Joint Discussion Paper
Series in Economics

by the Universities of

Aachen · Gießen · Göttingen
Kassel · Marburg · Siegen

ISSN 1867-3678

No. 01-2022

Jens Klose and Peter Tillmann

The Real and Financial Impact of COVID-19 Around the World

Coordination: Bernd Hayo • Philipps-University Marburg
School of Business and Economics • Universitätsstraße 24, D-35032 Marburg
Tel: +49-6421-2823091, Fax: +49-6421-2823088, e-mail: hayo@wiwi.uni-marburg.de

The Real and Financial Impact of COVID-19 Around the World*

Jens Klose†
THM Business School Gießen, Germany

Peter Tillmann‡
Justus-Liebig-University Gießen, Germany

January 3, 2022

Abstract

In this paper, we study the impact of the COVID-19 pandemic in estimated panel VAR models for 92 countries. The large cross section of countries allows us to shed light on the heterogeneity of the responses of stock markets and NO_2 emissions as high-frequency measures of economic activity. We quantify the effect of the number of infections and four dimensions of policy measures: (1) containment and closure, (2) movement restrictions, (3) economic support and (4) adjustments of health systems. Our main findings show that a surprise increase in the number of infections triggers a drop in our two measures of economic activity. Propping up economic support measures, in contrast, raises stock returns and emissions and, thus, contributes to the economic recovery. We also document vast differences in the responses across subsets of countries and between the first and the second wave of infections.

Keywords: COVID-19, lockdown-measures, panel VAR

JEL classification: E44, E52, E62

*We thank the Martin Baumgärtner and David Finck for critical discussions on an earlier draft of this paper.

†Email: jens.klose@w.thm.de

‡Email: peter.tillmann@wirtschaft.uni-giessen.de

1 Introduction

In early 2020, the COVID-19 pandemic hit the world economy leading to a sharp deterioration of economic activity. A part of this economic decline was due to the change in behavior of individuals in response to the virus: consumers were reluctant to travel, visit shops and eat in restaurants. In addition, some consumers and workers were quarantined. Another source of decline was the response of governments: policy deliberately shut down large parts of public life in order to contain the spread of the virus. This includes restrictions on the movement and gathering of people and stay home requirements. Hence, the economic consequences of the pandemic were driven by both voluntary restraint and officially mandated lockdowns. At the same time, governments around the world also put together rescue packages to support businesses and households and to stabilize the economy. Importantly, the timing of the spread of the virus, the policy responses and also their economic impact differs across countries.

In this paper, we quantify the impact of both the spread of the virus itself and the different facets of the policy responses for a large set of countries. As a key contribution, we estimate panel vector autoregression (VAR) models for 92 countries. Thus, we almost cover the whole world economy. The large cross section of countries also allows us to shed light on the heterogeneity of the responses. We classify countries according to their income level, their development status or their geographic location and estimate the models for different groups of countries. Furthermore, we take account of the fact that the responses of economic activity to governmental interventions differ across the first and the second wave of COVID-19 infections and estimate separate wave-specific VAR models. Importantly, our approach does *not* rest on the assumption that the waves are synchronized across countries.

We face three challenges when estimating the impact of the pandemic: first, we need to measure the fallout of the virus on a high-frequency. Standard macroeconomic time series are available on a monthly or quarterly frequency only. Therefore, we use two variables which are available on a daily frequency for a very broad set of countries: the return on a country's stock market and the growth rate of NO_2 emissions. The first reflects the response of expected future economic activity, while the latter is positively correlated with current industrial production and real GDP. Over longer horizons, however, we see a negative correlation between emissions and economic growth (see e.g. Wang and Wang, 2020) due to the transition to more sustainable economies. But as we focus on the rather short period of the COVID-pandemic, the negative long-run correlation between activity and emissions should be negligible, such that the drop in production reduces emissions. In fact, we find for our sample a mean correlation of industrial production and the monthly average of our daily NO_2 emissions of about 0.38, while the median correlation is even higher at about 0.49. The corresponding correlation with quarterly real GDP are 0.3 and 0.42, respectively. Second, we need to measure the variety of governmental responses. The set of indicators collected in the Oxford COVID-19 government response tracker (Hale et al., 2021) allows us to construct four categories of the policy responses, whose impact we estimate empirically: (1) containment and closure, (2) movement restrictions, (3) economic support and (4) adjustments of health systems. Third, we need to identify the model, i.e. we need to separate the impact of the virus itself from the consequences of the lockdown. We achieve identification through a straightforward recursive ordering of our variables. Fortunately, the nature of the pandemic lends itself to a recursive ordering: the number of infections does not contemporaneously respond to lockdown measures but needs at least one day. Policy, in contrast, is allowed to respond contemporaneously to the number of infections. This allows us to separate these two driving forces of economic activity. In addition, stock returns and emissions can respond immediately to both the number of infections and changes in policy, while the opposite response needs at least one day.

Our main findings are as follows. First, economic activity is sensitive to the spread of the pandemic and the different layers of government interventions. A surprise increase in the number of infections triggers a drop in our two measures of economic activity. Both, stock returns and NO_2 emissions fall as a response to closure policies and restrictions of the movements of people. Propping up economic support measures, in contrast, raises stock returns and emissions and, thus, contributes to the economic recovery.

Second, we detect interesting cross-sectional differences. Once we distinguish between developed and developing countries, we show that stock prices in advanced economies are more sensitive to the number of infections than in developing countries. Tightening lockdown measures reduces stock market valuations in developed countries more than in developing countries. In addition, a tighter lockdown significantly reduces emissions in developing countries. Advanced economies, in contrast, exhibit an increase in emissions following a tightening of lockdowns. We find similar differences once we split the sample along the lines of income levels or the geographical region of countries.

Third, we distinguish between the first and the second wave of infections. As a common pattern, we find that the responses of stock prices are much stronger in the first wave compared to the second. This finding pertains to the responses to the number of infections and the tightening of lockdowns. The positive impact of economic support measures found in the full sample stems from the first wave only. During the first wave, emissions fall as a response to lockdowns, but remain insensitive during the second wave. Restrictions on the movement of people during the first wave significantly reduce emissions, while restrictions during the second wave have no significant effect on emissions. Consistently, economic support raises emissions in the first wave, but not in the second.

Overall, our findings imply that lifting lockdowns will be expansionary, with the effect being unevenly distributed across countries. The extent of cross-country heterogeneity should be taken into account when designing policies and making forecasts about the economic consequences of the pandemic.

The remainder of the paper is organized as follows: In section 2 a literature review is presented. Section 3 describes in detail the data set used. Section 4 explains our modeling structure. In section 5, the results are presented, while section 6 finally concludes.

2 Literature review

The literature on the economic effects of the COVID-pandemic is rapidly expanding. In this literature review, we discuss the papers most closely related to our research and the research gaps filled by our paper in this context. Since our paper is a global study, we focus on other studies of this kind. Therefore, we leave aside the national studies conducted with a focus on the COVID-pandemic.

The first strand of literature focuses on the nexus between COVID cases or fatalities, containment measures and economic activity. In this category, Deb et al. (2020) and Furceri et al. (2021) use a local projections framework to trace the effect of lockdowns on a range of high-frequency indicators such as emissions, vessel trade and extent of mobility. The intensity of lockdown is measured by the stringency index. However, the authors put the stringency index directly into the local projections. They show the effect of a change in the index itself, which is not necessarily a surprise change. Put differently, there is a large forecastable component in the stringency index, which should be taken into account.

Chen et al. (2020) use electricity usage and labor market indicators for the US and Europe as proxies for economic activity and show that a spread of the pandemic and containment measures reduce economic activity, i.e. lower electricity usage and higher unemployment claims. Milani (2021) uses a set of 41 countries in order to estimate the economic effects of COVID-19 by employing Google Trends data with respect to the fear of unemployment. He chooses a global-VAR framework, i.e. a system of interacted single-country VAR models. Using data for the US and UK, Baker et al. (2020a) construct a COVID induced uncertainty index based on Baker et al. (2020b) and show that large parts of the contraction in economic activity can be attributed to a rise in this uncertainty.[1] Caggiano et al. (2020) estimate the effects of a COVID induced uncertainty shock on the global financial cycle and industrial production in a VAR-framework. They show that this shock lowers economic output and the financial cycle significantly. Feyen et al. (2021) investigate the financial sector policy response to the COVID-crisis, sorting 155 jurisdictions into more or less developed economies to cope with different effects of the various groups.

The most extensively investigated effect of the COVID-pandemic in economics is - as a third strand of literature - the response of stock markets to the pandemic and containment measures. There are three approaches to cover stock prices on an international level in this context: First, by using some global or international stock index, second, by focusing on cross-country comparisons and third, by using a panel structure to cope with the overall stock performance in a set of countries. The analysis by Dong et al. (2021) falls into the first category. The authors use the MSCI emerging Asia and MSCI world index in a time-varying parameter framework in order to observe changes in the estimated coefficients before and after the start of the COVID-pandemic. Brueckner and Vespignani (2021) focus their research on the second category of cross-country analysis by investigating in a VAR-framework the effects of the COVID-pandemic on Australian and US stock markets. Rehman et al. (2021) concentrate on the stock markets of the G7 countries in their wavelet analysis. Conducting an event-study using a sample of 63 different countries, Kapar et al. (2021) show that stock markets decline almost all over the world in response to the COVID-pandemic and resulting containment measures. Davis et al. (2021) conduct a thorough analysis on the daily evolution of 35 stock markets in the wake of the COVID-pandemic. They show that stock prices first dropped and recovered later. However, there are three exceptions from this overall pattern: China, South Korea and Taiwan.

A panel analysis with respect to stock markets is executed by Alexakis et al. (2021). They investigate the effects of COVID-cases and containment measures as well as country-spillovers on 45 stock markets and find evidence of negative spillover

[1] Ludvigson et al. (2020) follow a similar approach to Baker et al. (2020b) by focusing on the impact of a disaster in the US on uncertainty and economic performance in a VAR-framework. Concerning uncertainty, they use three different measures: First, macroeconomic uncertainty (Jurado et al., 2015), second, financial uncertainty (Ludvigson et al., 2019) and economic uncertainty (Baker et al. 2016).

effects from containment measures. Chatjuthamard et al. (2021) use a panel with 43 different stock indices and verify that the growth rate of COVID-cases significantly reduces the stock market performance. Heyden and Heyden (2020) use a panel of US and European stocks to conduct an event analysis on the effects of the arrival of COVID in a country and the first policy responses on those stocks. Klose and Tillmann (2021) also use an event-study for 29 European stock market indices and evaluate the effects of COVID-cases as well as monetary and fiscal support measures taken. Shafiullah et al. (2021) turn this analysis upside down by investigating whether the drop in stock markets can predict the size of the economic stimulus packages in times of the COVID-pandemic. Conceptually closest to our analysis is Zhuo and Kunamoto (2020), who use a panel of 15 countries to investigate the effects of the COVID-pandemic and containment measures using a panel-VAR. However, the approach in this paper focuses on a larger set of countries, for a longer sample period and a more detailed breakdown of containment measures.

In order to judge upon the economic effects of the COVID-pandemic and of containment measures, we need high frequency data. One of these variables is emission of greenhouse gases, as those (at least in the short term) should be higher if companies are producing and people are traveling to work. Therefore, we use emission as an indicator of economic activity. The effects of COVID-pandemic on emissions have been investigated extensively in environmental science. Most of these studies concentrate on CO_2-emissions and find for various countries or cities that emissions decline during the COVID-pandemic (Adhikari et al., 2021, Kumar et al., 2022, Schulte-Fischedick et al., 2021, Ray et al., 2021). Those find that the COVID-pandemic has reduced CO_2-emissions. Some articles focus on a broader set of emission gases. Gettelman et al. (2020) use a forecasting model on the period of the COVID-pandemic to investigate the effects of a broad set of greenhouse gases on the climate. Yang et al. (2021) perform a meta study for various countries or regions with respect to a variety of emission gases before and after the start of the COVID-pandemic. Even though not a cross-country study, Asna-ashary et al. (2020) estimate in a panel-VAR for Iranian regions the effects of the COVID-pandemic on air pollution measured by PM 2.5, i.e. particulate matter.

To the best of our knowledge, there is currently only the paper by Mzoughi et al. (2020) dealing with the consequences of the COVID-pandemic on stock markets (here measured as stock market volatility) and emissions (measured as CO_2-emissions) simultaneously. They use global data in a VAR-framework and find that CO_2-emissions fall and stock market volatility increases once the COVID-infections rise, although their results appear to be hardly significant.

This paper contributes to the literature in several ways: First, we employ more detailed data on containment measures by building four different groups, thus being able to identify differences between policies. Second, we rely on a larger set of countries than most of the studies mentioned above. Therefore, we have the opportunity to not only investigate the overall (global) effects, but also subdivide our sample geographically and with respect to the development status. Third, we rely on an extended sample period compared to the other studies. We have the advantage of being able to identify different waves of the pandemic in the countries and thus possible differences among the response to the COVID-cases and containment policies in the various waves. Finally, we focus on financial and real activity variables separately to investigate whether there are differences in their reactions to the COVID-pandemic and containment measures.

3 The data set

In this section, we explain the construction of the variables for our panel VAR analysis. As we are interested in the financial and real impact of the COVID-pandemic and the underlying policy responses, we use a daily frequency as COVID-cases or deaths are typically reported on a day-to-day basis. We approximate the financial response by the evolution of the leading stock indices of the sample countries. The real effects are approximated by the emission of nitrogen dioxide (NO_2) as it is a byproduct of the combustion of fossil fuels, i.e. resulting from energy production and mobility. Thus, we expect a positive correlation between NO_2-emissions and economic activity as, e.g. more energy is needed for production purposes and more people travel to work. The variable covering the severity of the pandemic is the number the reported COVID-cases. We use those instead of the alternative of reported COVID-deaths as the cases are typically seen as leading indicator, i.e. the more people are currently infected, the higher the number of deaths in about one to two weeks.

3.1 Policy response variables

Our main contribution is an analysis of the effects of policy changes due to the COVID-pandemic on financial and real variables in a large panel of countries. In order to capture these policy changes, we rely on the data of the University of Oxford COVID-19 government response tracker (Hale et al., 2021). We use all ordinally measured variables as those are directly comparable across countries. Hale et al. (2021) cluster those variables into three groups: (1) Containment and closure,

(2) Economic response and (3) Health systems. We follow this categorization but divide the containment and closure measures into two sub-categories representing closures on the one hand and movement restrictions on the other hand. Hence, we work with four categories of policy responses: (1) Containment and closure, (2) Movement restrictions, (3) Economic support and (4) Health systems.

The closure category contains four different policy measures. The same is true for the movement category. The economic response category comprises two policy measures and the health system category summarizes six policy measures. A detailed description of the different measures based on Hale et al. (2021) and the ordinal steps is presented in Table (1). All indicators are ordinally scaled, where a value of 0 means that the measure is not implemented at all and the highest number reflects the strictest implementation of a certain measure. The highest realization of each indicator may differ from measure to measure. Moreover, an additional 0/1 variable is introduced for certain measures signaling whether the measure was targeted either geographically, with respect to a specific sector or costs. So, for example, if the measure was geographically targeted to a certain region in a country on a certain day only, the value of the index would be 0. If it was a general measure applied throughout the whole country, it would be 1 instead.

In order to guarantee that each measure has the same importance in our four groups, we calculate variables ranging from 0 (the measure is not implemented at all) to 100 (the measure is implemented in its strictest way) in line with recommendations of Hale et al. (2021). This means that for the measures with ordinal steps only but without a general or targeted indication, the variables are calculated as

$$x_{it} = 100 \times \frac{m_{it}}{M}. \tag{1}$$

In equation (1), x_{it} is the variable between 0-100 of country i at day t, while m_{it} is the realization of the measure as presented in Table (1) for the very same country on the same day and M stands for the maximum realization of the measure which is constant over countries and time. If the measure has a general or targeted 0/1-indicator, the variables are computed according to

$$x_{it} = 100 \times \frac{m_{it} - 0.5(1 - g_{it})}{M}. \tag{2}$$

In this equation, g_{it} is the general or targeted indicator of a certain country on a certain day which could be 0 or 1. This adjustment guarantees that in case of a targeted action, there is a discount of 0.5 to the ordinal measure. By construction, in case of no actions taken (thus m_{it} being zero), g_{it} equals one in order to guarantee that x_{it} cannot fall into negative territory.

Finally, the different variables calculated with the formulas above are merged into the four different groups by using the arithmetic mean in line with the calculations of, e.g. the stringency index in Hale et al. (2021), which does, however, differ in its composition from our groups.

The series on COVID-cases, stock prices and NO_2-emissions are rather volatile. Therefore, we calculate five-day moving averages of percentage growth rates in order to smooth them. To correspond with those five-day moving averages, we apply the same procedure to the changes in the four policy intervention categories.

As we focus on the period of the COVID-pandemic, our sample period starts on 31st January 2020. The speed by which the COVID-pandemic spread differed across continents and countries. While some countries already struggled to contain the pandemic, others were still untouched. As a consequence, our panel is unbalanced. For every country, the sample begins with the first occurrence of the virus. The end of the sample is uniformly the 16th April 2021.[2] Within this period, most countries faced several waves of the COVID-pandemic. In total, our panel covers 92 countries, see Table (2). For those countries, we were able find stock prices or data on NO_2-emissions or both. The number of COVID-cases, as well as the policy measures are available for all 92 countries.

While we estimate a panel VAR with all 92 countries jointly, we also differentiate the sample in order to shed light on the differences across country groups. We implement this differentiation in three dimensions. The categorization of countries to different groups is shown in Tables (3), (4) and (5). First, the countries are grouped according to their development status. The classification used in this context follows United Nations (2020). We group the countries into developed, transition and developing countries. Second, the countries are grouped with respect to their income level following the definition of the World Bank.[3] According to this classification, the countries are sorted into one of the following four categories: high-income, upper-middle-income, lower-middle-income or low-income countries. The third differentiation is geographical. Here the countries are associated with their continent, i.e. Africa, Asia, Europe, North and Middle America, South America or Australia.

[2]Since we explicitly model only the period since the outbreak of the COVID-pandemic, the critique to the use of VAR-models in this context as recently expressed by Lenza and Primiceri (2020) or Ng (2021) does not apply to our analysis.

[3]See https://datahelpdesk.worldbank.org/knowledgebase/articles/906519.

3.2 Pandemic waves

In most countries, the pandemic spread in waves. We evaluate whether the responses to stock prices and NO_2-emissions differ across the successive waves of COVID-infections.[4] Importantly, these waves were not synchronized across countries such that we cannot implement a simple sample split.

In order to identify the waves, we slightly modify a classification algorithm introduced by the British Office for National Statistics (2021).[5] We rely on three variables to measure waves. First, the daily growth rate of new infections. In order to account for the weekly cyclicality in some countries, we use the smoothed series of new cases series provided by *Our World in Data* to calculate the daily growth rates. Second, the reproduction rate (R) measures how many people an infected person infects on average. Third, the positivity rate measuring the percentage of positive COVID-19 tests.

The daily growth rate of COVID-infections and the R rate determine the start of a wave. A wave begins if two criteria are met simultaneously: first, the daily growth rate is positive for ten weekdays in a row (i.e. for day t and the nine preceding weekdays).[6] Second, the R rate needs to exceed unity in order for a wave to start meaning that one infected person infects more than one other person and, thus, the pandemic spreads. The end of a wave is determined by the positivity rate. If the positivity rate falls to the lowest quantile over all observations of each country, a wave is supposed to have ended. With this approach, we are well in line with the definition of the British Office for National Statistics (2021), who defines a wave to end if the positivity rate falls below 0.1% in England. We come up with an almost similar threshold for the United Kingdom at a slightly different time period. However, our quantile approach has the advantage of identifying wave ends for other countries, i.e. even those which face constantly higher positivity rates than the United Kingdom.

Using this approach, we are able to identify the waves for each country as shown in Table (6). Due to missing data of at least one of our indicator variables, we had to delete 16 countries from the analysis. Moreover, for three countries, no waves could be detected. For the large majority of the remaining countries, we detect

[4] Goldstein et al. (2021) show that containment measures loose their effectiveness with respect to the spread of the pandemic after about four months. Hence, the effect of lockdowns is unstable over time. The authors refer to "lockdown fatigue" to characterize this finding.

[5] Finck and Tillmann (2021) use a smooth-transition model to differentiate between different stages of the pandemic.

[6] With this definition we are a bit less restrictive than the British Office for National Statistics (2021) who use a 15 day period of continuous positive growth rates. Our approach allows us to identify more short-lived waves, like for example, seen in Australia.

two COVID-waves. This holds for 45 out of the remaining 73 countries. For 27 countries, we detect only one wave and only one country faced three waves (the US). Note that the last wave often ends with the end of our sample period. Thus it has to be assumed that the wave continues beyond the end of our sample period.

In the empirical analysis below, we estimate the panel VAR model separately for the first and the second COVID-waves.

4 Model

We estimate a panel VAR model in order to capture the dynamics of the variables. This class of models is particularly attractive for our purpose because it allows us to estimate the dynamic effect of lockdown shocks for a large set of countries. Our model is given by

$$\mathbf{A}\mathbf{y}_{it} = \mathbf{d}_i + \mathbf{F}_1\mathbf{y}_{it-1} + ... + \mathbf{F}_s\mathbf{y}_{it-s} + \varepsilon_{it}, \tag{3}$$

with s lags for country $i = 1, ..., N$ and time $t = s + 1, ..., T$, where the $n \times 1$ vector $\mathbf{y}_{it}$ contains the endogenous variables. The $n \times 1$ vector $\mathbf{d_i}$ collects the country fixed-effects and the $n \times n$ matrices $\mathbf{A}$ and $\mathbf{F_1}, ..., \mathbf{F_s}$ contain the VAR coefficients. The structural shocks are in $\boldsymbol{\varepsilon}_{it}$ with $\boldsymbol{\varepsilon}_{it} \sim N(0, \mathbf{\Sigma\Sigma}')$.

The 3×1 vector of endogenous variables is

$$\mathbf{y}_{it} = \begin{bmatrix} cases_{it} & indi^j_{it} & y_{it} \end{bmatrix}' \tag{4}$$

The number of new COVID-19 infections is $cases_{it}$, while the category j of the policy response indicator is denoted by $indi^j_{it}$ ranging from 1 to 4. The third endogenous variable in the VAR, y_{it}, is either the daily stock return or the level of NO_2 emissions in country i. In order to keep the VAR model as compact as possible, we use either stock returns *or* emissions as our third variable. We impose the restriction that the autoregressive coefficients are identical across countries. Below, we shed light on the strictness of this assumption by distinguishing between groups of countries. The estimated VAR includes two lags of the endogenous variables.

Since we are interested in the causal effect of lockdown shocks on the other endogenous variables, we need to impose identifying restrictions onto the VAR model. We chose a recursive identification scheme which amounts to imposing an order on the contemporaneous interaction among the variables. We assume that $\mathbf{A}$ is lower-triangular. Premultiplying the VAR model with $\mathbf{A}^{-1}$ recovers the reduced-form model

$$\mathbf{y}_{it} = \mathbf{c}_i + \mathbf{B}_1\mathbf{y}_{it-1} + ... + \mathbf{B}_s\mathbf{y}_{it-s} + \mathbf{A^{-1}\Sigma}\varepsilon_{it}, \tag{5}$$

with $\boldsymbol{\varepsilon}_{it} \sim N(0, \mathbf{I}_k)$, where $\mathbf{c}_i = \mathbf{A}^{-1}\mathbf{d}_i$ and $\mathbf{B}_j = \mathbf{A}^{-1}\mathbf{F}_j$. $\boldsymbol{\Sigma}$ is an $n \times n$ matrix with standard deviations on the main diagonal.

Fortunately, the nature of the variables lends itself to a straightforward ordering: We assume that the number of infections responds with a lag of at least one day to a tightening or easing of lockdowns as reflected in the change of the policy response indicator. Policymakers can, in contrast, respond contemporaneously to a change in the number of infections. Hence, the COVID cases are ordered first and the policy response sub-component is ordered second. The third variable can respond contemporaneously to either the policy response index or the number of COVID cases, while these two variables need at least one day to respond to changes in the third variable. We believe this recursive scheme to be an innocuous constraint.

5 Results

We present the estimates in terms of impulse response functions. In each figure, we show the response of the third variable, the variables whose responses we are mostly interested in, to a shock in the number of COVID cases or the sub-component j of the policy response index. A shock is an unexpected change in either of these variables, e.g. a surprise tightening of lockdowns or an unexpected increase in the number of COVID cases. Each figure also shows the 95% confidence band around the estimated impulse responses.

5.1 Worldwide results

Figure (1) depicts the response of stock prices to the five shocks we consider, an increase in the number of cases or an increase in one of the four sub-components of the policy response index. Stock prices fall significantly after a shock to the number of COVID cases. This response, like most other responses, is highly statistically significant. The peak response occurs five days after the shock. A tightening of lockdowns also reduces the valuation of the stock market. Stock returns fall by 0.02 percentage point after an increase in the closure-component of the index by one standard deviation, but recover after about five days. If authorities extend economic support to the economy as reflected by an unexpected increase in the Economic Support sub-component, stock prices strongly recover after about 3 days, while they initially fall possibly due to negative news given with the support measure that the crisis is more severe. These responses are all consistent with our economic intuition. The response of stock prices to a tightening in the restrictions of movements, in contrast, is puzzling. Stock prices appreciate after such a tightening, which could be explained based on the notion that a restriction of movements is considered an effective containment of the spread of the virus, which raises expected future economic conditions. The stock markets seem insensitive to changes in the health-dimension of the policy response index. This finding prevails in all other impulse response functions.

Figure (2) reports the responses of NO_2 emissions. A surprise increase in the number of infections reduces the level of emissions. Likewise, a stricter closure policy or a tightening of restrictions to the movement of people lead to a significant fall in emissions. Since emissions closely reflect economic activity such as industrial production and transportation, these results show the large economic cost of lockdowns. More generous economic support, in contrast, tends to increase emissions. Hence, economic support is effective in containing the economic costs of the pandemic.

5.2 Developed versus developing countries

We now differentiate between countries on the basis of their level of development. We estimate the panel VAR model separately for developed countries as well as developing countries, as explained in the previous section.[7] Figure (3) shows the estimated impulse responses of stock prices. In advanced economies, stock prices are more sensitive to the number of COVID-cases compared to developing countries. A tighter lockdown depresses the stock market of developed economies more than the market in developing economies. One reason to explain this differential might be a higher level of compliance with the closure rules in advanced countries. Likewise, stock prices in rich economies respond more strongly to measures of economic support. Again, we find a counterintuitive, positive response of the stock market to restrictions of peoples' mobility. This response is particularly pronounced for developed economies.

Figure (4) documents the impulse responses of NO_2 emissions across developed and developing countries. The most striking difference cross country groups can be observed for the response of emissions to our proxy for closure policies. In developing countries, we observe a significant drop in emissions after a tightening of the lockdown. In developed countries, in contrast, emissions increase. Hence, the negative response for the full sample, see Figure (2), is driven by the large number of developing countries in our sample. There are two potential explanations for this differential response. First, the sectoral composition of developing economies might

[7] Results for the third category, the transition countries, have been excluded due to large confidence bands because of the low number of observations. Those results are, however, available from the authors upon request.

be tilted towards manufacturing, i.e. emission-intensive, industries, while the service sector dominates in developed countries. Thus, a lockdown that equally depresses both manufacturing production and the services sectors results in a stronger fall in emission in developing countries. This explains why one response is stronger negative than the other. A second explanation offers a reason for why emissions actually increase in richer economies. An important source of NO_2 emissions is transportation. In advanced economies, a tighter lockdown motivates people to switch from public transportation to individual vehicles, which raises emissions. This option is not easily available in poorer countries.

5.3 Differing income levels

We now split the sample according to the World Bank's classification of countries' income levels. While stock prices in high-income countries fall upon new information about COVID-cases in high-income countries, see Figure (5), they remain unaffected in low-income countries. Economic support props up the stock market of high-income and upper-middle income countries, but remain ineffective with respect to stock prices in lower-middle income and low income countries. Importantly, the economic support index reflects whether or not national authorities undertook fiscal efforts to stabilize the economy. It does not, however, measure the volume of fiscal policy packages. Hence, the nature and the absolute magnitude of the fiscal interventions strongly differ across countries, which explains why stock markets in poor countries remain insensitive to economic support.

The level of NO_2 emissions, see Figure (6), also exhibits unequal responses across income levels.[8] Closing down shops, offices and factories has a particularly strong effect on emissions in lower-middle income countries, where emissions fall by about 1%. This also implies that an eventual lifting of the lockdown strongly boosts emissions, and hence economic activity, in these countries. In the other income groups, this response is much weaker and often insignificant. A similar picture emerges from the responses to a restriction of the movement of people. This measure is particularly effective in reducing emissions in poorer countries.

5.4 Geographical differences

Now we study the regional variation in the impulse responses. For each variable of interest, the figures show the impulse response functions derived for a specific

[8] Note that NO_2 data for low income countries are not available, so no estimation results can be presented for this group of countries.

continent against the responses of the rest of the world, i.e. the remaining countries.

The most remarkable difference across countries is the heterogeneity in the responses to economic support packages. In Africa, Asia and North America, see Figures (7), (8) and (10), stock prices remain insensitive to economic support measures. In Europe, South America and Australia, see Figures (9), (11) and (12), in contrast, we find a significant increase in stock prices after the adoption of economic support measures.

The positive response of stock markets to economic support measures in Europe is consistent with the positive effect of economic support on European emissions on impact, see Figure (15). In Europe, a higher number of COVID infections reduce emissions - an effect we do not find for most other regions. In South America, see Figure (17) movement restrictions and closures significantly reduce emissions.

5.5 The effects across waves

The spread of the pandemic progressed in waves. Policy measures in the first wave of infections might be more or less effective than in the second wave. While in the first wave, policy faced enormous uncertainty about both the spread of the virus, the effectiveness of containment policies and the macroeconomic collateral damage, authorities gathered experience and knowledge over time. Hence, the policy interventions during the second wave could be more precisely targeted, both in terms of timing and scope. As a consequence, the responses of stock markets and emissions to policy interventions could vary over time.

In section 2.2, we determined the timing of the COVID-waves for each sample country. Importantly, we do not assume that waves occur simultaneously across countries. Such a situation could be captured by a simple sample split. Instead, we identify country-specific waves before estimating the panel VAR model for the first and the second wave separately. The resulting responses of stock prices are shown in Figure (19). All five impulse responses suggest a common pattern: the responses are much stronger in the first wave compared to the second. Stock prices fall strongly in the first wave as a response to an increase in the number of infections, while the drop is much smaller in the second wave. Likewise, closing down the public life triggers a depreciation of the stock market during the first wave but not the second. The responses to economic support measures across the two waves exhibit a striking difference: during the first wave, supportive policy contributes strongly to an increase in equity market valuation. During the second wave, in contrast, stock prices fall mildly as a response to economic support. The puzzling response of stock prices to movement restrictions is mostly driven by the response during the first wave. Apparently, markets appreciate restrictions of movements as a sign that authorities take the pandemic seriously.

The responses of NO_2 emissions across the two waves, which are shown in Figure (20), are in line with our expectations. In both waves, the responses of emissions to changes in the number of infections remains insignificant. Closures reduce emissions during the first wave, but not in the second. Put differently, closures significantly constrained economic activity in the first wave, but remained relatively innocuous in the second. The response of emissions to movement restrictions and health measures is consistent with that: restrictions during the first wave significantly reduce emissions, while restrictions during the second wave have no significant effect on emissions. These results suggest that lockdown measures lead to a significant contraction of economic activity. Economic support packages adopted by governments cushioned some of these effects. During the first wave of infections, NO_2 emissions increase in the first months after new support measures are announced. In the second wave, in contrast, economic support measures remain ineffective in stimulating economic activity as reflected in NO_2 emissions.

Hence, the impact of policy interventions on both stock prices and emissions are strongly dependent on the state of infections. A policy that is effective during the first wave might no longer be effective in the second wave of infections.

6 Conclusions

In this paper, we estimated the impact of the COVID-19 pandemic and the policy-responses to the pandemic in a large panel of countries. In order to track the economic impact on a high frequency, we concentrate on the response of stock returns and the growth rate of NO_2 emissions. These variables are available on a daily frequency, while conventional indicators such as industrial production, inflation and employment are available on a monthly frequency only. Importantly, the large cross-sectional dimension allows us to split the sample along the lines of several dimensions and compare the responses across sub-samples.

We find that both measures of economic activity are sensitive to the spread of the virus and the policy responses, respectively. A surprise increase in the number of infections triggers a drop in our two measures of economic activity. Both, stock returns and NO_2 emissions fall as a response to closure policies and restrictions of the movements of people. Propping up economic support measures, in contrast, raises stock returns and emissions and, thus, contributes to the economic recovery. These responses strongly differ across subsamples. For example, tightening lockdown measures reduces stock market valuations in developed countries more than in developing countries. In addition, a tighter lockdown significantly reduces emissions in developing countries. Advanced economies, in contrast, exhibit an increase in emissions following a tightening of lockdowns. We also distinguish between the first and the second wave of infections. We find that the responses of stock prices are much stronger in the first wave compared to the second. This finding pertains to the responses to the number of infections and the tightening of lockdowns. The positive impact of economic support measures found in the full sample stems from the first wave only. Consistently, economic support raises emissions in the first wave, but not the second.

Our findings have a number of policy implications: First, since we have verified that there is considerable heterogeneity across country groups, there is no common recipe to fight the COVID pandemic in all countries. Our results instead suggest that the optimal mix of policy measures to stabilize the economy depends on national characteristics and thus needs to be designed on a country level. This does not mean that countries can and should not learn from the experiences of others. But to do so, at least the degree of development, the income level and geographical properties, among possible other socio-economic factors, should be taken into account.

Second, the effectiveness of policy measures seems to be time-varying, i.e. the effects are larger in the first wave than in the second. Thus it can be assumed that policy measures have lower effects the longer the pandemic lasts, or the more waves an economy experiences. This could be interpreted as bed news since stabilization measures need to be bolder in late waves to have the same quantitative effect than in earlier waves. However, it could also be seen as good news since we have also shown that the response of activity to the COVID-pandemic is also reduced for later waves. Thus, the need for stabilizing measures should be lower, as the economies seem to learn how to live with the COVID pandemic.

Tables

Table 1: Government response indicator

Indicator	Description	Ordinal Steps	General or Targeted Measure
Closure measures			
School closing	Closing of schools and universities	0 = No measure 1 = Recommend closing, or all schools open with alterations 2 = Require closing some levels 3 = Require closing all levels	Geographical 0 = Targeted 1 = General
Workplace closing	Closings of workplaces	0 = No measure 1 = Recommend closing, or work from home 2 = Require closing some sectors 3 = Require closing all but essential sectors	Geographical 0 = Targeted 1 = General
Cancel public events	Canceling public events	0 = No measure 1 = Recommend canceling 2 = Require canceling	Geographical 0 = Targeted 1 = General
Restrictions on gatherings	Cut-off size for bans on gatherings	0 = No restrictions 1 = Restrictions > 1000 people 2 = Restrictions 101-1000 people 3 = Restrictions 11-100 people 4 = Restrictions < 10 people	Geographical 0 = Targeted 1 = General
Movement measures			
Close public transport	Closing of public transport	0 = No measure 1 = Recommend closing or reduced volume, route, availability 2 = Require closing	Geographical 0 = Targeted 1 = General
Stay at home requirements	Orders to "shelter in place" and otherwise confine at house	0 = No measure 1 = Recommend not leaving home 2 = Require not leaving house with exceptions 3 = Require not leaving house with minimal exceptions	Geographical 0 = Targeted 1 = General
Restrictions on internal movement	Restrictions on internal movement	0 = No measure 1 = Recommend not to travel between regions and cities 2 = Internal movement restrictions in place	Geographical 0 = Targeted 1 = General
International travel controls	Restrictions on international travel	0 = No measure 1 = Screening 2 = Quarantine arrivals from high-risk regions 3 = Ban of arrivals from some regions 4 = Ban on all regions or total border closure	
Economic response measures			
Income support	Government covering salaries or providing direct cash payments, universal basic income	0 = No income support 1 = Less than 50% replacement 2 = More than 50% replacement	Sectoral 0 = Only formal sector 1 = Also informal sector
Debt/contract relief	Government freezing financial obligations	0 = No relief 1 = Narrow relief 2 = Broad relief	
Health systems measures			
Public information campaigns	Presence of public information campaigns	0 = No campaign 1 = Public officials urging caution about COVID-19 2 = Coordinated public information campaign	Geographical 0 = Targeted 1 = General
Testing policy	Testing strategies	0 = No testing policy 1 = Only to those who have symptoms and meet specific criteria 2 = Anyone with symptoms 3 = Testing for everyone	
Contact tracing	Use of measure to trace contacts	0 = No contact tracing 1 = Limited contact tracing (not for all cases) 2 = Comprehensive contact tracing (for all cases)	
Facial coverings	Policies of facial coverings outside home	0 = No policy 1 = Recommended 2 = Required in some situations 3 = Required all public places with other people present or all situations when social distancing is impossible 4 = Required outside home	Geographical 0 = Targeted 1 = General
Vaccination policy	Policies for vaccine delivery to different groups	0 = No availability 1 = Available to one of the following groups: Key workers, vulnerable groups, elderly groups 2 = Available to two of the following groups: Key workers, vulnerable groups, elderly groups 3 = Available to all of the following groups: Key workers, vulnerable groups, elderly groups 4 = Available to the three groups above plus partial additional availability 5 = Universal availability	Costs 0 = individual cost 1 = no or minimal individual costs
Protection of elderly people	Policies to protect elderly people	0 = No measure 1 = Recommended isolation, hygiene and visitor restrictions in Long Term Care Facilities (LTCF) or elderly people to stay at home 2 = Narrow restrictions for isolation, hygiene and visitor restrictions in LTCF or elderly people to stay at home 3 = Extensive restrictions for isolation, hygiene and visitor restrictions in LTCF or elderly people to stay at home	

Notes: Indicators and description based on Hale et al. (2021).

Table 2: Country sample and data availability

Country	Stock-Prices	NO2-Emission	Policy-Measures
Argentina	X	X	X
Australia	X	X	X
Austria	X	X	X
Bangladesh	X		X
Belgium	X	X	X
Bolivia		X	X
Bosnia and Herzegovina	X	X	X
Brazil	X	X	X
Bulgaria	X	X	X
Cambodia	X		X
Canada	X	X	X
Chile	X	X	X
China	X	X	X
Colombia	X	X	X
Croatia	X	X	X
Cyprus	X	X	X
Czechia	X	X	X
Denmark	X	X	X
Ecuador	X		X
Egypt	X		X
Estonia	X	X	X
Finland	X	X	X
France	X	X	X
Georgia	X	X	X
Germany	X	X	X
Ghana	X		X
Greece	X	X	X
Hong Kong	X	X	X
Hungary	X	X	X
Iceland	X	X	X
India	X	X	X
Indonesia	X		X
Iran		X	X
Ireland	X	X	X
Israel	X	X	X
Italy	X	X	X
Jamaica	X		X
Japan	X	X	X
Jordan		X	X
Kazakhstan		X	X
Kenya	X		X
Kosovo		X	X
Kuwait	X	X	X
Latvia	X		X
Lebanon	X		X
Lithuania	X		X

Country	Stock-Prices	NO2-Emission	Policy-Measures
Luxembourg	X	X	X
Malaysia	X		X
Malta	X		X
Mauritius	X		X
Mexico	X	X	X
Mongolia		X	X
Morocco	X		X
Netherlands	X	X	X
New Zealand	X	X	X
Nigeria	X		X
Norway	X	X	X
Oman	X		X
Pakistan	X		X
Panama	X		X
Peru	X	X	X
Philippines	X	X	X
Poland	X	X	X
Portugal	X	X	X
Qatar	X		X
Romania	X	X	X
Russia	X	X	X
Saudi Arabia	X	X	X
Serbia	X	X	X
Singapore	X		X
Slovakia	X	X	X
Slovenia	X		X
South Africa	X	X	X
South Korea	X	X	X
Spain	X	X	X
Sri Lanka	X		X
Sweden	X	X	X
Switzerland	X	X	X
Taiwan	X	X	X
Tanzania	X		X
Thailand	X	X	X
Tunisia	X		X
Turkey	X	X	X
Uganda	X		X
Ukraine	X		X
United Arab Emirates	X	X	X
United Kingdom	X	X	X
United States of America	X	X	X
Venezuela	X		X
Vietnam	X	X	X
Zambia	X		X
Zimbabwe	X		X

Notes: X marks availability of at least some variables for the country.

Table 3: Classification developed versus developing countries

Country	Developed	Transition	Developing
Argentina			X
Australia	X		
Austria	X		
Bangladesh			X
Belgium	X		
Bolivia			X
Bosnia and Herzegovina		X	
Brazil			X
Bulgaria	X		
Cambodia			X
Canada	X		
Chile			X
China			X
Colombia			X
Croatia	X		
Cyprus	X		
Czechia	X		
Denmark	X		
Ecuador			X
Egypt			X
Estonia	X		
Finland	X		
France	X		
Georgia		X	
Germany	X		
Ghana			X
Greece	X		
Hong Kong			X
Hungary	X		
Iceland	X		
India			X
Indonesia			X
Iran			X
Ireland	X		
Israel			X
Italy	X		
Jamaica			X
Japan	X		
Jordan			X
Kazakhstan		X	
Kenya			X
Kosovo		X	
Kuwait			X
Latvia	X		
Lebanon			X
Lithuania	X		
Luxembourg	X		
Malaysia			X
Malta	X		
Mauritius			X
Mexico			X
Mongolia			X
Morocco			X
Netherlands	X		
New Zealand	X		
Nigeria			X
Norway	X		
Oman			X
Pakistan			X
Panama			X
Peru			X
Philippines			X
Poland	X		
Portugal	X		
Qatar			X
Romania	X		
Russia		X	
Saudi Arabia			X
Serbia		X	
Singapore			X
Slovakia	X		
Slovenia	X		
South Africa			X
South Korea			X
Spain	X		
Sri Lanka			X
Sweden	X		
Switzerland	X		
Taiwan			X
Tanzania			X
Thailand			X
Tunisia			X
Turkey			X
Uganda			X
Ukraine		X	
United Arab Emirates			X
United Kingdom	X		
United States of America	X		
Venezuela			X
Vietnam			X
Zambia			X
Zimbabwe			X

Notes: X marks the classification of a country into a category. Classification according to United Nations (2020).

Table 4: Classification via income levels

Country	High	Upper-Middle	Lower-Middle	Low
Argentina		X		
Australia	X			
Austria	X			
Bangladesh			X	
Belgium	X			
Bolivia			X	
Bosnia and Herzegovina		X		
Brazil		X		
Bulgaria		X		
Cambodia			X	
Canada	X			
Chile	X			
China		X		
Colombia		X		
Croatia	X			
Cyprus	X			
Czechia	X			
Denmark	X			
Ecuador		X		
Egypt			X	
Estonia	X			
Finland	X			
France	X			
Georgia		X		
Germany	X			
Ghana			X	
Greece	X			
Hong Kong	X			
Hungary	X			
Iceland	X			
India			X	
Indonesia			X	
Iran		X		
Ireland	X			
Israel	X			
Italy	X			
Jamaica		X		
Japan	X			
Jordan		X		
Kazakhstan		X		
Kenya			X	
Kosovo		X		
Kuwait	X			
Latvia	X			
Lebanon		X		
Lithuania	X			

Country	High	Upper-Middle	Lower-Middle	Low
Luxembourg	X			
Malaysia		X		
Malta	X			
Mauritius		X		
Mexico		X		
Mongolia			X	
Morocco			X	
Netherlands	X			
New Zealand	X			
Nigeria			X	
Norway	X			
Oman	X			
Pakistan			X	
Panama	X			
Peru		X		
Philippines			X	
Poland	X			
Portugal	X			
Qatar	X			
Romania		X		
Russia		X		
Saudi Arabia	X			
Serbia		X		
Singapore	X			
Slovakia	X			
Slovenia	X			
South Africa		X		
South Korea	X			
Spain	X			
Sri Lanka		X		
Sweden	X			
Switzerland	X			
Taiwan	X			
Tanzania				X
Thailand		X		
Tunisia			X	
Turkey		X		
Uganda				X
Ukraine			X	
United Arab Emirates	X			
United Kingdom	X			
United States of America	X			
Venezuela		X		
Vietnam			X	
Zambia			X	
Zimbabwe			X	

Notes: X marks the classification of a country into a category. Classification according to World Bank.

Table 5: Geographical classification

Country	Africa	Asia	Europe	N.-M. America	S. America	Australia
Argentina					X	
Australia						X
Austria			X			
Bangladesh		X				
Belgium			X			
Bolivia					X	
Bosnia and Herzegovina			X			
Brazil					X	
Bulgaria			X			
Cambodia		X				
Canada				X		
Chile					X	
China		X				
Colombia					X	
Croatia			X			
Cyprus			X			
Czechia			X			
Denmark			X			
Ecuador					X	
Egypt	X					
Estonia			X			
Finland			X			
France			X			
Georgia		X				
Germany			X			
Ghana	X					
Greece			X			
Hong Kong		X				
Hungary			X			
Iceland			X			
India		X				
Indonesia		X				
Iran		X				
Ireland			X			
Israel		X				
Italy			X			
Jamaica				X		
Japan		X				
Jordan		X				
Kazakhstan		X				
Kenya	X					
Kosovo			X			
Kuwait		X				
Latvia			X			
Lebanon		X				
Lithuania			X			
Luxembourg			X			
Malaysia		X				
Malta			X			
Mauritius	X					
Mexico				X		
Mongolia		X				
Morocco	X					
Netherlands			X			
New Zealand						X
Nigeria	X					
Norway			X			
Oman		X				
Pakistan		X				
Panama				X		
Peru					X	
Philippines		X				
Poland			X			
Portugal			X			
Qatar		X				
Romania			X			
Russia			X			
Saudi Arabia		X				
Serbia			X			
Singapore		X				
Slovakia			X			
Slovenia			X			
South Africa	X					
South Korea		X				
Spain			X			
Sri Lanka		X				
Sweden			X			
Switzerland			X			
Taiwan		X				
Tanzania	X					
Thailand		X				
Tunisia	X					
Turkey			X			
Uganda	X					
Ukraine			X			
United Arab Emirates		X				
United Kingdom			X			
United States of America				X		
Venezuela					X	
Vietnam		X				
Zambia	X					
Zimbabwe	X					

Notes: X marks the classification of a country into a category. N.-M. America = North and Middle America, S. America = South America.

Table 6: COVID-wave classification

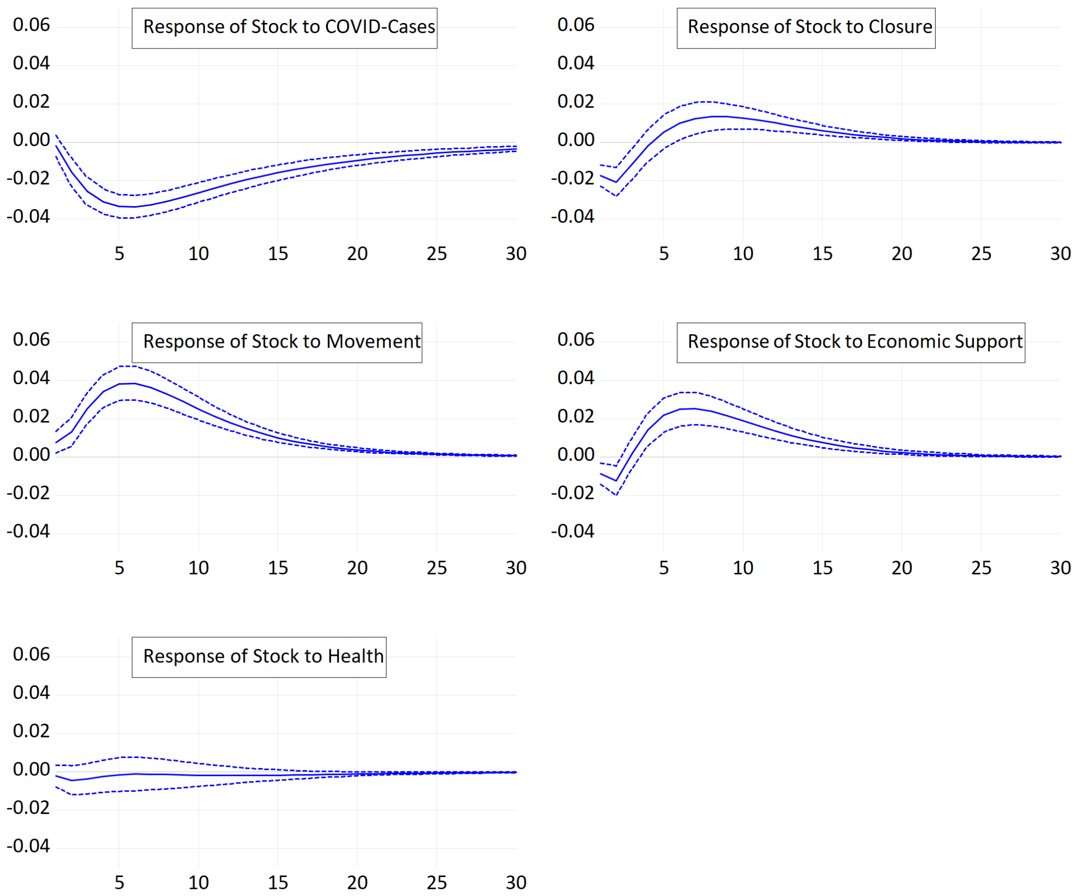
Country	First wave	Second wave	Comments
Argentina	05/14/20 - 02/16/21	04/05/21 - 04/16/21	
Australia	03/13/20 - 05/11/20	06/22/20 - 09/25/20	
Austria	03/03/20 - 05/27/20	08/10/20 - 04/16/21	
Bangladesh	04/03/20 - 02/04/21	03/03/21 - 04/16/21	
Belgium	03/13/20 - 05/01/20	10/01/20 - 04/16/21	
Bolivia	05/04/20 - 11/06/20	12/08/20 - 04/09/21	
Bosnia and Herzegovina	06/19/20 - 01/07/21	03/10/21 - 04/16/21	
Brazil			missing data
Bulgaria	10/02/20 - 04/16/21		
Cambodia			missing data
Canada	03/11/20 - 06/29/20	09/16/20 - 04/16/21	
Chile	03/20/20 - 11/06/20	01/07/21 - 04/16/21	
China			missing data
Colombia	03/13/20 - 02/12/21	03/10/21 - 04/16/21	
Croatia	03/13/20 - 05/01/20	08/10/20 - 04/16/21	
Cyprus	10/07/20 - 04/16/21		
Czechia	03/13/20 - 03/24/21		
Denmark	03/23/20 - 06/11/20	09/02/20 - 03/23/21	
Ecuador			no wave detected
Egypt			missing data
Estonia	09/16/20 - 04/16/21		
Finland	09/30/20 - 04/16/21		
France	03/13/20 - 05/28/20	08/03/20 - 04/16/21	
Georgia			missing data
Germany			missing data
Ghana			no wave detected
Greece	06/30/20 - 07/28/20	10/12/20 - 04/16/21	
Hong Kong			missing data
Hungary	03/13/20 - 06/05/20	08/26/20 - 04/16/21	
Iceland	03/05/20 - 05/04/20		
India	03/12/20 - 12/30/20	02/25/21 - 04/16/21	
Indonesia	03/13/20 - 04/29/20	08/25/20 - 03/26/21	
Iran	05/05/20 - 06/25/20	10/14/20 - 04/16/21	
Ireland	04/02/20 - 06/11/20	09/24/20 - 04/16/21	
Israel	05/29/20 - 04/05/21		
Italy	02/24/20 - 06/09/20	09/18/20 - 04/16/21	
Jamaica	03/01/21 - 04/16/21		
Japan	03/20/20 - 05/11/20	11/05/20 - 04/16/21	
Jordan	09/07/20 - 01/15/21	02/22/21 - 04/16/21	
Kazakhstan	04/10/20 - 04/24/20	10/26/20 - 04/16/21	
Kenya	03/08/21 - 04/16/21		
Kosovo			missing data
Kuwait	04/16/20 - 12/02/20	01/27/21 - 04/16/21	
Latvia	03/13/20 - 05/29/20	10/08/20 - 04/16/21	
Lebanon			missing data
Lithuania	03/13/20 - 05/12/20	09/16/20 - 04/16/21	

Country	First wave	Second wave	Comments
Luxembourg	03/10/20 - 05/25/20	10/07/20 - 04/16/21	
Malaysia	12/30/20 - 04/16/21		
Malta	10/02/20 - 04/16/21		
Mauritius			missing data
Mexico	04/06/20 - 03/26/21		
Mongolia	11/09/20 - 12/01/20	01/27/21 - 04/16/21	
Morocco	03/13/20 - 05/22/20	10/06/20 - 04/16/21	
Netherlands			missing data
New Zealand	03/16/20 - 05/01/20		
Nigeria	12/03/20 - 03/12/21		
Norway	03/03/20 - 06/10/20	10/19/20 - 04/16/21	
Oman			missing data
Pakistan	03/09/20 - 08/27/20	11/02/20 - 04/16/21	
Panama	11/19/20 - 03/09/21		
Peru	07/13/20 - 10/22/20		
Philippines	02/22/21 - 04/16/21		
Poland	03/10/20 - 05/18/20	07/21/20 - 04/16/21	
Portugal	03/19/20 - 05/04/20	08/26/20 - 03/17/21	
Qatar	04/15/20 - 10/13/20	01/15/21 - 04/16/21	
Romania	03/05/20 - 05/11/20	07/03/20 - 04/16/21	
Russia	03/12/20 - 08/07/20	09/28/20 - 04/16/21	
Saudi Arabia	04/09/20 - 11/20/20	02/01/21 - 04/16/21	
Serbia	03/27/20 - 08/31/20	10/05/20 - 04/16/21	
Singapore	03/13/20 - 10/05/20		
Slovakia	09/23/20 - 04/16/21		
Slovenia	08/11/20 - 04/16/21		
South Africa	05/07/20 - 04/16/21		
South Korea	02/20/20 - 04/17/20	08/07/20 - 04/16/21	
Spain	02/26/20 - 04/29/20	07/09/20 - 04/16/21	
Sri Lanka	11/24/20 - 04/16/21		
Sweden	03/20/20 - 08/27/20	09/18/20 - 04/16/21	
Switzerland	08/10/20 - 04/16/21		
Taiwan			no wave detected
Tanzania			missing data
Thailand	03/10/20 - 05/14/20	04/05/21 - 04/16/21	
Tunisia			missing data
Turkey	03/17/20 - 08/21/20	11/06/20 - 04/16/21	
Uganda	08/07/20 - 04/16/21		
Ukraine	03/19/20 - 05/13/20	07/23/20 - 04/16/21	
United Arab Emirates	03/27/20 - 04/16/21		
United Kingdom	02/24/20 - 07/02/20	07/23/20 - 04/08/21	
United States of America	03/02/20 - 05/29/20	06/22/20 - 09/10/20	third wave detected 10/13/20 - 03/10/21
Venezuela			missing data
Vietnam			missing data
Zambia	12/17/20 - 04/16/21		
Zimbabwe	12/29/20 - 03/05/21		

Notes: Missing data signals that at least one of the three variables needed for the computation of the waves is not available or there are too few observations to compute meaningful results.

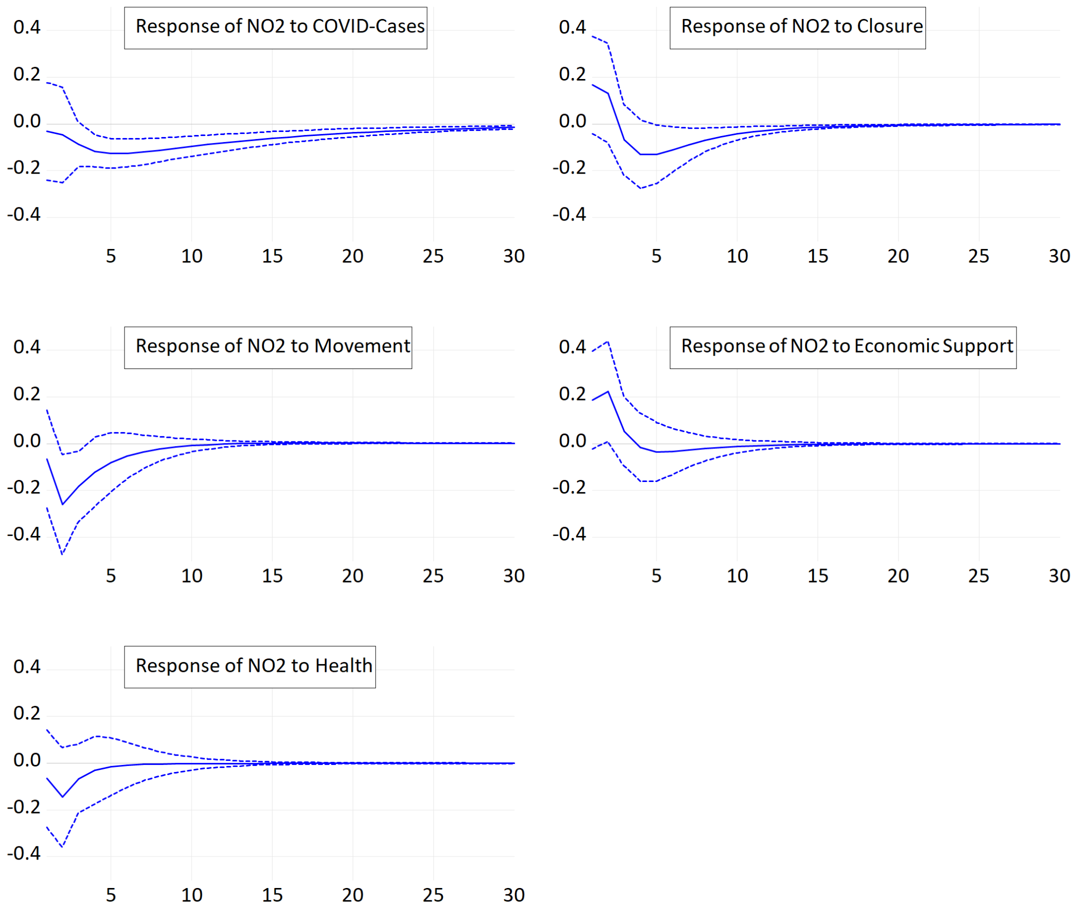
Figures

Figure 1: Stock-price reaction (full sample)



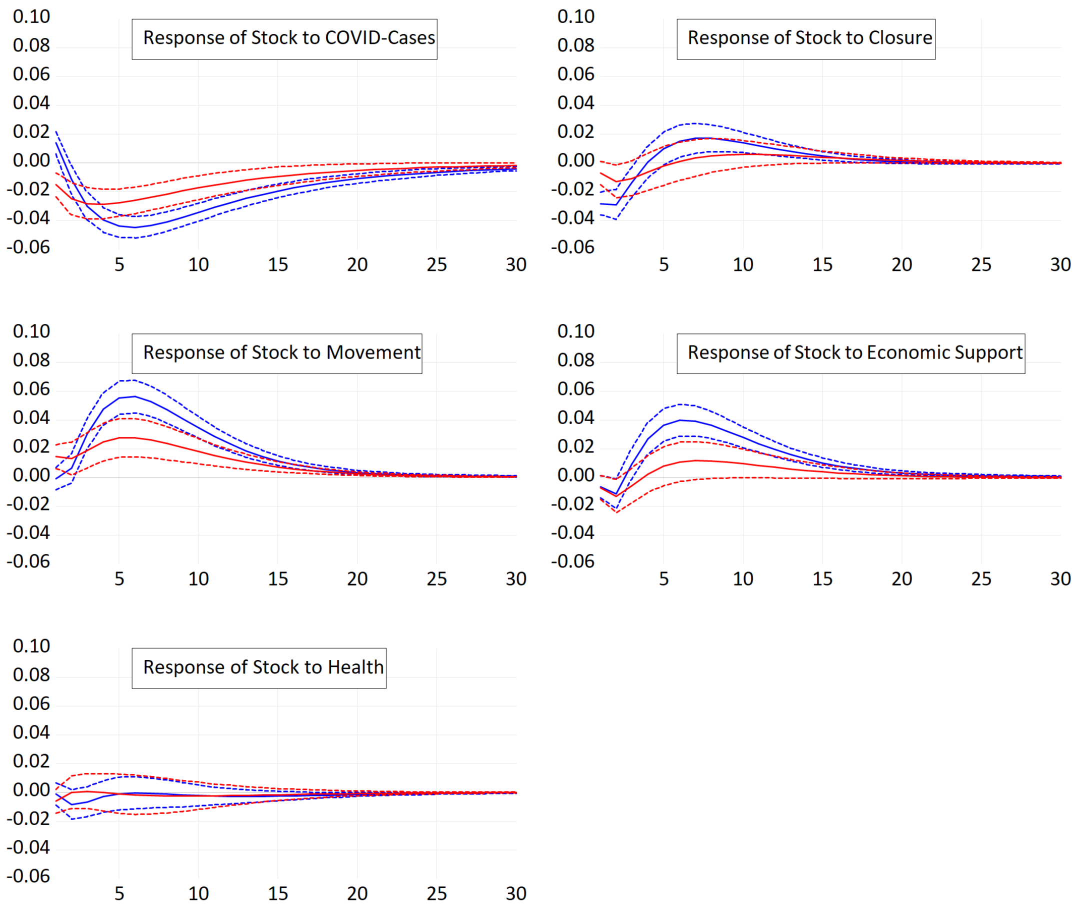
Notes: Impulse responses of stock prices to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval.

Figure 2: NO_2-emission reaction (full sample)



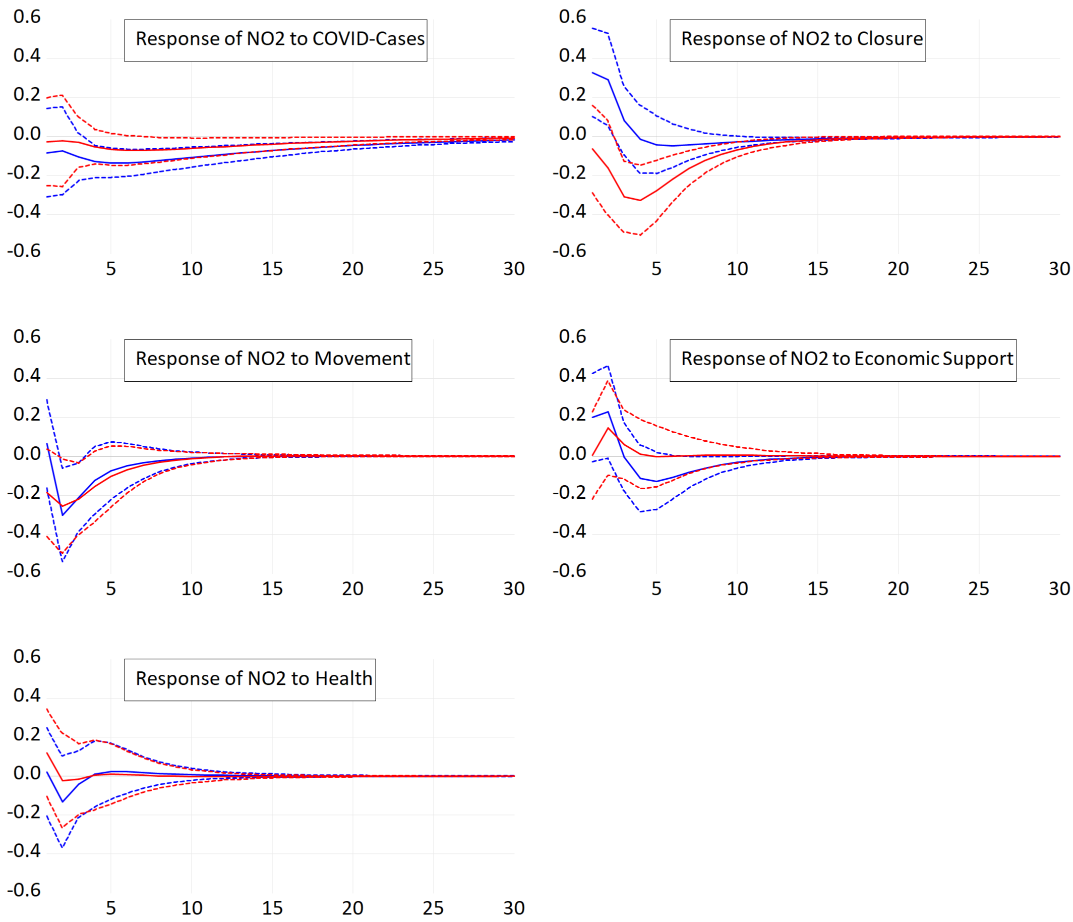
Notes: Impulse responses of NO_2 emissions to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval.

Figure 3: Stock-price reaction for differing development status



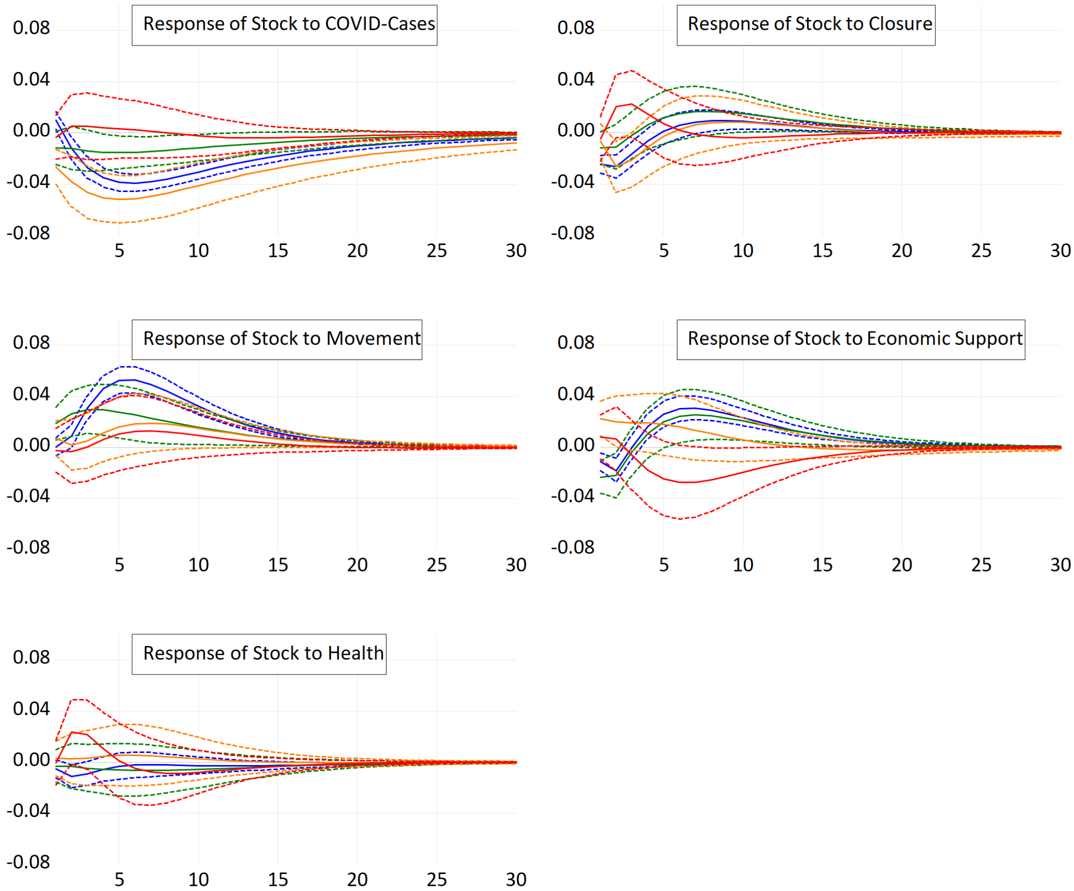
Notes: Impulse responses of stock prices to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for developed countries, while the red lines give the responses of developing countries. The classification of countries follows United Nations (2020).

Figure 4: NO_2-emission reaction for differing development status



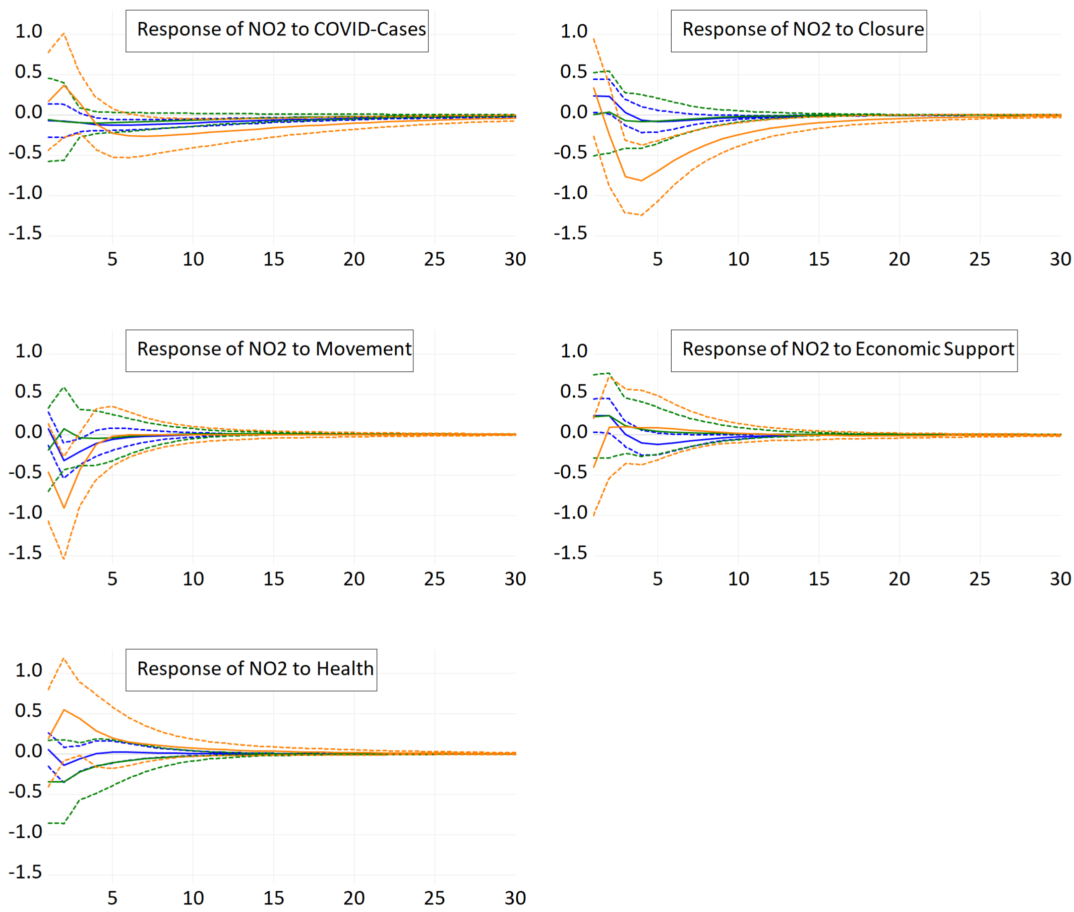
Notes: Impulse responses of NO_2 emissions to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for developed countries, while the red lines give the responses of developing countries. The classification of countries follows United Nations (2020).

Figure 5: Stock-price reaction for different income levels



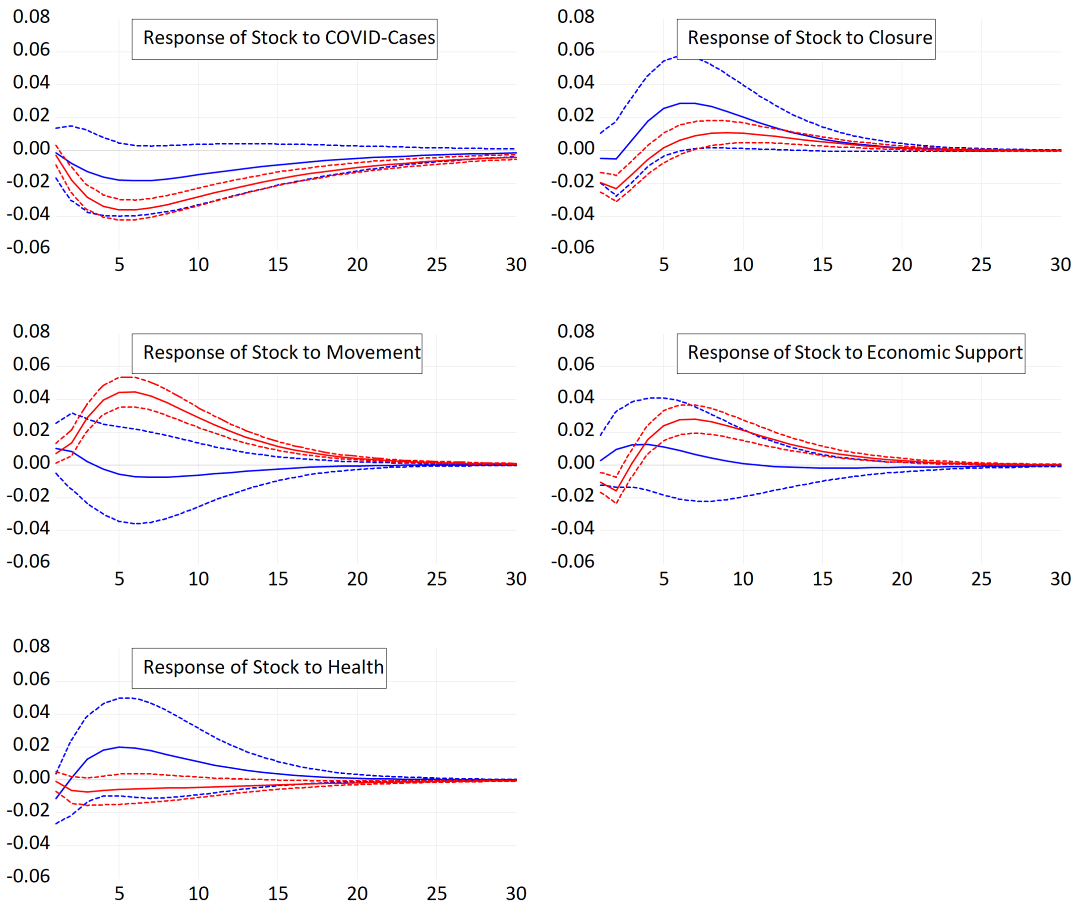
Notes: Impulse responses of stock prices to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for high-income countries, the green lines for upper middle income countries, the orange lines for lower-middle income countries and the red lines give the responses of low-income countries. The classification of countries follows the World Bank classification https://datahelpdesk.worldbank.org/knowledgebase/articles/906519.

Figure 6: NO_2-emission reaction for different income levels



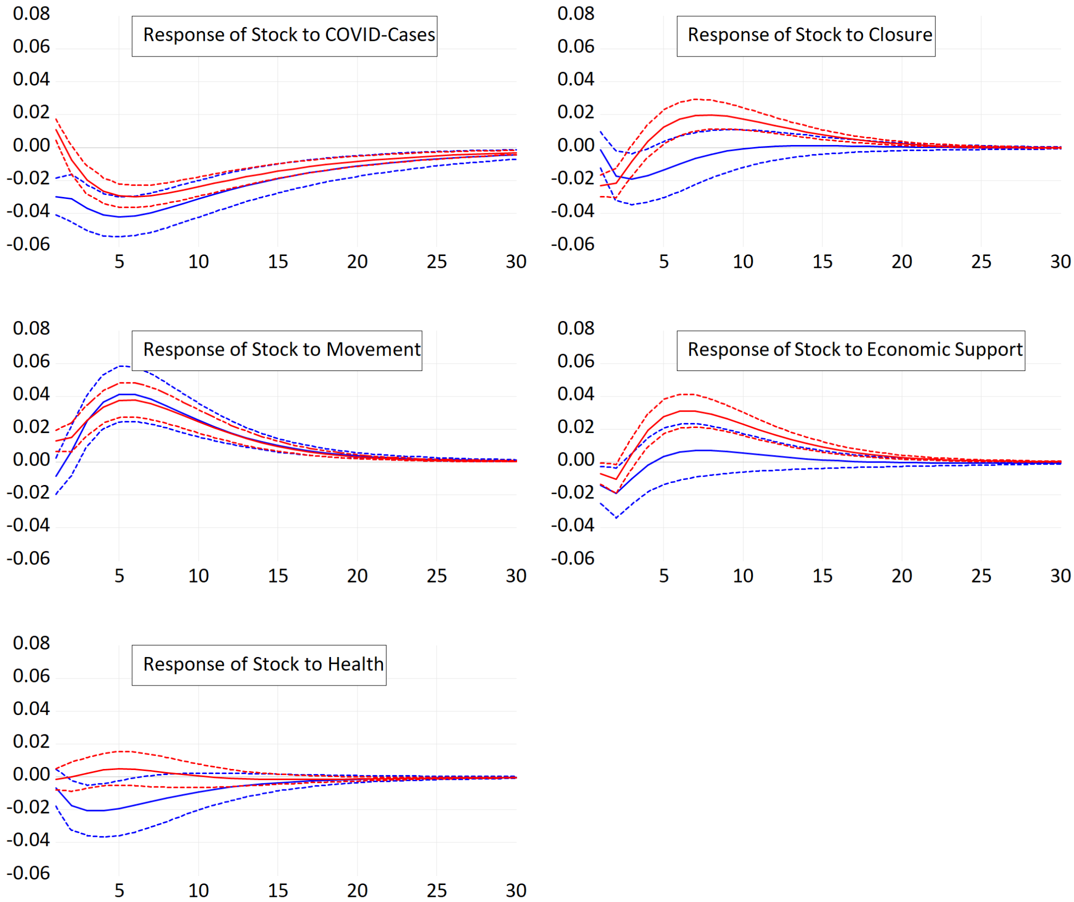
Notes: Impulse responses of NO_2 emissions to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for high-income countries, the green lines for upper middle income countries and the orange lines for lower-middle income countries. The classification of countries follows the World Bank classification https://datahelpdesk.worldbank.org/knowledgebase/articles/906519.

Figure 7: Stock-price reaction Africa versus the rest of the world



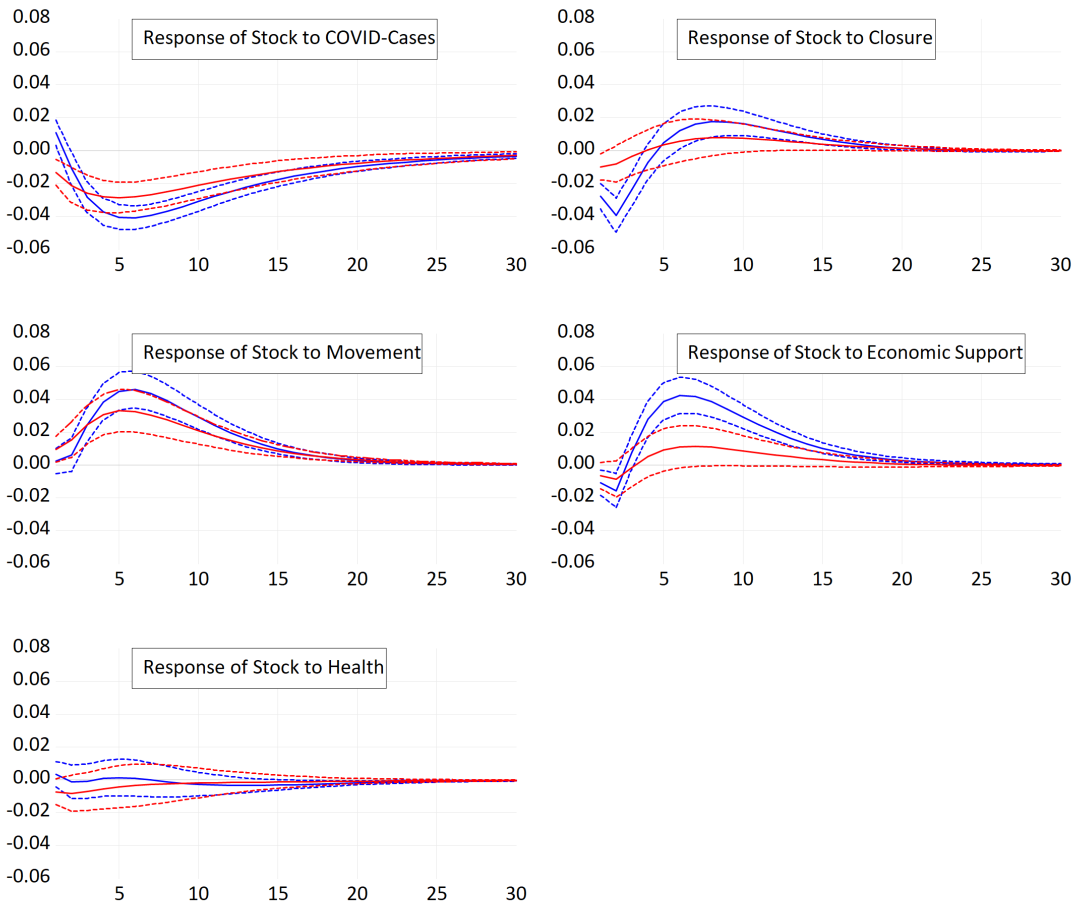
Notes: Impulse responses of stock prices to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for African countries, the red lines for the countries in the rest of the world.

Figure 8: Stock-price reaction Asia versus the rest of the world



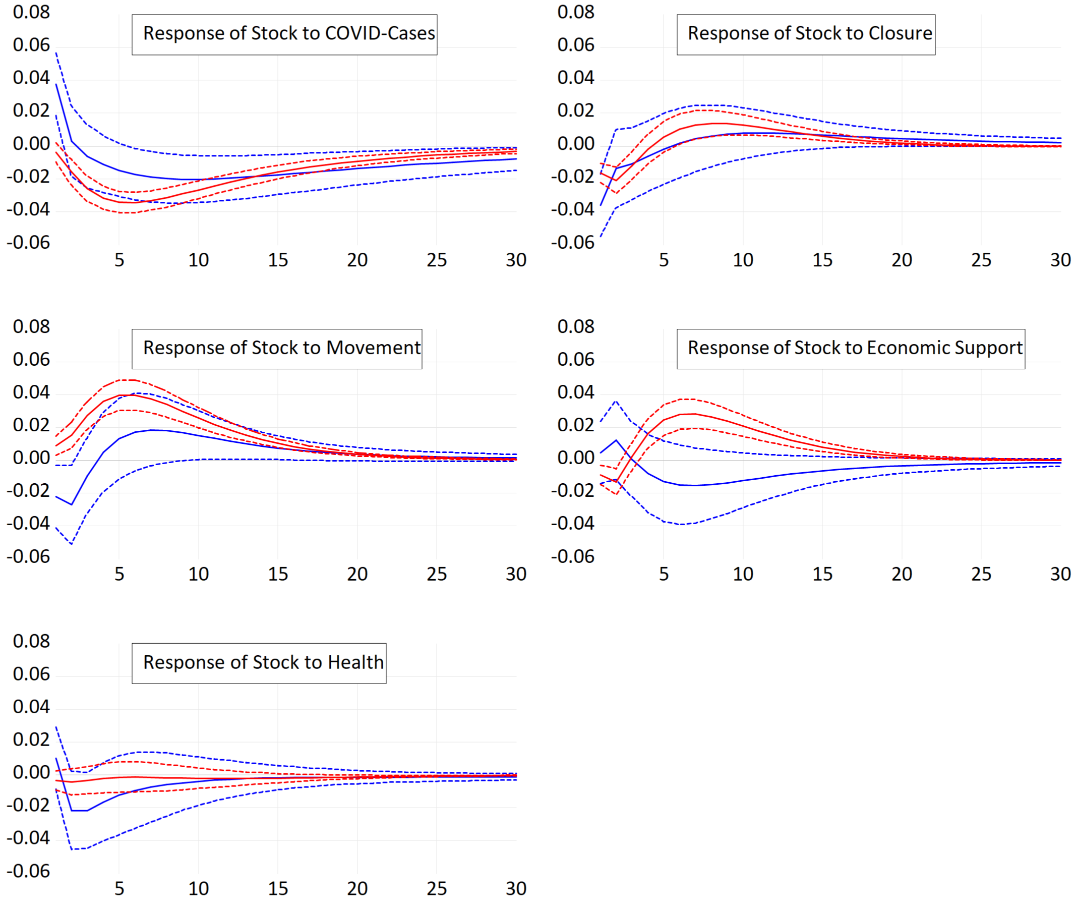
Notes: Impulse responses of stock prices to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for Asian countries, the red lines for the countries in the rest of the world.

Figure 9: Stock-price reaction Europe versus the rest of the world



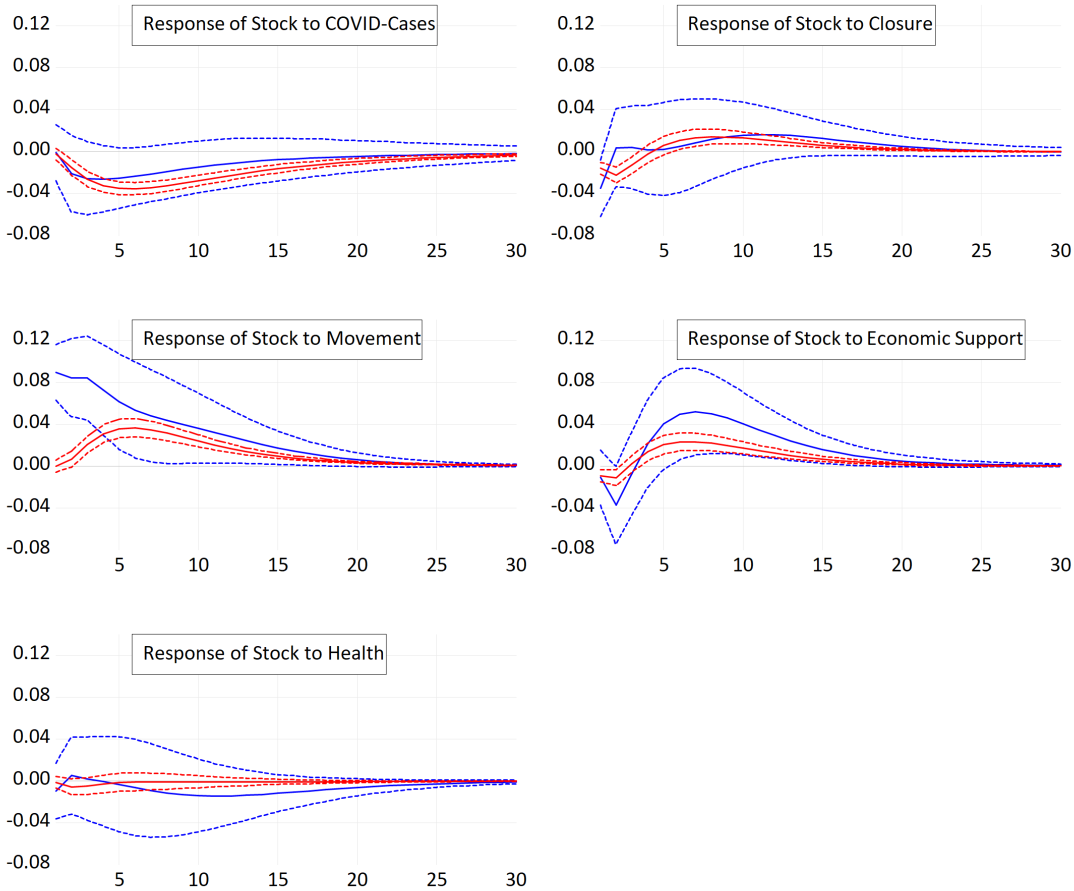
Notes: Impulse responses of stock prices to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for European countries, the red lines for the countries in the rest of the world.

Figure 10: Stock-price reaction North and Middle America versus the rest of the world



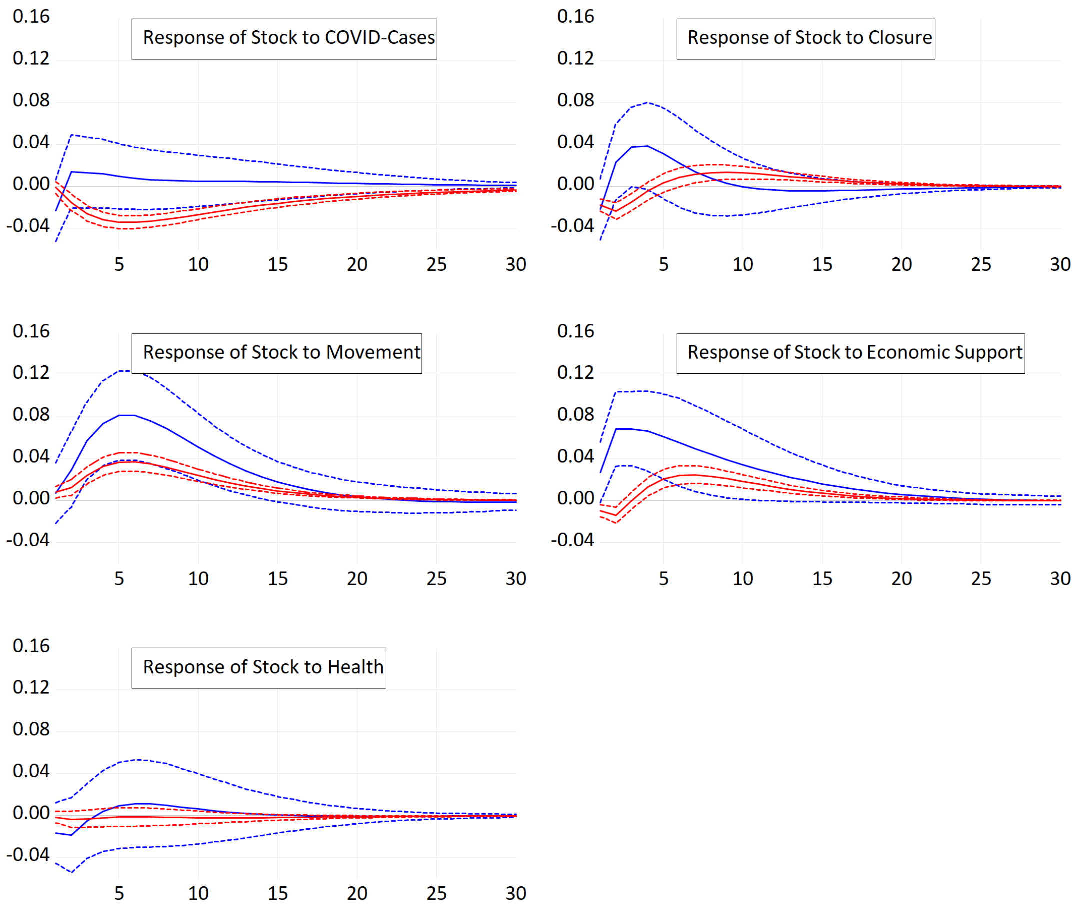
Notes: Impulse responses of stock prices to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for North and Middle American countries, the red lines for the countries in the rest of the world.

Figure 11: Stock-price reaction South America versus the rest of the world



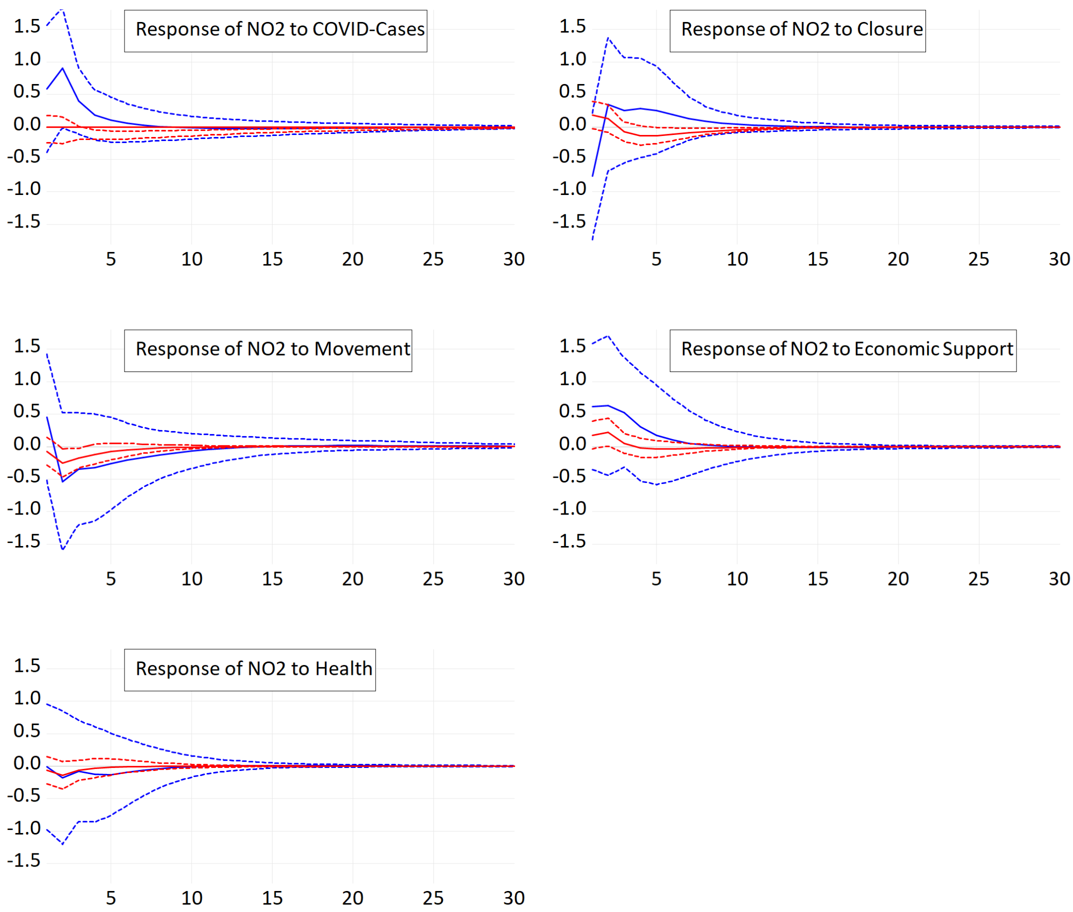
Notes: Impulse responses of stock prices to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for South American countries, the red lines for the countries in the rest of the world.

Figure 12: Stock-price reaction Australia versus the rest of the world



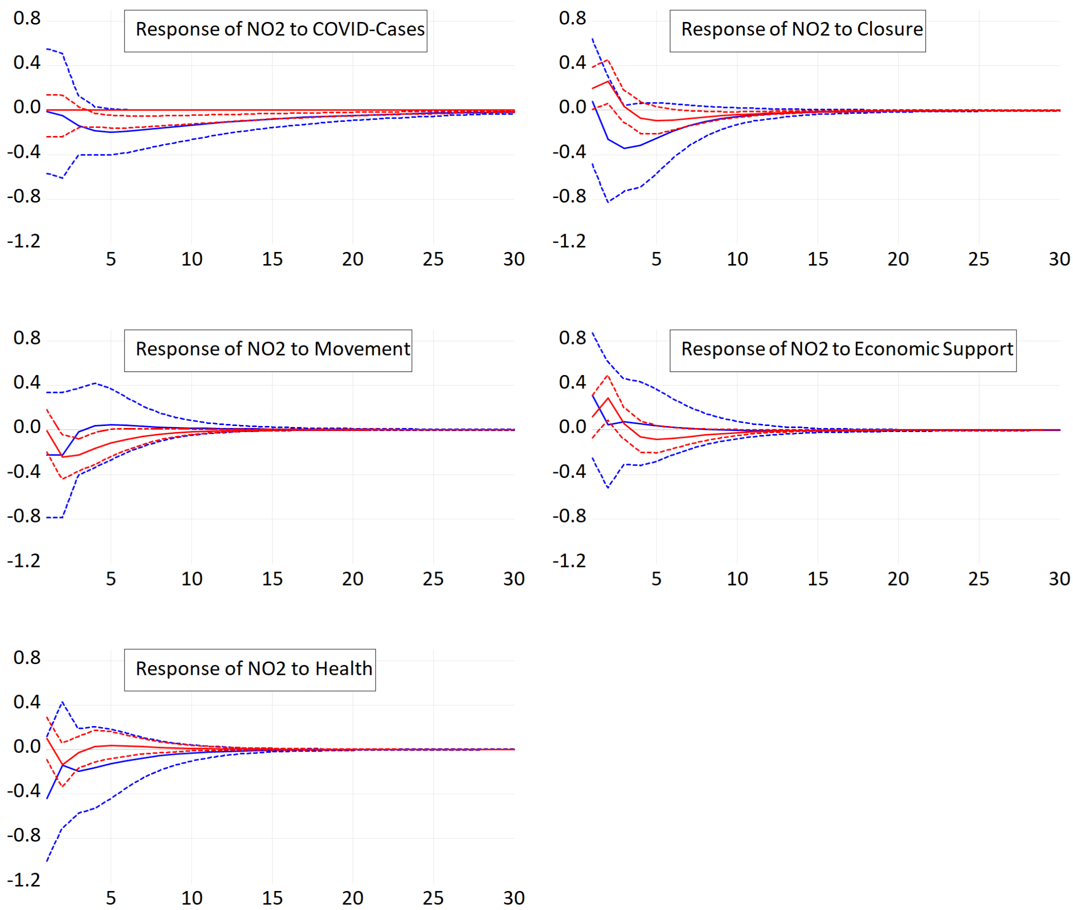
Notes: Impulse responses of stock prices to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for Australien countries, the red lines for the countries in the rest of the world.

Figure 13: NO_2-emission reaction Africa versus the rest of the world



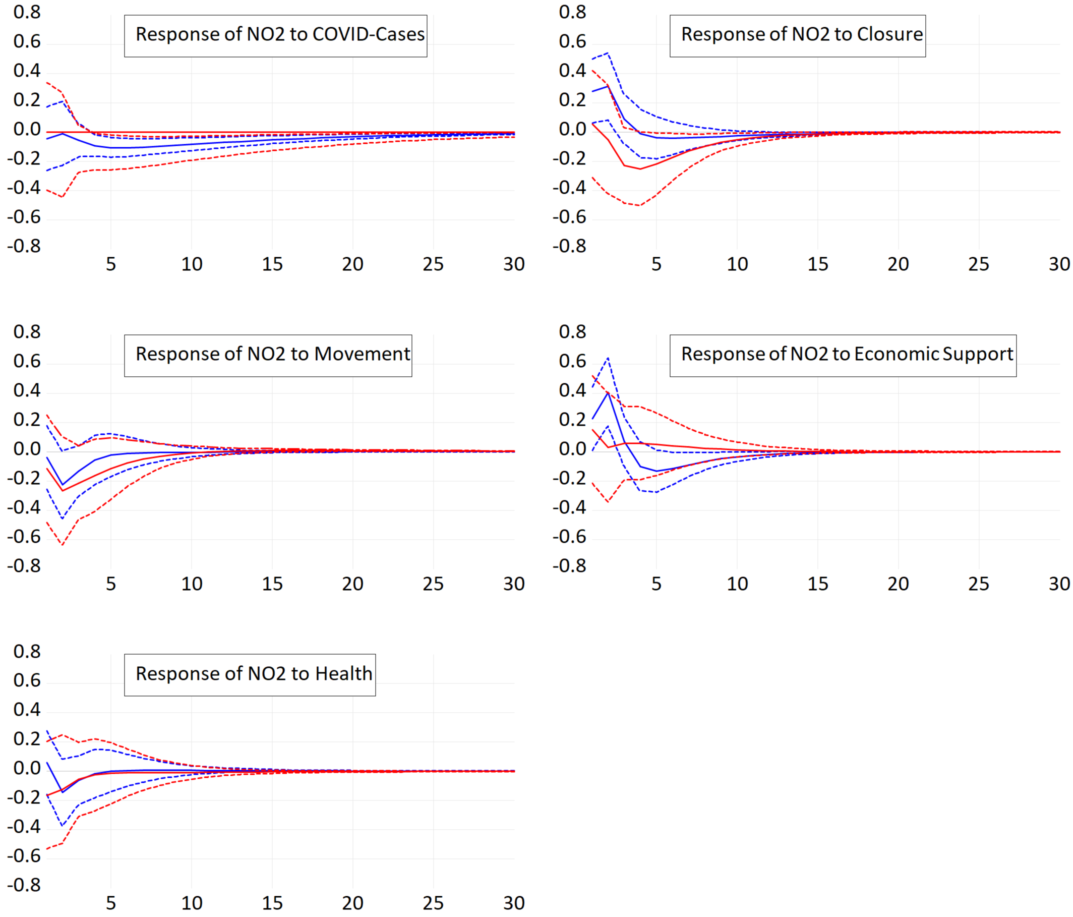
Notes: Impulse responses of NO_2-emission to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for African countries, the red lines for the countries in the rest of the world.

Figure 14: NO_2-emission reaction Asia versus the rest of the world



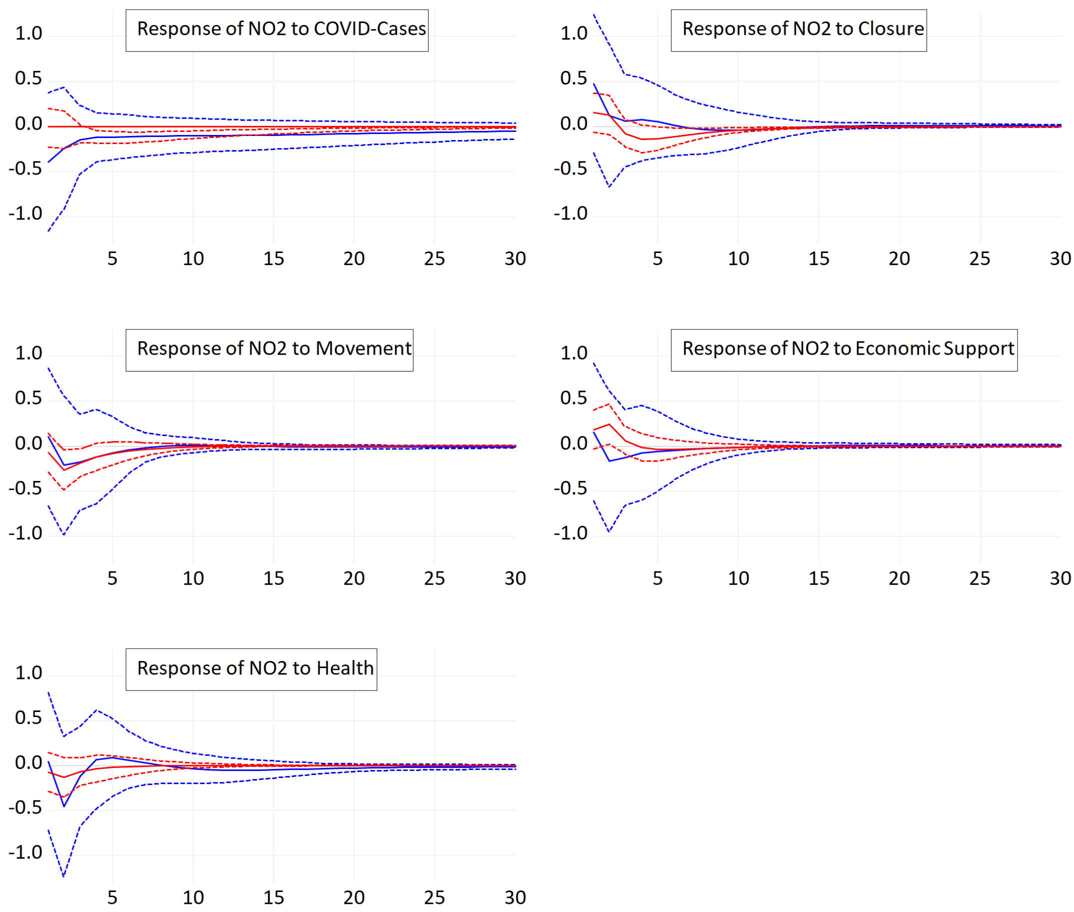
Notes: Impulse responses of NO_2-emission to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for Asian countries, the red lines for the countries in the rest of the world.

Figure 15: NO_2-emission reaction Europe versus the rest of the world



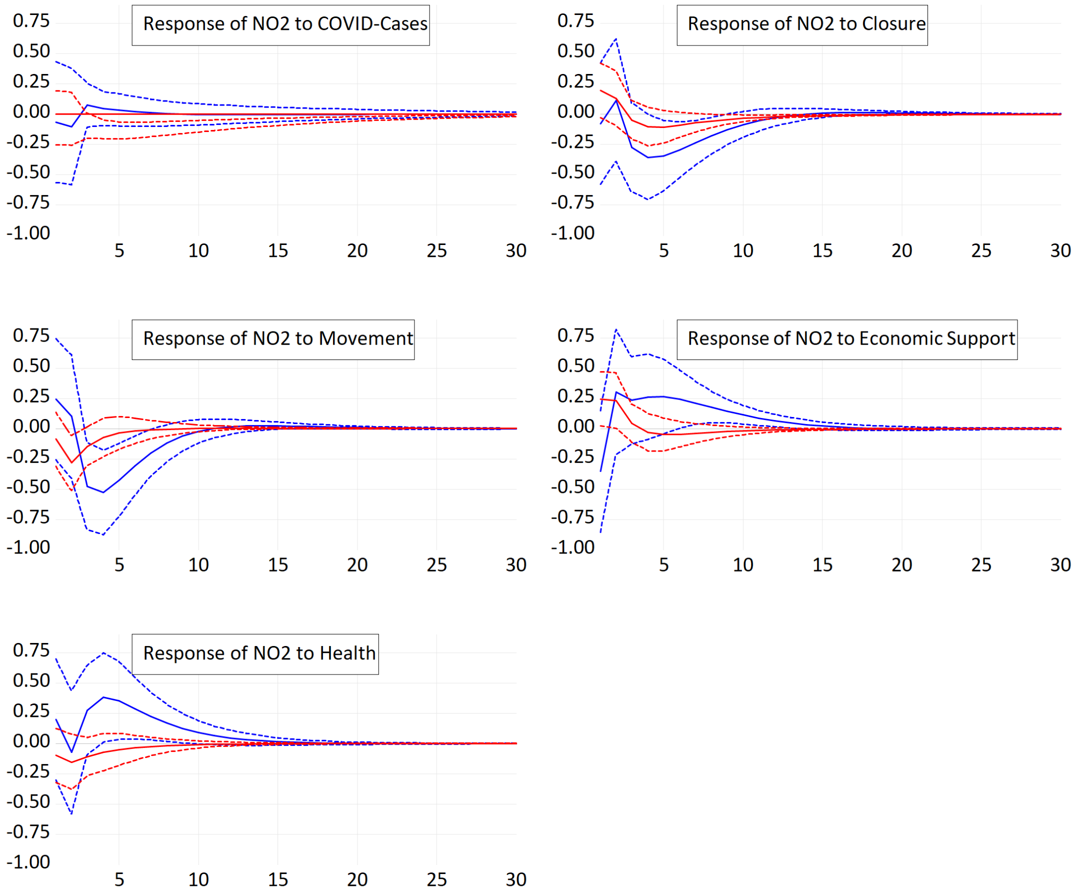
Notes: Impulse responses of NO_2-emission to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for European countries, the red lines for the countries in the rest of the world.

Figure 16: NO_2-emission reaction North and Middle America versus the rest of the world



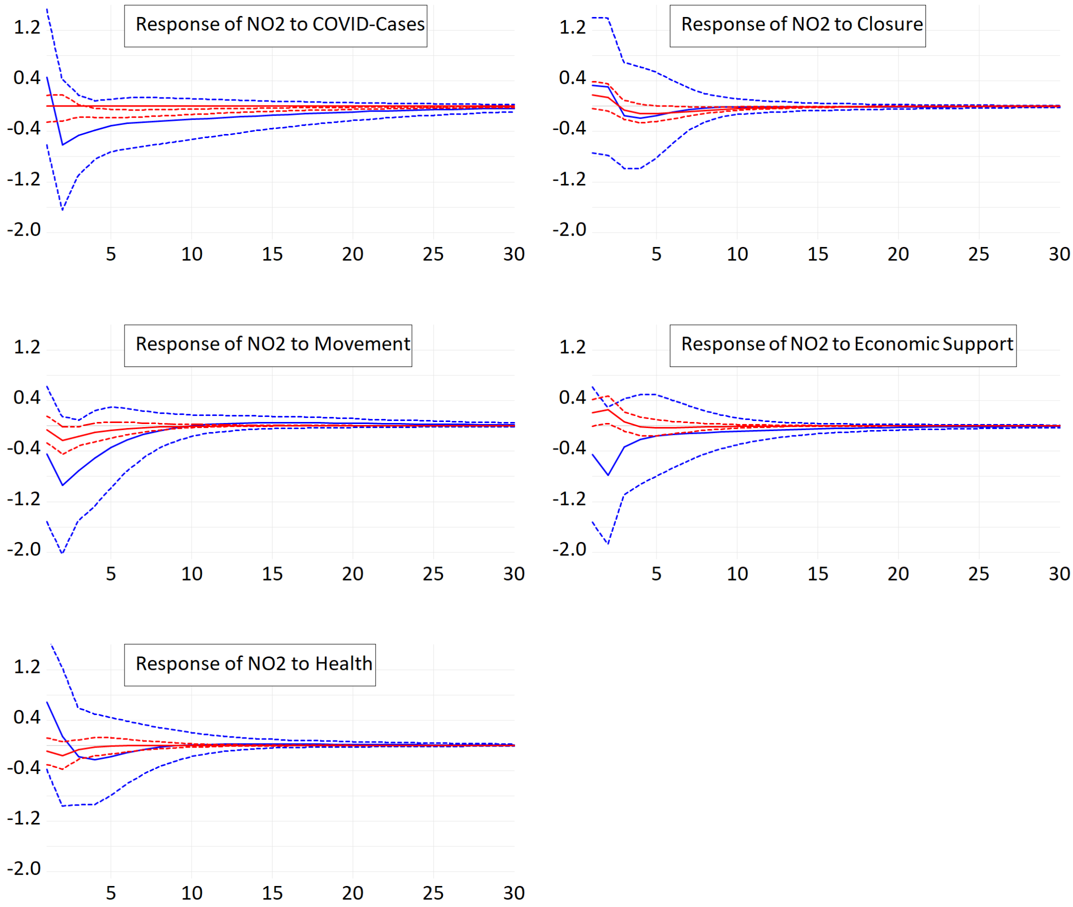
Notes: Impulse responses of NO_2-emission to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for North and Middle American countries, the red lines for the countries in the rest of the world.

Figure 17: NO_2-emission reaction South America versus the rest of the world



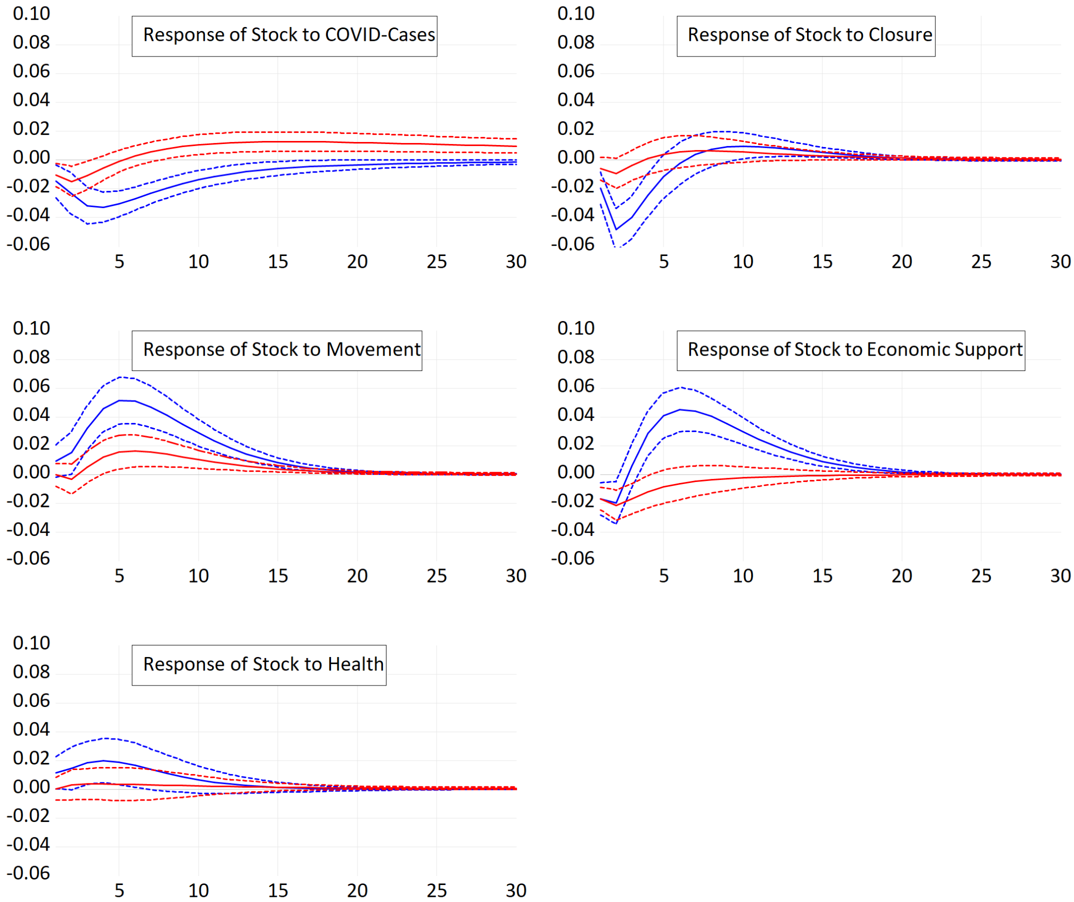
Notes: Impulse responses of NO_2-emission to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for South American countries, the red lines for the countries in the rest of the world.

Figure 18: NO_2-emission reaction Australia versus the rest of the world



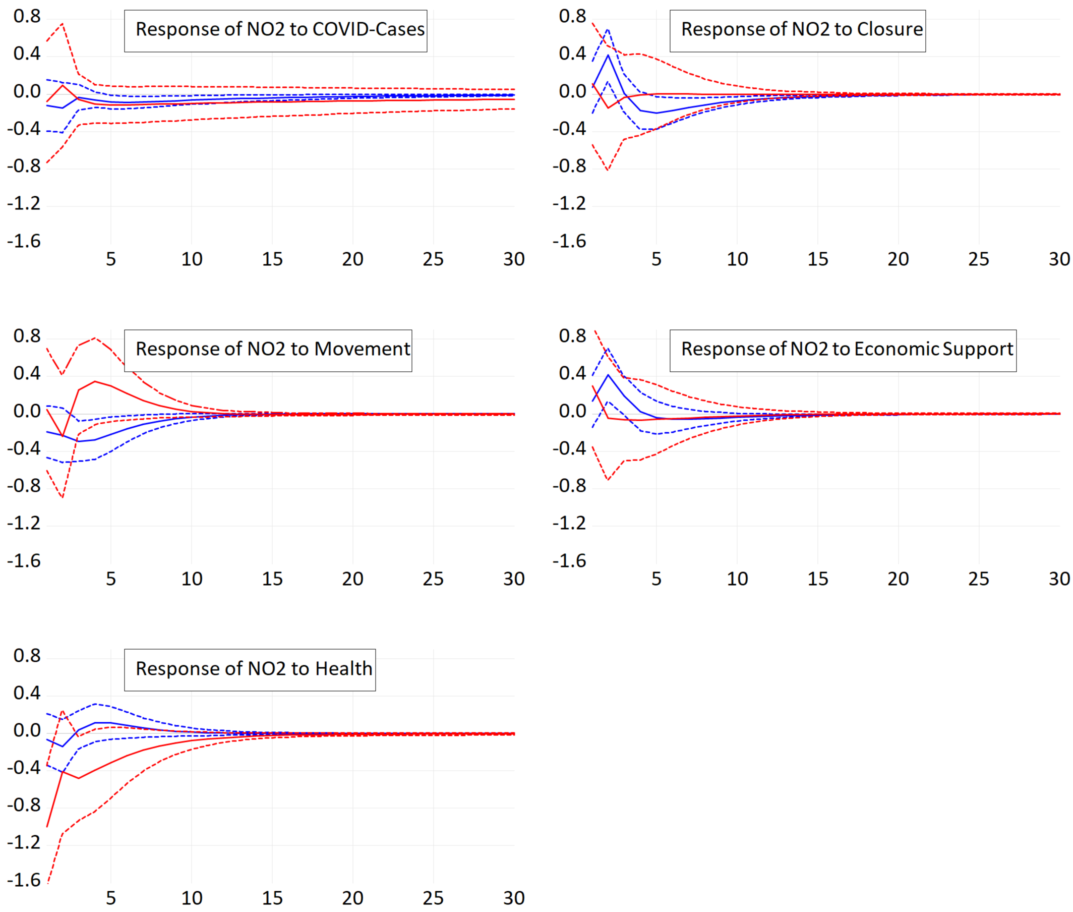
Notes: Impulse responses of NO_2-emission to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses for Australian countries, the red lines for the countries in the rest of the world.

Figure 19: Stock-price reaction for different COVID-waves



Notes: Impulse responses of stock prices to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The blue lines are the responses in the first COVID-wave while the red lines are those for the second COVID-wave.

Figure 20: NO_2-emission reaction for different COVID-waves



Notes: Impulse responses of NO_2-emission to a one standard deviation shock in COVID cases and the four indicators of government responses. The dashed lines indicate the 95% confidence interval. The dashed lines indicate the 95% confidence interval. The blue lines are the responses in the first COVID-wave while the red lines are those for the second COVID-wave.

References

[1] Adhikari, A., J. Sengupta and C. M. Hussain (2021): "Declining carbon emission/concentration during COVID-19: A critical review on temporary relief", *Carbon Trends* 5, 100131.

[2] Alexakis, C., K. Eleeftheriou, P. Patsoulis (2021): "COVID-19 containment measures and stock market returns: An international spatial econometrics investigation", *Journal of Behavioral and Experimental Finance* 29, 100428.

[3] Asna-ashary, M., M. R. Farzanegan, M. Feizi and S. M. Saddati (2020): "COVID-19 outbreak and air pollution in Iran: A panel VAR analysis", *MAGKS Discussion Paper* No. 16-2020, Marburg.

[4] Baker, S. R., N. Bloom and S. J. Davis (2016): "Measuring economic policy uncertainty", *The Quarterly Journal of Economics* 131(4), 1593-1636.

[5] Baker, S. R., N. Bloom, S. J. Davis and S. J. Terry (2020a): "COVID-induced economic uncertainty", *NBER Working Paper* 27771, Cambridge, MA.

[6] Baker, S. R., N. Bloom and S. J. Terry (2020b): "Using disasters to estimate the impact of uncertainty", *NBER Working Paper* 27167, Cambridge, MA.

[7] British Office for National Statistics (2021): "Coronavirus (COVID-19) infection survey technical article: waves and lags of COVID-19 in England, June 2021", Release Date: 29 June 2021.

[8] Brueckner, M. and J. Vespignani (2021): "COVID-19 infections and the performance of stock markets: An empirical analysis for Australia", *Economic Papers* 40(3), 173-193.

[9] Caggiano, G., E. Castelnuovo and R. Kima (2020): "The global effects of COVID-19-induced uncertainty", *Economics Letters* 194, 109392.

[10] Chatjuthamard, P., P. Jindahra, P. Sarajoti, S. Treepongkaruna (2021): "The effect of COVID-19 on the global stock market", *Accounting & Finance* 61, 4923-4953.

[11] Chen, S., D. Igan, N. Pierri, A. F. Presbitero (2020): "Tracking the economic impact of COVID-19 and mitigation policies in Europe and the United States", *IMF Working Paper* No. 20/125, International Monetary Fund.

[12] Davis, S. J., D. Liu and X. S. Sheng (2021): "Stock prices and economic activity in the time of coronavirus", forthcoming *IMF Economic Review.*

[13] Deb, P., D. Furceri, J. D. Ostry and N. Tawk (2020): "The economic effects of Covid-19 containment measures", *IMF Working Paper* No. 20/158, International Monetary Fund.

[14] Dong, X., L. Song and S. M. Yoon (2021): "How have the dependence structures between stock markets and economic factors changed during the COVID-19 pandemic?", *North American Journal of Economics and Finance* 58, 101546.

[15] Feyen, E., T. A. Gispert, T. Kliatskova, D. S. Mare (2021): "Financial sector policy response to COVID-19 in emerging markets and developing economies", *Journal of Banking and Finance* 133, 106184.

[16] Finck, D. and P. Tillmann (2021): "Pandemic shocks and household spending", forthcoming, *Oxford Bulletin of Economics and Statistics.*

[17] Furceri, D., S. Kothari and L. Zhang (2021): "The effects of Covid-19 containment measures on the Asia-Pacific region", forthcoming *Pacific Economic Review.*

[18] Gettelman, A., R. Lamboll, C. G. Bardeen, P.M. Forster and D. Watson-Parris (2021): "Climate impacts of COVID-19 induced emission changes", *Geophysical Research Letters* 48(3), e2020GL091805.

[19] Goldstein, P., E. Levy Yeyati and L. Sartorio (2021): "Lockdown fatigue: the diminishing effects of quarantines on the spread of Covid-19", *CID faculty working paper* 391, Cambridge, MA.

[20] Hale, T., J. Anania, N. Angrist, T. Boby, E. Cameron-Blake, M. Di Folco, L. Ellen, R. Goldszmidt, L. Hallas, B. Kira, M. Luciano, S. Majumdar, R. Nagesh, A. Petherick, T. Phillips, H. Tatlow, S. Webster, A. Wood and Y. Zhang (2021): "Variation in government responses to COVID-19", BSG Working Paper 2020/032, Version 12.0, Oxford.

[21] Heyden, K. J. and T. Heyden (2020): "Market reactions to the arrival and containment of COVID-19: An event study", *Finance Research Letters* 38, 101745.

[22] Jurado, K., S. C. Ludvigson and S. Ng (2015): "Measuring Uncertainty", *The American Economic Review* 95, 161-182.

[23] Kapar, B., S. Buigut and F. Rana (2021): “Global evidence on early effects of COVID-19 on stock markets”, forthcoming *Review of Financial Economics.*

[24] Klose, J. and P. Tillmann (2021): ”Covid-19 and financial markets: a panel analysis for European countries”, *Jahrbücher für Nationalökonomie und Statistik* 241, 297-347.

[25] Kumar, A., P. Singh, P. Raizada, C. M. Hussain (2022): “Impact of COVID-19 on greenhouse gases emissions: A critical review”, *Science of the Total Environment* 806, 150349.

[26] Lenza, M. and G. Primiceri (2020): ”How to estimate VAR after March 2020”, *NBER Working Paper* 27771, Cambridge, MA.

[27] Ludvigson, S. C., S. Ma and S. Ng (2019): ”Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?”, *American Economic Journal: Macroeconomics* 13(4), 369-410.

[28] Ludvigson, S. C., S. Ma and S. Ng (2020): ”COVID-19 and the macroeconomic effects of costly disasters”, *NBER Working Paper* 26987, Cambridge, MA.

[29] Milani, F. (2021): ”COVID-19 outbreak, social response, and early economic effects: a global VAR analysis of cross-country interdependencies”, *Journal of Population Economics* 34, 223–252.

[30] Mzoughi, H., C. Urom, G. S. Uddin and K. Guesmi (2020): ”The effects of COVID-19 pandemic on oil prices, CO_2 emissions and the stock market: Evidence from a VAR model”, *unpublished.*

[31] Ng, S. (2021): ”Modeling macroeconomic variations after COVID-19”, *NBER Working Paper* 29060, Cambridge, MA.

[32] Ray, R. L., V. P. Singh, S. K. Singh, B. S. Acharya and Y. He (2021): “What is the impact of COVID-19 pandemic on global carbon emissions?”, forthcoming *Science of the Total Environment.*

[33] Rehman, M. U., S. H. Kang, N. Ahmad and X. V. Vo (2021): “The impact of COVID-19 on the G7 stock markets: A time.frequency analysis”, *North American Journal of Economics and Finance* 58, 101526.

[34] Schulte-Fischedick, M., Y. Shan and K. Hubacek (2021): “Implications of COVID-19 lockdowns on surface passenger mobility and related CO_2 emission changes in Europe”, *Applied Energy* 300, 117396.

[35] Shafiullah, M., U. Khalid and S. M. Chaudhry (2021): "Do stock markets play a role in determining COVID-19 economic stimulus? A cross-country analysis", forthcoming *The World Economy*.

[36] United Nations (2020): "World economic situation and prospects", New York.

[37] Wang, Q and S. Wang (2020): "Is energy transition promoting the decoupling economic growth from emission growth? Evidence from the 186 countries", *Journal of Cleaner Production* 260, 120768.

[38] Yang, M., L. Chen, G. Msigwa, K. H. D. Tang and P. S. Yap (2021): "Implications of COVID-19 on global environmental pollution and carbon emissions with strategies for sustainability in the COVID-19 era", forthcoming *Science of the Total Environment*.

[39] Zhou, J. and M. Kumamoto (2020): "Stock market reactions to COVID-19 and containment policies: A panel VAR approach", *Economics Bulletin* 40(4), 3296-3305.