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US POLICY RESPONSES TO THE COVID-19 PANDEMIC AND SECTORAL STOCK INDICES: A FRACTIONAL INTEGRATION APPROACH

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Abstract

This paper uses fractional integration to assess the impact of US policy responses to the COVID-19 pandemic on 10 US sectoral stock indices from 1 January 2020 to 11 June 2021. The results provide evidence of mean reversion in most cases and suggest that the Effective Federal Funds Rate and monetary and fiscal announcements are the most effective policy tools.

Keywords: Covid-19 pandemic; US sectoral stock indices; fractional integration

JEL Classifications: C22, C32, G15

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1. Introduction

Following an initial outbreak in Wuhan, China in December 2019 the Covid-19 pandemic (classified as such by the World Health Organisation (WHO) on March 11, 2020) has had unprecedented effects on the health and economic situation of most countries in the world (Busko and Bezinovic, 2021); specifically, it has caused huge death losses (Shahzad et al., 2021)[1] as well as a sharp decline in world output. For instance, during the period from 2019 Q4 to 2020 Q4, US GDP fell by 5%, and the US unemployment rate had risen from 4.4% to 13.3% by March 2020.[2] Increased uncertainty and the subsequent panic selling also affected stock markets. For example, the Dow Jones Index (DJI) declined by 7.79% on 9 March 2020 and by a further 9.9% on 12 March 2020, the latter being one of the sharpest falls ever documented in US history. Additionally, 10-year US Treasury Bond Yields fell by 0.67%.[3] Several studies have already been carried out to examine the effects of the Covid-19 pandemic on aggregate stock market indices. Among them, Wei and Han (2021) concluded that the pandemic has significantly weakened the transmission of monetary policy to financial markets; Ashraf (2020) reported that stock markets were negatively impacted by government announcements of restrictions, whilst policies imposing quarantining and testing had a positive effect; Narayan et al. (2021b) found that stock markets in the G7 were positively affected by economic support and travel bans; Zhang et al. (2020) provided evidence that policy interventions during the pandemic in some cases increased market uncertainty (see also Sharif et al., 2020; Takyi and Bentum-Ennin, 2020; Baker et al., 2020; Baffes and Nagle, 2020; Conlon and McGee, 2020; Le et al., 2021; Zaremba et al., 2021; Insaidoo et al., 2021; Tiwari et

[1] https://healthwise.punchng.com/covid-19-global-death-toll-hits-177822-as-over-2571880-cases-declared-in-193-countries/
[2] https://www.statista.com/statistics/188185/percent-chance-from-preceding-period-in-real-gdp-in-the-us/
[3] 10 year Treasury rate: https://ycharts.com/indicators/10_year_treasury_rate

al., 2021a,b; etc). However, it is also important to assess possible effects on sectoral stock indices. For instance, stock prices in the energy, industrials and travel sectors experienced heavy losses; similarly, financial institutions and banks saw their earnings and stock prices plummet as a result of a sharp increase in the share of non-performing loans coupled with the decrease in interest rate margins resulting from lower policy rates (the recorded loss was 39%, more than in the US stock market as a whole).

National governments have adopted various policy measures in response to the pandemic (Caporale and Cerrato, 2020; Hale et al., 2020). The US, one of the hardest hit countries,[4] introduced a number of containment measures restricting social interaction (such as workplace, schools and restaurants closures), domestic and international travel; monetary measures such as lower policy rates and more quantitative easing (e.g., US); fiscal measures such as income support and debt relief schemes. The aim of the present study is to examine the effects of those measures and of the pandemic itself on US sectoral stock indices. It is well known that the introduction by the US government of relief schemes such as the Coronavirus Aid, Relief, and Economic Security (CARES) Act saw US aggregate stock indices, namely the NASDAQ, S&P 500 and DJI, rise by 7.33%[5], 7.3%[6] and 7.73% respectively.[7] Although Bouri et al. (2021) and Mazey and Richardson (2020) provide some evidence on the impact of the Covid-19 pandemic on sectoral stock indices in the case of New Zealand, and Huynh et al. (2021a) in the case of Australia, to the best of our knowledge the current study is the first to carry out sectoral analysis for the US and to examine

[4] US COVID statistics https://www.worldometers.info/coronavirus/country/us/

[5] NASDAQ composite index: https://www.marketwatch.com/investing/index/comp

[6] S&P 500 index: https://www.marketwatch.com/investing/index/spx

[7] Dow Jones industrial average: https://www.marketwatch.com/investing/index/djia

the factors that have driven returns and affected the stability of different sectors in stock markets (Bhargava et al., 2012) during the most recent stress period. Note that Huynh et al. (2022) analysed the impact of the Covid-19 pandemic on the 46 largest capitalization firms in the Eurozone and found higher connectedness in the early months of 2020 and higher risk transmission in the case of industrial manufacturing and consumer products; by contrast, we focus on the sectoral level in the US. Also, Narayan et al. (2021a) used a quantile regression framework and found heterogeneous effects of the Covid-19 pandemic on sectors of the market in Australia (these being positive in the case of health, information technology and consumer staples); however, they only measured the direct impact of the pandemic using the cumulative number of cases; by contrast, we also take into account the effects of a wide range of policies in our analysis for the US and allow for long-lived effects of shocks using an appropriate methodology. Specifically, whilst previous studies on Covid-19 and stock markets (Salisu and Vo, 2020, Ashraf, 2020; Baker et al., 2020; Corbet et al., 2020; Okorie and Lin, 2021; Mazur et al., 2021 Le et al., 2021) are based on the classical I(0)/I(1) dichotomy between stationary and non-stationary series, the current one uses a fractional integration (or I(d)) modelling approach which allows for fractional values of the integration/cointegration parameter d and therefore for a much wider range of possible stochastic behaviours of the series under examination.

It is common knowledge that financial markets are affected by external events such as natural disasters and environmental developments and that they also respond to pandemics, as already seen in the case of the Severe Acute Respiratory Syndrome (SARS) and Ebola Virus Disease (EVD) outbreaks. It is therefore of interest to analyse how they have reacted to the Covid-19 pandemic. The novel contribution of our study to this area of the literature is twofold: first, it considers in the US case not only the direct impact of the Covid-19 pandemic but also the effects of a wide range of policies adopted by the US government to counteract it; second, it uses an econometric approach that improves upon earlier ones by providing a framework which is more informative about the degree of persistence of the examined series and thus also has important implications for policy-makers and investors. Note that Narayan et al. (2021c) used word searches from newspaper articles to construct a COVID index, a medical index, a vaccine index, a travel index, an uncertainty index, and an aggregate COVID-19 sentiment index as proxies for the effects of the pandemic; also, Huyhn et al. (2021) analysed feverish sentiment in the global financial markets during the Covid-19 period. However, our focus is different, since we are interested in policy effects as well as the direct effects of the pandemic through the increased mortality rate, and therefore their type of analysis would be out of context here.[8]

The layout of the paper is as follows: Section 2 describes the data; Section 3 outlines the econometric framework; Section 4 presents the main empirical findings; Section 5 offers some concluding remarks.

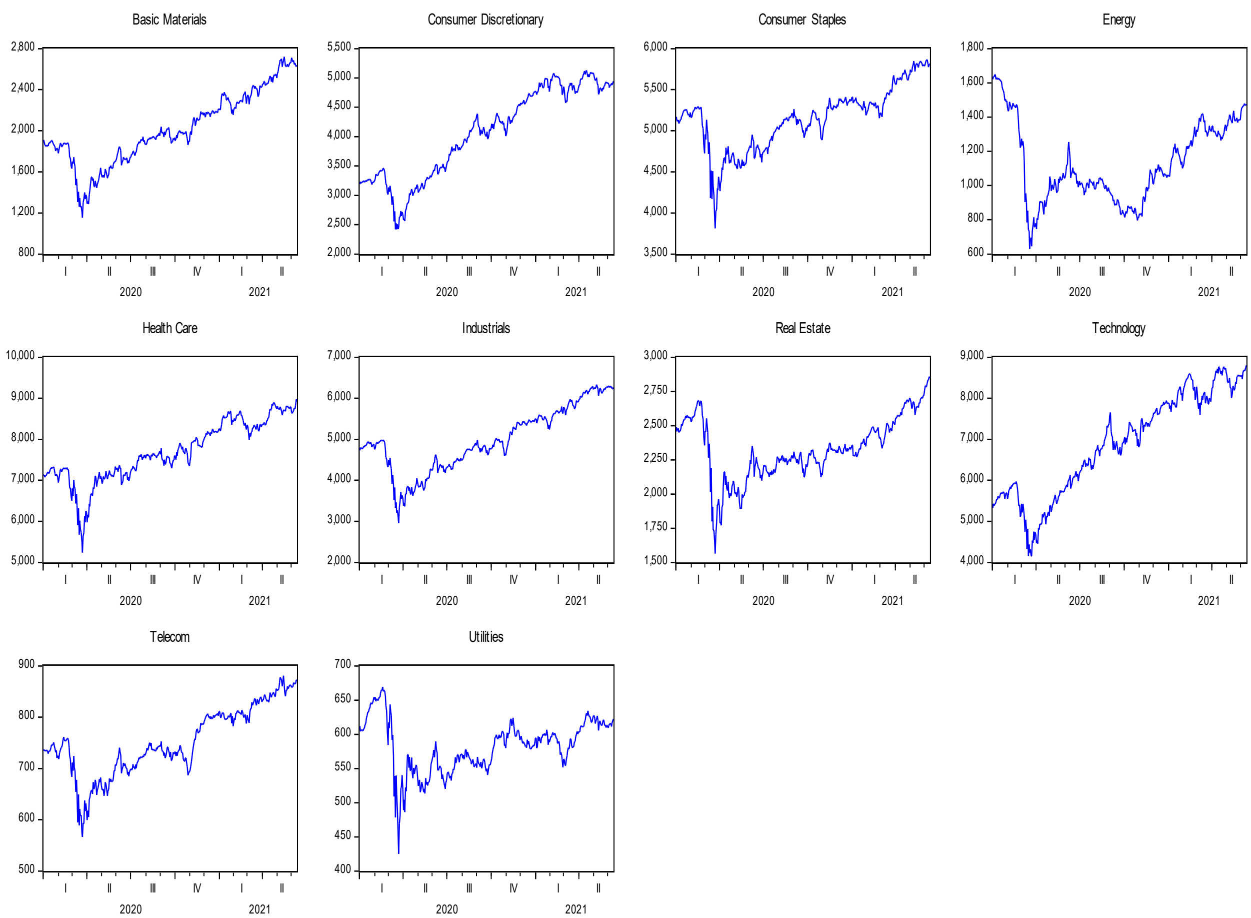
2. Data Sources and Description

Goodell and Huynh (2020) examined the reactions of US industries to sudden COVID-related news announcements; they focused on stock trading by US legislators in late January through February 2020 and identified 15 industries with abnormal returns. Their analysis covered 49 industries in the US, where industry portfolios were constructed by assigning each NYSE, AMEX and NASDAQ stock to an industry portfolio at the end of June of each year on the basis of its four-digit SIC code at that time. By contrast, in the present study we focus only on the same 10 sectoral

[8] For a useful, comprehensive survey of the literature on the economic and financial impact of the Covid-19 pandemic and additional references see Narayan (2021).

indices from the S&P500 as in Hanif et al. (2021) and Shahzad et al. (2021) since this aggregate index measures the investment performance of the stocks most extensively traded in the US and is regarded as a benchmark for international investors to assess the state of global financial markets. More specifically, we obtained daily US sectoral stock indices for Technology, Telecom, Health Care, Real Estate, Consumer Staples, Consumer Discretionary, Industrials, Basic Materials, Energy and Utilities from 1 January 2020 to 11 June 2021 from Thomson Reuters Datastream. Figure 1 below contains plots of these series. They all appear to be rather volatile and to have experienced a sharp drop in the early part of 2020, shortly after the initial Covid-19 outbreak.

Figure 1 Time series plots of the sectoral stock indices



The Covid-19 policy response measures have been taken from the Oxford Coronavirus Government Response Tracker (https://ourworldindata.org/policy-responses-covid.com). The Containment and Health Index is a composite measure based on: workplace closures, school closures, public events cancellations, public gatherings restrictions, public transport closures, stay-at-home restrictions, public campaigns restrictions, internal movement restrictions, restrictions on international travels, testing policy, magnitude of contact tracing, covering of face and vaccine policy. The index on any given day is calculated as the mean score of the thirteen metrics, each taking a value between 0 and 100. A higher score indicates a stricter response (i.e. 100 = strictest response).

The fiscal policy response variables include: income support, which provides information about the extent to which the US government has covered salaries or provided universal basic income, direct cash payments, or similar, to people who lost their jobs or could not work; debt or contract relief, which indicates whether the US government froze loan repayments and other types of utility payments, banned evictions etc. during the pandemic. Finally, the effective Federal Funds rate is included to account for monetary policy responses.

We also construct shift dummies corresponding to key dates when the US government made monetary policy and fiscal policy announcements. In the case of the former, the chosen date is 15 March 2020, when the Federal Funds rate was lowered by 150bp to 0-0.25bp. As for fiscal announcements, the following dates were selected: 28 December 2019, when President Trump signed a US $ 868bn (about 4.1 percent of GDP) coronavirus relief and government funding bill as part of the Consolidated Appropriations Act of 2021; 8 August 2020, when he issued executive orders, mostly to address the expiration of certain Coronavirus reliefs provided by previous legislation; 11 March 2021, when the House of Representatives approved the American Rescue

Plan, which provides further relief with an estimated cost of $1,844bn (about 8.8 percent of 2020 GDP).

Finally, following Ozkan et al. (2021), the direct impact of the pandemic is taken into account by using two alternative measures of the Covid-19 mortality rate (DR), namely (i) the ratio of the number of confirmed Covid-19 deaths to the total number of confirmed cases, which is known as the case-fatality rate (DR1), and (ii) the crude fatality rate (DR2), defined as the number of deaths per 100,000 of the population.

3. Econometric Framework

We consider the following regression model (Robinson, 1994):

$$y(t) = \beta^T z(t) + x(t); \qquad (1 - L)^d x(t) = u(t). \tag{1}$$

where *y(t)* is the observed time series representing each of the industry stock market indices in turn, namely Technology (TECH), Telecom (TEL), Health Care (HEALTH), Real Estate (RE), Consumer Staples (CS) Consumer Discretionary (CD), Industrials (IDS), Basic Materials (BM), Energy (ENE) and Utilities (UTI): β is a (8.x1) vector of unknown parameters including a constant and seven other coefficients; $z(t) = (1, \text{CHI}(t), \text{ISP}(t), \text{DRP}(t), \text{EFFR}(t), \text{MMFPM}(t), \text{FP}(t), \text{DR}(t))^T$ is a vector including the (weakly) exogenous regressors, where CHI stands for the Containment Health Index, ISP for Income Support Policy, DRP for Debt-Relief Policy, EFFR for the Effective Federal Funds Rate, MMFPM and FP are two dummies corresponding to policy announcements concerning (i) Monetary and Macro-Financial Policy Measures and (ii) Fiscal Policy, and DR for the Mortality Rate**.** *x(t),* namely the errors in the regression model, are assumed to be an *I(d)* process with the differencing parameter *d* to be estimated from the data; finally *u(t)* is an *I(0)* process, which is assumed to be a white noise process. Note that the second equation in (1) implies that *x(t)* is integrated of order *d* (where *L* is the lag operator, i.e., $L^k x(t) = x(t-k)$), and thus this equation describes time dependence; note that if $d > 0$ the series displays long memory, with higher values of d indicating higher dependence between the observations, even if they are far apart in time.

The estimation is carried out for the d-differenced regression following the approach developed in Robinson (1994); his procedure tests the null hypothesis:

$$H_o : d = d_o, \qquad (2)$$

in (1) for any real value d_o, and the limit distribution is standard Normal (Robinson, 1994). Thus, under the null hypothesis H_o (2), the two equalities in equation (1) can be expressed as

$$\tilde{y}(t) = \beta^T \tilde{z}(t) + u(t) \qquad (3)$$

where $\tilde{y}(t) = (1-L)^{d_o} y(t)$ and $\tilde{z}(t) = (1-L)^{d_o} z(t)$, and noting that *u(t)* is *I(0)* by construction, the estimation of β can be carried out using OLS (GLS) (see, e.g. Gil-Alana and Robinson, 1997 for a full description of this procedure).

The approach described above is more general and flexible than standard methods based on the dichotomy between I(0), stationary variables and I(1), non-stationary ones. In particular, unlike standard unit root tests, it does not restrict the differencing parameter to be an integer and it allows it instead to take any real value, including fractional ones. As a result, it captures a much wider range of stochastic processes and provides information not only on whether or not they are mean-reverting but also on their speed of adjustment towards the long-run equilibrium in response to shocks and on their degree of persistence (which is measured by the differencing or fractional integration parameter).

4. Empirical Results

Table 1 reports the estimated coefficients under the assumption of white noise errors when using DR1 as the mortality rate. It can be seen that in this case the estimated value of d for most sectoral stock indices is significantly below 1, the only exceptions being Basic Materials, Energy and Real Estate. Thus the null hypothesis I(1) is rejected in favour of I(d, d < 1) for the following sectoral stock indices: Consumer Discretionary, Consumer Staples, Health, Industrials, Technology, Telecom and Utilities. This implies mean reversion, which is not consistent with the market efficiency hypothesis according to which prices should be unpredictable.

As for the other coefficients in Table 1, we note that the constant is significant in all 10 cases; CH(t) is positive and significant in the case of the Health Sector; EEFR(t) is positive and significant in all cases except Basic Materials and Energy; MMFPM(t) is positive and significant for Consumer Discretionary, Consumer Staples, Health, Real Estate, Technology and Telecom; finally, FP(t) is insignificant for all sectors except Consumer Discretionary, Health, Technology and Telecom.

Table 2 displays the estimated coefficients under the assumption of white noise errors for the log regression including DR1 as the mortality rate. The results are similar to those in Table 1. However, DR1(t) is now negative and significant for four sectors, i.e. Consumer Staples, Health, Technology and Telecom. This is not surprising in the case of Consumer Staples since most firms operating in this sector went into lockdown during the pandemic period, which led to a drop in sales and revenue.

[INSERT TABLE 1 & 2 ABOUT HERE]

Table 3 contains the estimated regression results for the original data under the assumption of white noise errors and DR2 as the mortality rate. It can be seen that the estimated value of d is around 1 for only 3 sectors, namely Basic Materials, Energy and Real Estate Sector, which implies mean reversion (d significantly below 1) in seven out of the ten sectoral stock indices during the COVID-19 period. As for the other coefficients, the constant is found to be positive and significant for all sectors. Further, it appears that the Containment and Health restrictions CH(t), as well as the Income Support Policy, ISP(t) and Debit Relief Policy, DRP(t), had no impact on US sectoral stock indices. By contrast, changes in the Effect Federal Funds Rate EFFR(t) had a positive and significant effect on all sectors except Energy and Industrial. Monetary and fiscal announcements, denoted by MMFP(t), and Fiscal Policy (FP(t)), had a positive and significant impact on several sectoral stock indices. In particular, MMFP(t) had a positive impact on six sectoral stock indices, specifically Consumer Discretionary, Consumer Staples, Health, Real Estate, Technology, Telecom and Utilities. As for FP(t), it is significant for only four sectors, namely Consumer Discretionary, Health, Technology and Telecom. Finally, the coefficient on DR2 is significant and negative for Health, Technology, Consumer Staples and Telecom.

Table 4 displays the log regression results with DR2 as the mortality rate. In this case DR2 is found to have a significant and negative effect on all sectors except Energy. Changes in EFFR(t), FP(t) and MMFP(t) are found to have affected several sectoral stock indices. For instance, changes in EFFR(t) had a significant and positive impact on all sectors except Basic Materials and Energy, and policy announcements, MMFP(t), had a positive effect in most cases, the exceptions being Basic Materials, Energy and Industrials.

[INSERT TABLE 3 & 4 ABOUT HERE]

To summarise, the results provide evidence of mean reversion for seven sectoral stock indices (Consumer Discretionary, Consumer Staples, Health, Industrials, Technology, Telecom and Utilities), with orders of integration close to (though significantly smaller than) 1 in all these cases. By contrast, three indices (Basic Materials, Energy and Real Estate) are found to be highly persistent ($d \geq 1$), with shocks having permanent effects. These results are robust to making different assumptions about the residuals. More specifically, when allowing u(t) in equation (1) to be weakly autocorrelated by using the non-parametric approach of Bloomfield (1973), the estimates of d are practically the same as those reported in Tables 1 - 4, which confirms the conclusions previously reached concerning the stochastic properties of the series of interest. [9] As for the policy responses, it appears that the containment and health restrictions, income support policy, and debit relief policy have had no impact. By contrast, changes in the Effect Federal Funds Rate have had a significant and positive effect on all sectors except Energy and Industrial, and similarly monetary and fiscal announcements have had a positive and significant effect in most cases. Finally, the higher mortality rate caused by the Covid-19 pandemic has affected negatively most sectoral stock indices.

5. Conclusions

This paper examines the impact of US COVID-19 policy responses on US sectoral stock indices (for Technology, Telecom, Health Care, Real Estate, Consumer Staples, Consumer Discretionary, Industrials, Basic Materials, Energy and Utilities) from 1 January 2020 to 11 June 2021 using fractional integration methods. It is the first to analyse this issue for the US using fractional

[9] These results are not reported for reasons of space but are available from the authors upon request.

integration and including a wide set of variables accounting for both the direct impact of the pandemic and policy responses, both of which are missing from most previous contributions. The results provide evidence of mean reversion in most cases and suggest that the Effective Federal Funds Rate and monetary and fiscal announcements are the most effective policy tools, whilst the mortality rate had a negative impact.

These findings imply that monetary policy is the most effective tool for governments to provide support to financial markets affected by the greater uncertainty resulting from an external shock such as the Covid-19 pandemic – whilst fiscal policy might work better to boost the real economy, monetary measures appear to be the most appropriate ones to improve investor sentiment**.** Further, since we find evidence of significant announcement effects, policy-makers should use this tool as well to boost confidence in the financial sector in the event of a crisis. Our results have also important implications for investors: the differences we have detected between sectors in terms of their degree of persistence suggest that there are portfolio diversification opportunities and thus that suitable investment strategies based on exploiting them can generate additional profits.

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Table 1: Estimated coefficients with white noise errors and DR1 as the Mortality Rate										
Regressor	Original data									
	BMAT	CDISCRET	CSTAPLES	ENERGY	HEALTH	INDUS	RESTATE	TECH	TELE	UTI
D	0.95 (0.88, 1.03)	0.92* (0.86, 0.99)	0.86* (0.78, 0.94)	1.04 (0.98,1.11)	0.83* (0.75, 0.91)	0.93* (0.87, 0.99)	0.93 (0.86,1.02)	0.83* (0.78,0.90)	0.82* (0.76,0.89)	0.89* (0.81,0.98)
Const.	**1863.787** **(38.03)**	**3096.772** **(38.14)**	**5064.812** **(53.30)**	**1508.450** **(36.97)**	**6937.7521** **(48.41)**	**4578.767** **(38.85)**	**2355.439** **(37.57)**	**5145.770** **(31.79)**	**715.453** **(52.33)**	**594.101** **(39.84)**
CHI	-0.842 (-0.44)	2.848 (0.93)	-2.025 (-0.60)	-1.548 (-0.86)	**7.542** **(1.65)**	-2.934 (-0.65)	-2.847 (-1.19)	5.649 (1.04)	-0.062 (-0.13)	-0.424 (-0.78)
ISP	-24.753 (-0.93)	-2.855 (-0.06)	-30.139 (-0.58)	-12.874 (-0.55)	-15.731 (-0.20)	-39.226 (-0.61)	-10.714 (-0.31)	36.214 (0.41)	-6.111 (-0.82)	-7.230 (-0.89)
DRP	-0.235 (-0.06)	-0.121 (-0.01)	1.098 (0.01)	-0.202 (-0.06)	7.823 (0.07)	-0.721 (-0.07)	-0.610 (-0.01)	7.381 (0.05)	0.551 (0.05)	-0.044 (0.003)
EFFR	27.862 (1.36)	**63.414** **(1.87)**	**62.782** **(1.78)**	21.344 (1.19)	**117.151** **(1.95)**	**102.354** **(2.09)**	**85.246** **(3.26)**	**137.381** **(2.03)**	**12.300** **(2.15)**	**11.372** **(1.83)**
MMFP	20.411 (0.54)	**102.703** **(1.65)**	**175.715** **(2.41)**	6.265 (0.19)	**166.384** **(1.71)**	78.399 (0.86)	**66.608** **(1.68)**	**172.994** **(1.69)**	**19.724** **(1.83)**	14.479 (1.26)
FP	-21.675 (-0.57)	**122.927** **(1.97)**	40.007 (0.54)	-0.957 (-0.02)	**369.551** **(3.55)**	50.729 (0.56)	20.912 (0.43)	**382.622** **(3.07)**	**17.959** **(1.70)**	-4.658 (-0.40)
DR1	-13.217 (-0.03)	-5.476 (-0.08)	-173.849 (-0.23)	-17.770 (-0.05)	-281.771 (-0.24)	-57.926 (-0.06)	-49.083 (-0.010)	-222.504 (-0.17)	-36.504 (-0.33)	-12.451 (-0.10)

NB: In this table, we define the sector indices as : BMAT= Basic Material; CDISCRET = Consumer Discretionary; CSTAPLES = Consumer Staples; ENERGY= Energy; HEALTH = Health; INDUS = Industrials; RESTATE = Real Estate; TECH = Technology; TELE = Telecom; UTI = Utilities. Additionally, CHI = Containment and Health Index, ISP = Income Support Policy, DRP = Debt-Relief Policy, EFFR = Effective Federal Funds Rate, MMFPM and FP are two dummies corresponding to policy announcements concerning (i) Monetary and Macro-Financial Policy Measures and (ii) Fiscal Policy respectively. DR1 = the ratio of the number of confirmed Covid-19 deaths to the total number of confirmed cases, which is widely referred to as the case-fatality rate. * indicates evidence of mean reversion at the 5% level. The values in parenthesis are the 95% confidence bands in the case of d whilst in the other cases they are t-values. The significant cases at the 5% level are in bold.

Table 2: Estimated coefficients with white noise errors and DR1 as the Mortality Rate

Regressor	Logged Data									
	BMAT	CDISCRET	CSTAPLES	ENERGY	HEALTH	INDUS	RESTATE	TECH	TELE	UTI
d	0.93 (0.86, 1.01)	0.89* (0.83, 0.96)	0.83* (0.72, 0.93)	1.00 (0.94, 1.07)	0.79* (0.70, 0.88)	0.90* (0.84,0.98)	0.93 (0.84,1.02)	0.79* (0.73,0.86)	0.78* (0.70,0.86)	0.86* (0.77,0.96)
Const.	**7.518 (249.02)**	**8.030 (330.25)**	**8.525 (399.17)**	**7.344 (164.42)**	**8.839 (380.92)**	**8.416 (286.00)**	**7.750 (255.22)**	**8.541 (290.02)**	**6.568 (301.54)**	**6.378 (227.88)**
CHI	-0.0004 (-0.37)	0.001 (1.23)	-0.0003 (-0.49)	-0.001 (-0.73)	**0.001 (1.66)**	-0.0007 (-0.65)	-0.001 (-1.20)	0.001 (1.34)	0.0002 (0.04)	-0.0006 (-0.68)
ISP	-0.014 (-0.89)	-0.0005 (-0.04)	-0.006 (-0.55)	-0.011 (-0.47)	-0.002 (-0.16)	-0.008 (-0.55)	-0.005 (-0.31)	0.008 (0.51)	-0.008 (-0.70)	-0.013 (-0.89)
DRP	0.0004 (0.02)	0.001 (0.05)	0.005 (0.32)	0.0002 (0.08)	0.015 (0.80)	0.0005 (0.02)	0.000009 (0.04)	0.016 (0.70)	0.013 (0.81)	0.001 (0.07)
EFFR	**0.022 (1.78)**	**0.025 (2.53)**	**0.015 (1.72)**	**0.030 (1.72)**	**0.020 (2.06)**	**0.030 (2.47)**	**0.044 (3.48)**	**0.030 (2.45)**	**0.020 (2.19)**	**0.024 (2.06)**
MMFP	0.012 (0.56)	**0.034 (1.83)**	**0.036 (2.21)**	0.006 (0.17)	0.024 (1.34)	0.020 (0.89)	**0.032 (1.68)**	**0.033 (1.65)**	**0.028 (1.70)**	0.025 (1.15)
FP	-0.008 (-0.38)	**0.031 (1.66)**	0.009 (0.56)	0.0008 (0.02)	**0.048 (2.70)**	0.013 (0.58)	0.009 (0.40)	**0.056 (2.48)**	**0.028 (1.66)**	-0.006 (-0.28)
DR1	-0.066 (-0.28)	-0.151 (-0.79)	**-0.458 (-2.70)**	-0.015 (-0.04)	**-0.833 (-4.46)**	-0.583 (-0.62)	-0.008 (-0.35)	**-0.810 (-3.41)**	**-0.701 (-3.98)**	-0.211 (-0.76)

NB: In this table, we define the sector indices as : BMAT= Basic Material; CDISCRET = Consumer Discretionary; CSTAPLES = Consumer Staples; ENERGY= Energy; HEALTH = Health; INDUS = Industrials; RESTATE = Real Estate; TECH = Technology; TELE = Telecom; UTI = Utilities. Additionally, for the regressors, CHI = Containment and Health Index, ISP = Income Support Policy, DRP = Debt-Relief Policy, EFFR = Effective Federal Funds Rate, MMFPM and FP are two dummies corresponding to policy announcements concerning (i) Monetary and Macro-Financial Policy Measures and (ii) Fiscal Policy respectively. DR1 = the ratio of the number of confirmed Covid-19 deaths to the total number of confirmed cases, which is widely referred to as the case-fatality rate. * indicates evidence of mean reversion at the 5% level. The values in parenthesis are the 95% confidence bands in the case of d whilst in the other cases they are t-values. The significant cases at the 5% level are in bold.

Table 3: Estimated coefficients with white noise errors and DR2 as the Mortality Rate										
Regressor	Original Data									
	BMAT	CDISCRET	CSTAPLES	ENERGY	HEALTH	INDUS	RESTATE	TECH	TELE	UTI
d	0.95 (0.89, 1.03)	0.93* (0.88, 0.99)	0.88* (0.83, 0.95)	1.04 (0.98, 1.11)	0.86* (0.82, 0.92)	0.93* (0.88,0.99)	0.94 (0.87,1.02)	0.86* (0.82,0.91)	0.86* (0.82,0.91)	0.89* (0.83,0.98)
Const.	**1863.950** **(38.00)**	**30.97.331** **(37.84)**	**50.70.897** **(46.24)**	**1588.483** **(37.00)**	**6951.644** **(47.28)**	**4579.163** **(33.75)**	**2356.518** **(21.14)**	**5144.462** **(30.93)**	**716.733** **(50.76)**	**594.237** **(39.82)**
CHI	-0.8195 (-0.43)	2.8315 (0.90)	-1.752 (-0.50)	-1.538 (-0.86)	8.206 (1.57)	-2.804 (-0.62)	-2.879 (-1.18)	5.941 (1.01)	-0.031 (-0.06)	-0.387 (-0.70)
ISP	-24.735 (-0.93)	-3.2493 (-0.07)	-30.004 (-0.57)	-12.888 (-0.55)	-16.598 (-0.28)	-39.189 (-0.61)	-10.725 (-0.31)	28.999 (0.32)	-6.551 (-0.85)	-7.230 (-0.89)
DRP	0.1201 (0.03)	1.6811 (0.02)	8.104 (0.10)	-0.303 (0.09)	22.455 (0.19)	1.100 (0.01)	1.467 (0.03)	18.037 (0.14)	1.746 (0.16)	0.591 (0.05)
EFFR	**27.8690** **(1.66)**	**62.9506** **(1.85)**	**60.834** **(1.71))**	21.357 (1.19)	**112.306** **(1.83)**	**102.356** **(2.08)**	**84.781** **(3.23)**	**135.645** **(1.95)**	**11.774** **(2.00)**	**11.364** **(1.83)**
MMFP	20.4404 (0.54)	**103.946** **(1.65)**	**184.094** **(2.49)**	6.208 (0.18)	**186.637** **(1.65)**	79.195 (0.87)	**67.946** **(1.71)**	**190.497** **(1.69)**	**21.808** **(2.01)**	**14.777** **(1.69)**
FP	-21.1905 (-0.56)	**124.513** **(1.97)**	46.240 (0.62)	-1.151 (-0.03)	**394.707** **(3.47)**	53.995 (0.54)	21.146 (0.43)	**395.138** **(3.07)**	**18.121** **(1.65)**	-3.774 (-0.32)
DR2	-89955.86 (-0.16)	-602303.77 (-0.70)	**-1111355.56** **(-1.68)**	102932.65 (0.14)	**-2533229.0** **(-2.24)**	-522838.61 (-0.43)	-215798.03 (-0.31)	**-209367.5** **(-1.65)**	**-198134.66** **(-1.83)**	-93847.44 (-0.71)

NB: In this table, we define the sector indices as : BMAT= Basic Material; CDISCRET = Consumer Discretionary; CSTAPLES = Consumer Staples; ENERGY= Energy; HEALTH = Health; INDUS = Industrials; RESTATE = Real Estate; TECH = Technology; TELE = Telecom; UTI = Utilities. Additionally, for the regressors, CHI = Containment and Health Index, ISP = Income Support Policy, DRP = Debt-Relief Policy, EFFR = Effective Federal Funds Rate, MMFPM and FP are two dummies corresponding to policy announcements concerning (i) Monetary and Macro-Financial Policy Measures and (ii) Fiscal Policy respectively; DR2 = crude fatality rate defined as the number of deaths per 100,000 of the population. * indicates evidence of mean reversion at the 5% level. The values in parenthesis are the 95% confidence bands in the case of d whilst in the other cases they are t-values. The significant cases at the 5% level are in bold.

Table 4: Estimated coefficients with white noise errors and DR2 as the Mortality Rate										
Regressor	Logged Data									
	BMAT	CDISCRET	CSTAPLES	ENERGY	HEALTH	INDUS	RESTATE	TECH	TELE	UTI
d	0.95 (0.92, 1.01)	0.95* (0.92, 0.98)	0.94* (0.91, 0.97)	1.00 (0.95, 1.07)	0.93* (0.90, 0.95)	0.95* (0.92,0.99)	0.95 (0.91,1.01)	0.91* (0.89,0.94)	0.91* (0.89,0.94)	0.92* (0.88,0.97)
Const.	**7.519 (245.46)**	**8.030 (320.38)**	**8.527 (389.51)**	**7.344 (164.49)**	**8.842 (376.08)**	**8.418 (280.66)**	**7.751 (252.76)**	**8.536 (272.87)**	**6.570 (289.53)**	**6.381 (223.04)**
CHI	-0.0004 (-0.38)	0.0009 (0.97)	-0.0004 (-0.50)	-0.001 (-0.73)	0.001 (1.17)	-0.0008 (-0.70)	-0.001 (-1.14)	0.001 (0.98)	-0.00001 (-0.01)	-0.006 (-0.61)
ISP	-0.015 (-0.92)	-0.001 (-0.09)	-0.006 (-0.52)	-0.011 (-0.48)	-0.002 (-0.19)	-0.010 (-0.63)	-0.005 (-0.30)	0.003 (0.20)	-0.010 (-0.84)	-0.013 (-0.84)
DRP	0.002 (0.07)	0.002 (0.11)	0.003 (0.18)	-0.0003 (-0.009)	0.004 (0.25)	0.002 (0.08)	0.001 (0.07)	0.007 (0.31)	0.005 (0.32)	0.004 (0.18)
EFFR	**0.022 (1.72)**	**0.025 (2.39)**	**0.014 (1.75)**	**0.030 (1.72)**	**0.018 (1.91)**	**0.029 (2.73)**	**0.043 (-3.42)**	**0.030 (2.35)**	**0.019 (2.01)**	**0.023 (1.94)**
MMFP	0.014 (0.59)	**0.035 (1.84)**	**0.041 (2.48)**	0.006 (0.17)	**0.029 (1.68)**	0.022 (0.97)	**0.033 (1.73)**	**0.040 (1.68)**	**0.035 (2.03)**	**0.029 (1.66)**
FP	-0.008 (-0.33)	**0.032 (1.69)**	0.010 (0.54)	0.0007 (0.02)	**0.052 (2.91)**	0.012 (0.54)	0.019 (0.50)	**0.060 (2.51)**	**0.026 (1.72)**	-0.003 (-0.14)
DR2	**-605.36 (-1.72)**	**-742.361 (-2.58)**	**-883.731 (-3.68)**	17.755 (0.02)	**-1159.258 (-4.70)**	**-708.688 (-2.06)**	**-652.31 (-1.85)**	**-1465.47 (-4.88)**	**-1063.934 (-4.89)**	**-859.875 (-2.99)**

NB: In this table, we define the sector indices as : BMAT= Basic Material; CDISCRET = Consumer Discretionary; CSTAPLES = Consumer Staples; ENERGY= Energy; HEALTH = Health; INDUS = Industrials; RESTATE = Real Estate; TECH = Technology; TELE = Telecom; UTI = Utilities. Additionally, for the regressors, CHI = Containment and Health Index, ISP = Income Support Policy, DRP = Debt-Relief Policy, EFFR = Effective Federal Funds Rate, MMFPM and FP are two dummies corresponding to policy announcements concerning (i) Monetary and Macro-Financial Policy Measures and (ii) Fiscal Policy respectively; DR2 = crude fatality rate defined as the number of deaths per 100,000 of the population. * indicates evidence of mean reversion at the 5% level. The values in parenthesis are the 95% confidence bands in the case of d whilst in the other cases they are t-values. The significant cases at the 5% level are in bold.