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The Relative Industry Specific Effects of COVID-19 on Market Volatility and Liquidity

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By Callin Christensen

Abstract:

Understanding how historical events affect market volatility and liquidity can provide crucial information to financial analysts, investment professionals, and managers in the event that similar circumstances resurface. In this study, I look at how a global pandemic (COVID-19) can introduce frictions into the market and cause disrupt the generation or flow of available information, this could cause prices to deviate significantly from their equilibrium values. I also hypothesize that these inefficiencies may have a greater effect on some industries than others. My analysis seems to confirm this hypothesis. I observe that the global COVID-19 pandemic leads to statistically significant increases in the volatility of industries such as Meals, Games, and Mines relative to the market. I also find that the pandemic leads to significant liquidity deterioration relative to the market in industries including ElcEq, Carry, and Other.

1. Introduction

On Jan 21st, 2020 the first case of COVID-19, or the "Novel Coronavirus", was confirmed in the United States. This came on the tailwinds of COVID-19 ravaging through Asia and Europe. For the first time in recent memory, entire cities are shut down, with millions of people confined to their homes – all in an attempt to combat the spread of the virus. On Jan 30th, the World Health Organization (WHO) declared a global public health emergency. On Feb. 29th the first death was recorded in the United States, after which the Federal Open Market Committee (FOMC) lowered the target fed funds rate. On March 9th, a level-1 circuit breaker triggered following a 7% decline in the S&P 500, and by Mach 18th the 4th the market had hit its fourth trading halt in two weeks[1]. With global economies roiling amidst the COVID-19 uncertainty, market volatility spiked with the VIX reaching as high as 82.69 on Marth 13th (compared to its three-year average of 16.58) as markets tried frantically to incorporate all available and expected information into security prices.

[1] For more info about COVID-19 critical events visit: https://www.who.int/news-room/detail/08-04-2020-who-timeline---covid-19; https://fraser.stlouisfed.org/timeline/covid-19-pandemic#49; https://www.nbcnews.com/health/health-news/coronavirus-timeline-tracking-critical-moments-covid-19-n1154341

Figure 1. Market-Wide Volatility around COVID-19
The figure plots average market return volatility measured at the stock-day level as the natural log of the daily high ask price minus the natural log of the daily low bid price and then averaged across stocks for each day of the sample period. from January 3, 2020 to March 25, 2020.

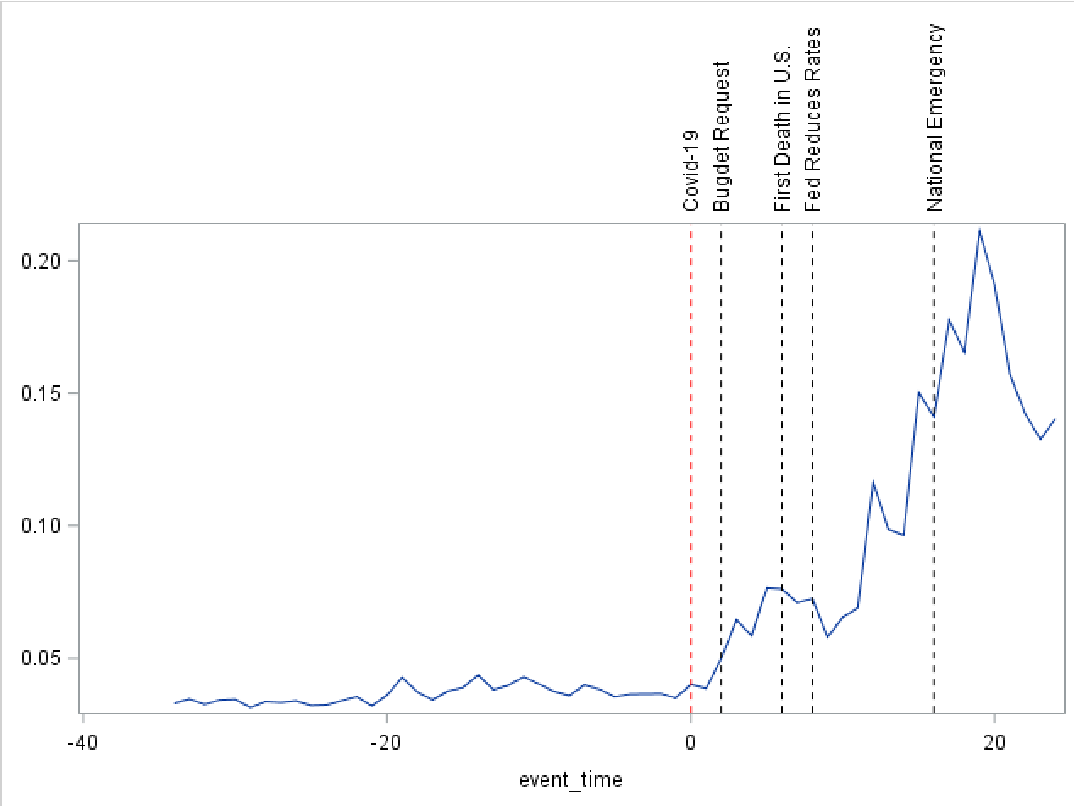


Figure 1 provides a visual display of average market return volatility during the sample timeframe of Jan 3, 2020, to March 25, 2020. As you can see, there was a drastic spike in volatility directly following the COVID-19 outbreak in the US. The pandemonium that ensued in the wake of the COVID-19 pandemic may have a meaningful effect on market efficiency. In 1945 Friedrich Hayek asserted that market prices play a critical role in communicating information to – and coordinating relevant information from – market participants (Hayek 1945) with similar points made by Friedman (1977). Similarly, the efficient market hypothesis of Samuelson (1965) and Fama (1965) maintain that all available information is instantly and completely reflected in market prices. Thus, in the event of a perfectly competitive market, stock prices should follow a random walk as investors continually revise their unbiased future expectations. However, if frictions were to enter the market and disrupt the generation or flow of available information, this could cause prices to deviate significantly from their equilibrium values. The strains from the COVID-19 pandemic might just introduce some of these frictions into the market, making it difficult for investors to correctly value assets as price volatility spikes and market liquidity diminishes.

The focus of this article is to provide historical evidence identifying the industry specific effects that COVID-19 had on market volatility and liquidity. Specifically, I seek to provide an unbiased analysis on the industry specific effects of a global pandemic so that, in the event of a future disaster requiring social quarantining and supply chain disruptions, future researchers can have a baseline expectation. Current financial economic theory makes it clear that markets incorporate industry specific exposure into current prices.[2] As such, it is expected that the effect of the COVID-19 pandemic volatility and liquidity will vary dependent on the market expected exposure. The findings of this analysis reinforce this expectation and show that a pandemic of global proportions has a significant effect on industry specific risk and liquidity.

This descriptive article adds to the rapidly growing literature surrounding COVID-19 and summarizes the industry specific exposure to an unexpected disaster, such as a pandemic, which disrupt the labor force and supply chains. There have been many studies surrounding the midrange economic impacts of the COVID-19 pandemic, such as its effect on projected GDP growth or the plausibility of subsequent demand shortages (Fernandes, 2020; Gormsen and Koijen, 2020; Guerrier et al., 2020). There are also a number of analysis focusing on the impact of the pandemic on a country based on exposure to highly effected areas (Ramelli and Wagner, 2020), the countries

[2] Research supporting this includes Hayek (1945), Samuelson (1965), Fama (1965), and Friedman (1977) among others.

fiscal capacity (Garding, Martin, and Nagler, 2020), and its historical involvement with similar small scale pandemics (Ru, Yang, and Zou, 2020). In this spirit I seek to add to the literature documenting the direct impacts of this global pandemic specifically on U.S. firms. Although the far-reaching effects are currently unobserved, there is already an abundance of research revolving around the COVID-19 pandemic and said pandemic's financial and economic impacts.

2. Data Description

The data used in the analysis come from three primary sources. Compustat annual filings from 2019 are used to determine industries based on historical SIC codes. However, if the historical SIC code is missing for a particular firm, the Center for Security Prices (CRSP) SICCD codes as of December 31, 2019 are used instead. The empirical analysis is then estimated using 1,710 industry-day observations between January 3, 2020 and March 25, 2020. The trade characteristics are measured using data from the NYSE Daily Trade and Quote (DTAQ) database. The empirical analysis is conducted by measuring stock-day level variables and averaging them across the Fama and French 30 industries using equal weighting.

The variables of interest in this analysis include Range-Based Volatility (*Rvolt*) and Amihud's Illiquidity measure (*Illiq*). *Rvolt* is measured as the difference between the natural log of the daily high ask price and the natural log of the daily low bid price. Alizadeh, Brandt, and Diebold (2002) show that *Rvolt* is an efficient measure of stochastic volatility that is robust to microstructure noise. *Illiq* is measured as the absolute value of the daily return divided by dollar volume – scaled by 10^6. Amihud (2002) argues that Illiq can be interpreted as a rough estimate of price impact, or the price response to trading volume. A higher *Illiq* value represents a less liquid security, as the daily price response associated with one dollar of trading volume is larger. Amihud (2002) found that higher expected *Illiq* raises expected returns, while higher unexpected *Illiq* leads to lower stock returns. By observing industry specific liquidity reactions to the COVID-19 pandemic, markets can more efficiently assimilate the effects of any future pandemics into market prices.

I use, as control variables throughout this analysis, the following: *Price*, Trade size (*Tradesize*), *Volume*, market capitalization (*MCAP*), industry ($Industry_i$), *Post*, and *Nasdaq*. *Nasdaq* is included as dummy variable and denotes the percentage of the industry listed on the Nasdaq exchange. In compiling each industry average Nasdaq figure, the dummy variable is equal to 1 if the specific stock is listed on the Nasdaq Stock Exchange and 0 if it is listed on the NYSE/AMEX. $Industry_i$ is a dummy variable which is equal to one for the i^{th} industry and zero for the remaining 29 Fama French industries. *Post* is an indicator variable which equals one if the industry stock-day observation is between February 20,2020 and March 25, 2020[3] and zero if it falls between January 3, 2020 and February 19, 2020. *MCAP* is the equal-weighted industry average market capitalization. *Volume* represents the industry average total share volume and likewise, *Tradesize* measures the industry average number of shares executed per trade. *Price* is the equal-weighted industry average transaction price.

[3] The *Post* period refers to the time period directly following the outbreak of COVID-19 in the US.

Table 1. Summary Statistics

This table summarizes the variables used in the empirical analysis. The variables are measured at the stock-day level and then averaged across the Fama and French 30 industries using equal-weighting. We use Compustat annual filings during 2019 to determine industries based on historical SIC codes. However, if the historical SIC code is missing for a particular firm, we use CRSP SICCD codes as of December 31, 2019 instead. The statistics below are then estimated using these 1,710 industry-day observations between January 3, 2020 and March 25, 2020. The trade characteristics are measured using data from the NYSE Daily Trade and Quote (DTAQ) database. *Price* is the average transaction price. *Tradesize* is the average number of shares executed in a given trade. *Volume* is the total share volume. *Rvolt* is range-based volatility, or the natural log of the daily high ask price minus the natural log of the daily low bid price. *Illiq* is Amihud's (2002) illiquidity measure, or the absolute daily return divided by dollar volume (scaled by 10^6). Market capitalization (*MCAP*), which is closing price times shares outstanding, is measured using data from CRSP on December 31, 2019.

Variable	Mean	Median	Std. Dev.	Minimum	Maximum
Price	52.16	50.41	20.53	9.61	111.81
MCAP (in $billions)	12.14	8.97	13.44	0.51	75.40
Tradesize	116.37	104.29	67.97	57.22	1274.22
Volume (in 100,000s)	180.22	131.98	152.97	11.72	1312.55
Rvolt	0.0670	0.0436	0.0509	0.0150	0.3170
Illiq	0.1250	0.0786	0.1359	0.0001	0.9846
Nasdaq	0.4283	0.4298	0.1945	0.0000	0.8558

Table 1 shows the summary statistics for each of the variables of interest. Table 1 introduces he variables that are used in the empirical analysis. Price is reported in $US, with a cross industry average of $52.16. The average sample MCAP is 12.14 and is reported in billions of $US. The average daily cross industry trade size in the sample 116.37. Volume is reported in 100,000s of shares and has an average of 180.22. Rvolt, the natural log difference between the daily high and low, has a cross industry average of .067. The total sample Amihud Illiquidity Measure is .1250, and nearly 43% of the stocks analyzed in our sample were listed on the Nasdaq as seen by the Nasdaq measure of 0.4283.

Table 2. Correlation Matrix

This table reports Pearson correlation coefficients for the variables used in the analysis with p-values in brackets. The variables are measured at the stock-day level and then averaged across the Fama and French 30 industries using equal-weighting. We use Compustat annual filings during 2019 to determine industries based on historical SIC codes. However, if the historical SIC code is missing for a particular firm, we use CRSP SICCD codes as of December 31, 2019 instead. The statistics below are then estimated using these 1,710 industry-day observations from January 3, 2020 to March 25, 2020. The variables have previously been defined.

	Price	MCAP	Tradesize	Volume	Rvolt	Illiq	Nasdaq
Price	1	0.27724	-0.03384	-0.21505	-0.42370	-0.07638	0.12693
		(< .0001)	(0.1618)	(< .0001)	(< .0001)	(0.0016)	(< .0001)
MCAP		1	-0.05342	0.46282	-0.07097	-0.08384	-0.30193
			(0.0272)	(< .0001)	(0.0033)	(0.0005)	(< .0001)
Tradesize			1	0.20865	0.18333	0.18363	0.05463
				(< .0001)	(< .0001)	(< .0001)	(0.0239)
Volume				1	0.47370	0.16212	-0.25287
					(< .0001)	(< .0001)	(< .0001)
Rvolt					1	0.37664	0.00147
						(< .0001)	(0.9515)
Illiq						1	0.24284
							(< .0001)
Nasdaq							1

The next step is to calculate the Pearson Correlation Coefficients for each of the variables of interest, which you will find Table 2 along with the corresponding p-values reported below its respective coefficient in parenthesis. I observe that the measure for market risk, *Rvolt*, is positively correlated with volume and negatively correlated with price; both are significant at a .01 level. This means that there is some statistically significant relationship wherein stocks with higher trading volume on average tend to have mare risk and stocks with a higher price tend to have less risk on average ceteris paribus. However, with such a naïve approach no causal relationship can be inferred.

Table 3. Industry Descriptions
This table reports the number of firms in the Fama and French 30 industries in alphabetical order. We use Compustat annual filings during 2019 to determine industries based on historical SIC codes. However, if the historical SIC code is missing for a particular firm, we use CRSP SICCD codes as of December 31, 2019 instead.

Industry	Description	# of Firms
Autos	Automobiles and Trucks	50
Beer	Beer & Liquor	8
Books	Printing and Publishing	14
BusEq	Business Equipment	228
Carry	Aircraft, Ships and Railroad equipment	24
Chems	Chemicals	59
Clths	Apparel	31
Cnstr	Construction and Construction Materials	89
Coal	Coal	8
ElcEq	Electrical Equipment	34
FabPr	Fabricated Products and Machinery	87
Fin	Banking, Insurance, Real Estate, Trading	569
Food	Food Products	49
Games	Recreation	44
Hlth	Healthcare, Medical Equipment, Pharmaceutical Products	520
Hshld	Consumer Goods	35
Meals	Restaurants, Hotels, Motels	52
Mines	Precious Metals, Non-Metallic and Industrial Metal Mining	17
Oil	Petroleum and Natrual Gas	96
Other	Everything Else	88
Paper	Business Supplies and Shipping Containers	30
Rtail	Retail	116
Servs	Personal and Business Services	381
Smoke	Tobacco Products	3
Steel	Steel Works Etc	25
Telcm	Communication	54
Trans	Transportation	62
Txtls	Textiles	6
Util	Utilities	79
Whlsl	Wholesale	84

In this analysis I categorize all stocks based on 2019 Compustat annual filings to determine industry based on historical SIC codes. Table 3 includes a description on each of the Fama and French 30 industries used in this sample, as well as the number of firms competing in each industry. Industry stock-day observations are created by taking an equal weighted average of each company in the industry.

In March 2020 tensions rose between two large suppliers in the Oil industry, Russia and OPEC. As such, much of what is observed in this analysis pertaining to the Oil industry may be attributable to this conflict. Due to this conflict I do not seek to focus on nor interpret the resulting data produced in this analysis on the Oil industry. However, I do report the data in an attempt to maintain the data integrity of the complex and interconnected nature of the financial market.

3. Empirical Results

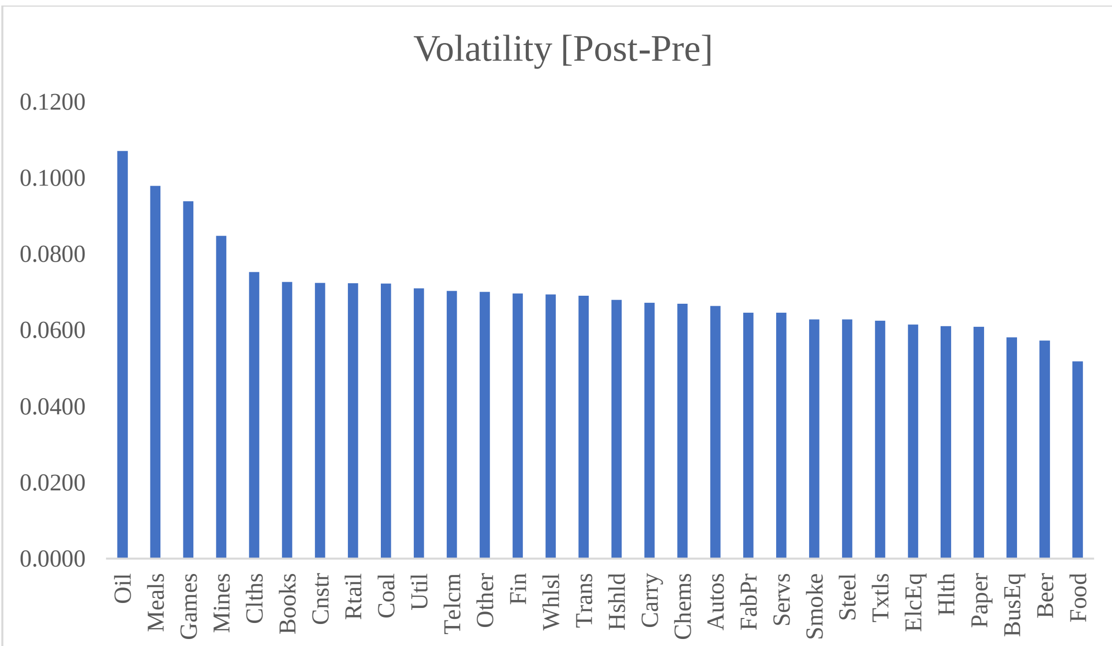
In this section, I look at the industry specific effect the COVID-19 pandemic on volatility and liquidity. First, I inspect the industry specific effects of the COVID-19 pandemic on *Rvolt* to see which, if any, industries have a significant volatility-pandemic relationship in the sample. I then conduct a similar analysis on *Illiq* to determine which industries experience the greatest liquidity-pandemic relationship. I then create two econometric models that will allow me to look at the industry specific effects of the pandemic on volatility and liquidity by comparing the pre-post pandemic statistics for both, relative to the rest of the market.

3.1. Pandemic Related Volatility

3.1.1 Univariate Analysis

To begin dissecting the industry specific effect of the COVID-19 pandemic on *Rvolt*, the measure of range volatility is used as the proxy measure of risk, I calculate the difference between the sample post pandemic period (*post*) of Feb 20th through March 25th and the sample pre pandemic period (*pre*) which is Jan 3rd through Feb 19th. This gives me the results found in Figure2 which graphs the measure of *Rvolt[post-pre]*. This measure of *Rvolt [post-pre]* denotes the increase in *Rvolt*, which is the proxy measure of risk, that occurred during the predefined pandemic time widow of Feb 20th through March 25th. In other words, *Rvolt[post-pre]* indicates the increase in industry specific risk caused by the pandemic[4]. As you can see in Figure 2 the industries that had the largest increase in risk around the COVID-19 pandemic timeframe were Meals, Games and Mines with increases in *Rvolt* reaching two to three times their pre pandemic levels.

Figure 2. Industry Volatility around COVID-19 – Univariate
This figure plots average differences in daily range-based volatility by industry surrounding the COVID-19 outbreak. The industries are identified using the Fama and French 30 classifications. We use Compustat annual filings during 2019 to determine industries based on historical SIC codes. However, if the historical SIC code is missing for a particular firm, we use CRSP SICCD codes as of December 31, 2019 instead. We identify the pre-period as January 3, 2020 to February 19, 2020 and the post-period as February 20, 2020 to March 25, 2020. The post-pre values with accompanying t-statistics are found in Table A1.



[4] For a detailed look at the *Rvolt [post-pre]* calculation and the corresponding t-values of each calculation see Table A1

3.1.2 Multivariate Analysis

Next I look at the relationship between each industries *Rvolt* and the COVID-19 pandemic. Observing this relationship will help me understand the effect that the pandemic had on the industry specific risk. I do this by estimating the equation:

$$Rvolt_{i,t} = \alpha + \beta_1 Industry_i + \beta_2 Post_t \times Industry_i + \beta_3 Ln(Price)_{i,t} + \beta_4 Ln(MCAP)_{i,t} + \beta_5 Ln(Tradesize)_{i,t} + \beta_6 Ln(Volume)_{i,t} + \beta_7 Nasdaq_i + \delta_t + \varepsilon_{i,t}\ .$$

In this model $Rvolt_{i,t}$, which I use as a proxy measure of risk and is calculated as the natural log of the daily high minus the natural log of the daily low, is the dependent variable. The independent variable I am interested in is an interaction term I create denoted in this model as $Post_t$ x $Industry_i$. $Post_t$ is an indicator variable which is 0 if the observation is before the pandemic timeframe (Jan 3rd-Feb 19th) and 1 if it is after (Feb 20th-March 25th). $Industry_i$ is also an indicator variable which is 1 when $t=t$ and is otherwise 0. This interaction term, $Post_t$ x $Industry_i$, is a difference-in-difference term allows me to observe the effect of the pandemic on the treatment group ($Industry_i$) relative to the control group. The importance of observing the effect on each industry relative to all other industries is that I am controlling for all other unobservable macroeconomic factors. I also include the following independent variables: $Industry_i$ indicates whether each observation is part of the industry in question. $Ln(Price)_{i,t}$ is the natural log of price. $Ln(MCAP)_{i,t}$ is the natural log of market capitalization. $Ln(Tradesize)_{i,t}$ is the natural log of trade size. $Ln(Volume)_{i,t}$ is the natural log of volume. $Nasdaq_i$ is a categorical variable equal to one if the firm is listed on the NASDAQ and zero otherwise. δ_t is a variable used to control for day fixed effects[5]. I then run this regression thirty times varying *i* to find the effects for

[5] To control for day fixed effects, I create n day variables (covering n days in the time frame June 3rd-March 25th). This variable is equal to 1 if the observation day is equal to the day variable and zero otherwise. I then include (n-1) day variables in the regression to control for any day fixed effects.

each of the Fama and French 30 industries. In this analysis I am only interested in the coefficient for the $Post_t$ x $Industry_i$. The results of the regressions are summarized in Figure 3.

Figure 3. Industry Volatility around COVID-19 Outbreak – Multivariate Diff-in-Diff
This figure plots select results from the following regression equation estimated for each industry separately, but including all other industries as controls:

$$Rvolt_{i,t} = \alpha + \beta_1 Industry_i + \beta_2 Post_t \times Industry_i + \beta_3 Ln(Price)_{i,t} + \beta_4 Ln(MCAP)_{i,t} + \beta_5 Ln(Tradesize)_{i,t} + \beta_6 Ln(Volume)_{i,t} + \beta_7 Nasdaq_i + \delta_t + \varepsilon_{i,t} .$$

$Rvolt_{i,t}$ is range-based volatility measured as the natural log of the daily high ask price minus the natural log of the daily low bid price. *Industry* is a dummy variable equal to one if the observation is in the i^{th} industry and zero for the other 29 Fama and French industries. We use Compustat annual filings during 2019 to determine industries based on historical SIC codes. However, if the historical SIC code is missing for a particular firm, we use CRSP SICCD codes as of December 31, 2019 instead. $Post_t$ is an indicator variable equal to one if the industry-day observation is between February 20, 2020 and March 25, 2020 and zero if between January 3, 2020 and February 19, 2020. We also include day fixed effects, δ_t, but in doing so must remove the time-invariant $Post_t$ indicator. The remaining independent variables have previously been defined, and are measured at the industry-day level by taking equal-weighted averages across stock-day observations. For brevity, we plot the estimated coefficient on the interaction term only for each regression. The estimated coefficients with accompanying t-statistics are found in Table A2.

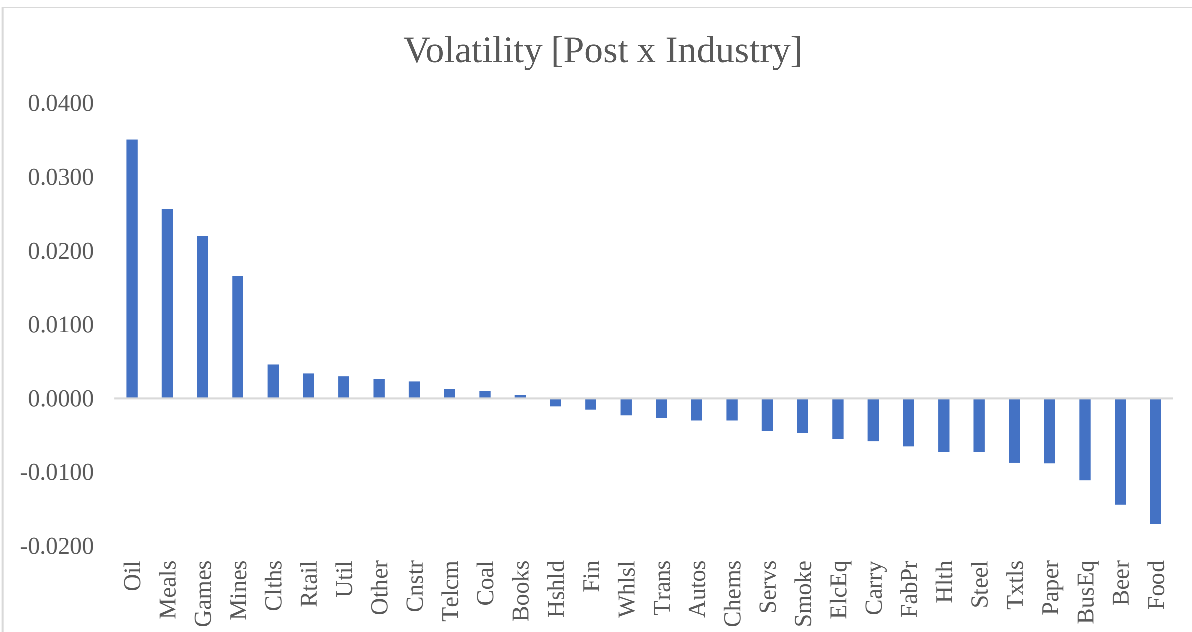


Figure 3 illustrates summarizes the results of this model and helps visually display the industries whose risk increased the most relative to the other industries and other macroeconomic factors due to the COVID-19 pandemic. As you can see from Figure 3 the pandemic effected the relative risk of Meals, Games, and Mines the most with each reporting *[*$Post_t$ x $Industry_i$*] Rvolt* betas of .026, .022, and .017 respectively. Using Meals as an example for explanation, the pandemic increased the Meals industry risk, *Rvolt*, by .026 or 2.6 percentage points. This makes sense because the Meals industry consists of Restaurants, Hotels, and Motels which have all suffered due to the social distancing and quarantine restrictions instituted to curb the spread of COVID-19. I also observe the opposite effect on industries including Food, Beer and Paper who saw a decrease in risk with *[post*$_t$ x *industry*$_i$*] Rvolt* betas of -0.017, -0.014, and -0.0089 respectively indicating a decrease in risk around the pandemic outbreak. The t-values corresponding to the results in Figure 3 are reported in Table A2.

3.2. Pandemic Related Illiquidity

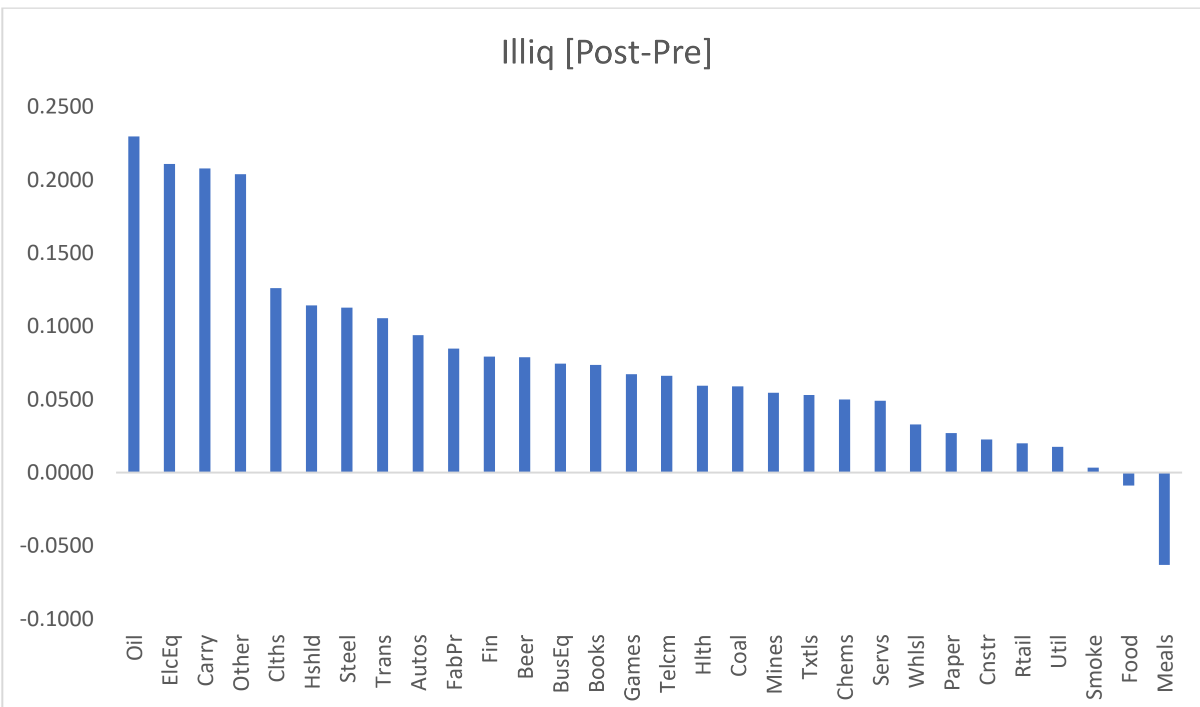
3.2.1 Univariate Analysis

Next I will analyze the industry specific effect of the COVID-19 pandemic on *Illiq*, the Amihud illiquidity measure calculated as the absolute daily return divided by the dollar volume (scaled by 10^6), I calculate the difference between the sample post pandemic period (*post*) of Feb 20th through March 25th and the sample pre pandemic period (*pre*) which is Jan 3rd through Feb 19th. This gives me the results found in Figure 4 which graphs the measure of *Illiq[post-pre]*. This measure of *Illiq[post-pre]* denotes the increase in *Illiq*, which is the proxy measure of liquidity, that occurred during the predefined pandemic time widow of Feb 20th through March 25th. In other words, *Iliq[post-pre]* indicates the decrease in industry specific liquidity around the pandemic timeframe. As you can see in Figure 4 the industries that had the largest decrease in liquidity around the COVID-19 pandemic were ElcEq, Carry and Other with increases in the Amihud Illiquidity measure, *Illiq*, ranging between two to over two and a half times their pre pandemic levels. I also find that the Food and Meals industry had an increase in liquidity during the COVID-

19 pandemic[6]. Table 1 summary statistics report that the average daily market volume increased drastically from nearly 1.3 million to just under 2.5 million in the sample period. It would make sense that a large increase in trade volume could lead to an improved liquidity situation despite the global pandemic.

Figure 4. Industry Illiquidity around COVID-19 – Univariate

This figure plots average differences in daily Amihud (2002) illiquidity by industry surrounding the COVID-19 outbreak. *Illiq* is defined as the absolute daily return divided by dollar volume (scaled by 10^6). The industries are identified using the Fama and French 30 classifications. We use Compustat annual filings during 2019 to determine industries based on historical SIC codes. However, if the historical SIC code is missing for a particular firm, we use CRSP SICCD codes as of December 31, 2019 instead. We identify the pre-period as January 3, 2020 to February 19, 2020 and the post-period as February 20, 2020 to March 25, 2020. The post-pre values with accompanying t-statistics are found in Table A3.



[6] For a detailed look at the *Rvolt [post-pre]* calculation and the corresponding t-values of each calculation see Table A3

3.2.2 Multivariate Analysis

I now look at the industry specific relationship between *Illiq* and the COVID-19 pandemic. This relationship identifies the unique effect of the pandemic on each treatment industry's liquidity. I do this by estimating the equation:

$$Illiq_{i,t} = \alpha + \beta_1 Industry_i + \beta_2 Post_t \times Industry_i + \beta_3 Ln(Price)_{i,t} + \beta_4 Ln(MCAP)_{i,t} + \beta_5 Ln(Tradesize)_{i,t} + \beta_6 Ln(Volume)_{i,t} + \beta_7 Nasdaq_i + \delta_t + \varepsilon_{i,t}\ .$$

In this model $Illiq_{,t}$, which is the Amihud illiquidity measure that I use as a proxy measure of liquidity, is the dependent variable. The independent variable I am interested in is an interaction term I create denoted in this model as $Post_t$ x $Industry_i$. $Post_t$ is an indicator variable which is 0 if the observation is before the pandemic timeframe (Jan 3rd-Feb 19th) and 1 if it is after (Feb 20th-March 25th). $Industry_i$ is also an indicator variable which is 1 when t=t and is otherwise 0. This interaction term, $Post_t$ x $Industry_i$, is a difference-in-difference term allows me to observe the effect of the pandemic on the treatment group ($Industry_i$) relative to the control group. The importance of observing the effect on each industry relative to all other industries is that I am controlling for all other unobservable macroeconomic factors. I also include the following independent variables: $Industry_i$ indicates whether each observation is part of the industry in question. $Ln(Price)_{i,t}$ is the natural log of price. $Ln(MCAP)_{i,t}$ is the natural log of market capitalization. $Ln(Tradesize)_{i,t}$ is the natural log of trade size. $Ln(Volume)_{i,t}$ is the natural log of volume. $Nasdaq_i$ is a categorical variable equal to one if the firm is listed on the NASDAQ and zero otherwise. δ_t is a variable used to control for day fixed effects[7]. I then run this regression thirty times varying *i* to find the effects for each of the Fama and French 30 industries in this analysis I

[7] To control for day fixed effects, I create n day variables (covering n days in the time frame June 3rd-March 25th). This variable is equal to 1 if the observation day is equal to the day variable and zero otherwise. I then include (n-1) day variables in the regression to control for any day fixed effects.

am only interested in the coefficient for the *Post*$_t$ x *Industry*$_i$. The results of the regressions are summarized in Figure 5.

Figure 5. Industry Illiquidity around COVID-19 Outbreak – Multivariate Diff-in-Diff
This figure plots select results from the following regression equation estimated for each industry separately, but including all other industries as controls:

$$Illiq_{i,t} = \alpha + \beta_1 Industry_i + \beta_2 Post_t \times Industry_i + \beta_3 Ln(Price)_{i,t} + \beta_4 Ln(MCAP)_{i,t} + \beta_5 Ln(Tradesize)_{i,t} + \beta_6 Ln(Volume)_{i,t} + \beta_7 Nasdaq_i + \delta_t + \varepsilon_{i,t}\ .$$

Illiq is Amihud's (2002) illiquidity measure, or the absolute daily return divided by dollar volume (scaled by 10^6). *Industry* is a dummy variable equal to one if the observation is in the i^{th} industry and zero for the other 30 Fama and French industries. $Post_t$ is an indicator variable equal to one if the industry-day observation is between February 20, 2020 and March 25, 2020 and zero if between January 3, 2020 and February 19, 2020. We also include day fixed effects, δ_t, but in doing so must remove the time-invariant $Post_t$ indicator. The remaining independent variables have previously been defined, and are measured at the industry-day level by taking equal-weighted averages across stock-day observations. For brevity, we plot the estimated coefficient on the interaction term only for each regression in a bar graph. The estimated coefficients and accompanying t-statistics are found in Table A4.

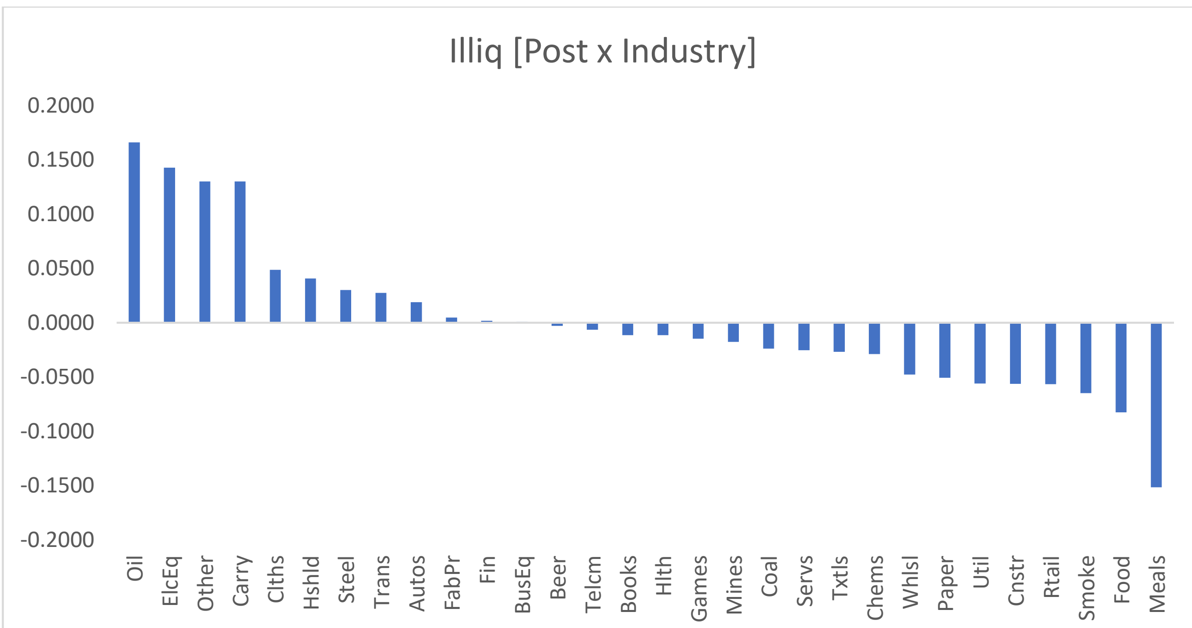


Figure 5 displays how the pandemic adversely effected ElcEq, Carry, and Other the most. ElcEq has a *[post*$_t$ x *industry*$_i$*] Illiq* beta of 0.14 while Carry and Other both had *[post*$_t$ x *industry*$_i$*] Illiq* betas of 0.13. This means that the pandemic increased these industries Amihud Illiquidity measures by .14 and .13 relative to the other industries and macroeconomic factors. On the other side of the spectrum Meals, Food and Smoke had *[post*$_t$ x *industry*$_i$*] Illiq* betas of -0.15, -0.08, and

-0.06 respectively, indicating that the pandemic decreased these industry's Amihud Illiquidity measures thus representing an improvement to the respective industry liquidity relative to relative to the other industries and other macroeconomic factors. The t-values corresponding to the results in Figure 5 are reported in Table A4.

4. Conclusion

The global COVID-19 pandemic tore through global economies, sequestering citizens to their homes for time periods ranging from a few days to two months. Millions of workers have been left without jobs requiring them to turn to governments to support them through this upheaval. Global markets are in turmoil as societies teeter along the edge of complete healthcare exhaustion and financial and economic ruin. It is clear that this unexpected outbreak effected markets across the world. This analysis provides a more in depth look at which industries were affected the most in terms of risk and liquidity.

I created an interaction variable $[Post_t$ x $Industry_i]$ which allowed me to observe the unique effect of the COVID-19 pandemic outbreak on each of the 30 industries included in this analysis relative to the remaining 29 industries. This interaction term also provides the important function of controlling for unobserved macroeconomic factors. This analysis maintained the expectation that industries would be affected significantly different by the pandemic.

I show that the pandemic significantly increased the risk in industries such as Meals, Games, and Mines, while other industries including Food, Beer, and Paper actually saw a decrease in risk as a result of the COVID-19 outbreak. I find similar results when analyzing from a liquidity perspective. The Meals, Food, Smoke, and Rtail industries all saw significant increases in liquidity, likely due to large increase in trading volume, while industries such as ElcEq, Carry, and Other experienced a deterioration of liquidity during the pandemic.

References

Alizadeh, Sassan, Michael W. Brandt, and Francis X. Diebold. "Range-Based Estimation of Stochastic Volatility Models." *SSRN Electronic Journal*, June 2002. https://doi.org/10.2139/ssrn.267788.

Amihud, Yakov. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets* 5, no. 1 (2002): 31–56. https://doi.org/10.1016/s1386-4181(01)00024-6.

"Cases in U.S." Centers for Disease Control and Prevention. Centers for Disease Control and Prevention, April 20, 2020. https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html.

Fama, E. (1965). The Behavior of Stock-Market Prices. *The Journal of Business, 38*(1), 34-105. https://www.jstor.org/stable/pdf/2350752.pdf?refreqid=excelsior%3Acd54a99d5f2ffe56f98bd4e0f28b980b

Fernandes, Nuno (2020). Economic effects of coronavirus outbreak (COVID-19) on the world economy, Working Paper.

Friedman, M. (1977). Nobel lecture: inflation and unemployment. *Journal of Political Economy, 85*(3), 451-472

Gerding, Felix, Thorsten Martin, and Florian Nagler (2020). The value of fiscal capacity in the face of a rare disaster, Working Paper.

Gormsen, N. J. and R. S. Koijen (2020). Coronavirus: Impact on stock prices and growth expectations. University of Chicago, Becker Friedman Institute for Economics Working Paper (2020-22).

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning (2020). Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages? Working Paper.

Hayek, F. (1945). The Use of Knowledge in Society. *The American Economic Review, 35*(4), 519-530.

Muccari, Robin, and Denise Chow. "Coronavirus Timeline: Tracking the Critical Moments of COVID-19." NBCNews.com. NBCUniversal News Group, April 8, 2020. https://www.nbcnews.com/health/health-news/coronavirus-timeline-tracking-critical-moments-covid-19-n1154341.

Ramelli, Stefano and Alexander F. Wagner, "Feverish Stock Price Reactions to COVID-19," 2020. Working Paper University of Zurich.

Ru, Hong, Endong Yang, and Kunru Zou, 2020, What do we learn from SARS-CoV-1 to SARS-CoV-2: Evidence from global stock markets, Working Paper.

Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly. *Industrial Management Review, 6*(2), 41.

"Timeline of Events Related to the COVID-19 Pandemic." FRASER. Accessed April 24, 2020. https://fraser.stlouisfed.org/timeline/covid-19-pandemic#43.

"WHO Timeline - COVID-19." World Health Organization. World Health Organization. Accessed April 24, 2020. https://www.who.int/news-room/detail/08-04-2020-who-timeline---covid-19.

Appendix

Table A1. Industry Volatility around COVID-19 – Univariate

This table plots average differences in daily range-based volatility by industry surrounding the COVID-19 outbreak. The industries are identified using the Fama and French 30 classifications. We use Compustat annual filings during 2019 to determine industries based on historical SIC codes. However, if the historical SIC code is missing for a particular firm, we use CRSP SICCD codes as of December 31, 2019 instead. We identify the pre-period as January 3, 2020 to February 19, 2020 and the post-period as February 20, 2020 to March 25, 2020. We report t-statistics in parentheses. We sort industries by post-pre values in ***descending order***.

Industry	Pre	Post	Post-Pre	t-value
Oil	0.0510	0.1581	0.1071	-6.9800
Meals	0.0300	0.1280	0.0980	2.1000
Games	0.0349	0.1288	0.0939	-2.1100
Mines	0.0441	0.1289	0.0848	-5.0300
Clths	0.0314	0.1067	0.0753	-3.0500
Books	0.0394	0.1121	0.0727	-3.9700
Cnstr	0.0324	0.1048	0.0725	-1.6400
Rtail	0.0400	0.1124	0.0723	-1.6300
Coal	0.0656	0.1379	0.0723	-4.1200
Util	0.0209	0.0919	0.0710	-4.0100
Telcm	0.0357	0.1060	0.0703	-2.5900
Other	0.0370	0.1071	0.0701	-4.2600
Fin	0.0263	0.0960	0.0697	-4.0900
Whlsl	0.0355	0.1049	0.0694	-3.8100
Trans	0.0353	0.1044	0.0691	-5.0100
Hshld	0.0360	0.1039	0.0680	-2.3900
Carry	0.0344	0.1016	0.0672	-3.6600
Chems	0.0357	0.1027	0.0670	-4.1900
Autos	0.0366	0.1030	0.0664	-5.0000
FabPr	0.0347	0.0994	0.0646	-3.8000
Servs	0.0368	0.1014	0.0646	-3.1000
Smoke	0.0272	0.0901	0.0629	-2.8600
Steel	0.0346	0.0975	0.0629	-1.8600
Txtls	0.0316	0.0941	0.0625	-2.6300
ElcEq	0.0415	0.1030	0.0615	-4.9600
Hlth	0.0571	0.1181	0.0611	-4.2800
Paper	0.0285	0.0894	0.0609	-1.2400
BusEq	0.0365	0.0947	0.0581	-3.9700
Beer	0.0277	0.0850	0.0573	-1.9000
Food	0.0298	0.0816	0.0518	0.4600

Table A2. Industry Volatility around COVID-19 Outbreak – Multivariate Diff-in-Diff

This table reports select results from the following regression equation estimated for each industry separately, but including all other industries as controls:

$$Rvolt_{i,t} = \alpha + \beta_1 Industry_i + \beta_2 Post_t \times Industry_i + \beta_3 Ln(Price)_{i,t} + \beta_4 Ln(MCAP)_{i,t} + \beta_5 Ln(Tradesize)_{i,t} + \beta_6 Ln(Volume)_{i,t} + \beta_7 Nasdaq_i + \delta_t + \varepsilon_{i,t}\ .$$

$Rvolt_{i,t}$ is range-based volatility measured as the natural log of the daily high ask price minus the natural log of the daily low bid price. *Industry* is a dummy variable equal to one if the observation is in the i^{th} industry and zero for the other 29 Fama and French industries. We use Compustat annual filings during 2019 to determine industries based on historical SIC codes. However, if the historical SIC code is missing for a particular firm, we use CRSP SICCD codes as of December 31, 2019 instead. $Post_t$ is an indicator variable equal to one if the industry-day observation is between February 20, 2020 and March 25, 2020 and zero if between January 3, 2020 and February 19, 2020. We also include day fixed effects, δ_t, but in doing so must remove the time-invariant $Post_t$ indicator. The remaining independent variables have previously been defined, and are measured at the industry-day level by taking equal-weighted averages across stock-day observations. For brevity, we record the estimated coefficient on the interaction term only from each regression and sort in ***descending order***. We report t-statistics in parentheses obtained from robust standard errors.

Industry	Post x Industry	t-stat	Adj. R^2	Controls	Day FE
Oil	0.0351	9.25	0.9252	Yes	Yes
Meals	0.0257	6.67	0.9221	Yes	Yes
Games	0.0220	5.63	0.9199	Yes	Yes
Mines	0.0166	4.23	0.919	Yes	Yes
Clths	0.0061	2	0.9184	Yes	Yes
Rtail	0.0046	1.16	0.9184	Yes	Yes
Util	0.0035	0.88	0.9199	Yes	Yes
Other	0.0030	0.77	0.9201	Yes	Yes
Cnstr	0.0026	0.68	0.9208	Yes	Yes
Telcm	0.0023	0.59	0.9193	Yes	Yes
Coal	0.0013	0.33	0.9181	Yes	Yes
Books	0.0010	0.26	0.9221	Yes	Yes
Hshld	0.0005	0.12	0.9204	Yes	Yes
Fin	-0.0011	-0.27	0.9183	Yes	Yes
Whlsl	-0.0015	-0.38	0.9188	Yes	Yes
Trans	-0.0023	-0.58	0.9181	Yes	Yes
Autos	-0.0027	-0.68	0.9182	Yes	Yes
Chems	-0.0030	-0.75	0.9184	Yes	Yes
Servs	-0.0030	-0.75	0.9192	Yes	Yes
Smoke	-0.0045	-1.13	0.9182	Yes	Yes
ElcEq	-0.0047	-1.19	0.9192	Yes	Yes
Carry	-0.0055	-1.39	0.9185	Yes	Yes
FabPr	-0.0058	-1.47	0.9194	Yes	Yes
Hlth	-0.0065	-1.65	0.9183	Yes	Yes
Steel	-0.0073	-1.89	0.9221	Yes	Yes
Txtls	-0.0073	-1.87	0.9200	Yes	Yes
Paper	-0.0087	-2.2	0.9185	Yes	Yes
BusEq	-0.0089	-2.26	0.9193	Yes	Yes
Beer	-0.0144	-3.64	0.9188	Yes	Yes
Food	-0.0170	-4.34	0.9202	Yes	Yes

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Table A3. Industry Illiquidity around COVID-19 – Univariate

This table reports average differences in daily Amihud (2002) illiquidity by industry surrounding the COVID-19 outbreak. *Illiq* is defined as the absolute daily return divided by dollar volume (scaled by 10^6). The industries are identified using the Fama and French 30 classifications. We use Compustat annual filings during 2019 to determine industries based on historical SIC codes. However, if the historical SIC code is missing for a particular firm, we use CRSP SICCD codes as of December 31, 2019 instead. We identify the pre-period as January 3, 2020 to February 19, 2020 and the post-period as February 20, 2020 to March 25, 2020. We report t-statistics in parentheses. We sort industries by post-pre values in ***descending order***.

Industry	Pre	Post	Post-Pre	t-value
Oil	0.153085	0.382696	0.229610837	-7.01
ElcEq	0.075615	0.286496	0.210880806	-6.47
Carry	0.096248	0.304146	0.207897947	-6.84
Other	0.172291	0.376104	0.20381237	-6.15
Clths	0.107405	0.233392	0.125986898	-6.44
Hshld	0.14608	0.260307	0.114226881	-7.17
Steel	0.180287	0.292908	0.112620982	-7.11
Trans	0.049288	0.154806	0.105517605	-6.78
Autos	0.0337	0.127666	0.093965808	-6.83
FabPr	0.070375	0.155093	0.084717647	-7.2
Fin	0.107615	0.186967	0.079352703	-6.65
Beer	0.132067	0.210942	0.078875623	-6.51
BusEq	0.076808	0.151273	0.074465164	-6.92
Books	0.028376	0.101988	0.073612312	-6.39
Games	0.13176	0.199022	0.067262007	-6.66
Telcm	0.265283	0.331386	0.066103045	-7.18
Hlth	0.098694	0.158099	0.059405307	-6.92
Coal	0.064963	0.12379	0.058826265	-6.6
Mines	0.020533	0.07501	0.054477646	-6.37
Txtls	0.032632	0.0857	0.053068097	-5.61
Chems	0.037058	0.087118	0.050060334	-6.83
Servs	0.147001	0.196104	0.049102208	-6.93
Whlsl	0.048275	0.081096	0.03282135	-6.88
Paper	0.042346	0.069305	0.026958798	-6.61
Cnstr	0.059192	0.081856	0.022664424	-6.64
Rtail	0.038852	0.058758	0.019905913	-6.37
Util	0.004783	0.022323	0.017539422	-7.33
Smoke	0.002184	0.0056	0.003415201	-7.01
Food	0.099552	0.090776	-0.00877581	-6.73
Meals	0.216779	0.153722	-0.063057	-5.99

Table A4. Industry Illiquidity around COVID-19 Outbreak – Multivariate Diff-in-Diff

This table records select results from the following regression equation estimated for each industry separately, but including all other industries as controls:

$$Illiq_{i,t} = \alpha + \beta_1 Industry_i + \beta_2 Post_t \times Industry_i + \beta_3 Ln(Price)_{i,t} + \beta_4 Ln(MCAP)_{i,t} + \beta_5 Ln(Tradesize)_{i,t} + \beta_6 Ln(Volume)_{i,t} + \beta_7 Nasdaq_i + \delta_t + \varepsilon_{i,t} .$$

Illiq is Amihud's (2002) illiquidity measure, or the absolute daily return divided by dollar volume (scaled by 10^6). *Industry* is a dummy variable equal to one if the observation is in the i^{th} industry and zero for the other 30 Fama and French industries. $Post_t$ is an indicator variable equal to one if the industry-day observation is between February 20, 2020 and March 25, 2020 and zero if between January 3, 2020 and February 19, 2020. We also include day fixed effects, δ_t, but in doing so must remove the time-invariant $Post_t$ indicator. The remaining independent variables have previously been defined, and are measured at the industry-day level by taking equal-weighted averages across stock-day observations. For brevity, we record the estimated coefficient on the interaction term only from each regression and sort in ***descending order***. We report t-statistics in parentheses obtained from robust standard errors.

Industry	Post x Industry	t-stat	Adj. R^2	Controls	Day FE
Oil	0.1661	5.28	0.2808	Yes	Yes
ElcEq	0.1429	4.38	0.2325	Yes	Yes
Other	0.1303	4.8	0.2545	Yes	Yes
Carry	0.1303	4.07	0.2494	Yes	Yes
Clths	0.0487	1.51	0.2326	Yes	Yes
Hshld	0.0409	1.27	0.2348	Yes	Yes
Steel	0.0302	0.94	0.2478	Yes	Yes
Trans	0.0275	0.85	0.2289	Yes	Yes
Autos	0.0188	0.58	0.2276	Yes	Yes
FabPr	0.0050	0.15	0.2225	Yes	Yes
Fin	0.0018	0.05	0.2226	Yes	Yes
BusEq	0.0010	0.03	0.2303	Yes	Yes
Beer	-0.0028	-0.09	0.223	Yes	Yes
Telcm	-0.0065	-0.2	0.2557	Yes	Yes
Books	-0.0114	-0.35	0.2419	Yes	Yes
Hlth	-0.0114	-0.35	0.2335	Yes	Yes
Games	-0.0148	-0.45	0.2225	Yes	Yes
Mines	-0.0178	-0.55	0.2344	Yes	Yes
Coal	-0.0241	-0.74	0.223	Yes	Yes
Servs	-0.0254	-0.78	0.2229	Yes	Yes
Txtls	-0.0267	-0.82	0.2242	Yes	Yes
Chems	-0.0288	-0.89	0.2231	Yes	Yes
Whlsl	-0.0477	-1.47	0.2313	Yes	Yes
Paper	-0.0506	-1.56	0.2244	Yes	Yes
Util	-0.0561	-1.74	0.2347	Yes	Yes
Cnstr	-0.0562	-1.73	0.2238	Yes	Yes
Rtail	-0.0566	-1.76	0.2381	Yes	Yes
Smoke	-0.0649	-2.01	0.2394	Yes	Yes
Food	-0.0827	-2.55	0.2278	Yes	Yes
Meals	-0.1516	-4.69	0.2364	Yes	Yes

Table A5. Industry Means

This table provides average values by industry for the variables used in the analysis. The variables, which have previously been defined, are measured at the stock-day level and then averaged across the Fama and French 30 industries using equal-weighting. The industries are identified using the Fama and French 30 classifications. We use Compustat annual filings during 2019 to determine industries based on historical SIC codes. However, if the historical SIC code is missing for a particular firm, we use CRSP SICCD codes as of December 31, 2019 instead. The statistics below are then estimated using these 1,710 industry day observations from January 3, 2020 to March 25, 2020.

Industry	Price	MCAP	Tradesize	Volume	Rvolt	Illiq	Nasdaq
Autos	41.96	5773131644	127	2876229	0.066	0.075	0.380
Beer	99.51	26380871701	95	1142500	0.053	0.167	0.625
Books	17.83	1458468696	116	804451	0.071	0.061	0.429
BusEq	62.14	17287514897	109	2104355	0.062	0.109	0.662
Carry	86.10	19625669616	105	1545229	0.064	0.187	0.208
Chems	60.47	6892682227	101	1038147	0.065	0.059	0.186
Clths	59.84	9731865864	85	1609883	0.064	0.163	0.355
Cnstr	83.53	3163635793	88	693193	0.064	0.069	0.315
Coal	17.31	509027926	107	604876	0.097	0.091	0.250
ElcEq	45.04	2473395043	119	1184203	0.069	0.168	0.588
FabPr	50.66	6484104419	88	688799	0.063	0.108	0.379
Fin	45.44	8850106146	85	1016022	0.057	0.142	0.650
Food	56.30	15400747142	91	1734598	0.053	0.096	0.490
Games	48.07	7910984609	128	2526638	0.076	0.161	0.591
Hlth	36.30	6060672015	127	976228	0.084	0.125	0.856
Hshld	49.64	16388303609	97	1281645	0.066	0.196	0.400
Meals	63.34	9674507164	99	1243885	0.073	0.189	0.596
Mines	38.50	8043277191	184	4266276	0.081	0.044	0.176
Oil	20.20	11453197934	166	4226918	0.098	0.254	0.198
Other	70.98	6277747645	351	1552291	0.068	0.262	0.580
Paper	44.83	9080778008	95	1098022	0.055	0.054	0.167
Rtail	73.90	21217769784	115	2059394	0.072	0.048	0.431
Servs	64.43	13201796598	109	1496485	0.065	0.169	0.619
Smoke	50.39	75396649848	106	5093409	0.055	0.004	0.000
Steel	26.37	2136737400	99	1476472	0.062	0.230	0.480
Telcm	61.90	21239173079	125	3621915	0.067	0.294	0.611
Trans	49.50	10962566556	99	2603457	0.066	0.096	0.581
Txtls	40.00	2294417529	80	259171	0.059	0.056	0.333
Util	56.01	14714890922	104	2556338	0.052	0.012	0.190
Whlsl	44.20	4098139323	90	685515	0.066	0.063	0.524