Acute Illness Symptoms among Investment Professionals and Stock Market Dynamics: Evidence from New York City

Online Appendix

A1. Panel of NYSE stocks: Sample construction and data sources

This section explains how I construct the unbalanced panel of 1,609 NYSE stocks used in the empirical analysis and provides details about the data sources. First, I use Thomson Reuters Datastream to identify stocks listed on the NYSE. Specifically, I apply the following set of filters: category = equities, exchange = NYSE, market = United States, currency = United States Dollar, type = equity, security = major, and quote = primary. I retain all active stocks that began trading by the end of December 2016.

To construct the dependent variables, for each stock in the sample I download from Bloomberg the daily time series of the following metrics (where the field mnemonic is shown in brackets): number of shares traded [PX_VOLUME], trading volume [TURNOVER], number of shares outstanding available to the public [EQY_FLOAT], opening price [PX_OPEN], previous session's closing price [PREV_SES_LAST_PRICE], daily low price [PX_LOW], daily high price [PX_HIGH], closing price [PX_LAST], closing bid [PX_BID] and ask price [PX_ASK], and total return index including dividends [TOT_RETURN_INDEX_GROSS_DVDS].

To construct the explanatory variables, for each stock in the sample I download from Bloomberg the daily time series of earnings announcement dates [ANNOUNCEMENT_DT], reported earnings per share (EPS) and EPS consensus estimate [IS_COMP_EPS_EXCL_STOCK_COMP], analysts' consensus recommendation [EQY_REC_CONS], number of analysts following the stock [TOT_ANALYST_REC], abnormal daily news flow [NEWS_HEAT_PUB_DAVG], news sentiment [NEWS_SENTIMENT_DAILY_AVG], market value of the company's outstanding shares [CUR_MKT_CAP], unadjusted price, i.e., the actual stock price as recorded on the day [PX_LAST "CapChg=No"], institutional ownership, i.e., percent of float shares held by institutions [PCT_FLT_SHARES_INSTITUTIONS], and company address [IR_ADDRESS_LINE_3].

A2. Illness incidence among 18-64 year old New Yorkers and stock market outcomes: Analysis by borough and syndrome category

To exploit the geographic variation in syndromic data, I re-estimate model (2) after replacing *ΔLogIllness18_64* with *ΔLogIllnessY18_64*, where the latter measures the daily change in the log of the number of ED visits made by the 18-64 age group in the *Y* borough of the City. According to the 2000 census, 32.6% (25.6%, 25.5%, 8.6%, 7.7%) of New Yorkers working in the finance & insurance industry live in Manhattan (Brooklyn, Queens, Staten Island, the Bronx). Data from the 2013-17 American Community Survey show similar proportions.[1] Consequently, one would expect to find more evidence of a relation between changes in acute illness incidence and stock market outcomes when focusing on the incidence of acute illness in Manhattan, Brooklyn, and Queens.

[1] Author's own calculations based on 2000 census data from http://www.city-data.com/ and 2013-17 American Community Survey data from https://factfinder.census.gov/.

Indeed, the estimates in panel A of Table A.1 reveal that only changes in illness incidence in these three boroughs are statistically significantly associated with the three trading activity proxies. Furthermore, the signs and sizes of the effects are consistent across the three boroughs. When it comes to volatility, only the coefficients for Brooklyn and Queens are statistically significant at conventional levels, though the one for Manhattan shows the same sign and a similar order of magnitude. As for the bid-ask spread, no significant relation is detected.

Somewhat surprisingly, only for the Bronx and Staten Island is there a statistically significant negative association between changes in acute illness incidence and stock returns. Nevertheless, the coefficient of interest is negative and of the same order of magnitude for all five boroughs.

To shed light on the syndrome categories that drive the relations described in Section 5.2 of the main body of the paper, I also re-estimate model (2) after replacing *ΔLogIllness18_64* with *ΔLogZ18_64*, where the latter measures the daily percentage change in the incidence of the *Z* syndrome category among 18-64 year old New Yorkers.

The estimates in panel B of Table A.1 indicate that the asthma, respiratory, and influenza-like syndrome categories play the dominant roles. Increases in their incidence are accompanied by economically and statistically significant reductions in market trading activity. Changes in the incidence of the asthma and respiratory syndrome categories also affect volatility. As for stock returns, though the coefficients are negative for all five categories, only changes in the incidence of the respiratory syndrome category are statistically significant. Lastly, though the coefficients are negative for all five categories, only increases in the incidence of the diarrhea syndrome category are accompanied by a statistically significant reduction in bid-ask spreads.

Table A.1. Acute illness incidence among 18-64 year old New Yorkers and stock market outcomes: Analysis by borough and syndrome category

	(1) ΔLogShares	(2) ΔLogVolume	(3) ΔLogTurnover	(4) ΔLogVolatility	(5) ΔSpread	(6) Return
Panel A. By borough:						
ΔLogIllnessBrooklyn18_64	-1.397**	-1.423**	-1.401**	-0.791*	-0.011	-0.043
	(0.628)	(0.625)	(0.628)	(0.467)	(0.007)	(0.037)
ΔLogIllnessBronx18_64	-1.039	-1.077	-1.041	-0.600	-0.012	-0.094**
	(0.755)	(0.752)	(0.755)	(0.502)	(0.010)	(0.038)
ΔLogIllnessManhattan18_64	-0.912*	-0.912*	-0.910*	-0.511	-0.004	-0.015
	(0.550)	(0.548)	(0.550)	(0.435)	(0.008)	(0.033)
ΔLogIllnessQueens18_64	-1.082**	-1.154**	-1.081**	-1.043**	-0.003	-0.023
	(0.517)	(0.517)	(0.517)	(0.414)	(0.007)	(0.030)
ΔLogIllnessStaten18_64	-0.178	-0.228	-0.177	0.192	0.003	-0.052*
	(0.420)	(0.419)	(0.420)	(0.383)	(0.006)	(0.029)
Panel B. By syndrome category:						
ΔLogInfluenza18_64	-0.742*	-0.822**	-0.740*	-0.283	-0.006	-0.023
	(0.415)	(0.414)	(0.415)	(0.373)	(0.007)	(0.031)
ΔLogVomiting18_64	0.146	0.104	0.151	0.075	-0.000	-0.044
	(0.504)	(0.503)	(0.504)	(0.430)	(0.005)	(0.033)
ΔLogDiarrhea18_64	-0.600	-0.623	-0.600	-0.055	-0.009*	-0.026
	(0.486)	(0.484)	(0.487)	(0.419)	(0.005)	(0.034)
ΔLogRespiratory18_64	-2.145**	-2.166**	-2.146**	-1.104**	-0.005	-0.088**
	(0.844)	(0.842)	(0.844)	(0.543)	(0.007)	(0.042)
ΔLogAsthma18_64	-1.063**	-1.110**	-1.065**	-1.127***	-0.014	-0.043
	(0.516)	(0.513)	(0.517)	(0.420)	(0.010)	(0.033)
SUE	No	No	No	No	No	Yes
Abs(SUE)	Yes	Yes	Yes	Yes	Yes	No
RecChng	No	No	No	No	No	Yes
Abs(RecChng)	Yes	Yes	Yes	Yes	Yes	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar FE	Yes	Yes	Yes	Yes	Yes	Yes
Behavioral Controls	Yes	Yes	Yes	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	3,558,469	3,558,469	3,552,538	3,556,131	3,453,250	3,557,760

Notes: this table displays the estimates generated by fitting model (2) after replacing *ΔLogIllness18_64* with *ΔLogIllnessY18_64* (panel A) or *ΔLogZ18_64* (panel B). Only the estimated coefficients on the illness incidence proxies are displayed. The intersection of each row and column represents a different regression: The dependent variable varies across columns, whereas the key explanatory variable, which is standardized to have zero mean and unit variance, varies across rows. In panel A, *ΔLogIllnessY18_64* measures the daily change in the log of the number of ED visits made by 18-64 year old New Yorkers who reside in the *Y* borough (*Y* = Brooklyn, Bronx, Manhattan, Queens, Staten Island); a visit is included in the count if it is related to any of the following syndrome categories: asthma, diarrhea, influenza-like, respiratory, vomiting. In panel B, *ΔLogZ18_64* measures the daily change in the log of the number of ED visits made by 18-64 year old New Yorkers, where a visit is included in the count if it is related to the *Z* syndrome category (*Z* = influenza-like, vomiting, diarrhea, respiratory, asthma). The remaining variables are as defined in Table 1. The calendar fixed effects consist of *Day*, *Month*, *Year*, *PreH*, and *PostH*. The behavioral controls consist of *SADOR*, *Cloudy*, *Sunny*, and *HighPollution*. In column 6 (1-5), the economic controls consist of *ΔADSBusConditions* (*Abs(ΔADSBusConditions)*) and *ΔMktUncertainty* (*Abs(ΔMktUncertainty)*). Each regression contains firm fixed effects. The t-statistics in parentheses are computed based on standard errors clustered by firm and day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

This last effect is consistent with the interpretation that investment professionals possess private information, and an exogenous reduction in their productivity improves liquidity by reducing adverse selection costs for less informed market participants.

More in general, all the patterns displayed in panel B are consistent with the literature showing that asthma (Ungar, et al., 2000), the flu, respiratory symptoms, and gastrointestinal problems (Lee, et al., 2021) interfere with usual functioning and cause productivity losses among employed individuals. These results also help to rule out reverse causality as an explanation, as - to the best of my knowledge - there exist no studies suggesting that daily stock market dynamics cause changes in the incidence of any of these syndrome categories.

A3. Additional controls

In principle, the effects discussed in Section 5.2 of the main body of the paper (see also Table 4) might be caused by time-varying patterns in the arrival of new information. In particular, one may wonder whether changes in acute illness incidence among 18-64 year old New Yorkers affect news providers who work in the City and hinder the production and release of public news.

Secondly, pathogen threats and sickness behavior are known to drive psychological and biological responses that "promote resource conservation" and reduce risk tolerance (Prokosch, et al., 2019). As such, time-varying risk aversion, which urges investors to alter their portfolio allocations (Brunnermeier & Nagel, 2008), might be the culprit behind the observed phenomena.

To investigate these channels, I re-estimate model (2) after including among the regressors *AbNumStories*, which measures firm-specific abnormal news flow, and *Abs(ΔBEXRiskAversion)*, which represents the absolute value of daily changes in investor risk aversion (see Table 1). The estimates are reported in columns 1-3 of Table A.2. As expected, an abnormally high news flow increases market trading activity, and changes in investor risk aversion increase the number of shares traded and turnover.

Table A.2. Acute illness incidence among 18-64 year old New Yorkers and stock market outcomes: Additional controls

	(1) ΔLogShares	(2) ΔLogVolume	(3) ΔLogTurnover	(4) ΔLogVolatility	(5) ΔLogVolatility	(6) ΔSpread	(7) Return	(8) Return
ΔLogIllness18_64	-2.157**	-2.157**	-2.157**	-1.542**	-0.692	0.001	-0.080*	-0.081**
	(0.891)	(0.890)	(0.891)	(0.605)	(0.533)	(0.004)	(0.041)	(0.041)
SUE							0.752***	0.756***
							(0.105)	(0.105)
Abs(SUE)	6.634***	6.615***	6.686***	7.947***	5.317***	0.010**		
	(0.516)	(0.520)	(0.516)	(0.575)	(0.416)	(0.005)		
RecChng							6.153***	5.992***
							(0.429)	(0.416)
Abs(RecChng)	35.768***	35.169***	35.283***	32.393***	18.626***	-0.008		
	(1.959)	(1.920)	(1.942)	(1.998)	(1.359)	(0.008)		
AbNumStories	14.708***	14.732***	14.590***	15.535***	9.739***	-0.003*		
	(0.295)	(0.295)	(0.293)	(0.318)	(0.247)	(0.002)		
NewsSentiment							0.365***	0.357***
							(0.020)	(0.020)
ΔBEXRiskAversion						0.000	-0.975***	-0.975***
						(0.002)	(0.231)	(0.231)
Abs(ΔBEXRiskAversion)	1.053*	0.813	1.050*	2.084***	1.664***			
	(0.619)	(0.585)	(0.621)	(0.584)	(0.493)			
ΔLogTurnover					0.397***	-0.000***		-0.001***
					(0.006)	(0.000)		(0.000)
ΔLogVolatility						0.000***		
						(0.000)		
Δ(1/P)						0.024		
						(0.032)		
ΔLogMarketCap						-0.238***		
						(0.041)		
ΔSpread							-0.008	-0.009
							(0.007)	(0.007)
Firm FE & calendar FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Behavioral & economic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,864,146	2,864,146	2,860,527	2,863,060	2,859,486	2,767,176	695,454	694,714

Notes: this table displays the estimates generated by fitting model (2) with the inclusion of additional controls. *Δ(1/P)* and *ΔLogMarketCap* measure the change in the inverse of the company's stock price and the change in the log of the company's market value, respectively. The remaining variables are as defined in Table 1. The calendar fixed effects consist of *Day*, *Month*, *Year*, *PreH*, and *PostH*. The behavioral controls consist of *SADOR*, *Cloudy*, *Sunny*, and *HighPollution*. In columns 7-8 (1-6), the economic controls consist of *ΔADSBusConditions* (*Abs(ΔADSBusConditions)*) and *ΔMktUncertainty* (*Abs(ΔMktUncertainty)*). Each regression contains firm fixed effects. The t-statistics in parentheses are computed based on standard errors clustered by firm and day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

However, the relation between *ΔLogIllness18_64* and market trading activity is still intact. Consequently, there is no room to argue that the effect of *ΔLogIllness18_64* on trading activity is mediated by the amount of news produced by local news providers.

To shed light on what drives the relation between *ΔLogIllness18_64* and volatility, I re-estimate model (2) with the addition of *Abs(ΔBEXRiskAversion)* (column 4 of Table A.2) and *ΔLogTurnover* (column 5). While the addition of the risk aversion proxy does not alter the sign, size, and statistical significance of the coefficient on *ΔLogIllness18_64*, this coefficient is no longer statistically different from zero when *ΔLogTurnover* is also included in the equation. This suggests that the negative impact that increased rates of acute illness among 18-64 year old New Yorkers exert on volatility is mediated by reduced trading activity.

To control for additional determinants of bid-ask spreads (Madhavan, 2000; Wyart, et al., 2008), I re-estimate model (2) with the inclusion among the regressors of *ΔLogTurnover*, *ΔLogVolatility*, *Δ(1/P)*, and *ΔLogMarketCap*. The latter two variables measure the change in the inverse of a company's stock price and the change in the log of a company's market value, respectively. The estimates in column 6 of Table A.2 show that, even after controlling for these factors, the coefficient on *ΔLogIllness18_64* is small in size and statistically indistinguishable from zero.

Lastly, I focus on the negative relation between *ΔLogIllness18_64* and stock returns. In principle, reduced returns may result from the arrival of negative news, reduced trading activity (Karpoff, 1987), reduced liquidity, or time-varying risk aversion (Kamstra, et al., 2003). In particular, one may wonder whether increased rates of acute illness among 18-64 year old New Yorkers affect news providers working in the City and translate into heightened media pessimism and negative news sentiment (Tetlock, 2007).

Consequently, I re-estimate model (2) with the inclusion of *NewsSentiment*, *ΔBEXRiskAversion*, *ΔSpread* (column 7 of Table A.2), and *ΔLogTurnover* (column 8). As expected, the coefficients on *NewsSentiment* and *ΔBEXRiskAversion* are positive and negative, respectively. The coefficient on *ΔSpread* is statistically indistinguishable from zero, and the coefficient on *ΔLogTurnover* is, somewhat unexpectedly (Datar, et al., 1998; Hong & Yu, 2009), negative. Nevertheless, the effect of *ΔLogIllness18_64* on returns survives, indicating that it can be explained neither by economic news nor by changes in investor risk aversion, market trading activity, and liquidity. This leaves the door open to a behavioral interpretation of the relation in question, which is discussed in Section 5.6 of the main body of the paper.

A4. New York City's emergency departments

The taxi trip analysis in Section 5.1 of the main body of the paper employs information about the location of the 51 hospitals in New York City that have an emergency department. To construct this list of hospitals, I consult the website of the New York State Department of Health. The hospitals that the search returned are displayed in Table A.3. Using OpenStreetMap, I manually transform the address of each hospital into latitude/longitude coordinates, which are reported in the last two columns of the table.

Table A.3. GPS coordinates of New York City's hospitals with an emergency department

Hospital	Address	ZIP code	Latitude	Longitude
Bellevue Hospital Center	462 First Avenue	10016	40.739060	-73.975350
BronxCare Hospital Center	1650 Grand Concourse	10457	40.843510	-73.910660
BronxCare Hospital Center	1276 Fulton Avenue	10456	40.831410	-73.903180
Brookdale Hospital Medical Center	1 Brookdale Plaza	11212	40.655590	-73.913170
Brooklyn Hospital Center - Downtown Campus	121 Dekalb Avenue	11201	40.690550	-73.977920
Coney Island Hospital	2601 Ocean Parkway	11235	40.586120	-73.964820
Elmhurst Hospital Center	79-01 Broadway	11373	40.744770	-73.885650
Flushing Hospital Medical Center	45th Avenue & Parsons Blvd	11355	40.755450	-73.816760
Harlem Hospital Center	506 Lenox Avenue	10037	40.814690	-73.939280
Interfaith Medical Center	1545 Atlantic Avenue	11213	40.678570	-73.937510
Jacobi Medical Center	1400 Pelham Parkway	10461	40.854550	-73.845860
Jamaica Hospital Medical Center	89th Avenue & Van Wyck Expressway	11418	40.700370	-73.816490
Kings County Hospital Center	451 Clarkson Avenue	11203	40.656670	-73.943460
Kingsbrook Jewish Medical Center	585 Schenectady Avenue	11203	40.659820	-73.933210
Lenox Health Greenwich Village	30 Seventh Avenue	10011	40.737770	-74.000830
Lenox Hill Hospital	100 East 77th Street	10021	40.773640	-73.960860
Lincoln Medical & Mental Health Center	234 East 149th Street	10451	40.817030	-73.924360
Long Island Jewish Forest Hills	102-01 66th Road	11375	40.729040	-73.851550
Long Island Jewish Medical Center	270-05 76th Ave	11040	40.753890	-73.708320
Maimonides Medical Center	4802 Tenth Avenue	11219	40.639540	-73.998830
Metropolitan Hospital Center	1901 First Avenue	10029	40.785030	-73.944970
Montefiore Med Center - Jack D Weiler Hosp of A Einstein College Div	1825 Eastchester Road	10461	40.849130	-73.846200
Montefiore Medical Center - Henry & Lucy Moses Div	111 East 210th Street	10467	40.880080	-73.879830
Montefiore Medical Center - Montefiore Westchester Square	2475 St. Raymond Avenue	10461	40.840530	-73.848450
Montefiore Medical Center-Wakefield Hospital	600 East 233rd Street	10466	40.893770	-73.861070
Mount Sinai Beth Israel	First Ave at 16th Street	10003	40.733170	-73.982050
Mount Sinai Brooklyn	3201 Kings Highway	11234	40.618670	-73.942980
Mount Sinai Hospital	One Gustave L Levy Place	10029	40.790030	-73.953170
Mount Sinai Hospital - Mount Sinai Hospital of Queens	25-10 30th Avenue	11102	40.768100	-73.924940
Mount Sinai Morningside	1111 Amsterdam Avenue	10025	40.805060	-73.961510
Mount Sinai West	1000 10th Avenue	10019	40.769660	-73.987090
New York Community Hospital of Brooklyn, Inc	2525 Kings Highway	11229	40.613890	-73.948560
New York-Presbyterian Brooklyn Methodist Hospital	506 Sixth Street	11215	40.667830	-73.979140
New York-Presbyterian Hospital - Allen Hospital	5141 Broadway	10034	40.873270	-73.912860
New York-Presbyterian Hospital - Columbia Presbyterian Center	622 West 168th Street	10032	40.839750	-73.941450
New York-Presbyterian Hospital - New York Weill Cornell Center	525 East 68th Street	10021	40.764700	-73.954000
New York-Presbyterian/Lower Manhattan Hospital	170 William Street	10038	40.710320	-74.004970

New York-Presbyterian/Queens	56-45 Main Street	11355	40.747260	-73.825200
North Central Bronx Hospital	3424 Kossuth Avenue & 210th Street	10467	40.880360	-73.881390
NYU Langone Health-Cobble Hill	83 Amity Street	11201	40.689910	-73.998080
NYU Langone Hospital-Brooklyn	150 55th Street	11220	40.646760	-74.020980
NYU Langone Hospitals	550 First Avenue	10016	40.742300	-73.973560
Queens Hospital Center	82-68 164th Street	11432	40.717880	-73.806070
Richmond University Medical Center	355 Bard Avenue	10310	40.636170	-74.105520
St Johns Episcopal Hospital So Shore	327 Beach 19th Street	11691	40.598680	-73.753460
St. Barnabas Hospital Health System	4422 Third Avenue	10457	40.852540	-73.891460
Staten Island University Hosp-North	475 Seaview Avenue	10305	40.585250	-74.085020
Staten Island University Hosp-South	375 Seguine Avenue	10309	40.517160	-74.196760
University Hospital of Brooklyn	445 Lenox Road	11203	40.654910	-73.944420
Woodhull Medical & Mental Health Center	760 Broadway	11206	40.699330	-73.942750
Wyckoff Heights Medical Center	374 Stockholm Street	11237	40.704140	-73.917710

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