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Policy uncertainty sensitivity, COVID-19 and industry returns in the United States

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Abstract

This paper examines if industries with higher economic policy uncertainty (EPU) sensitivity also respond differently to the evolution of COVID-19 pandemic. Initially, industries are allocated into decile portfolios according to their sensitivity to the US-EPU shocks, then portfolio returns are conditioned against changes in daily cases and deaths, respectively. After controlling for the standard risk-factors of equity returns, neither the cases nor deaths can load significantly against the returns of portfolio with the highest negative EPU exposure. However, industries which respond positively to the US-EPU shocks also respond positively to increases in cases and deaths.

Keywords: Policy uncertainty; COVID-19; Industry returns
JEL Classification Codes: G10, G11

1. Introduction

The COVID-19 pandemic brought about unprecedented policy decisions by the governments worldwide. As a result, the economic policy uncertainty (EPU) index of Baker (2016) has reached its highest level ever and stayed well above its pre-pandemic levels until the end of 2020. Several empirical papers document the negative impact of policy uncertainty on financial markets (e.g. Arouri et al., 2016; Bali et al., 2017, Bernal et al., 2016; Dakhlaoui and Aloui, 2016; Demir and Ersan, 2018; Hu et al., 2018; Phan et al., 2018). Also, there are empirical papers which show the negative impact of the COVID-19 pandemic on the financial markets (e.g., Baker et al., 2020; Shazad et al., 2020; Zaremba et al., Zheng et al., 2020).

There are several important channels which the COVID-19 pandemic may influence uncertainty about government policies as well as financial markets. First, due to initial lockdown decisions by the governments, economic activity has suddenly stopped (Huynh et al. 2022). Subsequent policy uncertainty shocks increased concerns about the future of business environment which led investors to revise their cash-flow expectations and risk perceptions (e.g., Landier and Thesmar, 2020). As a result, stock prices depressed. Empirical evidence shows that COVID-19 has led to a decline in liquidity (Baig et al., 2021), an increase in co-

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movement among equity market returns (Akhtaruzzaman et al., 2020), systematic risk spillovers (Huynh et al. 2022), and to a shift in the structure of the risk-return relationship (Azimli, 2020). Furthermore, Zaremba et al. (2020) document that return volatility is positively related to the stringency of government restrictions and the uncertainty related to future policy paths. The second channel is the flight to safety behavior amid to uncertainty. Investor loss aversion is more sensitive to acute loses than gains (Tversky and Kahneman, 1998). Amid to bad news, investors may sell their holdings of risky stocks and shift their portfolios towards safer assets (Sarwar, 2017), leading to depressed stock prices. For instance, Huynh et al. (2021) document a negative relationship among their novel feverish sentiment index and global stock returns. Accordingly, the COVID-19 pandemic should affect policy uncertainty and returns as well as the uncertainty-return association.

Against this backdrop, we examine if industries with higher return sensitivity to policy uncertainty shocks in the US respond differently to the evolution of the COVID-19 pandemic. Initially, innovations in the daily US-EPU index are extracted by using an ARMA (1, 1) model and the sensitivity of daily industry returns to daily EPU shocks are estimated by using a GARCH (1, 1) model. Then all the industries are ranked and allocated into investment portfolios according to their EPU sensitivity. Finally, returns of these portfolios are respectively conditioned against the changes in daily cases and deaths while also controlling for the 5-risk-factors of Fama and French (2015).

2. Methods

Initially, the sensitivity of daily industry returns to daily shocks in the US-EPU index is examined. According to Hu et al. (2018), the volatility of returns is time varying. Therefore, Bollerslev's (1986) GARCH (1, 1) model should be used in estimations which corrects for the autoregressive conditional heteroscedasticity in error term. Motivated by this, the GARCH (1, 1) model is used to measure the sensitivity of industry-level returns to volatility in the US-EPU shocks which are extracted from the residuals of ARMA (1, 1) model (see, Section 3). The GARCH (1, 1) model which also controls for a systematic factor (i.e. market portfolio returns proxied by daily returns on the S&P500 equity index) takes the following form;

$$r_{i,t} = \delta_0 + \delta_1 \Delta Log(EPU)_t + \delta_2 \Delta Log(EPU)_{t-1} + \delta_3 \Delta Log(EPU)_{t-2} + \delta_4 S\&P500_t + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sigma_t Z_t, Z \sim iidN(0,1) \tag{2}$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 s.t. \omega > 0, \alpha > 0, \beta > 0, \alpha + \beta < 1 \tag{3}$$

where r represents industry returns for 49 different industries, Δlog(EPU) is the logarithm of daily US-EPU shocks from ARMA (1, 1), and S&P500 is the daily returns on the market equity index.

Having the sensitivity coefficients of industry returns to EPU shocks (i.e. Δlog(EPU)), industries are ranked according to the sum of Δlog(EPU) coefficients, $\boldsymbol{\delta}_1$, $\boldsymbol{\delta}_2$ and $\boldsymbol{\delta}_3$, and then allocated into five equally-weighted portfolios. To examine if the portfolios with higher negative (positive) EPU exposure are more prone to confirmed cases (deaths) or not, the following equation is used;

$$r_{i,t} - r_{f,t} = \alpha_i + b_i(r_{m,t} - r_{f,t}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + d_i \Delta log(COV_t) + e_{i,t} \tag{4}$$

where r_i indexes the daily portfolio returns; r_f is the daily rate on one-month T-bills; r_m indexes the daily returns on the S&P500 equity index; SMB (small-minus-big) tracks the daily difference in returns between portfolios consisting of small market-cap stocks and big market-cap stocks; HML (high-minus-low) tracks the daily difference in returns between portfolios consisting of high valuation ratio stocks (i.e. B/M) and low valuation ratio stocks; RMW (robust-minus-weak) tracks the daily difference in returns between portfolios consisting of high (i.e., robust) profitability stocks minus low (i.e., weak) profitability stocks; CMA (conservative-minus-aggressive) tracks the daily difference in returns between portfolios consisting of low (i.e., aggressive) investment stocks minus high investment (i.e., aggressive) stocks[1]; and Δlog(COV) indexes the logarithmic change in the 3-day moving average of cases (Δlog(Cases3)), or deaths (Δlog(Death3)).

A probable problem in modelling industry returns and the evolution of COVID-19 relationship is the omitted variable bias. Using the benchmark model of Fama and French (2015) should alleviate this problem; because according to them, SMB, HML, RMW and CMA are diversified portfolios which expose to unknown state variables. And when these four factors are combined with the market portfolio and risk-free asset, the resulting combination is the relevant multifactor efficient set which incorporates all the pricing information relevant to asset prices.

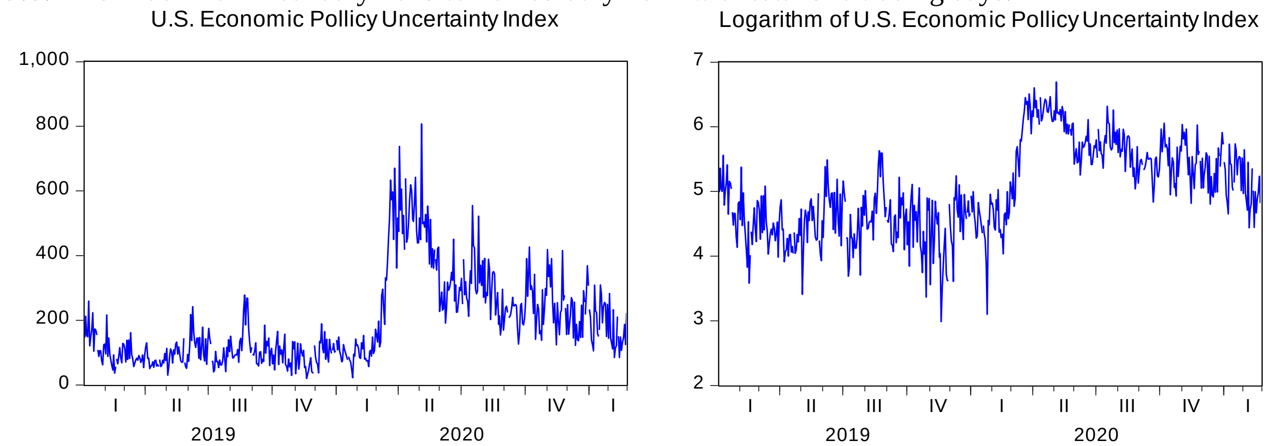
3. Data

In the empirical tests, we use the news based daily US-EPU index of Baker et al. (2016) (*www.policyuncertainty.com*). This index is found to have a significant relationship with the key macroeconomic variables in the U.S. (Hu et al., 2018). Motivated from the papers such as by Ashraf (2020) and Sergi et al. (2021), we use daily cases and deaths to proxy the evolution of the pandemic. However, instead of daily changes, we use the logarithmic change in the 3-day moving average of cases and deaths. The intuition behind using the 3-day moving average is to minimize the information loss about the number of cases which are recorded during the weekends when the stock market is closed. The data related to cases and deaths are obtained from *ourworldindata.org*.

Figure 1 plots the daily US-EPU index from 2 January 2019 to 26 February 2021, the level form on the left-panel and the logarithmic form on the right-panel. There is a clear indication that the index spiked during the first quarter of 2020. It is also visible that the level form of the US-EPU shows high variability when it reaches to high levels. This pattern may indicate that the level of US-EPU series is suffering from a heteroscedasticity problem. But the logarithmic form (right-panel) shows less variability at higher levels which may imply the mitigation of this problem. Further, to formally test if the logarithmic transformation can solve this problem, the Augmented Dickey Fuller (ADF) test is employed with constant and without trend, since there is no indication of trend in series. The result of ADF rejects the null hypothesis that the logarithm of daily EPU series has a unit root at 1% level. However, the ADF test indicates a unit root problem for the level form of US-EPU. Accordingly, the logarithm of the daily EPU index is used to extract residuals as the shock. Different ARMA (p, q) models are estimated to identify the best AR (p) and MA (q) combination which offers the most favorable information criterion for the best model-fit (please see Appendix Table A1). We use the Akaike Information Criterion (AIC), Schwarz Information Criterion (SBIC) and Hannan-Quinn Criterion (HQ) to select the ARMA (p, q). The results reported in Appendix Table A1 favor the use of ARMA (1, 1) given its low AIC and lowest SBIC and HQ values. Eq. 5 used to extract the shocks can be given as follows:

[1] Fama and French (2015) rank all the stocks at the end of each June according to their size, book-to-market ratio, profitability and investment values and then divide the sorts into two groups, big (B) and small (S), and independently three book-to-market, three profitability and three investment groups based on 30th, and 70th percentile of the variables. The size groups are matched independently with book-to-market, profitability and investment groups. Starting from July, the monthly value-weighted returns are calculated until the next June. Portfolios are rebalanced annually. Factor SMB returns were calculated as the average difference between intersection portfolios of small and big stocks. Other factors are constructed in a similar way. For further details, please refer to the online data library of Kenneth French (*https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*).

Figure 1. Daily U.S. EPU index. The figure plots the level (left) and the logarithm (right) of the daily U.S. EPU index from 2 January 2019 to 26 February 2021 with total 540 trading days.



$$\log\,(\mathrm{EPU})_t = \mu + \emptyset \log\,(EPU)_{t-1} + \varepsilon_{t-1} + \theta \varepsilon_{t-1} \qquad (5)$$

Eq.5 extracts μ value of 5.025, $\emptyset$ coefficient of 0.978 and θ coefficient of -0.616. These estimates are all significant at 1% level and ARMA (1, 1) model has an adjusted R^2 value of 0.761.

Table 1 reports the descriptive statistics for the variables used in the empirical tests. Panel A reports statistics related to the logarithmic change in the daily US-EPU (Δlog(EPU)), as well as the logarithmic change in the 3-day moving average of cases (Δlog(Cases3)) and deaths (Δlog(Cases3)). Panel B and Panel C reports statistics for the daily industry returns and the five-factors of Fama and French (2015), respectively.

Table 1. Descriptive statistics.

Panel A: Economic Policy Uncertainty, Cases and Deaths								
Variables	*Mean*	*Median*	*Max*	*Min*	*SD*	*Skew.*	*Kurtosis*	*Obs.*
Δlog(EPU)	-0.001	-0.002	0.984	-1.289	0.338	-0.194	3.420	543
Δlog(Cases3)	9.984	10.960	13.698	0	3.370	-2.069	6.154	276
Δlog(Deaths3)	0.993	0.985	1.737	0.576	0.078	2.650	39.967	250
Panel B: Industry Returns								
Industry	*Mean*	*Median*	*Max*	*Min*	*SD*	*Skew.*	*Kurtosis*	*Obs.*
Agriculture	0.09	0.26	8.84	-10.64	2.32	-0.62	6.94	277
Aircraft	0.21	0.03	15.80	-14.77	3.65	-0.12	7.08	277
Apparel	0.18	0.19	13.07	-15.41	3.29	-0.17	7.05	277
Automobiles	0.31	0.18	10.86	-12.59	2.93	-0.51	6.37	277
Banking	0.10	0.12	10.01	-13.06	2.99	-0.26	6.36	277
Beer & liquor	0.13	0.16	7.85	-10.17	1.93	-0.59	8.80	277
Business services	0.24	0.40	8.37	-13.59	2.61	-1.02	8.43	277
Business supplies	0.13	0.07	9.44	-13.3	2.87	-0.58	6.68	277
Candy & soda	0.28	0.44	9.17	-12.61	2.75	-0.61	6.17	277
Chemicals	0.25	0.39	8.24	-11.91	2.73	-0.76	6.14	277
Coal	0.30	0.13	19.77	-14.23	4.43	0.51	5.36	277
Computer hardware	0.26	0.43	13.36	-13.87	2.81	-0.45	8.92	277
Computer Software	0.29	0.52	8.34	-11.66	2.27	-1.05	8.59	277
Construction	0.28	0.27	13.62	-17.93	3.30	-0.57	9.08	277
Construction material	0.21	0.21	12.84	-13.39	2.84	-0.75	8.53	277
Consumer goods	0.24	0.35	8.61	-12.34	2.48	-0.87	8.14	277

Table 1. Descriptive statistics (cont'd).

Panel B: Industry Returns								
Industry	*Mean*	*Median*	*Max*	*Min*	*SD*	*Skew.*	*Kurtosis*	*Obs.*
Defense	0.26	0.14	11.59	-8.95	2.40	0.41	5.95	277
Electrical equipment	0.37	0.18	11.42	-13.38	2.98	-0.41	5.98	277
Electronics	0.30	0.43	9.52	-10.61	2.42	-0.76	7.20	277
Entertainment	0.29	0.29	14.81	-19.44	3.68	-0.70	10.22	277
Fabricated product	0.19	0.01	16.28	-15.32	3.63	0.13	7.18	277
Food products	0.09	0.14	7.81	-8.61	1.72	-0.47	9.44	277
Healthcare	0.31	0.31	32.22	-16.04	3.26	2.66	38.19	277
Insurance	0.07	0.07	11.55	-12.51	2.51	-0.5	8.62	277
Lab equipment	0.27	0.33	12.15	-11.57	2.28	-0.54	10.29	277
Machinery	0.21	0.24	10.78	-12.68	2.86	-0.73	7.49	277
Medical equipment	0.26	0.37	8.12	-10.99	2.21	-0.95	8.21	277
Mining	0.28	0.47	11.26	-16.41	3.65	-0.57	6.49	277
Other	0.23	0.34	8.91	-13.43	2.30	-1.55	13.64	277
Personal services	0.20	0.3	10.73	-14.77	2.94	-0.57	8.22	277
Petroleum & gas	0.27	0.17	25.22	-27.99	5.11	0.30	9.30	277
Pharmaceutical	0.31	0.42	9.31	-12.17	2.46	-0.90	7.82	277
Precious metals	0.39	0.40	28.02	-14.00	4.50	1.10	9.72	277
Printing & publishing	0.10	0.09	8.91	-14.63	2.87	-0.54	6.61	277
Real estate	0.22	0.24	10.52	-14.64	2.90	-0.86	8.70	277
Recreation	0.50	0.60	22.25	-10.91	2.86	1.17	16.29	277
Restaurants & hotels	0.22	0.27	16.76	-19.12	3.43	-0.24	10.49	277
Retail	0.31	0.40	12.35	-12.86	2.79	-0.22	8.21	277
Rubber & plastic	0.35	0.22	8.93	-12.37	2.45	-0.46	7.07	277
Ship & railroad eqp.	0.20	0.27	9.51	-13.17	3.01	-0.63	5.68	277
Shipping containers	0.05	-0.07	10.87	-11.5	2.70	-0.30	6.75	277
Steel works	0.19	0.09	9.30	-13.25	3.12	-0.48	5.80	277
Telecommunication	0.18	0.22	8.63	-11.59	2.58	-0.64	7.31	277
Textiles	0.22	0.19	10.49	-14.84	2.97	-1.03	8.51	277
Tobacco products	0.11	0.13	10.41	-11.88	2.37	-0.41	9.32	277
Trading	0.20	0.26	10.78	-13.34	2.54	-0.88	9.93	277
Transportation	0.18	0.27	11.85	-11.91	2.82	-0.57	7.08	277
Utilities	0.02	0.10	12.45	-11.59	2.35	0.01	10.16	277
Wholesale	0.22	0.15	9.13	-11.33	2.60	-0.59	7.29	277
Panel C: Factor returns								
Factors	*Mean*	*Median*	*Max*	*Min*	*SD*	*Skew.*	*Kurtosis*	*Obs.*
Mkt-rf	0.10	0.24	9.34	-12.00	2.11	-0.68	11.11	277
SMB	0.07	0.04	5.73	-4.58	1.10	0.30	5.97	277
HML	-0.07	-0.17	6.70	-4.89	1.61	0.32	4.33	277
RMW	-0.02	-0.06	1.70	-1.79	0.61	0.17	2.92	277
CMA	-0.02	-0.01	2.43	-2.26	0.53	-0.24	6.15	277

Note: This table documents the descriptive statistics of variables. Panel A reports the daily US Economic Policy Uncertainty (EPU) Index of Baker et al. (2016), shocks in the daily US-EPU index (Δlog(EPU)), shocks in the 3-day moving average of daily confirmed COVID-19 cases Δlog(Cases3), and shocks in the 3-day moving average of the daily confirmed COVID-19 related deaths Δlog(Cases3). Δlog(EPU) is the residual series of the logarithm of the daily US EPU index from an ARMA (1, 1) model. Estimation for the US EPU shocks is from 2 January 2019 to 26 February 2021. Data related to COVID-19 cases and deaths is retrieved from *ourworldindata.org*. Panel B reports the daily returns of 49 industries according to Securities and Exchange Commission (SEC) industry classifications. And Panel C reports daily returns on the five risk factors, the systematic risk (i.e., mkt-rf), and the firm-specific risk factors (i.e. SMB, HML, RMW and CMA). Daily industry and factor returns are from the online data library of Kenneth French (*mba.tuck.dartmouth.edu*).

4. Results

Table 2 reports the average value of the summation of the coefficient estimates of $\Delta\log(EPU)_t$, $\Delta\log(EPU)_{t-1}$, and $\Delta\log(EPU)_{t-2}$ for each of the five portfolios. The portfolio with the highest negative exposure (p1) to the US-EPU shocks (-0.234) has a mean daily return of 0.178%. And the portfolio with the highest positive exposure (p5) to the US-EPU shocks (0.309) has a mean daily return of 0.252%. The difference between the mean returns of p5 and p1 is 0.074%, which is not statistically significant; implying that investors do not require a premium for negative exposure to the US-EPU shocks.

We further examine if industries with different exposure to the US-EPU also respond differently to the COVID-19 pandemic. Panel A of Table 3 reports the coefficient estimates from conditioning the number of cases and the five risk-factor of Fama and French (2015) against the industry portfolio returns. Details for portfolios are provided in Table 2A in the Appendix.

According to the results, cases variable loads positively and significantly against the returns of p4 and p5, i.e. portfolios with the highest positive US-EPU exposure. The p5 includes industries such as drugs, food and beverage, agriculture, entertainment, microchips, electronic equipment, petroleum and gas, fabricated products and precious metals. Overall, these industries may benefit from the evolution of pandemic in several ways. For instance, returns of the drugs industry tend to be higher when cases are increasing, since investors may evolve expectations that the sale of drugs will increase as the pandemic proceeds. Previous empirical evidence by Goodell and Huynh (2020) shows that the pharmaceutical industry experiences positive abnormal returns after two weeks of initial announcements about the COVID-19. Agriculture and food and beverage industries produce goods that are essential to people's survival; while the entertainment industry may benefit from the increasing number of cases due to increasing sales of online products. However, the positive exposure of industries such as petroleum and gas, fabricated products and microchips may be related to the increasing prices. The pandemic greatly disrupted the supply chain which led to the shortage of supply of important commodities which are mainly produced by these industries, hence leading to increasing prices. However, the intuition for the positive exposure of precious metals industry is that investors tend to shift their portfolio toward safe assets during turbulence. The empirical literature reports safe-haven properties of precious metals such as gold (e.g., Dutta et al., 2000) and silver (e.g., Azimli, 2022) during the post-COVID-19 period. Accordingly, the flight to safety behavior may explain the positive exposure of precious metals industry to the increase in the number of cases.

The results further show that changes in the number of cases cannot load significantly against the returns of portfolio with the highest negative exposure to the US-EPU shocks (p1). The p1 includes industries such as producers of machinery, mining, tobacco, shipping and containers, paper and printing, clothes, consumer goods and books. Unlike the industries of p5 which benefitted from the ongoing pandemic and uncertainties, expectations about these industries

Table 2. The economic policy uncertainty sensitivity of portfolio returns

	P1	*P2*	*P3*	*P4*	*P5*	*P5-P1*
$\delta_1\Delta Log(EPU)_t + \delta_2\Delta Log(EPU)_{t-1} + \delta_3\Delta Log(EPU)_{t-2}$	-0.234	-0.117	-0.038	0.028	0.309	0.543***
Mean daily returns	0.178	0.267	0.171	0.255	0.252	0.074
Standard deviation of returns	2.664	2.363	2.428	2.671	2.484	0.918
Reward-to-volatility ratio	0.067	0.113	0.070	0.095	0.101	0.081

Notes: This table reports the sensitivity of portfolio returns to the US-EPU index and descriptive statistics for five decile portfolios sorted according to the policy risk (EPU) exposures. Industry portfolios are ranked from the negative highest to the positive highest EPU exposure. *** indicates statistical significance at 1% level.

Table 3. The sensitivity of returns to daily confirmed cases in the US economic policy uncertainty ranks.

Portfolio sorts	*Alpha*	r_m -r_f	*SMB*	*HML*	*RMW*	*CMA*	COV_{Cases}	*Adj.* R^2
Panel A: Pricing effect of changes in 3-day moving average daily cases								
p1 (highest (-))	-0.017	0.916***	0.707***	0.428***	0.063	-0.082	0.009	0.948
	(-0.158)	(44.705)	(15.103)	(8.680)	(0.745)	(-0.752)	(0.851)	
p2	0.032	0.904***	0.767***	0.129***	-0.052	-0.054	0.010*	0.966
	(0.434)	(40.788)	(19.407)	(3.525)	(-1.030)	(-0.832)	(1.673)	
p3	0.040	0.914***	0.555***	0.234***	-0.053	-0.192***	0.002	0.956
	(0.520)	(56.466)	(9.562)	(6.921)	(-0.640)	(-3.029)	(0.310)	
p4	-0.097	0.948***	0.931***	0.216***	0.170**	-0.342***	0.021**	0.953
	(-0.859)	(39.163)	(15.534)	(3.901)	(2.106)	(-3.128)	(2.248)	
p5 (highest (+))	-0.142	0.898***	0.787***	0.197***	-0.312***	-0.159	0.026**	0.911
	(-1.303)	(30.473)	(11.561)	(3.381)	(-3.232)	(-1.190)	(2.450)	
Panel B: Pricing effect of changes in 3-day moving average daily deaths								
p1 (highest (-))	0.047	0.924***	0.686***	0.441***	0.026	-0.072	0.040	0.949
	(0.102)	(46.004)	(13.928)	(9.153)	(0.311)	(-0.652)	(0.084)	
p2	0.508	0.913***	0.763***	0.130***	-0.077	-0.040	-0.366	0.967
	(1.424)	(39.480)	(17.491)	(3.437)	(-1.365)	(-0.583)	(-1.046)	
p3	-0.032	0.918***	0.555***	0.321***	-0.050	-0.186***	0.097	0.956
	(-0.063)	(53.861)	(9.301)	(6.706)	(-0.552)	(-2.687)	(0.196)	
p4	-0.975	0.954***	0.925***	0.210***	0.186**	-0.348***	1.108*	0.953
	(-1.401)	(31.488)	(14.606)	(3.826)	(2.102)	(-2.975)	(1.642)	
p5 (highest (+))	-0.893	0.895***	0.791***	0.195***	-0.310***	-0.165	1.034*	0.910
	(-1.556)	(26.648)	(10.608)	(3.193)	(-3.067)	(-1.159)	(1.774)	

Notes: This table reports the coefficient estimates from conditioning the five-factors of Fama and French (2015) and changes in either number of confirmed cases (Panel A) or number of deaths (Panel B) related to COVID-19 against five decile portfolios constructed by ranking industries according to their exposure against the economic policy uncertainty (EPU) index. The estimation period is from 22 January 2020 to 26 February 2021, corresponding to 277 trading days. *t*-statistics in parentheses are adjusted according to the Newey and West (1987). ***, **, and * indicate statistical significance at 1%, 5% and 10% level, respectively.

may evolved during the early stages of COV|ID-19; since due to initial lockdowns the production of machinery, consumer goods, clothes and mining activities were suddenly stopped. International trade as well as supply chain have been disrupted and the sales of shipping and containers industry declined. The sudden shift from conventional education to online greatly influenced the sales of books and paper and printing industries. The prospects of these policy sensitive sectors should be primarily driven by policy decisions from the government and less by the increase in the number of cases. Accordingly, returns of these industries are captured by the shocks in policy decisions and not by the number of cases. In Panel B we test the predictive power of confirmed COVID-related deaths. The Δlog(Death3) variable also loads positively against the returns of p4 and p5 but with a lower significance level.

Differing from previous studies such as by Ashraf (2020) which examine the impact of cases and deaths on the aggregate stock market returns, we examined how different industries are influenced by the evolution of the pandemic after accounting for the US-EPU and known risk factors to equity returns. Our results imply that after controlling for policy uncertainty shocks and the known risk-factors, the returns of industries which positively expose to policy shocks increase with the evolution of the pandemic. These results imply that not all the business opportunities are equal and that some of the sectors are benefitted from the pandemic.

5. Concluding remarks

Using the industry-level daily returns from the US, we analyze if industries with higher (lower) sensitivity to the daily US-EPU shocks also respond differently to the changes in the COVID-19 related cases and deaths. The results indicate that after controlling for the known risk-factors to equity returns, neither cases nor deaths can load significantly against the returns of industries which expose negatively to policy uncertainty shocks. A possible explanation is that the prospects of these policy sensitive sectors should be primarily driven by policy decisions of the government and less by the increase in cases. However, results also suggest that industries which respond positively to policy uncertainty shocks also respond positively to the increasing number of cases and deaths because: (i) investors may evolve expectations that the sales of such industries will increase as the pandemic proceeds, (ii) lower supply of their products will drive up prices, or (iii) investors would want to include their products into their portfolios as safe assets during the post-COVID-19 period. These results have important policy implications for investors, portfolio managers and policy makers. Investors and portfolio managers may use these results to optimize their portfolios during the post-COVID-19 period. Policy makers can also use these results to identify the vulnerable industries and initiate rescue measures to attain financial stability during turbulences like the COVID-19.

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Appendix A

Table A1. Model selection to extract the US economic policy uncertainty shocks.

		AR(p)				
		0	1	2	3	4
Panel A: Akaike Information Criterion (AIC)						
MA(q)	0	2.10439	0.91954	0.74477	0.72594	0.69325
	1	1.57951	0.68288	0.68573	0.68118	0.68407
	2	1.25363	0.68596	0.68920	0.68287	0.68653
	3	1.15284	0.68148	0.68210	0.68077	0.68424
	4	1.08733	0.68357	0.68551	0.67775	0.68414
Panel B: Schwartz Criterion (SBIC)						
MA(q)	0	2.11230	0.94328	0.77643	0.76551	0.74073
	1	1.58879	0.71453	0.72530	0.72866	0.73947
	2	1.26600	0.72553	0.73668	0.73827	0.74984
	3	1.16832	0.72896	0.73775	0.74408	0.75547
	4	1.08733	0.73896	0.74882	0.74900	0.76328
Panel C: Hannan-Quinn (HQ)						
MA(q)	0	2.10748	0.92882	0.75715	0.74141	0.71182
	1	1.58879	0.69525	0.70112	0.69975	0.70573
	2	1.26600	0.70143	0.70777	0.70453	0.71129
	3	1.16832	0.70004	0.70376	0.70552	0.71209
	4	1.05841	0.70523	0.71027	0.70560	0.71508

Notes: The comparison of different ARMA (p, q) models to identify the best AR (p) and MA (q) combination having the most favorable information criterion for the best model-fit. To this aim, Akaike Information Criterion (AIC), Schwarz Information Criterion (SBIC) and Hannan-Quinn Criterion (HQ) are used to select the ARMA (p, q).

Table A2. Portfolio compositions and industry exposures to the US-EPU shocks.

P1	P2	P3	P4	P5
Coal (-0.408)	Health care (-0.151)	Beer and liquor (-0.080)	Retail (-0.010)	Drugs (0.079)
Mining (-0.300)	Guns (-0.151)	Financial (-0.062)	Wholesales (-0.005)	Food and beverage (0.092)
Containers (-0.286)	Trans (-0.149)	Insurance (-0.056)	Restaurant and hotel (0.004)	Entertainment (0.095)
Books (-0.223)	Software (-0.119)	Soda (-0.068)	Chemicals (0.006)	Other (0.176)
Consumer goods (-0.209)	Steel (-0.109)	Business services (-0.021)	Construction (0.007)	Agriculture (0.224)
Machinery (-0.207)	Rubber (-0.104)	Shipping (-0.018)	Medical equipment (0.017)	Microchips (0.255)
Paper and printing (-0.192)	Banks (-0.103)	Aircraft (-0.015)	Automobiles (0.055)	Electronic equipment (0.285)

Table A2. Portfolio compositions and industry exposures to the US-EPU shocks (cont'd).

P1	P2	P3	P4	P5
Clothes (-0.184)	Lab equipment (-0.098)	Utilities (-0.014)	Real estate (0.067)	Petroleum and Gas (0.363)
Tabaco products (-0.174)	Building material (-0.096)	Personal services (-0.011)	Hardware (0.069)	Fabricated Products (0.438)
Telecommunication (-0.156)	Toys (-0.092)		Textiles (0.072)	Precious Metals (1.084)

Notes: The table reports the industry compositions and the sum of coefficients, in parentheses, industry exposure to the US-EPU shocks extracted using the following GARCH (1, 1) model;

$$r_{i,t} = \delta_0 + \delta_1 \Delta Log(EPU)_t + \delta_2 \Delta Log(EPU)_{t-1} + \delta_3 \Delta Log(EPU)_{t-2} + \delta_4 S\&P500_t + \varepsilon_t$$

$$\varepsilon_t = \sigma_t Z_t, Z \sim iidN(0,1)$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 s.t. \omega > 0, \alpha > 0, \beta > 0, \alpha + \beta < 1$$

where r represents the industry returns for 49 different industries; Δlog(EPU) is the logarithm of the daily US-EPU shocks from ARMA (1, 1); and S&P500 is the daily returns on the market equity index.