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Abstract

In September 2008, a six-year-old article about the 2002 bankruptcy of United Airlines' parent company resurfaced on the Internet and was mistakenly believed to be reporting a new bankruptcy filing by the company. This episode caused the company's stock price to drop by as much as 76 percent in just a few minutes, before NASDAQ halted trading. After the "news" had been identified as false, the stock price rebounded, but still ended the day 11.2 percent below the previous close. We explore this natural experiment by using a simple asset-pricing model to study the aftermath of this *false news shock*. We find that, after three trading sessions, the company's stock was still trading below the two-standard-deviation band implied by the model and that it returned to within one standard deviation only during the sixth trading session. On the seventh day after the episode, the stock was trading at the level predicted by the asset-pricing model. We investigate several potential explanations for this finding, but fail to find empirical evidence supporting any of them. We also document that the false news shock had a persistent negative effect on the stock prices of other major airline companies. This is consistent with the view that contagion effects would have dominated competitive effects had the bankruptcy actually taken place.

Key words: false news, natural experiment, United Airlines, noise, market efficiency, contagion

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1 Introduction

A central question of financial economics is whether markets are efficient. Among other things, market efficiency requires that asset prices react to news about fundamentals, as opposed to noise. However, in most circumstances relevant information and noise arise simultaneously, and cannot be easily separated. Agents have to make inference about fundamentals from possibly noisy pieces of information, and thus the noise component usually affects agents' investment decisions. In this paper we explore a natural experiment that allows us to study a stock market's reaction to an information release for which the noise component can be singled out very cleanly.

On September 8, 2008, an old article about the 2002 bankruptcy of United Airlines' parent company (henceforth UA) resurfaced on the Internet and was mistakenly believed to be reporting a new bankruptcy filing by the company.[1] This caused the company's stock price to drop by as much as 76% in just a few minutes, before NASDAQ halted trading. After the false news had been identified as such, the stock price rebounded, but still ended the day 11.2% below the previous close. Trading volumes skyrocketed during these extreme price movements.

The episode can be thought of as comprising two pieces of information: the "news" that UA had filed for bankruptcy protection again, and the subsequent statements by UA and the media companies involved in the article's release clarifying that it pertained to the 2002 bankruptcy filing. The clarification statements were widely circulated shortly after the large price drop, and were publicly available when trading resumed. Moreover, the false news appears to have made its way to the main sources of financial information by sheer accident. This justifies our assumption that the episode provides a natural experiment to study the effects of what we refer to as a *false news shock*: two pieces of information that cancel each other. Given this shock, we are left with the task of trying to make sense of the 11.2% drop of UA's stock price on that day and its slow recovery on subsequent days.

In order to study the impact of the false news shock on UA's stock price, we need a so-called "counterfactual": the path that the stock price would likely have followed in the absence of the false news. In Section 3 we construct such a counterfactual path using a simple factor pricing model for UA's stock return. In particular, we postulate that the excess return on UA stock depends linearly on the excess returns of three factors: the "market" (as proxied by the S&P 500), the "airline industry" (as proxied by Bloomberg's World Airline Index), and crude oil. We estimate the asset-pricing model using data until the day before the false news impacted the market. The model captures the dynamics of UA excess returns quite well, explaining about 40% of its variation at both daily and intraday frequencies. We use our model to construct point estimates and standard-error bands for UA's stock price given the

[1] Although the article referred to United Airlines' parent company (UAL Corp.), throughout the paper we refer to the episode as pertaining to United Airlines. UAL Corp. was traded at NASDAQ under the ticker symbol "UAUA" at the time of the episode. In October 2010, UAL Corp. completed a merger with Continental Airlines Inc. The new United Continental Holdings, Inc. trades under the ticker symbol "UAL".

evolution of the three pricing factors on the day of the false news event, and over subsequent trading sessions.

We find that after three trading sessions UA shares were still trading below the two-standard-deviation band implied by the model, and only returned to within one standard deviation of the model-implied price on the sixth trading session after the event. On the seventh day after the episode - and for quite a few days thereafter - the shares traded essentially at the level predicted by the asset-pricing model. These findings are robust to different specifications of the factor model.

Throughout our analysis we maintain the assumption that the two pieces of information that comprise the false news shock exactly cancel each other, in the sense that after the clarification statements investors fully understood that the article was six years old, and that UA had not filed for bankruptcy protection again. However, it is possible that the false news shock had indirect asset-pricing effects not captured by our factor model - e.g., by affecting the liquidity of UA shares or investors' views about the quality of information about UA's fundamentals. We explore these possibilities in Section 5. However, we fail to find empirical evidence that is supportive of the theory-based explanations that we entertain. In that section we also investigate a more idiosyncratic potential explanation, motivated by the special circumstances in which the episode took place - namely, in the week before the bankruptcy of Lehman Brothers. Specifically, we consider the possibility that UA's financial conditions around that time made it particularly susceptible to changes in market perceptions about the health of the U.S. financial sector, due to high borrowing needs in a context of tightening borrowing constraints and lending standards. We augment the asset-pricing model with a factor that captures the market's assessment of U.S. banks' health, and repeat our counterfactual analysis.[2] While the financial factor comes out as extremely statistically significant, it does not affect any of our conclusions, as the changes in the estimated counterfactual and error bands are negligible.

In Section 6 we analyze the evolution of the stock prices of other major U.S. airlines during the episode (American Airlines, Continental Airlines, Delta Airlines and U.S. Airways). We find a very similar, although attenuated, pattern. On September 8, 2008, their share prices experienced maximum drops in the range of -25.6% to -31.8%, and ended the day between -2.5% to -5.3% relative to the previous closing price. The timing of the sharp price moves coincides with UA's. Employing the same type of factor pricing model as for UA, we construct a counterfactual path for the stock price of each of these four companies and find that the effects of the false news shock originated from the article on UA were also persistent. Finally, we document that intraday trading volumes for all five stocks spiked up considerably during the sharp price movements. We discuss our findings in the context of the literature on the "contagion and competitive effects of bankruptcy" (e.g. Lang and Stulz 1992).

Our paper adds to the available evidence on systematic deviations from informationally frictionless

[2] We thank an anonymous referee for suggesting this potential explanation to us.

and efficient markets. Huberman and Regev (2001) document that a front-page New York Times article about an old scientific discovery had a huge impact on the stock price of the company responsible for it (EntreMed), even though the scientific findings had been published in *Nature* and covered by a not-so-prominent New York Times article more than five months before. The prominent article also had spillover effects on the stock prices of other biotechnology companies. The authors conclude that "enthusiastic public attention" may induce important movements in stock prices in response to old news that may have been overlooked by a large fraction of market participants.

Like Huberman and Regev (2001), our paper provides very clean evidence on the importance of media vehicles in transmitting information to market participants and affecting how they perceive the world. While it is usually taken for granted that people receive and act on information transmitted by various media outlets, most models have no role for them - information is simply "received" (or inferred) by agents without any reference to concrete communication channels. There is, however, a growing body of literature that aims at estimating the asset-pricing impact of news identified through application of linguistic tools to newspaper articles. Tetlock (2007) constructs a media-based measure of "sentiment" towards stock markets from a linguistic analysis of the Wall Street Journal's "Abreast of the Market" column. He finds that high negative sentiment predicts lower returns for the Dow-Jones index over the next few days followed by a reversion, and that unusually high or low pessimism predicts high trading volume. Sinha (2009) uses a sentiment score from Thomson-Reuters to measure the tone of news articles and constructs portfolios based on past sentiment. He finds that a portfolio long in positive- and short in negative-sentiment firms is positively correlated with a long-short momentum portfolio and generates positive returns. Tetlock, Saar-Tsechansky and Mackassy (2008) use the fraction of negative words in firm-specific news articles to predict future earnings and stock returns. They find that negative language predicts negative earnings, even when they control for analysts' forecasts and historical accounting data. They also document that stock prices respond with a one-day delay to negative language in the firm-specific news.

The papers summarized in the previous paragraph share the feature that they measure sentiment in news articles without assessing whether the information contained in the articles is actually novel. Accordingly, they are only loosely related to Huberman and Regev (2001), who document the asset-pricing impact of an article that contained old news about a company. Tetlock (2009) is somewhat closer to Huberman and Regev's work. He constructs empirical proxies to capture the degree to which a news story about a company is stale, such as the presence of another news story in the prior week, the presence of an extreme abnormal stock return in the prior week, or high media coverage in the past month. Tetlock (2009) sorts individual stocks into calendar-time portfolios based on the firms' recent public news. He documents that return reversals after news events are stronger when these events have a higher content of stale information according to his empirical proxies of news staleness.

While our paper is close to Huberman and Regev (2001) and Tetlock (2009) in some dimensions, there is a crucial distinction, associated with the difference between the concept of stale (or old) news, and that of false news. The old news in the EntreMed case studied by Huberman and Regev (2001), and likely in many of the stale news identified by Tetlock (2009), refer to factors which at the time were still potentially important for the future profitability of the firm. In contrast, in the United Airlines event that we study, the "news" that produced a significant and persistent deviation of the company's stock price from its fundamental value was simply false: there was no new bankruptcy filing, and the reemergence of the six-year-old article should not matter for the company's profitability going forward. To the best of our knowledge, this particular nature of a false news event is unique to the episode that we document and study.

Finally, when we first circulated our paper in February 2009 we were unaware of any other work on the UA episode. Since then we learned of two such papers. Lei and Li (2010) take a market microstructure approach, and use the episode to study how investors traded on September 8, 2008 to exploit their short-lived information. They find that during the sharp price movements associated with our false news event, investors used "intermarket sweep orders" - a liquidity-demanding type of limit orders - and traded aggressively. This led to a significant increase in the frequency of trades, and in the number of markets where trades are executed, but not in the size of trades. Marshall et al. (2010) is somewhat closer to our paper. They focus on the time it took for UA and other stocks to react to the false news shock as a way to test a specific theory, the so-called "gradual information diffusion hypothesis." They find that other airline stocks and supplier firms recovered quickly,[3] whereas UA's stock price took a few days to recover fully.[4] They conclude that this is inconsistent with the gradual information diffusion hypothesis, and with the findings of Cohen and Frazzini (2008). Thus, their paper should be seen as complementary to ours, in that they analyze - and dismiss - a specific theory of persistent "mispricings" that we do not entertain in our analysis.

Our paper is organized as follows. In the next section we provide a description of the episode. Section 3 describes our pricing model and the data used in the estimation. Section 4 presents our results, and discusses robustness issues. Section 5 provides an analysis of possible explanations for our findings. Section 6 documents the impact of the false news shock on the stock prices and trading volumes of other major airlines. The last section concludes.

[3] Their finding that the effects of the false news shock on other airline stocks faded quickly might appear to be inconsistent with our finding of persistent "contagious" effects on other major U.S. airlines. This, however, is not the case. The reason is that Marshall et al. (2010) do not analyze individual airline stocks, and focus instead on broad industry indices. Their finding is thus fully consistent with the behavior of the airline industry index that we use in our factor model, which fell only modestly during the episode, and fully recovered during the same day.

[4] The authors use a reference stock price based on "pre-stale-news-release levels," and conclude that UA's stock "did not return to its pre-rumor level until five days later."

2 The Episode

The episode took place on Monday, September 8, 2008, and was covered in detail in the main newspapers on subsequent days. Here we provide a summary based on articles published on Bloomberg and in the New York Times, Financial Times, and Washington Post during the week of the event.[5]

On Sunday, September 7, 2008, an article first published on December 10, 2002, in the Chicago Tribune about UA's bankruptcy filing allegedly made its way to the list of most viewed business-related articles on the webpage of the Sun-Sentinel, a Florida newspaper. Apparently the article contained no dates that explicitly tied it to the 2002 bankruptcy.[6] It was found and scanned by a Google News program, which then indexed it so that it could be included in Google News' pages, and made available in Internet-search results. On Monday, September 8, the article caught the attention of an employee of a financial information company who was searching the Internet for news about recent bankruptcies. The employee sent a summary of the article with a link to the Sun-Sentinel webpage to the Bloomberg Professional service at around 10:53 AM.

At that time, UA's stock price was trading at \$11.85, after having traded as high as \$12.45 on that morning - and from a close of \$12.30 on the previous session. Around 10:57 AM UA's stock price started to drop very sharply, and reached a low of \$3.00 per share at 11:00 AM, a few minutes before the headline citing the article appeared on Bloomberg News terminals (around 11:03 AM). Around 11:07 AM, NASDAQ halted trading on UA stock. By then, a significant fraction of the drop had been reverted, and the stock was already trading at around \$8. At 11:16 AM, Bloomberg posted a headline citing a denial by United Airlines. At 11:29 AM, Bloomberg posted a first correction saying that "...the story regarding a United Airlines bankruptcy is a mistake. An old story from December 2002 was inadvertently published today." At 12:14 PM, Bloomberg then posted the statement "UAUA: UAL Corp. says reports that it filed for bankruptcy are completely untrue." Trading resumed at 12:30 PM, with the stock priced near \$11.25. It ended the session at \$10.92 - down 11.2% from the previous day's close. Trading volumes shot up significantly during the sharp price movements, and as a result the total volume on the day of the event was roughly three times larger than on either of the two adjacent trading days. In subsequent days, the stock price fell as low as \$9.12 (on September 11), and on September 15 it finally traded above the level of prices seen just prior to when the false news impacted the market.

At the close of the trading session prior to September 8, 2008, UA had a market capitalization of approximately \$1.6 billion. The figures for the other four airlines that we analyze in Section 6 ranged from \$900 million for U.S. Airways to \$2.8 billion for American Airlines. At the lowest price triggered

[5] For the interested reader, Marshall et al. (2010) also provide a detailed account of the episode.

[6] However, the article contained other clues that could have easily made it clear to an informed reader that the story was old, including a reference to UA's 97-cent share price (it was trading around \$12 at the opening on September 8).

by the false news shock the loss in market value was roughly \$1.2 billion for UA alone, and roughly \$3.5 billion for the five airlines combined. At the September 8 closing prices, the loss in market value for the five airlines exceeded \$500 million.

2.1 Two pieces of "news"

Two pieces of information arrived in connection with the reappearance of the 2002 article. The first one is the "news" that UA had filed for bankruptcy protection again. Without knowledge that the information was based on a six-year-old article, this amounted to a substantial piece of (negative) fundamental information about UA that "justifies" the steep price drop observed on the morning of September 8, 2008. The second piece of information is the clarification that the article was six years old, which "justifies" the rebound in the stock price.

A review of articles published on Bloomberg News and on the Internet on Monday, September 8, shows that the information that the Chicago Tribune article was six years old became widely available at 11:16 AM, when Bloomberg posted a first correction, and thus well before trading in UA stock resumed at 12:30 PM. The second piece of news involved clarification statements from United Airlines, the Chicago Tribune, and Bloomberg. Even if one attaches some uncertainty as to whether investors had access to all the statements during the September 8 trading session, and took them at face value, the episode was widely covered by the main media on the subsequent day. Thus, in our quantitative analysis we maintain the assumption that the two pieces of news cancel each other, in the sense that after the clarification statements investors fully understood that the article was six years old, and that UA had not filed for bankruptcy protection again.

3 Pricing model and data

In order to study the impact of the false news shock, we need to construct a "counterfactual" path that UA's stock price would likely have followed in the absence of the false news. To this end, we postulate a simple three-factor model for the excess return on UA's stock:

$$r_{UA,t} - r_t = c + \beta_M \left(r_{M,t} - r_t \right) + \beta_A \left(r_{A,t} - r_t \right) + \beta_O \left(r_{O,t} - r_t \right) + e_t, \tag{1}$$

where $r_{UA,t}$, r_t, $r_{M,t}$, $r_{A,t}$, and $r_{O,t}$ denote the (logarithmic) returns between periods $t-1$ and t on, respectively, UA's stock, a one-period risk-free nominal bond, the market portfolio, the airline-industry portfolio, and crude oil. The loadings on the factors are given by the coefficients β_M, β_A and β_O, and c is a constant. We think it is natural to expect estimates of β_M and β_A to be positive, and estimates of β_O to be negative. Finally, e_t is an error term that captures the idiosyncratic component in UA's stock return.

We estimate (1) by Ordinary Least Squares (OLS) using the effective federal funds rate as the risk-free rate, the S&P 500 as the proxy for the market portfolio, Bloomberg's World Airline Index as the measure of the airline-industry portfolio,[7] and the price of crude oil futures as reported in Bloomberg under the code "CL1 Comdty". Our baseline specification uses 15-minute intraday data, but we also estimate the model with daily data. All daily data are from Bloomberg. Intraday data for UA's stock price are from Thomson-Reuters. Intraday data for the S&P 500, Bloomberg's World Airline Index and oil futures are from Bloomberg.[8] In our estimations with intraday data, we use a sample from March 3, 2008 through September 5, 2008 (the day before the event). Our sample with daily data starts on August 1, 2007. Finally, we perform our counterfactual analysis on data for the period September 8, 2008 - September 24, 2008.

We use the estimated pricing model to ask the following counterfactual question: "what would have happened to the stock price of UA if the false news shock had not occurred?". Let t_0 denote the day of the event (or, in the case of intraday data, the first trading period on that day). Knowledge of the realizations of $r_{M,t}$, $r_{A,t}$, $r_{O,t}$, and r_t for $t \geq t_0$ allows us to construct an estimate of what the return on UA's stock would have been in the absence of any variation in the firm-specific component of the stock return in (1):

$$\widehat{r}_{UA,t} = r_t + \widehat{c} + \widehat{\beta}_M \left(r_{M,t} - r_t\right) + \widehat{\beta}_A \left(r_{A,t} - r_t\right) + \widehat{\beta}_O \left(r_{O,t} - r_t\right), \ t \geq t_0, \tag{2}$$

where "hatted" variables denote estimates. Then we can add our estimates of $\widehat{r}_{UA,t}$ for $t \geq t_0$ to UA's (log) stock price at the close of the last trading session prior to the event, denoted s_{UA,t_0-1}, to obtain point estimates for what UA's (log) stock price would have been in the absence of the false news shock (and of any other non-zero realization of e_t):

$$\widehat{s}_{UA,t} = s_{UA,t_0-1} + \sum\nolimits_{j=t_0}^{t} \widehat{r}_{UA,j}, \ t \geq t_0. \tag{3}$$

In addition, we can construct confidence intervals for the estimates $\widehat{s}_{UA,t}$ using the standard error from the OLS regression, denoted $\widehat{\sigma}_e$. Specifically, a k-standard-error band for $\widehat{s}_{UA,t}$ can be obtained as:[9]

$$\widehat{s}_{UA,t} \pm \sqrt{t - (t_0 - 1)} k \widehat{\sigma}_e. \tag{4}$$

[7] Although UA was included in the index during our sample period, its weight was small (of the order of 2%). Thus, for simplicity we do not incorporate that information in our estimation.

[8] We assume that r_t is constant during the day. For the intraday data on oil futures we use the ask price, stored under the code "CL1 Comdty BarTp=A". Bloomberg only makes intraday data available for relatively short periods of time (up to approximately six months). We first downloaded intraday data shortly after the episode, in September 2008. Subsequently, around March 2009 we downloaded additional intraday data and found small discrepancies in the quotes for oil futures under the code "CL1 Comdty". We spliced the two "vintages" of these data using the 9:30AM quotes for September 8, 2008.

[9] This construction does not adjust for the estimation uncertainty regarding the factor loadings. Doing so has no discernible effect on our analysis and conclusions. The reason is that, as we report in the next section, the regression coefficients are precisely estimated. For results that take into account estimation uncertainly, see Subsection 4.1.

4 Results

Table 1 presents the results for the estimation based on intraday data (15-minute intervals) for the period March 3, 2008 - September 5, 2008, and on daily data for the period August 1, 2007 - September 5, 2008. The factor loadings have the expected signs and are highly statistically significant. Moreover, the results are consistent across the two sampling frequencies.

Table 1: Three-factor model - United Airlines

Parameters and test statistics	Frequency: Intraday$^{a)}$	Frequency: Daily
$\widehat{\beta}_M$	1.90^{***} (0.17)	1.53^{***} (0.31)
$\widehat{\beta}_A$	1.36^{***} (0.21)	1.63^{***} (0.28)
$\widehat{\beta}_O$	-1.24^{***} (0.10)	-1.33^{***} (0.22)
$\widehat{c}$	$-6 \text{ x } 10^{-5}$ (0.0002)	$7 \text{ x } 10^{-4}$ (0.004)
R^2	0.40	0.42
$\#\ Obs$	3394	278
$\widehat{\sigma}_e$	0.013	0.06
$F: \beta_M = \beta_A = \beta_O = 0$	762^{***}	66.15^{***}
$Durbin-Watson$	1.93	2.02
$White\ heteroskedasticity\ F-test$ (*p-value*)	13.53^{***} (0.00)	1.04 (0.41)
$Breusch-Godfrey\ F-test\ for\ serial\ correlation$ (*p-value*)	$1.63^{*b)}$ (0.06)	$0.87^{c)}$ (0.46)

Notes: Newey-West robust standard errors in parentheses (8 lags for intraday, 5 lags for daily), unless indicated otherwise. a) 15-minute intervals. b) 15 lags. c) 3 lags. ***(*) denotes statistical significance at the 1% (10%) level.

Figure 1 presents the results of our counterfactual analysis based on intraday data, as described by equations (2)-(4). The series are transformed back into levels, so that "Actual UA" corresponds to $\exp(s_{UA,t})$, "Counterfactual UA" corresponds to $\exp(\hat{s}_{UA,t})$, and so on. Low-k and High-k correspond to, respectively, lower and upper k-standard-error bands. The results with daily data are very similar, and for completeness they are presented in Figure 2.

We focus on the intraday data (Figure 1), since they provide a more nuanced picture of the episode. After the sharp price movements that occurred before trading was halted in the morning of September 8, UA's stock price remained below the lower two-standard-error band implied by the model until the end of the September 10 trading session. During the September 11 and 12 trading sessions, the stock price narrowed the gap relative to the counterfactual path implied by the model, and closed just below the lower one-standard-error band. In the first hours of trading on Monday, September 15, UA's stock price surpassed the lower one-standard-error band, and on the subsequent day moved almost exactly to the level implied by our counterfactual analysis. It remained very close to the counterfactual level for quite a few days thereafter.

One might question the reliability of our estimated standard-error bands when it comes to making statements about confidence levels, and drawing the lines between the different stages of the convergence process of UA's stock price back to our estimated counterfactual path. We would like to stress that our main finding can be conveyed without any reference to the statistical significance of the deviations of UA's stock price from our estimated counterfactual path. Rather, our core point rests on the "economic significance" of those asset-price deviations. The deviations from the model-implied path during the convergence process are as large as -25%, and the average deviation in the week of the event (excluding September 8) is -19%.[10] In contrast, the average deviation on the day that UA's stock finally crosses the counterfactual path implied by our model (September 16) is only -1.6%. Moreover, this good performance of the factor model is not merely a feature of the first couple of days after UA's stock price convergence. As Figure 1 shows, the model's performance remains extremely good over a pretty long "forecasting horizon". In fact, over the period September 16-24 the average deviation of the realized stock price from the model-implied level is a meager 0.3%. Having said that, in a series of robustness exercises that we present in the next subsection, we find that our baseline narrative is robust to alternative factor models and methods for computing standard errors.

4.1 Robustness

We performed the same analysis using counterfactuals and error bands based on factor models estimated with intraday data at other frequencies, and our findings are unchanged. We also computed confidence bands using a bootstrap method, as a way to account for sampling uncertainty in the parameter estimates of our factor model, as well as the possibility of a non-standard distribution of residuals.[11] The results are very similar to those reported in Figure 1. Finally, we estimated an expanded version of the factor model that includes the Fama-French "Small Minus Big", "High Minus Low" and "Momentum" factors, using daily data. Under this alternative counterfactual, UA's stock price still traded below the two-standard-error band implied by the model for the same three-day period after the event (September 8-10). It then traded below the one-standard-error band for one day, and on the sixth session after the event it traded almost at the exact counterfactual path implied by the augmented factor model. For brevity we do not present these robustness results here, and report the estimates and methodological details in the Appendix.

[10] All statistics reported in this paragraph are based on 15-minute data and the associated factor model.

[11] Notice that prior to using a bootstrap method we never made any reference to the "confidence levels" associated with our standard-error bands, as this would have required making potentially controversial distributional assumptions about the residuals. As we argued in the previous subsection, the standard-error or confidence bands are not central to our main findings.

Figure 1: Counterfactual analysis, United Airlines (UA) - intraday data

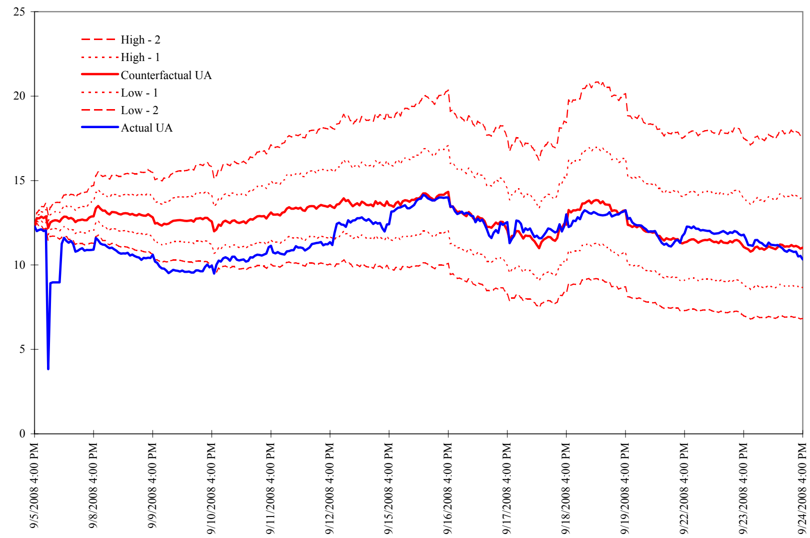
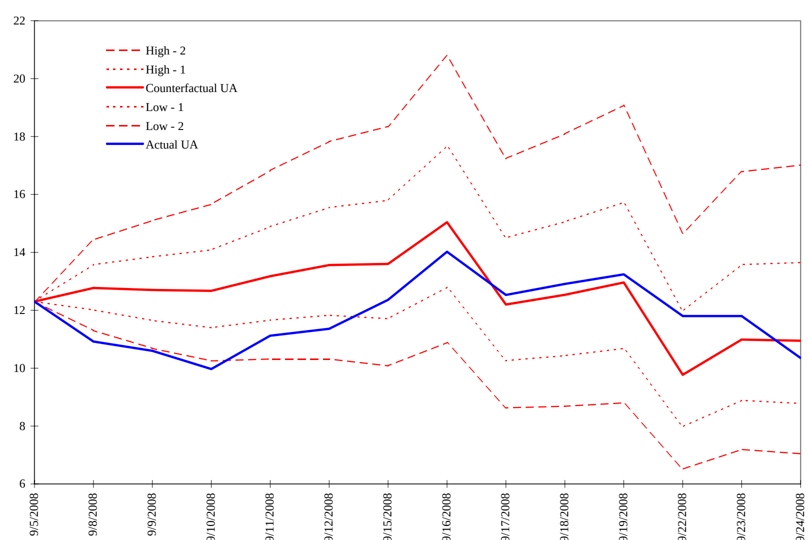


Figure 2: Counterfactual analysis, United Airlines (UA) - daily data



5 Discussion

Throughout the paper we maintain the assumption that the two pieces of information that comprise the false news shock cancel each other. This implies that they should have no direct effect on investors' views of the company's fundamentals, and thus no effect on the fundamental price of UA shares. However, this assumption does not preclude the possibility that the episode had indirect asset-pricing effects that could be persistent. These effects would show up as persistent deviations from the counterfactual level for UA's stock price implied by our factor model. In this section we discuss potential indirect effects of the false news shock, in search of explanations for our findings.

5.1 Liquidity

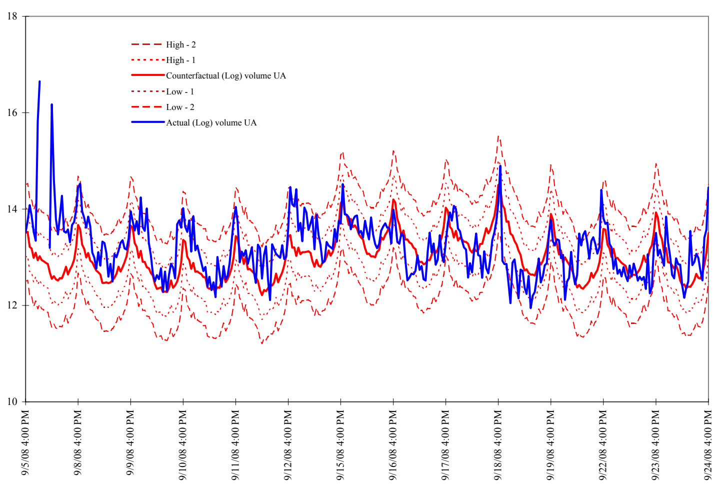
One possible explanation for the failure of UA's share price to return to its pre-episode equilibrium value following the false news shock involves multiple equilibria that imply different levels of liquidity. Amihud and Mendelson (1986) present a model and supporting empirical evidence showing that, all else equal, investors demand a higher return on illiquid securities. This suggests that the price of a stock suffering an exogenous adverse liquidity shock should fall, in order to compensate buyers through higher expected future returns. Building on this work, Dow (2004) presents a model in which a security may exhibit multiple equilibria depending on its level of liquidity - in a simple case, a "normal" equilibrium and a "low-liquidity" equilibrium, which is characterized by a higher bid-ask spread, lower volume and a lower price.

Thus, we consider the possibility that the false news event and subsequent halt of trading in UA stock acted as an exogenous negative shock to liquidity, moving the stock temporarily from a normal equilibrium to a low-liquidity equilibrium. In this interpretation, widened bid-ask spreads during the period of rapid price movement may have deterred some liquidity traders from trading in the stock. Even after the news was shown to be false, the lack of participating liquidity traders might have resulted in a persistently higher bid-ask spread, yielding a new equilibrium with lower liquidity, a lower stock price and lower trading volume. If this were the case, the slow return of UA's stock price to its model-predicted value could be interpreted as a drift back towards the normal-liquidity equilibrium, with the corresponding excess return compensating those traders who were willing to hold the stock during the low-liquidity post-event period.

We do not find evidence to support this explanation. To investigate the hypothesis of abnormally low liquidity following the event, we first examined UA's daily bid-ask spreads from the database of the Center for Research in Security Prices (CRSP) for our full sample. We expressed them both in absolute (dollar-value) and proportional (percentage of mid-price) terms. On the day of the event (September 8), the closing absolute spread was \$0.06. This value, while high, is only about one standard deviation above the sample mean. More notably, on the following days, with the stock still trading at a low price relative to the level implied by the factor model, the recorded closing absolute spreads never exceed \$0.03, which is only slightly above the mean of that statistic for all trading days in 2008. Proportional bid-ask spreads show a very similar pattern. Hence, in terms of bid-ask spreads we do not find evidence to support the story of a persistently low stock price due to persistently low liquidity.

We also performed a formal statistical analysis of one of the implications of the liquidity explanation by estimating a regression model for intraday trading volume of UA shares. In particular, we modeled the log of the number of UA shares traded in 15-minute intervals as dependent on its own lags, dummy variables for all but one of the intraday trading intervals, as well as a proxy for trading volume in the entire stock market. For the latter, we use trading volume in the exchange-traded fund (ETF) "IVV", which tracks the S&P 500 index. The exact specification and the estimation results of the regression model for UA volume are provided in the Appendix. As can be seen from the regression diagnostics, the model fits the series of intraday log volume very well. Based on this model, we can perform a counterfactual analysis of UA trading volume on the days after the event in the same spirit as we have done for the evolution of its share price.[12] The result of this exercise is provided in Figure 3. This chart shows the counterfactual path of UA log volume from September 8 through September 24 along with the one- and two-standard-error bands around this path. One can think of that counterfactual path as the evolution of UA log volume in the absence of the false news shock. The superimposed (blue) line shows the actual behavior of UA log volume over this time period. We can draw at least two conclusions from this chart. First, trading volume in UA shares is well captured by the model. Second, and most importantly, actual trading volume was not particularly low with respect to our counterfactual path for trading volume on the days after the event. If anything, actual volume tended to be above its model-implied path over that period. Hence, we do not find evidence to support the claim that the slow return of UA's share price to its fundamental value can be rationalized by a slow transition from a low-liquidity equilibrium back to a normal-liquidity equilibrium.

Figure 3: Counterfactual analysis for intraday log volume - United Airlines



[12] We tried to develop an empirical model for UA's bid-ask spread, as a way to perform a formal statistical analysis of the evolution of such spread after the event. However, we failed to find a satisfactory specification.

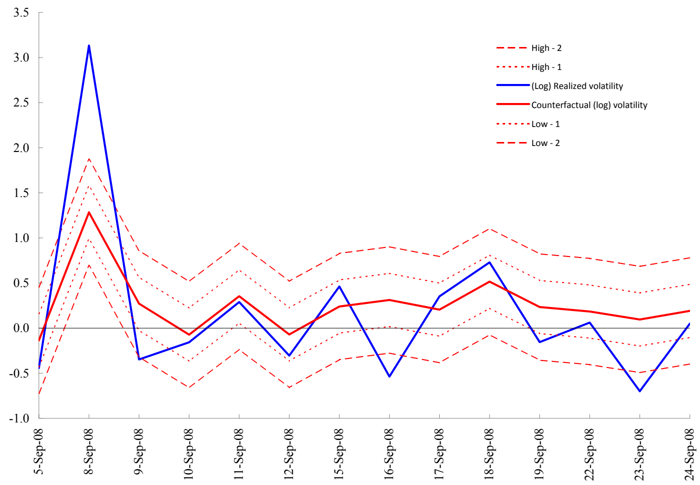
5.2 Ambiguity aversion

Another theory-based explanation of our findings builds on Epstein and Schneider (2008). The authors develop a model based on ambiguity aversion in which, when faced with news of uncertain quality, investors take a worst-case assessment of the quality or precision of news. This leads to an asymmetry in their response to news, as investors react more strongly to bad than to good news. In an environment in which ambiguity-averse investors need to rely on news of uncertain quality to learn about a possible change in fundamentals, shocks to information quality may have persistent negative effects on prices, for given fundamentals. If one assumes that the false news shock amounted to a deterioration in the quality of information regarding UA, at first pass it appears that Epstein and Schneider's results may provide a coherent qualitative explanation of the evolution of UA's share price on September 8 and the subsequent days. It is therefore worthwhile to analyze whether the UA event is in line with the predictions of their model.

Epstein and Schneider show that in their model ambiguity about the quality of news induces a premium which uncertainty-averse investors require to hold a risky asset. Their framework delivers three main asset-pricing predictions. First, in their model idiosyncratic risk is priced. This is in contrast to standard asset-pricing models, in which only undiversifiable (systematic) risk commands a risk premium. In the absence of this prediction, their model could be readily dismissed as an explanation of our findings, which clearly originated from an event that is firm-specific in nature. This prediction of their model is arguably supported by our findings, as the systematic negative deviations of UA's share price from the level implied by our pricing model are consistent with idiosyncratic risk being priced.

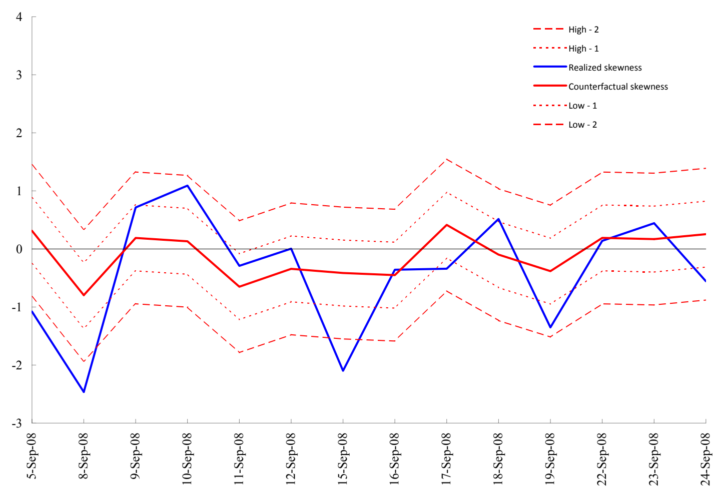
The second main prediction of the Epstein-Schneider model is that ambiguous signals generate excess volatility of stock returns with respect to the volatility of fundamentals. This prediction of the model also implies that after a shock to information quality, the conditional volatility of excess returns should go up with respect to the volatility of fundamentals. Given a model for volatility, one can test this prediction empirically. Following Andersen et al. (2003), we use realized volatility as a proxy for conditional volatility. In particular, we compute daily series of realized volatility for $r_{UA,t}$, $r_{M,t}$, $r_{A,t}$, and $r_{O,t}$ using the standard deviation of logarithmic excess returns at the 15-minute frequency. We then estimate a simple regression model relating (the log of) realized volatility of UA returns to its own lag as well as the (log of) realized volatilities of the fundamental pricing factors. The exact specification and the estimation results of the regression model for UA realized volatility are provided in the Appendix. We estimate the model using data through September 5, 2008, the day before the event. Based on the estimated coefficients from that model and the evolution of realized volatility of the pricing factors over the subsequent days we can then construct a counterfactual path of UA realized volatility in the same spirit as for the return or volume regressions described above. The result of this exercise is provided in Figure 4. This chart shows the model-implied counterfactual path of UA's conditional volatility along with the one- and two-standard-error bands. We superimpose the actual path of UA realized volatility over the same period. At least two observations emerge from this plot. First, unsurprisingly, realized volatility of UA returns is considerably higher than what would be implied by fundamentals on September 8, the day of the false news release. However, on all subsequent days the actual path of UA realized volatility does not exceed the one-standard-error band implied by the model. Indeed, actual realized volatility fell below the two-standard-error band implied by the model on three of the following days. Hence, according to this model, we are not able to find evidence that there is excessive volatility in UA returns after the release of the false news.

Figure 4: Counterfactual analysis for log realized volatility - United Airlines



The third main prediction of the Epstein and Schneider's model is that a negative shock to information quality should result in a more negatively skewed return distribution, especially at high frequencies - which correspond to low discount factors. The intuition behind this result is that ambiguity-averse investors will weigh signals about fundamentals more heavily the less favorable they are. Thus, according to the model, the more ambiguous signals are, the more negatively skewed returns should be expected to be. In order to assess whether this prediction of the model holds in the data subsequent to the release of the false news, we estimate a model for realized skewness in the same vein as the model for realized volatility described above. We construct daily measures of skewness for UA returns as well as for the returns on the three pricing factors by computing the realized skewness of the 15-minute frequency returns over each day. The exact regression specification is provided in the Appendix. Again, we estimate the model using data through September 5, 2008, the day before the release of the false news. Based on the estimated coefficients from that model and the evolution of realized skewness of the pricing factors over the subsequent days we can then construct a counterfactual path of UA realized skewness in the same way as in the previously discussed regressions. The result of this exercise is provided in Figure 5. According to this chart, and in line with the intuition of the Epstein-Schneider model, skewness is low relative to fundamentals on September 8, the day of the event. However, on the four trading days following the event, when its shares were trading more than two standard deviations below the model-implied price, realized skewness in UA returns was actually higher than that predicted by the model. Hence, according to this simple empirical model, there is no evidence that the hypothesized shock to information quality resulted in a more negatively skewed distribution of UA returns at high frequencies.

Figure 5: Counterfactual analysis for realized skewness - United Airlines



Altogether, we thus find at best mixed evidence that would point to the ambiguity aversion story as the explanation for United Airlines' slow share price recovery after the false news shock. While the model's prediction that idiosyncratic risk is priced is supported by our findings, two other main implications of the model do not appear to be supported by the data.

5.3 Linkages with the financial industry

A more idiosyncratic potential explanation for the puzzling behavior of UA's share price on September 8 and subsequent days relates to its linkages with the U.S. financial sector, which itself was in turmoil in September 2008. According to this explanation, UA's fate might have been linked to that of Lehman Brothers through JP Morgan Chase which was an important counterparty for both institutions.[13]

Indeed, as documented in several news reports,[14] in July 2008 UA had reached an agreement with Chase Bank, the consumer and commercial banking subsidiary of JP Morgan Chase, which significantly strengthened UA's cash position. The deal provided for a $600 million transfer to UA from the advance purchase of frequent flier miles as well as for a reduction of UA's reserve requirement under its credit-card cooperation with Chase that would free up an additional $350 million. The agreement was announced on July 22, 2008, as part of UA's second quarter earnings statement which documented a net loss of $1.19 per share, excluding a special charge for "goodwill impairment". Despite the loss, UA's share price surged by 67% on July 22, likely due to the positive news about the agreement with

[13]We thank an anonymous referee for suggesting this potential explanation to us.

[14]For instance, Marketwatch's article http://www.marketwatch.com/story/ual-gets-1-billion-cash-infusion-stock-soars-despite-loss?dist=msr_10

Chase. More recently, it has become apparent that JP Morgan Chase, Lehman Brother's main clearing bank, required Lehman to post up to $5 billion of additional collateral for loans in the week before September 15, 2008, when the investment bank filed for bankruptcy.[15] This is precisely the week when the false news shock hit.

Given these close financial ties between United Airlines and JP Morgan Chase on the one hand, and JP Morgan Chase and Lehman Brothers on the other, it appears worthwhile to analyze whether the two events might be linked to one another. Indeed, investors who were informed that JP Morgan Chase had demanded additional collateral from Lehman Brothers might have concluded that JP Morgan Chase was likely to extract collateral also from UA. This, in turn, would likely have pushed UA into insolvency. Even though the bankruptcy news was revealed to be false on September 8, the lingering of financial sector uncertainty in the week of the event and on subsequent days could thus potentially explain the slow recovery of UA's share price on and after September 8.

We explore this candidate explanation of our findings by extending the baseline factor model with a proxy for financial conditions. In particular, we use the excess return on ETF "XLF", which tracks the performance of the Financial Select Sector of the S&P 500 Index, as an additional pricing factor. As we show in the Appendix, the coefficient on the financial sector factor "XLF" is highly statistically significant. The coefficients on the airlines index and on crude oil are largely unchanged after the introduction of this additional pricing factor. However, the slope coefficient on the aggregate equity market, albeit still highly statistically significant, is cut to less than half the value in our benchmark regression specification. This confirms the view that United's share price was closely related to the performance of the financial sector before the September 8 event. Yet, as shown in Figure 6, this extension of the factor model produces no meaningful change to our counterfactual analysis, and therefore does not affect any of our conclusions.[16]

6 "Contagion"

In this section we study the impact of the false news shock on the stock prices of other major U.S. airlines. We estimate a factor model like the one in equation (1) for each of the following companies: American Airlines (AMR), Continental Airlines (CAL), Delta Airlines (DAL) and U.S. Airways (LCC), and construct a counterfactual stock price for each company using equations analogous to (2)-(4), where UA is replaced with the respective airline. Intraday data for the stock prices of those four companies are from Thomson-Reuters, in 15-minute intervals. The results of OLS regressions are reported in Table 2. The bottom line is that they are similar to our findings for UA.

The counterfactual analyses are presented in Figures 7-10. The results for American Airlines and Continental Airlines are extremely similar to UA's - with the clear exception that the price drops around 11:00 AM on September 8, 2008 are significantly smaller. The pattern for Delta Airlines and U.S. Airways is slightly different, in that on the day of the false news event their stock prices do return

[15] http://www.nytimes.com/2010/05/27/business/27lehman.html

[16] We also considered models with measures of credit market conditions. In particular, we estimated factor models with an extra factor given by the excess return on the "JNK" and "HYG" Exchange-traded funds, which track the performance of, respectively, the Barclays Capital High Yield Very Liquid Index and the iBoxx $ Liquid High Yield Index. None of these factors produced statistically significant coefficients.

Figure 6: Counterfactual analysis with financial factor - United Airlines

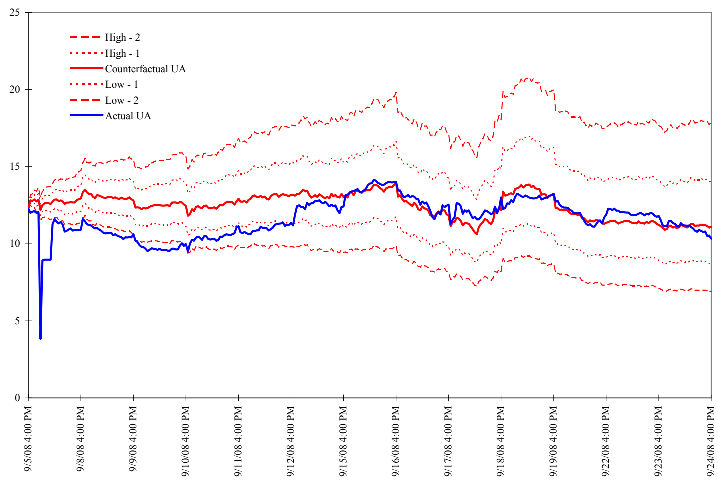


Table 2: Three-factor model for other airlines - intraday data

	Company			
Parameters and test statistics	AMR	CAL	DAL	LCC
$\widehat{\beta}_M$	2.00^{***} (0.16)	1.94^{***} (0.15)	1.45^{***} (0.18)	2.17^{***} (0.17)
$\widehat{\beta}_A$	1.15^{***} (0.19)	1.14^{***} (0.19)	1.33^{***} (0.20)	1.38^{***} (0.27)
$\widehat{\beta}_O$	-1.06^{***} (0.07)	-1.10^{***} (0.08)	-0.93^{***} (0.08)	-1.32^{***} (0.12)
$\widehat{c}$	1 x 10^{-4} (0.0002)	9 x 10^{-5} (0.0002)	7 x 10^{-5} (0.0002)	8 x 10^{-5} (0.0002)
R^2	0.49	0.49	0.40	0.42
$\#\ Obs$	3394	3394	3394	3394
$\widehat{\sigma}_e$	0.01	0.01	0.011	0.014
$F: \beta_M = \beta_A = \beta_O = 0$	1096^{***}	1117^{***}	754^{***}	802^{***}
$Durbin-Watson$	2.04	2.07	2.13	2.16
$White\ heteroskedasticity\ F-test$ (*p-value*)	52.35^{***} (0.00)	28.17^{***} (0.00)	51.92^{***} (0.00)	47.80^{***} (0.00)
$Breusch-Godfrey\ F-test$ $for\ serial\ correlation^{a)}$ (*p-value*)	0.62 (0.86)	1.80^{**} (0.029)	2.11^{***} (0.007)	2.81^{***} (0.000)

Notes: Newey-West robust standard errors in parentheses (8 lags), unless indicated otherwise. a) 15 lags. ***(**) denotes statistical significance at the 1% (5%) level.

to a level that is somewhat closer to the counterfactual level implied by the model. However, it is still the case that it takes a few days for their stock prices to return to within one standard deviation of the model's predicted price, and one week until they trade at the level implied by the factor models. Finally, Figure 11 shows intraday trading volumes in 15-minute intervals for all five airline companies. It is clear that volumes skyrocketed during the sharp price movements. Thus, overall it appears that the effects of the false news shock were "contagious".[17]

One can think of opposing forces that may have affected the stock prices of the other four airlines in connection with the episode. On the one hand, there may be an effect on competition in the airline industry. All else equal, the information that a competitor had been suddenly removed from the market should have been a positive for other U.S. airlines. At least this would be the natural implication of standard models of imperfect competition used in the Industrial Organization literature. On the other hand, the news of UA's bankruptcy may have conveyed negative information about components of cash flows (revenues and costs) that are common to UA and the other airlines. In addition, the common view that the bankruptcy of one firm may have negative effects on customers and suppliers of competing firms can also justify the negative response of the stock prices of the other airlines. In fact, these opposing forces are at the core of the discussion about the "contagion and competitive effects of bankruptcy" (e.g. Lang and Stulz 1992).

The empirical literature on contagion and competitive effects of bankruptcy typically looks at stock market returns around actual bankruptcy announcements to draw lessons about which effect dominates under which circumstances. While some bankruptcy filings may be more unpredictable than others, it is reasonable to assume that almost always there is some degree of predictability in bankruptcy events.[18] As a result, clean identification of the causal effects of bankruptcy news is difficult. In contrast, our natural experiment allows us to address the following question: "what would have happened to the stock prices of AMR, CAL, DAL, and LCC if UA had indeed filed for bankruptcy in a completely unpredictable fashion on September 8, 2008?". While drawing general conclusions about the relative importance of contagion and competitive effects from our natural experiment might be problematic, our episode clearly shows that contagion effects would have dominated. This is consistent with the findings of Lang and Stulz (1992), according to which contagion effects typically dominate competitive effects in industries where firms are more highly leveraged, as is the case in the airline industry (Korteweg 2007).

[17] Given the evidence of similar share price declines and slow recoveries that we find for other airlines, and the fact that UA is included in the airline index that we use in our factor model - although with a small weight - one might argue that a clean counterfactual analysis should exclude the airline index from the pricing model. Note, however, that the Bloomberg airline industry index that we use has worldwide coverage, and wasn't affected nearly as much by the episode. In particular, according to our 15-minute data, that index fell at most 2% during the sharp price movements in the morning of September 8, and closed 0.45% *higher* on the day. Nevertheless, we have estimated a reduced factor model that only includes the S&P500 and crude oil as pricing factors. The counterfactual path and error bands implied by this model specification and error bands around it are extremely similar to the ones implied by our benchmark specification, not affecting any of our conclusions.

[18] For a recent effort in predicting corporate financial distress see Campbell et al. (2010).

Figure 7: Counterfactual analysis, American Airlines (AMR) - intraday data

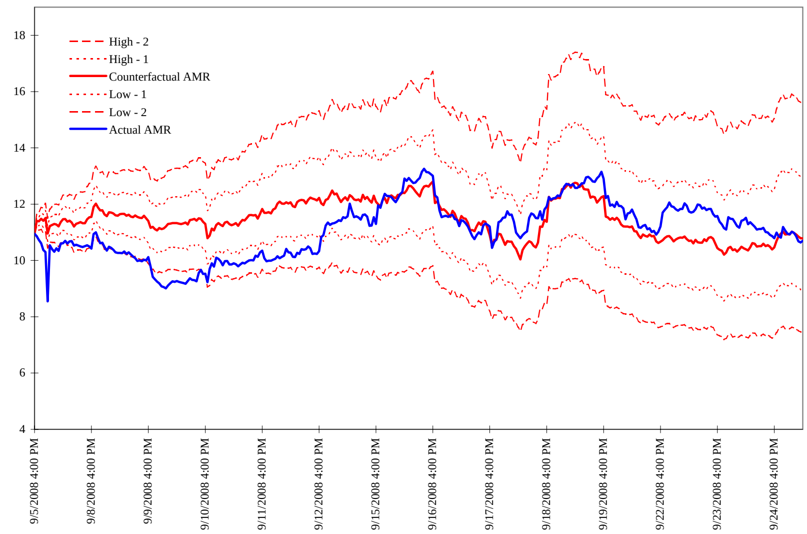


Figure 8: Counterfactual analysis, Continental Airlines (CAL) - intraday data

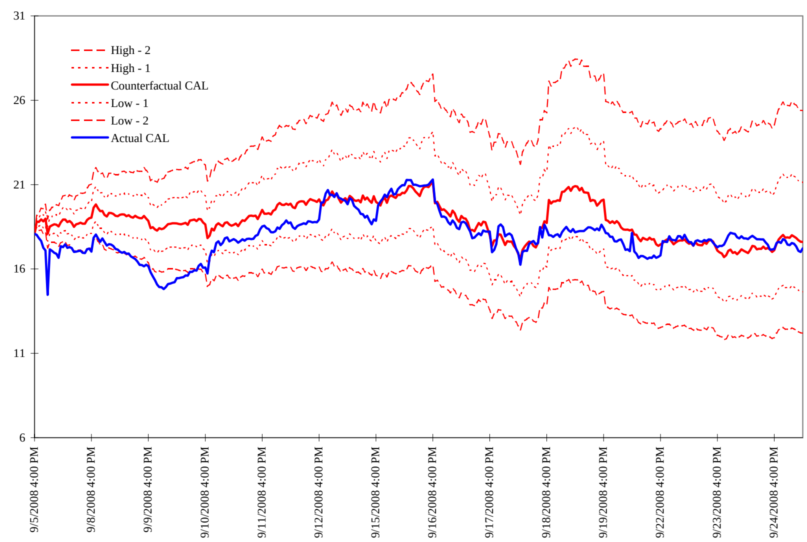


Figure 9: Counterfactual analysis, Delta Airlines (DAL) - intraday data

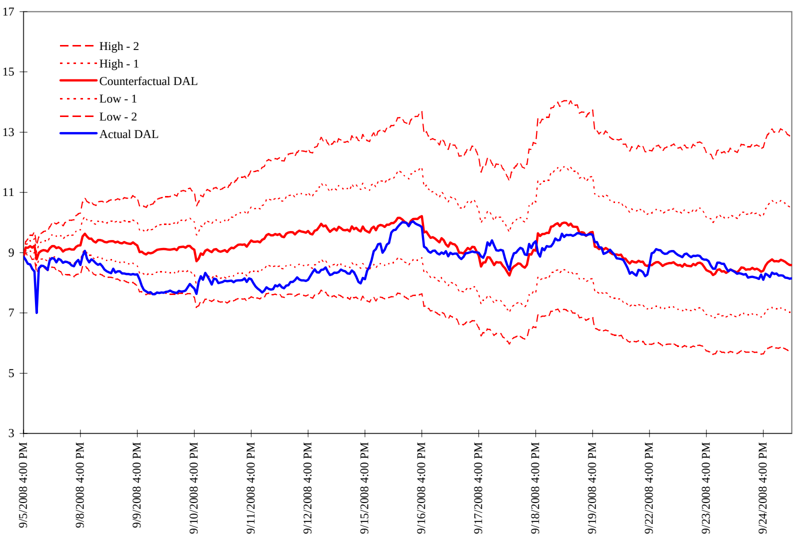


Figure 10: Counterfactual analysis, U.S. Airways (LCC) - intraday data

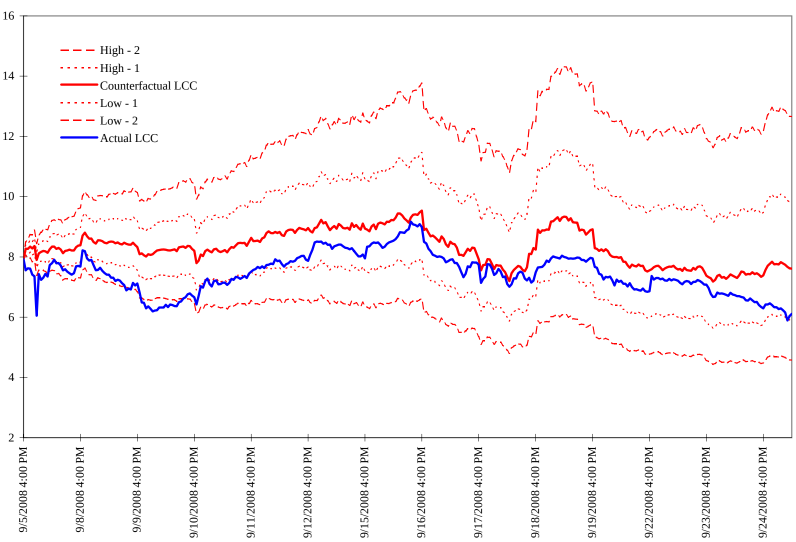
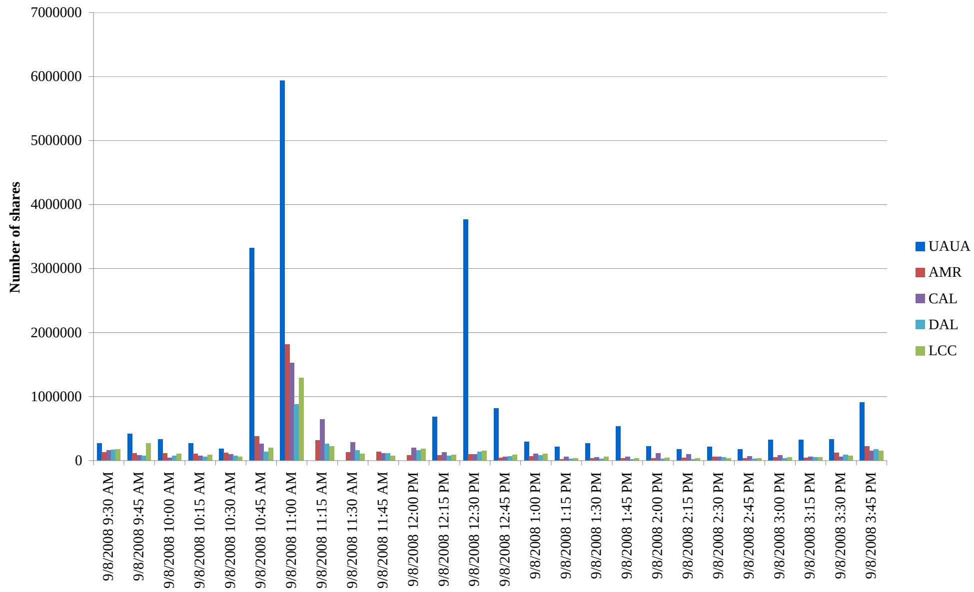


Figure 11: Intraday trading volumes on September 8, 2008 - 15-minute intervals



7 Conclusion

We explore a natural experiment to study the impact of a false news shock on the stock price of United Airlines. We find that the shock had a persistent effect on the level of UA's stock price: it took six trading sessions for the stock to return to within one standard error of the model-implied counterfactual path. On the seventh trading session after the episode, and for quite a few days thereafter, UA's stock price was essentially trading at the counterfactual path implied by our factor model.

We provide an in-depth analysis of two theories which could potentially rationalize our findings. According to the first, disrupted liquidity during a transition process might have resulted in the slow return of the share price back to its fundamental level. We do not find evidence of poor liquidity on the days following the false news shock. The second theory relies on ambiguity-averse traders as an explanation of a slow recovery back to the level implied by the asset-pricing model. We assess empirically whether the predictions of this theory are borne out by the data and find little supportive evidence. We also consider the hypothesis that the slow recovery of UA's stock price can be explained by the firm's linkages with the U.S. financial sector which itself was in turmoil in September 2008. While we do find a significant correlation between UA's returns and the returns on financial sector stocks prior to the event, the counterfactual path implied by a model augmented with a financial factor does not alter our conclusion that it took unusually long for UA's share price to return to the level predicted by the model.

A sudden bankruptcy of a firm may have contagious as well as competitive effects on other firms within the same industry (see e.g. Lang and Stulz 1992). We study the behavior of other major U.S. airlines and find a similar pattern for their stock prices on the days after the false news event. This finding leads us to argue that contagion effects would have dominated the competitive effects – had the bankruptcy actually taken place.

It is difficult to find other episodes that could be similarly characterized as a false news shock. There are a number of at first seemingly related cases that were subsequently shown to involve a fraud or hoax. In such cases, false news were deliberately produced to impact the stock price. This changes the nature of the trading environment, since some market participants trade with knowledge of the false news. It is reasonable to assume that the hoaxer takes advantage of the induced price movements by trading in the stock or its derivatives. One should thus expect a more complete reversal of the price movements produced by the false news, as the hoaxer trades to his or her advantage.

Some prominent examples of false news due to fraud involved Pairgain Technologies (on April 7, 1999; the company later merged with ADC Telecommunications in 2000), and Emulex Corporation (on August 25, 2000). Curiously, despite reports that the frauds became apparent before the end of the respective trading sessions, in both cases the stock price still ended the day moving "in the direction" that the false information would have justified.[19] Despite their different nature, we see these episodes as suggestive that our findings would generalize to other false news shocks.

Finally, one may reasonably argue that one week is not a long enough spell for the misvaluation of stocks to have relevant economic effects - beyond gains and losses by traders and investors. However, this is how long it took for the effects of a pure false news shock to dissipate. In most circumstances, relevant information ("signal") and noise arise simultaneously, and cannot be so easily separated.

[19] For the interested reader, the Pairgain episode involved fake news of a takeover, disseminated through an (illegitimate) Internet page that was set up to look like a Bloomberg News one. The stock price went up by more than 30% before the hoax was detected during the day. Pairgain's stock price still closed 10.3% higher. The Emulex case involved a false press release that the company was restating earnings results. The report made its way to Bloomberg News through an information firm that distributes press releases - the firm allegedly fell victim to a sophisticated fraud, which made the press release appear legitimate. Emulex's stock price fell by more than 58% before trading was halted. It ended the day 6.5% below the previous close.

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8 Appendix

8.1 Details of robustness analysis

8.1.1 Alternative sampling frequencies

The results for the three-factor model for United Airlines estimated on intraday data at 30- and 60-minute intervals are presented in Table 3. They are very close to our benchmark specification using intraday data at the 15-minute interval and do not affect our counterfactual analysis. For the sake of brevity, we therefore do not report the corresponding charts.

Table 3: Three-factor model - United Airlines, other frequencies

	Frequency	
Parameters and test statistics	30 min	60 min
$\widehat{\beta}_M$	1.89^{***} (0.22)	2.15^{***} (0.24)
$\widehat{\beta}_A$	1.39^{***} (0.24)	1.35^{***} (0.23)
$\widehat{\beta}_O$	-1.36^{***} (0.11)	-1.45^{***} (0.13)
$\widehat{c}$	$-1 \text{ x } 10^{-4}$ (0.0004)	$2 \text{ x } 10^{-4}$ (0.0009)
R^2	0.42	0.45
$\# \ Obs$	1697	913
$\widehat{\sigma}_e$	0.019	0.026
$F : \beta_M = \beta_A = \beta_O = 0$	405.9^{***}	247.09^{***}
$Durbin{-}Watson$	2.04	2.04

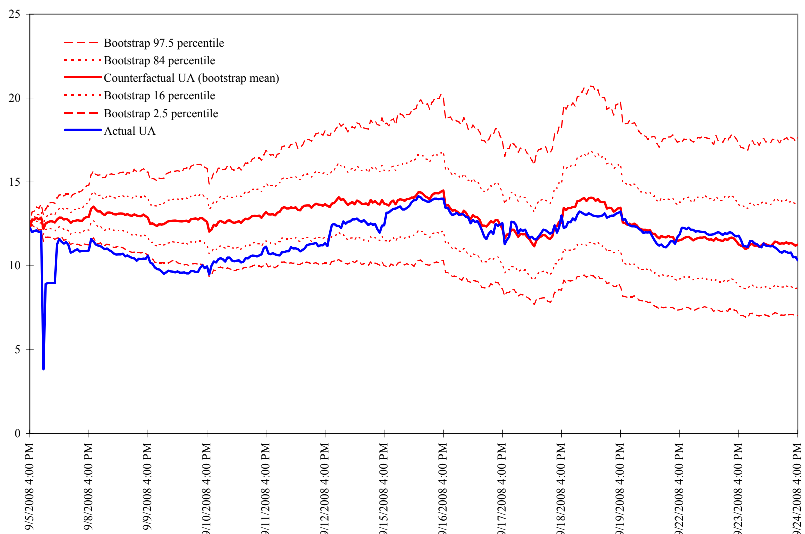
Notes: Newey-West robust standard errors in parentheses (8 lags).
*** denotes statistical significance at the 1% level.

8.1.2 Results based on bootstrap

The boostrap method that we implemented works as follows. For each bootstrap iteration, we randomly resample the residuals from the OLS regression (1) estimated over our (pre-event) sample, and add them to the fitted values in order to obtain a fictitious sample of United Airline's excess returns. Given this new sample of UA excess returns, we reestimate the model (leaving the right-hand-side variables unchanged) and compute ("predicted") counterfactual excess returns for the out-of-sample period of interest (September 8-24), based on the actual excess return data for the regressors and the new set of coefficient estimates. To the counterfactual (fitted) excess returns, we add a randomly sampled sequence of OLS residuals from the pre-event OLS regression in order to obtain a counterfactual ("realized") path of UA excess returns. From this counterfactual ("realized") path of excess returns, we then construct a path of counterfactual ("realized") prices for the out-of-sample period of interest, according to equation (3). Repeating this procedure many times produces a distribution of counterfactual ("realized") UA stock prices for the out-of-sample period of interest. From this distribution, we construct confidence bands as percentiles, and use the mean as the counterfactual level implied by the model.

Figure 12 presents results based on a thousand bootstrap iterations. It shows the mean counterfactual level, as well as 68% and 95% confidence bands. According to this chart, the 68% and 95% confidence bands constructed from the bootstrapped distribution are very similar to the one- and two-standard-error bands presented in Figure 1.

Figure 12: Counterfactual analysis, United Airlines (UA) - Bootstrap



8.1.3 Factor model with Fama-French factors

As a last robustness analysis we estimated an augmented version of the factor model that includes the Fama-French "Small Minus Big" (SMB), "High Minus Low" (HML) and "Momentum" (UMD) factors, using daily data from August 1, 2007 through September 5, 2008. The results are reported in Table 4, and the counterfactual analysis is presented in Figure 13.

Table 4: Factor model with Fama-French factors - United Airlines

Parameters and test statistics	Estimates
$\widehat{\beta}_M$	1.06^{***} (0.22)
$\widehat{\beta}_A$	1.36^{***} (0.24)
$\widehat{\beta}_O$	-0.86^{***} (0.17)
$\widehat{\beta}_{SMB}$	2.28^{***} (0.88)
$\widehat{\beta}_{HML}$	1.61 (1.33)
$\widehat{\beta}_{UMD}$	-1.05^{***} (0.25)
$\widehat{c}$	$-5 \text{ x } 10^{-4}$ (0.003)
R^2	0.51
$\# \ Obs$	278
$\widehat{\sigma}_e$	0.057
$F : \beta_M = ... = \beta_{UMD} = 0$	46.5^{***}
$Durbin{-}Watson$	2.12

Notes: Newey-West robust standard errors in parentheses (5 lags). *** denotes statistical significance at the 1% level. $\widehat{\beta}_{SMB}$, $\widehat{\beta}_{HML}$ and $\widehat{\beta}_{UMD}$ denote regression coefficients on Fama-French SMB, HML, and UMD factors.

8.2 Factor models for volume, realized volatility, and realized skewness

8.2.1 Volume

In order to study the impact of the false news shock on liquidity, we estimate the following factor model for trading volume of United Airlines shares:

$$Vol_{UA,t} = a+\phi_M Vol_{M,t}+\phi_{Lag1} Vol_{UA,t-1}+\phi_{Lag2} Vol_{UA,t-2}+\phi_{9:30} I_{9:30,t}+\phi_{10:00} I_{10:00,t}+...+\phi_{3:45} I_{3:45,t}+\varepsilon_t,$$

where $Vol_{UA,t}$, and $Vol_{M,t}$ denote the (log of the) trading volume in 15-minute intervals for United Airlines, and the ETF "IVV". The latter is designed to track the performance of the S&P 500 index and hence should provide a good proxy for trading volume in the equity market. Since there is a lot of high-frequency "seasonality" in the volume data, we also include dummy observations for all but one of the 26 fifteen-minute trading intervals that we partition the data into. These are denoted by $I_{9:30,t}$ $I_{10:00,t}$, ..., $I_{3:45,t}$, respectively.

The results of this regression are given in Table 5. The results for the counterfactual analysis of log volume for the period September 8 - September 24, 2008, based on the equation

$$\widehat{Vol}_{UA,t} = \widehat{a} + \hat{\phi}_M Vol_{M,t} + \hat{\phi}_{Lag1} \widehat{Vol}_{UA,t-1} + \phi_{Lag2} \widehat{Vol}_{UA,t-2} + ... + \hat{\phi}_{3:45} I_{3:45,t},$$

are illustrated in Figure 3.

Table 5: Factor model for intraday log volume - United Airlines

Parameters and test statistics	Estimates
$\widehat{\phi}_M$	0.08^{***} (0.01)
$\widehat{\phi}_{Lag1}$	0.64^{***} (0.02)
$\widehat{\phi}_{Lag2}$	0.25^{***} (0.02)
$\widehat{\phi}_{9:45}$	-0.38^{***} (0.06)
$\vdots$	$\vdots$
$\widehat{a}$	0.70^{***} (0.22)
R^2	0.77
$\# \ Obs$	$3,395$
$\widehat{\sigma}_\varepsilon$	0.50
$F: \widehat{\phi}_{M0} = ... = \widehat{\phi}_{3:45} = 0$	399.93^{***}
$Durbin-Watson$	2.02

Notes: Newey-West robust standard errors in parentheses (8 lags). *** denotes significance at the 1% level. Indicator variables for 15-minute intervals in the periods 10:00-12:45, 14:30-14:45, and 15:45-16:00 are significantly negative at the 1% level, and for the period 13:00-13:15 at the 5% level. The indicator for the period 15:30-15:45 is significantly positive at the 5% level. Indicators for all other intervals are statistically insignificant.

8.2.2 Realized volatility

In order to study the impact of the false news shock on volatility we estimate the following factor model for log realized volatility of United Airlines' intraday returns:

$$\sigma_{UA,t} = a + \gamma_M \sigma_{M,t} + \gamma_A \sigma_{A,t} + \gamma_O \sigma_{O,t} + \gamma_{Lag} \sigma_{UA,t-1} + \varepsilon_t,$$

where $\sigma_{UA,t}$, $\sigma_{M,t}$, $\sigma_{A,t}$, and $\sigma_{O,t}$ denote the log of the realized (annualized) volatility of, respectively, 15-minutes returns for United Airlines, the S&P 500 index, Bloomberg's World Airline Index, and crude oil. The results of this regression are given in Table 6. The results for the counterfactual analysis of log realized volatility for the period September 8 - September 24, 2008, based on the equation

$$\widehat{\sigma}_{UA,t} = \widehat{a} + \widehat{\gamma}_M \sigma_{M,t} + \widehat{\gamma}_A \sigma_{A,t} + \widehat{\gamma}_O \sigma_{O,t} + \widehat{\gamma}_{Lag} \widehat{\sigma}_{UA,t-1},$$

are illustrated in Figure 4.

Table 6: Factor model for log realized volatility - United Airlines

Parameters and test statistics	Estimates
$\widehat{\gamma}_M$	-0.12 (0.14)
$\widehat{\gamma}_A$	0.86^{***} (0.122)
$\widehat{\gamma}_O$	$-3.00 \text{ x } 10^{-3}$ (0.08)
$\widehat{\gamma}_{Lag}$	0.23^{**} (0.10)
$\widehat{a}$	1.70^{***} (0.29)
R^2	0.65
$\# \ Obs$	130
$\widehat{\sigma}_{\varepsilon}$	0.30
$F: \gamma_M = \gamma_A = \gamma_O = \gamma_{Lag} = 0$	57.55^{***}
$Durbin{-}Watson$	2.00

Notes: Newey-West robust standard errors in parentheses (8 lags). ** and *** denote statistical significance at the 5% and 1% levels, respectively.

8.2.3 Realized skewness

In order to study the impact of the false news shock on skewness we estimate the following factor model for realized skewness of United Airlines' intraday returns:

$$Skew_{UA,t} = a + \delta_M Skew_{M,t} + \delta_A Skew_{A,t} + \delta_O Skew_{O,t} + \delta_{Lag} Skew_{UA,t-1} + \varepsilon_t,$$

where $Skew_{UA,t}$, $Skew_{M,t}$, $Skew_{A,t}$, $Skew_{O,t}$,and $\sigma_{A,t}$ denote the realized skewess of 15-minutes returns for United Airlines, the S&P 500 index, Bloomberg's World Airline Index, and crude oil, respectively. The results of this regression are given in Table 7. The results for the counterfactual analysis of log realized volatility for the period September 8 - September 24, 2008, based on the equation

$$\widehat{Skew}_{UA,t} = \widehat{a} + \widehat{\delta}_M Skew_{M,t} + \widehat{\delta}_A Skew_{A,t} + \widehat{\delta}_{O,t} Skew_{O,t} + \widehat{\delta}_{Lag} \widehat{Skew}_{UA,t-1},$$

are illustrated in Figure 5.

8.3 Asset-pricing model with financial factor

The augmented factor pricing model is

$$r_{UA,t} - r_t = c + \beta_M (r_{M,t} - r_t) + \beta_A (r_{A,t} - r_t) + \beta_O (r_{O,t} - r_t) + \beta_F (r_{F,t} - r_t) + e_t,$$

where $r_{F,t}$ is the log return on the financial sector ETF "XLF". The estimation results are summarized in Table 8, and the counterfactual analysis is presented in Figure 6.

Table 7: Factor model for realized skewness - United Airlines

Parameters and test statistics	Estimates
$\widehat{\delta}_M$	0.08 (0.09)
$\widehat{\delta}_A$	0.34^{***} (0.08)
$\widehat{\delta}_O$	-0.19^{**} (0.07)
$\widehat{\delta}_{Lag}$	0.09 (0.08)
$\widehat{a}$	0.09^{*} (0.05)
R^2	0.36
$\#\ Obs$	130
$\widehat{\sigma}_{\varepsilon}$	0.57
$F: \delta_M = \delta_A = \delta_O = \delta_{Lag} = 0$	17.57^{***}
$Durbin-Watson$	2.07

Notes: Newey-West robust standard errors in parentheses (8 lags).*,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 13: Counterfactual analysis with Fama-French factors - United Airlines

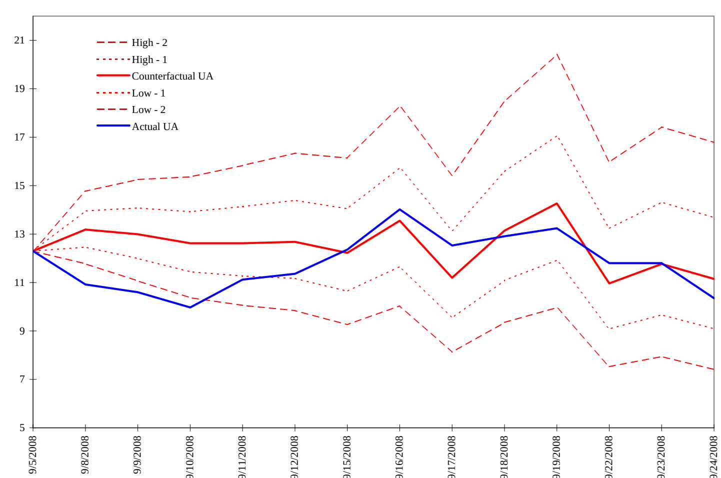


Table 8: Factor model with financial factor - United Airlines

Parameters and test statistics	Estimates
$\widehat{\beta}_M$	0.82^{***} (0.30)
$\widehat{\beta}_A$	1.24^{***} (0.21)
$\widehat{\beta}_O$	-1.20^{**} (0.10)
$\hat{\beta}_F$	0.59^{***} (0.15)
$\widehat{c}$	$-6.6 \text{ x } 10^{-5}$ (0.0002)
R^2	0.41
$\#\ Obs$	3394
$\widehat{\sigma}_\varepsilon$	0.013
$F : \beta_M = \beta_A = \beta_O = \beta_F = 0$	594^{***}
$Durbin{-}Watson$	1.92

Notes: Newey-West robust standard errors in parentheses (8 lags). ** and *** denote statistical significance at the 5% and 1% levels, respectively.