	8.5	13.4	20.8
BUD	259.1	53.5	83.6	123.4	680.9	20.7	31.6	46.2	1916.3	7.3	11.2	16.5
CAG	217.2	65.1	101.1	148.0	650.8	21.8	33.4	48.7	1757.8	7.8	12.1	18.1
CC	254.0	49.7	83.0	130.5	758.5	16.1	27.0	43.2	1660.1	7.8	12.5	19.5
CDN	147.9	83.9	142.3	226.3	480.7	25.6	43.6	68.8	983.4	13.4	21.2	32.9
CIN	100.1	146.3	220.2	320.8	267.8	51.5	79.9	119.3	947.0	14.2	22.3	33.8
CL	276.0	49.8	78.3	117.2	790.1	17.9	27.2	40.0	1897.8	7.3	11.2	16.7
CMA	118.7	120.2	183.5	270.8	356.7	35.6	57.7	90.7	1393.6	9.2	14.7	23.1
CSL	16.3	731.5	933.3	1182.5	94.8	136.8	222.8	350.1	363.8	33.6	56.8	92.6
CTL	72.7	199.6	300.4	434.6	303.4	45.2	70.4	105.1	897.4	14.5	23.4	36.1
DCN	90.0	151.8	240.4	364.6	324.1	41.2	64.9	98.7	891.9	14.4	23.1	36.2
DDS	157.7	83.0	134.5	208.1	232.7	55.0	90.6	141.7	907.0	13.6	22.6	36.3
DIS	992.3	13.7	21.7	32.1	3294.3	4.4	6.6	9.4	4456.0	3.2	4.8	7.0
DLX	127.7	110.8	170.4	250.0	185.7	73.5	115.2	174.1	664.6	19.8	31.7	48.6
EDE	21.8	764.6	975.3	1197.7	42.2	364.9	537.9	757.6	133.5	89.8	159.7	263.8
FED	9.3	869.1	1085.1	1303.7	37.4	394.0	563.9	775.2	156.8	80.0	133.4	218.5
FNM	643.4	20.7	32.6	49.4	1390.2	10.5	15.4	22.1	2956.5	4.5	7.0	10.8
G	508.5	27.8	42.9	62.9	1780.8	8.3	12.2	17.5	2007.8	7.0	10.7	15.7
GMT	38.8	391.3	559.2	769.4	116.1	114.5	183.4	281.3	521.2	22.9	39.1	64.1
GP	271.1	46.1	76.4	120.8	571.6	22.3	36.1	56.6	1284.4	10.4	16.4	24.9
GTK	96.2	135.9	225.9	359.4	82.6	168.3	270.2	421.2	710.6	17.8	29.4	46.3
HAL	276.9	44.9	75.8	120.4	1487.0	8.4	13.7	21.9	3245.6	4.1	6.4	9.9
HIT	28.0	509.6	712.3	963.3	102.8	132.4	209.6	313.1	152.9	83.5	137.1	217.2
HKF	20.9	765.2	992.8	1220.9	24.4	591.2	826.4	1092.8	181.1	64.5	113.8	188.1
HLT	188.9	61.7	109.0	179.9	619.7	20.1	34.2	53.4	1177.1	10.9	17.7	27.6
IR	175.3	79.0	124.1	186.6	452.1	30.1	47.3	71.6	1435.9	9.3	14.5	22.1
ISP	20.0	714.9	930.3	1165.5	22.0	686.2	918.0	1171.5	32.0	326.2	508.0	780.0
JCI	76.7	183.5	280.8	414.9	278.8	47.7	75.6	115.2	1072.2	12.3	19.5	29.8
JEC	39.4	398.9	569.0	777.5	76.1	180.6	284.1	431.0	593.3	20.8	34.3	55.4

(continued on next page)

Table 1 (*continued*)

	Tick size 1/8: Jan 4, 1993–Jun 23, 1997				Tick size 1/16: Jun 26, 1997–Jan 26, 2001				Tick size 1/100: Jan 29, 2001–Dec 31, 2003			
		Time between trades				Time between trades				Time between trades		
	Trades/day	Fast	Typical	Slow	Trades/day	Fast	Typical	Slow	Trades/day	Fast	Typical	Slow
JNJ	1028.5	13.3	20.9	30.9	1917.4	7.6	11.2	16.1	4701.4	3.2	4.6	6.5
K	209.6	62.0	101.4	156.3	397.1	33.6	53.4	81.1	1091.4	12.5	19.5	29.2
KEY	173.3	81.9	125.7	183.9	527.4	25.6	40.1	60.5	1466.1	9.0	14.2	21.8
KF	51.9	269.5	425.9	643.4	118.7	107.3	182.7	294.0	80.0	151.0	264.7	444.8
LEO	35.0	471.8	663.1	883.2	38.0	416.3	594.5	817.9	61.9	222.8	350.4	533.4
LLY	552.8	23.8	38.6	59.1	1925.6	7.0	10.9	16.5	3103.4	4.5	6.8	10.1
LM	18.9	672.4	867.0	1108.1	167.0	70.6	121.0	200.2	813.2	15.0	24.5	40.1
LNC	99.2	141.8	218.1	324.9	328.8	40.9	63.9	96.6	1279.6	10.1	16.2	25.1
LTC	30.7	496.6	666.4	859.6	95.4	146.6	230.8	339.0	64.6	214.0	339.6	521.5
LTD	330.7	38.3	64.4	100.0	391.5	32.6	53.6	83.7	1352.5	10.0	15.6	23.5
LUV	438.1	29.4	49.4	75.9	905.3	14.4	23.6	36.1	2080.7	6.6	10.3	15.3
MAS	155.0	87.6	138.7	209.2	390.6	35.3	54.7	81.1	1525.4	8.9	13.9	20.9
MUR	37.8	392.2	576.0	812.2	141.1	87.3	144.9	236.5	795.3	14.6	24.8	41.8
MYL	397.6	32.0	54.5	84.2	452.2	28.5	47.4	73.7	1168.1	11.4	18.0	27.6
N	101.2	122.9	208.7	340.6	242.7	50.1	84.8	138.2	759.7	15.7	26.6	43.4
NCC	128.6	112.4	171.7	255.2	430.0	32.4	50.1	74.7	1666.8	7.8	12.5	19.4
NFG	57.2	269.6	386.9	544.8	91.9	154.0	235.7	350.9	396.7	32.3	53.2	83.8
NPM	35.0	478.9	659.9	870.0	29.9	553.7	763.5	989.5	36.6	425.0	621.2	864.2
NQM	29.4	569.8	773.1	1007.0	27.2	623.3	835.9	1063.4	31.7	493.1	710.0	956.3
NQS	31.2	548.9	745.8	963.0	28.8	574.9	789.0	1021.0	29.8	538.6	754.4	1010.2
NSC	156.7	86.7	136.9	206.2	474.4	28.8	44.9	67.3	1358.2	9.5	15.2	23.8
NWK	63.9	208.3	321.7	476.3	74.3	174.5	287.8	446.4	111.4	123.4	198.6	299.0
PCP	36.5	402.7	572.2	790.1	142.2	89.2	147.5	230.4	553.2	23.0	37.4	58.8
PH	88.3	149.4	241.4	375.6	278.0	46.1	75.2	117.3	1101.3	11.6	18.7	29.2
PMT	51.0	306.8	446.3	622.0	48.3	323.3	469.8	655.5	63.4	240.3	355.0	506.3
PNM	44.5	344.2	505.5	706.7	76.1	189.3	287.7	423.2	392.0	31.4	52.7	85.1
POS	28.4	479.4	661.2	903.6	127.0	88.7	158.6	263.7	500.1	24.4	41.6	66.4
PSD	98.9	156.0	225.2	310.8	164.0	88.0	133.5	192.0	477.4	28.0	44.7	68.2
RAD	112.5	117.7	190.0	292.8	1176.4	11.1	17.9	27.4	1287.1	10.1	16.4	25.3
RGS	60.1	260.2	375.2	526.4	88.8	162.3	246.2	358.8	190.1	52.3	84.4	129.9
ROH	80.5	168.3	266.3	407.8	321.6	39.3	64.5	101.8	1154.5	10.9	17.9	28.2
RVT	27.6	596.4	803.7	1038.1	53.1	271.1	417.0	607.9	141.1	98.6	153.9	227.0
S	566.9	23.5	37.8	57.2	1015.1	13.5	21.0	31.4	2470.3	5.3	8.4	13.0
SNV	42.2	379.9	538.2	738.3	228.3	54.1	90.7	146.2	999.0	12.8	20.6	32.3
SPW	32.6	459.2	649.6	887.1	168.5	71.1	121.3	197.5	1118.1	10.2	17.5	29.7
SRR	123.4	112.7	177.3	263.5	118.7	116.4	184.5	275.6	173.5	71.9	122.4	198.7
STU	10.2	568.7	743.3	984.7	10.0	917.6	1154.4	1402.5	55.5	215.7	376.1	628.0
SVU	84.2	173.6	266.7	398.7	237.1	56.8	90.5	138.8	847.2	15.7	25.0	38.2
SWY	153.1	87.4	141.7	211.0	888.2	15.8	24.4	35.6	2015.6	7.0	10.6	15.6
TEK	88.1	158.1	249.0	370.5	277.9	45.0	74.5	118.1	634.6	21.1	33.2	50.4
TII	9.6	1107.9	1306.2	1499.4	17.8	810.0	1016.9	1268.3	65.3	199.9	321.5	508.1
TOL	58.6	240.1	372.0	555.2	105.8	128.4	204.3	310.3	1235.4	9.4	15.9	26.7
TRR	8.3	958.3	1170.7	1405.8	8.5	719.0	948.4	1225.9	223.9	48.6	88.4	156.5
TXU	324.9	45.6	68.4	97.1	515.6	27.7	41.9	61.0	1732.5	7.6	12.1	18.5
TYC	124.7	109.9	170.9	258.4	2135.9	6.6	10.0	14.5	6743.6	2.1	3.2	4.7
UFI	49.9	298.0	437.8	634.6	84.9	157.8	252.0	395.4	193.4	61.1	107.9	181.5
UGI	53.2	290.2	420.0	591.5	76.8	185.0	283.4	419.3	309.4	41.1	68.0	107.2
UHT	13.6	1039.0	1233.8	1422.1	15.3	913.0	1118.4	1337.4	86.4	155.8	243.8	373.1

Table 1 (*continued*)

	Tick size 1/8: Jan 4, 1993–Jun 23, 1997				Tick size 1/16: Jun 26, 1997–Jan 26, 2001				Tick size 1/100: Jan 29, 2001–Dec 31, 2003			
		Time between trades				Time between trades				Time between trades		
	Trades/day	Fast	Typical	Slow	Trades/day	Fast	Typical	Slow	Trades/day	Fast	Typical	Slow
UNP	232.1	60.3	94.0	139.8	533.0	26.3	40.5	60.1	1498.5	8.8	13.9	21.5
VFC	100.3	141.1	218.9	327.5	221.5	58.8	95.7	148.5	692.1	19.0	30.3	46.4
VOD	105.9	130.3	203.7	314.1	791.9	16.3	26.1	41.4	1335.5	10.8	16.1	23.4
WBK	15.6	781.6	978.1	1211.2	14.8	913.1	1123.5	1354.1	17.4	758.9	1000.7	1279.1
WEN	250.0	54.2	87.0	129.4	345.2	37.7	61.5	94.7	977.7	13.8	21.6	32.7
WGL	45.5	349.8	499.0	699.3	92.3	153.2	237.1	354.5	324.8	36.8	63.9	105.7

The numbers in the table report the average number of trades per day for each stock and statistics related to the time between trades, divided into the three sample subperiods. Fast, typical and slow inter-transaction times are calculated as the 20th, 50th, and 80th percentiles of the distribution of inter-transaction times for the given stock in the given subperiod.

final period, January 29, 2001 through the end of the sample period, contains trading with decimal pricing. Our analysis will be completed separately for each stock in the sample. To ease the presentation of some of our results, however, we group our 100 stocks into 10 deciles according to their average time between trades within each sample subperiod, with decile 1 corresponding to the most frequently traded stocks. A complete listing of the stocks in our sample, along with some statistics on their trading frequency, is given in Table 1.

3. Empirical framework

Our empirical results are based upon coefficients estimated from the two equation VAR model of returns and trades of Dufour and Engle (2000), which can be expressed as

$$r_t = \sum_{i=1}^{8} a_{ir} r_{t-i} + \lambda^r_{\text{open}} D_t x^0_t + \sum_{i=0}^{8} \left[\gamma^r_{ir} + \delta^r_{ir} \ln(1 + T_{t-i})\right] x^0_{t-i} + v_{1t} \tag{1}$$

$$x_t = \sum_{i=1}^{8} a_{ix} r_{t-i} + \lambda^x_{\text{open}} D_t x^0_t + \sum_{i=1}^{8} \left[\gamma^r_{ix} + \delta^r_{ix} \ln(1 + T_{t-i})\right] x^0_{t-i} + v_{2t} \tag{2}$$

The variable r_t is defined as the change in the natural logarithm of the midquote of a given stock that follows the trade at time t. Following Hasbrouck (1991), we define the variable x^0_t as an indicator of the trade direction of the trade occurring at time t. If the trade is initiated by the buyer, then $x^0_t = 1$. If the trade is initiated by the seller, then $x^0_t = -1$. We assume trades at a transaction price greater than the midquote were buyer-initiated and trades below the midquote were seller-initiated. For trades at the midquote, we assign the value of x^0_t according to the tick rule (see Lee and Ready, 1991). We define T_t as the time, in seconds, between the trade at time t and the trade at time $t-1$ and D_t as an indicator that is equal to 1 if trade t occurs during the first 30 min of the trading day.

We truncate the VAR model at 8 lags for all stocks and for all time subperiods. Hasbrouck (1991), Dufour and Engle (2000), and Spierdijk (2004) truncate their models at 5 lags, but Spierdijk et al. (2004) consider infrequently traded stocks and find 8 lags are the appropriate length. For simplicity in calculation, we uniformly adopt the longer lag length.[6] For the nine most actively traded deciles, we eliminate trade-to-trade returns that span a calendar date. However, to consider the evidence in Spierdijk et al., we keep overnight returns for the most infrequently traded stocks remaining in our sample, those in decile 10. For these stocks, we eliminate overnight returns whenever CRSP data indicates a stock split or dividend payment. Eqs. (1) and (2) were estimated by OLS, with standard errors corrected using White's (1980) methodology.

4. Results for Walt Disney

To set the stage for the full-sample results presented in Section 5, here we report in detail the results for a single actively traded stock. The stock we pick is the Walt Disney Company (ticker DIS). Table 2 presents coefficient estimates from the estimation of Eqs. (1) and (2), with separate results for each of the three subperiods. The first three columns of the top panel of Table 2 report the coefficient estimates from the return equation for the period with a 1/8 minimum tick size. The coefficients on lagged returns are negative, whereas the coefficients on the current trade indicator and its recent lags are positive. That returns are negatively autocorrelated and buys lead to positive returns are standard results first reported by Hasbrouck (1991). The coefficients on the first two lags of the interaction of the trade indicator and the time between trade variable are negative and significant. This matches the results found most often by Dufour and Engle (2000). The negative sign means trades arriving with shorter inter-transaction time (faster arrival) were correlated with larger price changes.

Contrast this finding with the results from the middle subperiod. The coefficient capturing the effect of the time between trades is now positive and statistically significant. That is, during the middle subperiod, trades of DIS arriving faster were correlated with smaller price changes. During the final subperiod, the coefficients on the interaction of inter-transaction time and trade sign again revert to their more expected negative sign.[7]

Thus far, we have discussed how the coefficients on the interaction of inter-transaction time and the trade indicator in the trade equation were of different signs during the different time periods. To get a better sense of the economic importance of these different coefficients, we calculate cumulative impulse response functions for Disney, which incorporate information from both the return and trade equations. Unlike research interested in modeling the distribution of inter-trade durations (e.g. Dufour and Engle, 2000 and Spierdijk, 2004), we focus on how differences in observed durations influence the price impact. Therefore, we calculate our impulse response functions in the following way. Based on the results of Spierdijk (2004), we assume inter-transaction time is exogenously given. Some trades of DIS, however, arrive much sooner after the previous trade than others. For each subperiod, we

[6] For virtually all stocks in the sample, Ljung-Box tests for serial correlation in the residuals fail to reject the hypothesis that 8 lags is sufficiently long. Variation in lag length in the few instances where rejection occurred had virtually no impact on the results reported.

[7] Although wanting to be cautious about making conclusions based on data from one stock, examination of the information content of inter-transaction time for Disney within smaller time windows identifies that the positive coefficients reported for the middle subperiod are related to the company's April 1998 announcement of a 3-for-1 stock split. Starting on that date, trading activity in Disney increased dramatically. To the extent market makers perceived the increase in trading activity as reflecting new interest in the stock caused by a pending stock split and unrelated to new fundamental information regarding the proper price level, the results reported in Table 2 make sense. That is, trades arriving much faster were viewed, on average, to be less informative about the price.

group all trades of DIS into five quintiles based on the time since the previous trade. To compute the cumulative impulse response of a fast trade, we randomly select 10,000 trades from the fastest quintile of trade arrivals. For each of these 10,000 trades, we use the actual series of inter-transaction times that follow these trades as the exogenous series of inter-transaction times needed to estimate the impulse response to an unexpected trade shock. We average across these 10,000 observations to report the (average) cumulative impulse response, depicted by the dark solid lines in Fig. 1. This exercise was then repeated for 10,000 draws from the set of trades within the quintile of slowest arriving trades, with the average depicted by the light solid line. Finally, variability of the results is shown by the dark and light dashed lines, which report the 10th and 90th percentiles across the 10,000 impulse responses for fast and slow trades, respectively.

Fig. 1 illustrates that the information contained in inter-transaction time varied across the three subperiods for Disney stock. In the first subperiod, a fast-arriving trade is estimated to lead to an average cumulative impact of 2.0 basis points of return on Disney stock. By contrast, a slow-arriving trade leads to an increased return of only 1.7 basis points. A test of the difference of these values is highly significant, with the *p*-value on the test of equality less than 1%.

As an empirical measure of the information content of inter-transaction time, define PI^i as the average long-run price impact of a trade estimated from 10,000 trades from quintile i. For subsequent analysis, we will define the information content of inter-transaction time as $(\mathrm{PI}^{\mathrm{Fast}}-\mathrm{PI}^{\mathrm{Slow}})\ /\ \mathrm{PI}^{\mathrm{Typical}}$, where Fast, Slow, and Typical relate to the fastest, slowest, and middle quintile of inter-transaction times for DIS (within each subperiod). In other words, our proxy for the information content of inter-transaction time measures the fraction of the stock's typical price impact that might be explained by representative differences in arrival rates. For Disney, we estimate the information content of inter-transaction time during the first subperiod to be $16.7\%=(2.0-1.7)\ /\ 1.8$.

Fig. 1 also illustrates that the liquidity of Disney stock, as measured by (the negative of) the price impact, did not increase through time. In particular, a trade of Disney stock had the greatest price impact of up to 2.3 basis points during the most recent period, which also corresponds to the period in which Disney stock traded the most frequently. This suggests that although higher trading frequency might proxy for greater liquidity in a cross-section of securities, increases in trading frequency *through time* do not necessarily imply increases in liquidity for a given security.

Note, too, that Fig. 1 indicates that the information content of inter-transaction time for Disney stock changed signs in the different subperiods. In the first and last period, faster arrival led to greater price impact, whereas in the middle period, faster arrival implied lower price impact. These findings match those suggested by the signs of the interaction coefficients in the return equation. In terms of our preferred measure of the information content of inter-transaction time, we estimate the information content of inter-transaction time to be -42.0% during the middle subperiod and $+29.1\%$ during the final subperiod. Explaining variation in the information content of inter-transaction time will be discussed when we explore results for the full sample of 100 stocks in the following section.

5. Results for the full sample

In this section, we analyze the importance of inter-transaction time for the full sample of 100 stocks. This entails estimating Eqs. (1) and (2) for each of the 100 stocks within each of the three subperiods. We then calculate impulse response functions drawing random samples from each

Table 2
Estimated Coefficients for the Disney Company (DIS)

Lag number	Tick size 1/8: Jan 4, 1993–Jun 23, 1997			Tick size 1/16: Jun 26, 1997–Jan 26, 2001			Tick size 1/100: Jan 29, 2001–Dec 31, 2003		
	Quote revision (a_i)	Trade (γ_i^r)	Trade * duration (δ_i^r)	Quote revision (a_i)	Trade (γ_i^r)	Trade * duration (δ_i^r)	Quote revision (a_i)	Trade (γ_i^r)	Trade * duration (γ_i^r)
Return equation									
0		0.005084	−0.00029		0.0017477	0.00062		0.009256	−0.0015
		(0.000093)	(0.000031)		(0.00003)	(0.000016)		(0.000106)	(0.000058)
1	−0.01092	0.002569	−0.00011	−0.015972	0.0008564	0.000464	−0.39063	0.007566	−0.00082
	(0.001162)	(0.000091)	(0.000031)	(0.00067)	(0.00003)	(0.000017)	(0.00135)	(0.000108)	(0.000059)
2	−0.01024	0.001235	0.0000268	−0.011533	0.0003658	0.0002984	−0.29849	0.005623	−0.00057
	(0.001179)	(0.00009)	(0.000031)	(0.00070)	(0.00003)	(0.000017)	(0.00134)	(0.00011)	(0.000059)
3	−0.00581	0.000482	0.0000887	−0.007743	0.000145	0.0001913	−0.2288	0.004256	−0.00049
	(0.001191)	(0.000090)	(0.000031)	(0.00072)	(0.00003)	(0.000017)	(0.00130)	(0.00011)	(0.000060)
4	−0.0061	0.000196	0.0000994	−0.004998	0.0000225	0.0001181	−0.17561	0.003566	−0.00058
	(0.001175)	(0.000090)	(0.000031)	(0.00072)	(0.00003)	(0.000017)	(0.00125)	(0.000111)	(0.000060)
5	−0.00422	0.0000339	0.0000409	−0.002327	−0.000085	0.0000873	−0.13312	0.002747	−0.00045
	(0.001157)	(0.000089)	(0.000031)	(0.00072)	(0.00003)	(0.000017)	(0.0012)	(0.00011)	(0.000060)
6	−0.00357	−0.00022	0.0000774	−0.000795	−0.000109	0.000077	−0.09634	0.002356	−0.00049
	(0.001157)	(0.00009)	(0.000031)	(0.00072)	(0.00003)	(0.000017)	(0.00114)	(0.00011)	(0.000060)
7	−0.00202	−0.00037	0.0000894	0.0001075	−0.000179	0.0000526	−0.06728	0.001869	−0.00043
	(0.001143)	(0.000090)	(0.000031)	(0.00072)	(0.00003)	(0.000017)	(0.00108)	(0.00011)	(0.000060)
8	−0.00418	−0.00056	0.000114	0.0015679	−0.000190	0.0000485	−0.04083	0.001425	−0.00027
	(0.001123)	(0.00009)	(0.00003)	(0.00072)	(0.00003)	(0.000017)	(0.00099)	(0.00011)	(0.00060)

Trade equation									
0									
1	−1.220837	0.217552	−0.01012	−0.2724	0.108984	0.010193	−2.30498	0.188231	0.005726
	(0.026487)	(0.00233)	(0.00079)	(0.021941)	(0.001148)	(0.000593)	(0.004561)	(0.001098)	(0.000618)
2	−0.845774	0.145627	−0.00979	−0.45827	0.101824	−0.00243	−1.58225	0.112134	−0.00163
	(0.025067)	(0.00229)	(0.00079)	(0.021588)	(0.001118)	(0.00059)	(0.005293)	(0.001085)	(0.000617)
3	−0.598367	0.101038	−0.00781	−0.39095	0.084405	−0.00646	−1.13586	0.073788	−0.00254
	(0.024881)	(0.00230)	(0.00079)	(0.021434)	(0.001119)	(0.00059)	(0.005822)	(0.001087)	(0.000618)
4	−0.400539	0.072856	−0.0067	−0.39526	0.073455	−0.00854	−0.82464	0.057614	−0.00517
	(0.024843)	(0.00229)	(0.00078)	(0.021373)	(0.001119)	(0.000589)	(0.006119)	(0.001087)	(0.000618)
5	−0.265244	0.058294	−0.00672	−0.31901	0.065234	−0.00982	−0.60728	0.047745	−0.00556
	(0.024867)	(0.00229)	(0.00078)	(0.021362)	(0.001118)	(0.000589)	(0.006234)	(0.001087)	(0.000618)
6	−0.167847	0.045145	−0.00483	−0.24621	0.059547	−0.00921	−0.42349	0.040697	−0.00549
	(0.024900)	(0.00229)	(0.00078)	(0.021351)	(0.001117)	(0.000589)	(0.006202)	(0.001086)	(0.000618)
7	−0.059488	0.044018	−0.00455	−0.20167	0.058706	−0.01089	−0.2677	0.035123	−0.00475
	(0.024919)	(0.00228)	(0.00078)	(0.021324)	(0.001114)	(0.000588)	(0.005983)	(0.001084)	(0.000618)
8	0.0016281	0.046589	−0.00625	−0.0653	0.057248	−0.01107	−0.13755	0.036235	−0.00535
	(0.024883)	(0.00225)	(0.00078)	(0.021289)	(0.001113)	(0.000587)	(0.005522)	(0.001073)	(0.000615)

Coefficient estimates and standard errors (in parenthesis) for the equations

$$r_t = \sum_{i=1}^{8} a_{ir} r_{t-i} + \lambda^r_{\text{open}} D_t x^0_t + \sum_{i=0}^{8} \left[\gamma^r_{ir} + \delta^r_{ir} \ln(1 + T_{t-i})\right] x^0_{t-i} + v_{1t}$$

$$x_t = \sum_{i=1}^{8} a_{ir} r_{t-i} + \lambda^x_{\text{open}} D_t x^0_t + \sum_{i=1}^{8} \left[\gamma^r_{ix} + \delta^r_{ix} \ln(1 + T_{t-i})\right] x^0_{t-i} + v_{2t}$$

estimated using data from the trading of stock of the Disney Company (DIS).
Robust standard errors in parentheses.

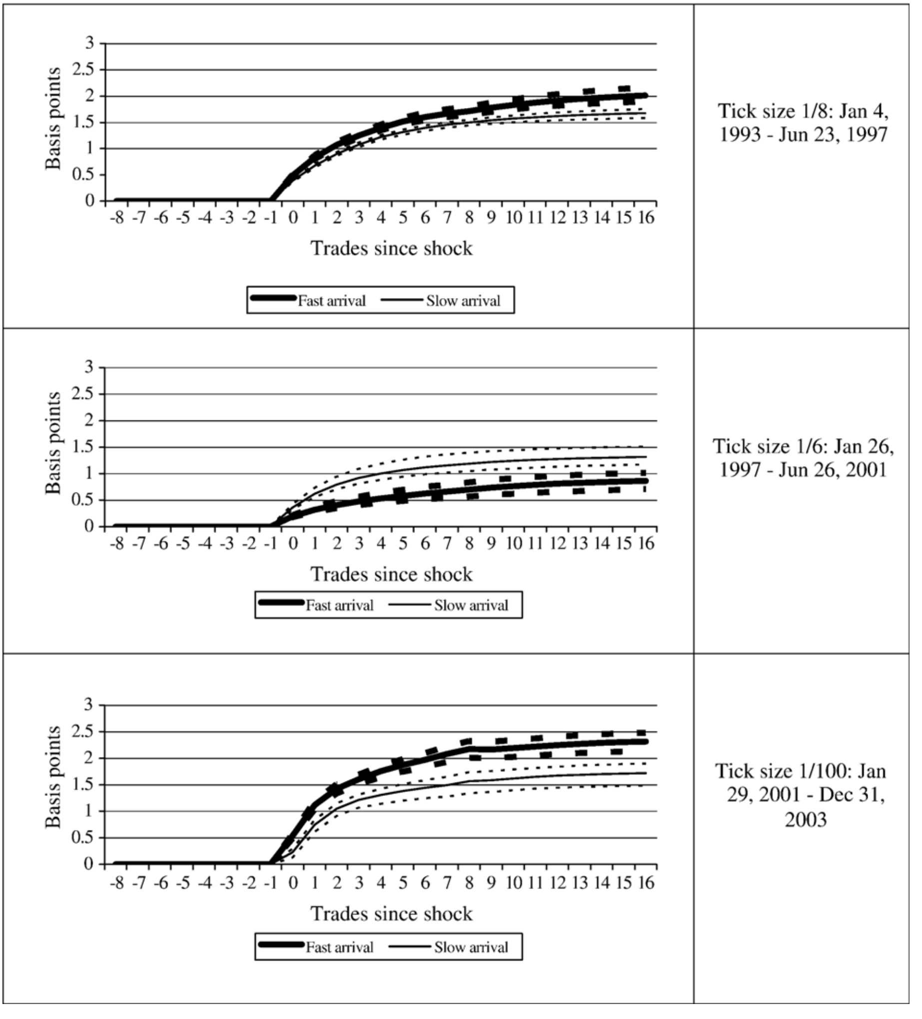

Fig. 1. Impulse response functions for the Disney company. The three panels graph the cumulative impulse response of an unexpected trade on the returns to Disney stock for fast and slow arrival times and for each of the three subperiods based on the model of Dufour and Engle (2000) (see Eqs. (1) and (2)). Solid lines are averages across 10,000 simulations. Dotted lines depict the 10th and 90th percentiles of the empirical distribution.

stock's inter-transaction time distribution within both the fast and slow quintiles.[8] Table 3 reports for each stock and for each subperiod the mean cumulative impulse response of stock return to a trade shock. The table groups stocks by deciles according to their average trading volume during the subperiod. For example, the first row of the table reports that the estimated

[8] Our sample sizes were set equal to the minimum of 10,000 or 10% of all transactions for each stock in each subperiod. Quintiles for each stock's inter-transaction time are reported in Table 1.

Table 3
Long-run price impact of a trade for sample stocks

Tick size 1/8: Jan 4, 1993–Jun 23, 1997				Tick size 1/16: Jun 26, 1997–Jan 26, 2001				Tick size 1/100: Jan 29, 2001–Dec 31, 2003			
Company	Fast	Slow	Difference	Company	Fast	Slow	Difference	Company	Fast	Slow	Difference
Most actively traded: decile 1											
ADM	3.4	2.2	1.2*	AMD	3.0	3.4	−0.3^	AMD	3.3	3.0	0.3*
AMD	4.8	4.0	0.8*	AXP	3.4	3.1	0.3*	AXP	2.1	2.1	0.0*
AXP	3.3	2.4	1.0*	BMY	2.1	1.9	0.2*	BMY	2.1	1.9	0.3*
BMY	1.3	1.2	0.1*	DIS	0.9	1.3	−0.5^	DIS	2.3	1.7	0.6*
DIS	2.0	1.7	0.3*	G	3.6	3.1	0.6*	FNM	1.8	1.7	0.1*
FNM	3.4	2.7	0.7*	JNJ	1.7	1.6	0.1*	HAL	3.2	2.9	0.3*
G	3.6	2.7	1.0*	LLY	2.7	2.7	0.0*	JNJ	1.4	1.2	0.2*
JNJ	2.0	1.6	0.5*	RAD	2.8	3.3	−0.5^	LLY	2.3	2.1	0.1*
LLY	3.7	2.9	0.8*	TYC	1.4	2.2	−0.8^	S	3.6	2.8	0.7*
S	3.3	2.6	0.8*	VOD	2.8	2.9	−0.1^	TYC	2.5	1.5	1.0*
Decile 2											
BLS	2.8	1.8	1.0*	ALA	5.2	4.0	1.2*	BJS	8.9	7.6	1.4*
CC	7.1	4.6	2.5*	BLS	2.6	2.5	0.1*	BLS	2.9	2.2	0.7*
CL	5.4	3.6	1.8*	BUD	4.2	3.2	1.0*	BUD	2.5	2.2	0.4*
HAL	5.9	4.2	1.7*	CC	5.9	5.3	0.6*	CAG	2.9	2.4	0.5*
HLT	6.2	4.4	1.9*	CL	5.2	4.3	0.8*	CC	5.6	4.4	1.2*
LTD	5.7	4.0	1.7*	FNM	2.5	2.1	0.4*	CL	2.8	2.4	0.4*
LUV	5.2	4.1	1.1*	HAL	4.2	3.6	0.6*	G	2.6	2.4	0.1*
MYL	6.9	4.5	2.4*	LUV	5.8	4.3	1.5*	LUV	4.1	3.1	1.0*
TXU	2.1	1.6	0.5*	S	2.9	2.7	0.2*	SWY	2.6	2.0	0.6*
WEN	5.2	3.0	2.2*	SWY	3.5	2.7	0.9*	TXU	3.5	2.1	1.4*
Decile 3											
BR	6.7	5.5	1.3*	ADM	4.3	3.2	1.1*	BR	4.0	3.5	0.5*
BUD	4.5	3.0	1.5*	BJS	8.8	6.8	2.0*	CMA	3.2	3.0	0.2*
CAG	4.9	3.1	1.8*	CAG	4.1	3.0	1.1*	IR	4.6	4.6	0.0*
CDN	13.4	11.7	1.7*	CDN	8.4	7.0	1.4*	KEY	3.0	2.6	0.4*
GP	5.2	3.7	1.5*	GP	6.3	4.8	1.4*	MAS	3.9	3.4	0.5*
IR	7.8	5.8	2.0*	HLT	5.0	3.5	1.5*	MYL	3.8	3.3	0.5*
K	5.9	4.3	1.6*	KEY	5.5	4.5	0.9*	NCC	2.8	2.8	0.1*
KEY	5.5	3.6	1.9*	MYL	10.0	6.7	3.3*	RAD	4.9	3.3	1.6*
SWY	7.1	5.2	2.0*	TXU	3.4	2.5	0.8*	TOL	5.6	5.2	0.4*
UNP	4.5	3.2	1.3*	UNP	5.5	3.8	1.6*	UNP	5.0	4.0	1.0*
Decile 4											
ASA	8.5	6.5	2.0*	BR	5.7	5.1	0.5*	ADM	3.4	2.7	0.7*
CMA	6.5	5.2	1.3*	CMA	6.6	5.4	1.2*	GP	4.9	4.0	0.8*
DDS	7.9	6.2	1.7*	IR	9.0	6.6	2.3*	HLT	4.8	3.9	0.9*
GTK	12.8	10.9	1.9*	K	7.0	5.4	1.6*	LNC	3.6	3.2	0.5*
MAS	7.5	5.1	2.4*	LTD	6.7	5.1	1.6*	LTD	5.1	4.4	0.6*
NCC	7.8	5.9	1.8*	MAS	7.2	5.4	1.8*	NSC	4.7	4.2	0.5*
NSC	6.3	4.7	1.6*	NCC	7.4	5.4	2.0*	PH	4.9	4.1	0.8*
SRR	12.2	6.8	5.4*	NSC	5.7	4.5	1.1*	ROH	5.6	4.4	1.2*
TYC	7.8	5.4	2.5*	ROH	9.2	6.3	2.9*	SPW	8.0	6.7	1.3*
VOD	6.2	5.3	1.0*	WEN	5.8	4.4	1.4*	VOD	3.4	2.3	1.0*

(continued on next page)

Table 3 (*continued*)

Tick size 1/8: Jan 4, 1993–Jun 23, 1997				Tick size 1/16: Jun 26, 1997–Jan 26, 2001				Tick size 1/100: Jan 29, 2001–Dec 31, 2003			
Company	Fast	Slow	Difference	Company	Fast	Slow	Difference	Company	Fast	Slow	Difference
Decile 5											
BOW	10.4	7.5	2.9*	ALK	8.0	6.3	1.6*	CDN	5.5	4.6	0.9*
CIN	6.7	3.7	3.0*	BOW	9.8	6.5	3.2*	CIN	3.6	2.9	0.7*
DLX	5.7	3.8	1.9*	CIN	5.7	4.7	1.1*	CTL	4.5	3.9	0.6*
LNC	8.8	5.9	2.9*	CTL	7.1	5.2	1.9*	DCN	5.3	4.0	1.3*
N	11.4	9.6	1.8*	DCN	7.2	5.6	1.6*	DDS	7.6	6.1	1.5*
PH	9.9	8.1	1.8*	JCI	7.9	5.7	2.2*	JCI	3.2	2.9	0.2*
PSD	3.3	3.0	0.3*	LNC	7.7	5.5	2.2*	K	3.8	3.3	0.5*
RAD	8.7	6.7	2.0*	PH	9.0	6.6	2.3*	SNV	3.9	3.5	0.4*
TEK	8.8	7.0	1.8*	SPW	11.4	7.9	3.4*	SVU	5.0	4.4	0.6*
VFC	6.7	5.0	1.8*	TEK	12.3	8.0	4.3*	WEN	4.2	3.6	0.6*
Decile 6											
ALK	13.8	10.5	3.2*	DDS	9.9	6.9	3.0*	ALA	6.1	4.3	1.8*
BJS	14.8	13.3	1.5*	DLX	8.4	6.3	2.1*	BEC	5.1	3.5	1.6*
CTL	10.1	8.0	2.1*	KF	11.0	9.1	1.9*	BOW	5.5	4.1	1.4*
DCN	9.7	7.4	2.3*	LM	15.8	10.5	5.3*	DLX	4.1	3.5	0.6*
JCI	9.3	6.7	2.6*	MUR	10.5	6.6	3.9*	GTK	5.2	6.1	−1.0^
KF	13.1	10.1	3.0*	N	10.2	8.6	1.6*	JEC	7.6	8.1	−0.5^
NWK	22.5	16.2	6.3*	PCP	12.1	7.2	4.9*	LM	6.4	4.9	1.5*
ROH	9.0	5.9	3.1*	SNV	8.5	7.4	1.1*	MUR	4.6	4.0	0.6*
SVU	8.1	5.5	2.5*	SVU	12.2	7.9	4.3*	N	5.4	4.7	0.7*
TOL	15.0	13.8	1.3*	VFC	11.0	8.9	2.1*	VFC	5.0	4.4	0.6*
Decile 7											
ACG	4.8	0.7	4.1*	BEC	10.8	6.3	4.6*	ACV	3.5	3.5	0.1*
ALA	7.1	5.1	1.9*	BGG	12.9	7.7	5.2*	ALK	8.1	6.0	2.1*
BGG	10.7	7.1	3.7*	CSL	14.0	8.1	5.9*	CSL	9.7	7.2	2.5*
BPT	9.7	7.7	2.0*	GMT	11.6	8.4	3.2*	GMT	6.4	4.4	2.0*
NFG	7.5	6.0	1.5*	HIT	8.0	5.6	2.3*	NFG	4.6	3.6	0.9*
PMT	4.0	1.3	2.8*	LTC	12.5	9.3	3.1*	PCP	6.2	4.9	1.3*
RGS	5.8	4.6	1.2*	POS	13.6	9.3	4.3*	PNM	5.4	3.6	1.8*
SNV	11.2	8.8	2.4*	PSD	5.7	4.1	1.6*	POS	8.2	6.0	2.1*
UFI	12.5	8.9	3.6*	SRR	15.3	9.7	5.7*	PSD	4.2	3.3	0.9*
UGI	10.0	7.4	2.6*	TOL	12.5	9.0	3.4*	TEK	6.4	5.2	1.2*
Decile 8											
ACV	16.2	15.6	0.6*	ACV	12.7	9.2	3.5*	ACG	3.7	2.6	1.2*
BDG	8.2	6.0	2.2*	ASA	13.6	10.5	3.1*	ASA	10.3	8.6	1.8*
GMT	11.4	8.1	3.3*	GTK	15.3	13.3	2.0*	ATO	6.5	5.6	0.9*
JEC	12.7	10.0	2.8*	NFG	10.1	6.3	3.8*	BGG	6.4	5.8	0.6*
MUR	11.3	8.8	2.5*	NWK	25.7	23.1	2.7*	BPT	8.6	6.7	1.9*
PCP	14.3	9.4	4.9*	PNM	13.5	9.2	4.3*	RGS	5.0	3.4	1.6*
PNM	11.3	7.0	4.3*	RGS	8.7	6.0	2.7*	TRR	15.9	8.0	7.9*
POS	16.4	11.4	5.0*	UFI	20.1	12.8	7.3*	UFI	20.4	13.6	6.9*
SPW	18.9	15.1	3.7*	UGI	11.3	8.5	2.8*	UGI	5.8	4.4	1.3*
WGL	10.4	6.2	4.2*	WGL	12.0	8.0	4.0*	WGL	6.0	4.5	1.6*

Table 3 (*continued*)

Tick size 1/8: Jan 4, 1993–Jun 23, 1997				Tick size 1/16: Jun 26, 1997–Jan 26, 2001				Tick size 1/100: Jan 29, 2001–Dec 31, 2003			
Company	Fast	Slow	Difference	Company	Fast	Slow	Difference	Company	Fast	Slow	Difference
Decile 9											
BEC	11.5	9.3	2.3*	ACG	8.1	4.5	3.5*	BDG	15.0	12.2	2.7*
HIT	9.0	6.6	2.5*	ATO	13.1	10.4	2.7*	EDE	8.8	6.4	2.4*
LEO	7.2	2.6	4.6*	BDG	15.2	10.9	4.3*	FED	11.3	8.0	3.2*
LM	20.6	16.8	3.7*	BPT	17.3	13.6	3.7*	HIT	7.8	4.8	3.0*
LTC	9.1	7.6	1.5*	EDE	12.3	9.5	2.8*	HKF	14.5	11.1	3.3*
NPM	8.5	5.3	3.2*	FED	21.6	21.5	0.1*	KF	9.5	6.9	2.6*
NQM	9.9	4.8	5.1*	JEC	12.0	8.3	3.6*	NWK	35.5	35.2	0.3*
NQS	6.9	4.2	2.6*	LEO	10.3	6.6	3.8*	RVT	7.3	5.4	1.9*
RVT	10.4	6.3	4.1*	PMT	5.9	3.9	1.9*	SRR	13.1	9.0	4.1*
STU	31.6	16.4	15.2*	RVT	8.2	7.9	0.3*	UHT	10.7	6.5	4.2*
Least actively traded: decile 10											
ATO	18.7	14.3	4.5*	HKF	34.2	24.9	9.2*	ISP	17.1	10.5	6.6*
CSL	17.8	13.6	4.3*	ISP	32.1	25.1	7.0*	LEO	9.8	7.4	2.4*
EDE	10.5	11.2	−0.7^	NPM	7.3	5.9	1.4*	LTC	20.2	13.3	6.9*
FED	40.5	31.0	9.5*	NQM	5.8	5.6	0.2*	NPM	9.4	6.4	3.0*
HKF	22.6	19.6	3.0*	NQS	6.1	4.6	1.5*	NQM	9.4	6.4	3.0*
ISP	26.0	22.7	3.3*	STU	22.5	16.8	5.8*	NQS	10.0	6.5	3.5*
TII	28.4	29.3	−0.8^	TII	28.5	22.5	6.0*	PMT	8.4	5.8	2.6*
TRR	69.5	56.7	12.8*	TRR	67.9	62.1	5.8*	STU	12.3	8.5	3.8*
UHT	16.7	12.8	3.9*	UHT	27.6	17.4	10.2*	TII	15.4	13.3	2.1*
WBK	13.5	11.7	1.8*	WBK	7.5	4.2	3.3*	WBK	8.8	7.1	1.8*

The numbers in the table report the long-run price impact of a trade (in basis points) for a given stock and a given time period. Long-run price impacts for fast arrival are average long-run impulse responses estimated from a two-equation VAR model (Eqs. (1) and (2)) across multiple simulations conditional upon the first inter-transaction time being in the fastest quintile of a given stock's inter-transaction time distribution. Results for slow arrival are derived analogously, although simulations were conditional on the first inter-transaction time being in the slowest quintile of a given stock's inter-transaction time distribution.

*Difference is positive and significant at 1% level.

^Difference is negative and significant at 1% level.

cumulative price impact of a trade of ADM stock is 3.4 basis points if the trade arrived at a speed among the fastest quintile of trades and 2.2 basis points if the trade arrived at a speed within the slowest quintile, giving a difference between fast and slow price impact of 1.2 basis points. The stars next to the 1.2 indicate that the fast-arrival impact is significantly greater than the slow-arrival impact (i.e. the p-value for the test of the difference in means being equal to zero was less than 1%).

The results presented in Table 3 indicate faster trading generally leads to greater price impact. Among our 100 stocks, the cumulative price impact of a fast-arriving trade was significantly greater than the impact of a slow-arriving trade in 98, 95, and 98 cases during the three subperiods, respectively. Exceptions to this general conclusion, although rare, were often for the most actively traded stocks. For example, during the middle subperiod, five of the ten most actively traded stocks actually had greater price impact for more slowly arriving trades. This suggests the relationship between inter-transaction time and price impact may be related to average trading frequency.

To explore this relationship between the information content of inter-transaction time and trading volume, we regressed each stock's information content against the natural log of its average time between trades and this inter-transaction time squared. We plot fitted values from this regression (solid line) as well as our actual estimates of information content (boxes) in Fig. 2. Recall that the information content of inter-transaction time is defined as the long-run difference between the fast-arrival price impact and slow-arrival price impact, expressed as a fraction of typical-arrival price impact.

Fig. 2 documents two facts new to the empirical microstructure literature. First, as trading volume has increased over time, the information content of inter-transaction time has fallen, but not disappeared. Over the 100 stocks in the sample, the mean information content was 34.1%, 26.3%, and 22.7% during the first, second, and third subperiod, respectively. These values are all highly significant. Further, the drop in average information content is significant

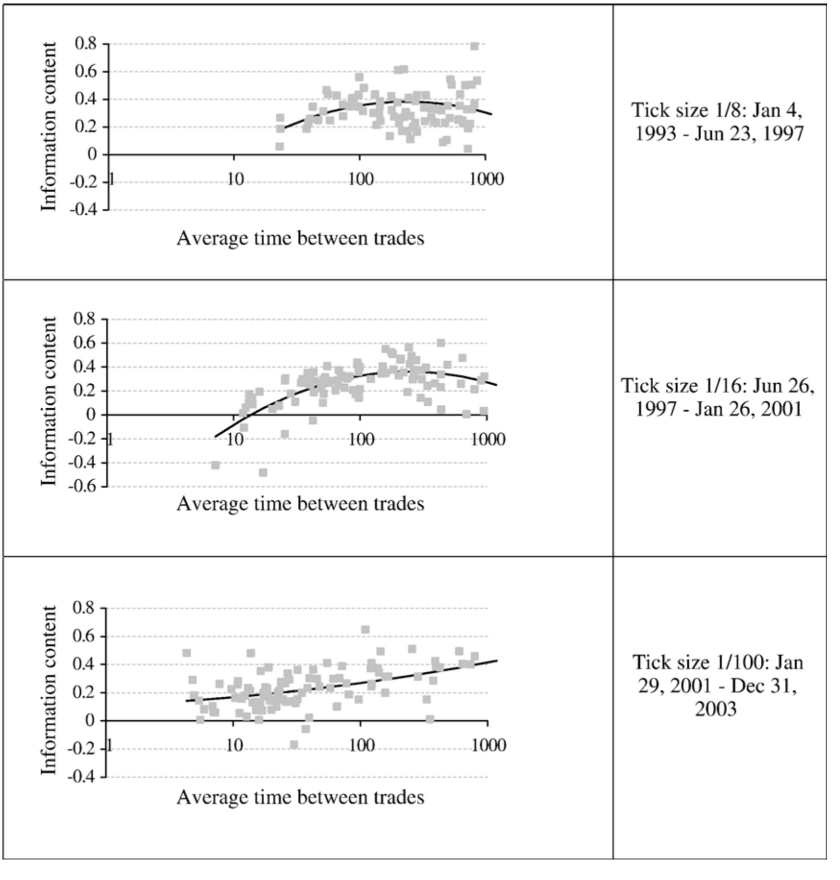

Fig. 2. Inter-transaction time and information content. The three panels graph the relationship between the information content of inter-transaction time and the average time between trades for the 100 stocks in the sample, separated into each of the three subperiods. Information content is defined as the difference between the estimated long-run cumulative price impact of a fast-arriving trade and a slow-arriving trade divided by the long-run impact of a trade arriving at an average arrival rate. Solid lines report fitted values from a regression of information content on the natural log of a stock's typical inter-transaction time and its square.

at the 1% level between subperiod 1 and subperiod 2, but not between subperiod 2 and 3 (p-value of 0.11). Second, the information content of inter-transaction time is lower for the most actively traded stocks. This is illustrated by the upward slope to the fitted value curves shown in Fig. 2.[9] On average, stocks in the most actively traded decile have an average information content of 11.4%. Differences in means tests do indicate that the average information content across stocks in the most actively traded decile are statistically significantly lower than that found in all other deciles. In particular, the average information content of inter-transaction time for a stock in the second most actively traded decile increases to 27.2%, and information content reaches its peak of 40.8% across stocks in decile 7. Average information content falls slightly for stocks traded less frequently, although the differences in estimated information content of inter-transaction time across stocks in these less-traded deciles declines are not statistically significant.

That the informativeness of inter-transaction time is lowest among the most actively traded stocks can be understood as a complementary result to that found by Easley et al. (2001). In their study, they estimate the fraction of trades of a given stock that is from informed versus uninformed traders. They document higher trading volume can be only partially explained by an increase in informed trading. That is, a large fraction of trading is due to uninformed traders. It may be the case, therefore, that the sheer volume of uninformed trading masks any possible role of inter-transaction time to carry information. This is consistent with the hypothetical situation presented in the introduction. That is, the time between trades conveys less information when a stock trades very frequently.

6. The role of trade direction

The results of the previous section suggest the information content of the time between trades is related to the trading frequency of the given stock. In this section we try to better our understanding of this result by exploring the relationship between the information content of inter-transaction time and the direction of a given trade. To do so, we empirically test further implications drawn from the microstructure literature. For instance, according to Easley et al. (2001), very rapid trading volume may primarily result from uninformed liquidity traders. As such, we would not expect these traders to be consistently buying or consistently selling a given stock. Rather, buys and sells would arrive randomly from such traders. Combine this notion with the intuition of Easley and O'Hara (1992). In their model, information events occur infrequently. Therefore, when private information exists, informed investors wish to trade. Presumably, however, these informed investors will wish to trade in the same direction conditional on a given piece of information. For example, if private information suggests the current price of a stock is too high, informed investors should be expected to sell until the price adjusts to its more appropriate value.

This intuition suggests the information content of the time between two trades may be related to whether or not the trades are in the same direction. Define a buy order following a buy order or a sell order following a sell order as a same-direction trade. Analogously, define reversing trades as a buy order following a sell order or a sell order following a buy order. The analysis in this section extends our empirical framework to account for possible differences in

[9] Both the log of inter-transaction time and its square were statistically significant at the 1% level during the first two subperiods and at the 10% level during the final subperiod.

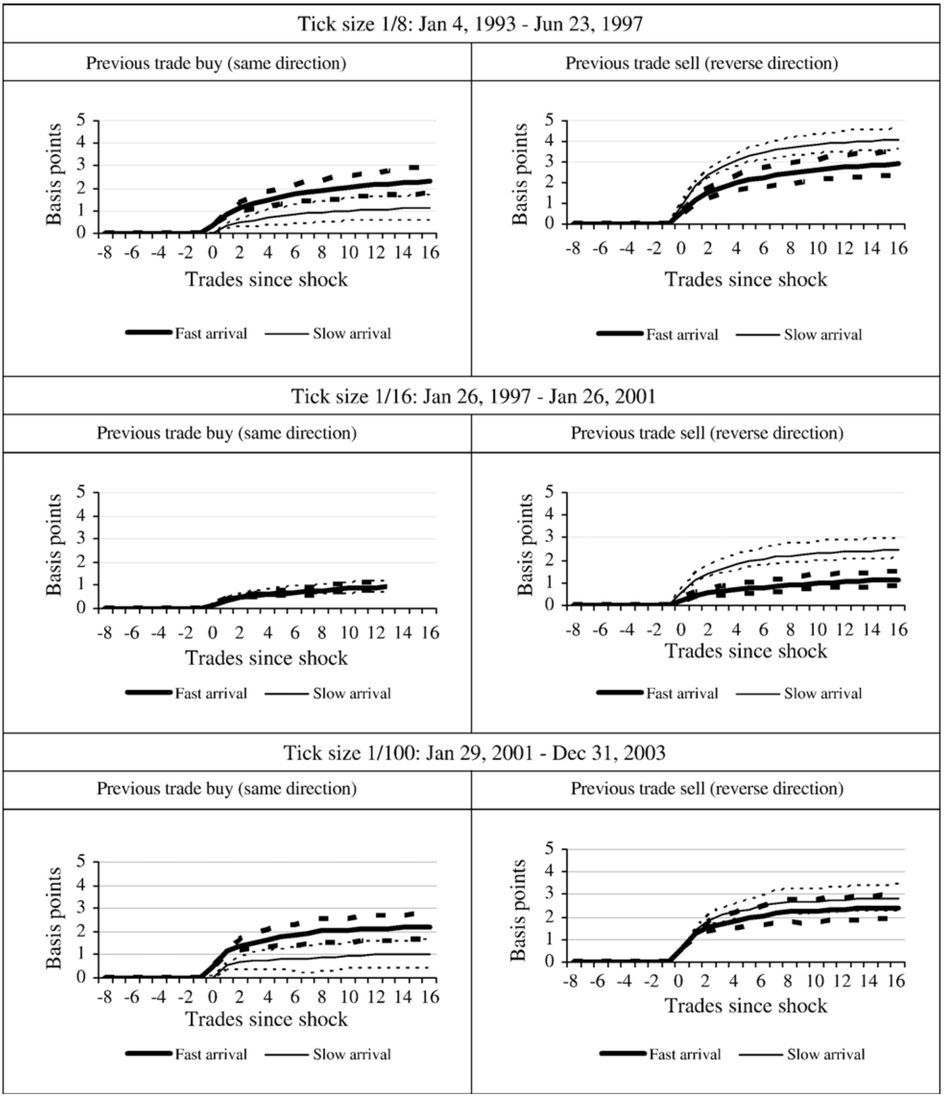

Fig. 3. Direction of trade and price impact. The three panels graph the cumulative impulse response of an unexpected trade on the returns to Disney stock for fast and slow arrival times based on a model that distinguishes same-direction and reverse-direction trades (see Eqs. (3)–(5)). Solid lines are averages across 10,000 simulations. Dotted lines depict the 10th and 90th percentiles of the empirical distribution.

the information content of a trade depending on whether the trade is same-direction or reversing. In particular, we analyze the information content of inter-transaction time for same-direction and reversing trades.

To explore the possible interaction between inter-transaction time and trade type (i.e. same-direction or reversing), we estimate the following three-equation model described by Eqs. (3)–(5) below. Eqs. (3) and (4) are simply enriched versions of Eqs. (1) and (2), whereas Eq. (5) explicitly models same-direction and reverse-direction trading in a linear way so that it can be incorporated into a VAR analysis (Hasbrouck, 1991).

$$\begin{aligned} r_t = {} & \sum_{i=1}^{8} a_{ir} r_{t-i} + \lambda^{r}_{\text{open}} D_t x^0_t + \sum_{i=0}^{8} \left[\gamma^{r}_{ir} + \delta^{r}_{ir} \ln(1+T_{t-i})\right] x^0_{t-i} \\ & + \sum_{i=0}^{8} \left[\gamma^{r}_{irs} + \delta^{r}_{irs} \ln(1+T_{t-i})\right] S_{t-i} x^0_{t-i} + \tau_{1t} \end{aligned} \tag{3}$$

$$\begin{aligned} x_t = {} & \sum_{i=1}^{8} a_{ix} r_{t-i} + \lambda^{x}_{\text{open}} D_t x^0_t + \sum_{i=1}^{8} \left[\gamma^{r}_{ix} + \delta^{r}_{ix} \ln(1+T_{t-i})\right] x^0_{t-i} \\ & + \sum_{i=1}^{8} \left[\gamma^{r}_{ixs} + \delta^{r}_{ixs} \ln(1+T_{t-i})\right] S_{t-i} x^0_{t-i} + \tau_{2t} \end{aligned} \tag{4}$$

$$\begin{aligned} S_t = {} & \sum_{i=1}^{8} a_{iS} r_{t-i} + \lambda^{S}_{\text{open}} D_t x^0_t + \sum_{i=1}^{8} \left[\gamma^{r}_{iS} + \delta^{r}_{iS} \ln(1+T_{t-i})\right] x^0_{t-i} \\ & + \sum_{i=1}^{8} \left[\gamma^{r}_{iSs} + \delta^{r}_{iSs} \ln(1+T_{t-i})\right] S_{t-i} x^0_{t-i} + \tau_{3t} \end{aligned} \tag{5}$$

In the above equations, the dummy variable S_t equals 1 when the trade at time t is same-direction and 0 otherwise. Thus, the above model allows the price impact and the time impact coefficients to vary depending on whether the trade is same-direction or reversing.

We use the parameter estimates derived from this estimation to calculate impulse response functions analogous to those presented in Fig. 1, only now distinguishing the cumulative response to a same-direction trade from the response to a reversing trade. To do so, we calculate the impulse response of stock returns to a trade shock and compare those results to the impulse response of stock returns to a simultaneous trade and same-direction shock. In Fig. 3, we plot the mean (and 10th and 90th percentiles) cumulative impulse response function for Disney stock.

The figure illustrates two features about the relationship between price impact and trade direction for Disney stock that are found to be true for virtually all stocks in the sample (see Table 4).[10] First, the long-run price impact of same-direction trades is lower than the long-run impact of reversing trades. This is consistent with the intuition of Peng (2001), who argues a reversing trade cannot be a second response to the same information that led to the preceding trade, but a same-direction trade can be a delayed response to the same information. On average, therefore, reversing trades are likely to contain more new informative about prices than same-direction trades.

More central to our focus, however, are our findings regarding how the information content of inter-transaction time varies according to whether a trade is same-direction or reversing. For same-direction trades, faster trade arrival is estimated to be more informative, as indicated by the fact faster arrival correlates with higher long-run price impact.[11] By contrast, faster arrival

[10] To conserve space, Table 4 reports values for only four deciles of stocks. Results for the full sample of 100 stocks are available upon request.

[11] Although this is not evident for Disney stock during the second subperiod, difference of means tests reported in Table 4 confirm that faster-arriving trades move prices more than slow-arriving trades for trades in the same direction.

Table 4
Long-run price impact of a trade for sample stocks — by trade direction

Tick size 1/8: Jan 4, 1993–Jun 23, 1997

Company	Same direction			Reverse direction		
	Fast	Slow	Difference	Fast	Slow	Difference
Most actively traded: decile 1						
ADM	4.2	1.7	2.6*	5.6	7.7	−2.1^
AMD	5.3	2.3	3.0*	7.0	12.1	−5.0^
AXP	3.8	1.4	2.4*	5.0	6.7	−1.8^
BMY	1.6	0.8	0.7*	2.0	3.1	−1.1^
DIS	2.3	1.1	1.2*	2.9	4.1	−1.2^
FNM	3.7	1.0	2.7*	5.6	8.6	−3.0^
G	3.9	1.3	2.5*	5.4	7.7	−2.2^
JNJ	2.2	0.8	1.4*	2.9	4.1	−1.2^
LLY	3.9	1.5	2.4*	5.6	8.4	−2.7^
S	3.9	1.4	2.5*	5.7	8.4	−2.7^
Decile 2						
BLS	3.3	0.8	2.5*	4.8	6.6	−1.9^
CC	9.7	3.0	6.7*	14.7	23.4	−8.6^
CL	5.5	1.3	4.2*	8.8	12.5	−3.7^
HAL	6.6	2.1	4.6*	10.1	16.2	−6.1^
HLT	6.9	1.9	5.0*	10.7	19.3	−8.6^
LTD	6.2	2.4	3.7*	8.5	11.9	−3.4^
LUV	5.5	2.2	3.3*	7.5	11.7	−4.2^
MYL	7.3	2.2	5.1*	9.8	13.7	−3.9^
TXU	2.5	1.3	1.2*	3.3	4.5	−1.1^
WEN	6.3	2.0	4.3*	8.5	10.7	−2.2^

Tick size 1/16: Jun 26, 1997–Jan 26, 2001

Company	Same Direction			Reverse direction		
	Fast	Slow	Difference	Fast	Slow	Difference
AMD	3.4	2.1	1.2*	3.9	7.4	−3.6^
AXP	3.8	1.3	2.5*	5.2	9.8	−4.6^
BMY	2.6	0.9	1.7*	3.3	5.6	−2.3^
DIS	1.0	1.0	0.0*	1.1	2.4	−1.3^
G	3.5	1.7	1.8*	4.3	6.0	−1.7^
JNJ	2.1	0.8	1.4*	2.7	4.6	−1.9^
LLY	2.6	1.6	1.0*	3.3	5.1	−1.8^
RAD	3.2	1.6	1.6*	3.9	9.1	−5.2^
TYC	1.6	1.4	0.2*	1.8	5.1	−3.3^
VOD	3.1	1.4	1.8*	4.3	9.4	−5.1^
ALA	6.0	2.4	3.6*	8.1	12.8	−4.7^
BLS	3.3	1.3	1.9*	4.5	7.9	−3.3^
BUD	5.1	1.4	3.7*	7.3	12.4	−5.0^
CC	6.9	2.1	4.8*	9.9	20.9	−11.0^
CL	4.7	1.8	2.9*	7.0	10.3	−3.3^
FNM	3.1	0.9	2.2*	4.5	7.2	−2.7^
HAL	4.6	2.0	2.6*	6.2	10.7	−4.5^
LUV	5.3	1.7	3.6*	6.8	9.4	−2.5^
S	3.6	1.5	2.0*	5.1	8.6	−3.5^
SWY	4.3	1.2	3.2*	6.1	10.0	−3.9^

Tick size 1/100: Jan 29, 2001–Dec 31, 2003

Company	Same direction			Reverse direction		
	Fast	Slow	Difference	Fast	Slow	Difference
AMD	3.2	2.2	0.9*	3.4	4.7	−1.3^
AXP	1.9	1.5	0.4*	2.1	2.9	−0.8^
BMY	2.0	1.3	0.7*	2.2	2.9	−0.7^
DIS	2.2	1.1	1.2*	2.4	2.9	−0.4^
FNM	1.7	1.2	0.5*	1.9	2.6	−0.8^
HAL	3.1	2.1	1.0*	3.4	4.7	−1.3^
JNJ	1.4	0.9	0.5*	1.5	1.8	−0.3^
LLY	2.1	1.6	0.5*	2.3	3.1	−0.8^
S	3.3	1.8	1.5*	3.7	4.8	−1.1^
TYC	2.5	0.9	1.6*	2.5	2.9	−0.4^
BJS	7.5	4.5	3.1*	8.5	11.2	−2.7^
BLS	2.7	1.3	1.4*	3.1	4.0	−0.9^
BUD	2.4	1.4	1.0*	2.8	4.0	−1.2^
CAG	2.7	1.5	1.1*	3.1	4.3	−1.1^
CC	5.3	2.8	2.4*	6.2	8.6	−2.4^
CL	2.5	1.7	0.8*	2.8	3.3	−0.5^
G	2.4	1.8	0.6*	2.7	3.6	−0.9^
LUV	3.8	1.9	1.9*	4.3	5.4	−1.1^
SWY	2.3	1.2	1.1*	2.8	3.7	−0.9^
TXU	3.3	1.0	2.3*	3.9	4.9	−0.9^

Decile 6																				
ALK	17.4	10.0	7.4*	27.0	44.4	−17.4^	DDS	11.6	4.9	6.7*	16.7	25.5	−8.8^	ALA	5.7	2.3	3.4*	7.5	10.6	−3.2^
BJS	18.8	13.2	5.6*	28.5	47.9	−19.4^	DLX	9.6	4.5	5.1*	14.2	20.8	−6.7^	BEC	4.4	2.1	2.3*	5.1	6.4	−1.3^
CTL	12.6	6.3	6.3*	19.3	27.4	−8.1^	KF	11.4	6.3	5.1*	16.8	30.6	−13.8^	BOW	4.6	2.3	2.4*	5.5	7.0	−1.5^
DCN	10.2	3.7	6.5*	17.4	26.7	−9.3^	LM	17.9	7.2	10.6*	26.2	43.9	−17.7^	DLX	3.7	2.6	1.1*	4.2	5.1	−0.9^
JCI	9.3	4.0	5.4*	15.4	26.3	−10.9^	MUR	13.0	6.8	6.3*	16.6	24.3	−7.8^	GTK	4.9	5.4	−0.4^	5.4	8.0	−2.6^
KF	15.0	7.5	7.6*	22.9	36.4	−13.5^	N	10.7	6.4	4.3*	15.3	23.1	−7.9^	JEC	7.0	6.7	0.3*	7.9	11.3	−3.4^
NWK	25.8	10.0	15.8*	43.2	74.2	−31.0^	PCP	14.4	6.5	7.8*	20.1	30.8	−10.7^	LM	5.3	2.8	2.5*	6.2	7.6	−1.4^
ROH	11.8	5.5	6.4*	18.7	29.7	−11.0^	SNV	9.9	5.2	4.7*	14.2	22.6	−8.4^	MUR	4.1	2.8	1.2*	4.7	6.5	−1.8^
SVU	8.3	2.3	5.9*	14.2	21.2	−6.9^	SVU	10.9	3.3	7.7*	16.1	21.6	−5.6^	N	4.5	2.9	1.6*	5.3	7.5	−2.2^
TOL	16.0	9.5	6.6*	25.9	43.0	−17.0^	VFC	9.9	5.4	4.4*	13.6	20.5	−6.9^	VFC	4.3	3.2	1.2*	4.9	6.0	−1.1^
Least actively traded: decile 10																				
ATO	19.6	11.3	8.3*	30.2	52.2	−22.0^	HKF	34.5	18.0	16.5*	47.6	76.1	−28.5^	ISP	16.1	7.1	9.1*	22.1	29.5	−7.4^
CSL	21.6	10.2	11.4*	34.5	58.5	−24.0^	ISP	36.2	24.9	11.3*	49.8	80.9	−31.1^	LEO	9.2	5.0	4.2*	11.6	16.9	−5.4^
EDE	14.9	14.0	0.9*	17.4	22.3	−4.9^	NPM	8.4	6.0	2.4*	10.8	13.9	−3.1^	LTC	22.2	13.9	8.3*	27.2	35.4	−8.1^
FED	54.5	36.3	18.1*	69.4	85.5	−16.1^	NQM	6.1	4.8	1.3*	8.4	13.4	−5.0^	NPM	10.2	6.9	3.2*	11.3	12.6	−1.3^
HKF	26.9	14.9	12.0*	43.1	72.0	−28.9^	NQS	8.1	5.6	2.5*	9.5	10.8	−1.3^	NQM	8.4	4.8	3.6*	9.4	9.3	0.1
ISP	33.8	21.1	12.6*	47.7	75.7	−27.9^	STU	30.2	21.1	9.1*	34.8	47.6	−12.8^	NQS	10.4	6.4	4.0*	11.4	11.0	0.5*
TII	36.9	30.8	6.1*	53.9	98.3	−44.4^	TII	32.0	22.5	9.6*	43.8	70.3	−26.5^	PMT	7.4	3.1	4.3*	9.7	12.0	−2.3^
TRR	74.7	52.0	22.7*	92.4	122.5	−30.2^	TRR	78.2	63.6	14.6*	89.7	170.6	−81.0^	STU	10.8	4.5	6.2*	13.9	19.6	−5.7^
UHT	19.3	12.1	7.2*	27.3	40.3	−13.0^	UHT	32.2	21.2	11.0*	37.7	48.7	−11.0^	TII	14.6	11.2	3.4*	17.1	23.0	−5.9^
WBK	22.6	13.9	8.7*	36.7	60.9	−24.2^	WBK	20.0	18.9	1.1**	19.1	16.2	2.9*	WBK	5.7	1.3	4.4*	11.3	24.3	−13.0^

The numbers in the table report the long-run price impact of a trade (in basis points) for a given stock, a given time period, broken down by same-direction and reverse-direction trades. Long-run price impacts for fast arrival are average long-run impulse responses estimated from a three-equation VAR model (Eqs. (3), (4), and (5)) across multiple simulations conditional upon the first inter-transaction time being in the fastest quintile of a given stock's inter-transaction time distribution. Results for slow arrival are derived analogously, although simulations were conditional on the first inter-transaction time being in the slowest quintile of a given stock's inter-transaction time distribution. The table reports results for selected stocks only.

*Difference is positive and significant at 1% level.

^Difference is negative and significant at 1% level.

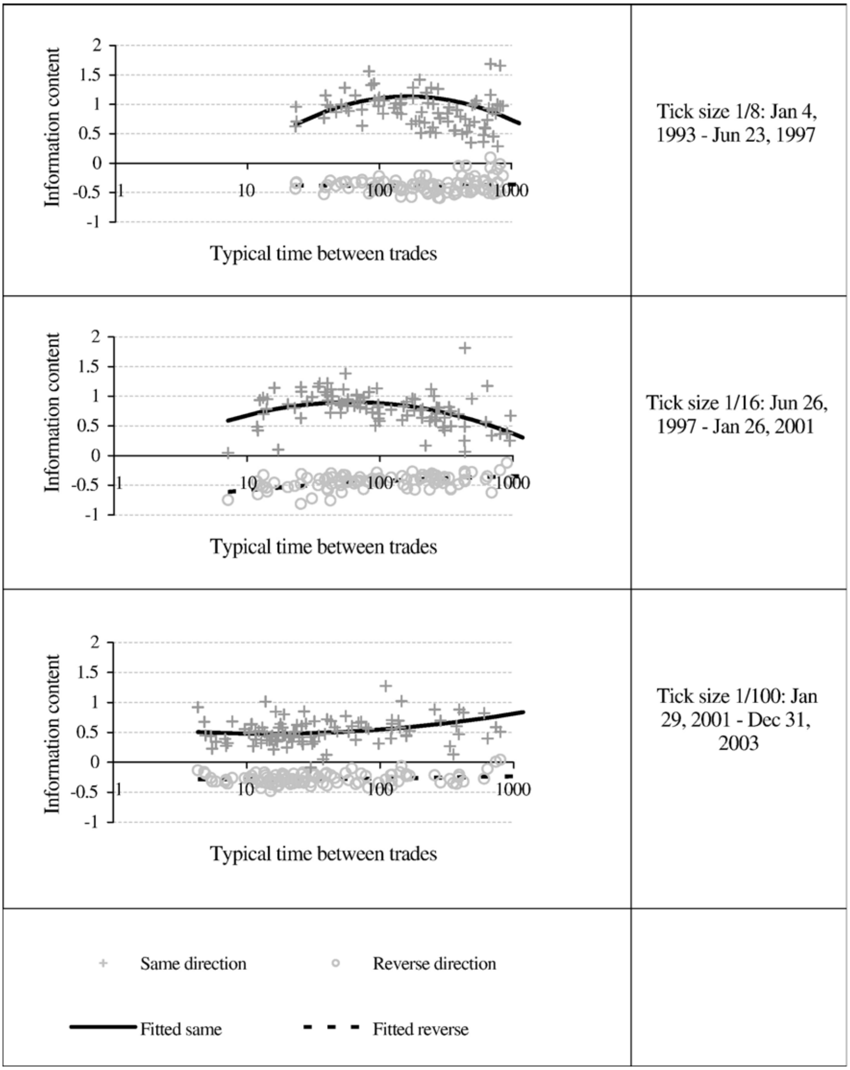

Fig. 4. Inter-transaction time and information content. The three panels graph the relationship between the information content of inter-transaction time and the typical time between trades for the 100 stocks in the sample, separated into each of the three subperiods. In each panel, the information content of same-direction trades is shown separately from the information content of reverse-direction trades. Information content is defined as the difference between the long-run cumulative price impact of a fast-arriving trade of a given type and a slow-arriving trade of the same type divided by the long-run impact of a trade arriving at a typical-arrival rate. Solid lines report fitted values from a regression of information content on the natural log of a stock's typical inter-transaction time and its square.

correlates with lower price impact for reversing trades. Previous literature suggests an interpretation of these findings. Consider a market maker observing a second consecutive buy order. If this trade arrives soon after the first, market makers may increase their assessment that a positive news event has occurred (Easley and O'Hara, 1992). Thus, faster arriving same-direction trades might be more informative than slower-arriving same-direction trades.

Consider the case, however, when a sell order follows the initial buy. It is unlikely that the two trades are related to the same bit of information. In particular, if the reversing trade arrives quickly after the first trade, market makers will likely assume the trade is unrelated to whatever news may have motivated the initial buy. Rather, faster arrival of a reversing trade may indicate the presence of more liquidity traders clustering together as predicted by Admati and Pfleiderer (1988).

Values of the information content of inter-transaction time for all 100 stocks in the sample, estimated separately for same-direction and reversing trades, are plotted in Fig. 4. As the figure documents, the information content of inter-transaction time is positive for same-direction trades and negative for reverse-direction trades. Further, the magnitude of information content is greater for same-direction trades. The average information content for same-direction trades across all stocks in the sample is 107.7%, 79.7%, and 53.0% during the three subperiods, respectively. This decline is statistically significant and is again consistent with the notion that faster trading reduces the information content of inter-transaction time. The magnitude of the information content is economically large, too. A magnitude of 100% means the difference in long-run price impact between fast and slow-arriving trades is equal to the long-run impact of a typical trade. This implies a fast trade moves prices approximately *three times more* than a slow-arriving trade.[12] Even during the last subperiod, an average information content of 53% implies fast trades move prices by 1.7 times more than slow-arriving trades. Analogous figures for reverse-direction trades are −38.0%, −43.8%, and −27.6%. Here, too, there is some evidence of a decline in the (absolute) magnitude of information content although the decline is only significant between the second and third subperiods. Fig. 4 also hints of a nonlinear relationship between information content of inter-transaction time and average time between trades, although this nonlinearity is only statistically significant for same-direction trades in the first two subperiods. In general, the message conveys the same overall intuition as was presented in Fig. 2. Specifically, inter-transaction time is less informative for the most actively traded stocks. Further, the information content of inter-transaction time is noticeably more important for same-direction trades than for reversing trades, and its economic magnitude is large.

7. Conclusion

In this paper, we apply the method of Dufour and Engle (2000) to a sample of 100 stocks over 11 years. Doing so allows us to document many features of the role inter-transaction time plays in the price discovery process. First, the information content of inter-transaction time conveys information for nearly all stocks throughout the sample period. In all subperiods of data analyzed, faster trading generally leads to greater price impact. We find, however, the information content of inter-transaction time, defined as the fraction of total typical price impact explained by the difference in fast-arrival impact less slow-arrival impact, varies with average trading volume. In particular, the information content of inter-transaction time is generally smallest for the most actively traded stocks. We then extend our analysis to consider whether trade direction relative to the previous trade influences the information content of inter-transaction time. We find faster arrival is substantially more informative for trades in the same direction than for trades in opposite directions. Further, faster arrival leads to greater price impact for same-direction trades but smaller

[12] This assumes the long-run price impact of a typical trade is approximately equal to the average of the long-run price impact of a fast and slow-arriving trade.

price impact for reverse-direction trades. Estimates of the magnitude of these relationships suggest variation in a trade's price impact can vary significantly according to its arrival rate and whether it is of the same or opposite direction as the previous trade.

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