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How Do Public Announcements Affect the Frequency of Trading in U.S. Airline Stocks?

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Abstract

This paper examines how news releases, key microstructure features of market activities and crude oil futures returns affect trading frequency in U.S. airline stocks. Using the autoregressive conditional hazard framework of Hamilton and Jordà (2002), we show that on average, trading intensity spikes prior and consequent to macroeconomic announcements, but decreases around firm-specific releases. We find that market microstructure variables have a small yet significant effect on trading frequency, with high trade volume and narrow bid/ask spread inducing higher trading intensity. Strong evidence is provided to indicate that the intraday crude oil futures returns are relevant for modelling the probability of a trade in airline stocks 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 impact of information arrival on 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 markets.

Exactly how 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 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 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 by directly modeling the trading intensity and by estimating the probability of trade in the next time interval, using the Autoregressive Conditional Hazard (ACH) model of Hamilton and Jordà (2002). In the current paper 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 American airline equities traded on the New York Stock Exchange (NYSE). The airline industry provides a unique and exciting context for jointly modelling the frequency of trading, market informational efficiency and “trading spillovers,” as discussed below. To the best of our knowledge, there are no empirical studies based on high-frequency airline equity data.

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

Instead, most authors investigate intraday behaviour of either a single stock (IBM, see for example Engle and Russell, 1995 and 1998, or Rydberg and Shephard, 2003) or the constituents of the Dow Jones Industrial Average (Andersen et al., 2001, Hasbrouck and Seppi, 2001 and Hansen and Lunde, 2005).

An important contribution of this research is its announcements and information dataset. This dataset 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 as company news published by Dow Jones Business News and PR Newswire. 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, crude oil futures prices and news arrival interact. Secondly, it facilitates an innovative investigation of the informational efficiency of crude oil futures prices.

The remainder of the paper is organized as follows: Section 2 briefly reviews papers that analyse the impact of public announcements on market microstructure, asset returns and 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) has been followed by a large volume of research, which draws on the efficient market hypothesis that capital markets are efficient mechanisms to process publicly available information. Early results, particularly the ones based on daily (or even less frequent) data, include the nonresponsiveness of asset prices to unexpected macroeconomic news surprises (Dwyer and Hafer, 1989 for Treasury bonds, 1985, 1985 for exchange rates) and smaller-than-expected responses to company-specific and other non-economic news (Damodaran, 1989, and Cutler et al., 1989, both of which are for equity markets). However, McQueen and Roley (1993) report that the relationship between 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 looks at how announcements affect return volatility and examines the statistical significance of announcement variables. Other papers analyse the relationship between 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 Treasury bonds. Their study finds that price volatility is significantly higher between 08.30 and 08.35,² when the major macroeconomic statistical releases are made. Fleming and Remolona (1999) document that the arrival of macroeconomic news induces a two-stage adjustment process for U.S. Treasury securities' returns, spreads and trading volume. They report that prices react sharply to announcements for a brief spell of a 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, find that the news provides "a powerful positive and strongly statistically significant contribution to movements in the conditional variance." Price reaction to a scheduled macroeconomic announcement occurs within the first few minutes, with volatility remaining higher than normal up to three (Ederington and Lee, 1995) to fifteen (Almeida et al., 1998) minutes after the release. Consistent with these 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

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

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. However, their results are not robust, with one-hour returns being hardly 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 only examine the impact of macroeconomic announcements, 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 from 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 use 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 an 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 just scheduled statistical releases. 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 following section. This is in contrast to most of the empirical studies that use simple regression techniques — or, in the case of the effects of news on the return volatility — the generalized autoregressive conditional heteroscedastic (GARCH) framework of Engle (1982) and Bollerslev (1986).

3 Autoregressive Conditional Hazard Model

The 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). The *hazard rate* (or *hazard function*) is defined as a (limiting) conditional probability of an event occurring at time t (the next time period), given the information set Ω_{t-1} known at time $t - 1$. 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 at time $t - 1$. Previous studies have used the ACH model to model the probability of change of the level of the federal funds target rate by the Federal Reserve System (Hamilton and Jordà, 2002, and Demiralp and Jordà, 2001) and to study the occurrence of jumps in S&P 500 futures and U.S. Treasury bond futures returns (Andersen et al., 2007).

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 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 past waiting times (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 by using a nonlinear threshold ACD model. A natural extension of the Zhang et al. (2001) work is to incorporate announcement variables into the ACD framework. However, it is often of more interest to know the likelihood of a trade in the next 5 or 15 seconds given the news release, than to know 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 durations 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 $\{t_1, t_2, \dots, t_n\}$ with the n th trade arriving at the end of time t_n and $t_1 <$

$t_2 < \dots < t_n$. Also consider an associated *counting process* $N(t)$, which is the cumulative number of trades that have occurred by the end of time t (so $N(t) = N(t-1)$ if a trade 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 n th trade 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 conditional expectation of the duration u_n is a weighted average of p past durations and q past expectations, that are known at time t_{n-1} . That is, given past observations $u_{n-1}, u_{n-2}, \dots$, the ACD(p, q) model implies that

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

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

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

where the expectation $\psi_{N(t)}$ is formulated at time t_{n-1} . The expected conditional 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

$$h_t \equiv \Pr(x_t = 1 \mid \Omega_{t-1}) = \Pr(N(t) \neq N(t-1) \mid \Omega_{t-1}), \quad (3)$$

where $x_t = 1$ if a trade happens within $(t-1, t]$ and $x_t = 0$ otherwise.³

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 announce-

³We 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,

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{\Pr(x_{t+\Delta t} = 1 \mid \Omega_t)}{\Delta t}.$$

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.

ments that occur *between* trades. This implies that the expected conditional duration ψ_t may change by the end of every (calendar) time interval, through

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

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

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

or

$$h_t = \frac{1}{\psi_t}. \quad (6)$$

The reciprocal relationship between the expected conditional 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 conditional duration is two minutes, then the probability of a trade occurring within the next minute is 0.5. Of course, changing the units in which time is measured affects the magnitude of the expected conditional duration and the corresponding hazard rate. For instance, if the expected conditional 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 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 conditional 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

$$h_t = \frac{1}{\psi_t}, \quad (7)$$

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

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

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

where $\theta = (\omega, \alpha', \beta', \delta')'$ denotes a vector of parameters.

4 Data Sources and Properties

4.1 Airlines Intraday Data

Our empirical analysis focuses on the transactions and order data for three airline companies listed on the New York Stock Exchange, observed during August and September 2006, and incorporates crude oil futures prices.

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 industry was estimated to be more than \$163 billion in 2000 (DRI-WEFA, Inc., 2002). Despite this, the behaviour of air travel is 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 and the Severe Acute Respiratory Syndrome (SARS) epidemic in 2003. The huge financial losses incurred by airlines (\$32.3 billion dollars between 2001 and 2004, ATA, 2006) presented enormous challenges to the industry, and forced many airlines to embark on programmes of severe cost-cutting, 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 U.S. airlines increased on average by 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 in June 2005 reached \$60 a barrel).

Our study is based on all stock transactions for shares in the top three

U.S. airlines listed on the NYSE⁴ over the period of August and September 2006 (see Smallen, 2006, for a ranking of U.S. airlines). These airlines are AMR Corporation (AMR), Southwest Airlines Co. (LUV) and U.S. Airways Group Inc. (LCC). During the sample period, crude oil prices reached a long-time peak of nearly \$77 a barrel in 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, the second-highest close of all time (Patterson, 2006). The 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). Receiving much media coverage, airline stocks were traded almost continuously, becoming a perfect candidate for an empirical intraday study. Figure 1 illustrates the price behaviour of the selected stocks and the Standard and Poor’s 500 Index over the sample period.

[FIGURE 1 ABOUT HERE]

The selected airlines jointly carried 268.1 million passengers on their flights in 2005, 35.95 percent of the industry total (Smallen, 2006). In particular, airlines belonging to AMR Corporation, American Airlines and American Eagle Airlines, carried 115.6 million passengers on their international and domestic flights during 2005, more than any other airline. American Airlines ranks amongst 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). American Eagle Airlines, a regional carrier, was the fastest growing of the top ten airlines, carrying 17.9 percent more passengers in 2005 than in 2004. The second largest airline, in both the size and growth rankings, was Southwest Airlines. Southwest is a domestic low-fare airline that provides frequent flights to 61 airports in 31 states throughout the United States (NYSE, 2006). LUV carried 88.4 million passengers in 2005 and experienced an annual growth of nine percent. Finally, the third largest airline corporation was U.S. Airways Group, the owner of U.S. Airways and America West Airlines, which jointly carried 64 million passengers on their flights in 2005.

⁴Traditionally, 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).

The intraday data for the empirical analysis was 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 the calculation of other variables with which financial econometricians are concerned, such as duration between trades, nominal and percentage price changes, bid-ask spreads and proportion of buys.

To get the data into a form suitable for analysis, we must first make several adjustments 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 a 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 observations for which 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 than \$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 transactions outside NYSE regular trading hours and in the first 15 minutes of each trading days are removed. Finally, we merge any simultaneous trades to eliminate zero trade durations by constructing volume-weighted average prices and summing up the total volume of the trades (Engle and Patton, 2004).

Table 1 presents the number of observations before and after the aggre-

gation of simultaneous trades, and the summary statistics of the aggregated data. All stocks are traded very 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, spreads 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 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 dynamic dependencies, that are characteristic for long memory processes. Further, both durations and trade frequency reveal very strong diurnality (see Figure 3). The probability of trade exhibits a U-shaped pattern over the course of the day, that is also characteristic for 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 lunchtime. Conversely, the time-of-day seasonality in trade durations exhibits an inverse U-shape, as first documented by Engle and Russell (1998).

[TABLE 1 AND FIGURES 2 – 3 ABOUT HERE]

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 preceded 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) 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), 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.⁵ This is not surprising, as oil —

⁵References to oil prices in Western news reports are usually either references to the spot price

“the lifeblood of America’s economy” (U.S. Department of Energy, 2006) — supplies more than 40 percent of U.S. total energy demands. This suggests that it will be useful to incorporate oil shocks into models of trading frequency in stock markets. The incorporation of shocks to the oil market is particularly relevant for modelling the frequency of trading in airline stocks, given that refined crude oil is used to produce a wide array of petroleum products, including diesel and jet fuels.

Unfortunately, the study of oil shocks is not an easy task, as oil prices are affected by a wide range of factors, and an oil shock cannot be 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 the summer of 2006), and in the Middle East in general (see Twin, 2006, and Evans, 2006, for the impact of the 2006 Israel–Lebanon conflict on oil prices). In addition, there are other factors affecting oil markets, such as OPEC announcements, reports from the U.S. Department of Energy regarding Strategic Petroleum Reserves, the circumstances of major oil companies (such as BP, Exxon, Mobil, Shell, ChevronTexaco and Conoco Phillips) and weather warnings (for example, almost all of the Gulf of Mexico’s refineries, that produce 25 percent of U.S. oil, were closed in August 2005 due to Hurricane Katrina — which resulted in what were then 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 spot 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 worldwide it is the most liquid and actively traded financial instrument on a physical commodity (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 oil related surprises, but it also incorporates a continuous information measure. It also allows for an innovative investigation of trading spillovers in the context of stock and crude oil futures markets. 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.

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 is the benchmark in oil pricing and is the underlying commodity of the NYMEX oil futures contracts (EIA, 2006).

4.3 Firm-Specific News Releases

The sample period of August and September 2006 has been chosen because it contains several days on which regular company announcements were made, a few days when other unscheduled announcements were released and several control (non-announcement) days. News releases such as monthly traffic reports, fare increases, launches of new air routes and CEO changes are included in the sample, together with news stories related to the August 2006 U.K. terror plot. 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 (<http://www.smithbarney.com>), where the identical news items are systematically published 15 minutes earlier than on the NYSE. Information about the number of analysed announcements for each company is provided in Table 2.

[TABLE 2 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, few announcements are recorded for June and July 2006, which implies that the August 2006 activity was higher than usual. In our empirical analysis, we partition firm-specific news into five groups: analyst reports, earnings related releases (such as new routes and fare 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 set of two output measures (real GNP and unemployment), three price indicators (the implicit price deflator for nonfarm business income, hourly compensation per worker and import prices) and a money sector measure (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 Goldman Sachs’s (2008) classifications of “medium” and “high” impact for news released during NYSE trading hours. Table 3 lists the macroeconomic statistics that are considered in this study along with the sample sizes (the partitioning following Goldman Sachs, 2008).

[TABLE 3 ABOUT HERE]

It should be noted that several federal agencies release 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 GDP growth are not included in the present analysis. The impact of these macroeconomic announcements on stocks can only be examined in the context of equity futures markets, since American stock exchanges have the same trading hours. Dungey et al. (2008a) show that news releases that occur outside of the normal trading hours are absorbed by the equity markets via the electronic equity futures markets, such as the Global Exchange (GLOBEX) Trading System.

In addition to macroeconomic announcements, we include the results of the U.S. Treasury Bill auctions in the dataset, since existing studies document that interest rates and interest rate spreads can predict the business cycle (see Harvey, 1988). Moreover, Stock and Watson (1989) find that two interest rate spreads — the difference between the six-month commercial paper rate and the six-month Treasury bill rate, and the difference between the ten-year and one-year Treasury bond rates — are important in their newly constructed index of leading economic indicators.

A few forward-looking indices are included in the announcement data. There are two consumer confidence measures: 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 the Dow Jones Industrial Average, Gulley and Sultan, 1998). We also analyse the effects of two national surveys of purchas-

ing managers, the ISM National Manufacturing Index and the ISM National Non-Manufacturing (Services) Index. We also include the Chicago Fed National Activity Index (CFNAI), Philadelphia Fed Business Outlook Survey and the Business Barometer Index published by the National Association of Purchasing Managers in Chicago.

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. These studies use consensus specialist forecasts as proxies for market expectations regarding scheduled macroeconomic releases. However, 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 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 precisely estimate the effect of information arrival on market activity. However, this precision comes at a cost, as the dataset grows from an average of 108,407 tick-by-tick observations over the two month period to 967,500 one-second observations.

We model the observed data, which has not been diurnally adjusted. Following Engle and Russell (1998), empirical researchers often choose to first filter out the deterministic time-of-the-day effects, using either cubic splines (*inter alia* Engle and Russell, 1998, and Bauwens and Giot, 1998) or Fourier flexible form (Andersen and Bollerslev, 1997 and 1998). However, this approach is not feasible in cases such as this one, in which the dependent variable is binary. Thus we model the deterministic and stochastic concurrently, with a uniform set of four time indicators employed to account for the intradaily seasonality in a parsimonious way. The time indicators are selected by the Bayesian Information Criterion (BIC). Table 4 reports results for the baseline model,

i.e. the univariate ACH(1,1) with four time indicators, specified as

$$h_t = \frac{1}{\psi_t} \quad (10)$$

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

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 $(14:00-14:59)$. Different specifications of time indicators and time periods, though not reported, yield very similar α_1 and β_1 estimates, but slightly worse BIC statistics on the overall.

The obtained parameter estimates are all statistically significant (a quasi-maximum likelihood estimator is applied to obtain robust standard errors) and similar to coefficients reported in intraday GARCH and ACD studies, with infrequent updating (small α_1), long memory in expected conditional hazards (β_1 close to one) and considerable persistence ($\alpha_1 + \beta_1$ very close to one). Andersen et al. (2007), who use the ACH(1,1) model to study the occurrence of jumps in five-minute financial returns, report similar coefficients, though their β_1 's are somewhat smaller. As in Hamilton and Jordà (2002) and Andersen et al. (2007), we find that the basic ACH(1,1) model is rather adequate. The model does a good job of predicting whether a trade will occur within the next time interval. The proportion of correct predictions is 58.52% for American Airlines, 60.85% for U.S. Airways Group and 57.07% for Southwest Airlines. Moreover, the diagnostic analysis of the standardized binary residuals, defined as

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

suggests that the baseline specification accounts for most of the diurnal seasonality and the dynamic dependencies in the data.

[TABLE 4 ABOUT HERE]

We employ the BIC selection criterion and likelihood ratio test to determine the duration lag structure and consequently decide to use the ACH(2,1) to model the data. To account for market microstructure effects, we include the relative bid/ask spread, logarithmic trade volume and return in all equations (see Dacarogna et al., 2001, for definitions and stylized facts). We also include returns of the current front-month NYMEX light, sweet crude oil futures contract. Table 5 reports parameter estimates for the univariate ACH(2,1) model with crude oil futures returns, market microstructure variables and

time indicators, i.e.

$$h_t = \frac{1}{\psi_t} \quad (13)$$

$$\begin{aligned} \psi_t &= \omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} \\ &+ \sum_{j=1}^4 \gamma_j I_{t \in \tau(j)} + \delta \mathbf{z}_{t-1}, \end{aligned} \quad (14)$$

where $\mathbf{z}_{t-1}$ denotes a vector of market microstructure covariates and crude oil futures returns. The market microstructure covariates at time $t - 1$ are assumed to be equal to their value at the last observed trade t_{n-1} . This model has both a better likelihood and better BIC statistics than the baseline ACH(1,1). Further, it predicts more precisely whether or not a trade will occur within the next second. The proportion of correct predictions is 58.87% for American Airlines, 60.90% for U.S. Airways Group and 57.56% for Southwest Airlines.

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. Finally, the diagnostic analysis of the standardized binary residuals indicates that the model accounts for the diurnal seasonality and almost all of the dynamic dependencies in the data (see the right panels of Figures 4 and 5).

[TABLE 5 AND FIGURES 4 – 5 ABOUT HERE]

Market microstructure variables have a small yet significant effect on trading frequency, with trade volume and price changes revealing more information than the relative bid/ask spread. The coefficients on the past trade volume are negative and strongly significant for all stocks, 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), Dufour and Engle (2000) and Dungey et al. (2008b). However, in contrast to predictions from the Easley and O’Hara (1992) model, but consistently with the Admati and Pfleiderer (1988) model, we find that trades are more likely to occur as the bid/ask spread narrows. This finding is in line with Dow (2005), who shows that the wide bid/ask spread is associated with a decline in trading intensity, and 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 estimate for Southwest Airlines

suggests that as prices rise, the conditional probability of trade significantly increases. This provides evidence in support of the Diamond and Verrecchia (1987) analysis, where positive returns are associated with shorter trade durations. However, opposite results are obtained for American Airlines and U.S. Airways Group.

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), who find 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 they did not break the \$1.00 per US gallon threshold until 2008 (Cox, 2005). 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 Effects of Public Announcements

How do public announcements affect the frequency of trading in stocks? We begin to answer this question by analysing the average hazard rates during particular announcement and non-announcement (control) days (see Figures 6 and 7). In general, trading intensity appears to be larger at times when firm-specific analyst reports are released. Further, trades are more likely to occur when American Airlines make earnings-related or 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 shares 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. In contrast, consumer spending and confidence announcements tend to increase hazard rates for U.S. Airways. Interestingly, there are almost no differences between the trading activity that occurs during announcement and non-announcement days for Southwest Airlines.

[FIGURES 6 – 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 (14), to denote observation windows of five minutes *before* an announcement ($A_{t,-1}$), the minute *during* which an announcement is made ($A_{t,0}$) and ten minutes *after* an announcement is made ($A_{t,1}$). Our choice of the lengths of observation windows is similar to 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 an adequate data fit as well as the largest number of significant parameters. As in Simonsen (2006), we find that changing the before-during-after time intervals to 15-5-20 minutes does not markedly vary the results, although less significant coefficients are obtained. Tables 6 – 10 present the empirical results for the 5-1-10 observation windows. The first three tables report the impact of individual and grouped macroeconomic announcements on the probability of trade in airline stocks. Tables 9 – 10 present the results for company news. The results in Table 9 show the average effect of any company release on the frequency of trading as well as the effect of firm-specific news. This has been further partitioned into five categories (analyst reports, earnings related releases, security related news, marketing announcements and others, as detailed in Table 2). Finally, the estimation results for the five most significant individual releases for each company are summarized in Table 10.

[TABLES 6 – 10 ABOUT HERE]

The first three columns of each table report the estimates of the *before*, *during* and *after* coefficients. The fourth column reports the total (accumulative) impact of an announcement over the entire observation window (16 minutes), calculated as the sum of the news dummies, i.e. $\sum_{\tau=-1}^1 A_{t,\tau}$. The total likelihood of each model is provided in the sixth column, followed by the likelihood ratio statistic that tests the joint significance of the announcement indicators (the restricted model is reported in Table 5). All coefficient estimates and test statistics provided in bold are significant at the 10% level. Finally, the last column indicates the difference in Bayesian Information Criteria between the full and restricted models. Parameter estimates of coefficients for durations, conditional durations, market microstructure variables, crude oil futures returns and time indicators are not reported in the tables, although the relevant explanatory variables are included in all estimated models. In general, the ACH and exogenous covariate coefficients do not vary markedly from the baseline values reported in Table 5, and the results are robust to excluding market microstructure variables and crude oil futures returns.

Our results reveal a statistically significant impact of macroeconomic information flows on the conditional probability of trade in stocks. The Business Barometer Index, Current Economic Conditions (“Beige Book”), Consumer Sentiment Index, Federal Reserve Policy announcements and the results of Treasury Bond auctions have a considerable and mostly positive impact on the frequency of trading in all three stocks (the median behaviour of trading frequency in the presence of these macroeconomic releases is presented in Figure 8). Other macroeconomic indicators significantly affect the hazard rates of at least one stock, as indicated by large likelihood ratio statistics that test the joint significance of the announcement indicators. The single exception is the release of the Housing Market Index, produced by the National Association of Home Builders/Wells Fargo, which had no impact on the frequency of trading in any stock during the analysed period. Whilst the inclusion of news arrival variables significantly increases the explanatory power of the ACH model, this contribution is usually not strong enough to improve the Bayesian Information Criterion.

[FIGURE 8 ABOUT HERE]

Consistent with the market microstructure theory that investors trade on information (Easley and O’Hara, 1992), we find that macroeconomic news inflow induces a contemporaneous and cumulative increase in trading activity. On average, the estimates of the individual news indicator coefficients and their sums are negative, implying shorter trade durations and larger hazard rates over the entire observation window (16 minutes). Hazard rates usually return to their pre-announcement levels within about 30 minutes. For the set of indicators that positively affect all three stocks (see Figure 8), the likelihood of trades occurring during the release is two to six times greater than the usual likelihood of trades occurring. In particular, announcements of the Federal Reserve target rate induce a significant spike in the hazard rates of all stocks. This result is intriguing as during the analysed sample period the changes in monetary policy were in line with market expectations and as such “market efficiency would dictate that the expected portion of an announcement should have no impact” (Almeida et al., 1998).

It is also interesting to note that Crude Oil Inventories and Natural Gas Reports, published weekly by the Energy Information Administration, are good predictors of the probability of trade in AMR and LCC stocks, but not in LUV stock. This is in line with our observation that crude oil futures returns are insignificant when modelling the frequency of trading in LUV stock, and yet they matter when analysing the other airline shares.

Further, the results indicate that timeliness matters to some extent. That is, statistics that are released shortly after the period they cover, such as the ISM Manufacturing Index or the Consumer Confidence Index, have a larger impact on the probability of trade than less timely indicators (see Fleming and Remolona, 1999, Andersen et al., 2003 and Veredas, 2006 for evidence from fixed interest and foreign exchange rates markets). Finally, we find that the sign and significance of the announcement variables do not change when the crude oil futures returns are excluded from the models.

The differences between the airlines are even more obvious when we analyse the impact of company-specific news. Firstly, the log likelihood ratio tests of the total significance of the announcement variables indicate that aggregated and categorized LCC and LUV specific news have a significant impact on trading frequency (although their contribution is not strong enough to improve the BIC statistic). By contrast, the aggregated and categorized announcement variables are both insignificant for American Airlines. This could be due to a large number of AMR specific releases during the analysed sample period, each of them having a very different informational content that simply cannot be averaged. This is further investigated by the means of estimating the impact of each announcement individually, as discussed below. Secondly, the accumulated impact of company announcements on durations is either zero or even positive, which in the latter case implies lower trading activity around the specific event. This result shows that investors process the information from (often unscheduled) company news less quickly than scheduled macroeconomic news. This finding is in line with the learning model of Kim and Verrecchia (1991) and the empirical evidence from the Treasury futures market of Li and Engle (1998).

Analysing the individual parameter estimates in Table 9, we find that on the aggregated and categorized level there is little evidence of changes in trading activity *before* AMR specific announcements, though releases labelled as others tend to significantly decrease the probability of trade. The evidence for LCC is mixed; earnings and security related releases induce a decrease in hazard rates, while analyst reports induce an increase. For Southwest Airlines, trading intensity increases significantly *before* any news release, as predicted by the information asymmetry model of Kyle (1985), in which a monopolistic informed trader places orders before their (insider) information becomes common knowledge in order to maximize their profits. Further, Kim and Verrecchia (1997) argue that anticipated announcements should induce higher pre-announcement activity than unanticipated announcements, and indeed all releases made by Southwest Airlines (apart from analyst reports) were

publicly pre-advertised. By contrast, the information sets for the other two companies include many unanticipated “breaking news” stories, such as security releases concerning the terrorist threat at London airport (10 August 2006).

During an announcement itself traders often seem to “pause” (indicated by positive 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 (Easley and O’Hara, 1992). In contrast, the *after* coefficients for American Airlines and U.S. Airways Group are overwhelmingly insignificant. This implies the intensity of trading returns quickly to the pre-announcement levels and suggests that market participants absorb new information almost immediately, as in the multiple informed trader model of Holden and Subrahmanyam (1992). Alternatively, Green (2004) argues that lower trading intensity following information flow indicates that uninformed (liquidity) traders are patient with their orders.

We find that 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.⁶ In contrast to the aggregated results discussed above, we observe that at least six out of ten news releases have a significant effect on the frequency of trading in stocks. Unscheduled airline 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. On average, the news dummy coefficients are positive for all companies, implying that there is a significant decline in the market activity prior and consequent to a company news release.

Figure 9 illustrates the above finding. The top panel, which contains plots of the average median behaviour of trading frequency in the presence of individual firm-specific announcements, is most striking. Hazard rates monotonically decrease within the window of 5 minutes before to 10–12 minutes after the release, and remain below the pre-announcement levels for more than 30 minutes. In particular, trades in LCC and LUV stocks are unlikely to occur, with the conditional probabilities of trade as low as 0.0507 and 0.0817,

⁶There are two instances, when AMR specific and macroeconomic news were released concurrently. To check the robustness of our individual company announcement results, we re-estimate the models with an indicator for all macro news, with the observation window of 1+10 minutes. Throughout, this dummy is statistically significant in models of AMR and LCC hazard rates (the coefficients are -0.0009 and -0.0020, respectively, which confirms our finding that macroeconomic releases increase the probability of trade), but our results remain unchanged.

respectively, compared with the average probabilities of 0.0955 and 0.1035. This contrasts with the second panel, which contains plots of median response of hazard rates to aggregated company releases. In this case, there is no response of AMR hazard rates, while the probability of trade in LUV stock significantly increases before and after releases. Analysis of the next three panels reveals that the conditional probability of trade in LUV stock increases during analyst reports and earnings related news, but falls during other announcements. The hazard lines for American Airline are almost flat, again indicating that averaging announcements is suboptimal. For U.S. Airways, we observe a sharp increase in frequency of trading shortly after analyst reports and after other news, but a decrease after earnings announcements.

[FIGURE 9 ABOUT HERE]

Why do market participants react differently to the same type of announcements? Kim and Verrecchia (1997) argue that since investors vary in skill at interpreting public information, news releases actually increase information asymmetry. Moreover, while the impact of individual firm-specific announcements is not systematic, there seems to be some evidence that good news increases the conditional probability of trade, whereas bad news induces a slow-down in trading activity. Examples of announcements that reduced the intensity of trading include AMR and LCC related security releases following the alleged terror plot at London airport (10 August) and then two jet diversions because of security concerns (25 August). On the other hand, favourable traffic reports, new routes announcements and affirmative analyst reports all tend to raise hazard rates. This is illustrated by a Standard & Poor's (S&P) Equity Research Services report on 10 August. The 10.05 news on this date contained information about American Airlines being specifically targeted by the terrorists. After a series of subsequent releases and updates, S&P Equity Research lowered its fundamental outlook on the airline sub-industry at 15.26. As a result, frequency of trading in AMR and LCC stocks declined even further. Interestingly, this report strongly affected the probability of trade in Southwest Airline stock, too, although in a positive way. The attempted terrorist attacks of the day and high oil prices were the main reasons for the downgrade. Yet LUV is a domestic carrier and it is well known for its successful jet-fuel hedging strategy. Hence, it is not surprising that investors were keen to trade more frequently in LUV stocks following the S&P analysis.

6 Conclusions

We modify the autoregressive conditional hazard framework of Hamilton and Jordà (2002) to study the impact of public news releases, crude oil futures prices and key microstructure features of market activities on trading frequency in airline stocks. We find that company and U.S. macroeconomic announcements significantly change the conditional probability of trade, but traders' reactions depend on the news informational content. On average, macroeconomic statistical releases increase the frequency of trading in stocks, in line with the theoretical model of Easley and O'Hara (1992). The impact depends on news timing, with indicators published earlier or containing unique information producing the strongest response. In contrast, firm-specific announcements tend to decrease trading intensity, especially when analysed individually. The effect is most pronounced for unscheduled airline security releases and other bad news. By comparison, good news such as favourable analysts' reports tend to increase the conditional probability of trade.

We also find that market microstructure variables have a small yet significant effect on trading frequency, with trade volume and returns revealing more information than the relative bid/ask spread. High trade volume and narrow bid/ask spread induce higher trading intensity. The results also clearly indicate that tick-by-tick crude oil futures returns are highly relevant for 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.

We provide evidence that the ACH model allows for efficient and flexible modelling of the conditional probability of trade in the next time interval. However, an interesting direction for future research would be to extend 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 could 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). Further extensions of the model could also include semiparametric and nonparametric estimation techniques, as in the closely related framework of Gerhard and Hautsch (2001).

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Table 1: Descriptive Statistics of 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
Ljung-Box Q(15) ^c	16,457	10,551	13,132
Ljung-Box Q(100) ^c	62,847	33,108	41,767
Bid/Ask 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
Ljung-Box Q(15) ^c	67,187	47,864	30,628
Ljung-Box Q(100) ^c	114,008	86,920	40,694
Trading Volume^d			
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
Ljung-Box Q(15) ^c	2,601	3,025	1,434
Ljung-Box Q(100) ^c	5,830	9,258	3,377
Proportion of Buys	55.24%	55.28%	54.11%
Market Value ^e	4.497	3.833	13.788

Notes: The table reports sample sizes and summary statistics for trade and quote data for AMR Corporation (AMR), U.S. Airways Group (LCC) and Southwest Airlines (LUV). *Sample period*: NYSE trades and quotes 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.

^c 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. Statistics provided in **bold** are significant at 5% level.

^d Number of shares traded.

^e Stock market-capitalisation of 1 August 2006, calculated by multiplying the number of shares outstanding by the closing price (in billions of USD). *Source*: CRSP database.

Table 2: Firm-Specific News Releases

	Aug 2006	Sep 2006
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: This table lists types of firm-specific news announcements included in the study and the total number of releases made between 9.45 and 16.00 during the sample period from 01 August to 30 September 2006. *Data source:* NYSE.

Table 3: 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. The grouping follows Goldman Sachs (2008). *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 4: Parameter Estimates of ACH(1,1) Models with Time Indicators

	AMR	LCC	LUV
ω	0.0008 [0.0002]	0.0029 [0.0003]	0.0043 [0.0008]
α_1	0.0011 [0.0001]	0.0011 [0.0001]	0.0011 [0.0001]
β_1	0.9985 [0.0001]	0.9984 [0.0001]	0.9981 [0.0002]
$I_{t \in (9:45-10:59)}$	0.0006 [0.0001]	0.0009 [0.0001]	0.0021 [0.0002]
$I_{t \in (11:00-11:59)}$	0.0014 [0.0001]	0.0014 [0.0002]	0.0028 [0.0004]
$I_{t \in (12:00-13:59)}$	0.0013 [0.0001]	0.0017 [0.0002]	0.0034 [0.0005]
$I_{t \in (14:00-14:59)}$	0.0006 [0.0001]	0.0006 [0.0002]	0.0015 [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: We model the conditional probability of trade (h_t) in stocks of AMR Corporation (AMR), U.S. Airways Group (LCC) and Southwest Airlines (LUV) as

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

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

where $I_{t \in \tau(j)}$ denotes time indicators. Coefficient estimates provided in **bold** are significant at the 5% level. Robust standard errors are provided in square brackets. The sample consists of 967,500 1-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006.

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 5: Parameter Estimates of ACH(2,1) Models with Crude Oil Futures Returns, Market Microstructure Variables and Time Indicators

	AMR	LCC	LUV
ω	0.0186 [0.0019]	0.0442 [0.0049]	0.0433 [0.0092]
α_1	0.0009 [0.0001]	0.0010 [0.0001]	0.0013 [0.0002]
α_2	0.0010 [0.0001]	0.0010 [0.0001]	0.0011 [0.0002]
β_1	0.9973 [0.0002]	0.9968 [0.0003]	0.9953 [0.0009]
oil_{t-1}	-0.0007 [0.0002]	-0.0017 [0.0003]	0.0001 [0.0004]
$return_{t-1}$	0.0023 [0.0012]	0.0124 [0.0024]	-0.0160 [0.0071]
$volume_{t-1}$	-0.0030 [0.0003]	-0.0061 [0.0006]	-0.0069 [0.0013]
$spread_{t-1}$	0.0001 [0.0001]	0.0028 [0.0004]	0.0030 [0.0006]
$I_{t \in (9:45-10:59)}$	0.0005 [0.0001]	0.0005 [0.0003]	0.0021 [0.0002]
$I_{t \in (11:00-11:59)}$	0.0015 [0.0002]	0.0014 [0.0003]	0.0049 [0.0012]
$I_{t \in (12:00-13:59)}$	0.0018 [0.0002]	0.0024 [0.0004]	0.0071 [0.0019]
$I_{t \in (14:00-14:59)}$	0.0006 [0.0002]	0.0006 [0.0003]	0.0028 [0.0010]
lnL	-378,707.3	-298,157.2	-317,386.1
LR stat ^a	1,311.2	1,954.8	831.2
BIC	757,579.9	596,479.8	634,937.5
CorrPredict ^a	58.87%	60.90%	57.56%

Notes: We model the conditional probability of trade (h_t) in stocks of AMR Corporation (AMR), U.S. Airways Group (LCC) and Southwest Airlines (LUV) as

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

where $I_{t \in \tau(j)}$ denotes time indicators and $\mathbf{z}_{t-1}$ denotes a vector of exogenous covariates: *oil* (the current month NYMEX light, sweet crude oil futures returns), *return* (the 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 the 5% level. Robust standard errors are provided in square brackets. The sample consists of 967,500 1-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases.

^a The *LR statistic* tests the joint significance of the variables *not* included in the baseline ACH(1,1) model (Table 4) and follows $\chi^2(5)$ under H_0 . Statistics provided in **bold** are significant at 5% level. *CorrPredict* refers to the proportion of correct predictions from the model that a trade occurs within the next time interval.

Table 6: Impact of Macroeconomic Announcements on the Probability of Trade in AMR Corporation Stock

	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: We model the conditional probability of trade (h_t) in AMR Corporation stock as

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

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 were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 10% level (robust standard errors). The sample consists of 967,500 1-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *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 a $\chi^2(1)$ statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 5) 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, i.e. $BIC_{full} - BIC_{restricted}$.

Table 7: Impact of Macroeconomic Announcements on the Probability of Trade in U.S. Airways Group Stock

	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: We model the conditional probability of trade (h_t) in U.S. Airways Group stock as

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

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 were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 10% level (robust standard errors). The sample consists of 967,500 1-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *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 a $\chi^2(1)$ statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 5) 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, i.e. $BIC_{full} - BIC_{restricted}$.

Table 8: Impact of Macroeconomic Announcements on the Probability of Trade in Southwest Airlines Stock

	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: We model the conditional probability of trade (h_t) in Southwest Airlines stock as

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

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 were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 10% level (robust standard errors). The sample consists of 967,500 1-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *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 a $\chi^2(1)$ statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 5) 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, i.e. $BIC_{full} - BIC_{restricted}$.

Table 9: Impact of Firm-Specific News Releases (*by Genre*) on the Probability of Trade

	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	0.0016	-0.0082	0.0012	-0.0055	-378,705.2	4.2	37.1
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	0.0224	-0.0226	0.0321	0.0318	-298,145.9	22.6	18.8
Security Related News	0.0320	0.0460	0.0091	0.0871	-298,137.4	39.6	1.7
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: We model the conditional probability of trade (h_t) in stocks of AMR Corporation, U.S. Airways Group and Southwest Airlines as

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

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 were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 10% level (robust standard errors). Insignificant results for AMR and LCC marketing announcements are not reported. The sample consists of 967,500 1-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *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 a $\chi^2(1)$ statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 5) 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, i.e. $BIC_{full} - BIC_{restricted}$.

Table 10: Impact of Most Significant Firm-Specific News Releases on the Probability of Trade

	Before	During	After	Total ^a	lnL	LR stat ^a	BIC diff ^a
AMR Corporation							
Earnings 04.08 11:00	0.0224	0.1430	0.0096	0.1750	-378,694.0	26.4	14.9
Security 10.08 15:30	-0.0123	0.0300	0.0065	0.0241	-378,695.7	23.2	18.2
Ticket Prices 18.08 12:10	0.0450	-0.2664	0.0373	-0.1841	-378,697.2	20.1	21.2
Security 10:08 10:05	0.0003	0.0806	-0.0042	0.0766	-378,697.6	19.3	22.0
Security 10:08 9:53	-0.0009	-0.0027	0.0067	0.0031	-378,698.0	18.5	22.8
U.S. Airways Group							
Ticket Prices 29.08 11:00	0.0610	0.3897	0.0477	0.4984	-298,135.0	44.5	-3.1
Other (New CEO) 14.09 11:30	-0.0261	-0.0102	-0.0039	-0.0401	-298,143.3	27.9	13.4
Security 10.08 12:57	0.0208	0.0856	0.0278	0.1341	-298,146.1	22.2	19.1
New Routes 22.09 14:44	-0.0810	0.0936	0.0161	0.0287	-298,149.6	15.1	26.2
Security 25.08 15:16	-0.0613	0.1228	0.1130	0.1745	-298,150.7	13.0	28.4
Southwest Airlines							
Analyst Report 03.08 15:34	0.0324	-0.1131	-0.0223	-0.1030	-317,203.0	366.2	-324.8
Ticket Prices 12.09 10:00	-0.0205	0.0454	0.0056	0.0304	-317,373.3	25.6	15.8
Analyst Report 10.08 15:26	-0.0208	0.0391	-0.0075	0.0108	-317,373.3	25.4	15.9
Other (Energy Policies) 02.08 14:03	-0.0166	0.0106	0.0262	0.0203	-317,380.5	11.2	30.2
Other (New CEO) 30.08 15:00	0.0014	-0.0151	0.0234	0.0097	-317,382.1	7.9	33.4

Notes: We model the conditional probability of trade (h_t) in stocks of AMR Corporation, U.S. Airways Group and Southwest Airlines as

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

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 were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 10% level (robust standard errors). Analysed announcements are ordered by the total significance of the model. The sample consists of 967,500 1-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *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 a $\chi^2(1)$ statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 5) 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, i.e. $BIC\ diff = BIC_{full} - BIC_{restricted}$.

Figure 1: Price Behaviour of Airline Stocks and the Standard and Poor's 500 Index

Notes: The figure graphs the price behaviour of airline stocks and the Standard and Poor's 500 Index, sampled at 5-minute intervals from NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source:* TAQ and CQG databases.

Figure 2: Sample Autocorrelation (left column) and Partial Autocorrelation Functions (right column) of Trade Durations

Notes: The main graphs illustrate the ACF (left column) and PACF (right column) for the first 500 lags of trade durations, and the inserts illustrate the PACF for the first 100 lags of trade durations. The dashed lines represent 95% confidence bounds. The sample consists of 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)

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. The sample consists of NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source:* TAQ database.

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

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 5. 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. The sample consists of 967,500 1-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source:* TAQ database.

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

Notes: The relevant parameter estimates are reported in Table 5. The main graphs illustrate the ACF (left column) and PACF (right column) for the first 500 lags of standardized binary residuals, and the inserts illustrate the PACF for the first 100 lags of standardized binary residuals. The dashed lines represent 95% confidence bounds. The sample consists of 967,500 1-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source:* TAQ database.

Figure 6: Effect of Macroeconomic Announcements on Trade Frequency

Notes: The solid lines represent trading frequency for announcement days and the dashed lines represent trading frequency for days when no macroeconomic announcements of this type 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. The sample consists of 967,500 1-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006.

Data source: TAQ database and Bloomberg.

Figure 7: Effect of Company Announcements on Trade Frequency

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. The sample consists of 967,500 1-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source:* TAQ database and NYSE.

Figure 8: Trading Frequency Responses to Macroeconomic Announcements

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 6 – 8. The x-axis denotes time in minutes, with the announcements time fixed at 0. The sample consists of 967,500 1-second observations based on 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 Firm-Specific Announcements

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 bounds. Both estimates are obtained using Monte Carlo simulations based on parameter estimates reported in Tables 9 – 10. The x-axis denotes time in minutes, with the announcements time fixed at 0. The sample consists of 967,500 1-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006.

Data source: TAQ database and NYSE.