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Industry Stock Prices around Covid-19

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By Dan Cardall

Abstract

In this study, I examine how market participants respond to global uncertainty around the Covid-19 pandemic. More specifically, I analyze the industries most affected by the outbreak. The pandemic has created events never before seen at such a global level. Governments closed their country's borders and quarantined their residents. Business owners closed their doors. These unforeseen events put the world economy at a standstill. I find that these decisions caused the U.S. stock markets to crash by more than 30%. The industries that experienced the most negative value-weighted abnormal returns were Carry, Meals, and Books. The industries that exhibited the most positive value-weighted abnormal returns were Transportation, Healthcare, and Smoke. Perhaps policies and financial assistance can be better allocated to those industries that suffered the most. Additionally, investment managers might be able to use this information to hedge against future losses, in the case of a similar pandemic.

I. Introduction

The United States (U.S.) and most of the world started 2020 with a strong economic outlook. Unemployment was low, the stock market was high, and most macroeconomic indicators suggested another bullish year. However, on January 20th, the U.S. reported its first known case of Covid-19. Three days later, China quarantined the province of Wuhan entirely from the rest of the country. Shortly thereafter, on January 31st, U.S. President, Donald Trump, evoked a travel ban on foreign nationals who had been to China in the previous 14 days. This immediately followed an announcement from the World Health Organization (WHO) concerning a public health emergency of international concern. Throughout the next several weeks, news of the virus continued as more cases were reported. By mid-February, concern was growing of a global pandemic and catastrophic loss of life. On February 29th, the U.S. reported its first death caused from the Covid-19 virus. On March 13th, President Trump declared a national emergency. Two days later, the Center for Disease Control issued advisory against gathering of more than 50 people. The state of New York was the first to close its schools and the rest of the country followed suit shortly after. The U.S. quickly followed the rest of the world into lockdowns and quarantines.

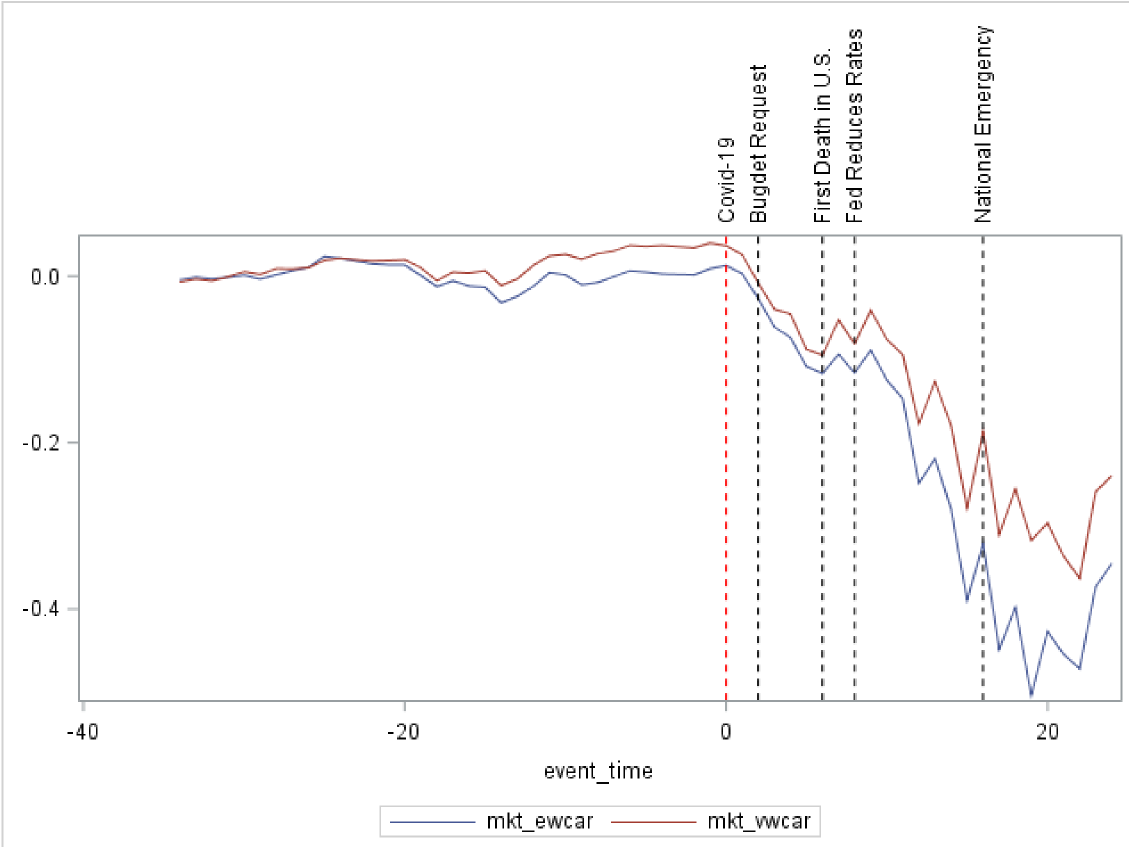

Figure 1 shows the cumulative market returns from January 2, 2020 to March 25, 2020. As can be seen in the figure, from February 20th to March 25th, prices dropped in a near free fall. On February 19th, 2020, the S&P 500 index achieved its all-time high of 3,393 points, and just over a month later it was at its year low of 2,192 points. In what felt like overnight, the U.S. economy, as well as the world economy, all but stopped. Governments implemented shutdowns and closures limiting the amount of business that could be conducted. Companies were forced to figure out how to work remotely in order to continue generated revenues. Many industries simply closed their doors, went home, and were told to wait for further notice. This had never happened before, at least not to this scale.

In this study, I take an unbiased approach to the data to examine how information concerning the Covid-19 pandemic is incorporated into equity prices. There are several studies concerning market prices and efficiency concerning the pandemic, such as firm value, financial policy, and international trading (see e.g., Amar et al., 2020; Ayed, Medini, and Lamouchi, 2020; Detemple, 2020; Mzoughi et al., 2020; Ramelli, Stefano and Wagner, 2020; Tashanova et al., 2020; Yan, 2020, among others). Traditional finance paradigms insufficiently explaining confidence of financial institutions as well as stock price volatility (Bansal, 2020). I contribute to this literature by showing that The industries that experienced the most negative value-weighted abnormal returns were Carry, Meals, and Books. Additionally, the industries that exhibited the most positive value-weighted abnormal returns were Transportation, Healthcare, and Smoke.

First Hayek (1945) and later Fama (1965), discussed the idea of "the man on the spot", where those with intimate knowledge of events relay information to markets through prices. As all participants in the market incorporate their knowledge of events into asset prices, it helps create a more complete view of the situation as it transpires. Hayek (1945) stated the following, "In most cases the noncentralized knowledge is the greater influencer since it responds more quickly and represents the more current state of events." The efficiency of the market in portraying that information can help all who consider the information relevant and important. This includes policymakers, regulators, and investors. Perhaps policies and financial assistance can be better allocated to those industries that suffered the most. Additionally, investment managers might be able to use this information to hedge against future losses, in the case of a similar pandemic.

II. Data Description

The data I use in the analysis come from three main sources. I use Compustat annual filings from 2019 to determine industries based on historical Standard Industrial Classification (SIC) codes. For those firms missing in Compustat, I use, from the Center of Research and Security Prices (CRSP) database, SICCD codes as of December 31, 2019 instead. The trade characteristics are measured using data from the New York Stock Exchange (NYSE) Daily Trade and Quote (DTAQ) database. The variables are measured at the stock-day level and averaged across the Fama and French 30 industries using equal-weighting. I then averaged the variables across the sample period from February 20, 2020 to March 25, 2020, leaving a cross-sectional sample of 30.

Variable	Mean	Median	Std. Dev.	Minimum	Maximum
Price	50.036	46.939	24.762	12.434	124.258
MCAP (in $billions)	10.9	9.17	9.24	.67	45.7
Tradesize	114.371	110.89	24.988	84.69	184
Volume (in 100,000s)	2.45	2.15	1.44	.15	6.49
Rvolt	.106	.101	.019	.078	.164
Illiq	.146	.127	.115	.005	.493
Nasdaq	.387	.417	.213	0	.957

Table 1 contains the summary statistics of the variables used throughout the analysis. *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 price minus the natural log of the daily low bid price. *Illiq* is Ahmud's (2002) illiquidity measure, or the absolute daily return divided by the dollar-volume (scaled by 10^6). *MCAP* is the market capitalization, or the price times the shares outstanding. *MCAP* is estimated using data from the center for Research in Security Prices (CRSP) on December 31, 2019. *Nasdaq* is a dummy variable used to determine which securities are traded on NASDAQ platform. The average price is $50.036. The average MCAP is $10.9 billion. The average trades size is 114.371 shares.

	Price	Tradesize	Volume	Rvolt	Illiq	MCAP	Nasdaq
Price	1						
Tradesize	-0.447	1					
Volume	-0.188	0.579	1				
Rvolt	-0.488	0.676	0.348	1			
Illiq	0.121	0.129	0.124	0.002	1		
MCAP	0.234	-0.013	0.498	-0.071	0.121	1	
Nasdaq	0.119	0.008	-0.287	-0.259	0.301	-0.26	1

Table 2 reports the Pearson correlation coefficients for the variables used in the analysis, with p-values in brackets. The correlation coefficients are produced using the previously mentioned cross-sectional data. This helps to see if the variables have correlation with each and, therefore may be conveying the same information. This also can be used in the decision to include the variables in the regression analysis.

Industry	Description	# of Firms
Autos	Automobiles and Trucks	41
Beer	Beer & Liquor	6
Books	Printing and Publishing	19
BusEq	Business Equipment	194
Carry	Aircraft, Ships, and Railroad Equipment	17
Chems	Chemicals	51
Clths	Apparel	22
Cnstr	Construction and Construction Materials	70
Coal	Coal	5
ElcEq	Electrical Equipment	32
FabPr	Fabricated Products and Machinery	84
Fin	Banking, Insurance, Real Estate, and Trading	471
Food	Food Products	47
Games	Recreation	37
Hlth	Healthcare, Medical Equipment, Pharmaceutical Products	219
Hshld	Consumer Goods	33
Meals	Restaurants, Hotels, and Motels	47
Mines	Precious Metals, Non-Metallic, and Industrial Metal Mining	21
Oil	Petroleum and Natural Gas	91
Other	Everything Else	678
Paper	Business Supplies and Shipping Containers	24
Rtail	Retail	114
Servs	Personal and Business Services	310
Smoke	Tobacco Products	5
Steel	Steel Works Etc.	26
Telcm	Communication	54
Trans	Transportation	53
Txtls	Textiles	7
Util	Utilities	72
Whlsl	Wholesale	92

Table 3 reports the number of firms used in each of the Fama and French 30 industries. As previously mentioned, I used Compustat annual filings from 2019 to determine industries based on historical SIC codes. For those firms missing in Compustat I used CRSP SICCD codes as of December 31, 2019 instead.

Industry	Price	Tradesize	Volume (in 100,000s)	Rvolt	Illiq	MCAP (in $billions)	Nasdaq
Autos	27.08	128.9387	39.6676	0.1016	0.0886	4.8672	0.2683
Beer	101.67	94.7984	9.6012	0.0779	0.1305	3.4068	0.5000
Books	47.93	132.3121	6.73	0.1283	0.1789	1.0742	0.5263
BusEq	53.92	110.3417	31.1339	0.0930	0.1681	18.3586	0.6753
Carry	81.02	122.1419	27.8526	0.1122	0.4014	25.6135	0.1765
Chems	54.63	103.1096	12.6567	0.0985	0.0646	6.7404	0.1765
Clths	49.60	94.4970	20.1513	0.0990	0.0536	11.2620	0.4091
Cnstr	83.36	90.2155	10.4058	0.1049	0.0369	3.4478	0.2286
Coal	12.43	128.1167	21.0778	0.1644	0.0361	0.8308	0.0000
ElcEq	46.13	124.6654	16.6031	0.0964	0.0433	2.8659	0.5625
FabPr	46.74	94.6422	22.3568	0.0958	0.2725	8.5150	0.3214
Fin	44.17	90.7961	16.7784	0.0946	0.1652	9.2969	0.5732
Food	124.26	86.3554	23.4131	0.0820	0.1559	19.3212	0.4255
Games	34.34	130.1512	30.0402	0.1267	0.1243	7.0915	0.4865
Hlth	54.57	120.2785	17.3434	0.1069	0.1388	12.6299	0.6575
Hshld	44.53	90.1683	18.2629	0.0984	0.2357	17.0396	0.2121
Meals	65.05	109.6016	23.9115	0.1258	0.1196	12.1046	0.4255
Mines	27.28	177.6121	44.1307	0.1138	0.0934	6.9088	0.1905
Oil	17.20	183.9998	64.9299	0.1548	0.2280	11.5785	0.1648
Other	24.82	152.4884	10.9214	0.1178	0.2397	3.0454	0.9572
Paper	37.60	84.6902	10.8162	0.0917	0.0311	4.1625	0.2083
Rtail	56.69	120.8389	29.3022	0.1130	0.0490	14.0492	0.3684
Servs	63.90	114.7932	20.6439	0.1001	0.2054	19.0811	0.4903
Smoke	30.77	121.9068	47.9487	0.1118	0.0269	45.6502	0.0000
Steel	23.56	111.4372	21.9627	0.0948	0.3051	3.5075	0.5000
Telcm	70.84	129.9791	45.9750	0.1045	0.4927	17.3380	0.5741
Trans	47.13	104.0964	44.6636	0.1011	0.0488	13.0479	0.5472
Txtls	26.85	87.1709	1.5024	0.0874	0.1816	0.6704	0.4286
Util	63.60	94.8621	32.4918	0.0890	0.0050	15.6790	0.1528
Whlsl	39.40128	96.1213	12.6303	0.1017	0.0681	9.0392	0.4022

Table 4 contains the average values by industry of the variables used during the analysis. Each security within an industry data was generated by using the stock-day level over the sample period and then compiled to generate averages for each industry. The observations are then averaged across the sample period from February 20, 2020 to March 25, 2020, leaving a cross-sectional sample of 30. The variables have previously been defined.

III. Empirical Results

In this section, I look at the cumulative abnormal returns (CARs) for each industry using four different methods. I want to see the results for each industry and how they are affected by Covid-19. I then want to know how each of the variables influenced the CARs to see if we could use the model to predicts behaviors in the event of another pandemic.

	Raw	No Market Model			Market Model	
Industry	CR	E-W	V-W	Industry	E-W	V-W
Oil	-0.65134	-0.29708	-0.37174	Carry	-0.20839	-0.26284
Carry	-0.54396	-0.18971	-0.26437	Meals	-0.21426	-0.25212
Books	-0.49329	-0.13904	-0.21369	Books	-0.1708	-0.24348
Meals	-0.47889	-0.12464	-0.1993	Oil	-0.09177	-0.20793
Autos	-0.44597	-0.09172	-0.16638	Txtls	-0.13498	-0.20778
Cnstr	-0.42976	-0.07551	-0.15016	Util	-0.19204	-0.18706
Mines	-0.42558	-0.07133	-0.14598	Mines	-0.09246	-0.17387
Clths	-0.41239	-0.05813	-0.13279	Fin	-0.09098	-0.15135
Txtls	-0.40878	-0.05453	-0.12919	Cnstr	-0.05809	-0.13397
Steel	-0.40859	-0.05434	-0.129	Paper	-0.03388	-0.10382
Paper	-0.39921	-0.04495	-0.11961	Autos	0.005672	-0.09632
Games	-0.39824	-0.04399	-0.11864	Clths	-0.03304	-0.09143
FabPr	-0.3927	-0.03844	-0.1131	Hshld	-0.02548	-0.0897
Fin	-0.37819	-0.02394	-0.09859	Beer	-0.06086	-0.08835
Hshld	-0.35973	-0.00548	-0.08014	Games	-0.01935	-0.0836
Whlsl	-0.35637	-0.00211	-0.07677	Telcm	-0.02424	-0.07709
Servs	-0.35197	0.002279	-0.07238	Whlsl	0.006751	-0.06481
Coal	-0.35071	0.003548	-0.07111	Rtail	0.01911	-0.06378
Rtail	-0.34842	0.005835	-0.06882	FabPr	0.020703	-0.05618
Chems	-0.34799	0.006268	-0.06839	ElcEq	0.019993	-0.05458
ElcEq	-0.34423	0.010024	-0.06463	Food	-0.04076	-0.05064
Telcm	-0.34234	0.011913	-0.06274	Steel	0.043717	-0.04987
Other	-0.32898	0.025269	-0.04939	Servs	0.008268	-0.04322
Trans	-0.30681	0.047439	-0.02722	Other	0.039156	-0.03308
BusEq	-0.29804	0.056217	-0.01844	Chems	0.085575	0.004411
Util	-0.28922	0.065034	-0.00962	Coal	0.097767	0.007508
Beer	-0.28139	0.072864	-0.00179	BusEq	0.082815	0.02507
Hlth	-0.25125	0.103005	0.028349	Trans	0.111241	0.035033
Food	-0.1808	0.173456	0.0988	Hlth	0.126561	0.054065
Smoke	-0.1733	0.180948	0.106292	Smoke	0.095355	0.061534

Table 5 contains the results of the CARs during the time period I am examining. Figure 3 is a visual representation of the CARS by industry. The abnormal returns were estimated as the daily difference between the return for a given security minus the sample market return. This was done using both an equal-weighted and value-weighted sample market return. This allows me to see what industries were affected the most during the pandemic period. The market model does attempt to hold constant some of the systematic risk which explains why the returns are, less deviated from their mean, than the no market model results. Using the market model value-weighted results, I find that the Carry industry, which includes aircrafts, ships, and railroads, has been the most affected, with a CAR of -26.28%. The second most affected industry, was Meals, which includes restaurants, motels, and hotels, with CAR of -25.2%. The third most affected industry is books, which includes printing and publishing, with a CAR return of -24.35%. The fourth most affected industry is Oil, with a CAR of -20.79%.[1] The fifth most affected industry is Textiles, with a -20.78% CAR. The Smoke industry, or tobacco products, showed the highest positive CAR at 6.15%. Healthcare, which includes health, medical equipment, and pharmaceuticals, also had a positive CAR at 5.41%. Transportation was the third highest positive CAR at 3.5%.

[1] It is important to note that there was an oil "war" happening between Russia and OPEC that began around March 8th, 2020, after an agreement could not be made concerning production with both parties deciding to continue over producing.

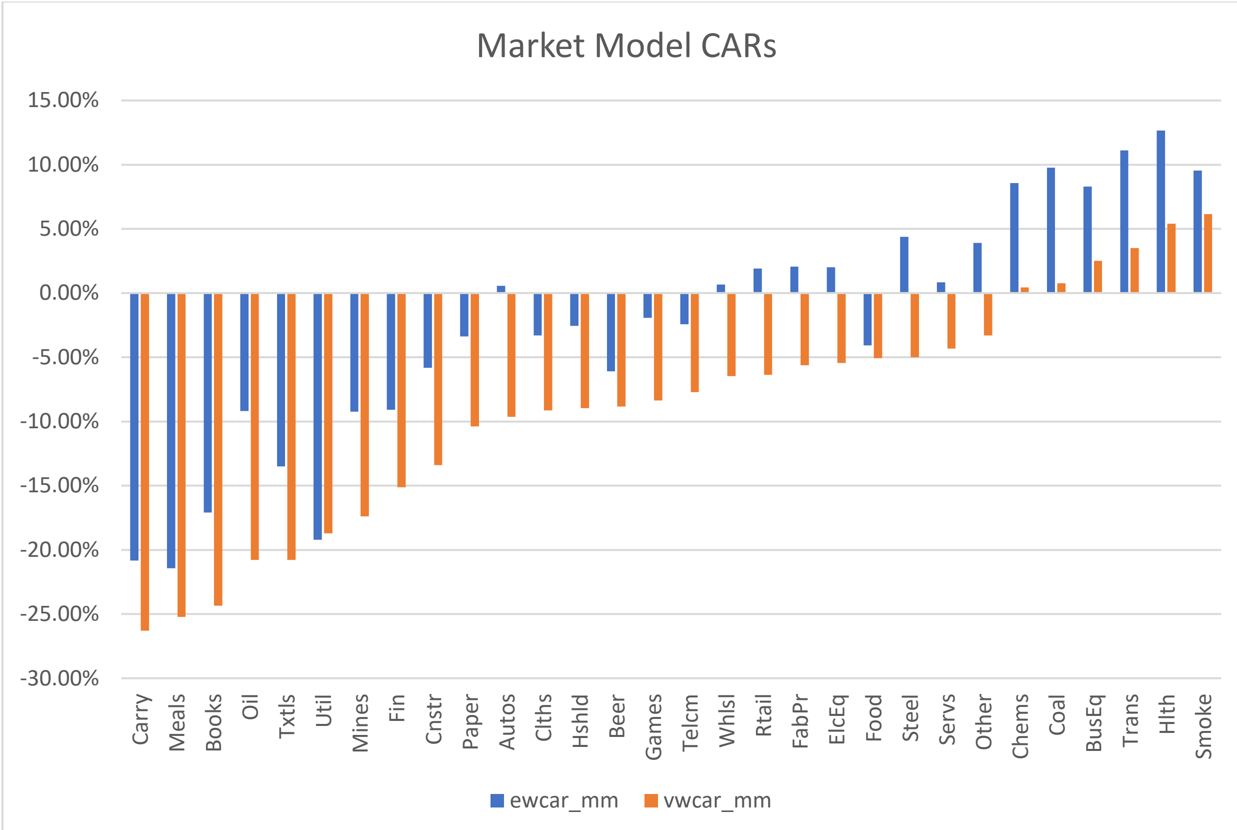

Table 6 contains the results from four multivariate tests that I performed using the cumulative abnormal returns from table 5. I did this to see if any of the variables included in this study were driving the CARs results produced in table 5. The following multivariate regression was estimated:

$$CAR_i = \alpha + \beta_1 Ln(Price_i) + \beta_2 Ln(MCAP_i) + \beta_3 Ln(Tradesize_i) + \beta_4 Ln(Volume_i) + \beta_5 Rvolt_i + \beta_6 Illiq_i + \beta_7 Nasdaq_i + \varepsilon_{i,t}$$

The dependent variable is the cumulative abnormal returns (CARs) for stock *i* over the period February 20, 2020 to March 25, 2020. The variables have previously been defined. The advantage of using the natural log with some of the variable is to be able to determine a percent change rather than a dollar change in relation to the CARs.

	No Market Model		Market Model	
Variable	E-W	V-W	E-W	V-W
lnprice	-0.014	-0.014	-0.100**	-0.076
	(0.045)	(0.045)	(0.047)	(0.044)
lnmcap	0.023	0.023	0.010	0.017
	(0.030)	(0.030)	(0.032)	(0.030)
lntradesize	-0.075	-0.075	-0.117	-0.132
	(0.139)	(0.139)	(0.145)	(0.136)
lnvolume	0.011	0.011	0.046	0.042
	(0.043)	(0.043)	(0.045)	(0.042)
rvolt	-1.638	-1.638	-0.651	-0.676
	(1.354)	(1.354)	(1.412)	(1.329)
illiq	-0.307*	-0.307*	-0.205	-0.230
	(0.154)	(0.154)	(0.160)	(0.151)
nasdaq	0.124	0.124	0.179*	0.176*
	(0.091)	(0.091)	(0.095)	(0.089)
Constant	-0.127	-0.201	0.039	-0.146
	(0.614)	(0.614)	(0.640)	(0.602)
Observations	30	30	30	30
R^2	0.398	0.398	0.313	0.322

IV. Conclusion

During the ongoing Covid-19 pandemic we have been overwhelmed with information. Sifting through what information is reliable and relevant is almost impossible. Applying Hayek's (1945) theory allows us to see what all those involved in the markets combined point of view is. I believe the markets are efficient although at times emotional. Evaluating the industries cumulative abnormal returns help to see the consequences of the governments policies. It allows us to see what industries were most affected and provides data to be considered in the future if such an event as Covid-19 should happen again. One thing to consider is that seeing the results in hind sight can lead us to try and predict future out comes. In this case there is not enough confidence or strength in the model to allow for such predictions. Unfortunately, the multivariate model only accounted for 30% of the of CARs leaving 70% still described in other variables not used. This also confirm Hayek's (1945) theory of decentralized knowledge.

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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 variables are then averaged across the sample period from February 20, 2020 to March 25, 2020, leaving a cross-sectional sample of 30. The statistics below are then estimated using these cross-sectional data. The trade characteristics are measured using data from the NYSE Daily Trade and Quote (DTAQ) database. Specifically, *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 price times shares outstanding, is estimated using data from the Center for Research in Security Prices (CRSP) on December 31, 2019.

Variable	Mean	Median	Std. Dev.	Minimum	Maximum
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Illiq	.146	.127	.115	.005	.493
Nasdaq	.387	.417	.213	0	.957

Table 2. Correlation Matrix

This table reports Pearson correlation coefficients for the variables used in the analysis, with p-values in brackets. The variables have previously been defined. 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 variables are then averaged across the sample period from February 20, 2020 to March 25, 2020, leaving a cross-sectional sample of 30. The correlation coefficients are then produced using these cross-sectional data. We report p-values in parentheses testing if the correlation coefficient is different from zero.

	Price	Tradesize	Volume	Rvolt	Illiq	MCAP	Nasdaq
Price	1						
Tradesize	-0.447	1					
Volume	-0.188	0.579	1				
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Nasdaq	0.119	0.008	-0.287	-0.259	0.301	-0.26	1

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	41
Beer	Beer & Liquor	6
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Steel	Steel Works Etc.	26
Telcm	Communication	54
Trans	Transportation	53
Txtls	Textiles	7
Util	Utilities	72
Whlsl	Wholesale	92

Table 4. Industry Means

This table provides average values by industry for the variables used in the analysis, where 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 variables have previously been defined. The variables are measured to the stock-day level and then averaged across industries using equal-weighting. The observations are then averaged across the sample period from February 20, 2020 to March 25, 2020, leaving a cross-sectional sample of 30.

Industry	Price	Tradesize	Volume (in 100,000s)	Rvolt	Illiq	MCAP (in $billions)	Nasdaq
Autos	27.08	128.9387	39.6676	0.1016	0.0886	4.8672	0.2683
Beer	101.67	94.7984	9.6012	0.0779	0.1305	3.4068	0.5000
Books	47.93	132.3121	6.73	0.1283	0.1789	1.0742	0.5263
BusEq	53.92	110.3417	31.1339	0.0930	0.1681	18.3586	0.6753
Carry	81.02	122.1419	27.8526	0.1122	0.4014	25.6135	0.1765
Chems	54.63	103.1096	12.6567	0.0985	0.0646	6.7404	0.1765
Clths	49.60	94.4970	20.1513	0.0990	0.0536	11.2620	0.4091
Cnstr	83.36	90.2155	10.4058	0.1049	0.0369	3.4478	0.2286
Coal	12.43	128.1167	21.0778	0.1644	0.0361	0.8308	0.0000
ElcEq	46.13	124.6654	16.6031	0.0964	0.0433	2.8659	0.5625
FabPr	46.74	94.6422	22.3568	0.0958	0.2725	8.5150	0.3214
Fin	44.17	90.7961	16.7784	0.0946	0.1652	9.2969	0.5732
Food	124.26	86.3554	23.4131	0.0820	0.1559	19.3212	0.4255
Games	34.34	130.1512	30.0402	0.1267	0.1243	7.0915	0.4865
Hlth	54.57	120.2785	17.3434	0.1069	0.1388	12.6299	0.6575
Hshld	44.53	90.1683	18.2629	0.0984	0.2357	17.0396	0.2121
Meals	65.05	109.6016	23.9115	0.1258	0.1196	12.1046	0.4255
Mines	27.28	177.6121	44.1307	0.1138	0.0934	6.9088	0.1905
Oil	17.20	183.9998	64.9299	0.1548	0.2280	11.5785	0.1648
Other	24.82	152.4884	10.9214	0.1178	0.2397	3.0454	0.9572
Paper	37.60	84.6902	10.8162	0.0917	0.0311	4.1625	0.2083
Rtail	56.69	120.8389	29.3022	0.1130	0.0490	14.0492	0.3684
Servs	63.90	114.7932	20.6439	0.1001	0.2054	19.0811	0.4903
Smoke	30.77	121.9068	47.9487	0.1118	0.0269	45.6502	0.0000
Steel	23.56	111.4372	21.9627	0.0948	0.3051	3.5075	0.5000
Telcm	70.84	129.9791	45.9750	0.1045	0.4927	17.3380	0.5741
Trans	47.13	104.0964	44.6636	0.1011	0.0488	13.0479	0.5472
Txtls	26.85	87.1709	1.5024	0.0874	0.1816	0.6704	0.4286
Util	63.60	94.8621	32.4918	0.0890	0.0050	15.6790	0.1528
Whlsl	39.40128	96.1213	12.6303	0.1017	0.0681	9.0392	0.4022

Table 5. Industry No Market Model CARs around Covid-19

This table reports cumulative returns (CRs), no market model (NOMM) cumulative abnormal returns (CARs), and market model CARs at the industry level around the Covid-19 outbreak. We cumulate returns from February 20, 2020 to March 25, 2020. Abnormal returns are estimated as the daily differences between the return for a given stock minus the equal-weighted (E-W) or value-weighted (V-W) sample market return. The market model is estimated using E-W and V-W market returns and stock returns from October 1, 2018 to September 30, 2019. We average the stock-level CARs (or residuals from the market model) by industry, according to the Fama and French 30 industry 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 industry-day averages are then cumulated over the sample period. We sort industries by V-W returns.

	Raw	No Market Model		Market Model		
Industry	CR	E-W	V-W	Industry	E-W	V-W
Oil	-0.65134	-0.29708	-0.37174	Carry	-0.20839	-0.26284
Carry	-0.54396	-0.18971	-0.26437	Meals	-0.21426	-0.25212
Books	-0.49329	-0.13904	-0.21369	Books	-0.1708	-0.24348
Meals	-0.47889	-0.12464	-0.1993	Oil	-0.09177	-0.20793
Autos	-0.44597	-0.09172	-0.16638	Txtls	-0.13498	-0.20778
Cnstr	-0.42976	-0.07551	-0.15016	Util	-0.19204	-0.18706
Mines	-0.42558	-0.07133	-0.14598	Mines	-0.09246	-0.17387
Clths	-0.41239	-0.05813	-0.13279	Fin	-0.09098	-0.15135
Txtls	-0.40878	-0.05453	-0.12919	Cnstr	-0.05809	-0.13397
Steel	-0.40859	-0.05434	-0.129	Paper	-0.03388	-0.10382
Paper	-0.39921	-0.04495	-0.11961	Autos	0.005672	-0.09632
Games	-0.39824	-0.04399	-0.11864	Clths	-0.03304	-0.09143
FabPr	-0.3927	-0.03844	-0.1131	Hshld	-0.02548	-0.0897
Fin	-0.37819	-0.02394	-0.09859	Beer	-0.06086	-0.08835
Hshld	-0.35973	-0.00548	-0.08014	Games	-0.01935	-0.0836
Whlsl	-0.35637	-0.00211	-0.07677	Telcm	-0.02424	-0.07709
Servs	-0.35197	0.002279	-0.07238	Whlsl	0.006751	-0.06481
Coal	-0.35071	0.003548	-0.07111	Rtail	0.01911	-0.06378
Rtail	-0.34842	0.005835	-0.06882	FabPr	0.020703	-0.05618
Chems	-0.34799	0.006268	-0.06839	ElcEq	0.019993	-0.05458
ElcEq	-0.34423	0.010024	-0.06463	Food	-0.04076	-0.05064
Telcm	-0.34234	0.011913	-0.06274	Steel	0.043717	-0.04987
Other	-0.32898	0.025269	-0.04939	Servs	0.008268	-0.04322
Trans	-0.30681	0.047439	-0.02722	Other	0.039156	-0.03308
BusEq	-0.29804	0.056217	-0.01844	Chems	0.085575	0.004411
Util	-0.28922	0.065034	-0.00962	Coal	0.097767	0.007508
Beer	-0.28139	0.072864	-0.00179	BusEq	0.082815	0.02507
Hlth	-0.25125	0.103005	0.028349	Trans	0.111241	0.035033
Food	-0.1808	0.173456	0.0988	Hlth	0.126561	0.054065
Smoke	-0.1733	0.180948	0.106292	Smoke	0.095355	0.061534

Table 6. Cross-Sectional Regression of No Market Model Value-Weighted CARs around Covid-19

This table reports the results from the following cross-sectional regression equation:

$$CAR_i = \alpha + \beta_1 Ln(Price_i) + \beta_2 Ln(MCAP_i) + \beta_3 Ln(Tradesize_i) + \beta_4 Ln(Volume_i) + \beta_5 Rvolt_i + \beta_6 Illiq_i + \beta_7 Nasdaq_i + \varepsilon_{i,t}$$

where the dependent variable is the cumulative abnormal returns (CARs) for stock *i* over the period February 20, 2020 to March 25, 2020. Abnormal returns are estimated as the daily differences between the return for a given stock minus the equal-weighted (E-W) or value-weighted (V-W) sample market return. The market model is estimated using E-W and V-W market returns and stock returns from October 1, 2018 to September 30, 2019. We average the stock-level CARs (or residuals from the market model) by industry, according to the Fama and French 30 industry 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 industry-day averages are then cumulated over the sample period. All independent variables have previously been defined. We report *t*-statistics in parentheses obtained from robust standard errors.

	No Market Model		Market Model	
Variable	E-W	V-W	E-W	V-W
lnprice	-0.014	-0.014	-0.100**	-0.076
	(0.045)	(0.045)	(0.047)	(0.044)
lnmcap	0.023	0.023	0.010	0.017
	(0.030)	(0.030)	(0.032)	(0.030)
lntradesize	-0.075	-0.075	-0.117	-0.132
	(0.139)	(0.139)	(0.145)	(0.136)
lnvolume	0.011	0.011	0.046	0.042
	(0.043)	(0.043)	(0.045)	(0.042)
rvolt	-1.638	-1.638	-0.651	-0.676
	(1.354)	(1.354)	(1.412)	(1.329)
illiq	-0.307*	-0.307*	-0.205	-0.230
	(0.154)	(0.154)	(0.160)	(0.151)
nasdaq	0.124	0.124	0.179*	0.176*
	(0.091)	(0.091)	(0.095)	(0.089)
Constant	-0.127	-0.201	0.039	-0.146
	(0.614)	(0.614)	(0.640)	(0.602)
Observations	30	30	30	30
R^2	0.398	0.398	0.313	0.322

Figure 1. Market CARs around Covid-19

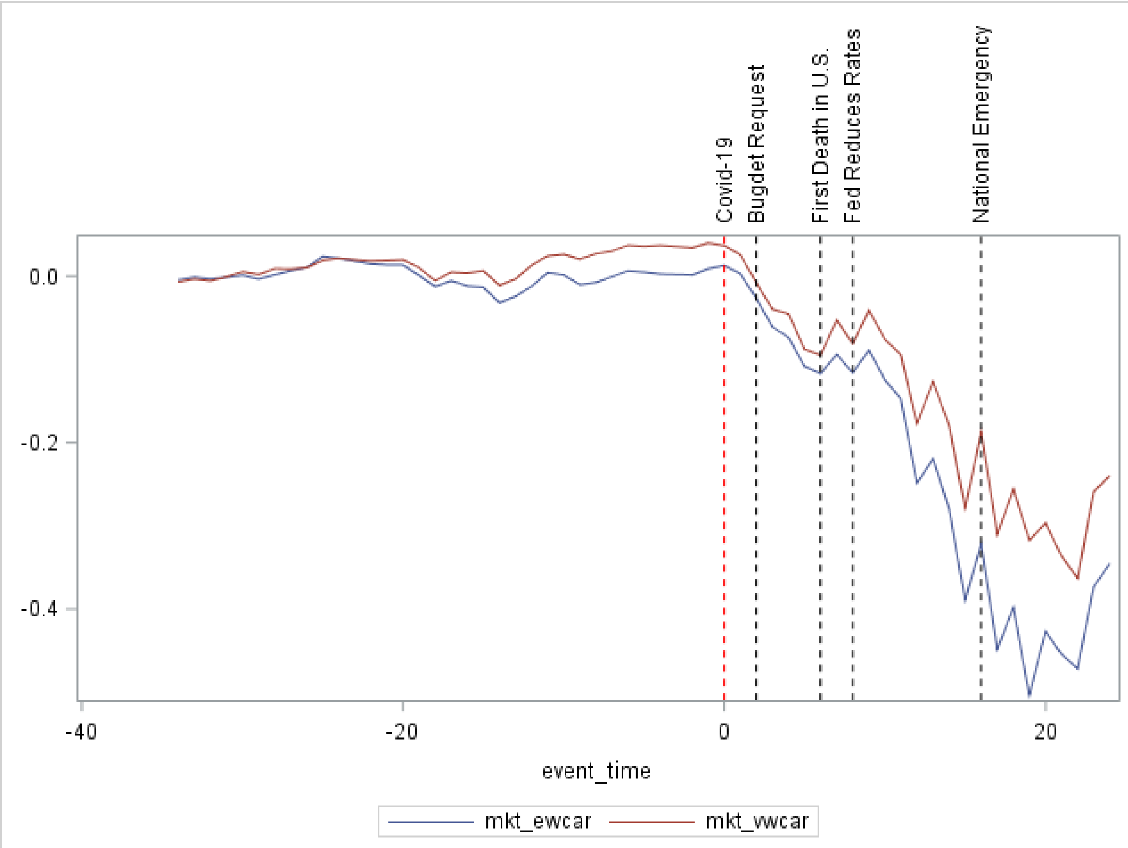

Figure 2. Industry No Market Model CARs around Covid-19

This figure plots no market model cumulative abnormal returns (CARs) at the industry level around the Covid-19 outbreak. We cumulate returns, by stock, from February 20, 2020 to March 25, 2020. Abnormal returns are estimated as the daily differences between the return for a given stock minus the equal-weighted (E-W) or value-weighted (V-W) sample market return. We then average the stock-level CARs by industry, according to the Fama and French 30 industry 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 industry-day averages are then cumulated over the sample period.

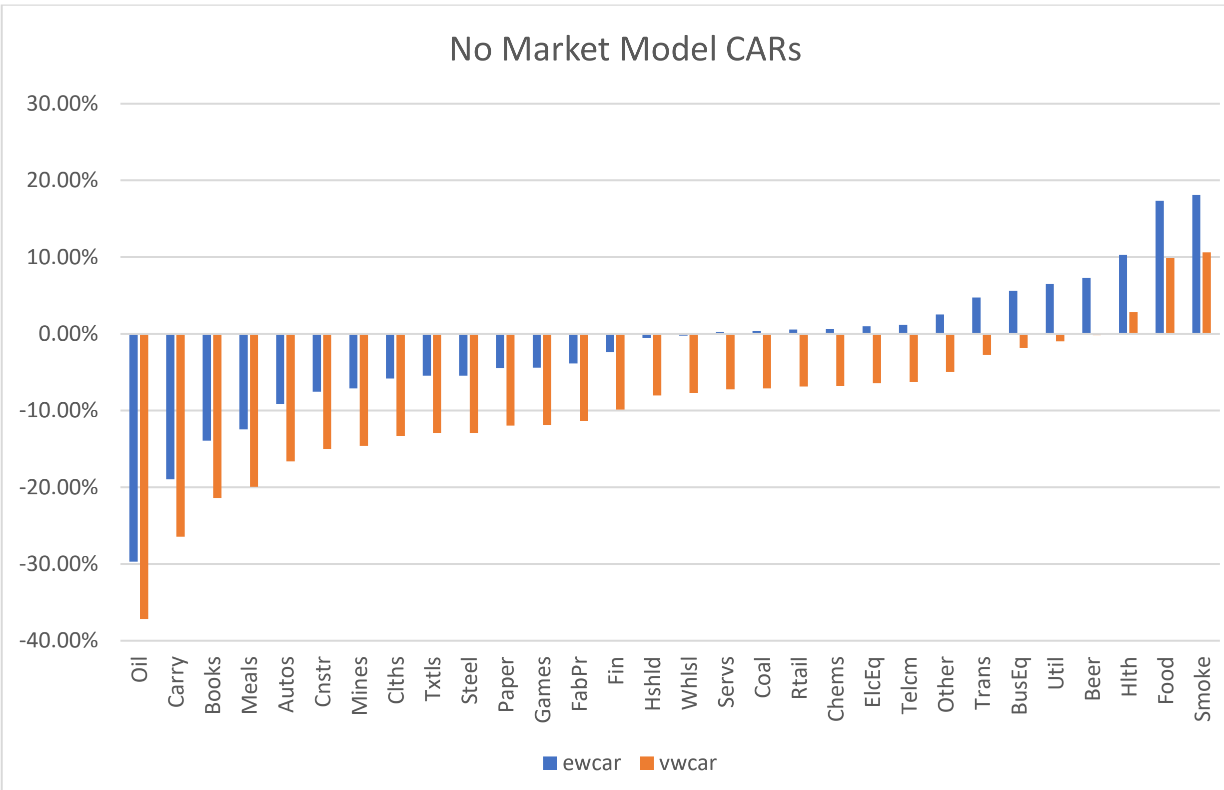

Figure 3. Industry Market Model CARs around Covid-19

This table reports market model cumulative abnormal returns (CARs) at the industry level around the Covid-19 outbreak. The market model is estimated using equal-weighted (E-W) and value-weighted (V-W) market returns and stock returns from October 1, 2018 to September 30, 2019. We cumulate residuals using the market estimates, by stock, from February 20, 2020 to March 25, 2020. We then average the stock-level CARs by industry, according to the Fama and French 30 industry 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 industry-day averages are then cumulated over the sample period.