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The COVID-19 pandemic, policy responses and stock markets in the G20

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ABSTRACT

This paper analyses the impact of the Covid-19 pandemic on stock market returns and their volatility in the case of the G20 countries. In contrast to the existing empirical literature, which typically focuses only on either Covid-19 deaths or lockdown policies, our analysis is based on a comprehensive dynamic panel model accounting for the effects of both the epidemiological situation and restrictive measures as well as of fiscal and monetary responses; moreover, instead of Covid-19 deaths it uses a far more sophisticated Covid-19 index based on a Balanced Worth (BW) methodology, and it also takes into account heterogeneity by providing additional estimates for the G7 and the remaining countries (non-G7) separately. We find that the stock markets of the G7 are affected negatively by government restrictions more than the Covid-19 pandemic itself. By contrast, in the non-G7 countries both variables have a negative impact. Further, lockdowns during periods with particularly severe Covid-19 conditions decrease returns in the non-G7 countries whilst increase volatility in the G7 ones. Fiscal and monetary policy (the latter measured by the shadow short rate) have positive and negative effects, respectively, on the stock markets of the G7 countries but not of non-G7 ones. In brief, our evidence suggests that restrictions and other policy measures play a more important role in the G7 countries whilst the Covid-19 pandemic itself is a key determinant in the case the non-G7 stock markets.

1. Introduction

It is well known that financial markets are affected by external events such as natural disasters and environmental developments (see, e.g., Caporale et al., 2019). They also respond to pandemics, as already seen in the case of the Severe Acute Respiratory Syndrome (SARS) and Ebola Virus Disease (EVD) outbreaks. For instance, Chen et al. (2007, 2009) employed an event study approach and found a negative impact of SARS on tourism and the wholesale and retail sector in Taiwan, but a positive one on the biotechnology sector, which meant that it was still possible to adopt profitable investment strategies by rearranging portfolios. Ichev and Marinc (2018) used both event study and regression methods and found that the Ebola outbreak affected mainly stock markets closer to the birthplace of

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the virus and stocks with more media coverage.

The current Covid-19 pandemic has generated a crisis that is unprecedented in terms of its global nature, the degree of uncertainty concerning effective containment and treatment measures, and its complexity resulting from a combination of supply and demand shocks which could bring about a prolonged recession in the absence of swift and decisive policy responses (see Baldwin and Weder di Mauro, 2020). In particular, the crisis threatened to spread from the real to the banking and financial sector, which was already vulnerable in many countries because of high leverage. Various governments therefore announced measures relying on financial institutions (mainly banks) providing loans to households and firms as well as guarantees to the lenders to avoid a wave of bankruptcies (see Caporale and Cerrato, 2020). Policies aimed at supporting bank lending conditions through funding cost relief and capital relief appear to have been successful in preventing banks' ability to supply credit from being severely affected (see Altavilla et al., 2020). There is also evidence that Quantitative Easing (QE) has been equally effective during the pandemic and that QE interventions have had sizeable real effects on output through their impact on long-term interest rates (see Rebucci et al., 2021).

Concerning specifically the effects on stock markets worldwide, Ramelli and Wagner (2020) provided some initial evidence indicating that these responded quickly to the Covid-19 outbreak as a result of concerns about future economic prospects. Their analysis at industry level reveals differences in cumulative returns across sectors and geographical regions, with a whipsaw pattern in some cases. Additional evidence at firm level shows heterogeneous responses depending on the degree of international exposure and also that concerns about corporate debt (leverage) and corporate liquidity (cash holdings) played an important role. It is clear that the impact of Covid-19 on global financial uncertainty was immediate and massive: as pointed out by Baker et al. (2020), in March 2020 the VIX (Chicago Board Options Exchange's Volatility Index), a forward-looking proxy for financial uncertainty, reached a higher level than during the Great Recession; these authors also found that during that period Covid-19 was mentioned in at least 90% of the newspaper articles used to construct the Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016).

US stock market volatility seems to have been driven mainly by rapidly changing attitudes towards risk or investor sentiment not related to economic fundamentals and policy responses (see Cox et al., 2020). Data from dividend futures have been shown to be useful to quantify investors' expectations about economic growth following the Coronavirus outbreak and the subsequent policy responses (see Gormsen and Koijen, 2020). Stock prices also appear to have exhibited strong predictive content for the collapse in economic activity caused by the pandemic; further, the US evidence suggests that the most successful policy responses involved very prompt virus containment efforts but not necessarily strict lockdowns on economic and social activity (see Davis et al., 2021). The imposition of the latter accounted for much of the decline in employment and consumer spending in the US during the early stages of the pandemic (see Coibion et al., 2020).

In another study, Al-Awadhi et al. (2020) investigated the effects of the Covid-19 pandemic on Chinese stock returns; more specifically, they employed a panel regression approach to estimate the effects of daily growth in both total confirmed cases and total deaths caused by Covid-19 on daily stock returns of companies included in the Hang Seng Index and Shanghai Stock Exchange Composite Index over the period from January 10 to March 16 in 2020. Their results indicate that both variables had a significant negative impact on the Chinese stock market. Further, some sectors, namely information technology and medicine, fared better than others; B-shares, which are mainly traded by foreign investors, saw a much sharper drop in their prices compared to A-shares which are predominantly traded by Chinese market participants, and similarly shares with high market capitalisation were more negatively affected. Interestingly, Albulescu (2020) has also found that the spread of Covid-19 geographically is linked to the degree of financial instability.

Salisu and Vo (2020) instead employed a panel data forecasting approach to assess the role of health news in predicting stock returns and found that they have a negative and statistically significant effect on stock returns, namely returns decline as more information is sought on health issues during the pandemic. Finally, using correlation analysis as well as graph theory and a minimum spanning tree (MST) approach, Zhang et al. (2020) found a substantial increase in risk in global financial markets.

Salisu and Vo (2020) evaluated the importance of health-news trends to forecast stock returns for a list of countries with high incidence of Covid-19; their results showed that a model incorporating a health-news index outperforms the benchmark historical average model; in addition, including macroeconomic factors and financial news improves the forecasting performance of the health news-based model. Štifanić et al. (2020) studied instead the effects of Covid-19 on Crude Oil price and three US stock indices: DJI, S&P 500, and NASDAQ Composite; their approach to forecasting commodity and stock prices integrates the stationary wavelet transform (SWT) and bidirectional long short-term memory (BDLSTM) networks.

The present paper contributes to this new, rapidly growing literature on the economic consequences of the Covid-19 pandemic by analysing its impact on stock market returns and their volatility in the case of the G20 countries. In particular, a dynamic panel model with fixed effects is estimated over the sample period March 2, 2020–February 17, 2021 at both the daily and monthly frequencies. Note that the existing empirical literature typically focuses only on either Covid-19 deaths or lockdown policies. This approach can produce misleading results, such as estimating artificially large negative effects of the former as a result of omitting the restrictive measures introduced by governments. By contrast, our analysis takes into account the effects of both the epidemiological situation and the restrictive measures adopted by governments as well as of fiscal and monetary responses; moreover, instead of Covid-19 deaths it uses a far more sophisticated Covid-19 index based on a Balanced Worth (BW) methodology (Herrero and Villar, 2018, 2020). Thus, the set of regressors includes: (i) a suitable Covid-19 index to measure the direct impact of the pandemic, (ii) a stringency index to capture the effects of lockdowns and other restrictive measures imposed to contain the spread of the virus, (iii) a variable corresponding to the fiscal support measures adopted by national governments to mitigate the economic impact of the pandemic, and (iv) the shadow short rate to measure the monetary policy response. Both the use of a comprehensive framework and of a suitably computed Covid-19 index improve considerably upon previous studies on this topic. Other important contributions of our analysis are its much wider coverage, since all G20 countries are included; the fact that it is carried out not only for stock market returns but also their volatility; finally, the fact that it also allows for heterogeneity by providing additional estimates for the G7 and the remaining countries separately. The layout of the paper is as follows. Section 2 outlines the econometric framework. Section 3 describes the data and the construction of the Covid-19 index. Section 4 discusses the empirical results. Section 5 offers some concluding remarks.

2. Modelling framework

As stated before, the aim of the empirical analysis is to investigate the effects of the Covid-19 pandemic and of policy responses on stock market returns and volatilities. For this purpose, a dynamic panel data model with fixed effects is estimated which takes the following form[2].

$$x_{i,t} = \alpha + \beta x_{i,t-k} + hCovid19_{Index_{i,t-1}} + \theta Fiscal_{Policy_{i,t-1}} + \varphi\, z_{i,t-1} + e_{\,t} \tag{1}$$

where $x_{i,t}$ stands in turn for stock market returns and volatility for country i at time t at both the monthly and daily frequency. An autoregressive structure is allowed with up to one lag ($k = 1$) for monthly data and five lags ($k = 5$) for daily data; insignificant lags are dropped. h and θ measure the impact of the Covid-19 index (*Covid19_Index*) and of fiscal policy (*Fiscal_Policy*) measures respectively on stock market returns (or volatility). z_{t-1} is a vector including the exogenous variables described in Section 3, namely a stringency index, lockdown measures, and short-term shadow rates.

Various model specifications are estimated. The *Covid19_Index* and *Fiscal_Policy* measures (our main variables of interest) are included in all cases. Model 1 and 2 examine their impact on stock market returns and volatilities. The set of regressors includes in turn a 0–1 dummy for lockdown measures (*Lockdown*) and a stringency index (*Stringency_Index*) (0–100) as possible determinants. Model 3 adds an interaction variable between the Covid-19 index and lockdown periods (i.e., *Covid-19_Index* × *Lockdown*). Both sets of models are estimated using monthly and daily data in turn. Finally, we control for heterogeneity by also performing the analysis separately for the G7 countries and the other countries in the sample. The estimated coefficients with the associated robust t-statistics are presented in Tables 3–6.

3. Data sources and description

This section describes the variables included in the econometric model, specifically stock market return and volatility (the dependent variables), a Covid-19 index and a fiscal variable, and also a set of exogeneous variables including a stringency index, a dummy for lockdown measures and the short-term shadow interest rate as a proxy for monetary policy responses.

3.1. Stock markets returns and volatility (dependent variables)

We use stock market returns (*Stock_Return*) and volatilities (*Stock_Volatility*) in turn as the dependent variables. Both series have been obtained at the daily (for working days) and monthly frequencies from Bloomberg. The sample period goes from March 2, 2020 to February 17, 2021 to match the Covid-19 data (see the following section 3.2). The list of all G20 stock market indices considered is displayed in Table 2, panel B. Stock market volatility (σ_n) is calculated as the realized volatility:

$$\sigma_n = \sqrt{\frac{1}{n\Delta t}\sum_{t=1}^{n}\left(\frac{P_t - P_{t-1}}{P_{t-1}} - \widehat{\mu}_n \Delta t\right)^2} \tag{2}$$

where

$$\widehat{\mu}_n = \frac{1}{n\Delta t}\sum_{t=1}^{n}\frac{P_t - P_{t-1}}{P_{t-1}} \tag{3}$$

We set Δt (the increment by time period) as one working day or one month for the daily and monthly frequencies respectively. P_t is the stock market index at time t, where t stands for either the day or the month. n is the nth day or month at the point of estimation for the corresponding parameter. $\widehat{\mu}_n$ is the estimated drift parameter (i.e., the realized mean).

3.2. The Covid-19 index

The source for the Covid-19 data is Our World in Data (https://ourworldindata.org/coronavirus), from which we collect the following daily series for the 20 main economies in the world (G20)[3]: new deaths from Covid-19 per million (*new_deaths*), intensive care unit (ICU) Covid-19 patients per million (*icu_patients*), hospitalized Covid-19 patients per million (*hospital_patients*), new Covid-19 tests per thousand (*new_tests*), and population for each country (*population*) between January 1, 2020 and February 18, 2021. The reported figures concern events that happened one day before, and thus the actual sample to consider goes from December 31, 2019 to

[2] Note that the random effect hypothesis was tested and rejected by means of Hausman test.

[3] These are Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, Saudi Arabia, South Africa, South Korea, Spain, Turkey, the United Kingdom and the United States.

Table 1
List of countries.

Country	Stock Index	G20	G7	Non-G7
Argentina	S&P MERVAL Index	×		×
Australia	S&P/ASX 200 Index	×		×
Brazil	BRAZIL IBOVESPA Index	×		×
Canada	S&P/TSX COMPOSITE Index	×	×	
China	CSI 300 Index	×		×
France	CAC 40 Index	×	×	
Germany	DAX Index	×	×	
India	S&P BSE SENSEX Index	×		×
Indonesia	JAKARTA COMPOSITE Index	×		×
Italy	FTSE MIB Index	×	×	
Japan	NIKKEI 225 Index	×	×	
Mexico	S&P/BMV IPC Index	×		×
Russia	MOEX Russia Index	×		×
Saudi Arabia	TADAWUL ALL SHARE Index	×		×
South Africa	FTSE/JSE AFRICA Index	×		×
South Korea	KOSPI Index	×		×
Spain	IBEX 35 Index	×		×
Turkey	BIST 100 Index	×		×
United Kingdom	FTSE 100 Index	×	×	
United States	S&P 500 Index	×	×	

Note: × denotes our inclusion of the corresponding country and stock index in G20, G7 or Non-G7 countries sampling.
The following table shows the list of G20 countries and their corresponding stock indices used in our analysis.

Table 2
Data description.

Variables	Sources	Description
Panel A. *Covid-19_Index* components		
New_cases	Covid-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University	New confirmed cases of Covid-19
New_deaths	Covid-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University	New deaths attributed to Covid-19 per 1,000,000 people
Icu_patients	European CDC for European countries/UK Government/Covid Tracking Project for the United States/Covid-19 Tracker for Canada	Number of Covid-19 patients in intensive care units (ICUs) on a given day per 1,000,000 people
Hospital_patients	European CDC for European countries/UK Government/Covid Tracking Project for the United States/Covid-19 Tracker for Canada	Number of Covid-19 patients in hospital on a given day per 1,000,000 people
New_tests	National government reports	New tests for Covid-19 per 1000 people
Population	United Nations, Department of Economic and Social Affairs, Population Division, World Population Prospects 2019 Revision	Population in 2020
Panel B. Fiscal policy, stringency index, lockdown and shadow short rate		
Fiscal_Policy	IMF database of fiscal policy responses to Covid-19. https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19	Above the line measures (i.e., additional spending and forgone revenue) as percent of GDP in three strands, as of June 12, September 11 and December 31 in 2020.
Stringency_Index	Oxford Covid-19 Government Response Tracker, Blavatnik School of Government	Government Response Stringency Index: composite measure based on 9 response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest response).
Lockdown	(1) The Global Covid-19 Lockdown Tracker in Aura Vision (https://auravision.ai/covid19-lockdown-tracker), (2) the Covid-19 Government Measures Dataset in ACAPS(https://www.acaps.org/covid-19-government-measures-dataset), and (3) various online news articles.	The overlapping dates across these three lockdown data sources are selected for each country in our sample. In daily frequency data, we create the lockdown dummy variable showing one if the date belongs to the lockdown period and zero otherwise in our daily frequency data. In monthly frequency data, this lockdown dummy variable shows one if any date within the corresponding month belongs to the lockdown period and zero otherwise.
Shadow_Short_Rate	Bloomberg	Morgan Stanley reported shadow short rates for each country in our sample. For countries with no available shadow short rates, we use the US one as a global proxy.

Note: The *Covid-19_Index* is constructed using the inputs from panel A as described in section 3.2.
The following table shows the variables, sources and descriptions for our *Covid-19_Index* components (Panel A) and Fiscal policy, stringency index, lockdown and shadow short rate (Panel B) used in our analysis.

February 17, 2021. Further, we remove the data for weekends when daily deaths, hospitalized patients, testing, etc., are normally lower because of delayed or missing Covid-19 reports. Then we obtain a balanced panel for the period from March 2, 2020 to February 17, 2021.

We create a $Covid19\_Index_{i,t}$ based on the population weighted daily infection rate ($Weighted\_Infection_{i,t}$: share of the population

Table 3
Summary statistics – monthly frequency.

Variables	Mean	Median	Std.	25th per	75th per	*N*
Panel A. G20 countries						
Stock_Return (%)	1.84	2.19	8.40	−2.49	6.09	216
Stock_Volatility (%)	5.13	4.81	1.85	3.85	5.91	216
Fiscal_Policy (%)	6.61	5.27	4.77	3.10	9.39	216
Stringency_Index	63.58	65.54	15.64	52.86	74.68	216
Shadow_Short_Rate (%)	−1.26	−1.15	0.86	−1.91	−0.59	216
Lockdown	0.31	0.00	0.47	0.00	1.00	216
CF_NCovid19_Index	0.13	0.05	0.17	0.01	0.20	216
Panel B. G7 countries						
Stock_Return (%)	1.41	2.13	7.41	−2.43	5.13	84
Stock_Volatility (%)	4.44	4.46	0.88	3.65	4.98	84
Fiscal_Policy (%)	10.23	11.03	4.20	6.82	14.03	84
Stringency_Index	61.20	64.21	14.82	49.57	71.00	84
Shadow_Short_Rate (%)	−1.48	−1.41	0.97	−2.46	−0.58	84
Lockdown	0.31	0.00	0.47	0.00	1.00	84
CF_NCovid19_Index	0.17	0.06	0.21	0.02	0.27	84
Panel C. Non-G7 countries						
Stock_Return (%)	2.09	2.26	9.17	−2.49	6.94	132
Stock_Volatility (%)	5.57	4.87	2.15	3.89	6.37	132
Fiscal_Policy (%)	4.31	3.48	3.52	2.08	5.32	132
Stringency_Index	64.91	67.71	16.70	54.23	77.74	132
Shadow_Short_Rate (%)	−1.13	−1.15	0.76	−1.67	−0.60	132
Lockdown	0.32	0.00	0.47	0.00	1.00	132
CF_NCovid19_Index	0.10	0.04	0.13	0.00	0.15	132

The following table shows the summary statistics for the monthly data for the G20 (Panel A), G7 (Panel B) and non-G7 (Panel C) countries. Stock returns (*Stock_Return*) and volatility (*Stock_Volatility*) are calculated as percentage returns and realized volatility, respectively, according to section 3.1. Fiscal policy (*Fiscal_Policy*) is the additional spending and forgone revenue) as a percentage of GDP. The stringency index (*Stringency_Index*) is a composite measure based on 9 response indicators (e.g., school closures, workplace closures, and travel bans) ranging between 0 and 100 where higher value indicates stronger restriction. Shadow short rate (*Shadow_Short_Rate*) is the short-term policy rate at the zero lower bound (zero or slightly negative) value. Lockdown (*Lockdown*) is the binary variable showing one if a month belongs to the lockdown period and zero otherwise. The Covid-19 index (*CF_NCovid19_Index*) is a Christiano-Fitzgerald filter applied Balanced Worth measure calculated using new deaths from Covid-19 per million (*new_deaths*), intensive care unit (ICU) Covid-19 patients per million (*icu_patients*), hospitalized Covid-19 patients per million (*hospital_patients*), new Covid-19 tests per thousand (*new_tests*), and population for each country (*population*). We show he mean, median, standard deviation (Std.), 25th percentile (25th per), 75th percentile (75th per) and total number of observations (*N*).

(*population*) newly infected by the Coronavirus on each day (*new_cases*)) and severity ($Severity_{i,t}$: a daily measure of the relative health situation of that population) for country *i* at day *t*:

$$Covid19_{Index_{i,t}} = Weighted_{Infection_{i,t}} \times Severity_{i,t} = \frac{new\_cases_{i,t}}{population_{i,t}} \times Severity_{i,t} \tag{4}$$

We use a Balanced Worth (BW) methodology (Herrero and Villar, 2018, 2020) to measure *Severity* on the basis of the different possible outcomes of Covid-19 infections including *new_deaths*, *icu_patients*, *hospital_patients* and *new_tests* categories.[4] We evaluate *Severity* for various populations affected by the virus, $G = \{1,2, \ldots, g\}$ over a set of health conditions $C = new\_deaths, icu\_patients, hospital\_patients, new\_tests$ ordered from worst to best. $a_{j,c} = \frac{n_{j,c}}{n_j}$ is the share of people within population *j* with health condition *c*. n_j and $n_{j,c}$ are the number of individuals in population *j* and those with health condition *c* resulting from the virus, respectively.

We then calculate the probability $p_{j,k}$ that an individual of population *j* exhibits a worse health condition than one of population *k*, with the health condition categories being ordered from worst to best:

$$\begin{aligned} p_{j,k} &= a_{j,new\_deaths}\left(a_{j,icu\_patients} + a_{j,hospital\_patients} + a_{j,new\_tests}\right) \\ &+ a_{j,icu\_patients}\left(a_{j,hospital\_patients} + a_{j,new\_tests}\right) + a_{j,hospital\_patients}\, a_{j,new\_tests} \end{aligned} \tag{5}$$

$e_{j,k} = e_{k,j}$ is the probability of a tie between individuals of population *j* and *k*. Accordingly, we define the probability $q_{j,k}$ of an individual of population *j* being under a worse health condition than one in population *k* as follows:

$$q_{j,k} = p_{j,k} + \frac{e_{j,k}}{2} \tag{6}$$

[4] Giovannetti et al. (2020) and Herrero and Villar (2020) use the number of patients that have recovered from Covid-19 as an input to construct this index for the Italian regions. However, such data are not available for the whole period of interest in the case of the 20 countries in our sample and therefore we use instead the number of daily Covid-19 tests per thousand people (*new_tests*).

Table 4
Summary statistics – daily frequency.

Variables	Mean	Median	Std.	25th per	75th per	*N*
Panel A. G20 countries						
Stock_Return (%)	0.12	0.17	1.75	−0.64	1.02	5060
Stock_Volatility (%)	1.60	1.49	0.51	1.37	1.62	5060
Fiscal_Policy	6.17	4.64	4.68	2.68	8.84	5060
Stringency_Index	65.25	68.06	16.01	55.09	75.93	5060
Shadow_Short_Rate (%)	−1.13	−1.04	0.92	−1.77	−0.50	5060
Lockdown	0.28	0.00	0.45	0.00	1.00	5060
CF_NCovid19_Index	0.06	0.02	0.09	0.00	0.09	5060
Panel B. G7 countries						
Stock_Return (%)	0.09	0.13	1.70	−0.64	1.00	1771
Stock_Volatility (%)	1.53	1.57	0.18	1.42	1.66	1771
Fiscal_Policy	10.17	11.03	4.23	6.82	14.65	1771
Stringency_Index	62.70	66.67	16.21	49.54	72.69	1771
Shadow_Short_Rate (%)	−1.43	−1.28	1.02	−2.48	−0.55	1771
Lockdown	0.38	0.00	0.49	0.00	1.00	1771
CF_NCovid19_Index	0.09	0.03	0.12	0.01	0.13	1771
Panel C. Non-G7 countries						
Stock_Return (%)	0.13	0.18	1.78	−0.66	1.03	3289
Stock_Volatility (%)	1.64	1.46	0.62	1.34	1.58	3289
Fiscal_Policy	4.02	3.11	3.28	2.19	4.73	3289
Stringency_Index	66.68	69.91	15.76	57.41	78.24	3289
Shadow_Short_Rate (%)	−0.98	−1.00	0.81	−1.55	−0.43	3289
Lockdown	0.23	0.00	0.42	0.00	0.00	3289
CF_NCovid19_Index	0.05	0.02	0.07	0.00	0.06	3289

The following table shows the summary statistics for the daily data for the G20 (Panel A), G7 (Panel B) and non-G7 (Panel C) countries. Stock returns (*Stock_Return*) and volatility (*Stock_Volatility*) are calculated as percentage retursn and realized volatility, respectively, according to section 3.1. Fiscal policy (*Fiscal_Policy*) is the additional spending and forgone revenue) as a percentage of GDP. The stringency index (*Stringency_Index*) is a composite measure based on 9 response indicators (e.g., school closures, workplace closures, and travel bans) ranging between 0 and 100 where higher value indicates stronger restriction. Shadow short rate (*Shadow_Short_Rate*) is the short-term policy rate at the zero lower bound (zero or slightly negative) value. Lockdown (*Lockdown*) is the binary variable showing one if a day belongs to the lockdown period and zero otherwise. The Covid-19 index (*CF_NCovid19_Index*) is a Christiano-Fitzgerald filter applied Balanced Worth measure calculated using new deaths from Covid-19 per million (*new_deaths*), intensive care unit (ICU) Covid-19 patients per million (*icu_patients*), hospitalized Covid-19 patients per million (*hospital_patients*), new Covid-19 tests per thousand (*new_tests*), and population for each country (*population*). We show he mean, median, standard deviation (Std.), 25th percentile (25th per), 75th percentile (75th per) and total number of observations (*N*).

Table 5
Correlation matrix – monthly frequency.

	(a)	(b)	(c)	(d)	(e)
Panel A. G20 countries					
Fiscal_Policy (a)	1***				
Stringency_Index (b)	−0.07	1***			
Shadow_Short_Rate (c)	0.24***	−0.18***	1***		
Lockdown (d)	−0.62***	0.02	−0.14**	1***	
CFN_Covid19_Index (e)	0.04	−0.21***	0.16**	0.07	1***
Panel B. G7 countries					
Fiscal_Policy (a)	1***				
Stringency_Index (b)	−0.45***	1***			
Shadow_Short_Rate (c)	−0.65***	0.28**	1***		
Lockdown (d)	0.52***	0.17	−0.74***	1***	
CFN_Covid19_Index (e)	−0.01	−0.46***	−0.11	0.01	1***
Panel C. Non-G7 countries					
Fiscal_Policy (a)	1***				
Stringency_Index (b)	−0.49***	1***			
Shadow_Short_Rate (c)	−0.27***	0.13	1***		
Lockdown (d)	−0.05	−0.02	−0.31***	1***	
CFN_Covid19_Index (e)	0.17**	−0.4***	0.04	0.35***	1***

The following table shows the Pearson's correlation matrix between the monthly frequency regressors for the G20 (Panel A), G7 (Panel B) and non-G7 (Panel C) countries. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Table 6
Correlation matrix – daily frequency.

	(a)	(b)	(c)	(d)	(e)
Panel A. G20 countries					
Fiscal_Policy (a)	1***				
Stringency_Index (b)	0.05***	1***			
Shadow_Short_Rate (c)	0.47***	−0.17***	1***		
Lockdown (d)	−0.26***	0.01	−0.01	1***	
CFN_Covid19_Index (e)	−0.03**	−0.17***	0.19***	0.06***	1***
Panel B. G7 countries					
Fiscal_Policy (a)	1***				
Stringency_Index (b)	−0.58***	1***			
Shadow_Short_Rate (c)	−0.66***	0.51***	1***		
Lockdown (d)	−0.37***	0.42***	0.15***	1***	
CFN_Covid19_Index (e)	−0.16***	−0.27***	0.05**	0.29***	1***
Panel C. Non-G7 countries					
Fiscal_Policy (a)	1***				
Stringency_Index (b)	−0.37***	1***			
Shadow_Short_Rate (c)	−0.18***	0.11***	1***		
Lockdown (d)	−0.08***	−0.07***	−0.18***	1***	
CFN_Covid19_Index (e)	0.3***	−0.46***	0.18***	0.04**	1***

The following table shows the Pearson's correlation matrix between the daily frequency regressors for G20 (Panel A), G7 (Panel B) and non-G7 (Panel C) countries. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Note that $p_{j,k} + p_{k,j} + e_{j,k} = 1$. Then the severity measures for the two populations j and k (s_j and s_k, respectively) are proportional to the corresponding probabilities of being relatively worse off, namely:

$$\frac{s_j}{s_k} = \frac{q_{j,k}}{q_{k,j}} = \frac{p_{j,k} + \frac{e_{j,k}}{2}}{p_{k,j} + \frac{e_{k,j}}{2}}$$

$$\Leftrightarrow s_j = \frac{\left(p_{j,k} + \frac{e_{j,k}}{2}\right) s_k}{p_{k,j} + \frac{e_{k,j}}{2}} \tag{7}$$

This pairwise severity comparison between two populations can be extended to a comparison among more than two populations by taking expectations as follows:

$$s_j = \frac{\frac{1}{g-1}\sum_{j\neq k}\left(p_{j,k} + \frac{e_{j,k}}{2}\right) s_k}{\frac{1}{g-1}\sum_{j\neq k}\left(p_{k,j} + \frac{e_{k,j}}{2}\right)} = \frac{\frac{1}{g-1}\sum_{j\neq k}\left(p_{j,k} + \frac{e_{j,k}}{2}\right) s_k}{\frac{1}{g-1}\sum_{j\neq k}\left(1 - \left(p_{j,k} + \frac{e_{j,k}}{2}\right)\right)}, j,k = 1,2,\dots g \tag{8}$$

In equation (8), the numerator is the average relative Covid-19 severity of population j with respect to the rest, and the denominator is the average relative Covid-19 severity of the populations other than j compared to population j.

The vector of s_j severity values is the BW which measures the relative severity of Covid-19 for different populations. This is obtained as the dominant eigenvector of a Perron matrix M:

$$M = \begin{pmatrix} (g-1) - \sum_{j\neq 1}\left(p_{j,1} + \frac{e_{j,1}}{2}\right) & p_{1,2} + \frac{e_{1,2}}{2} & \cdots & p_{1,g} + \frac{e_{1,g}}{2} \\ p_{2,1} + \frac{e_{2,1}}{2} & (g-1) - \sum_{j\neq 2}\left(p_{j,2} + \frac{e_{j,2}}{2}\right) & \cdots & p_{2,g} + \frac{e_{2,g}}{2} \\ \vdots & \vdots & & \vdots \\ p_{g,1} + \frac{e_{g,1}}{2} & p_{g,2} + \frac{e_{g,2}}{2} & \cdots & (g-1) - \sum_{j\neq g}\left(p_{j,g} + \frac{e_{j,g}}{2}\right) \end{pmatrix} \tag{9}$$

The Perron matrix M columns add up to $(g-1)$ and if M is irreducible this implies the existence, positivity and uniqueness of the BW vector (Herrero and Villar, 2018, 2020). In our analysis, each country i uses its own collection of populations G while the vector of s_j severity values based on the BW method above is used to produce $Severity_{i,t}$. We have implemented the algorithm from the Ivie website http://web2011.ivie.es/balanced-worth/to obtain the BW vectors.

In order to make our Covid-19 index comparable across the globe with a normalized figure between zero and one, we use a min-max normalization to create $NCovid19\_Index_{i,t}$ as follows:

$$NCovid19\_Index_{i,t} = \frac{Covid19\_Index_{i,t} - Min(Covid19\_Index)}{Max(Covid19\_Index) - Min(Covid19\_Index)} \tag{10}$$

The *Min*(*Covid19_Index*) and *Max*(*Covid19_Index*) are the minimum and maximum *Covid19_Index*, respectively, across our sample period and countries.

We then apply the Christiano-Fitzgerald filter (Christiano and Fitzgerald, 2003) to smooth the normalized Covid-19 index ($NCovid19\_Index_{i,t}$) and calculate the trend component ($CF\_NCovid19\_Index_{i,t}$) using band-pass approximations:

$$NCovid19\_Index_{i,t} = CF\_NCovid19\_Index_{i,t} + \overline{NCovid19\_Index_{i,t}} \tag{11}$$

We isolate the trend component $CF\_NCovid19\_Index_{i,t}$ with minimum and maximum oscillation periods p_l and p_u, respectively, where $2 \le p_l < p_u < \infty$. We set $p_l = 2$ and $p_u = 5$ to allow the oscillation period to be between minimum two and maximum five days, respectively, as our daily data excludes weekends. The process $CF\_NCovid19\_Index_{i,t}$ has power only in frequencies in the interval $\{(a, b) \cup (-b, -a)\} \in (-\pi, \pi)$. The process $\overline{NCovid19\_Index_{i,t}}$ has power only in the complement of this interval in $(-\pi, \pi)$. a and b belong to the interval $0 < a \le b \le \pi$ and are related to p_l and p_u by

$$a = \frac{2\pi}{p_u} \quad b = \frac{2\pi}{p_l} \tag{12}$$

The random walk filter approximation of $CF\_NCovid19\_Index_{i,t}$ is $CF\_NCov\widehat{id1}9\_Index_{i,t}$ computed as follows:

$$\begin{aligned} CF\_NCov\widehat{id1}9\_Index_{i,t} &= B_{i,0}NCovid19\_Index_{i,t} + B_{i,1}NCovid19\_Index_{i,t+1} + \cdots + B_{i,T-1-t}NCovid19\_Index_{i,T-1} + \widetilde{B_{i,T-t}}NCovid19\_Index_{i,T} \\ &+ B_{i,1}NCovid19\_Index_{i,t-1} + \cdots + B_{i,t-2}NCovid19\_Index_{i,2} + \widetilde{B_{i,t-1}}NCovid19\_Index_{i,1}, t \\ &= 3, 4, \ldots, T-2 \end{aligned} \tag{13}$$

where the filter weights are as below:

$$B_{i,m} = \frac{sin(mb) - sin(ma)}{\pi\, m}, B_{i,0} = \frac{b-a}{\pi}, \widetilde{B_{i,k}} = -\frac{1}{2}B_{i,0} - \sum_{m=1}^{k-1} B_{i,m}, m \ge 1 \tag{14}$$

The Christiano-Fitzgerald filter is suitable for different data frequencies and its random walk assumption optimizes the approximation better than other filters including the Hodrick–Prescott, Baxter–King ones and the Trigonometric Regression (Christiano and Fitzgerald, 2003; Baum, 2006). We display the computed *CF_NCovid19_Index* for each of the G20 countries in Fig. 1 where the absolute values on the y-axis are comparable across countries as they are already normalized using equation (10). For instance, one can see that this index peaked at 0.6 in the US compared to 0.03 in Australia and 0.00015 in China.[5] The various peaks in individual countries (for instance, two in Italy and three in South Korea) clearly correspond to different Covid-19 waves.

3.3. Fiscal policy measures

For the fiscal support measures taken by national governments in response to the Covid-19 pandemic the source is the International Monetary Fund (IMF)'s database of fiscal policy responses to Covid-19. Specifically, we collect the *above_the_line_measures* (i.e., additional spending and forgone revenue) as a percentage of GDP at three points in time, namely June 12, September 11 and December 31 in 2020.[6] For the sample period from January 1 to February 17 in 2021 we use extrapolated data.

3.4. Stringency index and lockdown measures

The *Stringency_Index* is collected from Our World in Data (https://ourworldindata.org/coronavirus) along with the other Covid-19 data. This index is a composite measure based on 9 response indicators (e.g., school closures, workplace closures, and travel bans) ranging between 0 and 100 where higher values indicate stricter measures. We then collect the lockdown dates from (1) the Global Covid-19 Lockdown Tracker in Aura Vision (https://auravision.ai/covid19-lockdown-tracker), (2) the Covid-19 Government Measures Dataset in ACAPS (https://www.acaps.org/covid-19-government-measures-dataset) and (3) various online news articles. Common dates across these three lockdown data sources are selected to create a lockdown dummy variable for each country which is equal to one for the lockdown periods and zero otherwise at the daily frequency, and equal to one if any date within the corresponding month includes the lockdown period and zero otherwise at the monthly frequency.

[5] Although in the case of China the *CF_NCovid19_Index* exhibits high oscillations during the initial period, its variance has in fact extremely small over the entire sample compared to the other countries.

[6] The IMF source also provides another Covid-19 fiscal policy measure called *liquidity_support* including equity, loans and guarantees as a percentage of GDP. However, this variable was found to be insignificant and thus it was dropped from the model.

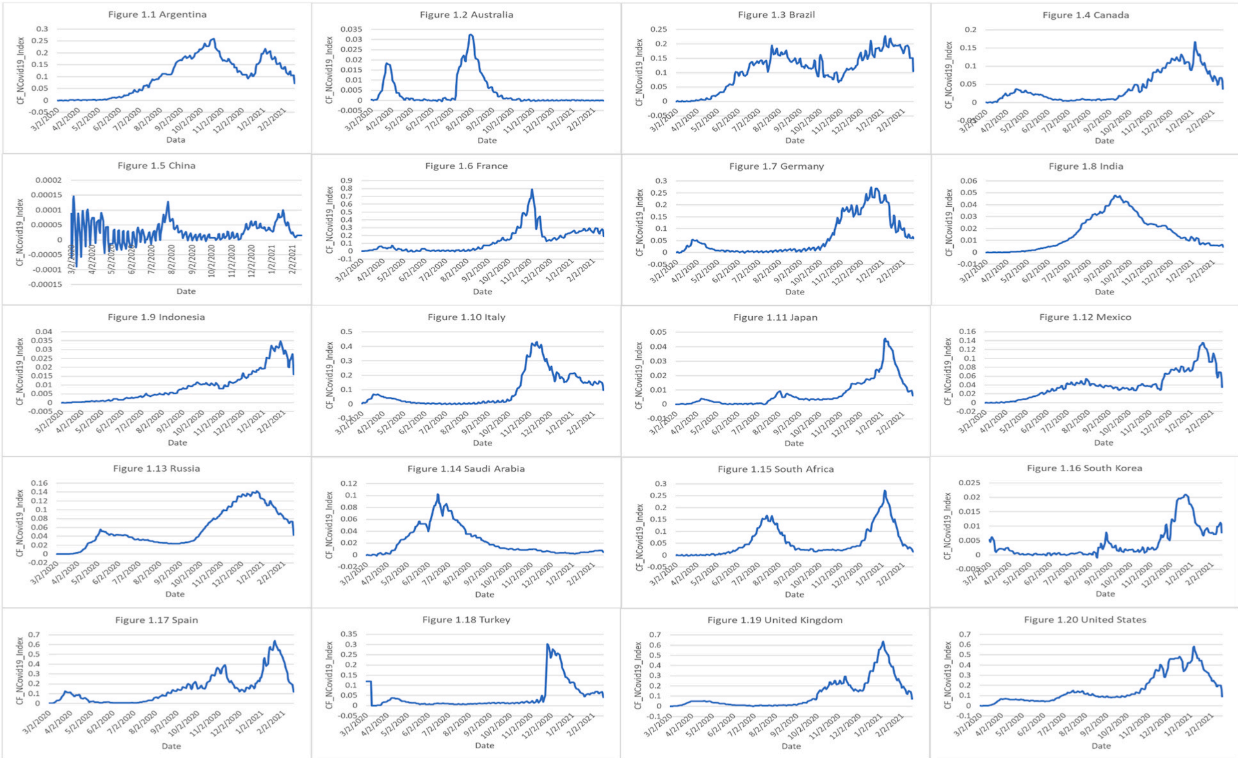

Fig. 1. Covid-19 indices for the G20 countries.

3.5. Short-term shadow rates

We use the short-term shadow rates (*Shadow_Short_Rate*) for each sample country to investigate the impact of monetary policy during the Covid-19 pandemic. These have been chosen as a quantitative measure of the overall stance of monetary policy when the conventional policy instrument (the short-term policy rate) is at the zero lower bound (zero or slightly negative value – see Kuusela and Hännikäinen, 2017). We use the Morgan Stanley reported shadow short rates for the countries for which they are available, and the US one as a proxy in the other cases.

Table 1 shows the list of G20 countries and the split between G7 and non-G7. Table 2 reports the sources and descriptions for the variables used to construct the Covid-19 Index (Panel A) and the others including fiscal policy, the stringency index, lockdowns and short-term shadow rates (Panel B).

Tables 3 and 4 display summary statistics for both the daily and monthly and data, winsorized at the 1st and 99th percentiles. The *CF_NCovid19_Index* indicates that the Covid-19 pandemic has affected more severely the G7 countries, where there have been more frequent lockdowns (*Lockdown*)[7] but less stringent restrictions (*Stringency_Index*) as well as a stronger fiscal stimulus (*Fiscal_Policy*) and lower shadow rates (*Shadown_Short_Rate*) compared to the non-G7 countries. Further, during the Covid-19 pandemic, the G7 countries experienced lower stock returns (*Stock_Return*) whilst the non-G7 countries exhibited higher stock market volatilitiy (*Stock_Volatility*). Finally, the correlation matrix for the monthly (Table 5) and daily (Table 6) series implies that there are no multicollinearity issues.

4. Empirical results

4.1. G20 countries

The estimates from the dynamic panel data model with fixed effects given by equation (1) indicate that the impact of the Covid-19 pandemic (*CF_NCovid19_Index*) has decreased stock market returns whilst increased stock market volatility in all G20 countries (Table 7). As already explained, our *CF_NCovid19_Index* is a composite BW measure of Covid-19 severity comprising related new deaths (*New_death*), intensive care unit admissions (*Icu_patients*), hospitalizations (*Hospital_patients*), and Covid tests (*New_tests*), which are weighted by the infection rate (*New_cases*) per population in each country (*Population*). Our results for stock market returns are consistent with the negative effect of Covid-19 confirmed cases and total deaths previously found for the Chinese stock market

[7] Given the way the lockdown dummies are constructed (see Section 3.4) we base our comparison on the daily variable.

Table 7
G20 countries.

Parameters	*Stock_Return*		*Stock_Volatility*	
	Coef.	P-values	Coef.	P-values
Panel A. Monthly frequency				
AR (1)	−0.140**	(0.031)	0.576**	(0.037)
CF_NCovid19_Index	−3.731	(0.223)	0.088**	(0.022)
CF_NCovid19_Index × *Lockdown*	−10.77**	(0.041)	0.028**	(0.016)
Lockdown	−0.161	(0.336)	0.222	(0.342)
Fiscal_Policy	1.670**	(0.011)	0.095	(0.132)
Stringency_Index	−0.091**	(0.044)	0.038	(0.112)
Shadow_Short_Rate	−6.779	(0.421)	0.181**	(0.022)
Fixed Effects	Yes		Yes	
Cluster	Yes		Yes	
F-test	31.45***		32.55***	
R^2	0.37		0.30	
N	228		228	
Parameters	*Stock_Return*		*Stock_Volatility*	
	Coef.	P-values	Coef.	P-values
Panel B. Daily frequency				
AR (1)	−0.054**	(0.038)	0.912**	(0.014)
CF_NCovid19_Index	−0.036**	(0.011)	0.005**	(0.034)
CF_NCovid19_Index × *Lockdown*	−0.001**	(0.018)	0.023**	(0.009)
Lockdown	−0.002	(0.543)	0.009	(0.661)
Fiscal_Policy	0.005	(0.211)	0.002	(0.301)
Stringency_Index	−0.005**	(0.035)	0.003	(0.138)
Shadow_Short_Rate	−0.004**	(0.047)	0.008	(0.444)
Fixed Effects	Yes		Yes	
Cluster	Yes		Yes	
F-test	21.89***		20.56***	
R^2	0.15		0.25	
N	5040		5040	

Note: *CF_NCovid19_Index* × *Lockdown* is the interaction term controlling for the effect of the Covid19_Index during lockdown periods only (*Lockdown* = 1).
The following table shows the Covid-19 impact (*CF_NCovid19_Index*) on stock returns (*Stock_Return*) and volatility (*Stock_Volatility*) for the G20 countries based on monthly (Panel A) and daily (Panel B) frequency data. We use the dynamic panel regression model with fixed effect including an autoregressive term *AR(1)* to generate these results. We report the *F*-statistics, R^2 and number of observations (*N*). The p-values are in the brackets. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

(Al-Awadhi et al., 2020), and the negative impact of Covid-19 related health news on the stock returns of the 20 worst hit countries reported by the Center for Disease Control and Prevention (CDC) as of March 30, 2020 (Salisu and Vo, 2020). The estimated increase in stock market volatility resulting from the Covid-19 pandemic is also in line with the conclusion reached by Baker et al. (2020) and Albulescu's (2020) according to whom this has increased global financial uncertainty proxied by the VIX. The finding that during lockdown periods corresponding to particularly severe Covid-19 conditions (*CF_NCovid19_Index* × *Lockdown*) stock market returns are lower is consistent with the results of Davis et al. (2021) indicating that the reduction in economic activity caused by lockdowns has a negative effect on returns, especially during periods when the epidemiological situation is at its worst. A Covid-19 related fiscal stimulus in the form of additional spending and forgone revenue (*Fiscal_Policy*) has a positive impact on stock market returns.[8] Government restrictions (*Stringency_Index*) including school closures, workplace closures, and travel bans during the Covid-19 pandemic reduce returns in a service-oriented economy as already found by Baker et al. (2020). The shadow short rate (*Shadow_Short_Rate*), a proxy for a near-zero central bank policy rate during unconventional monetary policy periods (Krippner, 2020), is estimated to have a significant negative impact on stock market returns and a positive one on volatility. This finding confirms the importance of including this measure of the monetary policy stance during period characterised by near-zero interest rates since conventional rates, for instance, could account for at most one third of the V-shaped trajectory of the stock market rebound in mid-March of 2020 and could not explain the drop in stock prices during the Covid-19 pandemic periods (see Cox et al., 2020).

4.2. G7 countries

Table 8 reports the results for the G7 countries. In this case there appears to be a significant negative impact on stock market returns of government restrictions (*Stringency_Index*) rather than the severity of Covid-19 (*CF_NCovid19_Index*), whilst both increase stock

8 The fiscal variable captures the effect of the fiscal stimulus announcement only, not the subsequent transmission to the real economy.

Table 8
G7 countries.

Parameters	*Stock_Return*		*Stock_Volatility*	
	Coef.	P-values	Coef.	P-values
Panel A. Monthly frequency				
AR (1)	−0.197	(0.565)	0.215	(0.111)
CF_NCovid19_Index	−2.767	(0.425)	0.243***	(0.005)
CF_NCovid19_Index × *Lockdown*	−0.340	(0.213)	0.064***	(0.002)
Lockdown	−0.221	(0.301)	0.053	(0.404)
Fiscal_Policy	1.585**	(0.043)	0.015	(0.513)
Stringency_Index	−0.137**	(0.036)	0.011	(0.432)
Shadow_Short_Rate	−5.470	(0.102)	0.218**	(0.017)
Fixed Effects	Yes		Yes	
Cluster	Yes		Yes	
F-test	25.16***		27.09***	
R^2	0.18		0.23	
N	84		84	
Parameters	*Stock_Return*		*Stock_Volatility*	
	Coef.	P-values	Coef.	P-values
Panel B. Daily frequency				
AR (1)	−0.109**	(0.025)	0.811**	(0.011)
CF_NCovid19_Index	−0.022	(0.397)	0.062**	(0.016)
CF_NCovid19_Index × *Lockdown*	−0.011	(0.408)	0.092**	(0.046)
Lockdown	−0.009	(0.421)	0.112	(0.301)
Fiscal_Policy	0.027**	(0.012)	0.075	(0.324)
Stringency_Index	−0.004	(0.674)	0.044**	(0.022)
Shadow_Short_Rate	−0.275**	(0.033)	0.003**	(0.035)
Fixed Effects	Yes		Yes	
Cluster	Yes		Yes	
F-test	27.17***		31.08***	
R^2	0.17		0.24	
N	1764		1764	

Note: See notes Table 7.
The following table shows the Covid-19 impact (*CF_NCovid19_Index*) on stock returns (*Stock_Return*) and volatility (*Stock_Volatility*) of the G7 countries based on monthly (Panel A) and daily (Panel B) frequency data. We use the dynamic panel regression model with fixed effect including an autoregessive term *AR(1)* to generate these results. We report the *F*-statistics, R^2 and number of observations (*N*). The p-values are in the brackets. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

market volatility. In other words, measures such as mandatory business closures, commercial activity restrictions and social distancing rather than the Covid-19 severity itself seem to have made stock prices plunge during the pandemic. The same conclusion was reached by Baker et al. (2020), who pointed out that even the much higher excess mortality rates of previous Spanish Flu (1918–19) and influenza pandemics (1957–58 and 1968) only left mild traces on stock markets whilst restrictions normally have a significantly more pronounced effect. Lockdowns during periods of severe Covid-19 conditions (*CF_NCovid19_Index* × *Lockdown*) mainly affect stock market volatility as opposed to returns. Covid-19 related fiscal policy measure (*Fiscal_Policy*) are effective in boosting stock market returns without increasing volatility. By contrast, a higher shadow short rate (*Shadow_Short_Rate*) appears to have a negative impact on stock returns while increasing volatility.

4.3. Non-G7 countries

Table 9 shows the estimates for the non-G7 countries. Unlike in the previous case, for this subgroup the severity of Covid-19 (*CF_NCovid19_Index*) not only increases volatility but also reduces returns significantly. Lockdowns under severe Covid-19 conditions (*CF_NCovid19_Index* × *Lockdown*) also have both those effects and so do restrictions such as workplace closures, travel bans, social distancing, etc. (*Stringency_Index*). However, a fiscal stimulus (*Fiscal_Policy*) only increases stock market volatility. According to Auerbach et al. (2021), although such measures are useful in the event of a slump, their marginal effect on the economy decreases with higher inequality, and in fact the average Gini coefficient for the non-G7 countries (41.78) is higher than for the G7 ones (34.27) (see Appendix I), which supports this argument. The near zero policy rate (*Shadow_Short_Rate*) is not very effective either in boosting returns but unlike the fiscal measures does not increase volatility. Finally, all results (for the G20 as a whole and the two subgroups – see Tables 7–9) are robust across the two frequencies, daily and monthly (see Panels A and B respectively), in the sense that the coefficients signs (though their significance) are the same.

Table 9
Non-G7 countries.

Parameters	*Stock_Return*		*Stock_Volatility*	
	Coef.	P-values	Coef.	P-values
Panel A. Monthly frequency				
AR (1)	−0.151**	(0.000)	0.531**	(0.027)
CF_NCovid19_Index	−25.14**	(0.032)	0.217**	(0.031)
CF_NCovid19_Index × *Lockdown*	−36.94**	(0.031)	0.098**	(0.046)
Lockdown	−1.56*	(0.051)	0.022*	(0.076)
Fiscal_Policy	0.472	(0.401)	0.014**	(0.012)
Stringency_Index	−0.115**	(0.012)	0.018	(0.165)
Shadow_Short_Rate	−1.542	(0.168)	−0.253	(0.202)
Fixed Effects	Yes		Yes	
Cluster	Yes		Yes	
F-test	28.97***		31.14***	
R^2	0.32		0.30	
N	144		144	
Parameters	*Stock_Return*		*Stock_Volatility*	
	Coef.	P-values	Coef.	P-values
Panel B. Daily frequency				
AR (1)	−0.035**	(0.036)	0.0901**	(0.027)
CF_NCovid19_Index	−0.053**	(0.042)	0.007**	(0.033)
CF_NCovid19_Index × *Lockdown*	−0.005*	(0.078)	0.005**	(0.019)
Lockdown	−0.003**	(0.032)	0.002**	(0.019)
Fiscal_Policy	0.003	(0.137)	0.003**	(0.028)
Stringency_Index	−0.002**	(0.046)	0.001**	(0.034)
Shadow_Short_Rate	−0.007*	(0.089)	0.001	(0.234)
Fixed Effects	Yes		Yes	
Cluster	Yes		Yes	
F-test	26.14***		24.99***	
R^2	0.20		0.18	
N	3276		3276	

Note: See notes Table 7.
The following table shows the Covid-19 impact (*CF_NCovid19_Index*) on stock returns (*Stock_Return*) and volatility (*Stock_Volatility*) of the non-G7 countries based on monthly (Panel A) and daily (Panel B) frequency data. We use the dynamic panel regression model with fixed effect including an autoregressive term *AR(1)* to generate these results. We report the *F*-statistics, R^2 and number of observations (*N*). The p-values are in the brackets. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

5. Conclusions

This paper examines the impact of the Covid-19 pandemic on stock market returns and their volatility in the case of the G20 countries. In contrast to the existing empirical literature, which typically focuses only on either Covid-19 deaths or lockdown policies, our analysis is based on a comprehensive dynamic panel model accounting for the effects of both the epidemiological situation and restrictive measures as well as of fiscal and monetary responses; moreover, instead of Covid-19 deaths it uses a far more sophisticated Covid-19 index based on a Balanced Worth (BW) methodology (see Herrero and Villar, 2018, 2020), and it also takes into account heterogeneity by providing additional estimates for the G7 and the remaining countries (non-G7) separately.

Our analysis produces a number of interesting findings and confirms the importance of distinguishing between different sets of countries. In particular, whilst for the G20 as a whole it would appear that the epidemiological situation has had a significant impact on both stock market returns and volatility (negative and positive, respectively), the estimation for the G7 and non-G7 subgroups reveals some key differences between these two sets of countries. Specifically, we find that the stock markets of the G7 are affected negatively by government restrictions more than the Covid-19 pandemic itself. By contrast, in the non-G7 countries both variables have had a negative impact. Further, lockdowns during periods with particularly severe Covid-19 conditions have decreased returns in the non-G7 countries whilst increased volatility in the G7 ones. Fiscal and monetary policy (the latter measured by the shadow short rate) have had positive and negative effects, respectively, on the stock markets of the G7 countries but not of non-G7 ones. In brief, our evidence suggests that restrictions and other policy measures have played a more important in the G7 countries whilst the Covid-19 pandemic itself has been the key determinant of stock market movements in the non-G7 economies during the period in question, the implication being that the focus should be on measures directly affecting the economy in the G7 and instead on ameliorating the epidemiological situation in the non-G7 ones.

Appendix I. Average Gini coefficients between 2011 and 2019 (the most recently available year)

Country	Ave. Gini coef.
Argentina	41.71
Australia	34.40
Brazil	53.01
Canada	33.37
China	40.10
France	32.48
Germany	31.17
India	35.70
Indonesia	39.02
Italy	35.20
Japan	32.90
Mexico	47.28
Russia	38.80
South Africa	63.00
South Korea	31.40
Spain	35.60
Turkey	41.29
United Kingdom	33.69
United States	41.11
G20 average	39.01
G7 average	34.27
Non-G7 average	41.78

Note: Saudi Arabia is not included due to unavailable Gini coefficients. The starting year 2011 has been chosen as India shows available Gini coefficients until then.
Source: World Bank.

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