

# The effects of intraday news flow on market liquidity, price volatility and trading activity

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## Abstract

This paper examines how the market performs in the presence of dealers during times that predominately reflect stressful market conditions. It examines this issue on the Nasdaq around unpredictable news events, i.e. the analyst recommendation changes. The sample period is 2004 at times where Nasdaq dealers were less constrained by regulation, and were actively providing liquidity on the system. The findings suggest that environments where dealers have affiliation with the analyst issuing the recommendation seem to perform particularly better as opposed to environments where they may not be. The results show narrower spreads, more trades and a more two-sided market when the report is issued by affiliated analysts, but a higher price volatility shortly before the release of the report. These results have important policy implications because they support the claim of market regulators. That is, there is an improvement in liquidity in the presence of informed dealers, as buyers and sellers are both in the market. This fact signals liquidity creation, and translates to more market stability in the period leading to the report release.

JEL classification: G1, G2.

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# 1 Introduction

Market liquidity is increasingly the focus among regulators and investors, and recognized as potential systemic risk. The current regulatory changes imposed by the Dodd-Frank and Basel III Accords have been initiated to reduce systemic risk in terms of strengthening the balance sheets and funding models of dealers<sup>1</sup>. Although the regulation has made the system less levered, it has also led to a reduction of market making by dealer banks causing some loss of market liquidity in the secondary markets, as explained by Duffie (2017). The fact that dealers are now subject to new regulations has significantly lowered their ability to continue providing market making services. Without the dealers smoothing trading, certain markets have seen extreme short-lived price disruptions accompanied by large order imbalances and evaporation of liquidity to the point of crash.

There are now growing concerns regarding the reduced capacity of dealers<sup>2</sup> to provide liquidity and signs of increasing fragility in the market<sup>3 4</sup>. There is even initiative by the CFTC Chairman Christopher Giancarlo in March 2017 to reduce regulatory burdens on dealers<sup>5</sup>. Market authorities and lawmakers argue that today's markets became fragile and unstable driven by structural imbalance in the ratio of the liquidity provided and liquidity demanded to the markets, and no longer seem to have built-in liquidity shock absorbers. They claim that the markets would be stable if dealers were providing continuous order flow during times of market stress<sup>6</sup>.

Therefore, it is crucial to understand how the market performs in the presence

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<sup>1</sup>The initiatives are aimed to reduce the probability of banks becoming source of illiquidity contagion, and protect from market abuse. In the United States, the trading requirement is implemented as part of the Dodd-Frank Act, with the Commodity Futures Trading Commission and the Securities and Exchange Commission. In Europe, it is implemented by the European Commission.

<sup>2</sup>Dealers and market makers are used interchangeably.

<sup>3</sup>Mark Carney, speech by the Governor of the Bank of England, 2014 Monetary Authority of Singapore Lecture.

<sup>4</sup>Jerome H. Powell, the Governor of the Board of Governors of the Federal Reserve System, "Making markets Fair and Effective for all", January 20, 2015.

<sup>5</sup>Speaking at the FIAs International Futures Industry Conference the day after President Trump nominated him to serve as chairman of the CFTC, acting chairman J. Christopher Giancarlo announced a new, forward-looking agenda for the regulator focused on fostering economic growth, enhancing US financial markets and right-sizing its regulatory footprint. He introduced a new initiative aimed at reducing regulatory burdens: Project Kiss Keep It Simple Stupid.

<sup>6</sup>Mary L. Shapiro, speech by the SEC Chairman, "Strengthening our equity market structure", Economic Club of New York, September 7, 2010.

of dealers over time periods that predominately reflect stressful market conditions. I evaluate this issue on the Nasdaq market circa 2004. Back then, Nasdaq dealers were less constrained by regulations as the Securities Exchange Commission (SEC) deregulated the minimum capital requirements for dealer banks freeing leverage from regulatory constraints. This enabled dealers to maintain a large market presence, see (Duffie, 2010). In the particular case of the Nasdaq, they were actively providing liquidity on the system (Karam, 2017). Like on any other dealer-based market, dealers on the Nasdaq acquired a certain market skill in stocks they choose to follow, see Schultz (2003). I explore liquidity and trading activity in the presence of these dealers in the market across a sample of stocks, around events that may create crowded exist, e.g. analyst recommendation changes. These news events are valuable to investors as shown by Womack (1996), are also exhibited with information asymmetry in the market and are associated with higher trading activity and higher price volatility, as shown by Irvine et al. (2007). Unlike scheduled announcements, the market may not prepared for these events. Consequently, investors might be unwilling to trade and liquidity might evaporate.

I consider two types of events: (i) the recommendation changes of affiliated analysts to market makers and, (ii) the recommendation changes of non-trading analysts (with no affiliation to market makers). I consider the case for dealers with affiliated analysts who are indeed informed (Schultz, 2003; Madureira and Underwood, 2008), and the difference in information which differentiates them from other dealers (the non-affiliated). I examine whether the market performs particularly better at times when information sharing among dealers is more important (the case of affiliation). Consistent with the notion that the forthcoming analyst report generates trading, environments where dealers have access to information from their analyst might increase their market making capacity at times of one-directional order flow. As a result, a two-sided market with narrower spreads might occur. I use the *difference-in-differences* to measure execution costs, price volatility, trading volume and Sarkar and Schwartz (2009) quote-sidedness for a sample of Nasdaq stocks over the two-hours before an event where the information is coming from an affiliated analyst as opposed to times where the information is coming from a non-trading analyst (with no affiliation with any market makers).

The analysis across 155 NASDAQ stocks shows that trading environments where dealers have affiliation with the analyst issuing the recommendation seem indeed to perform better as opposed to environments where they may not be. Findings suggest narrower inside spreads, more trades when the report is issued by affiliated analysts but higher price volatility shortly before the release of the report. Results suggest further that environments where affiliation exists appear to be significantly more two-sided.

The implication is that there is an improvement in liquidity in the presence of affiliated dealers as buyers and sellers are both in the market, and this fact signals liquidity creation in the period leading to the report release. The significance of all these results above does not depend on whether the non-news days or earnings announcements are used as the control sample in the *difference-in-differences* analysis.

In addition to the implications of this study to the current policy debate, it adds evidence to the literature on whether intraday news flow has an impact on market performance in the presence of dealers in the market. The theoretical literature in market microstructure expects news events to impact price setting of dealers, and this in turn affects the liquidity of the market, see for instance Glosten and Milgrom (1985) for the case of symmetrically uninformed dealers and Calcagno and Lovo (2006) for the case of asymmetrically informed dealers. Because news events are hampered with uncertainty about the asset value, this magnifies information asymmetry among market participants, which increases informed profits and thus decreases the liquidity supplied by dealers (Kim and Verrecchia, 1994). Few empirical studies examine the intraday news effects on trading activity and market liquidity, whether scheduled or unscheduled news (Ranaldo, 2008). Under these circumstances, prices become more responsive to supply shocks and hence liquidity might evaporate in a very short period of time. Maintaining a liquid market consists of reducing the uncertainty about the asset value and this requires dealers with sufficient risk bearing capacity to be able to process the news quickly in order to meet unexpected demands. Consistent with this view, environments where dealers have access to their analyst report appear to be less affected by the uncertainty around news events, and this translates to more market stability in the period leading to the report release.

## 2 Data and descriptive statistics

I collect recommendation changes from the Institutional Brokerage Estimates System (I/B/E/S) files for NASDAQ listed firms during the period from June 1st, 2004 to December 31, 2004. I collect also earning announcements for the sample stocks that I use to check the robustness of the results. The sample for the study is constructed by first selecting Nasdaq stocks for which both the date and the timing of the recommendations are available. Each observation in the database I/B/E/S represents a recommendation by a brokerage firm or individual analyst. I classify these recommendation changes into upgrades, downgrades or reiterations (no changes). I do not take into consideration the level of changes in the classification of recommendation. Most recommendations in the sample occur in the morning hours.

Data for companies are collected from the CRSP and the Nastraq database. The latter reports the best inside quotations in its inside file that I use to measure execution costs and price volatility. Volume is extracted from Nastraq trade files. To purge the Nastraq data of potential errors, I delete trades and quotations for which: (1) The trade price is zero or missing; (2) The quote is missing or negative; (3) The quoted bid-ask spread is negative; (4) The quoted bid or ask size is negative; (5) The trade and quote price is outside the regular hours. CRSP and Nastraq data need to be available for the stocks to be included in the final sample. This yields 155 stocks. Table 1 shows descriptive statistics for the 155 sample stocks. As shown in the table, the stocks in the sample tend to be large, with an average capitalization of \$5.90 billion, and more than 75% of the sample are large in size (\$4.39 billion). This may be explained by the fact that the sample is restricted to firms with analyst recommendation changes. These firms tend to be large and thus more followed by financial analysts. Daily share volume averages about 3.5 million shares, with a median about 1 million shares. Most stocks in the sample attract a relatively large number of market makers. On average, there are about 57 market makers active and the median number of active market makers is 55.

I use the market maker ID from NASTRAQ quote file in the matching with the I/B/E/S analyst code. This allows me to recognize the brokerage firms that can provide research coverage and market making for every Nasdaq stock in the sample. I identify the dealers with analyst affiliation, and divide the sample into recommendation changes coming from affiliated analysts to dealers, to the ones coming from a non-trading analyst.

### ***3 Difference-in-differences analysis***

In general, during unpredictable news events, one usually observes higher trading activity, higher trading volume, and increased volatility exposing market makers to a greater risk of holding undiversified portfolio. In response, market makers widen the bid-ask spreads, resulting in less liquidity available to meet client's demand. As market makers become more certain about the value of the asset, they will be more likely to provide liquidity and this leads to narrower spreads, as in Copeland and Galai (1983). Thus, they will be more likely to meet unexpected demands. In that sense, Madureira and Underwood (2008) document that Nasdaq market makers who have access to information generated by their financial analysts face less of an adverse selection problem. I test whether several standard measures of liquidity and trading activity improve in the case of affiliation. In what follows, I empirically compare market variables for each stock

in the cases the change in recommendation is coming from an affiliated analyst to a Nasdaq market maker to an event where the information is coming from a non-trading analyst. I use the *difference-in-differences* analysis to make this comparison. These strategies are panel data methods applied to sets of variables means in the case that some are in the affiliation sample and others are not (as a control sample). Thus, the affiliation is the cause variable of interest. The use of the same stocks is very important for identification to estimate what would have happened in the variable when affiliation changes. I describe the methodology for the market inside spread first, and then discuss the results for all the variables measuring market performance used in the study.

$$Spread_{i,t} = \beta_1 Changes_t + \beta_2 Affiliation_{i,t} + \beta_3 Affiliation_{i,t} * Changes_t + \alpha_i + \delta_t + \epsilon_{i,t} \quad (1)$$

Where *Spread* is the inside spread of stock *i* computed from the NBBO file (inside file) during the half-hour period that starts at time *t*; refer to the latter period as “interval *t*”.  $\delta_t$  is a time-specific fixed effect and  $\alpha_i$  is a stock-specific fixed effect. I consider the inside spreads of a given stock in the affiliation sample (Affiliation=1) before the news coming from the affiliated analyst and non-affiliation sample (Affiliation =0) before the news coming from a non-trading analyst, two hours prior to the announcement (Changes=1) and 20 days before the event period non-news events (Changes= 0). The effect of affiliation  $\beta_3$  is then obtained by:

$$DID = \beta_3 = \left\{ \begin{array}{l} (\mathbb{E}[Spread/Changes = 1, Affiliation = 1] \\ - \\ \mathbb{E}[Spread/Changes = 0, Affiliation = 1]) \\ - \\ (\mathbb{E}[Spread/Changes = 1, Affiliation = 0] \\ - \\ \mathbb{E}[Spread/Changes = 0, Affiliation = 0]) \end{array} \right\} \quad (2)$$

$\beta_3$  is the estimator which is called the *difference-in-differences* estimator, since one estimate the time difference for the affiliation and non-affiliation groups and then takes the difference. Note that the differencing step eliminates the fixed effect  $\alpha_i$  and the drift  $\delta_t$ . The model so far ignored the possibility that there remain observable differences in the factors that affect the spread on the day of the announcement and those of the day before the announcement. Then such differences must be controlled for. The standard solution is to include such controlling variables in the regression. I use the following variables defined by the literature that affect the inside spreads: the share

price volatility, the trade size and the share price itself, since it is well known that the inside spread is related positively to the price volatility and negatively to the trade size and share price. I include in the regression additional explanatory variables: the number of analyst following the stocks and the number of market makers, in order to control for the degree of competition across stocks. Note that the control variables are not orthogonalized. For example, the number of market makers and the number of analysts are correlated. Since they will not affect the *difference-in-differences* coefficient, I prefer to focus on the *Affiliation\*Changes* dummy. The model is then presented in equation (3):

$$\begin{aligned}
 Spread_{i,t} = & \beta_1 Changes_t + \beta_2 Affiliation_{i,t} + \beta_3 Affiliation_{i,t} * Changes_t + \beta_4 tradesize_{i,t} \\
 & + \beta_5 price_{i,t} + \beta_6 vol_{i,t} + \beta_7 mmcmt + \beta_8 No.analyst + \sum_{j=1}^4 \beta_j D_j + \sum_{h=1}^{12} \beta_h H_h + \epsilon_{i,t}
 \end{aligned}
 \tag{3}$$

Where *Tradesize* is the log of the trade size of stock *i* in “interval *t*”. *Price* is the log of the mid-point of the bid ask quotations of stock *i* in “interval *t*”; *vol* is the share price volatility in interval *t*, and provides a measure of the risk faced by market makers when trading stock *i*; *mmcmt* is the number of daily market makers following the stock. *No.analyst* is the number of analysts following a stock during the whole period of the study. Since the error terms will vary across the stocks, the model is estimated as a fixed panel model, in which case the firm specific residual may be a dummy variable. Moreover, in order to capture any deterministic component in the intraday dynamics of the spread, I control for the time of the day effect; the first “interval *t*” starts at 9:30 AM and the last ends at 4:00 PM, which produces 13 intervals per day. I use the last quote prior to the opening of the trading day as the first quote of the day, in order to compute the time-weighted spread of the first quote. Equation (3) includes dummies for each day of the week, *Dj*, in the sample.

### 3.1 Bid/Ask spreads

I measure the excess announcement trading costs by the inside quoted and effective spreads when there is affiliation. I estimate the parameters from Equation (2).

Table 2 shows a statistically significant change in the mean inside spread, represented by the *Affiliation\*Changes* dummy coefficient. The excess of inside spread prior to the announcement is lower than normal (-4.580) when there is affiliation, suggesting that the environment of affiliation offers lower transaction costs in the period leading to the announcement. I replicate the analysis by measuring the spread one hour before the

announcement instead of two hours. The results are quite similar. The *Changes* variable used in the regression separated dates on which there was a recommendation change from those on which there was no announcement. As a robustness check, the same study is replicated, where the variable *Changes* takes the value of zero on earnings days and the value of one on days of recommendation changes, as before. With this new *Changes* variable, the same regression equation (2) is estimated. If the *Affiliation\*Changes* turns out to be significant once again, then it provides further support that its significance does not depend on two different types of events (news and non-news days) being used in the regression. Most of the earning announcements in the sample are made in the afternoon. Unreported results are quite similar to the previous ones. Transactions costs are lower when affiliation exists as coefficients are significant. Taken together with the earlier ones, the results suggest that at times where there is information sharing between market makers and their financial analysts, market liquidity increases, i.e. lower transaction costs.

### 3.2 Price volatility, number of trades and market sidedness

Historical returns are now going to be utilized in order to measure the implications on stock return volatility. As in Andersen and Bollerslev (1998), the sum of squared returns (one-minute) over thirty minutes is computed, each return taken over a one-minute time interval, both during the two hours and during the control sample preceding the news release. Returns during the two hours preceding the news are very important for the purpose of the study, because critical information concerning the trade process and the impact of dealers' behavior needs to be taken into account. The midpoint quotations are used to obtain returns of each stock  $i$  over the one-minute interval mentioned above. One minute returns, squared, are summed over thirty minutes and the sum is used for obtaining an estimate of volatility. A concern with volatility is that large returns tend to cluster together followed by periods of relatively small returns (GARCH effects). This suggests that volatility is a temporally dependent (heteroskedastic) variable. Therefore, the volatility calculated as previously is likely to exhibit serial correlation. Since returns used in this study are computed using the midquote prices, any existing correlation would not come as a result of bid-ask bounce. In order to take into account the correlation, a separate equation for volatility is used in the regression which includes autoregressive terms (GARCH equation). I use the trading volume and the spread as control variables. The literature suggests that there is a positive linkage between transaction costs and price volatility. The theoretical support is that the informational arrival has the effect of widening the bid ask spreads and this induces an increase in volatility. This effect impacts prices, which become more volatile, since price changes



are in response to information flow. In Table 3, results show that the pre-announcement price volatility is significantly higher two hours before the news release compared to an hour of a non-announcement day. The coefficient of the interaction term is generally less significant but positive. For sensitivity analysis, I examine another measure of intraday volatility, i.e. the average volatility. The results are qualitatively the same.

Further results in Table 3 suggest that the affiliation is associated with a significantly higher number of trades. The pre-announcement increase in the number of trades might partially explain the reduction in the spread in the affiliation sample documented earlier. The price volatility increase simply reflects information flows given the pre-disclosure period has been a period of large revelation. Another plausible reason is that it might result from order arrivals coming on both sides of the market. To investigate this idea further, I use the market sidedness measure introduced by Sarkar and Schwartz (2009). It consists on computing the correlation between the number of seller-initiated trades and buyer-initiated trades in each interval. If the correlation is higher, this implies that the market is two-sided as a result of order arrivals at both sides of the market for the affiliation sample. Otherwise, the market is one-sided if the correlation is negative, suggesting that the arrival is more buy-triggered (sell) trades in the interval and accompanied by the arrival of fewer sell-triggered (buy) trades in the same interval. Results on the sidedness in Table 3 suggest that the market is more two-sided when affiliation exists: the correlation between the number of seller-initiated trades and the number of buyer-initiated trades is higher for the affiliation sample, which signals the creation of liquidity in the presence of affiliated market makers.

## 4 Discussion

The present empirical results focus on a specific period where Nasdaq dealers were less constrained by regulations and were maintaining market presence. The sample period used is 2004 at time where dealers were actively providing liquidity in Nasdaq listed firms on the Nasdaq system. Results here suggest that dealers with affiliation seem to be particularly bound to keep providing liquidity in stressed markets environments, specifically when they have access to their analyst report. While other factors are behind the reduction in market liquidity to today's equity markets, such as drastic structural changes and the implementation of the RegNMS since 2008, one can conjecture that the reduced market making by dealers caused by the new regulations does seem to aggravate the shocks to the markets during periods of market stress.

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**Table 1 – Descriptive statistics of stocks sample** – The table presents descriptive statistics for the 155 sample stocks during the period from June 1, 2004 to December 31, 2004. Market capitalization is computed as the mean daily market capitalization during the sample period using Center for Research in Security Prices (CRSP) data. Price per share is the mean of CRSP closing price during the sample period. Volatility is the standard deviation of daily returns during the sample period. Daily returns are computed from CRSP. Daily share volume is the daily mean share volume during the sample period using NASTRAD trade file. Proportional inside spread is the time-weighted mean inside half-spread during the sample period. Number of market makers is defined as the number of market makers who are active in a stock. Number of financial analysts is the number of financial analysts who are following a stock.

Variable	Mean	Std Deviation	25%	Quartile	
				50% (median)	75%
Market Capitalization (in \$ billions)	5.90	16.03	0.73	1.83	4.39
Price per share (in \$)	22.28	18.95	7.4	18.77	31.73
Volatility (in %)	2.86	1.16	2	2.65	3.54
Daily share volume (in shares)	3 586 530	9 070 623	465 405	1 058 659	2 794 922
Proportional inside spread	0.08	0.09	0.11	0.07	0.14
Number of market makers	57.35	18.26	43	55	70
Number of financial analysts	15.25	7.37	2	16	35

**Table 2 - Inside spreads prior to news' events** - Time-weighted spreads, effective and quoted, in an interval of thirty minutes, is regressed on constant and dummy variables in both periods: the first dummy variable, *Changes*, is set to one on the two hours before the announcement and 0 on hours of non-announcement days. The second dummy variable, *Affiliation*, equals one in the cases the observation belongs to the affiliation sample and zero otherwise Zero in both cases. The third dummy variable is used by multiplication (the interaction term) of the variables *Changes* and *Affiliation*. Control factors added to the regression are: price volatility, size of the trade, the price per share. There are recommendation changes for 155 stocks in the sample: 56% of recommendations are coming from non-trading analysts and 43% are done by affiliated analysts to market makers. Other control variables included in the regression also are the time of the day and day of the week effects; coefficients are not reported for brevity. The number in parentheses is the average standard error. The standard errors are corrected for contemporaneous correlation and heteroskedasticity. Boldface indicates significance.

Variable	Qspread	Espread
Constant	16.003 (8.682)	16.351 (13.765)
<i>Changes</i>	<b>4.73</b> (1.181)	<b>3.111</b> (1.873)
<i>Affiliation</i>	<b>-5.198</b> (1.67)	<b>-3.456</b> (2.648)
<i>Affiliation*Changes</i>	<b>-4.58</b> (1.181)	<b>-4.457</b> (2.469)
Price	<b>-0.297</b> (0.109)	<b>-1.1</b> (0.174)
Volatility	-0.006 (0.002)	<b>0.44</b> (0.003)
R-squared	0.14	0.40
No. of observations	11 647 855	11 647 855

**Table 3 - Price volatility, number of trades and quote-sidedness prior to news' events.**

This Table presents results on price volatility, volume and quote-sidedness two hours prior to the release of the recommendation changes with *Affiliation* =1 is compared to the one corresponding to observations with *Affiliation* =0. There are recommendation changes for 155 stocks in the sample: 56% of recommendations are coming from non-trading analysts and 43% are done by affiliated analysts to market makers. Other control variables included in the regression also are the time of the day and the fixed effects; coefficients are not reported for brevity. The standard errors in parentheses are corrected for contemporaneous correlation and heteroskedasticity. Boldface indicates significance.

Variable	Volatility	Ntrades	Sidedness
Constant	<b>0.102</b> (0.102)	<b>0.531</b> (0.099)	-0.089 (0.058)
<i>Changes</i>	<b>-0.044</b> (0.029)	<b>-0.501</b> (0.028)	<b>-0.041</b> (0.022)
<i>Affiliation</i>	<b>0.141</b> (0.041)	<b>0.142</b> (0.04)	0.014 (0.022)
<i>Affiliation*Changes</i>	<b>0.079</b> (0.038)	<b>0.038</b> (0.037)	<b>0.065</b> (0.026)
Spread	<b>0.116</b> (0.009)		
Trade Size	0.004 (0.009)		
R-squared	0.10	0.15	0.08
No. of observations	11 647 855	11 647 855	11 647 855