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Causal inference for the impact of economic policy on financial and labour markets amid the COVID-19 pandemic

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Abstract. The COVID-19 pandemic has turned the world upside down since the beginning of 2020, leaving most nations worldwide in both health crises and economic recession. Governments have been continually responding with multiple support policies to help people and businesses overcoming the current situation, from “Containment”, “Health” to “Economic” policies, and from local and national supports to international aids. Although the pandemic damage is still not under control, it is essential to have an early investigation to analyze whether these measures have taken effects on the early economic recovery in each nation, and which kinds of measures have made bigger impacts on reducing such negative downturn. Therefore, we conducted a time series based causal inference analysis to measure the effectiveness of these policies, specifically focusing on the “Economic support” policy on the financial markets for 80 countries and on the United States and Australia labour markets. Our results identified initial positive causal relationships between these policies and the market, providing a perspective for policymakers and other stakeholders.

Keywords: COVID-19 pandemic, causal analysis, economic policy, policy impact analysis, social forecast

1. Introduction

The COronaVIrus Disease (COVID-19) pandemic is imposing a heavy threat to our modern lives, resulting in millions of life losses together with high and rising costs in both social wellness and financial wealth. To halt the virus spread, multiple containment policies, such as social distancing, school and business closures, travel restrictions, and border closures, have been enforced in many countries. Consequently, the global economy was severely impacted with a predicted -3.5% contraction in 2020 global Gross Domestic Product (GDP), which is much worse than in the 2007–2009 Global Financial Crisis (GFC) [13]. In order to mitigate the strong negative impacts and damages caused by various containment policies to economics and finance, countries have launched multiply economic and financial aid and stimulus packages in different stages of the pandemic, which have taken certain effects on every country’s economic status and living condition.

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Fig. 1. Survival rates versus GDP growth rates (left) and employment rate (right) of countries in the COVID-19 pandemic.

In the year 2021, developed nations are estimated to experience an average of −5.4% decrease in GDP. That number for emerging and developing countries is −2.3% [29], which would be the weakest performance by this group in at least sixty years. The world trade volume in 2021 would be heavily impacted with a global decrease of −9.6% (−10.1% for advanced economies and −8.9% for emerging markets). This shared recession might reverse years of progress toward the development goals and push millions of people back into extreme poverty status [29].

We took a closer look at the overall situation of countries based on both their health data from the COVID-19 dataset [8] and their economic data from the Internation Monetary Fund (IMF) World Economic Outlook (WEO) [13]. The y-axis in the left plot of Fig. 1 is the GDP Growth Rate (per capita), measured by the projected changes in GDP (per capita) for each country in 2020. The y-axis in the right plot is the Employment Rate, measured by 100% minus the forecasted Unemployment Rates. The x-axis in both plots is the Recovery Rate, measured by the division of the number of recovered COVID-19 patients by the total infected cases for each country. This is a comparative analysis, so we set the middle points of both plots as the average values among the data for these countries only.

From Fig. 1 (left), Vietnam and China stood out with better situations in terms of both health and economic outcomes. These two countries were the very first to issue containment policies. The worst scenarios in both aspects were in the United States, the United Kingdom, Sweden, Netherlands, and a few other European countries. Most of these countries considered lock-down policy a bit too late when the infected number has been uncontrollably high.

Even though Italy, Spain, and Portugal were heavily suffered from the high number of confirmed COVID-19 cases during March and April, their lock-down policies had started to show some results as the ratio of recovered patients increases. The economies of these countries were still heavily suffered from this approach. Meanwhile, countries like Australia and New Zealand had effectively flattened the infection curve quite early on, and they also had to sacrifice their economic benefits, despite their early announcements of economic support policies in March.

Regarding the labour market in the right plot of Fig. 1, we can see a similar result for the United States, Sweden, France as their unemployment rates were significantly higher than in other countries. The labour market prospect was also dreadful in several nations with high numbers of COVID-19 cases, such as Brazil, Italy, and Portugal. Meanwhile, some other developed countries that already have a good general welfare pre-pandemic are showing the effectiveness of their support systems (e.g., Singapore, Switzerland, Japan, and Germany).

This initial data analysis shows that monetary and fiscal policies might play a vital role in economic recovery in the post-pandemic era. By June 2020, about 160 national governments had announced almost one thousand economic support policies. Had these monetary and fiscal measures substantially impacted these countries, causing early positive changes in economics and finance sectors during the COVID-19 pandemic, in terms of financial and labour market index? How strong were the causal effects? How the causal impact behave in different countries? Specifically, this analytical study aims to answer the following research questions:

Q1: What are the response and government policies amid the COVID-19 pandemic?

Q2: Did the government policies cause some impact on the financial market?

Q3: Did the economic support policies cause some impact on the financial market?

Q4: Did the economic support policies cause some impact on the labour market?

Since these economic and financial markets evolve in a time series manner amid the COVID-19 pandemic from 01/01/2020 to 22/03/2021, we aim to introduce a statistical machine learning method for such purpose, i.e., the causal inference over time series data and stochastic processes for 80 countries around the world. This causal analysis for the impact of economic support policies would significantly contribute to current literature, benefiting researchers, economists, policymakers, and international organizations interested in these topics.

2. Literature review

2.1. Research on impact of government policy

Regarding research on the impact of government policy during the COVID-19 pandemic, there have been some initial studies on the overall impact of all types of policies, focusing more on containment or health-related measures [7]. Their result showed that early containment policies such as school closure had significantly slowed down the infection rate, a similar conclusion to [31]. Other research also suggested that restriction on international travel is the biggest factor in preventing the virus spread [32] and reduces the health crisis impact.

Regarding the financial side of the crisis, several economists have analyzed how the COVID-19 pandemic affecting the world economy, using both real data and projected scenarios [10,15,16,18]. Baldwin and Tomiura [3] were focusing on the trade impact as several countries are still closing their borders. Some other researchers also initiate discussions on the impact on the stock market [22]. Other studies have been looking into some other financial indicators, particularly the foreign exchange markets [2] and gold and oil prices [17]. However, there has been not much research on the impact of monetary and fiscal policies for the COVID-19 pandemic on the economy, namely the financial and labour markets.

On the other hand, there have been numerous studies on the impact of monetary and fiscal policy for the last GFC [6,14,23]. Pastor and Veronesi [20] had analyzed the policies announced during the period 2007 to 2009 to measure their impacts on the stock market prices and volatility. They concluded that the policies had a negative effect on average, which means the market returns will go down on the announcement of the new policy. Ait-Sahalia et al. [1] also concluded that many of these measures had a negative impact, as the decisions to allow banks to fail, not to reduce the interest rate, or ad hoc bank bailouts tend to increase credit, liquidity risk and exacerbate market fears. It is worth noted that the GFC started from big banks and financial institutions, so the policies are quite different from the current COVID-19 crisis.

Moreover, both papers mentioned the uncertainty level as the key differentiation of the impact. The higher level of the surprise element, the worse the market returns would be. This is a big difference from the COVID-19 pandemic period as everyone is expecting benevolent responses from the governments, which minimizes the element of surprise. Pastor and Veronesi [20] also made a strong assumption in their model using a single-policy setting, while the real-world scenario of the COVID-19 pandemic had a multiple-policy setting. Furthermore, as these policies might not be effective immediately, it is worth considering a causal analysis of multiple different time lags and multiple-policy settings. This is the motivation for our causal inference approach for COVID-19 policy impact analysis in this paper.

2.2. Research on causal inference

The research about the causal relationship between two events has been extensively studied. In the past century, several different causality measures were proposed by statisticians and economists [9]. The earliest concept of causality for time series data was Granger causality, suggested by Granger [11]. Inspired by the Granger causality, different causality notions were suggested throughout the years, e.g., Sims causality [26], structural causality [33], and intervention causality [30].

Similar to Granger causality, Sims causality and structural causality also assume an observational framework. Meanwhile, intervention causality makes the much stronger assumption that intervention can be performed in the studies processes, which might be more suitable for a simulation environment rather than a real-life scenario like in our case. In this research, we use the Granger causality notion due to its proven effectiveness in multiple studies [24].

There are various approaches to causality inference, from classical statistical approaches to chaos and dynamic system theory approaches, with both parametric [19] and non-parametric causality measures [4,28]. In our specific context, we focus on the application of graphical approaches for causality inference in time series data as they are often used to model Granger causality in multivariate settings.

Some common graphical approaches for causality inference are SGS, PC, and FCI [27], which use principles of conditional dependence and application of the causal Markov condition to reconstruct the causal graph of the data generating process. SGS is considered as possibly more robust to nonlinearities, while the complexity of PC does not grow exponentially with the number of variables. The PC algorithm also cannot handle unobserved confounders, a problem which its extension, FCI, aims to remedy.

[25] considered these algorithms to be unsuitable to use with time series data, claiming the use of autocorrelation can lead to high false-positive rates. The authors suggested PCMCI, an advanced causality search algorithm, and claimed it is suitable for large datasets of variables featuring linear and nonlinear, time-delayed dependencies, given sample sizes of a few hundred or more, and that is showing consistency and higher detecting power with the reliable false positive control when compared with other algorithms. Therefore, we apply PCMCI with the Granger Causality notion to analyze the relationship and impact of government policy during the COVID-19 pandemic.

3. Methodology

3.1. Granger causality notion

Let X be a specific type of policy for a country (e.g. monetary support policy of a country) and Y be an index in the financial or labour markets (e.g. job index of a country). A naive interpretation of the problem may suggest simple approaches such as equating causality with high correlation. However, to infer the degree to which a variable X causes Y from the degree of X's goodness as a predictor of Y, the problem turns out to be much more complex. As a result, rigorous ways to approach this question were developed in multiple causal inference research. Granger Causality, proposed by [11], is based on contrasting the ability to predict a stochastic process Y using all the information in the universe, denoted with U, with doing the same using all information in U except for some stochastic process X, denoted as $U\backslash X$. We have:

$U_t = (U_{t-1}, \ldots, U_{t-\infty})$: all the information in the universe until time t
$X_t = (X_{t-1}, \ldots, X_{t-\infty})$: all the information in a type of government policies X until time t in a country
$\sigma^2(Y_t|U_t)$: variance of the residual of predicting financial or labour market index Y_t using U_i at time t
$\sigma^2(Y_t|U_t\backslash X_t)$: variance of the residual of predicting financial or labour market index Y_t using all information in U_t at time t except for X_t.

If $\sigma^2(Y_t|U_t) < \sigma^2(Y_t|U_t\backslash X_t)$ then we say that X "Granger-causes" Y (e.g. monetary support "Granger-causes" job index in Australia), and write $X \Rightarrow Y$. Discarding information X reduces the predictive power regarding Y, thus X contains some unique information regarding Y. If both $X \Rightarrow Y$ and $Y \Rightarrow X$, we say that "feedback" is occurring, and write $X \Leftrightarrow Y$. As noted by [11], the requirement of having access to all the information in the universe is extremely unrealistic. In real-world applications, U is replaced by a limited set of observed time series S, with $X \in S$. Set S in our research are information about the active COVID-19 cases, policy indexes, government policies, financial indexes, and labour market indicators (see Table 1. The above definition reads X "Granger-causes" Y with respect to S and a certain time $\{t-\tau, t-\tau+1, \ldots, t-1, t\}$. Furthermore, this definition does not specify the prediction method used for σ^2, and thus allows for both linear and non-linear models, but the use of the variance to quantify the closeness of prediction restricts this notion of causality to causality in mean.

3.2. Graph-based causality inference

A graphical approach is often used to model Granger causality for multivariate time series where each time series is considered to be a node in a Granger network, with directed edges denoting a causal link, possibly with a delay in time. The main structure of an example graph-based causality search algorithm, PC algorithm, which was named after the authors, Peter Spirtes and Clark Glymour [27], consists of:

- **Initialization**: The full undirected graph over all variables $\mathcal{X}$ is initialized, i.e., we assume there are causal connections between every pair of time series in set S.
- **Skeleton Construction**: Afterwards, edges are eliminated by testing for conditional independence with increasing degrees of dependence. We only keep the connected variables.
- **Edge elimination**: Finally, a set of statistical and logical rules are applied to determine the direction of edges (i.e. the causality) in the graph.

3.3. PCMCI

PCMCI [25] is a graph-based causality search algorithm for multivariate time series, which contains two steps PC_1 and MCI.

PC₁:This is a Markov set discovery algorithm based on the above PC-stable algorithm [5] that eliminates irrelevant conditions in each time series through an iterative process of independence testing. Starting with preliminary parents $\widehat{P}(X_t^j) = \{X_{t-1}^j, X_{t-2}^j, \ldots, X_{t-\tau_{\max}}^j\}$, it performs unconditional independence tests a significance level α_{PC} in the first iteration:

$$PC_1(\text{iter} = 0): \quad X_{t-\tau}^i \amalg X_{t-\tau}^j \tag{1}$$

In all of our models, we set $\alpha_{PC} = 0.05$ without any hyper-parameter tuning. In each of the next iterations, the algorithm sorts preliminary parents by their absolute test statistic value and performs conditional independence tests:

$$PC_1(\text{iter} = 1, 2, \ldots): \quad X_{t-\tau}^i \amalg X_{t-\tau}^j | \Omega \tag{2}$$

where Ω are the strongest ω parents in $\mathcal{P}(X_t^j)\backslash\{X_{t-\tau}^i\}$ at iteration ω. The algorithm converges if no more conditional test is possible. Since these tests are low dimensional compared to Granger causality, they have a higher detection power.

MCI: The Momentary Conditional Independence (MCI) test, which can address the false positive control for the highly-interdependent time series case, conditions on the parents of both variables in the potential causal link. To test whether lagged (back-shifted) X^i affects non-lagged X^j with time lag τ, we then have the MCI test:

$$\text{MCI}: \quad X_{t-\tau}^i \not\amalg X_t^j \mid \mathcal{P}(X_t^j)\backslash\{X_{t-\tau}^i\}, \mathcal{P}(X_{t-\tau}^i) \tag{3}$$

where $\mathcal{P}(X_t^i)$ is the set of parent nodes of X_t^i. This means MCI conditions on both the parents of X_t^j and the time-shifted parents of $X_{t-\tau}^i$.

To explain the PCMCI method graphically, we illustrated the two steps in Fig. 2.

The left two diagrams illustrated the PC_1 algorithms, with the blue and red colour edges represent the negative and positive causal links. The darker blue/red colour on each point of the time series indicates higher autocorrelation. Starting from a fully connected graph, all the weakest causal links between each time series pair are removed after each iteration step of the PC_1 algorithms, which are the lightest shade of red and blue edges. We continue the iteration until there is no more condition to test. In this way, PC_1 adaptively converges to typically only a few causal

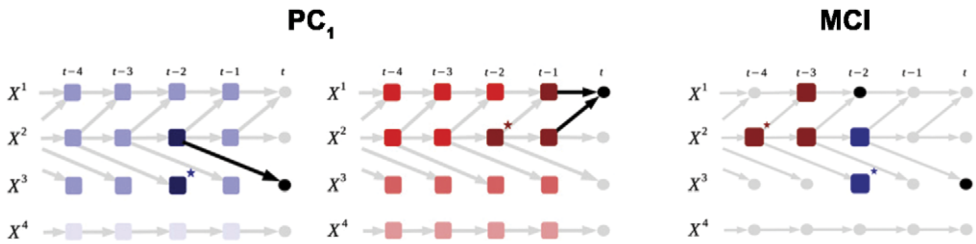

Fig. 2. Illustration of PCMCI algorithm (source: [25]).

Table 1
Basic statistics of multiple time series in our data

Symbol	Time series	mean	std	min	max
C_t^k	Active COVID-19 Cases	2,429,524.1	6,299,581.9	0.0	29,276,571.0
I_t^{1k}	Stringency Index	55.0	25.3	0.0	100.0
I_t^{2k}	Government Response Index	51.4	22.4	0.0	89.8
I_t^{3k}	Containment Health Index	52.2	22.3	0.0	92.0
I_t^{4k}	Economic Support Index	46.7	31.9	0.0	100.0
E_t^{1k}	Income Support policy	1.0	0.8	0.0	2.0
E_t^{2k}	Debt/Contract Relief policy	1.1	0.8	0.0	2.0
E_t^{3k}	Fiscal Measures policy (USD)	247,639,703.3	13,627,454,739.5	0.0	1,957,600, 000, 000.0
E_t^{4k}	International Support policy (USD)	17,286,109.3	3,656,218,426.5	0.0	834,353,051, 822.0
Y_t^{3k}	New Jobless Claim (US labour market)	188,616.1	200,882.1	28,714.3	981,000.0
Y_t^{4k}	Unemployment Rate (US labour market)	6.5	4.7	1.2	17.1
Y_t^{5k}	Job Index (AU labour market)	97.4	2.6	91.5	101.4
Y_t^{6k}	Wage Index (AU labour market)	97.2	2.7	90.7	102.5

links left, denoted by darker blue and red edges. However, there might be some false positives (marked with a star). The MCI conditional independence test will further eliminate these false-positive links and generate the final graph with only significant causal links.

For example, X^1 can be the financial index, X^2 can be the monetary support policy, X^3 can be the job index and X^4 can be the wage index for a country. We might infer from Fig. 2 that monetary support positively impacts job index at lag time $t = 2$, negatively impacts the financial index at lag time $t = 1$ and does not have any causal relationship with the wage index of that country.

4. Data

For this research, we use a total of 13 types of times series from 01/01/2020 to 22/03/2021 to test our hypotheses. The time series for each country are extracted from the four datasets as below, whereas the statistics can be found in Table 1.

4.1. Oxford COVID-19 government response tracker (OxCGRT) dataset

The Oxford COVID-19 Government Response Tracker (OxCGRT) dataset [12] collected systematic information on which governments had taken which measures, and when. The data was collected for 179 countries and territories from 01/01/2020 to 22/03/2021, including these metrics: **(1) COVID-19 Response Indexes**: Stringency Index, Government Response Index, Containment Health Index, and Economic Support Index (see [12] for more information on the calculation of these indexes); **(2) Economic Policies**: Income Support, Debt/Contract Relief, Fiscal Measures, and International Support; **(3) Containment and Closure policies**: Close School, Close Workplace, Cancel public events, Restriction on gatherings, Close public transport, Stay at home requirements, Restrictions on internal movement, International travel control; and **(4) Health System Policies**: Public information campaigns, Testing policy, Contact tracing, Emergency Investment in healthcare, and Investment in vaccines. Within the scope of this paper, we focus on the "COVID-19 Response Indexes" and "Economic Policies".

4.2. COVID-19 dataset

The COVID-19 Data was published by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University [8]. The dataset includes daily numbers of confirmed COVID-19 cases, deaths, recovered, active, new cases, new deaths, and new recovered for 186 countries and territories from 22/01/2020 to 22/03/2021. We used the number of Active cases from this dataset because we believe this number was the best figure to represent the current pandemic situation in each country. There were only a few countries with Active cases in the period between 01/01/2020 and 21/01/2020, and the difference between the number of total cases and active cases was not large (since the numbers of deaths/recovered are still low). Therefore, we used the number of confirmed cases from the OxCGRT dataset to fill the missing values for that period.

4.3. Financial market dataset

We first manually selected a major index to represent the financial market for each country in the OxCGRT dataset. However, not all countries and territories have such index and historical price data available. This was mainly due to the fact that some regions listed in the dataset did not have a stock exchange market (e.g. Vatican). Therefore, we had a final dataset with historical financial index close prices and trading volume from 01/01/2020 to 22/03/2021 for 80 countries. We then used Python to scrape these data from Investing.com. Table 5 in the appendix listed all the countries and their nominal financial indexes in the final dataset.

4.4. Labour market dataset

Since the labour market measures were different for each country, we had manually obtained the data for Australia and the United States for our analysis. The criteria to select these two countries are (1) the availability of high quality data and (2) countries with different labour markets and COVID-19 health situations (see Fig. 1). For consistency, these measures were also obtained for the period between 01/01/2020 and 22/03/2021.

For the United States, we obtained the weekly Unemployment Rates (Insured) and Initial Jobless Claims (Seasonally Adjusted) from the Federal Reserve Bank of St. Louis Economic Data (FRED).[1] To transform weekly data into daily time series, we used the same Unemployment Rates and divide the weekly New Jobless Claims by 7 for each day in the previous week. The higher these measures were, the worse the United States labour market was at that point in time.

For Australia, we obtained the weekly Jobs Index and Wages Index from the Australian Bureau of Statistics (ABS).[2] These estimates included indexes to present the changes in the labour market during the COVID-19 coronavirus period. To compare changes over time, the recorded 100$^{\text{th}}$ confirmed coronavirus case (i.e., the week ending 14$^{\text{th}}$ March 2020) was used as the reference time point for constructing the indexes and was given an index value of 100.0. To convert the data from weekly to daily time series, we use linear interpolation for any missing daily values. Opposite to the United States market, the higher these measures were, the better the Australian labour market was at that point in time.

5. Empirical analysis

We conducted multiple analyses to answer the four research questions.

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[1] https://fred.stlouisfed.org/categories/32240

[2] https://www.abs.gov.au/ausstats/abs@.nsf/mf/6160.0.55.001

5.1. The response and government policies amid the COVID-19 pandemic (Q1)

Nations worldwide had responded and announced multiple measures amid the COVID-19 pandemic. We focused on the economic support policies in this research and began with some descriptive statistics of our data. The countries in our final dataset had different numbers of Active COVID-19 cases and varying levels of government and economic support policies. Up until 22/03/2021, these 80 countries had announced 4741 different policies. Out of those, there were 1409 "Income Support" policies, 1616 "Debt/Contract Relief" policies, 1240 "Fiscal Measures" polices, and 476 "International Support" policies. Some of these policies were either replacing or updating the previous announcements, which were counted multiple times.

Most of these policies were similar among multiple nations, mainly focusing on the immediate financial assistance to workers and businesses suffered from the COVID-19 pandemic. Very few measures were taken for "International Support" at this point as most countries were prioritizing all resources to help the local businesses. We mentioned a few specific policies for some special cases in the footnote for the next part of our work (information sources for our analysis are from the datasets). From our statistic summary in Table 1, the average amount of monetary support for the domestic market was about 250 million USD, more than 14 times higher than that for international aid. This huge difference was explainable considering all countries were sharing the same situation with the recession, which forced them to focus more on national policies than international ones.

Let Y_t^{1k} and Y_t^{2k} denoted the financial market close prices and trading volumes, respectively. We did not include them in Table 1 since the currencies are different and the trading volumes are varied for each country. As some of the government response indexes and economic support policies were discrete time series, we transformed the data with ϵ_t^{ik} which followed a Gaussian noise process with mean $\mu = 0$ and standard deviation $\sigma = 10^{-6}$. We tested the causal link:

$$X_{t-\tau}^{ik} + \epsilon_{t-\tau}^{ik} \Rightarrow Y_t^{jk} + \epsilon_t^{jk} \tag{4}$$

where X_t^{ik} and Y_t^{jk} were the causing and being caused variables respectively, e.g. the time series of a policy i and the financial index price j of the country k at time t. In our causal analysis experiments below, we considered the causal inference of multivariate time series at multiple time lags $\tau \in \{1, 2, \ldots, 13, 14\}$. This means we only analyze the causal relationships if the impact happened within 14 days since the announcement of the policy. We conducted our analysis using multiple subset S of different time series.

5.2. Causal impact of government policies on the financial market (Q2)

We constructed a PCMCI causal inference model with seven time series:

$$\text{Model 1}: \quad S1 = \left\{C_t^k, I_t^{1k}, I_t^{2k}, I_t^{3k}, I_t^{4k}, Y_t^{1k}, Y_t^{2k}\right\} \tag{5}$$

where C_t^k was the number of Active COVID-19 cases in country k at time t, I_t^{1k}, I_t^{2k}, I_t^{3k}, I_t^{4k} were the Stringency Index, Government Response Index, Containment Health Index, and Economic Support Index, respectively. Y_t^{1k} and Y_t^{2k} were the financial index price and trading volume time series of country k accordingly. The result in Table 2 presented the causal links between COVID-19 Response Index and the historical financial index for each country. We reported the most significant links (the highest causal t-value) and the corresponding time lag (the number of days for the causal effect to show its impact).

From Table 2, we can see that the causal impact of different types of policies varied among countries. According to the number of total significant links by each index, more than 50% of these 80 countries could see some positive economic effects from the government responses. This was aligned with the analysis conclusion of the financial crisis 2007–2009 [20], which claimed that most policies have negative effects. The impact of COVID-19 responses might be delayed as the pandemic is still spreading in many countries. Even though the causal relationships were detected at varied time lags, the average was about 6 or 7 days for all significant links, which showed that the financial markets were quick in reacting to the COVID-19 policies.

There were 49 markets where significant causal links were detected with the general index I_t^{1k} (Stringency Index). This means countries with a combined set of actions (Containment, Health, and Economic Policies) might get to a better financial market position rather than relying on only economic policies. However, it was also noted that I_t^{4k} (Economic Support Index) took less time to have an impact on the market than others (average time lag $\tau = 6.6$).

When we took a further look, some countries had a better economic recovery thanks to effective Containment and Health policies, denoted by significant causal links in column I_t^{3k} (Containment Health Index) and no links in column I_t^{4k} (Economic Support Index) for the financial price. Most of those countries were developing and emerging markets, which means they did not have a big budget for economic support via monetary and fiscal policies. By imposing early Containment and Health policies, they can help prevent and/or ease the financial crisis. The countries in this category were India, Jamaica, Kenya, Kuwait, Malaysia, and Zambia. For example, Malaysia had multiple periods of school closures and regional lockdowns in March, June, October 2020, and January 2021.

On the contrary, many countries' financial markets were impacted by I_t^{4k} (Economic Support Index) rather than I_t^{3k} (Containment Health Index). Most of these were developed countries, such as Japan, Netherlands, New Zealand, Norway, Qatar, Switzerland, and United Kingdom. Particularly, many European countries were in this category, which had some Economic Policies in place even before considering lockdown. Their approach was different from other countries mainly due to their confidence in the high-quality healthcare system and surplus national reserve position. We can see the different approaches between developed and developing countries at the beginning of the COVID-19 pandemic. However, now most countries are sharing similar policies where health and containment strategies are as equally important as economic support.

We also tested the causal effect of COVID-19 Response Indexes on market volatility. The average causal time lags of the impact on trading volumes were lower than the impact on the market prices, which indicated that the markets were sensitive at the current period of time, reacting quickly to new policy announcements. From our observation, I_t^{3k} (Containment Health Index) took a slightly longer time to create a market shock than I_t^{4k} (Economic Support Index) in terms of market volatility. It was important to note that increased financial trading activity did not necessarily imply a better economic situation.

5.3. *Causal impact of economic support policies on the financial market (Q3)*

We constructed another PCMCI causal inference model with seven time series:

$$\text{Model 2}: \quad S2 = \left\{C_t^k, E_t^{1k}, E_t^{2k}, E_t^{3k}, E_t^{4k}, Y_t^{1k}, Y_t^{2k}\right\} \tag{6}$$

where C_t^k was the number of Active COVID-19 cases in country k at time t, E_t^{1k}, E_t^{2k}, E_t^{3k}, E_t^{4k} were the Income Support policy, Debt/Contract Relief policy, Fiscal Measures policy, and International Support policy respectively. Y_t^{1k} and Y_t^{2k} were the financial index price and trading volume time series of each country k accordingly. The result in Table 2 presented the causal links between each COVID-19 Response Index and the historical financial index for each country. We reported only the most significant links (the highest causal t-value) and the corresponding time lags (the number of days for the causal effect to show its impact).

The average number of significant causal links in Table 3 was lower than that in Table 2. This result further confirmed that Economic Policies alone are less impactful than the combined government response. Furthermore, E_t^{4k} (International Support) caused a positive market return in only 23 countries, significantly less effective than the other three types of economic policies. It was worth noted that the International Support Policy generally involves charitable giving to a foreign country, which might not be considered as a supportive action for the domestic market. By the number of total significant links, we can see that E_t^{3k} (Fiscal Measures) were effective took fewer days to affect the financial markets on average (measured by the mean τ of all significant links). It was mainly because this set of policies directly impact the business owners. Therefore, they can lead to a quicker market response than E_t^{1k} (Income Support Policies), which were more related to salary workers.

We also investigated further the impact of these economic support policies on market volatility. The effects of all types of policies, excluding E_t^{4k} (International Support), were quite similar among all countries. We noted again that the increased trading activity did not always mean a better market condition. The results from Table 2 and Table 3 should only be used with caution.

Table 2
Causal links of COVID-19 response indexes on financial market

	Financial Index Close Price Y_t^{1k}								Trading Volume Y_t^{2k}							
	I_t^{1k}		I_t^{2k}		I_t^{3k}		I_t^{4k}		I_t^{1k}		I_t^{2k}		I_t^{3k}		I_t^{4k}	
Country	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ
Argentina	0.0921	6	0.0429	6	0.1064*	6	0.1048*	5	0.0952	13	0.0809	6	0.0735	13	0.0941	6
Australia	0.1989**	1	0.1803**	1	0.1727**	1	0.2197**	5	0.0203	11	0.0227	11	0.0230	11	0.0735	6
Austria	0.2107**	8	0.1316**	1	0.2005**	8	0.2058**	4	0.1787**	4	0.0623	4	0.1619**	4	0.1033*	1
Bahrain	0.1158*	7	0.0613	7	0.0638	7	0.0531	0	0.0722	1	0.0967*	1	0.0658	1	0.2207**	1
Bangladesh	0.1307**	0	0.1215*	0	0.1064*	0	0.1677**	0	0.0399	9	0.0437	9	0.0416	9	0.0500	14
Belgium	0.1209*	10	0.0792	10	0.1180*	10	0.1046*	7	0.1008*	2	0.0974*	3	0.0852	3	0.1222*	3
B&H	0.0047	7	0.0263	4	0.0000	0	0.0593	10	0.0499	9	0.0767	10	0.0821	10	0.1012*	12
Botswana	0.0414	2	0.0460	2	0.0462	2	0.0166	4	0.0539	13	0.0405	13	0.0439	13	0.0668	2
Brazil	0.0444**	4	0.0567**	8	0.0213*	4	0.0776**	8	0.0342**	9	0.0336**	6	0.0420**	10	0.0245**	0
Bulgaria	0.1052*	12	0.0917	3	0.0891	2	0.0615	4	0.1011*	8	0.0311	6	0.1051*	7	0.1157*	1
Canada	0.1672**	8	0.1483**	8	0.1591**	8	0.1016**	9	0.0448**	6	0.0579**	6	0.0532**	6	0.0549**	6
Chile	0.0521	9	0.0370	9	0.0454	10	0.0156	12	0.1013*	4	0.1101*	4	0.1069*	4	0.1245*	4
China	0.0769	3	0.0841	3	0.0794	0	0.0568	11	0.1101*	9	0.1071*	9	0.1088*	9	0.0711	10
Colombia	0.1916**	1	0.1441**	9	0.1393**	1	0.2757**	8	0.0292	13	0.0457	12	0.0536	12	0.0698	2
Costa Rica	0.0138	3	0.0175	3	0.0111	3	0.0176	0	0.0139	3	0.0176	3	0.0111	3	0.0176	0
Croatia	0.1220*	4	0.1135*	14	0.1208*	14	0.1315**	5	0.0930	14	0.1264*	14	0.0853	14	0.1467**	14
Cyprus	0.0270	14	0.0639	2	0.0385	1	0.0740	9	0.1233*	4	0.0883	4	0.0913	11	0.1553**	6
Denmark	0.0936	4	0.0915	4	0.0923	4	0.0911	12	0.1832**	9	0.1693**	9	0.1767**	9	0.0935	3
Ecuador	0.0428	0	0.0573	8	0.0579	8	0.0391	8	0.0969*	12	0.1047*	12	0.1012*	12	0.1116*	10
Egypt	0.1027*	6	0.0856	3	0.0985*	13	0.1686**	0	0.0320	13	0.0577	13	0.0561	13	0.0428	9
Finland	0.1414**	13	0.0808	13	0.0964*	13	0.0994*	8	0.3134**	9	0.3434**	9	0.3480**	9	0.2840**	9
France	0.1617**	3	0.1182*	8	0.1470**	3	0.1411**	8	0.1366**	10	0.0717	10	0.1276**	10	0.0885	4
Germany	0.0943	8	0.1182*	8	0.1073*	8	0.1022*	8	0.1653**	2	0.1181*	0	0.1153*	0	0.1053*	4
Greece	0.0832	10	0.1087*	14	0.1112*	14	0.1415**	12	0.0855	2	0.0456	3	0.0454	3	0.0386	6
Hungary	0.1150*	4	0.0988*	4	0.1224*	4	0.1483**	6	0.0049	9	0.0140	2	0.0223	9	0.0640	6
Iceland	0.1428**	9	0.1658**	4	0.1322**	4	0.1346**	3	0.0462	11	0.1936**	1	0.2561**	1	0.4003**	0
India	0.2795**	0	0.2876**	0	0.2826**	0	0.0800	12	0.0866	2	0.0996*	0	0.0968*	0	0.1680**	4
Indonesia	0.0768	12	0.0776	12	0.0810	12	0.0757	5	0.0935	0	0.1094*	0	0.1087*	0	0.0957	0
Iraq	0.0370	9	0.0618	9	0.0580	9	0.0114	8	0.0718	7	0.0716	5	0.0826	5	0.0707	10
Ireland	0.1388**	13	0.1384**	13	0.1043*	13	0.1057*	13	0.0443	8	0.0341	10	0.0318	8	0.0556	7
Israel	0.1202*	11	0.1354**	11	0.1272**	11	0.1952**	7	0.0457	5	0.0474	6	0.0463	6	0.0825	8
Italy	0.1194*	10	0.1155*	10	0.1183*	10	0.1317**	7	0.1344**	5	0.1325**	5	0.1317**	5	0.1035*	3
Jamaica	0.1219*	9	0.1406**	9	0.1450**	9	0.0766	13	0.2185**	13	0.2344**	13	0.2243**	13	0.0696	13
Japan	0.0438	8	0.1100*	9	0.0486	9	0.1361**	9	0.1164*	7	0.1232*	7	0.1266**	7	0.1090*	6
Jordan	0.1028*	2	0.1288**	2	0.1199*	2	0.1129*	14	0.0073	8	0.0068	2	0.0084	2	0.0102	6
Kazakhstan	0.1277**	2	0.1123*	3	0.1232*	3	0.1002*	2	0.0610	4	0.0645	14	0.0741	9	0.0987*	11
Kenya	0.1010*	14	0.1196*	14	0.1354**	14	0.0744	9	0.0841	2	0.1101*	2	0.1207*	2	0.0756	12
Kuwait	0.1491**	8	0.2238**	10	0.2251**	10	0.0726	11	0.0840	6	0.0858	6	0.0839	6	0.0454	14
Lebanon	0.1659**	13	0.1809**	13	0.1783**	13	0.1478**	13	0.1048*	13	0.0900	13	0.0914	13	0.0265	8
Malaysia	0.1809**	2	0.1390**	6	0.1247*	2	0.0841	6	0.1081*	7	0.1084*	7	0.1259*	7	0.0389	14
Mauritius	0.0920	13	0.0781	13	0.0794	13	0.1578**	7	0.0328	9	0.0510	9	0.0500	9	0.0736	2
Mongolia	0.0449	3	0.0501	3	0.0465	3	0.0473	13	0.1724**	0	0.1664**	0	0.1576**	0	0.0863	10
Morocco	0.1140*	10	0.0528	9	0.0522	6	0.0613	5	0.0749	1	0.0723	1	0.0873	1	0.0732	1
Namibia	0.1119*	6	0.0721	6	0.0804	6	0.0000	0	0.1276**	8	0.0795	8	0.0737	8	0.0551	14
Netherlands	0.1147*	10	0.0747	9	0.0862	10	0.1748**	7	0.1353**	0	0.1687**	0	0.1298**	0	0.1670**	3
New Zealand	0.1307**	1	0.1387**	1	0.1356**	1	0.2224**	7	0.0616	5	0.0687	0	0.0554	5	0.0958	3

Table 2

(Continued)

	Financial Index Close Price Y_t^{1k}								Trading Volume Y_t^{2k}							
	I_t^{1k}		I_t^{2k}		I_t^{3k}		I_t^{4k}		I_t^{1k}		I_t^{2k}		I_t^{3k}		I_t^{4k}	
Country	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ
Niger	0.0464	7	0.0778	7	0.0926	7	0.0601	9	0.0568	9	0.0471	9	0.0383	9	0.0611	6
Nigeria	0.0886	2	0.0845	2	0.0715	9	0.0575	2	0.0896	2	0.0800	2	0.0648	2	0.1339**	14
Norway	0.1119*	7	0.0938	14	0.0975*	14	0.1211*	4	0.0669	1	0.0867	1	0.1012*	1	0.0634	0
Oman	0.0403	3	0.0751	3	0.0673	3	0.0363	6	0.2649**	4	0.2464**	4	0.2717**	4	0.0000	0
Pakistan	0.1561**	8	0.1442**	8	0.1410**	8	0.1494**	1	0.0737	7	0.0781	12	0.0711	13	0.1034*	12
Peru	0.0985*	10	0.1111*	10	0.0965*	10	0.1087*	13	0.1072*	1	0.0639	9	0.0689	9	0.1127*	13
Philippines	0.1385**	5	0.0950	11	0.1042*	5	0.1085*	0	0.0700	10	0.0686	3	0.0670	3	0.0502	5
Poland	0.0965*	10	0.0857	10	0.0692	10	0.0854	10	0.1174*	3	0.1360**	9	0.1266**	9	0.1374**	9
Portugal	0.1271**	5	0.0866	10	0.0965	10	0.2205**	4	0.0897	14	0.1085*	0	0.1041*	14	0.1280**	11
Qatar	0.0829	10	0.1047*	10	0.0831	10	0.1142*	10	0.1339**	6	0.1424**	6	0.1385**	6	0.1056*	6
Romania	0.1027*	12	0.1321**	12	0.1362**	12	0.1213*	8	0.0828	13	0.0832	13	0.0737	13	0.0523	12
Russia	0.1822**	3	0.0593	14	0.0338	14	0.0868	1	0.1259**	10	0.0727	10	0.0698	4	0.0569	6
Rwanda	0.0577	4	0.0494	4	0.0490	4	0.0007	0	0.0455	9	0.0448	9	0.0488	9	0.0557	8
Saudi Arabia	0.0922	11	0.0779	8	0.0882	9	0.0547	11	0.0492	4	0.0589	4	0.0467	4	0.0233	7
Serbia	0.1544**	9	0.1538**	9	0.1589**	9	0.1608**	1	0.0613	2	0.0620	5	0.0732	1	0.0575	5
Singapore	0.0766	6	0.0592	6	0.0763	4	0.0650	13	0.0628	7	0.0639	11	0.0590	11	0.2357**	10
Slovenia	0.0577	9	0.0692	9	0.0707	9	0.0721	7	0.0508	7	0.0450	7	0.0414	7	0.0565	7
South Africa	0.1144*	10	0.1087*	10	0.1088*	10	0.1038*	7	0.1434**	4	0.1394**	4	0.1256*	4	0.3924**	0
Spain	0.1212*	10	0.1325**	5	0.1461**	5	0.1834**	7	0.0894	6	0.0809	2	0.0838	6	0.0638	3
Sri Lanka	0.0489	10	0.0542	10	0.0560	10	0.0430	11	0.0324	0	0.0464	8	0.0544	8	0.0145	2
Sweden	0.1975**	12	0.1723**	12	0.2115**	12	0.1316**	13	0.2843**	0	0.2283**	0	0.2457**	0	0.2505**	1
Switzerland	0.0734	2	0.0625	9	0.0684	9	0.1273**	5	0.1703**	3	0.1304**	3	0.1666**	3	0.2095**	1
Thailand	0.1545**	14	0.0662	14	0.1088*	14	0.1298**	6	0.0657	14	0.0540	0	0.0645	14	0.1093*	0
Tunisia	0.1101*	6	0.0972*	6	0.1015*	6	0.0754	2	0.0258	6	0.0199	0	0.0229	4	0.0528	5
Turkey	0.0920	8	0.0706	8	0.0742	8	0.0530	2	0.0955	8	0.0692	5	0.0938	8	0.0982*	2
Uganda	0.0993*	1	0.1139*	1	0.1265**	1	0.1441**	4	0.0628	11	0.0783	11	0.0659	11	0.0937	2
Ukraine	0.0204	11	0.0016	10	0.0023	5	0.0000	0	0.0678	9	0.1022*	9	0.0995*	9	0.1009*	0
UAE	0.1519**	2	0.0625	9	0.1032*	9	0.1371**	6	0.0507	2	0.0690	2	0.0642	2	0.0746	2
UK	0.0543*	2	0.0445*	2	0.0324	2	0.1045**	5	0.1624**	11	0.1752**	11	0.0809**	11	0.1104**	11
US	0.0431**	8	0.0366**	4	0.0575**	2	0.0607**	10	0.0082	6	0.0115	6	0.0121	6	0.0106	9
Venezuela	0.0803	4	0.0806	4	0.0813	4	0.0375	10	0.1452**	8	0.1365**	8	0.1467**	8	0.1095*	4
Vietnam	0.0887	7	0.0825	0	0.0885	7	0.0874	13	0.0598	1	0.0697	1	0.0696	1	0.1540**	9
Zambia	0.1616**	0	0.1389**	0	0.1428**	0	0.0855	12	0.1372**	13	0.1214*	13	0.1314**	13	0.0990*	8
Zimbabwe	0.0416	4	0.0623	4	0.0591	4	0.0052	0	0.1157*	11	0.1205*	2	0.1104*	2	0.1806**	2
Total links	49		38		43		43		33		33		34		37	
Mean lags τ		6.8		7.2		7.0		6.8		6.8		6.1		6.8		6.0

Note: * and ** denote significant links at 95% and 99% confidence levels respectively.

Overall, excluding E_t^{4k} (International Support), there were a few countries that had impactful economic policies across all three types E_t^{1k} (Income Support), E_t^{2k} (Debt Support), and E_t^{3k} (Fiscal Measures). These countries were Australia, Egypt, Finland, France, Ireland, Kazakhstan, Kuwait, Norway, Pakistan, Portugal, Spain, Thailand, Tunisia, and the United States. We then analysed how the Economic Policies affected the labour markets in these countries, nominally in Australia and the United States.

Table 3
Causal links of economic policies on financial market

	Financial Index Close Price Y_t^{1k}								Trading Volume Y_t^{2k}							
	E_t^{1k}		E_t^{2k}		E_t^{3k}		E_t^{4k}		E_t^{1k}		E_t^{2k}		E_t^{3k}		E_t^{4k}	
Country	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ
Argentina	0.0593	2	0.0368	3	0.1170*	8	0.0711	0	0.1112*	9	0.0845	7	0.0710	8	0.0618	12
Australia	0.1733**	5	0.1641**	0	0.1955**	8	0.0704	2	0.1516**	2	0.0958	2	0.0999*	9	0.1357**	0
Austria	0.0945	10	0.1857**	3	0.1990**	2	0.0572	6	0.0351	14	0.0993*	4	0.1831**	2	0.1412**	2
Bahrain	0.1402**	13	0.0557	0	0.1761**	2	0.0513	0	0.5393**	1	0.2040**	14	0.0449	7	0.0381	6
Bangladesh	0.0002	12	0.1404**	0	0.0147	0	0.0153	3	0.0627	0	0.0729	7	0.0632	5	0.1154*	13
Belgium	0.1817**	7	0.0768	13	0.1389**	4	0.0693	14	0.1242*	14	0.0565	6	0.2176**	0	0.1447**	4
B&H	0.0731	10	0.0731	10	0.1548**	13	0.1148*	12	0.1425**	3	0.1425**	3	0.1081*	6	0.0412	2
Botswana	0.0709	11	0.0091	4	0.0288	9	0.1166*	7	0.0769	10	0.0361	5	0.1281**	0	0.0771	5
Brazil	0.0157	12	0.0840**	7	0.0190*	6	0.0240**	5	0.0106	6	0.0310**	0	0.0047	2	0.0110	10
Bulgaria	0.0813	10	0.1042*	14	0.1541**	5	0.0743	13	0.1319**	0	0.1339**	7	0.1269**	13	0.1119*	11
Canada	0.1713**	9	0.0490**	5	0.0189	6	0.0108	3	0.0912**	6	0.0318*	6	0.0359**	0	0.0294*	4
Chile	0.0361	7	0.0600	4	0.1629**	0	0.0301	2	0.0415	0	0.0596	0	0.1191*	5	0.0501	11
China	0.1020*	3	0.0728	3	0.0779	4	0.0842	14	0.0406	1	0.0736	0	0.0943	11	0.0653	14
Colombia	0.0674	1	0.3259**	8	0.1194*	6	0.0556	9	0.0930	5	0.1002*	8	0.0640	3	0.0662	9
Costa Rica	0.0116	0	0.0255	0	0.0000	0	0.0417	0	0.0117	0	0.0256	0	0.0000	0	0.0417	0
Croatia	0.1420**	5	0.1123*	8	0.0757	1	0.1208*	10	0.0550	9	0.0489	11	0.0667	2	0.0822	0
Cyprus	0.0657	2	0.0755	9	0.1010*	2	0.1120*	7	0.0419	10	0.0661	6	0.0927	1	0.0443	4
Denmark	0.0972*	4	0.0844	12	0.1176*	4	0.0637	3	0.1198*	9	0.0314	10	0.0809	12	0.0546	13
Ecuador	0.0332	8	0.0222	8	0.0246	12	0.1140*	5	0.1212*	5	0.1420**	5	0.0803	1	0.0876	3
Egypt	0.1592**	7	0.2225**	0	0.1042*	0	0.0610	1	0.0508	9	0.0478	0	0.0637	7	0.1072*	3
Finland	0.1440**	8	0.0999*	11	0.0966*	11	0.1164*	13	0.2479**	9	0.2444**	9	0.0733	13	0.0600	0
France	0.2282**	8	0.1305**	8	0.1254*	6	0.0911	8	0.1866**	0	0.0968*	4	0.0523	2	0.0451	0
Germany	0.0853	3	0.0435	13	0.2443**	1	0.1090*	14	0.1149*	4	0.0980*	2	0.0484	2	0.0959	2
Greece	0.1138*	1	0.1210*	12	0.0962	1	0.0306	10	0.0226	7	0.0540	5	0.0583	6	0.0776	0
Hungary	0.0998*	13	0.1550**	6	0.0775	3	0.0758	13	0.0999*	13	0.0980*	4	0.1033*	13	0.0865	13
Iceland	0.0585	9	0.1293**	3	0.1150*	5	0.0691	2	0.1106*	11	0.4180**	0	0.0000	0	0.1258*	5
India	0.1203*	0	0.1632**	12	0.0511	1	0.0454	4	0.1328**	6	0.2430**	5	0.0809	6	0.0241	12
Indonesia	0.0835	7	0.1321**	5	0.1304**	5	0.0434	0	0.1057*	7	0.0941	0	0.0846	11	0.0978*	11
Iraq	0.0829	14	0.0829	14	0.0090	8	0.1370**	1	0.0123	2	0.0123	2	0.0930	7	0.0789	0
Ireland	0.0995*	13	0.0992*	6	0.1024*	6	0.1016*	13	0.0584	7	0.0146	7	0.0127	11	0.0395	0
Israel	0.1347**	6	0.0710	11	0.1329**	7	0.1034*	0	0.0403	7	0.0823	10	0.1012*	3	0.1135*	9
Italy	0.1571**	7	0.1149*	7	0.0779	0	0.0451	4	0.0815	3	0.1132*	3	0.0660	1	0.0867	10
Jamaica	0.0867	12	0.0627	13	0.2097**	14	0.0700	0	0.0688	12	0.0766	6	0.3459**	9	0.0682	12
Japan	0.2110**	1	0.1567**	9	0.0628	1	0.1281**	4	0.0936	14	0.1430**	6	0.0381	10	0.0261	12
Jordan	0.0995*	0	0.1181*	14	0.0222	5	0.0942	12	0.0080	9	0.0101	6	0.0000	0	0.0859	8
Kazakhstan	0.1486**	14	0.1385**	3	0.1671**	1	0.0670	14	0.0671	1	0.1496**	2	0.0964*	12	0.0853	5
Kenya	0.0693	6	0.1441**	7	0.0408	7	0.1044*	8	0.0493	3	0.1358**	2	0.0460	8	0.0726	14
Kuwait	0.1371**	13	0.0997*	11	0.1183*	8	0.0777	8	0.0495	8	0.0655	14	0.0611	3	0.0786	1
Lebanon	0.0876	9	0.1541**	13	0.0865	0	0.0161	0	0.0579	0	0.0286	8	0.0554	0	0.0035	13
Malaysia	0.0702	10	0.0936	6	0.0901	4	0.1029*	11	0.0952	6	0.0760	6	0.1067*	4	0.0864	6
Mauritius	0.1226*	9	0.1474**	7	0.0531	0	0.0498	9	0.0827	10	0.1011*	12	0.0766	8	0.0723	9
Mongolia	0.0961	13	0.0953	1	0.0281	14	0.0548	1	0.1042*	14	0.1137*	11	0.0624	4	0.0275	3
Morocco	0.1278**	0	0.0821	5	0.0345	8	0.0632	14	0.0779	3	0.0634	14	0.1430**	8	0.0614	4
Namibia	0.0004	12	0.0000	0	0.0004	12	0.0922	3	0.0742	7	0.1189*	4	0.0742	7	0.0681	1
Netherlands	0.2372**	7	0.0794	11	0.0937	14	0.0694	7	0.4137**	3	0.1063*	3	0.1500**	3	0.0260	9
New Zealand	0.1201*	13	0.0640	7	0.2644**	7	0.0788	2	0.1064*	4	0.0780	2	0.1763**	3	0.0912	7

Table 3

(Continued)

	Financial Index Close Price Y_t^{1k}								Trading Volume Y_t^{2k}							
	E_t^{1k}		E_t^{2k}		E_t^{3k}		E_t^{4k}		E_t^{1k}		E_t^{2k}		E_t^{3k}		E_t^{4k}	
Country	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ	t-value	τ
Niger	0.1150*	6	0.0684	9	0.1136*	1	0.0991*	9	0.0740	6	0.0394	9	0.0515	0	0.0503	5
Nigeria	0.0885	2	0.0327	12	0.0870	0	0.1312**	7	0.1263*	14	0.1180*	0	0.1040*	13	0.0634	0
Norway	0.0975*	4	0.1491**	1	0.1610**	3	0.0748	14	0.0533	11	0.1158*	6	0.0630	4	0.0291	12
Oman	0.0641	8	0.0736	10	0.0410	2	0.0381	12	0.4205**	0	0.0079	5	0.2721**	1	0.0704	5
Pakistan	0.1842**	8	0.1573**	1	0.1637**	9	0.0419	4	0.0633	5	0.0680	8	0.0715	10	0.0590	13
Peru	0.1193*	9	0.0805	13	0.1020*	7	0.1172*	4	0.1038*	2	0.1212*	8	0.1107*	0	0.0542	2
Philippines	0.1025*	4	0.0977*	0	0.1312**	9	0.0973*	8	0.0553	2	0.0623	5	0.0477	7	0.0870	11
Poland	0.0732	10	0.1374**	12	0.1257*	6	0.1353**	10	0.1313**	9	0.1227*	9	0.2181**	2	0.0843	6
Portugal	0.2168**	11	0.1747**	4	0.0968*	8	0.0693	2	0.1362**	7	0.1215*	11	0.0805	6	0.0222	1
Qatar	0.1778**	10	0.0543	6	0.1443**	9	0.0960	1	0.1111*	6	0.1161*	6	0.0863	3	0.1093*	1
Romania	0.0786	10	0.1224*	8	0.1951**	5	0.1021*	12	0.0747	12	0.0375	3	0.0572	14	0.0673	13
Russia	0.0670	14	0.0625	8	0.0960	8	0.0564	0	0.0794	7	0.0887	6	0.1057*	10	0.0789	13
Rwanda	0.0017	7	0.0000	8	0.0175	12	0.0560	0	0.0765	6	0.0810	4	0.1155*	10	0.0937	0
Saudi Arabia	0.0665	4	0.0375	12	0.1058*	4	0.0419	5	0.0485	2	0.0299	2	0.0370	5	0.0000	0
Serbia	0.1376**	6	0.1819**	6	0.0728	7	0.0718	13	0.0861	6	0.0823	7	0.0692	2	0.0903	5
Singapore	0.0743	13	0.0819	10	0.1325**	12	0.0554	4	0.0469	13	0.2548**	10	0.1381**	9	0.1139*	11
Slovenia	0.0783	7	0.0578	6	0.1289**	12	0.1084*	11	0.0943	1	0.0769	14	0.0425	11	0.0543	13
South Africa	0.0709	2	0.0993*	4	0.0787	2	0.0386	13	0.0251	3	0.2914**	0	0.0233	3	0.0536	8
Spain	0.1738**	6	0.1878**	7	0.2401**	6	0.0935	10	0.0923	2	0.0429	3	0.2873**	6	0.0771	13
Sri Lanka	0.1022*	12	0.0430	11	0.0100	11	0.0097	3	0.0837	1	0.0202	1	0.0063	11	0.0048	8
Sweden	0.2154**	13	0.0672	14	0.1994**	4	0.0568	3	0.2412**	1	0.0394	4	0.0998*	11	0.1386**	4
Switzerland	0.0652	5	0.1400**	5	0.2265**	4	0.0528	5	0.1150*	1	0.1948**	1	0.1042*	0	0.0689	13
Thailand	0.1459**	6	0.1198*	6	0.1314**	0	0.0735	4	0.1115*	0	0.0908	0	0.0531	7	0.0847	7
Tunisia	0.1109*	3	0.1278**	3	0.1313**	3	0.0772	12	0.0939	5	0.0769	5	0.1336**	5	0.0725	1
Turkey	0.0562	10	0.0552	8	0.1415**	6	0.0759	10	0.0589	2	0.0812	2	0.0414	14	0.2225**	11
Uganda	0.0095	5	0.1441**	4	0.0325	5	0.0724	12	0.0784	3	0.0917	9	0.0418	10	0.1031*	11
Ukraine	0.0000	0	0.0292	10	0.0048	10	0.0761	0	0.1434**	11	0.0715	4	0.0822	14	0.0562	10
UAE	0.1007*	5	0.1371**	6	0.0657	4	0.0844	3	0.1539**	11	0.0488	14	0.0668	9	0.0407	13
UK	0.0393	0	0.1020**	7	0.0791**	7	0.0417	13	0.1381**	11	0.0514*	5	0.0452*	3	0.0219	10
US	0.0890**	10	0.1171**	8	0.0176**	10	0.0190**	7	0.0104	4	0.0100	3	0.0144*	6	0.0154*	13
Venezuela	0.0564	14	0.0209	0	0.1153*	13	0.0715	12	0.0791	14	0.0566	3	0.0564	8	0.1085*	3
Vietnam	0.0459	6	0.1332**	13	0.0847	1	0.0364	14	0.0636	1	0.2115**	9	0.0855	12	0.0885	6
Zambia	0.0768	5	0.0855	12	0.0731	2	0.1388**	13	0.1161*	9	0.0732	10	0.0828	11	0.0512	3
Zimbabwe	0.0143	9	0.0680	4	0.0020	0	0.0730	3	0.0903	12	0.1015*	3	0.1164*	2	0.1227*	13
Total links	39		42		45		23		32		34		30		18	
Mean lags τ		7.4		7.2		5.5		6.8		6.0		5.5		6.1		6.9

Note: * and ** denote significant links at 95% and 99% confidence levels respectively.

5.4. *Causal impact of economic support policies on the labour market (Q4)*

Similar to the model for the financial markets, we constructed the PCMCI causal inference Models 3 and 4 for the United States and Australia labour market:

$$\text{Model 3}: \quad S3 = \{C_t^k, E_t^{1k}, E_t^{2k}, E_t^{3k}, E_t^{4k}, Y_t^{3k}, Y_t^{4k}\} \tag{7}$$

$$\text{Model 4}: \quad S4 = \{C_t^k, E_t^{1k}, E_t^{2k}, E_t^{3k}, E_t^{4k}, Y_t^{5k}, Y_t^{6k}\} \tag{8}$$

where C_t^k was the number of Active COVID-19 cases in country k at time t, E_t^{1k}, E_t^{2k}, E_t^{3k}, E_t^{4k} were the Income Support policy, Debt/Contract Relief policy, Fiscal Measures policy, and International Support policy respectively. Y_t^{3k} and Y_t^{4k} were "New Jobless Claim" and "Unemployment Rate" time series for the United States labour market. Y_t^{5k} and Y_t^{6k} were the "Job Index" and "Wage Index" time series for the Australian labour market. We analysed the labour market forecast model using the PCMCI approach, using the time series from 01/01/2020 to 01/06/2020 as the training dataset and the remaining data as the testing dataset.

Figure 3 illustrated the PCMCI causal graphs with only the significant causal links 95% confidence level between economic policies and labour market measures for the two countries using the training dataset. In subplots (a), the links in red indicated the positive causal relationships, while the blue ones implied negative causal impacts. The direction of the arrow was also the impacted causal direction between two edges. The small numbers on each link indicated the time lags when the impact was significant. For a better understanding, we also included the time series plot with only causal links affecting the two labour markets and their time lags in subplots (b).

We can see from the Fig. 3 for the United States that "Fiscal Measure" was considered as the cause for a higher number of "Unemployment Rate". However, as the current COVID-19 pandemic is still spreading in the United States, "Unemployment Rate" is expected to keep going up in the short term, regardless of the fiscal policy. On a brighter note, the blue link indicated that "Fiscal Measure" has some negative impact on the "New Jobless Claim", which means it helped lower the number of new people who were in need of financial support. "New Jobless Claim" was deemed as the cause for all three domestic economic support. This showed that the United States might have announced these policies after seeing an increasing number of jobless workers. The United States had some basic unemployment insurance programs before the COVID-19 pandemic. In late March, additional income support programs were layered on top of ordinary unemployment insurance. Unemployment insurance in the U.S. is state-specific but overseen by the U.S. Department of Labour. On average, unemployment insurance replaced about 50% of lost wages for a finite period of time. Since the economic and health situation in the United States is not recovered yet, it is still too early to conclude on the effectiveness of these policies.

On the other hand, Fig. 3 for Australia showed that "Fiscal Measures" policies were effective in improving the labour market condition for Australia, with positive red links. Meanwhile, "Income Support" and "Debt Relief" were considered to have a negative causal relationship, worsen the "Job Index" and "Market Index". This was an expected effect as the "Income Support" policies encourage more people to apply for unemployment benefits, which lessened the number of employed workers and lessen the wage. Since the GDP per capita in Australia was higher than in many other countries [13], the amount of monetary support was also significantly high. A total of 189 billion was being injected into the economy by all arms of Government in order to keep Australians in work and firms in the business. This included 17.6 billion for the Government's first economic stimulus package on 12/03/2020, 90 billion from the Reserve Bank of Australia and 15 billion from the Government to deliver easier access to finance, and 66.1 billion in the economic support package on 22/03/2020.

Regarding the impact time lags, it took only about 3 days for this causal link to affect the "Wage Index", while the "Fiscal Measure" took 6 days. However, the colours of these links were also worth noted as the lighter blue indicated a really weak negative impact, and the more positive links had a darker red colour. We can still conclude that monetary and fiscal policies had shown some early positive impacts on the Australian labour market.

We then used these detected causal links in the training dataset to build the models to forecast the numbers of New Claims and Unemployment Rates in the United States. For both models, we utilised the Gradient Boosting Regressor from Scikit-Learn [21] as the prediction algorithm. The Normalized Root Mean Square Error (NRMSE) reported in Fig. 4 showed that the model prediction accuracy is high. More importantly, we were more interested in explaining the models in terms of evaluating the significant causal links' suitability as the predictors. As we can see from the results, besides the COVID-19 Active Cases C_t^k, all other important predictors were the Economic policies. Additionally, all these predictors had the time lags τ less than 7 days, which were aligned with our previous findings. This further proved the effectiveness of our PCMCI approach for causal analysis and labour market forecasts in this social context. It was worth noted that we did not consider the forecast models for the Australian labour market since the two Job Index and Wage Index, which were defined by a set of evaluation rules by the Australian Bureau of Statistics, were not completely stochastic series like the New Claims in the United States labour market.

Finally, to test the robustness of these models, we used data from the United States and the Australian labour markets as the sample data to back-test the robustness of our models, using the classical statistics inference approach

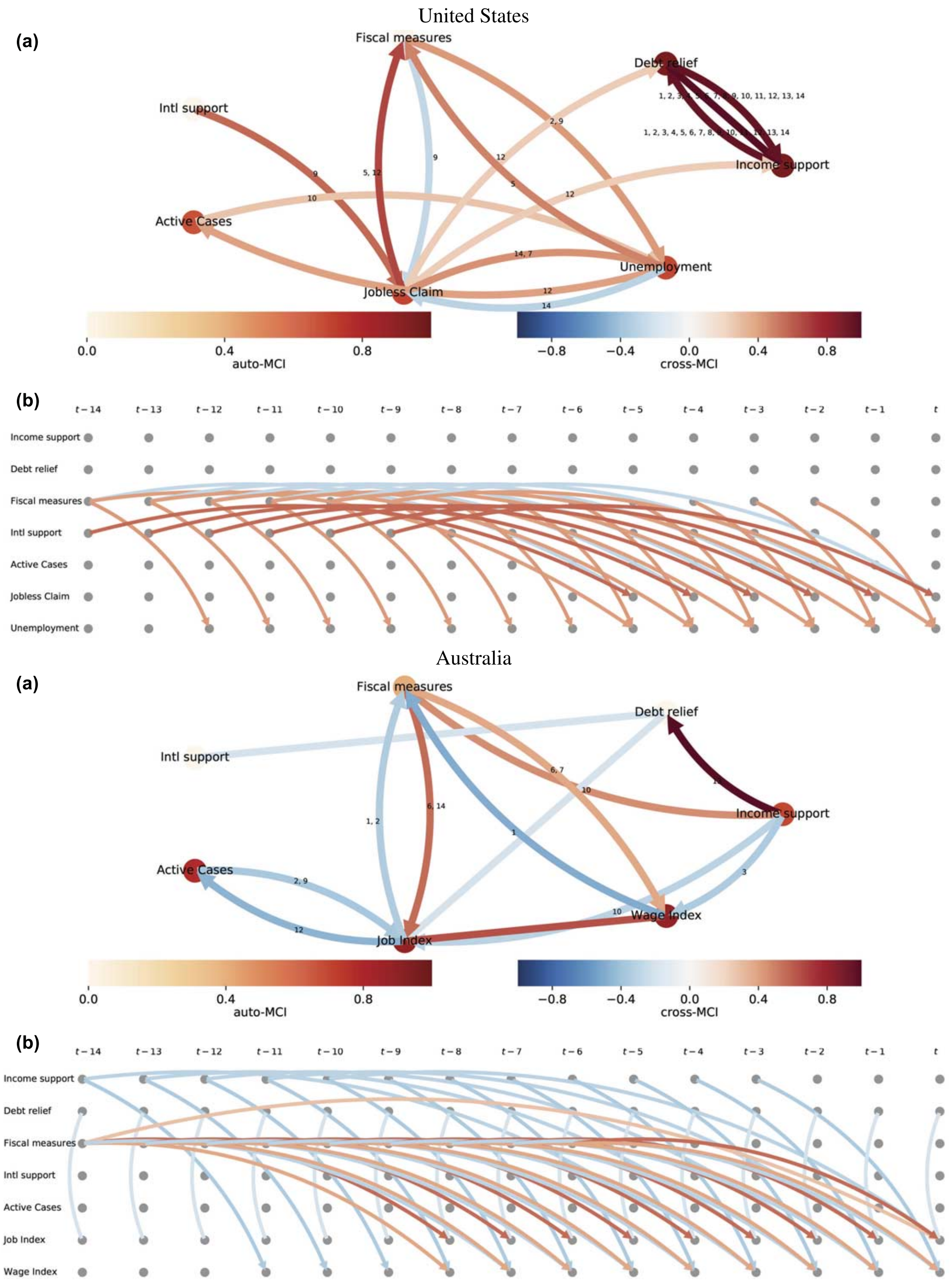
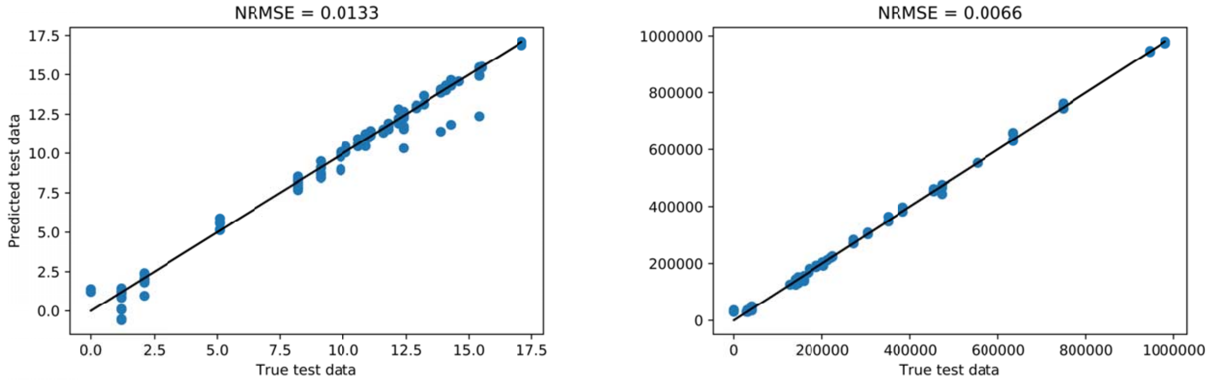


Fig. 3. Causal graph of economic policies and labour market for the United States (top) and Australia (bottom) (training dataset).

Unemployment Rates | New Claims



Top 3 predictors
C_t^k $(\tau = 7)$ $\alpha = 0.4970$
E_t^{2k} $(\tau = 6)$ $\alpha = 0.4970$
E_t^{1k} $(\tau = 1)$ $\alpha = 0.4587$

Top 3 predictors
E_t^{3k} $(\tau = 2)$ $\alpha = 0.3908$
E_t^{2k} $(\tau = 7)$ $\alpha = 0.3841$
E_t^{3k} $(\tau = 4)$ $\alpha = 0.3553$

Fig. 4. Forecast models for the numbers of unemployment rates (left) and new claims (right) of the United States (testing dataset).

Table 4
Comparing the causal analysis results of PCMCI and other statistical models using granger causality

Country	Causal Link	τ	PCMCI	F-test	chi2 test	Likelihood ratio test	Parameter F-test
			Correct Causal Links detected by PCMCI				
United States	$E_t^{3k} \Rightarrow Y_t^{3k}$	9	−0.2680	12.0963	125.4140	90.2067	12.0963
	$E_t^{3k} \Rightarrow Y_t^{4k}$	2	0.4220	16.3985	33.9202	30.5994	16.3985
Australia	$E_t^{3k} \Rightarrow Y_t^{5k}$	6	0.5610	10.4171	68.5664	56.2769	10.4179
	$E_t^{3k} \Rightarrow Y_t^{6k}$	6	0.3780	3.8408	25.2804	23.3276	3.8405
			False-positive links eliminated by PCMCI				
United States	$E_t^{3k} \Rightarrow Y_t^{3k}$	12		8.4178	122.7840	88.3183	8.4178
	$E_t^{3k} \Rightarrow Y_t^{4k}$	5		6.1948	33.4609	30.1665	6.1945
Australia	$E_t^{3k} \Rightarrow Y_t^{5k}$	11		6.7929	89.1642	69.1968	6.7927
	$E_t^{3k} \Rightarrow Y_t^{6k}$	13		4.5362	73.0604	58.7907	4.5360

with Granger Causality. In Table 4, we built statistical models with Granger Causality to back-test the significant causal links of "Fiscal Measures" on the United States and Australian labour markets. All the causal test statistics were significant at a 95% confidence level, which confirms our model results. Moreover, Granger Causality falsely detected links with multiple other time lags (only a few links are randomly reported here). These extra causal links were not considered as significant in the PCMCI model, so we did not have the PCMCI value for false-positive causal links in Table 4.

6. Discussion

Through our causal analysis with empirical data from various sources, we have answered our research questions:

Q1: Nations have taken multiple measures amid the COVID-19 pandemic, which can be categorized into three groups: "Containment", "Health", and "Economic" policy. Within our group of interests, there are four types of Economic Support policies, namely "Income Support", "Debt/Contract Relief", "Fiscal Measures", and "International Support". Since the post-pandemic economic fallout will be severe in multiple countries, policymakers should respond with targeted fiscal, monetary, and financial market policies to help impacted workers and organizations locally. On the global scale, multilateral collaboration is vital to recovering from the pandemic, including helping under-developed nations confronting both health and financing crises, especially for countries with weaker health systems. This was not the situation at the beginning of the pandemic as most countries were focusing on their own national problems, which leads to much less international support. As some countries are planning to reopen their borders in the next few months, we are seeing more international aids and cooperation, especially in vaccination and medication support for developing regions.

Q2: Using the combined general indexes of these policies, we analyze the causal relationship of different policy groups to the financial market. From the result in Table 2, we conclude that there are strong causal links observed in many countries. We also confirm that the "Economic Support" policy alone will have less impact on the market than when being combined with other Containment and Health policy. This aligns with previous researches for the GFC as multiple policies are needed at the same time to overcome the crisis. As per our study, some emerging businesses amid the COVID-19 pandemic are healthcare and technology-related, which are affecting the whole financial market on the recovery track. Further analysis of other types of measures, e.g., the impact of investment on vaccines, will reveal some more interesting insights and stimulate more discussions.

Q3: The causal analysis of each type of Economic Support policy on the financial market shows some significant links. "Income Support" tends to be a basic but effective policy in multiple countries. However, "Debt/Contract Relief" and "Fiscal Measure" are quicker to support the financial market prices. As the COVID-19 pandemic has not ended yet, it will be a bit early to have a final conclusion on the effectiveness of these Economic support policies. We believe longitudinal studies using less frequent time series data such as the GDP (per capita) would be essential to confirm the result of this research work. Moreover, in order to accurately assess the impact of the "International Support" policy, we have to further analyze the transnational money flows to see the impact of these aids on the receiving countries, not the giving nations.

Q4: Similarly, it is still a bit early to confirm the effectiveness of the Economic Support policy on the labour market. Still, from our analysis, there are some strong causal relationships observed already with these early data points. Particularly, "Fiscal Measure" is the most impacting policy for both Australia and the United States. Moreover, the market is affected in about 7 days on average, which is better for both salary workers and the fiscal balance of these countries. Once again, when the data is available, a longitudinal analysis using the unemployment rates of all countries will reassert the initial conclusion from this paper.

Last but not least, the forecast models using PCMCI causal links accurately predict the out-of-bag time series of the United States and the Australian labour markets, which might help economists and policymakers in future decisions for better social changes post-pandemic.

7. Conclusion

The COVID-19 pandemic had completely changed the world in 2020, leaving severe damage to all countries around the world, causing both health and financial crises. Governments had been proactive in responding to the pandemic, announcing numerous support policies, in three categories ("Containment", "Health" and "Economic" policies) on multiple levels for their citizens, local businesses, international organizations, and other nations. From our causal analysis using PCMCI, a graph-based causality search algorithm for multivariate time series, we can see that a combination of all different types of policies might cause a more positive result in more countries.

We analyzed the causal impact of the economic support policies on the financial markets for 80 countries. The results showed that the markets received some early positive effects caused by these policies, reacted in very short time lags, and began to slowly recover from the crisis. "Fiscal Measures" with a big stimulus package was considered to be effective on both the USA and Australian labour markets. Even though more longitudinal studies are required to further confirm the impact of all monetary and fiscal policies amid the COVID-19 pandemic, the initial results from this paper had significantly contributed to the current literature on this topic and can serve as a reference for economists, researchers, policymakers and international organizations.

Appendix. Final countries and financial indexes list

In Table 5, we list the chosen 80 financial indexes for 80 countries in our final dataset accordingly.

Table 5
List of countries and financial indexes in the final dataset

Country	Index	Country	Index	Country	Index
Argentina	S&P Merval	Indonesia	IDX Composite	Portugal	PSI 20
Australia	S&P/ASX 200	Iraq	ISX Main 60	Qatar	QE General
Austria	ATX	Ireland	ISEQ Overall	Romania	BET
Bahrain	Bahrain All Share	Israel	TA 35	Russia	MOEX
Bangladesh	DSE 30	Italy	FTSE MIB	Rwanda	Rwanda All Share
Belgium	BEL 20	Jamaica	JSE Market	Saudi Arabia	Tadawul All Share
B&H	BIRS	Japan	Nikkei 225	Serbia	Belex 15
Botswana	BSE Domestic Company	Jordan	Amman SE General	Singapore	STI Index
Brazil	Bovespa	Kazakhstan	KASE	Slovenia	Blue-Chip SBITOP
Bulgaria	BSE SOFIX	Kenya	Kenya NSE 20	South Africa	FTSE/JSE Top 40
Canada	S&P/TSX	Kuwait	FTSE Lujain Kuwait	Spain	IBEX 35
Chile	S&P CLX IPSA	Lebanon	BLOM Stock	Sri Lanka	CSE All-Share
China	Shanghai	Malaysia	KLCI	Sweden	OMXS30
Colombia	COLCAP	Mauritius	Semdex	Switzerland	SMI
Costa Rica	CR Indice Accionario	Mongolia	MNE Top 20	Thailand	SET
Croatia	CROBEX	Morocco	Moroccan All Shares	Tunisia	Tunindex
Cyprus	Cyprus Main Market	Namibia	NSX	Turkey	BIST 100
Denmark	OMXC20	Netherlands	AEX	Uganda	Uganda All Share
Ecuador	Guayaquil Select	New Zealand	NZX 50	Ukraine	PFTS
Egypt	EGX 30	Niger	NSE 30	UAE	MSCI UAE
Finland	OMX Helsinki 25	Nigeria	NSE 30	United Kingdom	FTSE 100
France	CAC 40	Norway	Oslo OBX	United States	S&P 500
Germany	DAX	Oman	MSM 30	Venezuela	Bursatil
Greece	Athens General Composite	Pakistan	Karachi 100	Vietnam	VN Index
Hungary	Budapest SE	Peru	S&P Lima General	Zambia	LSE All Share
Iceland	ICEX Main	Philippines	PSEi Composite	Zimbabwe	Zimbabwe Industrial
India	Nifty 50	Poland	WIG30		

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