How Do Public Announcements Affect the Frequency of Trading in Stocks?

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Abstract

This paper examines how news releases and key microstructure features of market activities affect trading frequency in airline stocks. Using the autoregressive conditional hazard framework of Hamilton and Jordà (2002), we show that trading intensity significantly changes before, during and after firm-specific and macroeconomic announcements, but traders' reactions strongly depend on the type and weight of the news. We find that market microstructure variables have a small yet significant effect on trading frequency, with trade volume and price changes revealing more information than relative bid/ask spread. The results also clearly indicate that the intraday crude oil futures price changes are relevant to modelling the probability of a trade within the next time period.

Keywords: trading frequency, hazard models, announcements effect

JEL Classification: C22, C51, G14

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1 Introduction

There is consistent evidence that public announcements affect intraday trading behaviour in financial markets. Numerous studies suggest a significant and instantaneous response of asset prices, return volatility and trading volume to macroeconomic and company news. However, the relationship between the impact of information arrival and the frequency of trading has been largely neglected in the literature. The present study explains patterns in trading frequencies and provides insights into the mechanics of price discovery and the informational effectiveness of the markets.

Exactly how the information is impounded in prices is one of the "big questions" in the market microstructure and price discovery literature.[1] Several theoretical models describe the impact of news on the trading behaviour of different groups of investors. The informed speculation theories of Kyle (1985), Admati and Pfleiderer (1988) and Easley and O'Hara (1992) assume information asymmetry amongst (informed and liquidity) market participants and suggest that variation in market liquidity is partly due to scheduled public announcements. Other theories describe the effect of news events on the return volatility (see Nofsinger and Prucyk, 2003, for a review). These models imply that traders respond promptly to unexpected changes in the microeconomic and macroeconomic settings and that the rate at which transactions take place (i.e. trading frequency) plays an important role in determining the dynamics of financial markets and the market efficiency. Trading frequency determines how quickly prices, volatility and volume respond to an announcement and how long any response lasts. This study differs from others that look at microstructure effects on stocks as it directly models the trading intensity and estimates the probability of trade in the next time interval, using the new Autoregressive Conditional Hazard (ACH) model of Hamilton and Jordà (2002).

The empirical investigation into the effects of macroeconomic and firm-specific news on trading frequency is conducted using high-frequency transaction and order data for three major American airline equities traded on the New York Stock Exchange (NYSE). An important contribution of this research is its announcements and information dataset that consists of a standard set of real-time United States (U.S.) government scheduled announcements (as in Andersen et al., 2003 or Albuquerque and Vega, 2006) as well

[1] O'Hara (1995) is the classic reference for the economics of market microstructure. Recent surveys include Madhavan (2000), Stoll (2003) and Biais et al. (2005). Price discovery process is discussed in Hellwig (1980), Milgrom and Stokey (1982), Easley and O'Hara (1987) and Easley and O'Hara (1992).

as company news published by newswires. This is further supplemented by the New York Mercantile Exchange (NYMEX) intraday futures crude oil contract price data. The significance of the present research design is twofold. Firstly, it allows for a unique study of how airline stocks and crude oil prices interact. Secondly, it facilitates an innovative investigation of the informational efficiency of the crude oil futures prices.

The remainder of the paper is organized as follows: the next section briefly reviews papers which analyse the impact of public announcements on the market microstructure, asset returns and the volatility. Section 3 discusses the most important features of the ACH model and its usefulness in modelling the frequency of trade. Data and its statistical properties are described in Section 4. Section 5 presents model estimates and summarises the effects of new releases and crude oil futures returns on trading frequency. Section 6 offers conclusions.

2 How Do Public Announcements Affect Financial Markets?

The pioneering event study of Fama et al. (1969), drawn on the efficient market hypothesis (Fama, 1965) that capital markets are efficient mechanisms to process publicly available information, has been followed by a large amount of research. Interestingly, early papers considering the study of Fama et al. (1969), particularly the ones based on daily (or even less frequent) data, often report little or no evidence for the relationship between interest rates or equity prices and the arrival of public information. Dwyer and Hafer (1989) find that three-month Treasury bill returns and 30-year Treasury bond returns practically do not respond to the unexpected part of the economic announcement (defined as the difference between the initial announced values of the series and the median analysts forecast). Hakkio and Pearce (1985), who use average of bid and ask quotes for spot exchange rates taken at 09.00, 12.00 and 16.30,[2] demonstrate that the exchange rate returns do not move in anticipation of the economic announcements and that they react to no economic news except for non-anticipated changes in the money stock. Damodaran (1989), in his study of a day-of-the-week pattern in the information content of dividend and earning announcements, finds that the announcements explain only a small fraction of the weekend effect in stock returns. Similarly, Cutler et al. (1989), who analyse fifty of the largest one-day price moves in

[2] All times quoted in this paper are New York times (i.e. Eastern Standard Time).

the Standard and Poor's Composite Stock Index since 1946, report that in most cases the information cited by the press as causing the market move "is not particularly important." However, McQueen and Roley (1993) report that the relationship between percentage changes in stock prices and macroeconomic surprises is significant if one allows for different states of the business cycle. In particular, they show that news of higher-than-expected real economic activity, when the economy is booming, lowers equity prices, while the same surprises during recession result in higher stock prices.

Once researchers start using high-frequency transaction data, macroeconomic news, including regularly scheduled macroeconomic announcements, is found to have a significant short-run impact on the intraday trading activities of financial markets. Much of the empirical literature studies how announcements affect the return volatility, using the generalized autoregressive conditional heteroscedastic (GARCH) framework of Engle (1982) and Bollerslev (1986), and examines the statistical significance of announcement variables. Other papers analyse the relationship between the public information arrival and asset returns, trading volume and bid-ask spread.

In the bond market, Ederington and Lee (1993) report that public announcements are a major source of price volatility in the Treasury bonds. Their study, based on five-minute futures returns, finds that the price volatility is significantly the highest between 08.30 and 08.35, when the major macroeconomic statistical releases are made, including the inflation indicators (CPI and PPI), employment reports and the Gross National Product (GNP). Fleming and Remolona (1999), who use one-minute data from the secondary market for U.S. Treasury securities, document that the arrival of macroeconomic news induces a two-stage adjustment process for returns, spreads and trading volume. They report that prices react sharply to the announcements for a brief spell of the first few minutes, with the bid-ask spread widening and a considerable reduction in volume. In a second stage, which lasts up to an hour, high trading volume (four times higher than that during non-announcement days), high return volatility and moderately wider than usual spreads are observed. Consistent results are reported by Bollerslev et al. (2000) and Balduzzi et al. (2001).

In the foreign exchange market, Bollerslev and Domowitz (1993), in an important paper that analyses the effect of news on the intraday volatility within the GARCH framework, find that the news provides "a powerful positive and strongly statistically significant contribution to movements in the conditional variance." Interestingly, they use the lagged bid-ask spread as a proxy for the news inflow, arguing that "news events which change traders' desired inventory positions result in order imbalances, with the potential of changing spreads" and that "news can be thought of as simply changing the relative demand and supply for the currency, which might also affect the spread." However, they reject hypotheses that other market activity variables have independent effects on the return volatility, in particular the intensity of quote arrivals.

In another FX study, Ederington and Lee (1995) use ten-second returns and tick-by-tick data to find that most of the price reaction to a scheduled macroeconomic announcement occurs within the first minutes, with volatility remaining higher than normal up to three minutes after the release. Working with slightly less frequent (5-minute) DEM/USD exchange rate returns, Almeida et al. (1998) demonstrate the same impact on returns within the first 15 minutes. Consistent with their findings, Andersen et al. (2003) show that conditional mean adjustments of exchange rates to news releases occur quickly, resulting in "jumps." However, they note that an announcement's impact depends on its timing relative to other related announcements.

Only a few empirical studies have highlighted the role of public information on the intraday price formation process in the equity markets. In general, stock prices and return volatility are also reported to respond to public announcements, but there are conflicting findings with regard to the speed at which the information is incorporated. For example, Adams et al. (2004) report that while CPI and PPI surprises have a significant negative impact on 15-minute investment returns, it takes up to 80 minutes for stock prices of large firms traded on the NYSE to adjust to the inflation news (this includes an hour before the release is made and the exchange opens). However, their results are not robust, with one-hour returns being barely affected by the announcements. This is in contrast to Jain (1988), who reports that CPI (but not PPI) and money-supply announcements are correlated significantly with one-hour investment returns.

A common aspect of most studies is that they examine the impact of macroeconomic announcements only, ignoring the role of firm-specific news. The few papers that do explore the role of company-related information in explaining price discovery concentrate on scheduled earning and dividend announcements, in isolation of other public releases. Moreover, there is no consensus on how fast stocks respond to such news. Patell and Wolfson (1984), in one of the first studies that uses intraday data, report that stock prices respond to dividend and earnings news "within a few minutes, at most," but — in contrast to jumps observed in the FX market — the impact of news is "spread evenly over the first several post-announcement trades" (Greene and Watts, 1996). Even slower reactions to substantial shifts in dividend policy are documented by Gosnell et al. (1996). More recently, Brooks et al. (2003), in a unique study that analyses the impact of unexpected negative company news events on the equity market (such as plane crashes or plant explosions), report a relatively slow reaction of traders, with the initial price reaction of over twenty minutes.

This work complements the study of Brooks et al. (2003) and focuses on the impact of both scheduled and unscheduled macroeconomic and firm-specific announcements rather than scheduled statistical releases only. Furthermore, this study closely investigates the impact of news events on trading frequency, and as such contributes to the debate about the equity markets efficiency. The research is methodologically innovative, in that it uses the ACH framework, as discussed in the proceeding section. This is in contrast to most of the empirical studies that use simple regression techniques — or, in case of the effects of news on the return volatility — ARCH/GARCH models.

3 An Autoregressive Conditional Hazard Model

An autoregressive conditional hazard (ACH) model of Hamilton and Jordà (2002) is a statistical tool used for modelling the dynamics of discrete-valued dependent variables. The ACH model is based on hazard models, commonly used in statistics to analyse duration/survival data (for an excellent introduction see Lancaster, 1990). *Hazard rate* (or *hazard function*) is defined as a (limiting) conditional probability of an event occurring in the next time period, given the information set Ω_{t-1} known at present. In our case, we examine the probability of a trade occurring by the end of the next time interval, given a news announcement and other information events in the previous time period.

It is a well-known fact that quotes and trades arrive at unevenly spaced time intervals, and the autoregressive conditional duration (ACD) framework of Engle and Russell (1998) is the most standard way of modelling high-frequency and irregularly spaced financial transaction data. In the ACD framework, the waiting time until the next trade is intertemporally correlated with the past durations. However, it is difficult to model the distribution of a duration when new information arrives within the analysed time interval (i.e. *between* the trades). Zhang et al. (2001) attempt to account for structural breaks in high-frequency data, that correspond to information events, using a nonlinear threshold ACD model. A natural extension of Zhang et al. (2001) work is to incorporate announcement variables into the ACD framework. However, it is often of more interest to know how likely it is that a trade will occur within the next 5 or 15 seconds, given the news release, than knowing how much time is expected to pass before the next trade occurs (Hamilton and Jordà, 2002). The autoregressive conditional hazard framework concentrates on the former issue whilst also utilising the ACD methodology of including past duration in the information set Ω_{t-1}. The ACD and ACH frameworks are explained in detail in Engle and Russell (1995, 1997 and 1998), Hamilton and Jordà (2002) and Demiralp and Jordà (2001). The most important features of the ACH model in the context of modelling high-frequency data are described below.

Consider a stochastic process that is a sequence of trade arrival times $\{t_1, t_2, \ldots, t_n\}$ with each nth trade arriving at the end of time t_n and $t_1 < t_2 < \cdots < t_n$. Also consider an associated *counting process* N_t, which is the cumulative number of events that have occurred by the end of time t (so $N_t = N_{t-1}$ if an event does not occur in the interval $(t-1, t]$ and $N_t = N_{t-1}+1$ if it does).

The length of time (the interval) between the $(n-1)$th and the nth arrival times is called a *duration* u_n, that is, $u_n = t_n - t_{n-1}$. The ACD(p, q) model predicts that the expected duration u_n is a weighted average of p past durations and q past expected durations, that are known at time t_{n-1}. That is, given past observations $u_{n-1}, u_{n-2}, \ldots$, the ACD(p, q) model implies that

$$\mathbb{E}[u_n | u_{n-1}, u_{n-2}, \ldots] \equiv \psi_n = \omega + \sum_{j=1}^{p} \alpha_j u_{n-j} + \sum_{j=1}^{q} \beta_j \psi_{n-j}. \tag{1}$$

Using the definition of the counting process, Hamilton and Jordà (2002) rewrite equation (1) as[3]

$$\psi_{N(t)} = \omega + \sum_{j=1}^{p} \alpha_j u_{N(t)-j} + \sum_{j=1}^{q} \beta_j \psi_{N(t)-j}. \tag{2}$$

The expected duration written as (2) is a *step function* that only changes if the trade occurs during time interval $(t-1, t]$, i.e. only when $N_t \neq N_{t-1}$. In this setting the *hazard rate* h_t is defined as

$$h_t \equiv \Pr\left(x_t = 1 \mid \Omega_{t-1}\right) = \Pr\left(N_t \neq N_{t-1} \mid \Omega_{t-1}\right), \tag{3}$$

[3]Please note that we use N_t and $N(t)$ interchangeably to denote the same process, with the latter notation used to avid double-subscripts, as in equation (2).

where $x_t = 1$ if the event of interest happens within $(t-1, t]$ and $x_t = 0$ otherwise.[4]

As with the ARCH and ACD models, equation (2) can be easily generalised to account for linear effects of exogenous variables $\mathbf{z}_{t-1}$ known at time $t-1$, such as public news releases, crude oil prices and market microstructure variables. However, these covariates (with the exception of market microstructure variables) are not restricted to change if and only if a trade occurs. Indeed, the key feature of the ACH model is its ability to study effects of announcements that occur *between* trades. This implies that the expected duration ψ_t may change by the end of every (calendar) time interval, through

$$\psi_t = \psi_{N(t)} + \delta \mathbf{z}_{t-1}. \tag{4}$$

where δ denotes a vector of parameters.

The relationship between the hazard rate and the conditional duration can be derived using properties of the geometric distribution. The expected length of time until the next trade is

$$\psi_t = \sum_{j=1}^{\infty} j \left(1 - h_t\right)^{j-1} h_t = \frac{1}{h_t}, \tag{5}$$

or

$$h_t = \frac{1}{\psi_t}. \tag{6}$$

The reciprocal relationship between the expected duration and the hazard rate makes sense intuitively: if the expected length of time until the next trade is, for example, four minutes, then the probability of a trade within the next minute is 0.25. Correspondingly, if the expected duration is two minutes, than the probability of a trade occurring within the next minute is 0.5. Of course, changing units in which time is measured affects the magnitude of the expected duration and the corresponding hazard rate. For instance, if the expected duration is $\psi = 2$ minutes or 120 seconds, then the probability of a trade within the next time period is 0.5, if time is measured in minutes, or 1/120, if time is measured in seconds. This highlights the need for avoiding lengthy time intervals, as the probability of a trade occurring within every such period

[4] We follow Hamilton and Jordà's 2002 definition of the hazard rate. However, in the duration literature a definition of an instantaneous rate of event occurrence per infinitesimally unit of time is often used. That is,

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr\left(x_t = 1 | \Omega_{t-1}\right)}{\Delta t}.$$

Scaling by Δt implies that the hazard rate can be any positive number. This is in contrast to the hazard rate implied by equation (3), which is bounded between 0 and 1.

is, uninterestingly, almost always equal to one.

Feasible estimation of the parameters of interest requires some model modification, though, as at the time of the $(n-1)$th trade (when the expectation about ψ_t is formulated) the value of N_t is unknown, as are the values of $u_{N(t)-j}$ or $\psi_{N(t)-j}$. To overcome this problem, Hamilton and Jordà (2002) specify the hazard rate as the reciprocal of the expected duration lagged one period. However, this approach does not utilize all the data available at time $t-1$, which prompts us to modify the model as per following

$$h_t = \frac{1}{\psi_t}, \tag{7}$$

$$\psi_t = \omega + \sum_{j=0}^{p-1} \alpha_{(j+1)} u_{N(t-1)-j} + \sum_{j=1}^{q} \beta_j \psi_{t-j} + \delta \mathbf{z}_{t-1}. \tag{8}$$

Then the parameters in (8) can then be estimated using maximum likelihood techniques, with the conditional log-likelihood specified as

$$\mathcal{L}(\theta) = \sum_{t=1}^{T} \left\{ x_t \log(h_t) + (1-x_t) \log(1-h_t) \right\} \tag{9}$$

where $\theta = (\omega, \alpha', \beta', \delta')'$. Possible extensions of the model could include semiparametric and nonparametric estimation techniques, as in the closely related framework of Gerhard and Hautsch (2001).

In Section 5, we show that the above specification of the model allows for efficient and flexible modelling of the conditional probability of trade in the next time interval, with the crude oil prices and announcement variables included in $\mathbf{z}_{t-1}$. Furthermore, we anticipate extending the model so that it can account for nonlinearities and asymmetry in the response of stock prices to information (asymmetries in adjusting to good/bad news are reported for example by Gosnell et al., 1996, in their study of dividend announcements). A smooth transition ACH framework will be developed for this purpose, in line with the research work of Teräsvirta and Anderson (1992), Anderson and Vahid (1998, 2001) and Anderson et al. (1999).

4 Data Source and Properties

4.1 Airlines Intraday Data

The airline industry provides a unique and exciting opportunity to model the frequency of trading whilst analysing markets informational efficiency and "trading spillovers" in context of the stock and crude oil futures prices, as discussed in section 4.2. However to the best of our knowledge, there are no empirical studies based on the high-frequency airline equity data. Instead, most authors investigate intraday behaviour of either a single IBM stock (Engle and Russell, 1995 and 1998, or Rydberg and Shephard, 2003, to name a few) or the constituents of the Dow Jones Industrial Average (see for example Andersen et al., 2001, Hasbrouck and Seppi, 2001 and Hansen and Lunde, 2005). In contrast to these studies, our empirical analysis focuses on the transactions and order data for three airline companies listed on the New York Stock Exchange (from the NYSE TAQ database), observed during August and September 2006.

Air transport is one of the world's largest industries, with a history of strong underlying growth in traffic volumes and revenues. The direct value of the U.S. commercial air transport was estimated to be more than $100 billion in 2000; $163 billion including aircraft, aircraft parts and airport expenditures (DRI-WEFA, Inc., 2002). Despite this, the behaviour of air travel is also highly cyclical, with growth falling dramatically when the economy is in a recession. After exhibiting strong growth during the late 1990s, the industry experienced an unexpected downturn in air travel resulting from the terrorist attacks in the U.S. on 11 September 2001, the Iraq war and the Severe Acute Respiratory Syndrome (SARS) epidemic in 2003. The huge financial losses incurred by airlines since 2001 ($32.3 billion dollars between 2001 and 2004, per ATA, 2006) have presented enormous challenges to the industry, and forced many airlines to embark on programmes of severe cost-cutting and fleet rationalisation, with some large U.S. carriers filing for bankruptcy (United Airlines and U.S. Airways).

A strong recovery in traffic volumes during 2004 coincided with the year of strongest global economic growth for three decades (UN-DESA, 2005). In 2005, the scheduled world airline industry generated revenues of nearly $413 billion (IATA, 2005). During 2003–2006, total operating revenues of the U.S. airlines increased on average 12.12 percent per annum (ATA, 2006), with a rise in the real passenger air transportation output of 21.93 percent in 2005 (BEA, 2006). However, the increase in total operating revenues did not translate into a profit recovery primarily due to the huge increase in fuel costs (world oil prices at some point in 2005 reached $70 a barrel).

During the analysed time period (August and September 2006), the crude oil prices reached a long-time peak of nearly $77 a barrel (early August 2006), and then fell more than $12 in mid-September (NYMEX, 2006). The Dow Jones Industrial Average rose to 11,669.39 on 26 September, its then highest close of 2006 and the second-highest close of all time (Patterson, 2006). Airline industry became "one of the hottest sectors," quickly recovering from the effects of the terrorist plot in London on 10 August and increased security measures. On average, major U.S. airline stock prices went up 15.3 percent between 20 August and 20 September, outperforming analyst rankings by 70–80 percent (Wenning, 2006). Figure 1 illustrates the price behaviour of three major airlines stocks and the Standard and Poor's 500 Index during this period. Receiving lots of media coverage, airline stocks were traded almost continuously, becoming a perfect candidate for an intraday empirical study.

[**FIGURE 1 ABOUT HERE**]

Out of seven U.S. listed airlines traded on the NYSE[5] in August 2006 (common stocks), AMR Corporation, Southwest Airlines Co. and U.S. Airways Group Inc. have been chosen for the further analysis, based on a ranking from the U.S. Department of Transportation, Bureau of Transportation Statistics (Smallen, 2006). Table 1 reproduces Table 3 of the 2005 ranking, which lists the top ten U.S. airlines, ranked by 2005 domestic and international enplanements (i.e. by the number of passengers traveling on private planes).

[**TABLE 1 ABOUT HERE**]

Airlines belonging to the AMR Corporation, American Airlines and American Eagle Airlines, carried together 115.6 million passengers on their international and domestic flights during 2005, more than any other airline. American Airlines ranks among the largest scheduled passenger airlines and the largest scheduled air freight carriers in the world (Smith Barney, 2006); during 2005 it provided scheduled jet service to approximately 150 destinations around the world (NYSE, 2006). The American Eagle Airlines, a wholly owned subsidiary of AMR, was the fastest growing of the top 10 airlines, carrying 17.9

[5] Traditionally, stocks of larger and more frequently traded firms are listed on the NYSE, rather than on Nasdaq or AMEX. This study focuses on large firms — and hence on the NYSE — to avoid thin-trading and insider-trading problems (see Easley et al., 1996, for discussion on how the probability of trading based on private information depends on trading volumes).

percent more passengers in 2005 than in 2004. The American Eagle carriers provide connecting service from eight of American's high-traffic cities to smaller destinations throughout the North America and the Caribbean (NYSE, 2006).

Second, in both the size and growth rankings were Southwest Airlines, which carried 88.4 million passengers in 2005; an annual growth of nine percent. Southwest is a domestic low-fare airline that provides frequent flights to 61 airports in 31 states throughout the United States. In 2005, the company operated 445 Boeing 737 (NYSE, 2006).

The next three positions in the top U.S. airlines ranking belonged to Delta, United and Northwest Airlines. Given that none of these airlines are currently listed on the NYSE, the U.S. Airways Group has been included in the analysis in their place. U.S. Airways direct and indirect subsidiaries, U.S. Airways and America West Airlines, respectively, jointly carried 64 million passengers on their flights in 2005, 50 percent more than Continental Airlines which were ranked sixth. In 2005, U.S. Airways operated 232 jet aircraft and provided service to 91 cities in North America and Europe. In the same year, the America West Express fleet was compromised of 62 regional aircrafts.

The intraday data for the empirical analysis is obtained from the NYSE Trade and Quote (TAQ) database, supplied by Wharton Research Data Services. TAQ contains time-stamped historical details of all individual trades and orders placed on U.S. stock markets. Each transaction contains a time stamp, measured in seconds after midnight, that reflects the time at which the transaction occurred, details of the actual trade price, the transaction volume (i.e. the total number of shares of a stock bought/sold) and the sales condition. Each quote record includes the order's date and time, bid price and size, offer price and size as well as quote condition. The richness of the data allows for calculation of other variables with which financial econometricians are concerned, such as duration between trades, nominal and percentage price changes, bid-ask spread and proportion of buys. By incorporating such variables into the model, we are able to examine how key microstructure features of market activities affect the trading frequency of stocks. Methodological issues and stylized facts about continuous–time datasets are discussed in Goodhart and O'Hara (1997), Guillaume et al. (1997) and Hautsch (2004). Theoretical studies that analyse market microstructure are outlined in O'Hara (1995) and include Kyle (1985), Admati and Pfleiderer (1988) and Easley and O'Hara (1992).

To get the data into a form suitable for analysis, we must first make several adjustments and apply filters to eliminate erroneous quotes and trades.

Firstly, we remove trades and orders posted on exchanges other than the NYSE. The NYSE quotes have been shown to determine (or, if not, to match) the national best quote most of the time (Blume and Goldstein, 1997) and since all trades on any exchange must be executed at the national best quote, Engle and Patton (2004) argue that other exchanges are simply not relevant.

Next we remove trades that are out of time sequence or cancelled (TAQ's CORR field other than zero or one) or have non-standard sales condition, such as delivery of the stock at some later date (TAQ's COND field not blank nor E). We also eliminate quotes that do not arrive under normal trading conditions or do not have news arrival indicators (TAQ's MODE field must be equal to 1, 2, 3, 4, 6, 10, 11, 12, 19, 20, 27, or 28). Further, we exclude trades and quotes with non-positive prices, or if the bid/ask/trade price is greater (less) than 150% (50%) of the previous bid/ask/trade price (Boehmer et al., 2005). Finally, we eliminate quotes with spreads larger that \$4 or less than \$0 (Huang and Stoll, 1994).

Once the data has been cleaned, we then match trades and quotes using the "two seconds rule" proposed by Lee and Ready (1991) and recently updated by Vergote (2005) (see also Piwowar and Wei, 2006). According to this algorithm, trades are matched with quotes that are time-stamped at least two seconds before the trade. Then we remove transactions that occurred outside the NYSE regular trading hours or within the first 15 minutes of each trading day, to remove the opening auction noise. Finally, we merge any simultaneous trades to eliminate zero trade durations (Engle and Patton, 2004). Table 2 presents the number of observations before and after the aggregation of simultaneous trades, and the summary statistics of the aggregated data. All stocks are traded extremely frequently, with trade durations averaging between 7 and 11 seconds. An average transaction has a volume of 519 to 1,144 shares and a bid-ask spread of 1 to 4 cents. We observe overdispersion in the distributions of trade durations and volumes (as the standard deviation exceeds the mean) and strong positive skewness, which indicates a declining proportion of long durations/large spreads/big volumes. All variables exhibit significant autocorrelation, as formally tested using the Ljung-Box statistics. This is further documented in Figure 2, that shows the autocorrelation (ACF) and partial autocorrelation functions (PACF) of trade durations. We observe positive, highly significant and very persistent autocorrelations, that are characteristic for long memory processes. Further, both durations and trade frequency reveal very strong diurnal seasonality (see Figure 3). The probability of trade exhibits a U-shaped pattern over the course of the day, that is also characteristic of volatility, trade volumes and bid/ask spreads. On average, trades are about twice as likely to occur during the opening auction and immediately prior to the market's close than during lunch-time. Conversely, the time-of-day seasonality in trade durations exhibits an inverse U-shape, as first documented by Engle and Russell (1998).

[TABLE 2 ABOUT HERE]
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4.2 Crude Oil Futures Prices

In his seminal paper, Hamilton (1983) points out that all but one of the U.S. recessions between the end of World War II and 1973 were proceeded by a sharp rise in the price of oil. Further, he finds a strong negative relationship between oil price changes and GNP growth. Subsequent empirical studies of Burbidge and Harrison (1984), Gisser and Goodwin (1986), Rotemberg and Woodford (1996), Mork (1989) and Raymond and Rich (1997), to name a few, confirm that there is a statistically significant negative correlation between oil prices and aggregated measures of economic activity. While this relationship is sometimes reported to be much weaker when the sample period is extended to the 1990s (Hooker, 1996), the new research attributes this to misspecification of the functional form. In particular, Hamilton (1996, 2003) and Balke et al. (1998) demonstrate that the relationship between crude oil prices and macroeconomic indicators is nonlinear.

Regardless of the functional form, all financial markets anticipate shocks to oil prices and respond to them quickly.[6] This is not surprising, as oil — "the lifeblood of America's economy" (U.S. Department of Energy, 2006) — supplies more than 40 percent of U.S. total energy demands. Studying shocks to oil market is particularly relevant to modelling frequency of trading of the airline stocks, given that refined crude oil is used to produce a wide array of petroleum products, including diesel and jet fuels. However, this is not an easy task, as oil prices are affected by a wide range of factors, and oil shock is not strictly defined (Hamilton, 2003). One should observe the current political situation and military developments in OPEC countries (with the Iranian uranium enrichment program being the most discussed news during summer 2006) and in the Middle East in general (see Twin, 2006 and Evans, 2006

[6]References to oil prices in Western news reports are usually either references to the spot price of either West Texas Intermediate (WTI, also known as Texas Sweet Light) as traded on NYMEX or the price of Brent as traded on the Intercontinental Exchange (ICE). WTI sets the benchmark in oil pricing and the underlying commodity of the NYMEX oil futures contracts (EIA, 2006).

for the impact of the recent Israel–Lebanon conflict on oil prices). However, there are other variables affecting oil markets, such as OPEC announcements, reports from the U.S. Department of Energy regarding Strategic Petroleum Reserve, the circumstances of major oil companies (such as BP, Exxon, Mobil, Shell, ChevronTexaco and ConocoPhillips) and weather warnings (for example, almost all of the Gulf of Mexico's refineries, that produce 25 percent of the U.S. oil, were closed in August 2005 due to Hurricane Katrina — which resulted in record crude oil prices of $US 70.85 a barrel, ABC News, 2005). Following all events and announcements that move oil prices is hardly feasible.

An alternative approach employed in this study is to include option or futures crude oil contract prices in the model. According to the efficient market hypothesis, these prices unbiasedly incorporate all information available to market participants. We choose to include the NYMEX light, sweet crude oil futures contract, as it is the most liquid and actively traded financial instrument on a physical commodity in the world (NYMEX, 2006). As such, the advent of tick-by-tick crude oil futures prices data in the model not only serves as a proxy for a (potentially) incomplete set of the oil surprises, but it also allows for an innovative investigation of trading spillovers and the informational efficiency of the crude oil futures prices. Current front-month light, sweet crude oil futures transaction data used in this study comes from the Comprehensive Quotes and Graphics (CQG), an official NYMEX data vendor.

4.3 Firm-Specific News Releases

Company announcements data has been collected from the NYSE website (`http://www.nyse.com`). The NYSE provides market participants with the latest company SEC filings, news stories and press releases, obtained from the Dow Jones Business News and PR Newswire. The time of the Dow Jones Business News announcements have been adjusted according to the dataset available from the Smith Barney webpage (`https://www.smithbarney.com`), where the identical news items are systematically published 15 minutes earlier than on the NYSE. Several interesting announcements are included in the sample, such as monthly traffic reports, fares raises and CEO changes. Moreover, news stories related to the August 2006 U.K. terror plot are incorporated in the dataset. Information about the number of analysed announcements for each company is provided in Table 3.

[TABLE 3 ABOUT HERE]

There are 42 AMR-related releases in August 2006, and nine announcements for both U.S. Airways Group and Southwest Airlines. The sample sizes for September 2006 are considerably smaller, with eight, three and one releases for AMR, LCC and LUV, respectively. However, similarly few announcements are recorded for June and July 2006, which implies that the August 2006 activity was higher as usual. In our empirical analysis, we partition firm-specific news into five groups: analyst reports, earnings related releases (such as new routes and fares announcements, or traffic reports), security related news, marketing announcements and others. We then study the effect of each announcement individually and jointly with the other releases of the same type.

4.4 Macroeconomic Announcements

There is extensive literature on macroeconomic factors which help to model and predict business cycles. When choosing variables that compactly approximate macroeconomic activities, Sims (1980) suggests using a relatively small system of two output measures (real GNP and unemployment), three price indicators (implicit price deflator for nonfarm business income, hourly compensation per worker and import prices) and a money sector statistics (the M1 series). However, investors seem to react to more than just six macroeconomic news releases, and in event studies authors tend to use the widest possible set of macroeconomic announcements. Examples include Dwyer and Hafer (1989), Balduzzi et al. (2001), Hautsch and Hess (2002) Nofsinger and Prucyk (2003), Andersen et al. (2003) and Albuquerque and Vega (2006). We follow their approach and include all of the most influential announcements made by the U.S. federal agencies. To determine the initial set of potentially "influential," or price sensitive announcements, we follow the free Internet financial services, such as `Yahoo` and `briefing.com`, and concentrate on statistics that have an importance ranking of A and B. Further, we only include releases made during the analysed NYSE trading hours (09.45 – 16.00 EST). Table 4 lists the macroeconomic statistics that are considered in this study along with the sample sizes.

[TABLE 4 ABOUT HERE]

It should be noted that several federal agencies release some key macroeconomic statistics at 08.30 (i.e. outside the NYSE trading hours). The implication is that the effects of announcing inflation indicators, unemployment figures and the GDP growth (reported by the Bureau of Labor Statistics and the Bureau of Economic Analysis, respectively) are not included in the present analysis. These macroeconomic announcements can be only examined in the context of interest and FX rates, since all American stock exchanges have the same trading hours (see for example Ederington and Lee, 1993). Also a few principal economic indicators published by the Federal Reserve, namely money stock measures (H.6) and factors affecting Reserve balances (H.4.1) are released outside the NYSE trading hours, generally at 16.30. However, according to Bloomberg, most investors judge monetary policy by the level of the federal funds rate and not the various money supply measures.

In addition to the macroeconomic announcements, we also include the results of the U.S. Treasury Bill auctions in the dataset, since interest rates and interest rate spreads have always been of particular interest to the researchers. Stock and Watson (1989) find that two interest rate spreads — the difference between the six-month commercial paper rate and six-month Treasury bill rate, and the difference between the ten-year and one-year Treasury bond rates — are important to include in their newly constructed index of leading economic indicators.

Moreover, a few forward-looking indices are included in the announcement data. There are two consumer spending statistics: the University of Michigan Consumer Sentiment Index (reported as useful in predicting current changes in consumer purchasing behaviour by Carroll et al., 1994) and the Conference Board's Consumer Confidence Index (found to have asymmetric effects on the returns and volatility of Dow Jones Industrial Average, Gulley and Sultan, 1998). These indices are based on monthly surveys of 500 and 5,000 U.S. consumers, respectively. We also analyse the effects of two national surveys of purchasing managers, the ISM National Manufacturing Index and the ISM National Non-Manufacturing (Services) Index. These indices are the most widely watched economic indicators produced by the private sector, with the former considered to be one of the best predictors of the business cycle over the years (Bloomberg, 2006). We also include the Chicago Fed National Activity Index (CFNAI) — a monthly index of economic activity and inflation compromised of 85 monthly indicators, such as "production and income; employment, unemployment and hours; personal consumption and housing; and sales, orders and inventories" (Federal Reserve Bank of Chicago, 2006). The CFNAI is based on the methodology that was used to construct the original Experimental Coincident Index of Stock and Watson, developed in 1989 and advanced in 1999. Further, the CFNAI equivalent from Philadelphia and the Business Barometer Index published by the National Association of Purchasing Managers in Chicago are included.

We analyse *periods* before, during and after the announcements are made. We would prefer to follow Dwyer and Hafer (1989), Damodaran (1989), Balduzzi et al. (2001) and Andersen et al. (2003) and analyse the effect of *unexpected* news (defined as the difference between expected and actual announcements). However, while it is possible to use consensus specialist forecasts as proxies for market expectations regarding scheduled macroeconomic releases (for example, market expectations from the International Money Market Services are widely considered to be fairly accurate and unbiased, see Pearce and Roley, 1985, McQueen and Roley, 1993 and Almeida et al., 1998), the majority of company announcements are not quantitative, which implies that the reliable decomposition into expected and unexpected components is not feasible. In this aspect, our study is similar to DeGennaro and Shrieves (1997), Ederington and Lee (2001) and Chang and Taylor (2003).

5 Empirical Results

5.1 ACH Estimates

The empirical analysis focuses on modelling the probability of a trade occurring within one-second intervals. This ultra-microstructure approach is dictated by the data: all three stocks are very frequently traded and about a fifth of all trade durations are equal to one second (the average trade duration ranges between 7.3 and 10.5 seconds). Working with one-second intervals allows us to estimate the effect of information arrival on market activity with precision unmatched by other studies. However, this precision comes at a cost, as the dataset grows considerably from 92,362 – 132,705 tick-by-tick observations over the two month period to 967,500 observations (for example, to have an equivalently big sample of 5-minute intervals, one would need 600 months, or 50 years of data).

We estimate the models using the observed, not diurnally adjusted data. Following Engle and Russell (1998), empirical researchers often choose to first filter out the deterministic time-of-the date effects and then fit the models to diurnally adjusted series. However, this approach is not feasible when the dependent variable is binary, which prompts us to estimating models with time indicators designed to account for the intradaily seasonality in a parsimonious way. Table 5 reports results for the baseline model, i.e. the univariate ACH(1,1) with four time indicators, specified as

$$h_t = \frac{1}{\psi_t} \tag{10}$$

$$\psi_t = \omega + \alpha_1 u_{N(t-1)-1} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} \tag{11}$$

where $I_{t\in\tau(j)}$ denotes the time indicators and j = (9:45–10:59), (11:00–11:59), (12:00–13:59) and (14:00–14:59). The obtained parameter estimates are all statistically significant and similar to these reported in intraday GARCH and ACD studies, with little updating in the process (small α_1), long memory in expected durations (β_1 close to one) and considerable persistence ($\alpha_1 + \beta_1$ very close to one). This model does not account for all autocorrelation in the data, but it still does a good job of predicting whether a trade will occur within the next time interval. The proportion of correct predictions from the model that a trade will occur within the next time interval is 58.52% for American Airlines, 60.85% for U.S. Airways Group 57.07% for Southwest Airlines.

[TABLE 5 ABOUT HERE]

After comparing the total likelihood, the BIC selection criterion and statistical significance of parameter estimates for various ACH specifications, we choose to model the data using the ACH(2,1) model. To account for the effects of market microstructure, we include relative bid/ask spread, logarithmic trade volume and logarithmic return in all equations, see Dacarogna et al. (2001) for definitions and stylized facts. We also include logarithmic returns of the current front-month NYMEX light, sweet crude oil futures contract. Table 6 reports parameter estimates for the univariate ACH(2,1) model with crude oil futures returns, market microstructure variables and time indicators.

[TABLE 6 ABOUT HERE]

The ACH(2,1) model with market microstructure variables and crude oil future returns has better likelihood and BIC statistics than the baseline ACH(1,1), and predicts more precisely whether a trade will occur within the next second. The model provides an accurate approximation to trade frequency dynamics, as documented in Figure 4 (the left panel) that plots the average observed and fitted hazard rates closely following each other. Finally, the diagnostic analysis of the standardized binary residuals, defined as

$$\varepsilon_t = \frac{x_t - \hat{h}_t}{\sqrt{\hat{h}_t \cdot \left(1 - \hat{h}_t\right)}}, \tag{12}$$

indicates that diurnal seasonality and most of the autocorrelation in the data are well accounted for (see right panel of Figure 4 and Figure 5).

[FIGURE 4 ABOUT HERE]
[FIGURE 5 ABOUT HERE]

Market microstructure variables have a small and significant effect on trading frequency, with trade volume and price changes revealing more information than relative bid/ask spread. The coefficients on past trade volume are negative and strongly significant for all stock, which implies that a higher volume per trade shortens the next conditional duration. This is consistent with the Easley and O'Hara (1992) model and previous empirical results of Bauwens and Giot (2000) and Dufour and Engle (2000). However, in contrast to predictions from the Easley and O'Hara (1992) model, we find that trades are more likely to occur as the bid/ask spread narrows. This finding is in line with Dufour and Engle (2000), whose empirical findings also imply that if there is any relationship between trade durations and bid/ask spread, it is positive but statistically weak. The evidence concerning the dynamic relationship of returns and trade frequency is mixed. The estimates for American Airlines and U.S. Airways suggest that as the prices rise, the conditional propagability of trade significantly decreases. However, directly opposite results are obtained for the Southwest Airlines.

We find that crude oil futures returns are significant in modelling the frequency of trading in AMR and LCC stocks, with higher crude oil futures prices significantly increasing hazard rates. This result confirms those of Sadorsky (1999) and Papapetrou (2001) that crude oil price movements are important in modelling monthly stock returns. However, for Southwest Airlines we consistently find no significant short-run spillovers from crude oil futures markets. Interestingly, Southwest Airlines are well known for their very effective "forward buy" jet-fuel futures program (Mandaro, 2008) and according to Cox (2005), they were not to break the $1.00 per US gallon threshold until 2008. The immunisation to short-run changes in crude oil prices implies that in case of this airline, the changes in crude oil futures returns do not affect the probability of trading.

5.2 Estimating the Effects of Public Announcements

How do public announcements affect the frequency of trading in stocks? We start by analysing the average hazard rates during particular announcements and non-announcement (control) days (see Figures 6 and 7. In general, trading intensity appears to be larger when firm-specific analyst reports are released. Further, trades are more likely to occur when American Airlines make earnings-related and other announcements, as predicted by the Easley and O'Hara (1992) model. However, the opposite appears to be true for U.S. Airways. In fact, trading intensity in LCC stock is considerably lower on days when earnings and security related releases are made. Amongst macroeconomic and monetary policy releases, Fed target rate announcements affect the probability of trade in all stocks most strongly. We also observe an increase in trading activity of AMR stock during days when sectoral production, orders, and inventories statistics are released, whereas consumer spending and confidence announcements tend to increase hazard rates for U.S. Airways. Interestingly, there are almost no differences in trading activity during announcement and non-announcement days for Southwest Airlines.

[FIGURE 6 ABOUT HERE]
[FIGURE 7 ABOUT HERE]

To study the short-run impact of news arrival on the probability of trade within the ACH framework, we include three announcement variables in equation 11, to denote observation windows of five minutes *before* an announcement, the minute *during* which an announcement is made and ten minutes *after* an announcement is made. In our choice of the length of observation windows we follow Simonsen (2006), who studies the impact of news arrival on trade durations in Swedish stocks and reports that the 5-1-10 observation windows provide the adequate data fit and the largest number of significant parameters. As Simonsen (2006), we also find that changing the before-during-after time intervals to 15-5-20 minutes does not markedly vary the results, though less significant coefficients are obtained.

We analyse the effect of firm-specific announcements in three ways. Firstly, we study the average effect of any company release on the frequency of trading. Secondly, we partition the releases into five categories, and estimate separate ACH models for each category (analyst reports, earnings related releases, security related news, marketing announcements and others, as detailed in Table 3). Thirdly, we consider the effect of each announcement individually. The results for the first two sets of models are reported in Table 7, whereas the estimation results for the five most significant individual releases for each company are summarized in Table [TO FOLLOW].

[TABLE 7 ABOUT HERE]

We start by testing the total significance of the announcement variables and also compare the differences in BIC between these models and the baseline ACH(2,1) models reported in Table 6. On the aggregated and categorized level, we find that LCC- and LUV-specific releases have a significant impact on trading frequency. However, while the inclusion of the news arrival variables significantly increases the explanatory power of the model, this contribution is in general not strong enough to improve the Bayesian Information Criterion. Only the publication of U.S. Airways earnings related news, analyst reports related to Southwest Airlines and a joint analysis of all LUV-specific news decreases (i.e. improves) the BIC. For American Airlines, we find that the aggregated and categorized announcement variables are jointly insignificant.

On the aggregated and categorized level there is little evidence of changes in trading activity *before* AMR-specific announcements, though we find that other releases tend to significantly decrease the probability of trade. The evidence for LCC is mixed; earnings and security related induce a decrease in the hazard rates, while analyst reports — an increase. For Southwest Airlines, we find that trading intensity increases significantly *before* almost any news release, as predicted by the information asymmetry model of Kyle (1985), in which the monopolistic informed trader places orders before their (insider) information becomes common knowledge in order to maximize their profits. Then *during* an announcement itself all traders seem to "pause" (indicated by positive and mostly significant coefficients) and will recommence trading only *after* a release, with the probability of trade in LUV stock significantly higher during the 10-minute interval subsequent to a news arrival. This is consistent with the market microstructure theory that investors trade on information (see, for example, Easley and O'Hara, 1992). In contrast, trading activity decreases after LCC-related news arrival, as observed earlier when analysing Figure 6. This result is more consistent with the multiple informed trader model of Holden and Subrahmanyam (1992), which in the current setting implies that the information is absorbed almost immediately and that trading intensity returns to pre-announcement levels shortly after a release.

We find that often it is more informative to analyse the impact of individual company announcements, as opposed to studying the aggregated effect of all news concurrently, regardless of their different informational content.

Unscheduled airlines security releases and announcements that are directly related to past or future earnings, such as traffic reports or favourable analysts' reports, have the largest impact on the conditional probability of trade. [RESULTS AND DISCUSSION TO FOLLOW]

Tables 8 – 10 report the impact of macroeconomic announcements on probability of trade in stocks.

[TABLE 8 ABOUT HERE]
[TABLE 9 ABOUT HERE]
[TABLE 10 ABOUT HERE]

- Announcements of Fed target rate (Federal Reserve policy indicator) induce a significant increase in the hazard rates of all stocks.
- Crude Oil Inventories and Natural Gas Report, published weekly by Energy Information Administration, are significant predictors of probability of trade in AMR and LCC stocks, but not LUV (this is consistent with the findings in that crude oil prices are insignificant in modelling the frequency of trading in LUV stock).
- ISM Indices and Consumer Sentiment/Confidence statistics are mostly important, as predicted.
- **Timeliness** and **surprises**. We observe that within each macroeconomic indicators group, news that are released earlier or contain new/unique information have larger impact on probability of trade, i.e. the timeliness observed by others, most notable Andersen et al. (2003).
- **Impulse response functions**. Reading individual coefficients is not very informative, given the non-linear and autoregressive structure of the model. Impulse response functions to be discussed.
- **Robustness check.** An inclusion/exclusion of the market microstructure variables does not change the results considerably. The trade, volume and spread coefficients do not change between models, neither do the ACH parameters.
- We have also re-estimated models reported in Tables 7 –10 (i.e. with aggregated and individual company-specific and macroeconomic news variables) without the crude oil futures returns. We find that the absence of the crude oil futures prices does not change the significance of the announcement variables, which contradicts the efficient market hypothesis that futures prices unbiasedly incorporate all information available to market participants.

[FIGURE 8 ABOUT HERE]
[FIGURE 9 ABOUT HERE]

6 Conclusions

Mixed results. The company and U.S. macroeconomic announcements significantly change the conditional probability of trade, but traders' reaction strongly depends on the news informational content. In particular, we find that the frequency of trading in smaller stocks increases significantly *before* a firm-specific news release, yet does not change considerably for larger airlines. Further, traders often seem to "pause" *during* the announcement itself, but then start trading more actively, and the probability of trade increases significantly for up to 20-30 minutes *after* the arrival of the majority of news. The effect is most pronounced for unscheduled airlines security releases and announcements that are directly related to past of future earnings, such as traffic reports or favourable analysts' reports. The impact of macroeconomic statistical releases depends on news timing, with indicators published earlier or containing unique information producing the strongest response. We also find that market microstructure variables have a small yet significant effect of trading frequency, with trade volume and returns revealing more information than the relative bid/ask spread.

The results also clearly indicate that the tick-by-tick crude oil futures returns are highly relevant to modelling the probability of trade within the next time period, with a notable exception of Southwest Airlines, renowned for their successful jet-fuel hedging program. However, the inclusion of crude oil futures prices does not change the significance of the announcement variables, which contradicts the efficient market hypothesis that futures prices unbiasedly incorporate all information available to market participants.

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Table 1: Top 10 U.S. Airlines

Rank	**Carrier**	**Passengers**[a]	**Growth**[b]
1	American Airlines[c]	98.096	7.1
2	Southwest Airlines	88.436	9.0
3	*Delta Airlines*	86.090	-0.9
4	*United Airlines*	66.765	-5.7
5	*Northwest Airlines*	56.514	2.0
6	Continental Airlines	42.806	5.1
7	U.S. Airways[d]	41.869	-1.3
8	America West Airlines[d]	22.130	4.7
9	American Eagle Airlines[c]	17.534	17.9
10	Alaska Airlines	16.758	2.9

Ranked by the 2005 Domestic and International Enplanements. *Source:* U.S. Department of Transportation, Bureau of Transportation Statistics. Companies *not* listed on the NYSE are *italised*.

[a] Passenger numbers in millions.

[b] Percentage change 2004–2005.

[c] Owned by AMR Corporation.

[d] Owned by U.S. Airways Group Inc.

Table 2: Descriptive Statistics of AMR Corporation (AMR), U.S. Airways Group (LCC) and Southwest Airlines (LUV) Trade and Quote Data.

	AMR	**LCC**	**LUV**
Sample Size[a]			
Initial Number of Observations	158,392	108,102	123,747
Percentage of Simultaneous Trades	16.22%	14.56%	19.07%
Final Number of Observations	132,705	92,362	100,154
Trade Duration[b]			
Mean	7.291	10.473	9.662
Std. Dev.	10.153	17.893	13.096
Skewness	3.942	5.685	3.593
Kurtosis	28.278	64.308	26.223
Q(15)	16,457	10,551	13,132
Q(100)	62,847	33,108	41,767
Spread (US cents)			
Mean	1.668	3.496	1.192
Std. Dev.	1.257	3.037	0.573
Skewness	4.798	3.600	8.319
Kurtosis	44.396	54.957	221.417
Q(15)	67,187	47,864	30,628
Q(100)	114,008	86,920	40,694
Trading Volume			
Mean	1,143.912	518.845	1,023.068
Std. Dev.	3,373.932	1,149.03	2,787.942
Skewness	38.730	17.480	50.908
Kurtosis	3,265.082	559.014	7,006.073
Q(15)	2,601	3,025	1,434
Q(100)	5,830	9,258	3,377
Proportion of Buys	55.24%	55.28%	54.11%
Market Value[d]	4.497	3.833	13.788

Notes: The Ljung-Box Q(15) and Q(100) statistics test the null hypothesis of no autocorrelation of orders 15 and 100 and follow $\chi^2(15)$ and $\chi^2(100)$ distributions under H_0, respectively (with the critical values at significance level of 5% equal to 25.00 and 124.34). *Sample period*: NYSE trades that occurred between 9.45 and 16.00 for August and September 2006. *Data source*: TAQ database.

[a] Number of trades before and after the aggregation of simultaneous trades.

[b] Aggregated trade durations, measured in seconds.

[d] Stock market-capitalisation of 1 August 2006, calculated by multiplying the number of shares outstanding by the closing price. *Source*: CRSP database.

Table 3: Firm-Specific News Releases

	Aug 2006[a]	**Sep 2006**[b]
AMR Corporation		
Analyst Reports	6	0
Earnings Related News	8	4
Security Related News	16	1
Marketing Announcements	10	6
Other Releases	2	3
U.S. Airways Group		
Analyst Reports	1	0
Earnings Related News	2	1
Security Related News	5	0
Marketing Announcements	1	0
Other Releases	1	2
Southwest Airlines		
Analyst Reports	3	0
Earnings Related News	3	1
Security Related News	0	0
Marketing Announcements	0	0
Other Releases	3	0

Notes: Firm-specific news announcements are partitioned into five groups: analyst reports, earnings related news (including new routes and new ticket prices announcements and traffic reports), security related news, marketing announcements and other releases. *Data source*: NYSE.

[a] The total number of announcements made during August 2006 between 9.45 and 16.00.

[b] The total number of announcements made during September 2006 between 9.45 and 16.00.

Table 4: U.S. Macroeconomic News Announcements

Announcement	Source[a]	Aug 2006	Sep 2006
Sectoral Production, Orders, and Inventories			
ISM Manufacturing Index	ISM	1	1
ISM Non-Manufacturing Index	ISM	1	1
Business Barometer Index	ChNAPM	1	1
Philadelphia Fed Business Outlook Survey	PhilFED	1	1
Chicago Fed National Activity Index	ChFED	1	1
Current Economic Conditions ("Beige Book")	FRB	1	1
Crude Oil Inventories Report	EIA	5	5
Natural Gas Report	EIA	5	4
Consumer Spending and Confidence			
Consumer Confidence Index	CB	1	1
Consumer Sentiment Index	UM	1	3
Housing and Construction			
New Single-Family Home Sales	DC	1	1
Existing Home Sales	NAR	1	1
Pending Home Sales Index	NAR	1	1
Housing Market Index	NAHB/WF	1	1
Federal Reserve Policy			
Target Federal Funds Rate	FRB	1	1
Federal Government Finances			
Treasury Bill Auctions	DT	9	8
Treasury Bond Auctions	DT	5	3

Notes: This table lists the U.S. macroeconomic news announcements included in the study and the total number of releases made during the sample period from 01 August to 30 September 2006. *Data source*: Bloomberg.

[a] Conference Board(CB), Department of Commerce (DC), Department of Treasury (DT), Energy Information Administration (EIA), Federal Reserve Bank of Chicago (ChFED), Federal Reserve Bank of Philadelphia (PhilFED), Federal Reserve Board (FRB), Institute for Supply Management (ISM), National Association of Home Builders/Wells Fargo (NAHB/WF), National Association of Purchasing Managers Chicago (ChNAPM), National Association of Realtors (NAR), University of Michigan (UM).

Table 5: Parameter Estimates of ACH(1,1) Models with Time Indicators for AMR, LCC and LUV.

	AMR	**LCC**	**LUV**
ω	**0.0008**	**0.0029**	**0.0043**
	[0.0002]	[0.0003]	[0.0008]
α_1	**0.0011**	**0.0011**	**0.0011**
	[0.0001]	[0.0001]	[0.0001]
β_1	**0.9985**	**0.9984**	**0.9981**
	[0.0001]	[0.0001]	[0.0002]
$I_{t\in(9{:}45-10{:}59)}$	**0.0006**	**0.0009**	**0.0021**
	[0.0001]	[0.0001]	[0.0002]
$I_{t\in(11{:}00-11{:}59)}$	**0.0014**	**0.0014**	**0.0028**
	[0.0001]	[0.0002]	[0.0004]
$I_{t\in(12{:}00-13{:}59)}$	**0.0013**	**0.0017**	**0.0034**
	[0.0001]	[0.0002]	[0.0005]
$I_{t\in(14{:}00-14{:}59)}$	**0.0006**	**0.0006**	**0.0015**
	[0.0001]	[0.0002]	[0.0003]
lnL	-379,362.9	-299,134.6	-317,801.7
BIC	758,822.3	598,365.7	635,699.9
CorrPredict[a]	58.52%	60.85%	57.07%

Notes:

$$
\begin{aligned}
h_t &= \frac{1}{\psi_t} \\
\psi_t &= \omega + \alpha_1 u_{N(t-1)-1} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}
\end{aligned}
$$

where $I_{t\in\tau(j)}$ denotes time indicators. Coefficient estimates provided in **bold** are significant at 5% level. Robust standard errors are provided in square brackets. *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006, with a total of 967,500 observations. *Data source*: TAQ database.

[a] *CorrPredict* refers to the proportion of correct predictions from the model that a trade occurs within the next time interval.

Table 6: Parameter Estimates of ACH(2,1) Models with Crude Oil Futures Returns, Market Microstructure Variables and Time Indicators for AMR, LCC and LUV.

	AMR	**LCC**	**LUV**
ω	**0.0186**	**0.0442**	**0.0433**
	[0.0019]	[0.0049]	[0.0092]
α_1	**0.0009**	**0.0010**	**0.0013**
	[0.0001]	[0.0001]	[0.0002]
α_2	**0.0010**	**0.0010**	**0.0011**
	[0.0001]	[0.0001]	[0.0002]
β_1	**0.9973**	**0.9968**	**0.9953**
	[0.0002]	[0.0003]	[0.0009]
oil_{t-1}	**-0.0007**	**-0.0017**	0.0001
	[0.0002]	[0.0003]	[0.0004]
$return_{t-1}$	**0.0023**	**0.0124**	**-0.0160**
	[0.0012]	[0.0024]	[0.0071]
$volume_{t-1}$	**-0.0030**	**-0.0061**	**-0.0069**
	[0.0003]	[0.0006]	[0.0013]
$spread_{t-1}$	0.0001	**0.0028**	**0.0030**
	[0.0001]	[0.0004]	[0.0006]
$I_{t\in(9:45-10:59)}$	**0.0005**	0.0005	**0.0021**
	[0.0001]	[0.0003]	[0.0002]
$I_{t\in(11:00-11:59)}$	**0.0015**	**0.0014**	**0.0049**
	[0.0002]	[0.0003]	[0.0012]
$I_{t\in(12:00-13:59)}$	**0.0018**	**0.0024**	**0.0071**
	[0.0002]	[0.0004]	[0.0019]
$I_{t\in(14:00-14:59)}$	**0.0006**	0.0006	**0.0028**
	[0.0002]	[0.0003]	[0.0010]
lnL	-378,707.3	-298,157.2	-317,386.1
BIC	757,579.9	596,479.8	634,937.5
CorrPredict[a]	58.87%	60.90%	57.56%

Notes:

$$h_t = \frac{1}{\psi_t}$$

$$\psi_t = \omega + \alpha_1 u_{N(t-1)-1} + \alpha_2 u_{N(t-1)-2} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + \delta \mathbf{z}_{t-1}$$

where $I_{t\in\tau(j)}$ denotes time indicators and $\mathbf{z}_{t-1}$ denotes a vector of exogenous covariates: *oil* (the logarithmic change in prices of the current month NYMEX light, sweet crude oil futures contract), *return* (the logarithmic return constructed from the share price series), *volume* (the logarithm of the number of shares traded), and *spread* (the relative bid/ask spread). All covariates have been scaled to have unit variances. Coefficient estimates provided in **bold** are significant at 5% level. Robust standard errors are provided in square brackets.
Sample period: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006, with a total of 967,500 observations.
Data source: TAQ and CQG databases.

[a] *CorrPredict* refers to the proportion of correct predictions from the model that a trade occurs within the next time interval.

Table 7: Impact of Firm-Specific News Releases (*by Genre*) on Probability of Trade of AMR, LCC and LUV.

	Before	During	After	Total[a]	lnL	LR stat[a]	BIC diff[a]
AMR Corporation							
All Company News	0.0011	**-0.0067**	0.0005	-0.0051	-378,705.2	4.2	37.1
Analyst Reports	-0.0019	0.0064	-0.0002	0.0043	-378,706.8	0.9	40.5
Earnings Related News	0.0002	-0.0080	0.0013	-0.0065	-378,706.3	2.0	39.3
Security Related News	0.0018	-0.0043	0.0003	-0.0023	-378,706.2	2.2	39.2
Other Releases	**0.0074**	-0.0181	-0.0006	-0.0113	-378,705.1	4.4	36.9
U.S. Airways Group							
All Company News	0.0077	-0.0052	0.0047	0.0071	-298,151.9	**10.6**	30.8
Analyst Reports	**-0.0202**	**0.1116**	0.0005	0.0919	-298,154.6	5.2	36.1
Earnings Related News	**0.0239**	-0.0223	**0.0330**	0.0346	-298,134.6	**45.2**	-3.8
Security Related News	**0.0318**	0.0458	0.0043	0.0819	-298,146.8	**20.7**	20.6
Other Releases	-0.0055	-0.0497	-0.0044	**-0.0596**	-298,146.6	**21.2**	20.2
Southwest Airlines							
All Company News	**-0.0124**	**0.0792**	**-0.0152**	**0.0516**	-317,323.1	**125.9**	-84.5
Analyst Reports	**-0.0103**	0.0285	**-0.0201**	-0.0019	-317,256.6	**258.9**	-217.6
Earnings Related News	**-0.0146**	**0.0457**	0.0040	**0.0351**	-317,377.2	**17.7**	23.6
Other Releases	-0.0022	-0.0138	**0.0230**	0.0070	-317,376.6	**18.8**	22.5

Notes:

$$h_t = \left[\omega + \alpha_1 u_{N(t-1)-1} + \alpha_2 u_{N(t-1)-2} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + \delta \mathbf{z}_{t-1} + \sum_{\tau=-1}^{1} \theta_\tau A_{t,\tau}\right]^{-1}$$

where $A_{t,-1}$ indicates the 5-minute period *before* an announcement, $A_{t,0}$ — the minute *during* which an announcement has occurred and $A_{t,1}$ — the 10-minute period *after* an announcement Parameter estimates of durations, conditional durations, exogenous covariates $\mathbf{z}_{t-1}$ and time indicators $I_{t\in\tau(j)}$ are not reported in the table, although they form part of the estimations. Coefficient estimates provided in **bold** are significant at 10% level (robust standard errors). Insignificant results for AMR and LCC marketing announcements are not reported. *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006, with a total of 967,500 observations. *Data source*: TAQ and CQG databases, NYSE.

[a] *Total* denotes the total impact of an announcement, calculated as $\sum_{\tau=-1}^{1} N_{t,\tau}$ and tested for significance using the χ^2 Wald statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 6) and follows $\chi^2(3)$ under H_0. Statistics provided in **bold** are significant at 10% level. *BIC diff* indicates the difference in BIC between the full and restricted models.

Table 8: Impact of Macroeconomic Announcements on Probability of Trade of AMR Corporation.

	Before	During	After	Total[a]	lnL	LR stat[a]	BIC diff[a]
Sectoral Production, Orders, and Inventories	-0.0008	**-0.0106**	-0.0003	**-0.0116**	-378,688.1	**38.4**	3.0
ISM Manufacturing Index	**-0.0082**	**0.0249**	0.0003	0.0169	-378,702.0	**10.5**	30.9
ISM Non-Manufacturing Index	-0.0040	-0.0035	-0.0017	-0.0092	-378,700.0	**14.5**	26.9
Business Barometer Index	**0.0121**	-0.0345	0.0021	-0.0203	-378,702.4	**9.8**	31.6
Philadelphia Fed Business Outlook Survey	0.0084	**-0.0541**	0.0001	**-0.0455**	-378,705.6	3.2	38.1
Chicago Fed National Activity Index	0.0016	0.0117	-0.0019	0.0114	-378,706.1	2.4	38.9
Current Economic Conditions ("Beige Book")	-0.0002	**-0.0519**	0.0002	**-0.0519**	-378,703.3	**7.9**	33.5
Crude Oil Inventories Report	-0.0017	**-0.0093**	**-0.0009**	**-0.0120**	-378,687.4	**39.8**	1.6
Natural Gas Report	0.0017	**-0.0203**	**0.0016**	**-0.0169**	-378,702.6	**9.3**	32.0
Consumer Spending and Confidence	**-0.0097**	0.0034	-0.0002	-0.0065	-378,697.8	**19.0**	22.4
Consumer Confidence Index	0.0051	**-0.0656**	-0.0010	**-0.0615**	-378,685.5	**43.6**	-1.9
Consumer Sentiment Index	– – –	**0.0125**	0.0004	**0.0129**	-378,703.9	**6.8**	20.7
Housing and Construction	-0.0028	-0.0003	0.0005	-0.0026	-378,705.5	3.5	37.9
New Single-Family Home Sales	**0.0156**	**-0.0933**	**0.0047**	**-0.0730**	-378,697.9	**18.8**	22.5
Existing Home Sales	-0.0009	0.0197	-0.0037	0.0151	-378,705.7	3.2	38.2
Pending Home Sales Index	**-0.0082**	**0.0249**	0.0003	0.0169	-378,702.0	**10.5**	30.9
Housing Market Index	-0.0101	0.1803	-0.0143	0.1559	-378,706.7	1.2	40.2
Federal Reserve Policy (Target Rate)	**-0.0124**	-0.0111	0.0023	**-0.0212**	-378,690.4	**33.7**	7.6
Federal Government Finances	0.0023	-0.0099	**0.0021**	-0.0055	-378,703.6	**7.4**	34.0
Treasury Bill Auctions	-0.0018	-0.0005	0.0010	-0.0014	-378,706.5	1.4	39.9
Treasury Bond Auctions	**0.0069**	-0.0215	**0.0046**	-0.0100	-378,698.9	**16.8**	24.5

Notes:

$$h_t = \left[\omega + \alpha_1 u_{N(t-1)-1} + \alpha_2 u_{N(t-1)-2} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + \delta \mathbf{z}_{t-1} + \sum_{\tau=-1}^{1} \theta_\tau A_{t,\tau}\right]^{-1}$$

where $A_{t,-1}$ indicates the 5-minute period *before* an announcement, $A_{t,0}$ — the minute *during* which an announcement has occurred and $A_{t,1}$ — the 10-minute period *after* an announcement Parameter estimates of durations, conditional durations, exogenous covariates $\mathbf{z}_{t-1}$ and time indicators $I_{t\in\tau(j)}$ are not reported in the table, although they form part of the estimations. Coefficient estimates provided in **bold** are significant at 10% level (robust standard errors). *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006, with a total of 967,500 observations. *Data source*: TAQ and CQG databases, Bloomberg.

[a] *Total* denotes the total impact of an announcement, calculated as $\sum_{\tau=-1}^{1} N_{t,\tau}$ and tested for significance using the χ^2 Wald statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 6) and follows $\chi^2(3)$ under H_0. Statistics provided in **bold** are significant at 10% level. *BIC diff* indicates the difference in BIC between the full and restricted models.

Table 9: Impact of Macroeconomic Announcements on Probability of Trade of U.S. Airways.

	Before	During	After	Total[a]	lnL	LR stat[a]	BIC diff[a]
Sectoral Production, Orders, and Inventories	**0.0043**	**-0.0309**	-0.0006	**-0.0272**	-298,147.9	**18.6**	22.8
ISM Manufacturing Index	0.0041	0.0421	**-0.0059**	0.0403	-298,154.6	5.1	36.2
ISM Non-Manufacturing Index	-0.0019	0.0418	-0.0024	0.0376	-298,156.2	1.8	39.5
Business Barometer Index	-0.0028	**-0.0555**	0.0030	**-0.0552**	-298,153.6	**7.3**	34.0
Philadelphia Fed Business Outlook Survey	**0.0164**	-0.0469	-0.0019	-0.0323	-298,155.3	3.8	37.6
Chicago Fed National Activity Index	0.0105	**-0.1522**	0.0011	**-0.1406**	-298,143.2	**28.0**	13.4
Current Economic Conditions ("Beige Book")	**0.1439**	**-0.5028**	0.0225	**-0.3363**	-298,149.4	**15.7**	25.7
Crude Oil Inventories Report	0.0028	**-0.0221**	-0.0020	**-0.0213**	-298,150.8	**12.9**	28.5
Natural Gas Report	0.0087	**-0.0599**	**0.0048**	**-0.0464**	-298,152.0	**10.3**	31.0
Consumer Spending and Confidence	0.0056	**0.0734**	**-0.0068**	**0.0722**	-298,147.2	**20.0**	21.3
Consumer Confidence Index	0.0080	0.0594	**-0.0090**	0.0584	-298,153.8	**6.8**	34.6
Consumer Sentiment Index	– – –	**0.0738**	**-0.0063**	**0.0675**	-298,150.3	**13.9**	27.5
Housing and Construction	-0.0043	**0.0362**	**-0.0057**	0.0262	-298,149.6	**15.2**	26.1
New Single-Family Home Sales	**-0.0131**	0.0166	**-0.0036**	-0.0001	-298,151.1	**12.3**	29.0
Existing Home Sales	0.0180	0.0576	**-0.0221**	0.0535	-298,141.7	**31.0**	10.4
Pending Home Sales Index	0.0041	0.0421	**-0.0059**	0.0403	-298,154.6	5.2	36.2
Housing Market Index	-0.0121	0.0429	0.0038	0.0346	-298,156.4	1.7	39.7
Federal Reserve Policy (Target Rate)	-0.0145	-0.0358	-0.0034	**-0.0537**	-298,147.4	**19.6**	21.7
Federal Government Finances	**0.0076**	**-0.0428**	**0.0037**	**-0.0316**	-298,151.8	**10.7**	30.6
Treasury Bill Auctions	-0.0018	**-0.0319**	0.0015	**-0.0322**	-298,153.3	**7.7**	33.6
Treasury Bond Auctions	**0.0259**	**-0.0806**	**0.0136**	-0.0411	-298139.0	**36.4**	4.9

Notes:

$$h_t = \left[\omega + \alpha_1 u_{N(t-1)-1} + \alpha_2 u_{N(t-1)-2} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + \delta \mathbf{z}_{t-1} + \sum_{\tau=-1}^{1} \theta_\tau A_{t,\tau}\right]^{-1}$$

where $A_{t,-1}$ indicates the 5-minute period *before* an announcement, $A_{t,0}$ — the minute *during* which an announcement has occurred and $A_{t,1}$ — the 10-minute period *after* an announcement Parameter estimates of durations, conditional durations, exogenous covariates $\mathbf{z}_{t-1}$ and time indicators $I_{t\in\tau(j)}$ are not reported in the table, although they form part of the estimations. Coefficient estimates provided in **bold** are significant at 10% level (robust standard errors). *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006, with a total of 967,500 observations. *Data source*: TAQ and CQG databases, Bloomberg.

[a] *Total* denotes the total impact of an announcement, calculated as $\sum_{\tau=-1}^{1} N_{t,\tau}$ and tested for significance using the χ^2 Wald statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 6) and follows $\chi^2(3)$ under H_0. Statistics provided in **bold** are significant at 10% level. *BIC diff* indicates the difference in BIC between the full and restricted models.

Table 10: Impact of Macroeconomic Announcements on Probability of Trade of Southwest Airlines.

	Before	During	After	Total[a]	lnL	LR stat[a]	BIC diff[a]
Sectoral Production, Orders, and Inventories	-0.0002	**-0.0148**	0.0005	**-0.0145**	-317,383.2	5.8	35.5
ISM Manufacturing Index	**-0.0147**	0.0179	**-0.0055**	**-0.0024**	-317,381.5	**9.1**	32.2
ISM Non-Manufacturing Index	-0.0020	-0.0153	0.0037	-0.0137	-317,385.5	1.2	40.2
Business Barometer Index	**-0.0111**	-0.0304	**0.0089**	**-0.0327**	-317,380.2	**11.7**	29.7
Philadelphia Fed Business Outlook Survey	0.0215	**-0.1491**	**0.0112**	**-0.1165**	-317,380.5	**11.2**	30.2
Chicago Fed National Activity Index	0.0064	-0.0040	**-0.0080**	-0.0056	-317,383.3	5.5	35.9
Current Economic Conditions ("Beige Book")	0.0012	-0.1532	0.0164	-0.1355	-317,380.0	**12.2**	29.2
Crude Oil Inventories Report	-0.0019	-0.0080	0.0005	-0.0093	-317,385.1	1.9	39.4
Natural Gas Report	0.0069	-0.0205	0.0021	-0.0115	-317,384.3	3.4	37.9
Consumer Spending and Confidence	-0.0033	**0.0411**	**-0.0050**	**0.0328**	-317,381.6	**8.9**	32.4
Consumer Confidence Index	0.0010	-0.0009	-0.0042	-0.0041	-317,385.1	1.9	39.5
Consumer Sentiment Index	– – –	**0.0584**	**-0.0053**	**0.0531**	-317,381.0	**10.2**	31.2
Housing and Construction	**-0.0124**	0.0231	**-0.0042**	0.0066	-317,379.4	**13.3**	28.0
New Single-Family Home Sales	**-0.0221**	**0.0700**	**-0.0080**	0.0400	-317,377.6	**16.9**	24.5
Existing Home Sales	0.0147	-0.0718	0.0022	**-0.0549**	-317,386.0	0.0	41.4
Pending Home Sales Index	**-0.0147**	0.0179	**-0.0055**	-0.0024	-317,381.5	**9.1**	32.2
Housing Market Index	-0.0112	0.1638	0.0102	0.1627	-317,385.1	1.9	39.4
Federal Reserve Policy (Target Rate)	**-0.0369**	-0.0224	**-0.0053**	**-0.0646**	-317,344.6	**82.9**	-41.6
Federal Government Finances	**0.0086**	**-0.0424**	**0.0120**	**-0.0218**	-317,364.8	**42.5**	-1.1
Treasury Bill Auctions	**0.0078**	**-0.0346**	**0.0117**	-0.0150	-317,371.9	**28.3**	13.1
Treasury Bond Auctions	0.0121	**-0.0767**	**0.0155**	**-0.0491**	-317,377.3	**17.6**	23.8

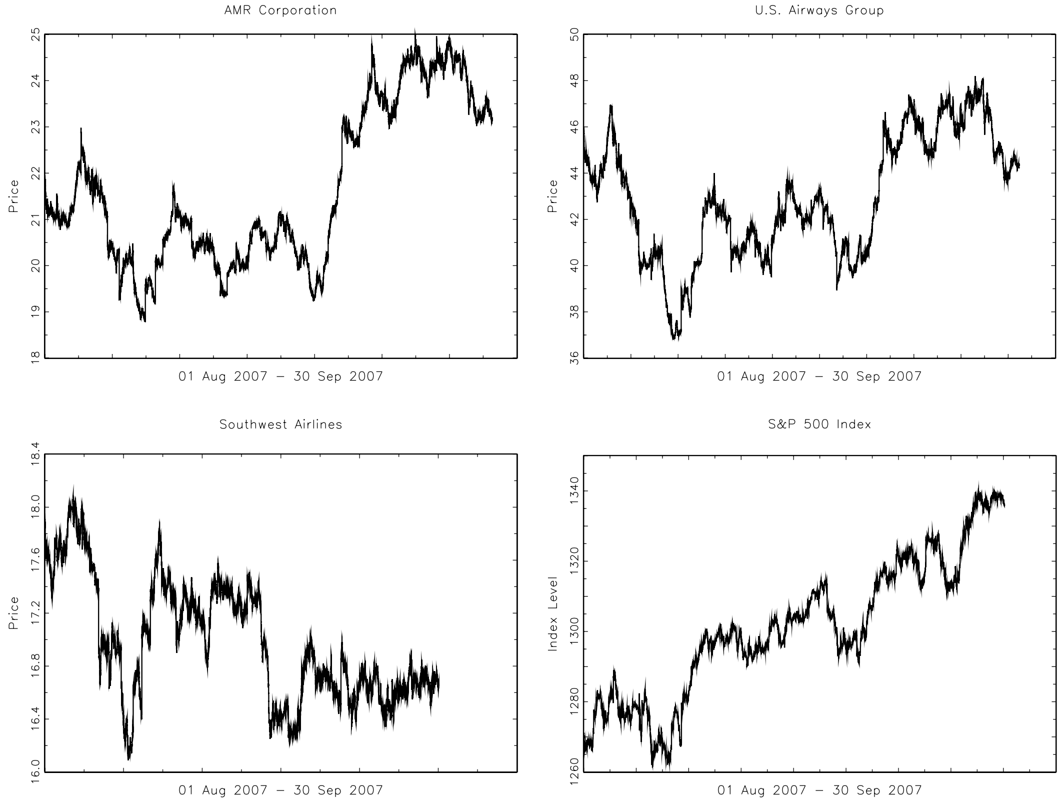
Notes:

$$h_t = \left[\omega + \alpha_1 u_{N(t-1)-1} + \alpha_2 u_{N(t-1)-2} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + \delta \mathbf{z}_{t-1} + \sum_{\tau=-1}^{1} \theta_\tau A_{t,\tau}\right]^{-1}$$

where $A_{t,-1}$ indicates the 5-minute period *before* an announcement, $A_{t,0}$ — the minute *during* which an announcement has occurred and $A_{t,1}$ — the 10-minute period *after* an announcement Parameter estimates of durations, conditional durations, exogenous covariates $\mathbf{z}_{t-1}$ and time indicators $I_{t\in\tau(j)}$ are not reported in the table, although they form part of the estimations. Coefficient estimates provided in **bold** are significant at 10% level (robust standard errors). *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006, with a total of 967,500 observations. *Data source*: TAQ and CQG databases, Bloomberg.

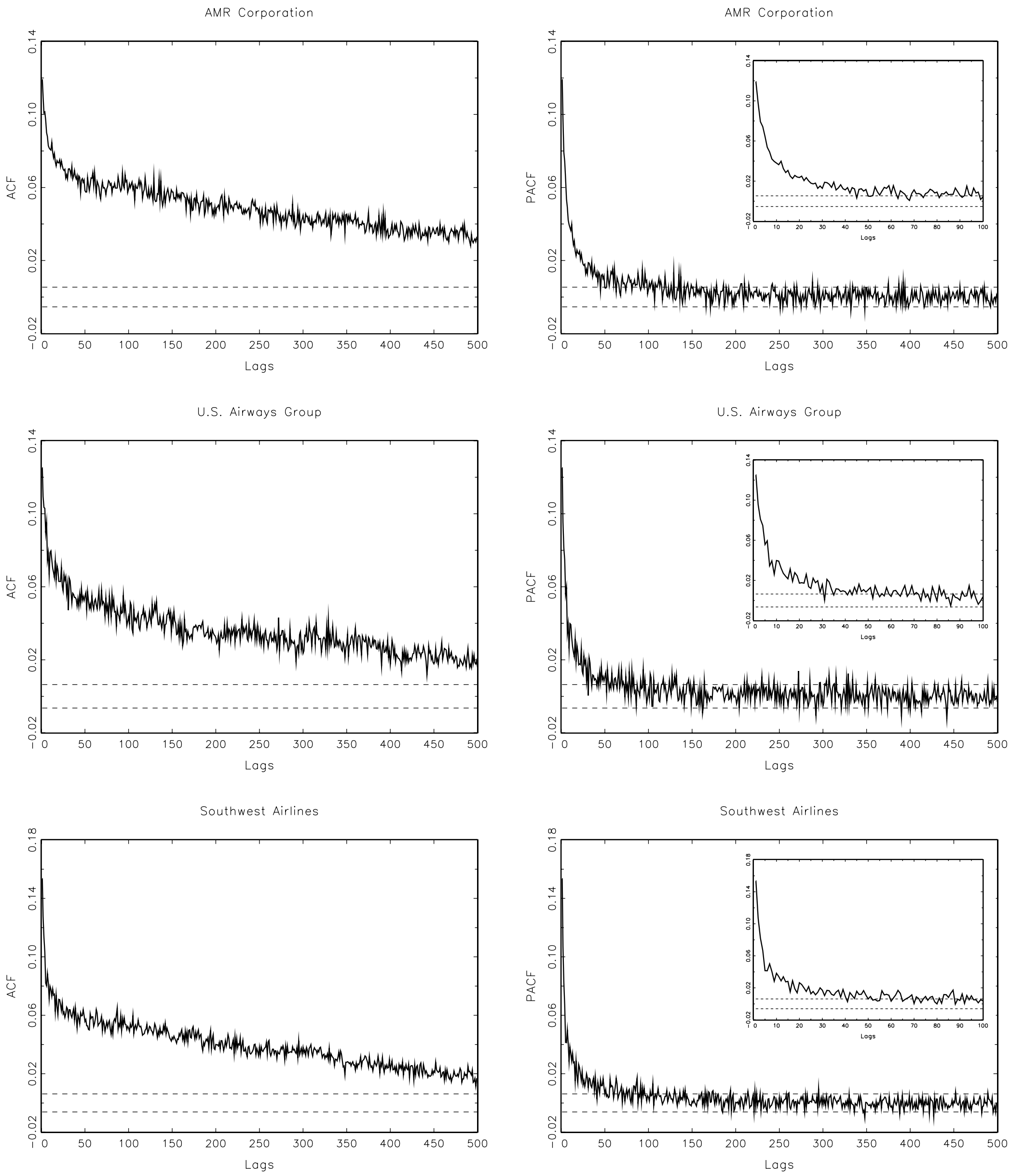
[a] *Total* denotes the total impact of an announcement, calculated as $\sum_{\tau=-1}^{1} N_{t,\tau}$ and tested for significance using the χ^2 Wald statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 6) and follows $\chi^2(3)$ under H_0. Statistics provided in **bold** are significant at 10% level. *BIC diff* indicates the difference in BIC between the full and restricted models.

Figure 1: Price Behaviour of the Airline Stocks AMR, LCC and LUV and the Standard and Poor's 500 Index.



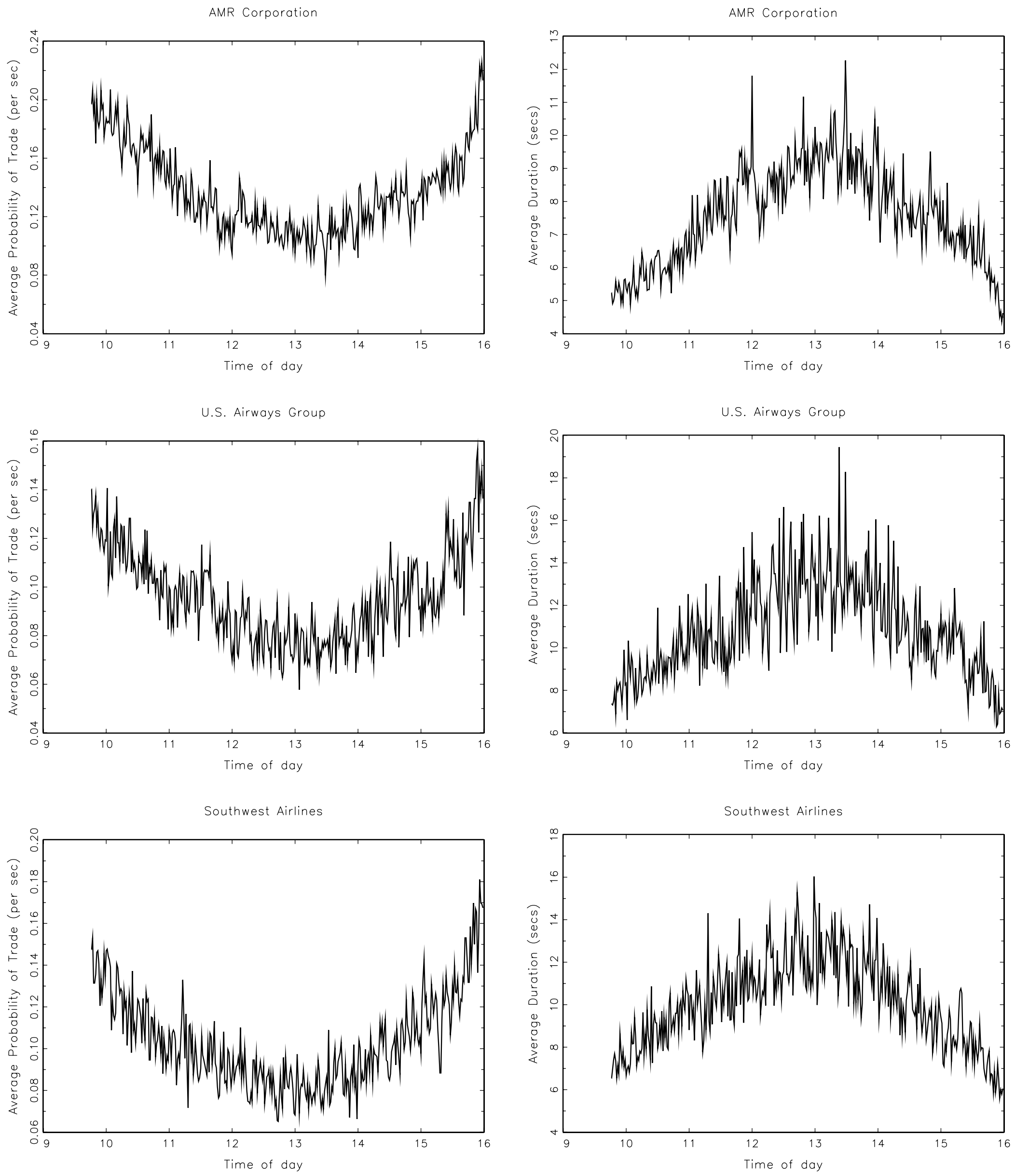
Notes: *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases.

Figure 2: Autocorrelation (left column) and Partial Autocorrelation Functions (right column) of Trade Durations for AMR, LCC and LUV.



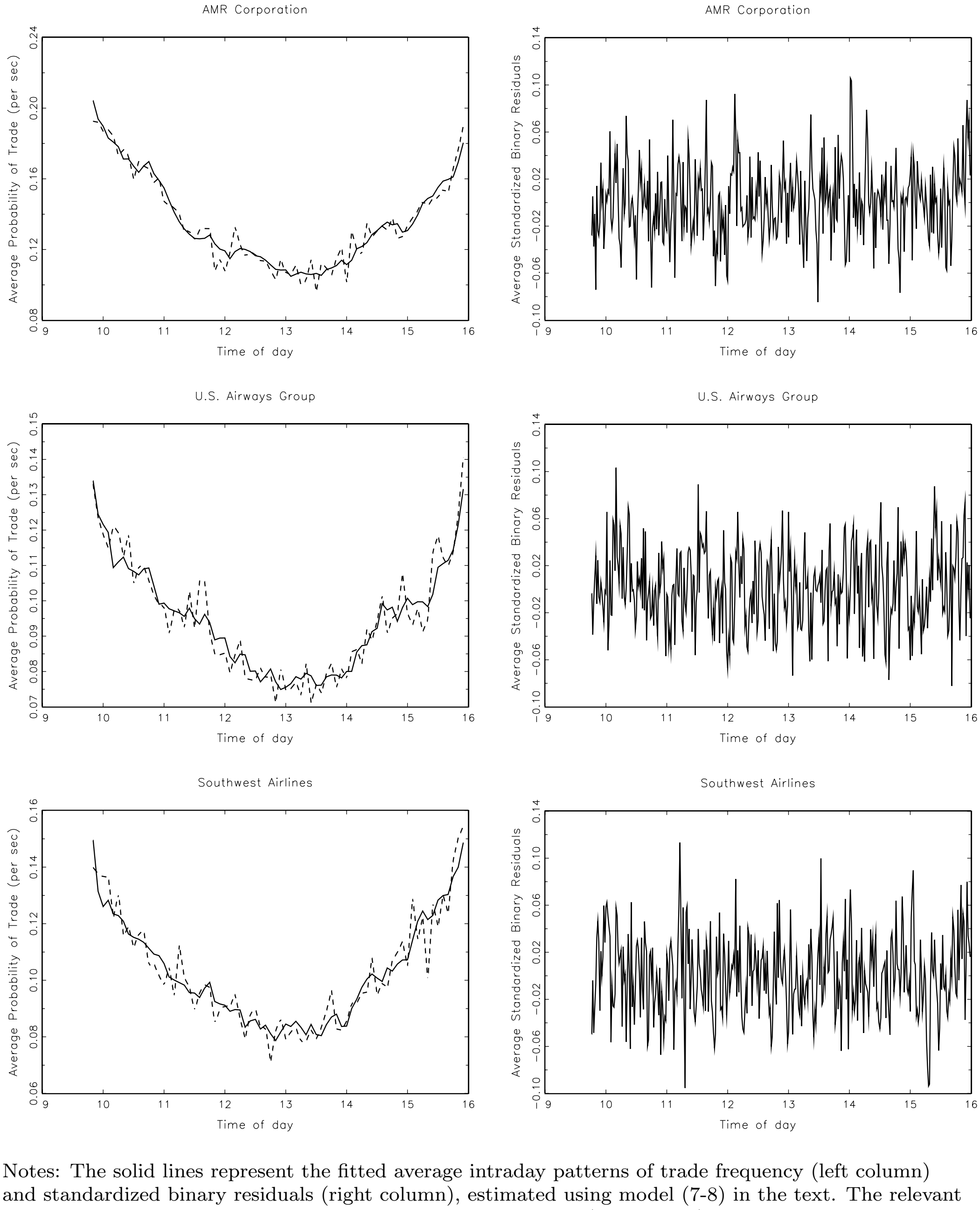
Notes: The x-axis denotes the lags in terms of durations. The dashed lines represent 95% confidence intervals. *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database.

Figure 3: Average Intraday Pattern of Trade Frequency (left column) and Trade Durations (right column) for AMR, LCC and LUV.



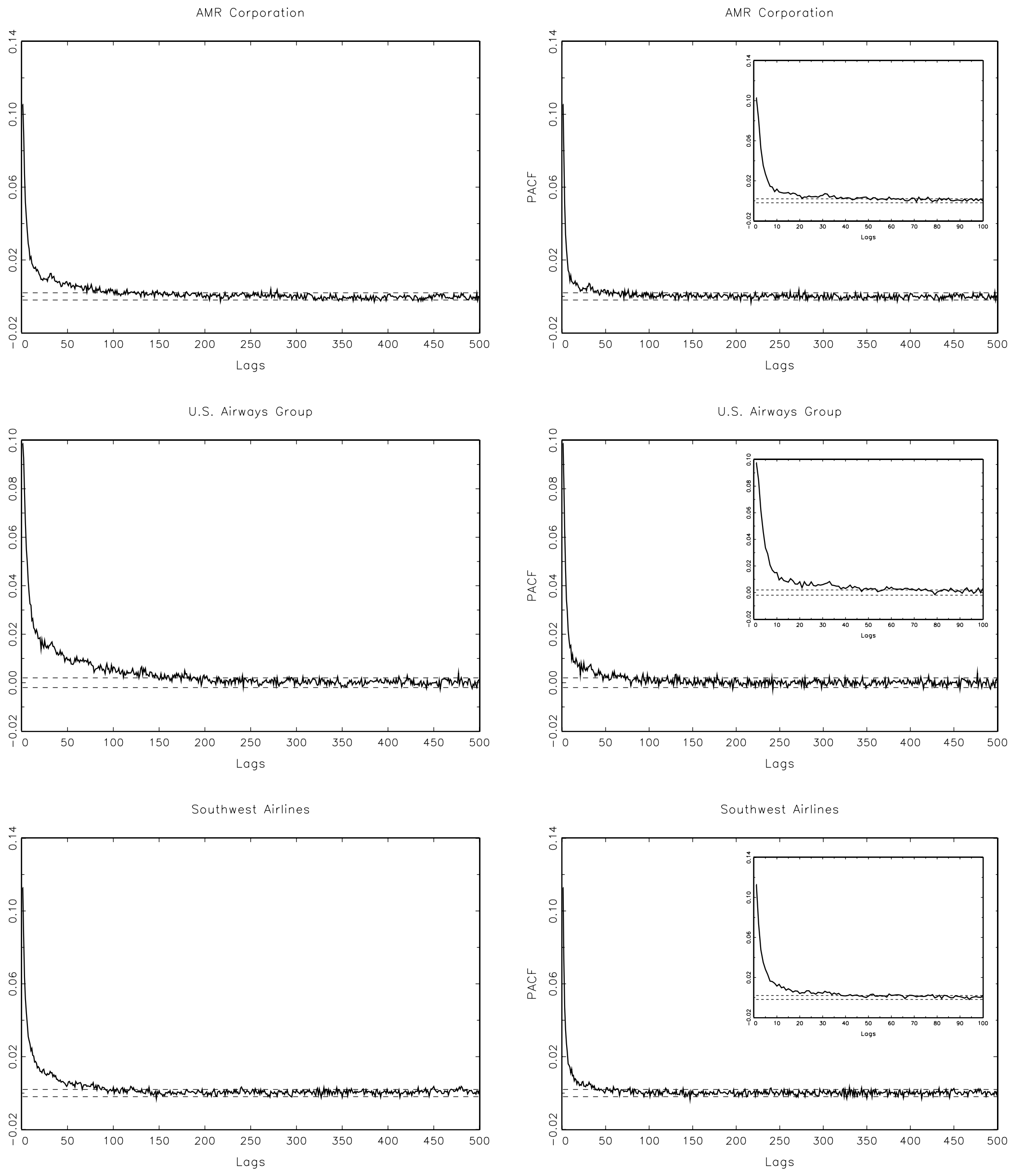
Notes: The time between trades is measured in seconds and the time of the day is measured in hours since midnight. The averages are based on 5-minute intervals of trading activity. *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database.

Figure 4: Model Diagnostics of ACH(2,1) Models: Intraday Pattern of Actual and Fitted Trade Frequency (left column) and Standardized Binary Residuals (right column) for AMR, LCC and LUV.



Notes: The solid lines represent the fitted average intraday patterns of trade frequency (left column) and standardized binary residuals (right column), estimated using model (7-8) in the text. The relevant parameter estimates are reported in Table 6. The dashed lines (left column) represent the observed intraday patterns of trade frequency. The averages are based on 5-minute intervals of trading activity. The time between trades is measured in seconds and the time of the day is measured in hours since midnight. *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database.

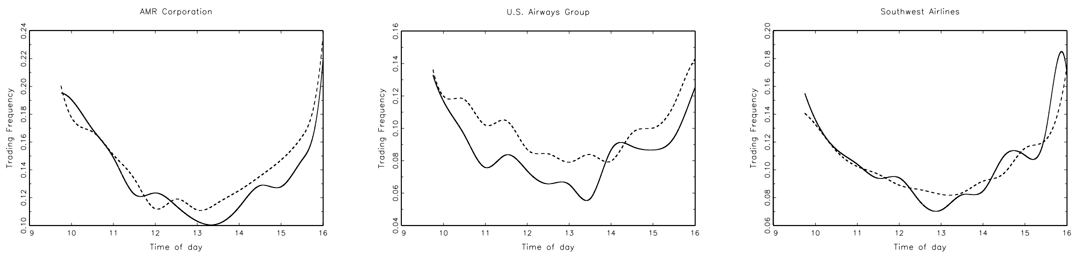
Figure 5: Model Diagnostics of ACH(2,1) Models: Autocorrelation (left column) and Partial Autocorrelation Functions (right column) of Standardized Binary Residuals for AMR, LCC and LUV.



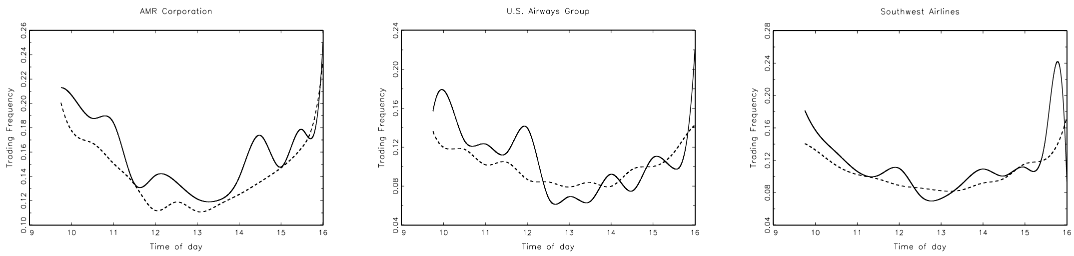
Notes: The relevant parameter estimates are reported in Table 6. The x-axis denotes the lags in terms of durations. The dashed lines represent 95% confidence intervals. *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database.

Figure 6: Effect of Company Announcements on Trade Frequency of AMR, LCC and LUV.

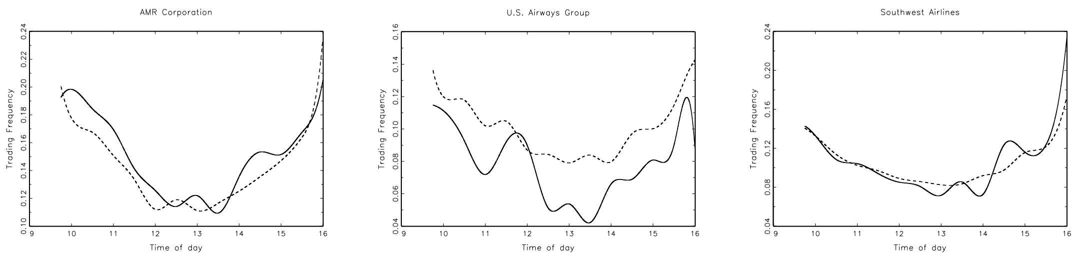
All Company News



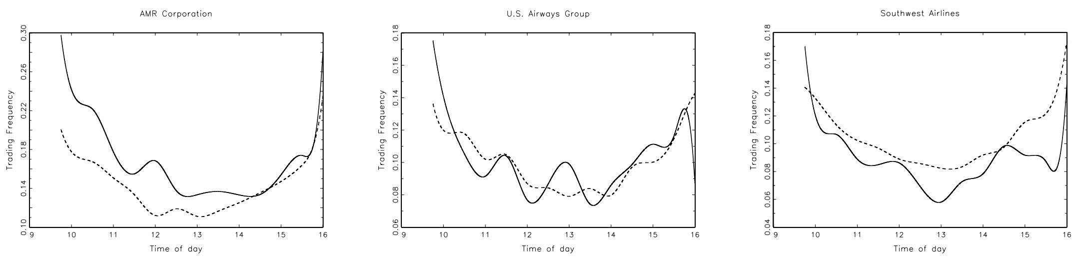
Analyst Reports



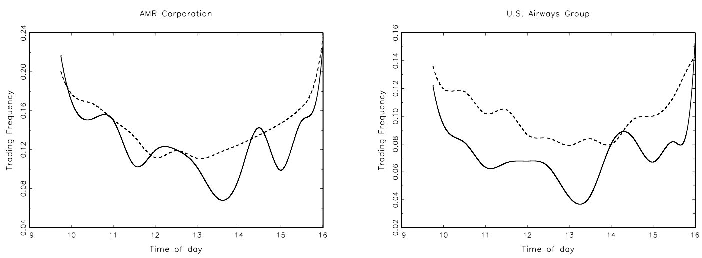
Earnings Related News



Other Releases



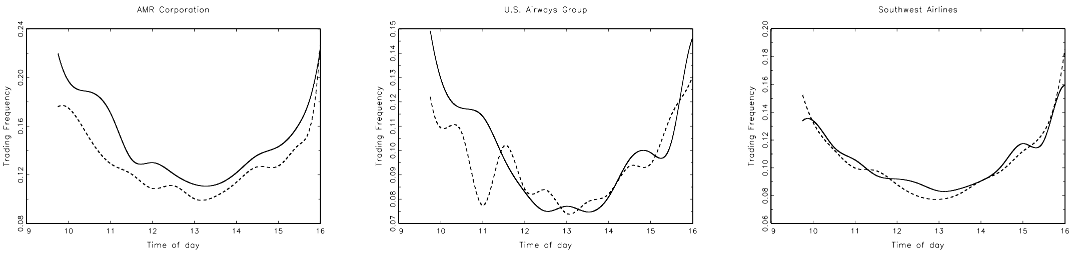
Security Related News



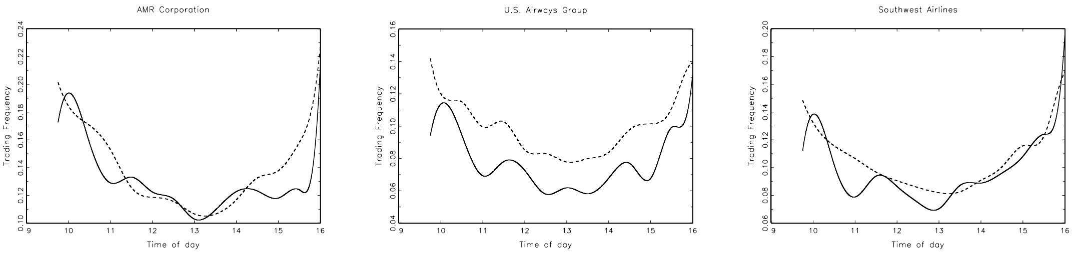
Notes: The solid lines represent trading frequency for announcement days and the dashed lines represent trading frequency for days when no firm-specific releases were made. Both estimates are obtained using cubic splines with half-hourly knots. The time between trades is measured in seconds and the time of the day is measured in hours since midnight. *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database and NYSE.

Figure 7: Effect of Macroeconomic Announcements on Trade Frequency of AMR, LCC and LUV.

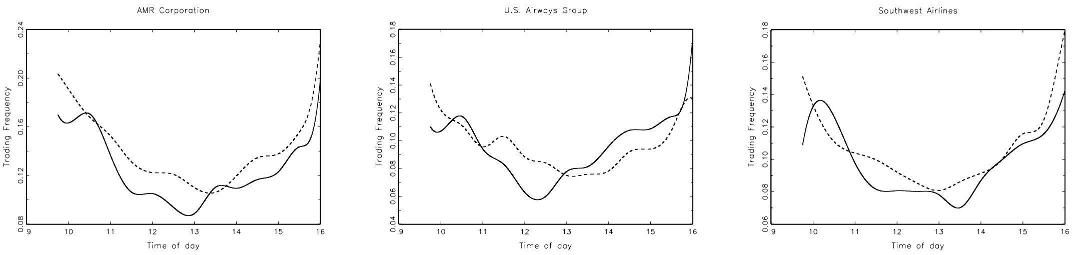
Sectoral Production, Orders, and Inventories



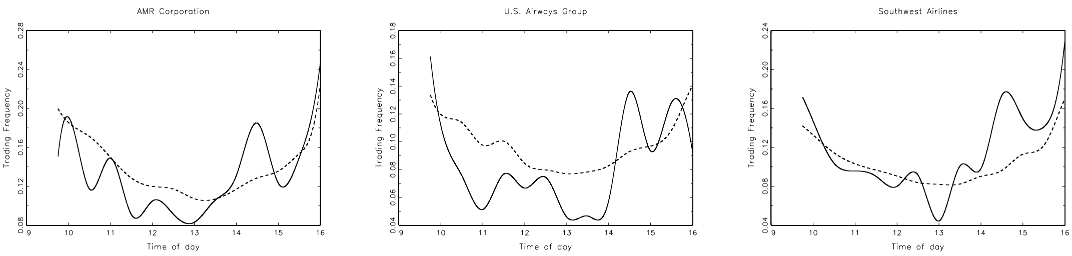
Consumer Spending and Confidence



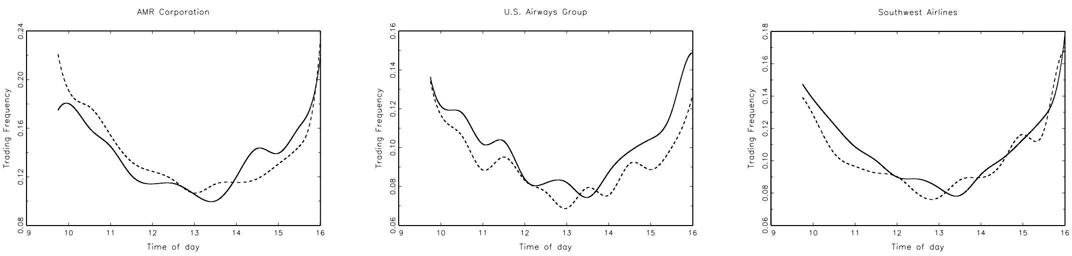
Housing and Construction



Federal Reserve Policy



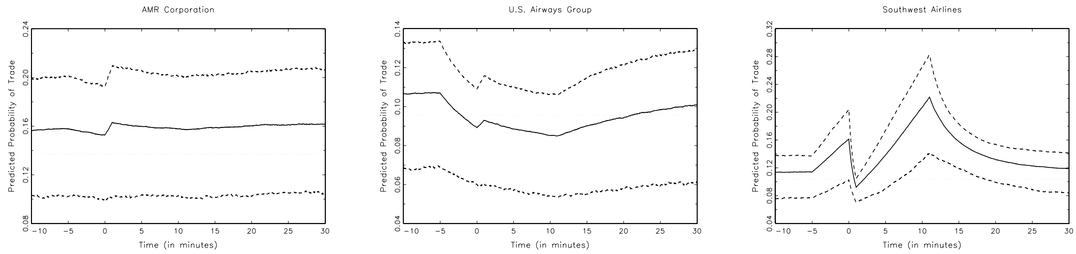
Federal Government Finances



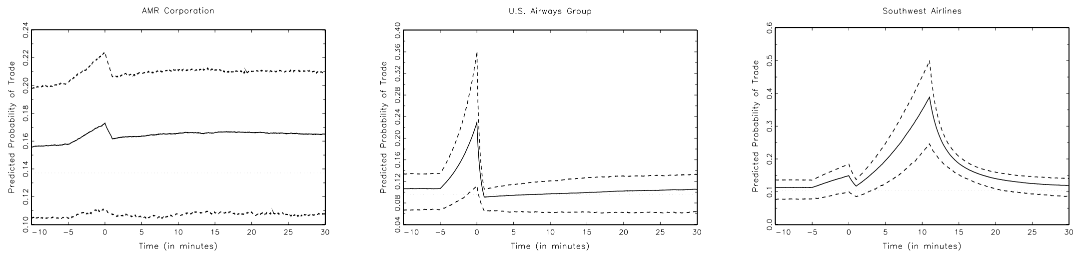
Notes: The solid lines represent trading frequency for announcement days and the dashed lines represent trading frequency for days during other days. Both estimates are obtained using cubic splines with half-hourly knots. The time between trades is measured in seconds and the time of the day is measured in hours since midnight. *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database and Bloomberg.

Figure 8: Trading Frequency Responses to Firm-Specific Announcements for AMR, LCC and LUV.

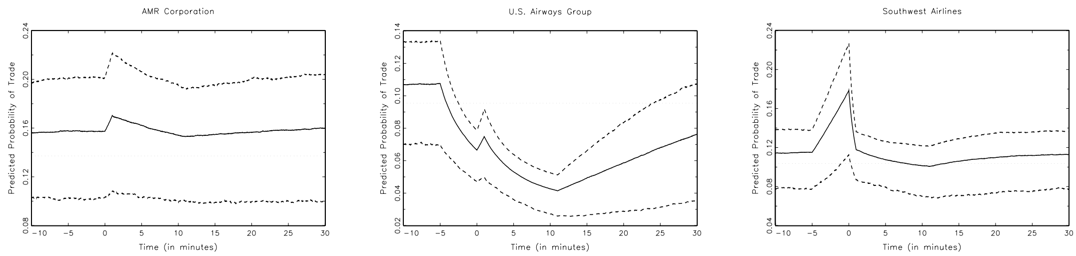
All Company News



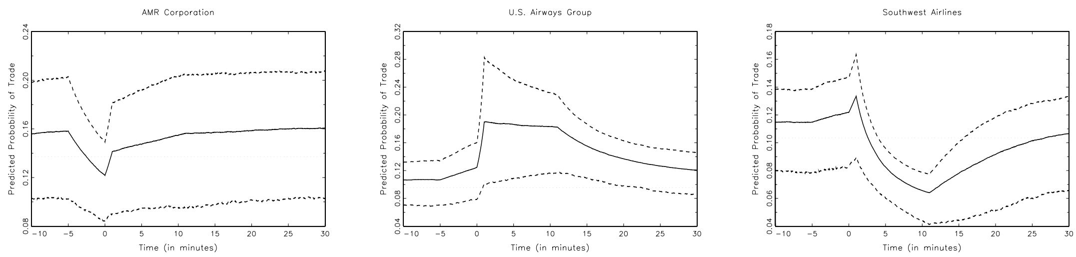
Analyst Reports



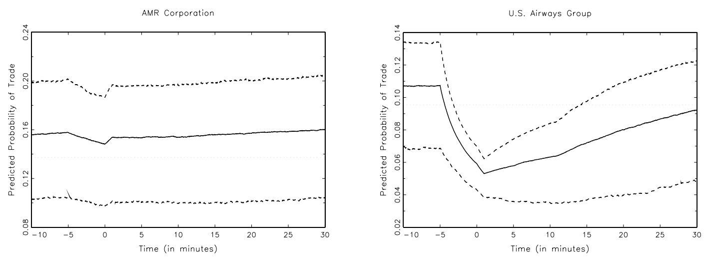
Earnings Related News



Other Releases



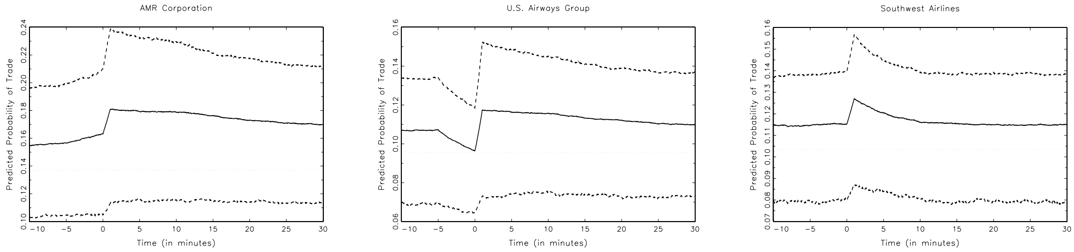
Security Related News



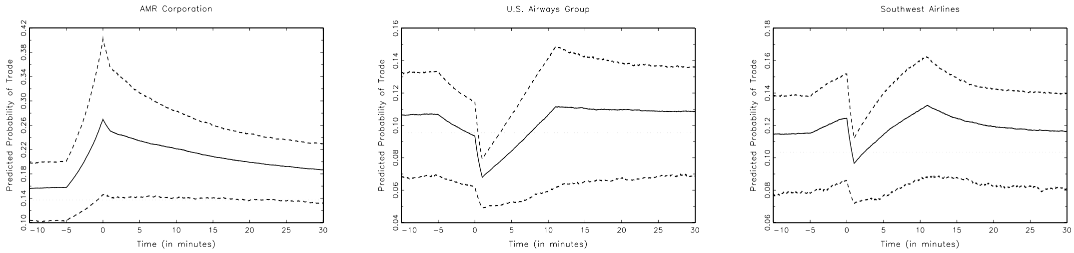
Notes: The solid lines represent the median behaviour of trading frequency in the presence of company releases, and the dashed lines represent the 95% confidence intervals. Both estimates are obtained using Monte Carlo simulations based on parameter estimates reported in Table 7. The dotted lines denote the average trading frequency, and the x-axis denotes time in minutes, with the announcements time fixed at 0. *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database and Bloomberg.

Figure 9: Trading Frequency Responses to Macroeconomic Announcements for AMR, LCC and LUV.

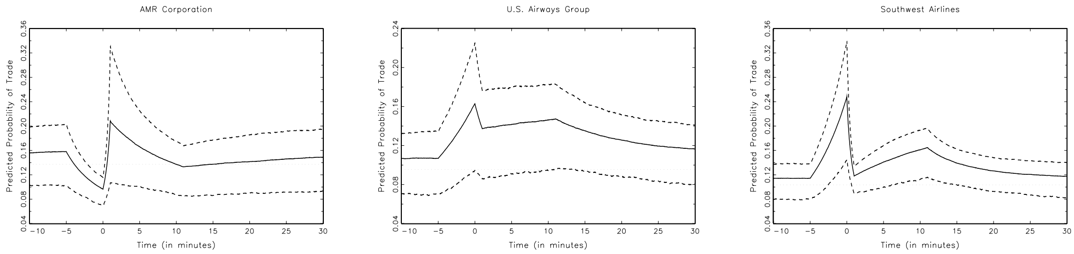
Sectoral Production, Orders, and Inventories



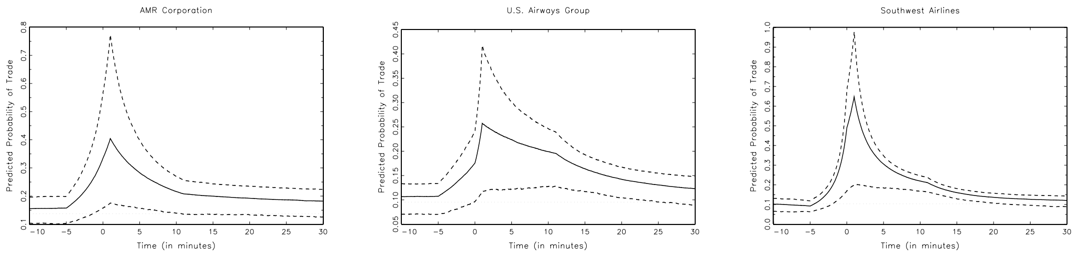
Consumer Spending and Confidence



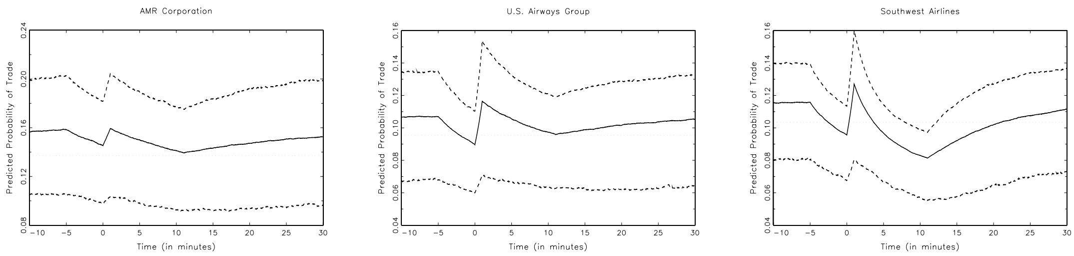
New Single-Family Home Sales



Federal Reserve Policy



Federal Government Finances



Notes: The solid lines represent the median behaviour of trading frequency in the presence of macroeconomic releases, and the dashed lines represent the 95% confidence intervals. Both estimates are obtained using Monte Carlo simulations based on parameter estimates reported in Tables 8 – 10. The dotted lines denote the average trading frequency, and the x-axis denotes time in minutes, with the announcements time fixed at 0. *Sample period*: NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database and Bloomberg.