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Do Stock Markets Catch the Flu?

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Abstract

We examine the impact of influenza on the U.S. stock market. A higher incidence of flu is associated with decreased trading, decreased volatility, and higher bid-ask spreads. We also find some evidence that more flu implies lower stock returns. Consistent with the flu affecting institutional investors and market-makers, the decrease in trading activity and volatility is primarily driven by the incidence of influenza in the greater New York City area. However, the effect of the flu on bid-ask spreads and returns is driven by the incidence of flu nationally. We provide estimates of the potential impacts of a pandemic on equity returns.

Keywords: stock markets, influenza, volume
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I. Introduction

We hypothesize that a higher influenza rate can disrupt equity markets as some key individuals would be either ill or absent from work helping tend for sick family members. These key individuals could include market-makers, institutional investors, or other participants in the financial markets. An existing literature documents how the flu causes individuals to miss work regardless of job characteristics such as job intricacy, authority, or stressfulness (see Mohren et al., 2005). A separate literature also discusses the general economic impacts of influenza (see, for instance, McKibbon and Sidorenko, 2006). The goal of this paper is to examine the implications of the flu on U.S. equity markets over a number of years where detailed flu incidence data is available.

We hypothesize that a higher rate of influenza would decrease volume and turnover. Similarly, a higher incidence of flu would coincide with decreases in trading volatility as the absence of key market participants reduces information flows and the production of information.[1] A greater incidence of flu could also be associated with a higher bid-ask spread as a decline in market participants would decrease liquidity and necessitate greater spreads. Alternatively, the decline in information production and volatility may partially offset this decline in liquidity. Moreover, the flu could also influence stock returns, either through the change in liquidity risk (see, for instance, Amihud and Mendelson, 1986) or because of a direct effect of flu on expected economic activity and expected returns.

Using data on NYSE traded stocks and weekly observations of flu samples from the CDC, we show that seasonal variation in the flu has an observable impact on U.S. equity

[1] A number of studies find that volatility is contemporaneously correlated with volume; see, for instance, Karpoff (1987), Bessimbinder and Seguin (1993), and Chordia, Roll, and Subramanyam (2002). See French and Roll (1986) and Fleming, Kirby, and Ostdiek (2006) on information production during the trading day.

markets. Specifically, greater flu incidence is associated with decreased trading, lower realized volatility, increased bid-ask spreads, and lower returns. We test whether these impacts on the market are due to the incidence of flu in the New York area, to the incidence of flu in the region close to the company's headquarters, or the overall incidence of the flu nationally. Coval and Moskowitz (1999) show that ownership is higher close to the company's headquarters, while institutional investors and traders are often located in or close to New York City. Consistent with a larger impact from market-makers and institutional investors, the effects on trading activity and volatility are largest when using flu incidence from the mid-Atlantic region which includes the New York area. We find that the headquarters location flu effect is smaller than the national effect, and this national effect dominates when examining the impacts on bid-ask spreads and returns. We also provide evidence that the impact of flu on trading activity and volatility drives the relation between flu and bid-ask spreads.

An existing literature documents the impact of seasonal affective disorder (SAD) on equity markets (see Kamstra, Kramer, and Levi, 2003). We therefore include the SAD onset variable introduced by Kamstra, Kramer, and Levi, (2007). In doing so, we obtain results consistent with both the SAD literature and our other findings. A separate literature identifies the effect of weather on stock returns (see Saunders, 1993; Hirshleifer and Shumway, 2003; and Goetzmann and Zhu, 2005). We therefore show that our analysis is robust to controlling for weather effects, specifically New York cloud-cover.

Lastly, we produce some rough estimates of how much a pandemic, like either the 1918-1920 or the 1957-58 outbreak, would impact equity returns. With the appearance of the H1N1 virus in 2009, growing concerns about the possibility of a disastrous pandemic have reappeared. As Potter (2001) describes, pandemics recur at 10 to 50 year intervals. The 20th century saw two well documented pandemics, in 1918-1920 and in 1957-1958. The 2009 H1N1 pandemic did not produce the number of fatalities associated with these prior pandemics.

Section II describes the data and method used in the analysis. Section III reviews our empirical analysis. Section IV relates our results to historical and predicted influenza outbreaks, and section V concludes.

II. Data and Method

The Centers for Disease Control and Prevention (CDC) collects data from laboratories on the number and percentage of positive flu samples tested by week and region of the country. We use a sample of this data from Fall 1997 through 2006.[2,3] As the incidence of flu is seasonal and as we expect some lag between when an individual becomes ill and when the lab test is performed, our primary measure is the percentage change in the number of flu samples testing positive in the subsequent week. This is computed as the change in the log of the number of flu cases plus one, and our results are largely robust to alternative measures. We use three measures of flu severity. The first measures the percentage change in the U.S. as a whole (*U.S. Flu*), the second measures the flu in the mid-Atlantic region (New York, New Jersey, and Pennsylvania) which includes New York City (*NY Flu*), and the third measures the flu in the region of the country where the firm is headquartered (*H.S. Flu*). Data on headquarters location is drawn from Compustat and matched with the nine regions for which the CDC provides separate flu data.

[2] See http://www.cdc.gov/flu/weekly/ussurvdata.htm. Sunday to Saturday CDC weekly data are converted to calendar weeks so as to match with the other data sets. This also allows the weekly dummies to consistently reflect the same calendar time period from year to year.
[3] Trade data after 2006 may not be comparable with earlier data due to the introduction of the NYSE hybrid system in late 2006 (see Hendershott and Moulton, 2009).

In order to assess the flu's impact on stock markets, we focus on NYSE trading of NYSE listed stocks. Using only NYSE data avoids a number of measurement problems with measuring NASDAQ volume (see, for example, Chordia, Roll, and Subrahmanyam, 2002). We perform an analysis both on aggregated market measures and on disaggregated individual stock data. The disaggregated sample is an unbalanced panel of weekly stock measures such as the number of trades over the week. We start with roughly 2.1 billion trades and matched quotes to form our 1.2 million weekly observations. We then further aggregate this unbalanced panel into a weekly index portfolio of NYSE stocks. We use daily CRSP data to measure cum dividend returns (and returns based on TAQ data provide similar conclusions).

To avoid spurious results, we first-difference those variables, such as trading volume, number of trades, and flu incidence, which are non-stationary. We use three variables to capture trading activity. We use the weekly percentage change, i.e. the growth rate, in dollar volume, *DVol*, equal to the change in the log dollar volume, and we use the weekly percentage change in the number of trades, *Trades*. Because these changes may be driven by large swings in the amount of trading of smaller, less liquid firms, we follow Kadapakkam, Krishnamurthy, and Tse (2005) and also consider a measure of the weekly change in turnover equal to $100 \times \ln\left(1 + \frac{Vol}{Shares}\right)$, where *Vol* refers to the number of shares traded in the given week and *Shares* equals the number of shares outstanding during the week. This measure corrects for the skewness typically observed in the distribution of volume.

We measure the bid-ask spread using the logarithm of the average weekly time-weighted effective percentage spread, *PSpread*.[4] Specifically, *PSpread* equals the difference between the trade price and the midpoint of the active quote divided by the midpoint of the active quote weighted by the time between trades. We use the level of the bid-ask spread in our analysis as past research indicates this measure is stationary (see for example, Engle and Patton, 2004). We also examine average weekly returns and weekly realized volatility. Realized volatility is calculated as the average unsigned 10 minute return over the week similar to the measure used in Andersen and Bollerslev (1998). As in Andersen, et. al. 2001, we use the logarithm of realized volatility to correct for skewness. We further consider the order imbalance (*OIB*), equal to the number of buy orders minus the number of sell orders divided by the total number of buy and sell orders (see for example, Chordia, Roll, and Subrahmanyam, 2004). We identify buy and sell orders as in Lee and Ready (1996); as in Bessembinder (2003), for recent TAQ data, we make no allowance for reporting lags when matching quotes to trades.

Our primary regressions include dummy variables for the week of the year and the calendar year. We also include a dummy variable for the period after the NYSE introduced decimalization:

$$depvar_{i,t} = \alpha + \Sigma\beta_{FluV}\Delta FluV_{i,t} + \gamma_{1-52}WDummy + \delta_{1-9}YDummy + \varphi DDummy + \varepsilon_{i,t}$$

where depvar equals our dependent variables: *DVol* , *Trades, Turnover, Volat, PSpread, and Return.* FluV equals *U.S. Flu*, *NY Flu*, or *H.S. Flu; DDummy* is the decimalization dummy, and *WDummy and YDummy* are weekly and yearly dummies.

[4] Consistent with prior studies, we use the logarithm of percentage spread because of skewness in this variable (see Benston and Hagerman, 1974).

In order to adjust for heteroskedasticity, we use robust standard errors in our aggregated data, and robust standard errors with firm-level clustering in the firm-level analysis. Thus these errors are robust both along the firm-dimension and, as we include week and year dummies, to clustering by week and year.

We fit additional regressions to measure the direct versus indirect impacts of flu on our variables of interest. For instance, we add turnover as an additional control to the volatility regressions; we add volume, volatility, the inverse of price, and the market-value of equity to the bid-ask spread regressions, and so on. We also control for weather effects and for Seasonal Affective Disorder (SAD) in some of our regressions. In order to correct for possible SAD effects, we drop our weekly dummies and follow Kamstra, Kramer, and Levi (2007) in including the SAD onset variable which measures the clinical growth rate of SAD instrumented by the number of hours of night.[5] As Goetzmann and Zhu (2005) show that the weather around New York City impacts U.S. securities' returns, we use a measure of cloud cover around LaGuardia Airport from the National Climatic Data Center as our weather control. Similar to Saunders (1993), we use two dummy variables, one for whether there are many clouds, more than 90% average weekly cloud cover, and another for whether there are few clouds, less than 40% average weekly cloud cover, during the hours of 6:00 AM to 6:00 PM EST.

III. Empirical Results

Table I provides summary statistics on our variables of interest. We have individual stock data from 1,213,949 firm-weeks over the nine years in our sample period. Panel A of

[5] As the SAD variable does not change from year to year, this variable would otherwise be collinear with the weekly dummies. The SAD onset data for North America is available at http://www.markkamstra.com/.

Table I provides means, medians, standard deviations, and extreme values. Panel B of Table I provides correlations between our primary measures. The flu in the greater NY region (i.e. mid-Atlantic region) is negatively correlated with the trading activity variables, volatility, and percentage spreads. U.S. flu exhibits a negative correlation with trading activity, percentage spread, and returns, and a positive correlation with volatility. Home state flu exhibits a negative correlation with trading activity and only a small correlation with the other tested variables. The relatively high correlation (0.426, 0.256, and 0.290 for U.S., greater NY, and home state, respectively) between flu and SAD onset suggests that explicitly adjusting for SAD may be necessary when weekly dummies are not included.

III.A. Index Portfolio Regression

To begin our analysis, we fit our primary regression specification using the aggregated sample which includes the weekly index portfolio of all NYSE stocks. Trading volume, number of shares outstanding, return, volatility, and percentage spread are averaged across all firms by week. Additionally, value-weighted averages are calculated for volatility, percentage spreads, and returns using each firm's market value of equity as weights. Using weekly observations from this aggregated portfolio, we regress each of the dependent variables on the U.S. and NY flu variables. We control for calendar and time effects with weekly and yearly dummy variables and we include a dummy for the period after the change to NYSE decimalization.[6] Table II reports the coefficients for the national and New York flu variables for each dependent variable.

[6] Including the weather variables or excluding the decimalization dummy from these regressions does not affect our results.

Panel A of Table II reports the estimated coefficients of regressions with dollar volume as the dependent variable. The first regression includes the national flu variable and the second regression includes the New York flu variable. Consistent with the hypothesis of a negative effect on trading activity, greater flu is associated with lower dollar volume, and this effect is significant at the 10% level for U.S. Flu. A one standard deviation increase in U.S. flu implies a 2.3% decline in aggregate dollar trading volume. Weekly dollar trading volume was approximately $240 billion in the second week of 2006 (when the flu was at its peak for that season), and thus a one standard deviation increase in national flu would imply a decline in trading of approximately $5.5 billion.

The effect of flu in New York on dollar volume is larger than the overall national effect; a one standard deviation increase in NY flu implies a 3.0% decline in dollar trading volume, and this effect is significant at the 1% level. The impact of flu outside of the New York area is statistically insignificant. These results suggest that the largest impact on dollar trading volume is due to the effect of flu on New York area traders.

Panel B of Table II considers the impact of flu on turnover. The impact of overall U.S. flu is negative and statistically significant at the 5% level, whereas the effect of NY flu on turnover is negative and significant at the 1% level. Again, the impact of flu outside of the New York area is statistically insignificant. Panel C provides similar results with the number of trades as the dependent variable. Again, the incidence of flu in the NY area is of primary importance, and similarly, the impact of overall U.S. flu and non-NY Flu is statistically insignificant. A one standard deviation increase in NY flu implies a 2.1% decline in the number of trades. These results again suggest that the effect of flu on trading activity is largely due to its impact on New York area traders.

Panels D and E of Table II provide regressions with equal-weighted and value-weighted volatility as the dependent variables.[7] Similar to the results for trading activity, the largest impact of flu is from the New York area. The impact of the incidence of flu in the NY area on volatility is negative and significant at the 10% level for equal-weighted volatility and at the 5% level for value-weighted volatility. To the extent that volatility reflects the incorporation of information production into prices, this result implies that greater absenteeism in the NY area implies lower information production as in French and Roll (1986).

Panels F and G of Table II provide regressions with equal-weighted and value-weighted percentage spreads as the dependent variable. U.S. flu incidence positively impacts equal-weighted percentage spreads, and this effect is significant at the 5% level. The impact of NY flu on equal-weighted spreads is statistically insignificant as are the impacts of U.S. and NY flu on value-weighted spreads. Thus, in contrast to the results for trading activity, national flu is of primary importance for percentage spreads. Further, as the results are only statistically significant for equal-weighted spreads, this suggests that the flu has a greater impact on the spreads of small firms, which may have fewer replacements for key traders.

Panels H through I of Table II provide regressions with equal-weighted and value-weighted returns as the dependent variables. The coefficients on the flu are not significant in any of these regressions, and we refine this analysis in our disaggregated sample below.

III.B Pooled Regressions

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[7] We include lag volatility as an additional independent variable in these regressions to control for the well-known persistence in volatility.

To continue are analysis, we test the impact of national, New York, and headquarters flu on our dependent variables of interest using our disaggregated sample, a weekly unbalanced panel containing firm-by-firm observations. Using each firm's observations and controlling for heteroskedasticity allows for greater precision than with aggregated data, and the results are largely consistent with those presented in aggregated data. For each dependent variable, we run three regressions, each including one of our flu variables: 1) national, 2) NY, and 3) headquarters' state flu. For volatility, percentage spread, and returns, we consider a fourth regression that includes controls commonly encountered in the literature. As in our primary specification, we include weekly dummies, yearly dummies, and a dummy for the NYSE change to decimalization. We also control for New York cloud cover. Table III reports the coefficients for the regressions using our trading activity measures. Tables IV, V, and VI report the coefficients on the volatility, percentage spread, and return regressions.

The first three columns of Table III provide regressions with dollar volume as the dependent variable. The first column includes just the national flu data as well as New York cloud-cover and the calendar and decimalization dummies. Consistent with the findings for the aggregated index portfolio, greater national flu is associated with lower dollar volume, and this effect is significant. A one standard deviation increase in U.S. flu implies a 1.9% decline in dollar trading volume. Given average weekly dollar trading volume of $240 billion in the second week in 2006, a one standard deviation increase implies an approximate decline in trading of $4.6 billion. This corresponds closely to the estimate of $5.5 billion obtained above using the index portfolio.

The second column of Table III considers the flu in the New York and non-NY regions, and the third column includes the flu in the regions where the firm is headquartered and the remainder of the U.S. outside of the headquarters state. As for the results using the index portfolio, the effect of the flu in New York is larger than the overall national and non-NY effect. A one standard deviation increase in NY flu implies a 2.6% decline in dollar trading volume. The impact of flu incidence in all regions outside New York is that one standard deviation increase in flu incidence implies a 1% decline in volume. The impact of headquarters' state flu is small compared to the New York effect. These results confirm the index portfolio results, and they are consistent with the notion that the largest impact of the flu on dollar trading volume is due to the effect of flu on New York area traders.

The second three columns of Table III provide similar results with turnover as the dependent variable. Again, the incidence of flu in the New York area is of primary importance. A one standard deviation increase in NY flu implies a 4.6% decline in turnover. The last three columns consider the impact of flu on the number of trades. Similar to the results for volume and turnover, the effect of NY flu is predominant. A one standard deviation increase in NY flu implies a 2% decrease in the number of trades. As with dollar volume and turnover, the impact of home state flu on trades is nearly an order of magnitude lower. These results again suggest that the flu effect is largely due to its impact on New York area traders.

Table IV considers the impact of flu on stock volatility. The first three columns of Table IV provide regressions with volatility as the dependent variable and the incidence of flu, cloud-cover, the calendar and decimalization dummies, and weekly and yearly dummies as independent variables. Volatility lagged one-week is also included to control for autocorrelation. Consistent with the aggregated sample results and with a reduction in information flow, the impact of flu on volatility is negative and the impact is strongest for flu in the New York region. A one standard deviation increase in NY flu implies an approximate 0.7% decrease in realized volatility.

To sort out the direct impact of flu on volatility and the indirect impact of flu through its impact on trading activity, we add turnover as a control in the last three columns of Table IV. The existing research finds a positive relationship between volume and volatility.[8] As expected, the coefficient on turnover is positive and significant. The effect of NY flu on volatility is diminished but remains negative and significant at the 0.1% level. After controlling for turnover, a one standard deviation increase in U.S. flu implies a decrease in volatility of approximately 0.5%.

Table V shows how the flu is related to the effective percentage spread. In contrast to the results for trading activity and volatility, the predominant impact on spreads is from the national flu variable. A one standard deviation increase in U.S. flu corresponds to a 1% increase in percentage spread. Regressions with NY area and non-NY area flu incidence or headquarters' area and non-headquarters area also suggest that the impact of bid-ask spreads is not localized to one portion of the country. Overall, the bid-ask spread regressions suggest that a greater incidence of leads to a less liquid market in which overall and informed trade is diminished and, in the net, market makers increase spreads.

Typical cross-sectional regression equations that model percentage spreads include contemporaneous volume, lagged volatility, inverse price, and market value as explanatory variables (see, for instance, Madhavan, 2000). We add these additional variables as controls in the last three columns of Table V. As expected, the coefficients on volume and market value are negative and significant, and the coefficients on lagged volatility and the inverse of price are

[8] Bessimbinder and Seguin (1993) find that volatility is positively related to volume (particularly unexpected volume) in futures markets. Chordia, Roll, and Subramanyam (2002) also find that volatility is positively related to volume in market portfolios.

positive and significant. The coefficient on the U.S. flu and NY flu variables remain significant at the 0.1% level; however, the magnitude of the coefficients on U.S. flu and non-H.S. flu are reduced by approximately 80% and the coefficient on non-NY flu is reduced by approximately 66%. Overall, the flu appears to impact percentage spreads primarily through its effects on volume and volatility.

Table VI considers the impact of flu incidence on returns. Returns may be affected both because greater flu incidence lowers real economic activity and also because of the impact of liquidity on returns.[9] That is, a large literature (see, for instance, Amihud and Mendelson, 1986) addresses the pricing of illiquidity. Given our results on volume and percentage spread, we expect a decrease in returns as liquidity decreases with greater flu incidence. Consistent with these hypotheses, we find that U.S., NY, and headquarters flu incidence is significantly associated with negative returns. A one standard deviation increase in U.S. flu decreases returns by approximately 0.04% per week, or about 0.9% on an annualized basis. Consistent with Saunders (1993), Hirshleifer and Shumway (2003), and Goetzmann and Zhu (2005), low New York cloud-cover days are related to higher returns.

We consider regressions including contemporaneous and lagged order imbalance and lagged bid-ask spread in the last three columns of Table VI. Chordia, Roll, and Subrahmanyam (2004) find that daily NYSE individual stock returns are positively related to contemporaneous order imbalance and negatively related to one-day lagged order imbalances. Chan and Fong (2000) find this relationship is strongest in large NYSE trades. Amihud and Mendelson (1986) find that returns are a concave function of bid-ask spreads. As markets adjust to reductions in

[9] Note that all these regressions include weekly dummies. Thus, while we expect some portion of flu to be predictable, the flu incidence after controlling for weekly effects can be interpreted as the unexpected flu activity.

liquidity, we expect higher levels of past percentage spreads to impact returns negatively. We also include controls for turnover and lagged volatility to test for any indirect impacts of flu on returns. As expected, the coefficients on order imbalance, OIB, and percentage spread are positive and statistically significant and the coefficient on lagged order imbalance is negative and statistically significant. The impact of turnover and lagged volatility on returns is insignificant except in the specification with headquarters' flu. However, the coefficients on U.S., NY, and headquarters' flu remain significant and similar in magnitude as that estimated without these additional controls. Thus, while contemporaneous OIB and percentage spread are closely related to returns, there appears to be additional information in flu incidence which affects returns.[10]

Overall these findings confirm that variation in flu incidence has an economically significant impact on the U.S. equity market. We find that a higher incidence of flu is associated with decreases in trading activity, realized volatility, and returns and increases in bid-ask spreads. The increase in bid-ask spreads appears to be driven indirectly from the effects of flu on turnover and volatility.

III.C. Seasonal Affective Disorder

Table VII considers regressions similar to those reported by Kamstra, Kramer, and Levi (2003, 2007) and DeGennaro, Kamstra, and Kramer (2006) with the impact of SAD onset, the U.S. flu variable, and cloud-cover controls on returns, and percentage spread.[11] Since the

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[10] In unreported regressions, we fit regressions with order imbalance as the dependent variable on flu activity. The results match closely to the results for returns. That is, we find a more negative order imbalance with greater flu incidence, and this result is strongest at the national level and robust to additional controls.

[11] Kamstra, Kramer, and Levi (2003, 2007) measure the influence of SAD on returns; DeGennaro, Kamstra, and Kramer (2006) measure the effects of SAD on NASDAQ inside spreads.

weekly SAD onset variable does not vary by year, we drop our weekly dummies as they would otherwise be collinear with SAD onset. However, interpreting the causation and significance of coefficients on flu becomes more difficult as flu incidence may be correlated with other seasonal effects. To compensate somewhat, we decompose our flu variable into weekly expected and unexpected flu in some of the regressions.

Column (1) of Table VII reports the impact of U.S. flu on percentage spread after controlling for SAD. Consistent with the index portfolio and pooled regressions, the effect of flu on percentage spreads is positive and statistically significant. The effect of SAD on percentage spreads is negative and statistically significant. This is consistent with the findings of DeGenarro, Kamstra, and Kramer (2006) that SAD variables are associated with lower NASDAQ bid-ask inside spreads (the spreads given by the lowest ask and highest bid among multiple dealers).

Column (2) of Table VII reports the impact of SAD on returns. Consistent with the findings of Kamstra, Kramer, and Levi, the coefficient on SAD onset is negative and statistically significant. Column (3) adds total U.S. flu as an independent variable; Column (4) decomposes U.S. flu into expected and unexpected flu incidence. After controlling for SAD and without weekly dummies, the impact of total U.S. flu on returns is positive and statistically significant. However, decomposition of the flu variable, in Column (4), indicates the impact is driven by expected flu; the impact of expected flu is positive and significant and the impact of unexpected flu is negative and insignificant. Thus, the anomalous results on flu in these return regressions are due to a lack of more comprehensive controls for seasonal variation in returns.

III.D. Robustness Checks

We perform a number of robustness checks. First, we repeat all our regressions using firm-level fixed effects. In all cases, the magnitudes and significance levels on our primary coefficients of interest remain effectively unaltered by using fixed effects regressions.

Second, we also analyze firm-by-firm impacts of the flu on our various measures. For this test, we restrict our sample to firms that have more than 104 weekly observations over the 468 weeks in our sample and at least 26 weeks in the first and last year the firms arise in the sample. We calculate the mean, median, number positive, number negative, and percent positive for each estimated by-firm coefficient on flu. We also calculate the probability of finding the percent positive assuming the null hypothesis that the distribution is a binomial variable with equal likelihood of being positive or negative, i.e., $p = 0.5$. The percent positive and p-values are consistent with our other results for all the variables we test; that is, the coefficients we find are significant hold for a significant proportion of the individual firms. These results are also robust to testing the firm-by-firm coefficients in a subset of the test sample where the coefficient on flu is significant at or below the 10% level.

Third, to rule out the notion that our results are driven by January and year-end calendar effects, we remove all observations in our disaggregated sample that are in the first and fifty-second week. Our primary results remain and in a few cases become stronger. For example, in the return regressions, the coefficient on the U.S. flu effect more than doubles.

IV. Pandemics and the U.S. Stock Market

We briefly compare our results with the outcomes of the two major 20th century pandemics, the 1918-1920 and 1957-1958 outbreaks. These calculations require numerous naive assumptions, such as a linear impact of our flu measures on stock returns, stability in how the flu impacts the stock market, and so on. However, we provide them because they may roughly illustrate the magnitudes involved.

While detailed data on the U.S. markets is not available from either of the prior 20th century pandemics, we can examine return behavior around those time periods and see whether it is roughly consistent with our estimates from seasonal flu variation. We therefore compare several months after the onset of the flu in each of the prior pandemics with stock returns over that time period. We use the historical NYSE stock return data from Schwert (1990).

The 1918-1920 pandemic had a less virulent outbreak in the U.S. during the Spring of 1918; however, the more lethal form of the disease reached the U.S. in September of 1918. The duration of the outbreak in the U.S. was relatively short (Barry, 2004). Approximately 500,000 deaths attributable to the flu occurred in the U.S. (U.S. Department of Health and Human Services, 2004).[12] The U.S. stock market over the September to December 1918 period rose by 0.22%, or 2.7% on an annualized basis. It should be noted that this time period also coincided with the end of World War I.

The 1957-1958 pandemic is typically dated in the U.S. from June 26, 1957, when a conference at Grinnell College suffered a severe outbreak. The disease then spread quickly across the U.S. Approximately 69,800 deaths occurred in the U.S. (U.S. Department of Health and Human Services, 2004). The U.S. stock market declined by 10%, or 23% on an annualized basis, from July 1, 1957 to December 1, 1957.

On average, approximately 36,000 people died annually in the U.S. from flu or flu-related complications in the 1990's (see Thompson et al. 2003).[13] Normalizing the fatality rates from the flu by the populations in the U.S. for 1918, 1957, and 1995 (103, 172, and 267 million,

[12] The 1918 flu was more fatal to young adults than typical flu outbreaks.
[13] See also http://www.cdc.gov/flu/about/disease/us_flu-related_deaths.htm.

approximately) gives approximate fatality rates of 0.00485, 0.00041, for the two pandemics and 0.00014, for an average year in the 1990's. Thus the 1957 pandemic had roughly three times the usual fatality rate, and the 1918 pandemic had roughly 36 times the usual fatality rate.

Since our flu variables are measured in percentage changes, significant increases in flu levels due to a pandemic would increase growth rates in the incidence of flu by approximately the difference between the log of the number of flu in the pandemic year and the log of the number of flu in a normal year. Given the roughly three times higher fatality rate in the 1957 pandemic, this corresponds to a 2.2 standard deviation change in the U.S. flu variable ($2.2 = 1.10/0.50$, as $\ln(3)$ is 1.10 and one standard deviation in U.S. flu in our sample is 0.50), and this would imply an additional -0.08% weekly return ($-0.08\% = -0.037\% \times 2.2$, as each one standard deviation increase in the U.S. flu variable corresponds to a 0.037% decrease in weekly returns) over the duration of the illness using our estimate with weekly dummies and national flu incidence shown in Table VI. A pandemic as severe as the 1918-1920 outbreak would be on the order of seven standard deviations away from the mean. This would imply a -0.26% decrease in stock returns per week.

V. Conclusion

The flu can impact financial market activity by incapacitating key individuals, such as traders and market makers, by affecting overall investing behavior, as well as by decreasing expectations about real economic activity. We study the impact of the flu on stock markets by examining weekly NYSE trading data, compiled from high-frequency TAQ data, and weekly CDC flu data. We consider the impact of flu on both an aggregated NYSE index portfolio and on all NYSE stocks. We find that a higher incidence of flu, particularly of flu in the NY area, is associated with a decrease in trading activity as measured by dollar volume, number of trades, and turnover. For instance, a one standard deviation increase in the flu in the NY area implies a decrease in mean trading activity from 2% to 4.6%, depending on the measure of trading activity used.

Greater incidence of flu is also associated with lower volatility, and this finding is consistent with greater absenteeism implying less information production. Bid-ask spreads also widen during high flu incidence weeks; however, this relation is primarily driven by changes in volume and volatility. Lastly, returns decline with greater flu activity, and this may reflect both the pricing of liquidity and decreased expectations about real economic activity. While the volume and volatility effects are more closely tied to NY area flu incidence, the effects of flu on bid-ask spreads and returns are more strongly associated with the incidence of flu nationally. Pandemics have fatality rates which are much greater than those associated with seasonal flu, and the data suggests an approximate magnitude of a pandemic on the equity markets.

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Table I: Summary Statistics

This table provides summary statistics in weekly frequencies on the variables used in this study. The sample is drawn from NYSE listed stocks traded on the NYSE from 1998 through 2006. *Return* is the weekly CRSP cum dividend return. *Turnover* is $100x\ln(1+\frac{Vol}{Shares})$, where *Vol* refers to the number of shares traded in the given week and *Shares* equals the number of shares outstanding during the week. *DVol* is the weekly dollar volume. *Trades* is the weekly number of trades. *Volatility* equals the average unsigned 10 minute return over the week (see Andersen and Bollerslev, 1998). *PSpread* is the average weekly time-weighted effective percentage spread calculated as the difference between the trade price and the midpoint of the active quote divided by the midpoint of the active quote weighted by the time between trades. *MV* is the firm's weekly market value of equity. *1/P* is the inverse of the weekly stock close. *OIB* is the weekly order imbalance equal to the number of buy orders minus the number of sell orders divided by the total number of buy and sell orders. The three flu variables are the percentage change in the number of flu cases in the subsequent week. This is measured as the change in the log of the number of flu cases plus one. *U.S Flu* is the percentage change in the U.S. as a whole, *NY Flu* is the percentage change in the mid-Atlantic region (New York, New Jersey, and Pennsylvania) which includes New York City and *H.S. Flu* is the percentage change in the region of the country where the firm is headquartered. *SAD onset* refers to the seasonal affective disorder onset variable as in Kamstra, Kramer, and Levi (2007).

	Obs.	Mean	Median	SD	Min.	Max.
Return(%)	1,213,949	0.230	0.112	5.684	-33.33	40.65
Turnover	1,213,949	1.782	1.080	3.139	0.006	63.09
PSpread(%)	1,213,342	0.474	0.253	0.797	0.018	10.53
Dvol (million)	1,213,949	65.79	7.410	196.97	0.005	2,595.0
Trades (thousand)	1,213,949	1.754	0.494	2.896	0.002	22.79
Volatility(%)	1,213,949	0.297	0.223	0.299	0.000	4.036
MV (billion)	1,213,949	43.90	6.666	170.90	0.000	5,929.0
1/P	1,213,949	0.086	0.050	0.333	0.001	256.0
OIB(%)	1,213,834	5.024	6.671	20.75	-100.00	100.00
U.S. Flu	1,213,949	-0.001	0.000	0.502	-4.157	2.764
NY Flu	1,213,949	-0.004	0.000	0.525	-2.015	2.197
H.S. Flu	854,999	-0.001	0.000	0.482	-2.974	2.639
SAD Onset	1,213,949	0.000	0.001	0.213	-0.431	0.431

Panel B: Correlations

	Return	Turnover	PSprd	Dvol	Trades	Volat	OIB	U.S. Flu	N.Y. Flu	H.S. Flu	SAD Onset	Cloudy
Return	1.000	-0.013	-0.026	0.052	0.018	-0.024	0.191	-0.004	0.001	-0.001	-0.024	0.000
Turnover	-0.013	1.000	0.009	0.625	0.454	0.063	0.009	-0.007	-0.029	-0.006	0.005	-0.011
PSpread	-0.026	0.009	1.000	0.010	0.016	0.699	-0.195	-0.002	-0.010	-0.010	-0.007	0.022
DVol	0.052	0.625	0.010	1.000	0.772	0.078	0.013	-0.010	-0.042	-0.009	0.005	-0.014
Trades	0.018	0.454	0.016	0.772	1.000	0.099	0.009	-0.009	-0.051	-0.012	0.006	-0.014
Volat	-0.024	0.063	0.699	0.078	0.099	1.000	-0.100	0.018	-0.007	-0.002	0.014	0.007
OIB	0.191	0.009	-0.195	0.013	0.009	-0.100	1.000	-0.003	-0.001	-0.001	0.009	-0.006
U.S. Flu	-0.004	-0.007	-0.002	-0.010	-0.009	0.018	-0.003	1.000	0.455	0.499	0.426	-0.002
NY Flu	0.001	-0.029	-0.010	-0.042	-0.051	-0.007	-0.001	0.455	1.000	0.464	0.256	0.010
H.S. Flu	-0.001	-0.006	-0.010	-0.009	-0.012	-0.002	-0.001	0.499	0.464	1.000	0.290	0.017
SAD Onset	-0.024	0.005	-0.007	0.005	0.006	0.014	0.009	0.426	0.256	0.290	1.000	0.039
Cloudy	0.000	-0.011	0.022	-0.014	-0.014	0.007	-0.006	-0.002	0.010	0.017	0.039	1.000

Table II: NYSE Index Portfolio Regressions

The following table reports coefficients for multivariate regressions using robust standard errors. Dummy variables for the week of the year and the calendar year are included to control for time effects. The dataset used is a weekly NYSE index portfolio formed from aggregating weekly individual NYSE traded stocks. The dependant variables are *DVol*, defined as the weekly percentage change in dollar volume measured by change in the log dollar volume; *Trades*, defined as the weekly percentage change in the number of trades; *Turnover*, defined as weekly change in turnover, $100x\ln(1+\frac{Vol}{Shares})$, where *Vol* refers to the number of shares traded in the given week and *Shares* equals the number of shares outstanding during the week; volatility, *Volat*, calculated as the logarithm of the average unsigned 10 minute return over the week (see Andersen and Bollerslev, 1998 and Andersen, et. al. 2001); *PSpread*, defined as the logarithm of the average weekly time-weighted effective percentage spread calculated as the difference between the trade price and the midpoint of the active quote divided by the midpoint of the active quote weighted by the time between trades; and *Return*, defined as the weekly CRSP cum dividend return. Both equal-weighted (EW) and value-weighted (VW) averages are formed for *Return*, *PSpread, OIB,* and *Volat*. Value-weighted averages use each firm's market value of equity as weights. The flu variables are the percentage change in the number of flu cases in the subsequent week. This is measured as the change in the log of the number of flu cases plus one. *U.S. Flu* is the percentage change in the U.S. as a whole, *NY Flu* is the percentage change in the mid-Atlantic region (New York, New Jersey, and Pennsylvania) which includes New York City, and *NonNY Flu* is the percentage change in all U.S. regions except the mid-Atlantic region. Similar to Saunders, 1993, *Many Clouds* is a dummy variable for whether there is more than 90% average weekly-cloud cover and *Few Clouds* is a dummy variable for whether there is less than 40% average weekly cloud-cover over LaGuardia Airport during the hours of 6:00 AM to 6:00 PM EST. Standard errors are reported in parentheses below the coefficients. The change in the dependent variable for a one standard deviation change in the flu variable is reported below the standard errors. a, b and c refer to significance at the 10%, 5%, and 1% levels, respectively.

	Flu				
	U.S.	NY	Non-NY	R^2	Obs.
Panel A – DVol					
	-0.0458a			0.431	467
	(-1.91)				
	-0.0226				
		-0.0578c	-0.0255	0.440	467
		(-2.94)	(-1.08)		
		-0.0302	-0.0124		

Panel B - Turnover					
	-0.0734b			0.398	467
	(-2.03)				
	-0.0363				
		-0.0892c	-0.0440	0.411	467
		(-3.12)	(-1.29)		
		-0.0466	-0.0215		
Panel C - Trades					
	-0.0282			0.353	467
	(-1.51)				
	-0.0139				
		-0.0400b	-0.0167	0.360	467
		(-2.53)	(-0.91)		
		-0.0209	-0.0081		
Panel D – EW Volat					
	-0.4368			0.971	467
	(-0.44)				
	-0.2161				
		-1.2627a	-0.0941	0.971	467
		(-1.85)	(-0.09)		
		-0.6602	-0.0458		
Panel E – VW Volat					
	-0.9481			0.922	467
	(-0.62)				
	-0.4690				
		-2.2869b	-0.4225	0.923	467
		(-2.25)	(-0.28)		
		-1.1958	-0.2058		
Panel F – EW PSpread					
	2.7937b			0.971	468
	(2.51)				

	1.3820				
		0.1653	2.7829b	0.971	468
		(0.29)	(2.30)		
		0.0864	1.3555		
Panel G – VW PSpread					
	-0.0259			0.931	468
	(-0.02)				
	-0.0128				
		1.9871	-0.9682	0.931	468
		(1.34)	(-0.71)		
		1.0390	-0.4716		
Panel H - EW Return					
	-0.0770			0.200	468
	(-0.32)				
	-0.0381				
		-0.0250	0.0166	0.200	468
		(-0.13)	(0.07)		
		-0.0131	0.0081		
Panel I - VW Return					
	-0.0981			0.154	467
	(-0.33)				
	-0.0485				
		-0.0251	0.0370	0.154	467
		(-0.09)	(0.13)		
		-0.0131	0.0180		

Table III: Regressions – Trading Activity

This table reports coefficients for pooled multivariate regressions using robust standard errors with firm-level clustering. Dummy variables for the week of the year and the calendar year are included to control for time effects. The dependent variables are *DVol*, defined as the weekly percentage change in dollar volume measured by change in the log dollar volume, *Trades*, defined as the weekly percentage change in the number of trades, and *Turnvover*, defined as the weekly change in turnover, $100x\ln(1+\frac{Vol}{Shares})$, where *Vol* refers to the number of shares traded in the given week and *Shares* equals the number of shares outstanding during the week. The five flu variables are the percentage change in the number of flu cases in the subsequent week. This is measured as the change in the log of the number of flu cases plus one. *U.S. Flu* is the percentage change in the U.S. as a whole, *NY Flu* is the percentage change in the mid-Atlantic region (New York, New Jersey, and Pennsylvania) which includes New York City, *NonNY Flu* is the percentage change in all U.S. regions except the mid-Atlantic region, *HS Flu* is the percentage change in the region of the country where the firm is headquartered, and *nonHS Flu* is the percentage change in all U.S. regions except the headquarters' region. Similar to Saunders, 1993, *Many Clouds* is a dummy variable for whether there is more than 90% average weekly-cloud cover and *Few Clouds* is a dummy variable for whether there is less than 40% average weekly cloud-cover over LaGuardia Airport during the hours of 6:00 AM to 6:00 PM EST. Standard errors are reported in parentheses below the coefficients. The change in the dependent variable for a one standard deviation change in the flu variable is reported below the standard errors. a, b and c refer to significance at the 5%, 1%, and 0.1% levels, respectively.

	DVol		Turnover		Trades	
US Flu	-0.0387c		-0.0650c		-0.0293c	
	(-27.46)		(-13.96)		(-33.04)	
	-0.0194		-0.0326		-0.0147	
NY Flu		-0.0491c		-0.0875c		-0.0372c
		(-37.93)		(-22.71)		(-46.13)
		-0.0258		-0.0459		-0.0195

NonNY Flu		-0.0206c			-0.0364c			-0.0174c	
		(-14.46)			(-7.91)			(-19.42)	
		-0.0101			-0.0179			-0.0085	
HS Flu			-0.0074c			-0.0129b			-0.0054c
			(-4.74)			(-2.90)			(-5.34)
			-0.0036			-0.0062			-0.0026
NonHS Flu			-0.0349c			-0.0559c			-0.0254c
			(-22.25)			(-11.44)			(-26.09)
			-0.0173			-0.0277			-0.0126
Many Clouds	-0.0287c	-0.0261c	-0.0291c	-0.0714c	-0.0668c	-0.0715c	-0.0151c	-0.0132c	-0.0146c
	(-11.65)	(-10.54)	(-10.79)	(-10.18)	(-9.51)	(-9.93)	(-9.96)	(-8.61)	(-8.80)
Few Clouds	0.0222c	0.0268c	0.0235c	-0.0046	0.0034	0.0016	0.0205c	0.0239c	0.0198c
	(7.81)	(9.45)	(7.54)	(-0.50)	(0.37)	(0.17)	(11.55)	(13.46)	(10.40)
R^2	0.039	0.040	0.045	0.012	0.012	0.015	0.069	0.071	0.081
Obs.	1,209,333	1,209,333	852,001	1,209,333	1,209,333	852,001	1,209,333	1,209,333	852,001

Table IV: Regressions - Volatility

This table report coefficients for pooled multivariate regressions using robust standard errors with firm-level clustering. Dummy variables for the week of the year and the calendar year are included to control for time effects. The dependent variable volatility, *Volat*, is calculated as the logarithm of the average unsigned 10 minute return over the week (see Andersen and Bollerslev, 1998 and Andersen, et. al. 2001). The five flu variables are the percentage change in the number of flu cases in the subsequent week. *U.S. Flu* is the percentage change in the U.S. as a whole, *NY Flu* is the percentage change in the mid-Atlantic region (New York, New Jersey, and Pennsylvania) which includes New York City, *NonNY Flu* is the percentage change in all U.S. regions except the mid-Atlantic region, *HS Flu* is the percentage change in the region of the country where the firm is headquartered, and *nonHS Flu* is the percentage change in all U.S. regions except the headquarters' region. *Turnvover* is the weekly change in turnover, $100x\ln(1+\frac{Vol}{Shares})$, where *Vol* refers to the number of shares traded in the given week and *Shares* equals the number of shares outstanding during the week. Similar to Saunders, 1993, *Many Clouds* is a dummy variable for whether there is more than 90% average weekly-cloud cover and *Few Clouds* is a dummy variable for whether there is less than 40% average weekly cloud-cover over LaGuardia Airport during the hours of 6:00 AM to 6:00 PM EST. Standard errors are reported in parentheses below the coefficients. The change in the dependent variable for a one standard deviation change in the flu variable is reported below the standard errors. a, b and c refer to significance at the 5%, 1%, and 0.1% levels, respectively.

	Volatility Regressions			With Additional Controls		
US Flu	-0.3459c			-0.1551a		
	(-4.74)			(-2.14)		
	-0.1735			-0.0778		
NY Flu		-1.3552c			-1.0880c	
		(-19.13)			(-15.45)	
		-0.7113			-0.5710	
NonNY Flu		0.0253			0.1284	
		(0.34)			(1.75)	
		0.0124			0.0631	
HS Flu			-0.1696a			-0.1170
			(-2.17)			(-1.52)
			-0.0817			-0.0563

NonHS Flu			-0.2975c			-0.0940
			(-3.50)			(-1.12)
			-0.1476			-0.0466
Turnover				3.0674c	3.0616c	3.8468c
				(22.88)	(22.86)	(33.47)
Lag Volat	0.8162c	0.8162c	0.8048c	0.8204c	0.8205c	0.8108c
	(247.70)	(247.70)	(192.46)	(250.76)	(250.75)	(196.21)
Many Clouds	-1.3029c	-1.2387c	-1.2043c	-1.0693c	-1.0196c	-0.9145c
	(-9.73)	(-9.25)	(-8.13)	(-8.05)	(-7.68)	(-6.23)
Few Clouds	-0.8080c	-0.6879c	-0.9366c	-0.8031c	-0.7074c	-0.9551c
	(-5.07)	(-4.33)	(-5.39)	(-5.06)	(-4.47)	(-5.55)
R^2	0.723	0.723	0.713	0.730	0.731	0.723
Obs.	1,203,814	1,203,814	849,895	1,203,814	1,203,814	849,895

Table V: Regressions - Percentage Effective Bid-Ask Spread

This table reports coefficients for pooled multivariate regressions using robust standard errors with firm-level clustering. Dummy variables for the week of the year and the calendar year are included to control for time effects. The dependent variable, *PSpread*, is the average weekly time-weighted effective percentage spread, calculated as the difference between the trade price and the midpoint of the active quote divided by the midpoint of the active quote weighted by the time between trades. The five flu variables are the percentage change in the number of flu cases in the subsequent week. *U.S. Flu* is the percentage change in the U.S. as a whole, *NY Flu* is the percentage change in the mid-Atlantic region (New York, New Jersey, and Pennsylvania) which includes New York City, *NonNY Flu* is the percentage change in all U.S. regions except the mid-Atlantic region, *HS Flu* is the percentage change in the region of the country where the firm is headquartered, and *nonHS Flu* is the percentage change in all U.S. regions except the headquarters' region. *Volume* is the logarithm of weekly dollar volume, *Volat* is calculated as the logarithm of the average unsigned 10 minute return over the week (see Andersen and Bollerslev, 1998 and Andersen, et. al. 2001), *1/P* is the inverse of the weekly stock close, and *MV* is the logarithm of the firm's weekly market value of equity. Similar to Saunders, 1993, *Many Clouds* is a dummy variable for whether there is more than 90% average weekly-cloud cover and *Few Clouds* is a dummy variable for whether there is less than 40% average weekly cloud-cover over LaGuardia Airport during the hours of 6:00 AM to 6:00 PM EST. Standard errors are reported in parentheses. The change in the dependant variable for a one standard deviation change in the flu variable is reported below the standard errors. a, b and c refer to significance at the 5%, 1%, and 0.1% levels, respectively.

	Bid-Ask Spread Regressions			With Additional Controls		
Flu-US	2.0060c			0.3626c		
	(22.61)			(4.83)		
	1.0061			0.1818		
Flu-NY		0.0847			-0.5526c	
		(1.64)			(-10.05)	
		0.0444			-0.2900	
Flu-NonNY		1.9498c			0.5904c	
		(21.75)			(7.88)	
		0.9576			0.2899	
Flu-HS			-0.3628c			0.2299b

			(-5.07)			(3.28)
			-0.1747			0.1107
Flu-NonHS			1.7214c			0.2984c
			(18.11)			(3.48)
			0.8539			0.1480
Volume				-19.961c	-19.963c	-20.598c
				(-69.22)	(-69.22)	(-56.03)
Lag Volat				0.5577c	0.5577c	0.5480c
				(75.75)	(75.76)	(57.21)
1/P				31.480c	31.478c	63.166c
				(6.78)	(6.78)	(7.11)
MV				-10.847c	-10.845c	-9.418c
				(-24.49)	(-24.49)	(-15.25)
Many Clds	-2.6718c	-2.6914c	-2.4351c	-0.7441c	-0.7194c	-0.8941c
	(-18.43)	(-18.55)	(-15.26)	(-6.03)	(-5.82)	(-6.28)
Few Clds	0.2600	0.2570	0.1587	-0.1554	-0.0992	-0.0641
	(1.51)	(1.49)	(0.81)	(-1.03)	(-0.66)	(-0.36)
R^2	0.309	0.309	0.327	0.870	0.870	0.863
Obs.	1,213,138	1,213,138	854,714	1,205,674	1,205,674	850,626

Table VI: Regressions - Returns

This table reports coefficients for pooled multivariate regressions using robust standard errors with firm-level clustering. Dummy variables for the week of the year and the calendar year are included to control for time effects. The dependent variable, *Return*, is defined as the weekly CRSP cum dividend percentage return. The three flu variables are the percentage change in the number of flu cases in the subsequent week. This is measured as the change in the log of the number of flu cases plus one. The five flu variables are the percentage change in the number of flu cases in the subsequent week. *U.S. Flu* is the percentage change in the U.S. as a whole, *NY Flu* is the percentage change in the mid-Atlantic region (New York, New Jersey, and Pennsylvania) which includes New York City, *NonNY Flu* is the percentage change in all U.S. regions except the mid-Atlantic region, *HS Flu* is the percentage change in the region of the country where the firm is headquartered, and *nonHS Flu* is the percentage change in all U.S. regions except the headquarters' region. *OIB* is the weekly order imbalance, equal to the number of buy orders minus the number of sell orders divided by the total number of buy and sell orders. *PSpread* is the logarithm of the average weekly time-weighted effective percentage spread, calculated as the difference between the trade price and the midpoint of the active quote divided by the midpoint of the active quote weighted by the time between trades. *Turnover* is the weekly change in turnover, $100x\ln(1+\frac{Vol}{Shares})$, where *Vol* refers to the number of shares traded in the given week and *Shares* equals the number of shares outstanding during the week. Volatility, *Volat*, is calculated as the logarithm of the average unsigned 10 minute return over the week (see Andersen and Bollerslev, 1998 and Andersen, et. al. 2001). Similar to Saunders, 1993, *Many Clouds* is a dummy variable for whether there is more than 90% average weekly-cloud cover and *Few Clouds* is a dummy variable for whether there is less than 40% average weekly cloud-cover over LaGuardia Airport during the hours of 6:00 AM to 6:00 PM EST. Standard errors are reported in parentheses. The change in the dependant variable for a one standard deviation change in the flu variable is reported below the standard errors. a, b and c refer to significance at the 5%, 1%, and 0.1% levels, respectively.

	Return Regressions		With Additional Controls	
US Flu	-0.0733c		-0.0732c	
	(-5.56)		(-5.64)	
	-0.0368		-0.0367	
NY Flu		-0.0364b		-0.0422c
		(-2.99)		(-3.53)
		-0.0191		-0.0222

NonNY Flu		0.0265a			0.0271a	
		(1.97)			(2.04)	
		0.0130			0.0133	
HS Flu			-0.0403b			-0.0416b
			(-2.78)			(-2.92)
			-0.0194			-0.0200
NonHS Flu			-0.0510b			-0.0577c
			(-3.23)			(-3.74)
			-0.0253			-0.0286
OIB				0.0578c	0.0578c	0.0618c
				(59.31)	(59.31)	(51.17)
Lag OIB				-0.0234c	-0.0234c	-0.0243c
				(-44.41)	(-44.39)	(-36.76)
Lag PSpread				0.0009c	0.0009c	0.0011c
				(10.30)	(10.29)	(10.84)
Turnover				-0.0043	-0.0043	-0.0388c
				(-0.56)	(-0.56)	(-3.67)
Lag Volat				0.0002	0.0002	0.0013c
				(1.37)	(1.34)	(6.30)
Many Clouds	-0.0285	-0.0236	-0.0614a	-0.0412	-0.0362	-0.0701b
	(-1.31)	(-1.08)	(-2.54)	(-1.91)	(-1.68)	(-2.96)
Few Clouds	0.6930c	0.7024c	0.7107c	0.6310c	0.6408c	0.6349c
	(26.48)	(26.83)	(24.75)	(24.44)	(24.82)	(22.65)
R^2	0.025	0.025	0.027	0.060	0.060	0.067
Obs.	1,213,949	1,213,949	854,999	1,205,823	1,205,823	850,705

Table VII: Regressions including SAD

The following table reports coefficients for pooled multivariate regressions using robust standard errors with firm-level clustering. Dummy variables for the week of the year and the calendar year are included to control for time effects. The dependent variables are *PSpread*, the logarithm of the average weekly time-weighted effective percentage spread calculated as the difference between the trade price and the midpoint of the active quote divided by the midpoint of the active quote weighted by the time between trades; *OIB*, defined as the weekly order imbalance equal to the number of buy orders minus the number of sell orders divided by the total number of buy and sell orders; and *Return*, defined as the weekly CRSP cum dividend return. *U.S. Flu* is the percentage change in the number of U.S. flu cases in the subsequent week. This is measured as the change in the log of the number of flu cases plus one. *Expflu* is the weekly average of *U.S. Flu* for each of the 52 calendar weeks. *Unexpflu* is the difference between *U.S. Flu* and *Expflu*. *SAD onset* refers to the weekly seasonal affective disorder onset variable as in Kamstra, Kramer, and Levi (2007). Similar to Saunders, 1993, *Many Clouds* is a dummy variable for whether there is more than 90% average weekly-cloud cover and *Few Clouds* is a dummy variable for whether there is less than 40% average weekly cloud-cover over LaGuardia Airport during the hours of 6:00 AM to 6:00 PM EST. Standard errors are reported in parentheses. The change in the dependent variable for a one standard deviation change in the flu variable is reported below the standard errors. a, b and c refer to significance at the 5%, 1%, 0.1% levels, respectively.

	PSpread	Return		
U.S. Flu	0.7427c		0.0794c	
	(7.78)		(7.12)	
	0.3725		0.0398	
UnexpFlu				-0.0145
				(-1.12)
				-0.0052
ExpFlu				0.2515c
				(13.86)
				0.0851
SAD Onset	-2.5579c	-0.6942c	-0.7752c	-0.9450c
	(-6.81)	(-28.76)	(-29.05)	(-31.87)
Many Clouds	-1.4259c	-0.0092	-0.0052	0.0028
	(-10.52)	(-0.47)	(-0.27)	(0.15)

Few Clouds	1.0806c	0.6566c	0.6652c	0.6652c
	(6.55)	(26.74)	(27.09)	(27.10)
Obs.	1,213,138	1,213,949	1,213,949	1,213,949
R^2	0.308	0.003	0.003	0.003