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Do Stock Markets Catch the Flu?

Brian C. McTier, Yiuman Tse, and John K. Wald*

Abstract

We examine the impact of influenza on stock markets. For the United States, a higher incidence of flu is associated with decreased trading, decreased volatility, decreased returns, and higher bid-ask spreads. 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 related to the incidence of flu nationally. International data confirm our findings of a decrease in trading activity and returns when flu incidence is high.

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, and 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, Swaen, Kant, Van Schayck, and Galama (2005)). A separate literature also discusses the general economic impacts of influenza (see, e.g., McKibbin and Sidorenko (2006)). The goal of this paper is to examine the implications of the flu primarily for U.S. equity markets over a number of years where detailed flu incidence data are available.

We hypothesize that an increase in the rate of influenza would decrease equity market volume and turnover. Similarly, an increase in the incidence of flu would coincide with a decrease in return volatility as the absence of key market

*McTier, b.mctier@wsu.edu, College of Business, Washington State University Vancouver, PO Box 644750, Pullman, WA 99164; Tse, tseyi@umsl.edu, College of Business Administration, University of Missouri-St. Louis, 1 University Blvd, St. Louis, MO 63121; and Wald, john.wald@utsa.edu, College of Business, University of Texas at San Antonio, 1 UTSA Cir, San Antonio, TX 78249. We thank Hendrik Bessembinder (the editor), Dana Forgione, Oliver Hansch, Mark Kamstra, Lisa Kramer (the referee), and seminar participants at UTSA and WSUV for their helpful comments.

participants reduces information flows and the production of information.[1] An increase in flu incidence 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, e.g., 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 Centers for Disease Control and Prevention (CDC), our tests suggest that seasonal variation in the flu has an observable effect on U.S. equity markets. Specifically, greater increases in flu incidence are associated with decreases in trading, lower realized volatility, widening 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 City area, to the incidence of flu in the region close to the company's headquarters, or to the overall incidence of the flu nationally. Coval and Moskowitz (1999) show that individual investor stock ownership is higher close to the company's headquarters, while institutional investors and traders are often located in or close to New York City. Engelberg and Parsons (2011) show that these local investors react more to stories in local media outlets, whereas Loughran and Schultz (2004) show that locally significant holidays and blizzards affect trading patterns, while cloudiness around the headquarters has no effect. However, consistent with a larger impact from market makers and institutional investors, the effects on trading activity and return volatility are largest when using flu incidence from the mid-Atlantic region, which includes the New York City area. We find that flu incidence in the region where the firm is headquartered is not as correlated with trading activity as the overall U.S. or New York City flu effects.

International data on flu incidence are more limited, but we also consider how international indicators of influenza activity from Google are related to trading volume and returns. For our sample of 25 countries and 15 major international cities with available data, we find a significant negative relation between increases in influenza activity and stock trading volume. We also find some evidence of a negative relationship between flu activity and stock returns.

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 to controlling for New York City cloud cover.

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

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Section II describes the data and method used in the analysis. Section III reviews our empirical analysis, and Section IV concludes.

II. Data and Method

A. Data

The CDC collects data from laboratories on the number and percentage of positive flu samples tested by week and region of the country.[2] We use a sample of these data from the beginning of 1998 through the end of 2006.[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 1.[4,5] We use 3 measures of flu severity: The 1st measures the percentage change in the United States as a whole ($\Delta LogUSFlu$); the 2nd measures the flu in the mid-Atlantic region (New York, New Jersey, and Pennsylvania), which includes New York City ($\Delta LogNYFlu$); and the 3rd measures the flu in the region of the country where the firm is headquartered ($\Delta LogHRegionFlu$). Data on headquarters location is drawn from Compustat and matched with the 9 census regions for which the CDC provides separate flu data.[6]

We study the effect of the flu on stock markets by examining weekly trading data, compiled from high-frequency NYSE trade and quote (TAQ) data from 1998 to 2006.[7] In order to assess the flu's relation to stock markets, we focus on NYSE trading of NYSE listed stocks. Using only NYSE data avoids a number of problems with measuring NASDAQ volume (see, e.g., Atkins and Dyl (1997) or Chordia et al. (2002)). We perform an analysis both on aggregated market

[2]The CDC omitted data for the summers during 1998–2002, and we fill these time periods with zeros. Excluding the missing summer weeks from the analysis produces similar results.

[3]See http://www.cdc.gov/flu/weekly/ussurvdata.htm. Sunday to Saturday CDC weekly data are converted to annual calendar weeks so as to match the other data sets. This also allows the weekly dummy variables to consistently reflect the same calendar time period from year to year.

[4]Rather than adding 1, some papers (see, e.g., Llorente, Michaely, Gideon, and Wang (2002)) add the value that makes the distribution of the log of the sum most normal. We cannot reject the hypothesis of normality after adding 1, and our results are not particularly sensitive to this parameter.

[5]As our flu variables measure percentage change in flu incidence, their magnitudes will be greatest at the onset of the flu season. The growth rate in absenteeism is also highest at the onset of the flu. See http://www.cdc.gov/flu/tools/fluworkloss/index.htm# for estimated absenteeism rates in flu outbreaks.

[6]The 9 U.S. Census Bureau divisions are New England (CENS-D1): Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont; Middle Atlantic (CENS-D2): New Jersey, New York, Pennsylvania; East North Central (CENS-D3): Illinois, Indiana, Michigan, Ohio, Wisconsin; West North Central (CENS-D4): Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota; South Atlantic (CENS-D5): Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia; East South Central (CENS-D6): Alabama, Kentucky, Mississippi, Tennessee; West South Central (CENS-D7): Arkansas, Louisiana, Oklahoma, Texas, Mountain (CENS-D8): Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming; and Pacific (CENS-D9): Alaska, California, Hawaii, Oregon, Washington.

[7]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 (2011)).

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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 further aggregate this unbalanced panel into an equal-weighted weekly index portfolio of NYSE stocks and a panel of 9 regional index portfolios of NYSE stocks. We use daily Center for Research in Security Prices (CRSP) data to measure cum dividend returns (returns based on TAQ data provide similar conclusions).

To reduce concerns about stationarity and to measure our variables as flows, we fit our models using first differences. We use 3 variables to capture trading activity. We use the weekly percentage change in dollar volume, $\Delta LogDVol$, equal to the change in the log of dollar volume, and we use the weekly percentage change in the number of trades, $\Delta LogTrades$. 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 $100 \times \log(1 + Volume/Shares)$, where *Volume* refers to the number of shares traded in the given week and *Shares* equals the average number of shares outstanding during the week. This measure corrects for the skewness typically observed in the distribution of volume. Note that our dependent variables and flu incidence are measured as flows rather than stocks for comparability.

We measure the bid-ask spread, $\Delta Spread$, as $100 \times (Spread_t - Spread_{t-1})$, where *Spread* is the average weekly time-weighted effective percentage spread calculated as 100 times 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 (see DeGennaro, Kamstra, and Kramer (2008) for a discussion of NYSE specialists' quotes vs. NASDAQ inside spreads). We also examine average weekly percentage 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, Bollerslev, Diebold, and Ebens (2001), we use the logarithm of realized volatility to correct for skewness. We further consider the percentage 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, e.g., Chordia et al. (2002)). We identify buy and sell orders as in Lee and Ready (1991). We follow Bessembinder (2003) and make no allowance for reporting lags when matching quotes to trades.

We also check our results using a smaller international sample of flu activity based on Google Flu Trends.[8] Google collects flu data for a number of countries by aggregating Google search data for keywords associated with flu. Ginsberg, Mohebbi, Patel, Brammer, Smolinski, and Brilliant (2009) describe the Google methodology and how it correlates with doctor visits for influenza in the United States. Google's international sample is more recent and less tested than its U.S. sample; thus, some caution is required when considering these results.

[8]See http://www.google.org/flutrends/about/how.html for a description of the Google flu data.

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Our primary measure for the international flu incidence data is the first difference of the log of 1 plus the estimated flu incidence from Google Flu Trends.[9] We expect that searching the Internet about flu occurs on average before the patient is physically tested. Thus, we expect the estimated flu incidence from Google Flu Trends to be more contemporaneously correlated with actual flu incidence than the CDC measures, and we use the contemporaneous first difference (we discuss the robustness of our results to this assumption later).

We compile international stock market data from 25 country market indices where we are able to gather both stock market data and Google flu data. Our full panel includes flu and stock market data for Argentina (MERVAL), Australia (S&P ASX200), Austria (Austrian Traded), Belgium (BEL20), Brazil (IBOVESPA), Bulgaria (SOFIX), Canada (S&P TSX Composite), Chile (IPSA), France (All Tradable), Germany (DAX), Hungary (Hungarian Traded), Japan (Topix), Mexico (IPC), Netherlands (AEX General), New Zealand (NZX All), Norway (OSE All Shares), Peru (IGBVL), Poland (WIG), Russia (MICEX), South Africa (JSE Africa), Spain (Madrid Index), Sweden (OMX Stockholm All Share), Switzerland (Swiss Market Index), Ukraine (PFTS), and the United States (NYSE Index). For 15 of these countries, we also consider a sample of the flu data from the cities/regions where the main exchange is located. These cities/regions for which flu and stock market data are available include Buenos Aries, Argentina; New South Wales, Australia; Vienna, Austria; Brussels, Belgium; Sao Paulo, Brazil; Ontario, Canada; Ile de France, France; Hessen, Germany; Distrito Federal, Mexico; North Holland, Netherlands; Lima, Peru; Gauteng, South Africa; Madrid, Spain; Zurich, Switzerland; and New York City, United States. We gather *Share Volume,* the total index constituent shares traded; *Dollar Volume,* the total value of the constituent index shares traded; and *Return,* the weekly cum dividend return from the Bloomberg Data Service. Similar to the construction of our NYSE variables, we consider $\Delta LogSVol$ and $\Delta LogDVol$, which equal the percentage change in the logarithm of weekly *Share Volume* and *Dollar Volume*, respectively.

B. Method

Our primary regressions using CDC flu include dummy variables for the week of the year and the calendar year (dropping one dummy from each series to avoid multicollinearity). We also include dummy variables for cloud cover over New York City and for the period after the NYSE introduced decimalization,

$$\begin{aligned} depvar_{i,t} &= \alpha + \Sigma\beta_{FluV}\Delta FluV_{i,t} + \theta_{1-2}CCDummy + \gamma_{1-51}WDummy \\ &\quad + \delta_{1-8}YDummy + \varphi DDummy + \varepsilon_{i,t}, \end{aligned}$$

where *depvar* equals our dependent variables: $\Delta LogDVol$, $\Delta LogTrades$, $\Delta Turnover$, $\Delta LogVolatility$, $\Delta LogSpread$, and *Return.* FluV equals $\Delta LogUSFlu$, $\Delta LogNYFlu$, $\Delta LogNonNYFlu$, $\Delta LogHRegionFlu$, or $\Delta LogNonHRegionFlu$;

[9]Google transforms the number of queries in a proprietary manner; thus, the number they report does not necessarily match the number of searches.

CCDummy are the dummy variables for Many Clouds and Few Clouds, *WDummy and YDummy* are weekly and yearly dummy variables, and *DDummy* is the decimalization dummy variable.[10]

For our regressions with Google international flu data, we drop the cloud cover and decimalization dummy variables, and we retain the yearly dummy variables. We also drop the weekly dummy variables, as we expect seasonal effects to vary for different countries. The dependent variables in the international Google regressions equal *ΔLogDVol*, *ΔLogSVol*, *ΔLogVolatility*, and *Return*, and FluV equals *ΔLogGoogleFlu.*

In order to adjust for heteroskedasticity and autocorrelation, we use robust standard errors (see Andrews (1991) and Zeileis (2004)) in our aggregated analysis, robust standard errors with region-level clustering in our aggregated regional analysis, robust standard errors with country-level clustering in our international panel analysis, and robust standard errors with firm-level clustering in the firm-level analysis. We also add year dummy variables to all regressions and week dummy variables to all but the Google regressions; thus, our analysis is robust to these time effects as well (see Petersen (2009) for a discussion on clustering).

We fit additional regressions with our CDC flu variable 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, and we add volume, volatility, the inverse of price, and the market value of equity to the bid-ask spread regressions. We also control for weather effects and for SAD in some of our regressions. In order to correct for possible SAD effects, we drop our weekly dummy variables and follow Kamstra et al. (2007) in including the SAD onset variable, which measures the clinical growth rate of SAD instrumented by the number of hours of night.[11] As Hirshleifer and Shumway (2003) and 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 2 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 6:00AM–6:00PM EST.

III. Empirical Results

Table 1 provides summary statistics on our variables of interest. We have individual U.S. stock data from 1,213,949 firm-weeks over the 9 years in our sample period. Panel A of Table 1 provides means, medians, standard deviations, and extreme values for the stock trading variables. Panel B provides means, medians, standard deviations, and extreme values for the flu variables and SAD onset.

[10]In an alternative specification, we also examine the levels of volatility rather than changes, and those results are similar. Fleming et al. (2006) show that using estimated intraday volatility provides superior estimates to using a daily generalized autoregressive conditional heteroskedasticity specification.

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

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TABLE 1

Summary Statistics

Table 1 provides summary statistics in weekly frequencies on the variables used in this study. Both raw (as collected) and transformed variables are reported. Panel A reports summary statistics for the market variables. The sample is drawn from NYSE listed stocks traded on the NYSE from the beginning of 1998 through the end of 2006. Here, *Return* is the weekly CRSP cum dividend percent return. *Turnover* is 100 × log(1 + *Volume*/*Shares*), where *Volume* refers to the number of shares traded in the given week and *Shares* equals the average number of shares outstanding during the week; *ΔTurnover* is the first difference of *Turnover*; *Spread* is the average weekly time-weighted effective percentage spread calculated as 100 times 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; *ΔSpread* is $100\times(Spread_t - Spread_{t-1})$; *DollarVolume* is the weekly dollar volume and *NumTrades* is the weekly number of trades; *ΔLogDVol* and *ΔLogTrades* are the first differences of the logarithm of *DollarVolume* and the logarithm of *NumTrades*, respectively; *RealizedVolatility* equals the average unsigned 10-minute return over the week; *ΔLogVolatility* is the logarithm of *RealizedVolatility* (see Andersen and Bollerslev (1998) and Andersen et al. (2001)); *OIB* is the weekly percentage order imbalance equal to 100×(*buyorders* − *sellorders*)/(*buyorders* + *sellorders*); *MarketValue* is the firm's weekly market value of equity calculated as the product of the weekly stock closing price and the average number of shares outstanding during the week; *LogMV* is the logarithm of *Market Value*; and 1/*P* is the inverse of the weekly stock close. Panel B reports summary statistics for the flu and SAD onset variables. The flu variable is the number of flu cases that test positive in a given week. *US Flu* is the number of positive cases in the United States as a whole; *NY Flu* is the number of positive cases in the mid-Atlantic region (New York, New Jersey, and Pennsylvania), which includes New York City; *NonNY Flu* is the difference between the number of U.S. and NY positive cases; *ΔLogUSFlu*, *ΔLogNYFlu*, and *ΔLogNonNYFlu* are the percentage changes in the corresponding raw flu variables in the subsequent week, measured as the change in the logarithm of 1 plus the raw flu variable; *Average ΔLogUSFlu* is the average of *ΔLogUSFlu* by week; *UnexpectedUSFlu* is the difference between *ΔLogUSFlu* and *Average ΔLogUSFlu* for that week; and *SADOnset* refers to the seasonal affective disorder onset variable as in Kamstra et al. (2007). Panel C reports correlations between the transformed variables.

Variables	No. of Obs.	Mean	Median	SD	Min.	Max.
Panel A. Market Variables						
Return	1,213,949	0.239	0.112	6.002	−94.480	450.000
Turnover	1,213,949	1.898	1.080	7.047	0.000	653.700
ΔTurnover	1,209,333	−0.012	−0.011	2.803	−294.000	585.900
Spread (%)	1,213,342	0.477	0.253	0.848	0.000	45.770
ΔSpread	1,208,234	0.001	0.000	0.354	−24.500	27.170
DollarVolume (billions)	1,213,949	0.067	0.007	0.216	0.000	13.100
ΔLogDVol	1,209,333	−0.004	−0.017	0.629	−8.368	7.366
NumTrades (thousands)	1,213,949	1.758	0.494	2.926	0.001	41.350
ΔLogTrades	1,209,333	0.000	−0.004	0.411	−6.063	5.861
RealizedVolatility (%)	1,213,949	0.298	0.223	0.325	0.000	20.270
ΔLogVolatility	1,203,814	−0.001	−0.006	0.402	−39.290	40.700
OIB	1,213,834	5.024	6.671	20.750	−100.000	100.000
MarketValue (billions)	1,213,949	4.390	0.667	17.090	0.000	592.900
LogMV (thousands)	1,213,949	13.480	13.410	1.846	3.497	20.200
1/P	1,213,949	0.086	0.050	0.333	0.001	256.000
Panel B. CDC Flu and SAD Onset Variables						
US Flu (hundred)	468	3.247	0.269	5.989	0.000	38.920
ΔLogUSFlu	468	−0.001	0.000	0.481	−4.157	2.629
Average ΔLogUSFlu	468	−0.001	−0.030	0.327	−1.051	0.977
Unexpected ΔLogUSFlu	468	0.000	0.020	0.353	−3.106	1.652
NY Flu (hundred)	468	0.290	0.014	0.571	0.000	3.219
ΔLogNYFlu	468	−0.004	0.000	0.519	−2.015	2.197
NonNY Flu (hundred)	468	2.957	0.251	5.485	0.000	35.710
ΔLogNonNYFlu	468	−0.001	0.000	0.473	−4.157	2.398
SADOnset	468	0.000	0.000	0.214	−0.431	0.431

Panel C. Pearson Product Moment Correlations

Variables	Return	ΔTurnover	ΔSpread	ΔLogDVol	ΔLogTrades	ΔLogVolat	OIB	ΔLogUSFlu	ΔLogNYFlu	ΔLogHRegFlu	SADOnset	Cloudy
Return	1.000											
ΔTurnover	−0.009	1.000										
ΔSpread	−0.079	0.006	1.000									
ΔLogDVol	0.054	0.497	−0.007	1.000								
ΔLogTrades	0.019	0.356	−0.004	0.770	1.000							
ΔLogVolat	−0.060	0.138	0.173	0.223	0.273	1.000						
OIB	0.185	0.007	−0.032	0.013	0.009	−0.013	1.000					
ΔLogUSFlu	−0.015	−0.001	0.003	0.003	0.008	0.008	−0.004	1.000				
ΔLogNYFlu	−0.005	−0.019	0.001	−0.034	−0.041	−0.016	−0.002	0.447	1.000			
ΔLogHRegFlu	−0.003	−0.003	0.000	−0.005	−0.008	0.000	−0.001	0.501	0.460	1.000		
SADOnset	−0.023	0.004	0.004	0.004	0.005	0.008	0.010	0.444	0.258	0.291	1.000	
Cloudy	0.000	−0.008	0.003	−0.014	−0.014	0.000	−0.006	−0.002	0.010	0.017	0.039	1.000

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Panel C provides correlations between our primary measures. Changes in flu incidence in the greater NY region (i.e., mid-Atlantic region) are negatively correlated with the trading activity variables. The U.S. flu and home region flu variables exhibit only a small correlation with the other tested variables. The relatively high correlation (0.444, 0.258, and 0.291 for the United States, greater NY, and home region, respectively) between flu and SAD onset suggests that explicitly adjusting for SAD may be necessary when weekly dummy variables are not included.

A. Index Portfolio Regression

To begin our analysis, we fit our primary regression specification using the fully aggregated U.S. sample, which includes the weekly index portfolio of all NYSE stocks. The trading volume, number of shares outstanding, and return variables are averaged across all firms by week. Using weekly observations from this aggregated portfolio, we regress each of the dependent variables on the U.S. and New York flu variables. Additionally, we fit our primary regression specification using the regionally aggregated sample, which includes the 9 regional weekly index portfolios of all NYSE stocks. In these regressions, we use flu incidence by region and match it with the aggregated stock volumes and returns for firms headquartered in each region. This larger sample size increases the precision of our regressions. Using weekly observations from this aggregated portfolio, we regress each of the dependent variables on the home region flu variables. These regressions also include weekly and yearly dummy variables and a dummy variable for the period after the change to NYSE decimalization.[12] The rows of each panel of Table 2 report the estimated coefficients on our flu variables from 3 regressions for each of our primary dependent variables. The 1st regression reports the results using the national flu variable; the 2nd regression reports the results using New York and non-New York flu variables; and the 3rd regression reports the results using the home region and nonhome region flu variables.

Panel A of Table 2 reports the estimated coefficients from regressions with the percentage change in dollar volume as the dependent variable. Consistent with the hypothesis that the flu has a negative effect on trading activity, greater increases in flu are associated with decreases in dollar volume, and this effect is significant at the 5% level for New York flu in the 2nd regression reported in the 2nd row. A 1-standard-deviation increase in New York flu implies a 2.4% decline in aggregate dollar trading volume. Weekly dollar trading volume was approximately $240 billion in the 2nd week of 2006 (when the flu was at its peak for that season), and thus a 1-standard-deviation increase in New York flu would imply a decline in trading of approximately $6 billion. Neither the overall U.S. flu incidence nor the incidence of flu outside the New York area is significant in this analysis. These results largely reflect the smaller sample size for this fully aggregated analysis, and the notion that flu incidence in New York, the major U.S. financial center, is of primary importance. In contrast, the overall national

[12] Including the weather variables or excluding the decimalization dummy variable from these regressions does not affect our results. The results are roughly similar with a value-weighted regression.

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flu has a significant effect in both the disaggregated U.S. regressions and in the international regressions discussed later.

The 3rd regression considers our regional variables, and we again find that greater flu incidence is associated with lower trading activity. However, flu incidence in the region where the firm is headquartered is not significant; instead, the combined national flu incidence is negative and significant at the 1% level in

TABLE 2

NYSE Index Portfolio Regressions

Table 2 reports coefficients on flu incidence for multivariate regressions using robust standard errors, and for the regressions using regional variables, robust standard errors with region-level clustering. Dummy variables for the week of the year, the calendar year, and the time period after the NYSE introduced decimalization are included to control for time effects. The data set used is an equal-weighted weekly NYSE index portfolio formed from aggregating weekly individual NYSE traded stocks. The dependent variables are $\Delta LogDVol$, defined as the weekly percentage change in dollar volume measured as the first difference of the logarithm of dollar volume; $\Delta Turnover$, defined as weekly change in turnover, $100 \times \log(1 + Volume/Shares)$, where *Volume* refers to the number of shares traded in the given week and *Shares* equals the average number of shares outstanding during the week; $\Delta LogTrades$, defined as the weekly percentage change in the number of trades; and *Return*, defined as the weekly CRSP cum dividend percentage return. The flu variables are the percentage change in the number of flu cases in the subsequent week, measured as the change in the logarithm of the number of flu cases plus 1. Here, $\Delta LogUSFlu$ is the percentage change in the United States as a whole; $\Delta LogNYFlu$ is the percentage change in the mid-Atlantic region (New York, New Jersey, and Pennsylvania), which includes New York City; $\Delta LogHRegionFlu$ is the percentage change in flu in the region where the company is headquartered; $\Delta LogNonNYFlu$ is the percentage change in all U.S. regions except the mid-Atlantic region; and $\Delta LogNonHRegion\ Flu$ is the percentage change in all U.S. regions except the region where the company is headquartered. Weather controls are included as in 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 6:00AM–6:00PM EST. The equation fit for the 1st row of each panel with $\Delta LogUSFlu$ as an independent variable is

$$depvar_t = \alpha + \beta_{US\,Flu}\Delta LogUSFlu_t + \theta_{1-2}CCDummy + \gamma_{1-51}WDummy + \delta_{1-8}YDummy + \varphi DDummy + \varepsilon_t,$$

where $depvar_t$ equals $\Delta LogDVol$, $\Delta Turnover$, $\Delta LogTrades$, and *Returns* in the following 4 panels; *CCDummy* are the dummy variables for Many Clouds and Few Clouds; *WDummy* are the dummy variables for the week of the year; *YDummy* are the yearly dummy variables; and *DDummy* is a dummy variable equal to 1 after decimalization. The 2nd equation fit in each panel instead uses the $\Delta LogNYFlu$ and $\Delta LogNonNYFlu$ variables, and the 3rd equation fit in each panel instead uses the $\Delta LogHRegionFlu$ and $\Delta LogNonHRegionFlu$ variables. Robust *t*-statistics are reported in parentheses below the coefficients. The change in the dependent variable for a 1-standard-deviation change in the flu variable is reported below the *t*-statistic in square brackets. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

Coefficients on ΔLogFlu						
US	NY	Non-NY	HRegion	Non-HRegion	R^2	No. of Obs.
Panel A. Dependent Variable: $\Delta LogDVol$						
−0.0191 (−0.87) [−0.0092]					0.427	467
	−0.0470** (−2.31) [−0.0244]	−0.0114 (−0.55) [−0.0059]			0.434	467
			−0.0061 (−0.78) [−0.0032]	−0.0205*** (−4.43) [−0.0106]	0.375	4,203
Panel B. Dependent Variable: $\Delta Turnover$						
−0.0392 (−1.27) [−0.0188]					0.395	467
	−0.0739** (−2.53) [−0.0383]	−0.0271 (−0.90) [−0.0140]			0.405	467
			−0.0120 (−1.04) [−0.0062]	−0.0398*** (−4.15) [−0.0207]	0.308	4,203

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TABLE 2 (continued)
NYSE Index Portfolio Regressions

Coefficients on ΔLogFlu						
US	NY	Non-NY	HRegion	Non-HRegion	R^2	No. of Obs.
Panel C. Dependent Variable: ΔLogTrades						
−0.0075 (−0.42) [−0.0036]					0.350	467
	−0.0325* (−1.96) [−0.0168]	−0.0050 (−0.31) [−0.0026]			0.356	467
			−0.0060 (−1.08) [−0.0031]	−0.0066*** (−3.59) [−0.0034]	0.344	4,203
Panel D. Dependent Variable: Returns						
−0.2272 (−1.05) [−0.1092]					0.206	468
	−0.0958 (−0.48) [−0.0497]	−0.0474 (−0.21) [−0.0246]			0.205	468
			−0.0242 (−0.26) [−0.0126]	−0.2342*** (−3.18) [−0.1215]	0.182	4,212

this regression. Thus, these results suggest that the largest impact on dollar trading volume is due to the effect of flu on New York area traders, whereas flu incidence in the state where the firm is located does not have an important effect.

Panel B of Table 2 considers the impact of flu on stock turnover. The effect of New York area flu on turnover and the effect of national flu excluding the region where the firms are located are both negative and significant at the 5% and 1% levels, respectively. Similar to the regressions with dollar volume reported in Panel A, the impacts of U.S. flu, flu outside of the New York area, or flu in the region where the firm is located are statistically insignificant. Panel C provides similar results with stock trades as the dependent variable. Again, the incidence of flu in the New York area is of primary importance, although these fully aggregated results are only marginally significant. A 1-standard-deviation increase in New York area flu implies a 1.7% decline in the number of trades. These results are also consistent with the effect of flu on trading activity being due primarily to its impact on New York area traders.

Panel D of Table 2 provides regressions with returns as the dependent variables. Increasing national flu incidence outside the region where the firms are located is associated with decreasing returns, and this effect is significant at the 1% level. A 1-standard-deviation increase in flu outside the home region implies a 0.1% decrease in returns. The impacts of U.S. flu, NY flu, and non-NY flu incidence on returns in the fully aggregated sample are insignificant. Thus, flu appears to affect returns, but not based on the region where the firm is headquartered, and this result is not visible with the fully aggregated data. We next consider the results for international data, then for our fully disaggregated sample.

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B. International Flu Effects

International data on flu incidence have recently become available through Google. Google Flu Trends reports information on key words associated with flu for a variety of countries and cities. We consider regressions of the percentage change in share volume, percentage change in dollar volume, and returns of the national stock index on the percentage change in estimated flu incidence from Google Flu Trends. We retain yearly dummy variables but exclude weekly dummies from these regressions, as we expect seasonal effects to vary for different countries. In Panel A of Table 3, we present regressions for the full panel of 25 countries for which we were able to find stock market data, with a subpanel including only the 18 Northern hemisphere countries and a subpanel including only the 7 Southern hemisphere countries. For the full sample as well as the Northern hemisphere sample, flu incidence is negatively and significantly related

TABLE 3

Regressions: Google Flu Trends

Table 3 reports coefficients for multivariate regressions using robust standard errors and multivariate panel regressions using robust standard errors clustered by country or city/region. The All Countries Panel includes flu and stock market data for Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, France, Germany, Hungary, Japan, Mexico, Netherlands, New Zealand, Norway, Peru, Poland, Russia, South Africa, Spain, Sweden, Switzerland, Ukraine, and the United States. The All Cities/Regions Panel includes flu and stock market data for Buenos Aries, New South Wales, Vienna, Brussels, Sao Paulo, Ontario, Ile de France, Hessen, Distrito Federal, North Holland, Lima, Gauteng, Madrid, Zurich, and New York City. The dependent variables are *ΔLogSVol*, defined as the weekly percentage change in index constituent shares traded measured as the weekly change in the logarithm of index share volume; *ΔLogDVol*, defined as the weekly percentage change in the value of index constituent shares traded, measured as the weekly change in the logarithm of the value of index share volume; and *Return*, measured as the weekly cum dividend return. The flu variables are the weekly percentage changes in the estimated flu incidence from Google Flu Trends. This is measured as the first difference of the logarithm of the weekly estimate of flu incidence in the country or city/region. Here, *ΔLogCountryFlu* is the percentage change in each country as a whole, *ΔLogCityRegionalFlu* is the percentage change in the cities/regions where the main exchange is located, *ΔLogUSFlu* is the percentage change in the United States as a *whole*, *ΔLogNYNJFlu* is the percentage change in the combined New York and New Jersey region, and *ΔLogNYCityFlu* is the percentage change in New York City. Dummy variables for the calendar year are included to control for time effects. Robust *t*-statistics are reported in parentheses below the coefficients. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	ΔLogSVol	ΔLogDVol	Return
Panel A. Country Panel Regressions			
All Countries Panel			
Intercept	−0.0301**	−0.0434***	0.0109***
	(−2.27)	(−3.68)	(5.52)
ΔLogCountryFlu	−0.0446**	−0.0555***	−0.0034***
	(−2.29)	(−2.67)	(−2.80)
R^2	0.001	0.002	0.029
N	9,273	9,116	9,430
Northern Hemisphere Countries Panel			
Intercept	−0.0541***	−0.0598***	0.0075***
	(−4.32)	(−4.31)	(10.17)
ΔLogCountryFlu	−0.0393*	−0.0445**	−0.0030**
	(−1.82)	(−2.14)	(−2.20)
R^2	0.001	0.002	0.030
N	6,409	6,329	6,533
Southern Hemisphere Countries Panel			
Intercept	0.0098	−0.0105	0.0167***
	(0.48)	(−1.06)	(4.08)
ΔLogCountry Flu	−0.0591	−0.1006	−0.0046
	(−1.14)	(−1.32)	(−1.63)
R^2	0.001	0.002	0.028
N	2,864	2,787	2,897

(continued on next page)

TABLE 3 (continued)
Regressions: Google Flu Trends

	ΔLogVol	ΔLogDVol	Return
Panel B. City/Region Regressions			
All Cities/Regions Panel			
Intercept	−0.0325**	−0.0379***	0.0114***
	(−2.33)	(−3.31)	(4.94)
ΔLogCityRegionalFlu	−0.0740***	−0.0883***	0.0003
	(−2.92)	(−3.39)	(0.24)
R^2	0.003	0.005	0.028
N	5,903	5,903	5,934
Northern Hemisphere Cities/Regions Panel			
Intercept	−0.0513***	−0.0536***	0.0069***
	(−4.01)	(−3.81)	(8.08)
ΔLogCityRegionalFlu	−0.0634**	−0.0716***	0.0004
	(−2.43)	(−2.91)	(0.34)
R^2	0.005	0.006	0.028
N	4,101	4,101	4,101
Southern Hemisphere Cities/Regions Panel			
Intercept	0.0021	−0.0130	0.0207***
	(0.08)	(−1.19)	(7.25)
ΔLogCityRegionalFlu	−0.1540***	−0.2277***	0.0018
	(−2.81)	(−3.63)	(0.60)
R^2	0.002	0.005	0.030
N	1,802	1,802	1,833
Panel C. US and New York City/Region Regressions			
US Flu			
Intercept	0.0173	0.0210	0.0081**
	(0.28)	(0.35)	(2.10)
ΔLogUSFlu	−0.3292***	−0.3235***	−0.0032
	(−2.72)	(−2.74)	(−0.32)
R^2	0.043	0.044	0.028
N	411	411	411
NY/NJ Regional Flu			
Intercept	0.0033	0.0060	0.0069*
	(0.06)	(0.11)	(1.86)
ΔLogNYNJFlu	−0.2049**	−0.1958**	0.0023
	(−2.51)	(−2.47)	(0.28)
R^2	0.029	0.029	0.028
N	411	411	411
NY City Flu			
Intercept	−0.0022	0.0011	0.0072**
	(−0.04)	(0.02)	(1.98)
ΔLogNYCityFlu	−0.1917***	−0.1848***	0.0013
	(−2.89)	(−2.89)	(0.17)
R^2	0.029	0.029	0.027
N	411	411	411

to share and dollar volume, and to returns. For the smaller Southern country panel, while the estimated coefficients are similar, none are significant.

In Panel B of Table 3, we consider regressions using Google city/region flu data, which include the location of the primary national stock market. We consider the 15 city/region areas for which we are able to find both Google and stock market data. We also consider a subset of the 10 Northern hemisphere cities and another of the 5 Southern hemisphere cities. We find negative and significant coefficients on our flu variables in the regressions with our volume variables for all 3 samples, but for these local flu measures, we find no relation between flu and returns. Additionally, consistent with our U.S. CDC results, the estimated

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coefficients on the city/region flu variables have greater magnitude than the corresponding regressions using national flu data. This again suggests that these results are partly driven by the effect of flu on professional traders.

In Panel C of Table 3, we consider regressions with estimated flu incidence from Google Flu Trends for the United States, New York City, and the combined New York State and New Jersey region. Consistent with our results using CDC flu data, the estimated coefficients in the share and dollar volume regressions are negative and significant, while the estimated coefficients on returns are insignificant.

C. Disaggregated Regressions

To continue our analysis, we test the impact of U.S. national and New York 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 provides greater precision than using the aggregated data, and the results are largely consistent with those presented using aggregated data. For each dependent variable, we run 2 regressions, one using the national CDC flu variable and one using the NY and non-New York region CDC flu. In unreported regressions, we also examine the effect of home region flu and nonhome region flu incidence on each of our dependent variables. Consistent with the aggregated regional tests above, changes in the rate of national and New York flu incidence have a greater association with our variables of interest than home-region flu incidence; thus, we find little effect of local ownership. For volatility, percentage spread, and returns, we consider a 3rd regression that includes controls commonly encountered in the literature. We also include weekly dummy variables, yearly dummy variables, and a dummy variable for the NYSE change to decimalization in these regressions as well as controls for New York cloud cover. Table 4 reports the coefficients on our flu variables for the regressions with our trading activity measures. Tables 5, 6, and 7 report the coefficients from the volatility, percentage spread, and return regressions.

Columns 1 and 2 of Table 4 provide regressions with dollar volume as the dependent variable. Column 1 includes just the national flu data as well as New York cloud cover and the calendar and decimalization dummy variables. Consistent with the estimated coefficients for the aggregated portfolios and the international sample, increasing national flu is associated with lower dollar volume, and this effect is significant at the 1% level.

Column 2 of Table 4 considers the flu in the New York and non-NY regions. Similar to the results using aggregated portfolios and the international city/region sample, the effect of the flu in New York is larger than the overall national and non-NY effects. A 1-standard-deviation increase in New York flu implies a 2.0% decline in dollar trading volume. Given average weekly dollar trading volume of $240 billion in the 2nd week in 2006, a 1-standard-deviation increase in New York flu implies an approximate decline in trading of $4.8 billion. This corresponds closely to the estimate of $6 billion obtained above using the index portfolio.

Columns 3 and 4 of Table 4 provide similar results with turnover as the dependent variable. Again, the incidence of flu in the New York area is of primary importance. A 1-standard-deviation increase in NY flu implies a 4.3% decline in

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TABLE 4

Regressions: Trading Activity

Table 4 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 *ΔLogDVol*, defined as the weekly percentage change in dollar volume, measured by the change in the logarithm of dollar volume; *ΔTurnvover*, defined as the weekly change in turnover, $100 \times \log(1 + Volume/Shares)$, where *Volume* refers to the number of shares traded in the given week and *Shares* equals the average number of shares outstanding during the week; and *ΔLogTrades*, defined as the weekly percentage change in the number of trades. The flu variables are the percentage changes in the number of flu cases in the subsequent week. This is measured as the change in the logarithm of the number of flu cases plus 1. Here, *ΔLogUSFlu* is the percentage change in the United States as a whole; *ΔLogNYFlu* is the percentage change in the mid-Atlantic region (New York, New Jersey, and Pennsylvania), which includes New York City; and *ΔLogNonNYFlu* is the percentage change in all U.S. regions except the mid-Atlantic region. Weather controls are included as in 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 6:00AM–6:00PM EST. The equation fit for columns 1, 3, and 5 with *US Flu* as an independent variable is

$$depvar_{i,t} = \alpha + \beta_{US\,Flu}\Delta LogUSFlu_t + \theta_{1-2}CCDummy + \gamma_{1-51}WDummy + \delta_{1-8}YDummy + \varphi DDummy + \varepsilon_{i,t},$$

where $depvar_{i,t}$ equals either *ΔLogDVol*, *ΔTurnover*, or *ΔLogTrades*, in the following regressions. *CCDummy* are the dummy variables for Many Clouds and Few Clouds; *WDummy* are the dummy variables for the week of the year; *YDummy* are the yearly dummy variables; and *DDummy* is a dummy variable equal to 1 after decimalization. The 2nd, 4th, and 6th regressions include *ΔLogNYFlu* and *ΔLogNonNYFlu* as independent variables instead of *ΔLogUSFlu*. Robust *t*-statistics are reported in parentheses below the coefficients. The change in the dependent variable for a 1-standard-deviation change in the flu variable is reported below the *t*-statistics in square brackets. *, **, and *** refer to significance at the 5%, 1%, and 0.1% levels, respectively.

	ΔLogDVol		ΔTurnover		ΔLogTrades	
	1	2	3	4	5	6
ΔLogUSFlu	−0.0135***		−0.0434***		−0.0060***	
	(−9.23)		(−5.06)		(−6.44)	
	[−0.0065]		[−0.0208]		[−0.0029]	
ΔLogNYFlu		−0.0391***		−0.0822***		−0.0291***
		(−29.51)		(−12.64)		(−35.13)
		[−0.0203]		[−0.0426]		[−0.0151]
ΔLogNonNYFlu		−0.0076***		−0.0277***		−0.0037***
		(−5.16)		(−3.42)		(−3.95)
		[−0.0036]		[−0.0131]		[−0.0018]
Many Clouds	−0.0272***	−0.0251***	−0.0774***	−0.0732***	−0.0141***	−0.0126***
	(−10.83)	(−10.01)	(−5.91)	(−5.61)	(−9.23)	(−8.22)
Few Clouds	0.0238***	0.0262***	0.0037	0.0092	0.0219***	0.0235***
	(8.24)	(9.11)	(0.24)	(0.60)	(12.18)	(13.11)
R^2	0.038	0.039	0.005	0.005	0.068	0.069
No. of obs.	1,209,333	1,209,333	1,209,333	1,209,333	1,209,333	1,209,333

turnover. Columns 5 and 6 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 1-standard-deviation increase in NY flu implies a 1.5% decrease in the number of trades. These results are consistent with the hypothesis that the flu effect is largely due to its impact on New York area traders.

Table 5 considers the impact of flu on stock volatility. Columns 1 and 2 of Table 5 provide regressions with change in the log of volatility as the dependent variable and the change in log of flu, cloud cover, the calendar and decimalization dummy variables, and weekly and yearly dummy variables as independent variables. Consistent with a reduction in information flow, increasing New York flu is associated with lower volatility, and this effect is highly significant. In contrast, the U.S. and non-New York effects are small and only marginally significant. A 1-standard-deviation increase in NY flu implies an approximate 0.6% decrease in realized volatility.

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TABLE 5

Regressions: Volatility

Table 5 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, $\Delta LogVolatility$, 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 flu variables are the percentage change in the number of flu cases in the subsequent week. Here, $\Delta LogUSFlu$ is the percentage change in the United States as a whole; $\Delta LogNYFlu$ is the percentage change in the mid-Atlantic region (New York, New Jersey, and Pennsylvania), which includes New York City; $\Delta LogNonNYFlu$ is the percentage change in all U.S. regions except the mid-Atlantic region; and $\Delta Turnvover$ is the weekly change in turnover, $100 \times \log(1 + Volume/Shares)$, where *Volume* refers to the number of shares traded in the given week and *Shares* equals the average number of shares outstanding during the week. Weather controls are included as in 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 6:00AM—6:00PM EST. The equation fit in column 1 is

$$\Delta LogVolatility_{i,t} = \alpha + \beta_{US\,Flu}\Delta LogUSFlu_t + \theta_{1-2}CCDummy + \gamma_{1-51}WDummy + \delta_{1-8}YDummy + \varphi DDummy + \varepsilon_{i,t},$$

where *CCDummy* are the dummy variables for Many Clouds and Few Clouds; *WDummy* are the dummy variables for the week of the year; *YDummy* are the yearly dummy variables; and *DDummy* is a dummy variable equal to 1 after decimalization. Column 2 replaces $\Delta LogUSFlu$ with $\Delta LogNYFlu$ and $\Delta LogNonNYFlu$. Columns 3 and 4 repeat columns 1 and 2 with *Turnover* as an additional independent variable. Robust *t*-statistics are reported in parentheses below the coefficients. The change in the dependent variable for a 1-standard-deviation change in the flu variable is reported below the *t*-statistics in square brackets. *, **, and *** refer to significance at the 5%, 1%, and 0.1% levels, respectively.

	Volatility Regressions		With Additional Controls	
	1	2	3	4
ΔLogUSFlu	0.0023 (1.93) [0.0011]		0.0029* (2.48) [0.0014]	
ΔLogNYFlu		−0.0119*** (−12.05) [−0.0062]		−0.0107*** (−10.79) [−0.0056]
ΔLogNonNYFlu		0.0030* (2.46) [0.0015]		0.0034** (2.81) [0.0018]
ΔTurnover			0.0142*** (7.33)	0.0142*** (7.33)
Many Clouds	−0.0050** (−2.65)	−0.0044* (−2.33)	−0.0039* (−2.07)	−0.0033 (−1.79)
Few Clouds	−0.0109*** (−6.16)	−0.0102*** (−5.80)	−0.0109*** (−6.19)	−0.0104*** (−5.88)
R^2	0.006	0.006	0.015	0.015
No. of obs.	1,203,814	1,203,814	1,203,814	1,203,814

The existing research finds a positive relationship between volume and volatility.[13] Therefore, we consider turnover as an additional control. As we use the first difference of the log of volatility, we add the first differences of our turnover variable in columns 3 and 4 of Table 5. As expected, the coefficient on change in turnover is positive and significant. The effect of NY flu on volatility is only slightly diminished and still implies a decrease in volatility of approximately 0.6% for a 1-standard-deviation increase in New York flu.[14]

Table 6 considers how the flu is related to the effective percentage spread. In contrast to the results for trading activity and volatility, both the national and

[13] Bessembinder and Seguin (1993) find that volatility is positively related to volume (particularly unexpected volume) in futures markets. Chordia et al. (2002) also find that volatility is positively related to volume in market portfolios.

[14] In unreported robustness tests, we instead consider levels of volatility, and we add lagged volatility as a control variable. Our conclusions using that specification are similar.

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New York flu variables are significantly related to bid-ask spreads. One-standard-deviation increases in U.S. or New York flu variables imply an increase of approximately 0.002 in the percentage spread. These results 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 flu leads to a less liquid market in which overall and informed trade is diminished and, in the net, market makers increase spreads.

Cross-sectional regression equations that model percentage spreads typically include contemporaneous volume, volatility, inverse price, and market value as

TABLE 6

Regressions: Percentage Effective Bid-Ask Spread

Table 6 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, $\Delta Spread$, is defined as $100 \times (Spread_t - Spread_{t-1})$, where *Spread* is the average weekly time-weighted effective percentage spread calculated as 100 times 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 flu variables are the percentage changes in the number of flu cases in the subsequent week. Here, $\Delta LogUSFlu$ is the percentage change in the United States as a whole; $\Delta LogNYFlu$ is the percentage change in the mid-Atlantic region (New York, New Jersey, and Pennsylvania), which includes New York City; and $\Delta LogNonNYFlu$ is the percentage change in all U.S. regions except the mid-Atlantic region. Also, $\Delta LogDVol$ is the weekly percentage change in dollar volume measured as the change in the logarithm of dollar volume; $\Delta LogVolatility$ is calculated as the change in the logarithm of the average unsigned 10-minute return over the week (see Andersen and Bollerslev (1998) and Andersen et al. (2001)); $\Delta 1/P$ is the inverse of the weekly closing stock price; and *LogMV* is the logarithm of the firm's weekly market value of equity. Weather controls are included as in 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 6:00AM–6:00PM EST. The equation fit in column 1 is

$$\Delta Spread_{i,t} = \alpha + \beta_{US\,Flu}\Delta LogUSFlu_t + \theta_{1-2}CCDummy + \gamma_{1-51}WDummy + \delta_{1-8}YDummy + \varphi DDummy + \varepsilon_{i,t},$$

where *CCDummy* are the dummy variables for Many Clouds and Few Clouds; *WDummy* are the dummy variables for the week of the year; *YDummy* are the yearly dummy variables; and *DDummy* is a dummy variable equal to 1 after decimalization. Column 2 replaces $\Delta LogUSFlu$ with $\Delta LogNYFlu$ and $\Delta LogNonNYFlu$. Columns 3 and 4 repeat columns 1 and 2 but add controls for $\Delta LogDVol$, $\Delta LogVolatility$, $\Delta 1/P$, and the first difference of *LogMV*. Robust *t*-statistics are reported in parentheses. The change in the dependent variable for a 1-standard-deviation change in the flu variable is reported below the *t*-statistics in square brackets. *, **, and *** refer to significance at the 5%, 1%, and 0.1% levels, respectively.

	Bid-Ask Spread Regressions		With Additional Controls	
	1	2	3	4
ΔLogUSFlu	0.0042***		0.0024**	
	(4.96)		(2.99)	
	[0.0020]		[0.0011]	
ΔLogNYFlu		0.0027***		0.0022**
		(3.33)		(2.84)
		[0.0014]		[0.0012]
ΔLogNonNYFlu		0.0017*		0.0008
		(2.17)		(1.00)
		[0.0009]		[0.0004]
ΔLogDVol			−0.0231***	−0.0231***
			(−13.00)	(−12.99)
ΔLogVolatility			0.1343***	0.1343***
			(14.20)	(14.20)
Δ1/P			0.8149***	0.8149***
			(11.86)	(11.86)
ΔLogMV			−0.1313***	−0.1313***
			(−8.84)	(−8.84)
Many Clouds	−0.0002	−0.0004	−0.0000	−0.0001
	(−0.15)	(−0.24)	(−0.02)	(−0.10)
Few Clouds	−0.0019	−0.0023	0.0006	0.0004
	(−0.97)	(−1.15)	(0.35)	(0.21)
R^2	0.001	0.001	0.046	0.046
No. of obs.	1,208,234	1,208,234	1,203,710	1,203,710

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explanatory variables (see, e.g., Madhavan (2000)). As we use the first difference of the percentage spread, we add the first differences of these additional variables as controls in columns 3 and 4 of Table 6. 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 positive and significant. The coefficients on the U.S. flu and NY flu variables remain significant at the 0.1% level, and the magnitude of the coefficient on U.S. flu decreases. Thus, the association between flu and spreads is not solely through the impact of flu on these other variables.

Table 7 considers the impact of flu incidence on returns. Returns may be affected both because greater flu incidence lowers real economic activity and

TABLE 7

Regressions: Returns

Table 7 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 flu variables are the percentage changes in the number of flu cases in the subsequent week. This is measured as the change in the logarithm of the number of flu cases plus 1. Here, $\Delta LogUSFlu$ is the percentage change in the United States as a whole; $\Delta LogNYFlu$ is the percentage change in the mid-Atlantic region (New York, New Jersey, and Pennsylvania), which includes New York City; and $\Delta LogNonNYFlu$ is the percentage change in all U.S. regions except the mid-Atlantic region. Also, *OIB* is the weekly percentage 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 $\Delta Spread$ is defined as $100 \times (Spread_t - Spread_{t-1})$, where *Spread* is the average weekly time-weighted effective percentage spread calculated as 100 times 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. Weather controls are included 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 6:00AM–6:00PM EST. The equation fit in column 1 is

$$Returns_{i,t} = \alpha + \beta_{US\,Flu}\Delta LogUSFlu_t + \theta_{1-2}CCDummy + \gamma_{1-51}WDummy + \delta_{1-8}YDummy + \varphi DDummy + \varepsilon_{i,t},$$

where *CCDummy* are the dummy variables for Many Clouds and Few Clouds; *WDummy* are the dummy variables for the week of the year; *YDummy* are the yearly dummy variables; and *DDummy* is a dummy variable equal to 1 after decimalization. Column 2 replaces $\Delta LogUSFlu$ with $\Delta LogNYFlu$ and $\Delta LogNonNYFlu$. Columns 3 and 4 repeat columns 1 and 2 but add controls for *OIB*, *Lagged OIB*, and $\Delta Spread$. Robust *t*-statistics are reported in parentheses. The change in the dependent variable for a 1-standard-deviation change in the flu variable is reported below the *t*-statistics in square brackets. *, **, and *** refer to significance at the 5%, 1%, and 0.1% levels, respectively.

	Return Regressions		With Additional Controls	
	1	2	3	4
ΔLogUSFlu	−0.2305***		−0.2068***	
	(−16.18)		(−14.73)	
	[−0.1196]		[−0.0994]	
ΔLogNYFlu		−0.0962***		−0.0997***
		(−7.27)		(−7.65)
		[−0.0499]		[−0.0517]
ΔLogNonNYFlu		−0.0455**		−0.0261
		(−3.18)		(−1.86)
		[−0.0236]		[−0.0135]
OIB			0.0581***	0.0581***
			(59.37)	(59.36)
Lag OIB			−0.0240***	−0.0240***
			(−42.81)	(−42.78)
ΔSpread			−1.4771***	−1.4773***
			(−18.94)	(−18.95)
Many Clouds	−0.0356	−0.0309	−0.0773***	−0.0734**
	(−1.55)	(−1.34)	(−3.39)	(−3.21)
Few Clouds	0.6880***	0.7093***	0.6291***	0.6502***
	(24.34)	(25.06)	(22.45)	(23.17)
R^2	0.023	0.023	0.062	0.062
No. of obs.	1,213,949	1,213,949	1,198,922	1,198,922

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because liquidity impacts returns. That is, a large literature (see, e.g., 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 increasing U.S. and NY flu incidences have negative and significant impacts on returns, with the largest impact appearing from overall U.S. flu. A 1-standard-deviation increase in U.S. flu decreases returns by approximately 0.12% per week, or about 6.1% 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.

In columns 3 and 4 of Table 7, we consider the effect of additional controls in the returns regressions. As Chordia and Subrahmanyam (2004) find that daily NYSE individual stock returns are positively related to contemporaneous order imbalance and negatively related to 1-day lagged order imbalances, we include contemporaneous and lagged order imbalance and our bid-ask spread measure. As expected, the coefficients on contemporaneous order imbalance, *OIB*, are positive and statistically significant; the coefficient on lagged order imbalance is negative and statistically significant; and the coefficient on percentage spread is negative and statistically significant. However, the coefficients on U.S. and NY flu remain significant and similar in magnitude to those estimated without these additional controls. Thus, while the additional controls we include are closely related to returns, the relationship between changes in flu incidence and returns is not solely through these other variables.[15]

Overall, these findings suggest 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 increases in bid-ask spreads and decreases in trading activity, realized volatility, and returns.

D. Additional Tests

We perform several additional checks on our results. First, we repeat all our regressions using either firm-, region-, or country-level fixed effects. In all cases, the magnitudes and significance levels on our primary coefficients of interest remain effectively unaltered in the fixed effects regressions.

Next, we consider the impact of SAD as a possible confounding variable. Table 8 considers regressions similar to those reported by Kamstra et al. (2003), (2007) and DeGennaro et al. (2008) with the impact of SAD onset, the U.S. flu variable, and cloud cover controls on returns and percentage spread.[16] As the weekly SAD onset variable does not vary by year, we drop our weekly dummy variables, which would otherwise be collinear with SAD onset.

[15]In unreported regressions, we fit regressions with order imbalance as the dependent variable on our measures of flu activity. The results closely match 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.

[16]Kamstra et al. (2003), (2007) measure the influence of SAD on returns; DeGennaro et al. (2008) measure the effects of SAD on NASDAQ inside spreads and NYSE quoted spreads.

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TABLE 8

Regressions Including SAD

Table 8 reports coefficients for pooled multivariate regressions using robust standard errors with firm-level clustering. Dummy variables for calendar years are included to control for time effects. The dependent variables are $\Delta Spread$, defined as $100 \times (Spread_t - Spread_{t-1})$, where *Spread* is the average weekly time-weighted effective percentage spread calculated as 100 times 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 percentage return. Here, *OIB* is the weekly percentage 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; $\Delta LogVolatility$ is calculated as the change in 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; *LogMV* is the logarithm of the firm's weekly market value of equity; $\Delta LogUSFlu$ is the percentage change in the number of U.S. flu cases in the subsequent week, measured as the change in the logarithm of the number of flu cases plus 1; and *SADOnset* refers to the weekly seasonal affective disorder onset variable as in Kamstra et al. (2007). Weather controls are included 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 6:00AM–6:00PM EST. The equation fit in column 1 is

$$\Delta Spread_{i,t} = \alpha + \beta_{US\,Flu}\Delta LogUSFlu_t + \phi_{SAD}SADOnset_t + \theta_{1-2}CCDummy + \delta_{1-8}YDummy + \varphi DDummy + \varepsilon_{i,t},$$

where *CCDummy* are the dummy variables for Many Clouds and Few Clouds; *WDummy* are the dummy variables for the week of the year; *YDummy* are the yearly dummy variables; and *DDummy* is a dummy variable equal to 1 after decimalization. Column 2 additionally includes first differenced controls for *LogVolatility, 1/P*, and *LogMV*. The equation fit in column 3 is

$$Return_{i,t} = \alpha + \beta_{US\,Flu}\Delta LogUSFlu_t + \phi_{SAD}SADOnset_t + \theta_{1-2}CCDummy + \delta_{1-8}YDummy + \varphi DDummy + \varepsilon_{i,t}.$$

Column 4 adds controls for *OIB, Lagged OIB, and* $\Delta Spread$. Robust *t*-statistics are reported in parentheses. The change in the dependent variable for a 1-standard-deviation change in the flu variable is reported below the *t*-statistics in square brackets. *, **, and *** refer to significance at the 5%, 1%, 0.1% levels, respectively.

	ΔSpread		Return	
	1	2	3	4
ΔLogUSFlu	0.0021**	0.0005	−0.0651***	−0.0388**
	(3.00)	(0.70)	(−5.38)	(−3.25)
	[0.0010]	[0.0002]	[−0.0313]	[−0.0137]
SADOnset	0.0047***	0.0025**	−0.6332***	−0.6673***
	(5.19)	(3.00)	(−23.13)	(−24.38)
ΔLogDVol		−0.0229***		
		(−13.11)		
ΔLogVolatility		0.1343***		
		(14.26)		
$\Delta 1/P$		0.8152***		
		(11.87)		
ΔLogMV		−0.1326***		
		(−8.99)		
OIB				0.0585***
				(58.13)
Lag OIB				−0.0242***
				(−42.03)
ΔSpread				−1.3565***
				(−17.75)
Many Clouds	0.0031*	0.0024	−0.0210	−0.0210
	(2.21)	(1.77)	(−1.02)	(−1.03)
Few Clouds	−0.0034	−0.0009	0.6586***	0.5824***
	(−1.78)	(−0.56)	(24.70)	(22.23)
R^2	0.000	0.045	0.003	0.044
No. of obs.	1,208,234	1,203,710	1,213,949	1,208,224

Column 1 of Table 8 reports the impact of U.S. flu on changes in percentage spread after controlling for SAD. Consistent with the regressions above, the effect of flu on percentage spreads is positive and statistically significant. The effect of SAD on percentage spreads is also positive and statistically significant. This

finding is consistent with DeGennaro et al. (2008), who show that SAD is associated with greater NYSE quoted spreads. Column 2 adds the control variables included in the percentage spread regressions above. In this specification, the coefficient on U.S. flu is still positive but no longer significant.

Column 3 of Table 8 reports the impact of the flu and SAD on returns. Consistent with the prior results and with Kamstra et al. (2003), the coefficients on U.S. flu and on the SAD onset variables are negative and statistically significant. Column 4 adds the controls included in the return regressions above. The coefficient on U.S. flu is smaller in magnitude than in the other specifications but significant at the 1% level.

In order to further correct for predictable seasonal variation, in unreported regressions we estimate an average and an unexpected flu seasonal effect. The estimated coefficient on the unexpected flu variable is negative and significant, and similar in magnitude to the coefficient estimated in Table 7, where we adjust for seasonal variation using weekly dummy variables.

We are also concerned with possible robustness in the timing of our flu variables. We use the subsequent week of reported CDC flu because of reporting delays, whereas we use the current week of estimated flu incidence from Google Flu Trends (note that we also take first differences and logs of these variables). In order to test the robustness of these measures, in unreported regressions we include both the subsequent week and current week first difference measures of flu incidence. The coefficient on the current week first difference often differs in sign from our primary measure, and we therefore consider the overall flu effect by summing the coefficients. The sum of the 2 coefficients is significant, and our primary results are unchanged; the flu in the New York area is associated with decreases in trading volumes and volatilities, increases in spreads, and decreases in returns. Similar results hold for the Google data.

IV. Conclusion

The flu can impact financial market activity by incapacitating key individuals, such as traders and market makers, by affecting overall investing behavior, and 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 an aggregated NYSE index portfolio, aggregated NYSE regional index portfolios, and all NYSE stocks. We find that a higher growth rate in the incidence of flu, particularly of flu in the greater New York area, is associated with a decrease in trading activity as measured by dollar volume, number of trades, and turnover. For instance, a 1-standard-deviation increase in the flu in the New York area implies a decrease in mean trading activity in the range of 1.5%–4.3%, depending on the measure of trading activity used.

Increases in the incidence of flu are also associated with lower volatility, and this finding is consistent with greater absenteeism implying less information production. Further, bid-ask spreads widen during high flu incidence weeks. Lastly, returns decline with increasing flu activity, and this may reflect both the pricing of liquidity and decreased expectations about real economic activity. While the

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volume and volatility effects are more closely tied to New York area flu incidence, bid-ask spreads and returns are more strongly associated with the incidence of flu nationally.

We verify these results using international index data and measures of flu incidence for 25 countries and 15 international market center cities and regions from Google Flu Trends. The international data also show a significant negative effect of flu incidence on trading volume and stock returns. The results are consistent with the incidence of flu around the stock exchange impacting trading volume and volatility, and with the overall incidence of flu at the national level impacting market spreads and returns.

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