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Abstract: Lockdowns imposed to fight the Covid-19 pandemic have cross-border effects. In this paper, we estimate the empirical magnitude of lockdown spillovers in a set of panel local projections. We use daily indicators of economic activity such as stock returns, effective exchange rates, NO_2 emissions, mobility and maritime container trade. Lockdown shocks originating in the most important trading partners have a strong and significant adverse effect on economic activity in the home economy. For stock prices and exports, the spillovers can even be larger than the effect of domestic lockdown shocks. The results are robust with respect to alternative country weights used to construct foreign shocks, i.e. weights based on foreign direct investment or the connectedness through value chains. We find that lockdown spillovers have been particularly strong during the first wave of the pandemic. Countries with a higher export share are particularly exposed to lockdown spillovers.

Keywords: panel local projections, lockdown shocks, spillovers, Covid-19, pandemic

JEL classification: E32, F14, F20, F36, F42, F44

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1. Introduction

Throughout the world, governments shut down public life to contain the spread of the Covid-19 pandemic. Since February 2020, authorities have closed shops, factories and restaurants and imposed stay-at-home orders. While the availability of vaccines helped to contain the spread of the virus in 2021, lockdown remained a frequently used non-pharmaceutical intervention. As a result, the second quarter of 2020 saw an unprecedented drop in economic activity across most economies. The recession in 2020 was different from previous downturns because a large part of economic activity was deliberately wound down in order to fight the pandemic. The world economy partly recovered until mid-2021, though the long-term consequences of the pandemic for long-term growth remain uncertain.

While the drop in economic activity was in large parts due to lockdowns imposed domestically (and due to voluntary restraint of costumers and consumers), lockdowns also have cross-border effects. If authorities in the US, Australia or Japan restrict public life, the effects are felt in Korea because all three countries belong to the top ten export markets for Korean exporters. Hence, lockdowns affect economic activity in other countries. They spill over to other countries connected through trade and financial linkages. We refer to lockdown spillovers to characterize these cross-border effects. The purpose of this paper is to estimate the sign and the size of these spillovers.

We use the stringency index constructed by a team at the University of Oxford to measure the intensity of lockdowns for a large set of countries. Importantly, the duration and the intensity of lockdowns varied across countries. This cross-country variation helps to identify exogenous shifts in lockdowns. Since the imposition of lockdowns is forecastable based on the lockdown history and the number of new Covid-19 infections, we construct lockdown shocks, i.e. the non-forecastable component of the lockdown intensity for each economy. For a set of 13 sample countries, which comprises advanced small open economies as well as Asian emerging market economies, we not only use the domestic lockdown shock, but also construct a foreign lockdown shock, which is the weighted lockdown shock in the top ten trading partners of each country. To come back to the case of Korea mentioned before, the foreign lockdown shock for Korea consists of the weighted lockdown shock in the US, Australia, Japan as well as seven other economies. In the baseline model, the weights reflect the relative importance of the top ten export markets for each sample country.

In order to trace the impact of lockdowns after the outbreak of the coronavirus in early 2020, we cannot rely on standard macroeconomic time series on a monthly or even quarterly frequency. These low-frequency series do not reflect the spread of the pandemic within days or weeks. Instead, we estimate the impact of lockdown shocks on six dependent variables on a daily frequency: stock prices, the exchange rate, the level of NO_2 emissions, the extent of personal mobility and the levels of exports and imports. While the daily financial time series are easily available from standard sources, we use novel data from the Air Quality Index to measure emissions, data from the Google Mobility Reports to track mobility and data on maritime shipping from the Automatic Identification System of vessels to account for exports on a daily basis. Though undoubtedly noisy, these indicators are alternative measures of economic activity.

We then estimate a series of panel local projections, in which the domestic and the foreign lockdown shock drive each dependent variable. Our key findings are threefold: First, there are strong spillover effects from foreign lockdowns. If authorities tighten lockdown measures abroad, domestic stock returns fall, the domestic currency depreciates against the currencies of the main trading partners, NO_2 emissions fall, mobility is reduced and exports as well as imports shrink. These results remain broadly similar if we use alternative weights to construct foreign lockdown shocks. We use, for example, weights based on imports rather than exports, on the main sources of a country's stock of foreign direct investment (FDI) and weights that reflect the interconnection through global value chains in terms of the foreign value-added share in gross exports.

The size of lockdown spillovers differs across country groups. We split the sample into advanced small open economies and Asian emerging market economies, respectively. We find that the reduction in emissions and mobility is stronger in advanced small open economies than in Asian emerging market economies. Lockdown shocks originating in the US have a stronger effect on advanced economies, while Asian emerging markets are particularly exposed to Chinese lockdown shocks.

Second, lockdowns imposed abroad can have an even larger consequence for domestic real economic activity than domestic lockdowns. For our full panel, we find the fall in exports and stock prices to be significantly larger following a lockdown shock abroad compared to a shock at home. One explanation for this finding is the differential impact across sectors: the foreign lockdown shock hits the domestic export industry, while the domestic shock hits all industries. If the export industry is more emission-intensive and less able to let employees work from home compared to other sectors, the response should be stronger. Hence, a country that itself is reluctant to wind down economic activity might nevertheless suffer from the consequences of foreign lockdowns.

A third finding sheds light on the effectiveness of shocks over time. We show that lockdown spillovers were particularly strong in the first months of the pandemic until the summer of 2020 and much weaker thereafter. Moreover, countries with a larger export share are particularly exposed to lockdown spillovers.

The results have implications for policy. At the height of the first wave of the pandemic, there was very little room for an international coordination of lockdown policies. The need to contain the virus made quick decisions necessary, often within days or over the weekend. Hence, coordination of lockdowns might not be feasible. This stands in contrast to monetary and fiscal policy spillovers, which provide a rationale for policy coordination. Instead, a diversification of export markets and a reduction in the complexity of global value chains is conducive to limit the exposure to lockdowns in specific countries. Attempts to re-shore production capacities, in contrast, remain counterproductive.

There are two main limitations of this study. First, we study the effects of imposed lockdowns only. We cannot shed light on the empirical role of voluntary consumption restraint by households, a finding that contributes a lot to the observed decline in economic activity (see Goolsbee and Syverson, 2021). Second, we study the response of variables such as stock returns, exports and emissions. The empirical framework we adopt does not allow us to distinguish the relative effects of lockdowns on supply and demand.

This paper is related to several recent contributions to the literature. Hardly any of these papers, however, studies the empirical nature of spillovers of lockdowns.[1] The paper closest to ours is Deb et al. (2020). These authors also estimate panel local projections to quantify the effect of lockdowns on economic activity. Like our paper, they use data on emissions, mobility, exports and imports to measure economic activity on a high frequency. Furceri et al. (2021) use a local projection model for 11 economies in Asia-pacific to estimate the response of Covid-infections to various containment measures. As in Deb et al. (2020), however, the driving variable is the stringency index itself, not an identified surprise component. The difference with respect to our paper is twofold. First, we use

[1] Finck and Tillmann (2021) construct a pandemic shock, i.e. the unexpected number of casualties from the coronavirus, and estimate its impact on high-frequency consumer spending across income levels. Klose and Tillmann (2021 a,b) estimate the financial and real economic effects of the pandemic in Europe and for a large group of advanced and developing countries, respectively.

lockdown shocks rather than the stringency index itself. Deb et al. (2020) use the plain index. However, the index is partly forecastable. Thus, the index reflects the endogenous response of policy to other variables, not the unexpected changes of the index. Although the authors include contemporaneous control variables such as the number of infections, their impulse responses could be biased. In contrast to that, we construct series of unexpected variation in the stringency index. Second, we study the cross-border effects of lockdown shocks, not just their domestic impact.[2]

Verschuur et al. (2021) promote the high frequency AIS data obtained from vessel tracking to estimate the loss in global maritime trade due to lockdowns. However, they do not identify lockdown shocks, nor do they study the spillover effects of lockdowns. The authors show a drop in trade between seven and ten percent in the first eight months of 2020.[3] Other papers use more conventional trade data to evaluate the impact of lockdowns. Naturally, these papers have to resort to monthly or quarterly frequency. Berthou and Stumpner (2021) use detailed product and partner data for a large number of countries until November 2020. They provide evidence for a strong effect of lockdowns on trade. The impact found in the paper, however, is very heterogeneous across sectors. Espitia et al. (2021) estimate sector-specific gravity equations using disaggregated trade data for 28 countries up to June 2020. Their key finding is that the participation in global value chains magnifies the vulnerability to lockdowns imposed by trading partners. Hayakawa and Mukunoki (2020) distinguish between the effect of stay-at-home orders and workplace closures in trade using data until June 2020. While the former has no impact on trade, the latter does indeed lead to a reduction in foreign trade. The specific role of China is the focus of Liu et al. (2021). These authors ask how lockdowns imposed in China affect trade with China. They find a negative effect of lockdowns.

Guan et al. (2020) use a computational general equilibrium model to show that the losses in activity depend on the number of other countries in lockdown. In a multi-sector model with sector-specific labor supply shocks, Bonadio et al. (2021) show that one quarter of the pandemic-related loss in real GDP is due to the shock propagation through global value chains.

[2] Elenev et al. (2021) study spillovers effects of stay-at-home orders across US counties.

[3] Cerdeiro and Komaromi (2020) use high-frequency data of bilateral trade linkages in a “shift-share” research design taken adapted from regional economics. They find short-lived spillovers transmitted by trade relations.

Freund et al. (2021) draw conclusions for the post-Covid-19 future of global value chains from the 2011 earthquake off the coast of Japan. They find that countries shifted from imports from Japan to other advanced economies as well as developing countries. According to the authors, a similar pattern of shifting suppliers might be a consequence of the disruptions due to lockdowns.[4] Carvalho et al. (2021) also study disruptions following the 2011 Japanese earthquake. They show how the shock propagated through global supply chains.

Another strand of the literature calibrates SIR (Susceptible-Infected-Recovered) models. Engler et al. (2020) present a two-country SIR model with asynchronous lockdowns. The resulting exchange rate adjustment contributes to a reallocation of production towards the country, which is less hit by the pandemic. Cakmakli et al. (2021) calibrate a multi-sector SIR model of a small open economy to disaggregated data from Turkey. Their focus is on the optimal design of lockdowns. The optimal policy, i.e. the lower loss of lives and lowest level of economic costs, can be achieved with an early and globally coordinated lockdown of 39 days.

A lockdown does not only affect trade patterns, but also the flow of capital across borders. Goldbach and Nitsch (2021) use highly disaggregated data from the German balance of payments to trace the impact of lockdowns and other policy responses to the pandemic. The paper shows that stricter lockdown policies trigger a drop in German capital flows. As a result, the bilateral degree of financial integration falls. Ahmed at al. (2020) estimate a panel model for financial conditions in emerging markets. A tighter lockdown as reflected in a higher level of the stringency index triggers a depreciation of the national currency, an increase in CDS spreads and a drop in equity valuations after controlling for global financial conditions and idiosyncratic macroeconomic vulnerabilities.

Born et al. (2021) study the effect of the Swedish lockdown policy. In contrast to most other countries, the Swedish authorities did not impose a lockdown during the first wave of the pandemic. Using synthetic control methods, the authors show that a lockdown would have strongly reduced the number of infections and the number of deaths. Since there had been a substantial voluntary restraint of households, the additional output loss of a lockdown would have been small.

[4] For conceptual issues, theories and measurement related to global value chains see Antràs and Chor (2021).

2. Data

We estimate panel local projections for a full set of 13 countries as well as two subsets of countries. Group I covers advanced small-open economies, while group II includes Asian emerging market economies. Due to data availability, we do not consider a larger panel of countries. The sample countries should be representative for typical small open economies with close interconnections to the rest of the world. All countries are listed in Table (1). The case of Sweden is particularly interesting. Sweden did impose a much weaker lockdown compared to other European countries. A lesson from this paper is that a country is exposed to lockdown spillovers even if the domestic restrictions are relatively lax.

Table 1: Sample countries

country	group I	group II	country	group I	group II
Australia	X		Malaysia		X
Canada	X		New Zealand	X	
Germany	X		Singapore		X
Hong Kong SAR		X	Sweden	X	
Indonesia		X	Thailand		X
Japan	X		UK	X	
Korea		X			

2.1 Construction of shocks

We estimate a series of panel local projections. In each regression model, two exogenous shocks, a domestic and a foreign lockdown shock, drive the dependent variable. A lockdown shock is an unexpected change in the stringency of lockdowns. The notion of lockdown shocks defies the classification into either supply or demand disturbances. An expected tightening of restrictions affects the supply side and the demand side jointly. On the supply side, a regional or national lockdown implies that firms have to cut back production, as workers have to remain at home and some shops are forced to close. Because of tight supply chains, these disruptions propagate to other areas of the economy. On the demand side, a lockdown bars consumers from spending. Hence, an exogenous tightening of a lockdown has effects on the supply and the demand side. In this framework, we cannot differentiate between supply and demand.

Before we explain the estimated model, we now introduce the construction of these exogenous shocks. For each of the sample countries i, with $i = 1, \dots, 13$ and for more than 50 other trading partners, we utilize the stringency index calculated by a team from the University of Oxford, which is part of the Oxford Covid-19 Government Response Tracker (OxCGRT, see Hale et al., 2021).[5] This index measures the strictness of lockdown policies across different fields of public life. It is constructed from a set of ordinal sub-indicators, which measure containment and closure policies. Importantly, the index is available on a daily frequency and ranges between 0 and 100.

The stringency index reflects the aim of containing the spread of the pandemic. Hence, an increase in the number of new infections should prompt authorities to tighten the lockdown restrictions. Consequently, we cannot use the stringency index as an exogenous driving variable in the estimated local projections. We need to purge the index first from its predictable component.

We work with daily data and exclude weekends from our data set. In order to purge the stringency index from its predictable part, we regress the stringency index of each country on five lags, i.e. the realizations of one week, of itself, a linear time trend and the five-day moving average of the number of new COVID-19 infections. The residual of this regression is the component of the stringency index that cannot be explained by its own lags or the spread of the virus. The domestic lockdown shock, $\varepsilon_{i,t}^{dom}$, is the standardized residual of this regression for country i at day t.

The idea behind such a regression is that authorities tighten or lift lockdowns as a systematic response to the spread of the pandemic. As a matter of fact, authorities could respond to additional variables such as medical capacities or hospitalization rates. Below, we explore the results from a specification that also includes data on mobility. Unfortunately, however, data on medial capacities and hospitalization rates is not available for the large set of trading partners of our 13 sample countries. An additional caveat pertains to potential structural breaks of the implicit policy rule. The response of policy to the number of infections should change as testing capacity increases and authorities gather information about the nature of the pandemic. We check the properties of each shock series using the Ljung-Box Q-statistic for the null hypothesis of zero autocorrelation up to five lags. In most but not all cases, we cannot reject the null hypothesis.

Figure (1) shows the series of the stringency index for three countries, Australia, Hong Kong SAR and Korea, which move stepwise over the sample period. We can clearly see

[5] This index is available at https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker

how the timing and the intensity of lockdown differ across countries. Figure (2) depicts the domestic and foreign lockdown shocks, i.e. the residual of a regression of the stringency index on its lags, a trend and the number of new infections, and foreign lockdown shocks for all countries. It is important to stress that the lockdown shock as identified in this paper reflects a tightening of constraints on private behavior as imposed by the authorities. It does not reflect the voluntary restraint of economic agents in light of the danger of being infected. Goolsbee and Syverson (2021) emphasize that the latter is a powerful determinant of consumer behavior at the early stage of the pandemic.

For each sample country *i*, the foreign lockdown shock, $\varepsilon_{i,t}^{for}$, is the weighted lockdown shock in country *i*'s ten largest trading partners, i.e.

$$\varepsilon_{i,t}^{for} = \sum_{j(i)=1}^{10} \omega_{j(i)} \varepsilon_{j(i),t}^{dom} \,, \tag{1}$$

where $\varepsilon_{j(i),t}^{dom}$ is the domestic lockdown shock in trading partner *j* of country *i*. In our baseline model, the weights $\omega_{j(i)}$ are chosen based on the top ten export destinations calculated from the Direction of Trade Statistics (DOTS) database for the year 2018. Naturally, the weights add up to one, i.e.

$$\sum_{j(i)=1}^{10} \omega_{j(i)} = 1 \ . \tag{2}$$

For all sample countries, the list of the ten largest export markets covers all trade destinations, which are quantitatively relevant. Typically, the 10th largest export market reflects about 1% or 2% of the overall volume of exports. Hence, ignoring all other trading partners other than the top ten should not affect our results. Below, we introduce alternative country weights based on the volume of imports, the flow of foreign direct investment and the interconnectedness of country *i* through global supply chains.

Figure (3) reports the contemporaneous correlations of the domestic and foreign lockdown shocks for each sample country as a heatmap. We see that the domestic lockdown shocks are essentially uncorrelated across countries. This reflects the staggered timing across countries in which lockdowns were introduced and lifted. The foreign shocks, in contrast, are positively correlated, in particular for Asian economies. The reason is that most of the Asian economies share their most important export markets such as China and the US. Hence, lockdown shocks in China and the US feed into the foreign shocks of many sample countries. In a separate section below, we will also estimate the effect of shocks originating in the US and China directly.

2.2 Dependent variables

We estimate the impact of domestic and foreign lockdown shocks on six dependent variables. All these variables are available on a daily frequency. This contrast with standard macroeconomic aggregates such as GDP, consumption of unemployment, which are available on a much lower frequency only. We interpret these alternative series as indicators of economic activity. Specifically, we use asset prices, NO_2 emissions, data on mobility patterns and high-frequency data on maritime vessel trade. During the Covid-19 pandemic, these series, and many more, have become popular alternative measures of the business cycle. The specific variables are the following:

Stock prices. We use the country's main stock price index as a proxy for financial markets expected future economic activity. The data is taken from Thomson Reuters. We use the first difference of the log (times 100) of the stock market index. If a domestic or foreign lockdown reduces future economic activity, stock prices should fall.

Exchange rate. We use a country's nominal effective exchange rate (NEER) measured against a broad set of trade partners. The data is from the Bank for International Settlement's database. To estimate the model, we use the log (times 100) of the exchange rate index. An increase in the variable corresponds to an appreciation of the domestic currency. If a foreign lockdown reduces the demand for the domestic currency, e.g. because foreigners buy fewer domestic goods or the rest of the world invests less in the domestic economy, the value of the currency should fall. Hence, we expect a depreciation of the currency against the country's main trading partners.

NO_2 emissions. During the pandemic, measures of air quality have been used to track the high-frequency impact of lockdowns. Accordingly, we use the daily volume of NO_2 (nitrogen dioxide) emissions in a country's capital from the World Air Quality Index database.[6] NO_2 is released from burning fossil energy. Hence, it is a good indicator of private and commercial traffic and industrial production and, hence, of economic activity. We use the five-day moving average of the log (times 100) of NO_2 emissions. Unfortunately, the database does not offer NO_2 emissions for Malaysia and Singapore. For Malaysia, we use the

[6] The data is available under https://waqi.info/de/. Keola and Hayakawa (2021) also use emissions to track the impact of lockdowns across developed countries and high-income countries.

Air Quality Index instead. For Singapore, we use SO_2 emissions as a substitute. Both measures are also taken from the Air Quality Index database and are used as five-day moving averages in logs (times 100). We interpret the level of emissions as a proxy for economic activity. This is because emissions are highly correlated with manufacturing production and transportation. Hence, we expect a fall in emissions after a domestic or foreign lockdown shock, respectively. It is conceivable that the outbreak motivates commuters to avoid public transportation and switch to cars, which would ceteris paribus increase emissions. However, this effect is likely to be small.

Mobility. We use data from the Google Mobility Report to measure the changing patterns of human mobility.[7] The data records mobility from mobile devices. Specifically, we use the five-day average of the average of the categories "Retail and Recreation", "Transit Stations" and "Workplaces". With lockdowns barring people from stores, restaurants, public transportation, offices and factories, we expect a negative response to a domestic lockdown shock. Likewise, a foreign lockdown shock transmitted through a fall in trade should result in a drop in mobility.

Exports and imports. Cerdeiro et al. (2020) put together a database of daily vessel shipping. The data is obtained from the Automatic Identification System (AIS), which collects information on location, speed, direction and freight from ships with AIS transponders.[8] We retrieve the series "metric tons cargo" on vessels leaving the country or arriving at the country as measures of a country's exports and imports, respectively. Naturally, the data is a very noisy indicator of exports. This is because it reflects maritime trade only. In the regression, we use the log (times 100) of the five-day average of the data. For countries with land borders to their main trading partners, e.g. Germany and Canada, the data will most likely understate the response of exports. This is another reason for choosing countries for our sample, which have access to the sea and play an important role in maritime trade. Despite these limitations, we believe this data is a useful alternative to low-frequency data from the Direction of Trade statistics.

Theoretically, the effect of lockdowns on trade is ambiguous (see Baldwin and Tomiura, 2020, for this discussion). The reason is that both demand and supply effects coexist. If

[7] The data is available under https://www.google.com/covid19/mobility/.

[8] The data is available at https://comtrade.un.org/data/ais.

the domestic lockdown reduces the supply while demand remains unaffected, exports fall. If the drop in demand is larger than the fall in supply, a larger supply of exports is available for the rest of the world. Now consider the two-country case. If the foreign lockdown reduces foreign supply more than foreign demand, domestic exports increase. If the foreign lockdown leads to a stronger negative effect on foreign demand than supply, domestic exports fall. We see that the sign of the response of exports remains ambiguous.

A similar logic applies to the import response. Suppose a domestic lockdown has a negative effect on the domestic supply of goods and services. If domestic demand remains unchanged, the tighter lockdown increases the demand for imports. If domestic demand falls, probably because of a drop in income, a shift in expenditure due to the risk of infections or an increase in uncertainty, the lockdown results in lower imports.

3 The empirical model

We follow Anderson and Cesa-Bianchi (2021), Cacciatore et al. (2021), Corsetti et al. (2021), Jordà et al. (2020) and others and estimate a series of panel local projections. Local projections have been introduced by Jordà (2005) and became a highly popular tool to estimate the impact of exogenous shocks on economic time series without the need of specifying a full-scale multivariate model.[9]

The dependent variable for country i = 1, …, N at day $t+h$, $y_{i,t+h}$, which is either stock returns, the exchange rate change, NO_2 emissions, the extent of mobility or the volume of maritime exports and imports, is regressed on the realizations of two shocks at day t, $\varepsilon_{i,t}^{dom}$ and $\varepsilon_{i,t}^{for}$, according to the following regression

$$y_{i,t+h} = \alpha_{i,h} + \beta_h^{dom}\varepsilon_{i,t}^{dom} + \beta_h^{for}\varepsilon_{i,t}^{for} + \gamma_h \boldsymbol{X}_{i,t} + \delta_{i,h}t + u_{i,t+h}\,. \qquad (3)$$

We are mostly interested in the estimates for β_h^{dom} and β_h^{for} reflecting the impact of the domestic and foreign lockdown shock, respectively, on the dependent variable h periods in the future. The vector $\boldsymbol{X}_{i,t}$ collects a number of control variables, while $\alpha_{i,h}$ is a country-specific fixed-effect at horizon h and $\delta_{i,h}$ is the coefficient on a country-specific time trend. The key coefficients of interest, β_h^{dom} and β_h^{for} as well as the coefficients on the control variables are identical across sample countries.

[9] Plagborg-Moller and Wolf (2021) show that local projections and Vector Autoregressions estimate the same impulse responses.

The sample period is February 10, 2020 to April 09, 2021. We drop all weekends due to the lack of stock market and exchange rate data and the strong difference in the remaining variables between weekends and working days. Thus, the sample covers the beginning of the global pandemic at the start of 2020 until the spring of 2021, when the global vaccinations campaigns took off.[10] With more and more people vaccinated, the need for lockdowns falls and, consequently, the relationship between the stringency index and the number of infections changes.

For each estimation, the vector of control variables includes one lag of the dependent variable, the contemporaneous realization and one lag of the other five endogenous variables. It also includes the current value and the first lag of the economic support index for the domestic economy as well as the average economic support index for the 10 largest trading partners. The economic support index summarizes public measures of income support and debt relief and is also provided as a part of the OxCGRT database. We also include the current level of smoothed new infections as a control variable.

In line with the bulk of the literature on panel local projections, we compute confidence bands around the point estimates using Driscoll and Kraay (1998) standard errors. These errors control for cross-sectional correlation as well as serial correlation. Alternatively, we bootstrap standard errors following the suggestion of Kilian and Kim (2011).[11]

4 Results

We plot the estimated response coefficients, β_h^{dom} and β_h^{for}, as a function of h = 0, ..., 29. Since the two shock series are standardized, the coefficients reflect the effect of a shock one standard deviation in size on the dependent variable. In each figure, we plot the point estimates and 68% and 90% confidence intervals.

Figure (4) depicts the responses to a domestic lockdown shock for the panel of all sample countries. A domestic lockdown has a small effect on stock markets. Only the impact response is statistically significant. The nominal effective exchange rate index increases by 0.03 percent. Hence, the domestic currency appreciates in nominal terms against the main trading partners' currencies. This effect is small but statistically significant.

The level of NO_2 emissions does not exhibit a significant response in the first three to four weeks after the shock. Emissions strongly increase six weeks after the shock, potentially

[10] On March 11, 2020, the World Health Organization declared a pandemic.
[11] The results for bootstrapped confidence intervals are available upon request.

as a response to an eventual relaxation of movement restrictions. As mentioned before, NO_2 emissions might not fall because people switch from public transportation to individual cars.

The level of mobility sharply falls upon a domestic shock. Ten days after the occurrence of the shock, mobility is 0.8 percent lower than it would otherwise be. This effect is highly statistically significant and takes about six weeks to disappear. Exports and imports fall significantly by about 0.2 percent.

Figure (5) shows the responses to a foreign lockdown shock. All six variables fall significantly after the lockdown in the country's trading partners. Stock prices drop by 0.1 percent in the first three weeks after the foreign shock, which is larger than the response after a domestic shock. The domestic currency depreciates against the trading partners' currencies. The level of NO_2 emissions after four weeks is 0.8% lower than in the absence of the foreign lockdown shock. This response is larger than the adjustment following a domestic lockdown shock and has the expected sign. The extent of mobility falls by about one percentage point, which is also larger than the drop in mobility after the domestic lockdown shock. The country's exports shrink by 0.6% with the peak effect occurring four weeks after the shock. This suggests that the effect on global trade needs time to materialize. Imports fall by about 0.2 to 0.4 percent.

4.1 Subsamples

The Covid-19 pandemic spread in waves. While the world economy was caught by surprise by the first wave in the spring of 2020 and was largely unprepared, firms and households at least partly prepared for a second wave. This suggests that the macroeconomic effects of lockdown spillovers should be stronger at the beginning of the sample period and weaker in the remaining part of the sample.

To test this conjecture, we construct a dummy variable for the first wave, D_t^{1st}, which is equal to one between February and the end of June 2020 and zero thereafter. We allow the foreign lockdown shock to interact with the dummy variable,

$$y_{i,t+h} = \alpha_{i,h} + \beta_h^{dom}\varepsilon_{i,t}^{dom} + \beta_h^{for}\varepsilon_{i,t}^{for} + \beta_h^{for,1st}D_t^{1st}\varepsilon_{i,t}^{for} + \gamma_h \boldsymbol{X}_{i,t} + \delta_{i,h}t + u_{i,t+h}\,, \quad (4)$$

such that a negative estimate of $\beta_h^{for,1st}$ implies that the fall in economic activity following a lockdown shock is stronger during the first wave compared to later episodes. The estimated coefficients on the interaction term are shown in Figure (6).

The response of stock prices, the exchange rate, mobility and exports is significantly stronger during the first wave until the summer of 2020. For these four variables, the estimated coefficient on the interaction term is significantly negative. These findings corroborate the notion that the strength of cross-border lockdown spillovers was particularly strong at the beginning of the pandemic but weakened over time. For emissions and imports, in contrast, we do not find a clear pattern.

4.2 Variance decomposition

The impulse response analysis shows the impact of a shock one standard deviation in size. However, this does not reveal how important either shock was for the evolution of the variables over the sample period. We address this question now using a forecast error variance decomposition along the lines of Gorodnichenko and Lee (2020). These authors propose to proceed as follows: First, we estimate the baseline local projection model but exclude the two shock series. Second, for every horizon *h* we regress the estimated residual of this first-stage regression, i.e. the forecast error, separately on each shocks occurring between *t* and *t+h* while including the other shock in the vector of controls. The R^2 of this regression informs us about the share of fluctuations of the endogenous variables accounted for by each shock.

Figure (7) plots the shares of each shock as a function of *h* for each variable. The share of fluctuations attributable to either shock is relatively small and fluctuates over the projection horizon. The contributions of the shocks are smallest for imports and exports, where both the domestic and the foreign lockdown shock explain about one to three percent of the fluctuations after 30 days. For mobility, in contrast, the contributions are large. After 15 days, the domestic lockdown shock is responsible for 15% of the fluctuations of mobility and the foreign lockdown shock explains about 10% of the variation.

For stock returns and emissions, we find that the contribution of the foreign shock is larger than the contribution of the domestic shock. At first sight, it seems that the domestic shock should matter more. However, both shocks are asymmetric with respect to their impact at the sectoral level, and this can explain why the foreign shock accounts for a larger share. The domestic shock hits both the service sector and the industrial sector. The foreign shock, in contrast, has a stronger effect on the industrial sector, which is more export-oriented than the service sector. If the manufacturing sector is both more emission-intensive and better represented in the aggregate stock market index, it does not come as a surprise that the foreign shock accounts for a larger bulk of fluctuations.

4.3 Country groups

We now narrow the set of countries and estimate the model for the two country groups, the set of advanced small open economies and the set of Asian emerging market economies. Both subpanels respond similarly to domestic shocks. Therefore, we do not show the impulse responses following a domestic lockdown shock here.[12]

Figure (8) shows the response to the foreign shock for advanced small-open economies, while Figure (9) reports the adjustment of Asian economies. We find that the fall in stock prices is comparable across the two groups of countries. While the domestic currency appreciates in advanced economies, we find a significant depreciation in Asian emerging market economies. The maximum drop in emissions is again comparable across the two groups. In both cases, emissions fall by about 0.8% after the shock. The fall in mobility, in contrast, is larger in advanced economies, probably because working from home is easier for employees in advanced economies. Both exports and imports exhibit a similar response pattern across the two subsamples. In a separate model below, we shed light on the exposure of the two panels to lockdown shocks originating in China and the US.

4.4 Including China

Our baseline set of 13 sample countries does not include the People's Republic of China. China is included as a trading partner of all the 13 sample countries, but not in the set of countries for which we study the impulse responses. The Chinese economy is larger than any other economy in the sample. Furthermore, China is one of the most important trading partners for almost every economy in the sample. Hence, we need to assess how sensitive the nature of lockdown spillovers is with respect to the inclusion of China in the analysis. We add China as the 14th sample economy and estimate the baseline model with export weights. The impulse response functions for the foreign lockdown shock are shown in Figure (10).

[12] The results are available upon request.

Comparing the estimated responses with those from Figure (5) reveals that the sign, the size and the shape of the impulse responses remain unchanged if China is included. Having established that, we leave China out of the baseline model because as a large open economy, it is certainly different from the other countries in the sample.

5 Alternative weighting schemes

We also present the results from three specifications in which we use alternative weights ω_j. The first alternative uses import-based weights, i.e. the relative size of the ten largest source countries of imports of country *i*. The data also stems from the DOTS database. Figures (11) to (13) depict the resulting impulse response functions.

We find that with import weights, the results remain more or less unchanged. The spillover effects of foreign lockdowns trigger a strong adjustment of domestic economic activity. The spillovers with respect to mobility and exports are stronger in the group of advanced small-open economies compared to the group of Asian emerging market economies.

The second alternative weighting scheme reflects the ten largest source countries of foreign direct investment (FDI) into country *i*. This data (inward direct investment positions as of end-2019) is taken from the International Monetary Fund (IMF). In the calculation of source countries, we drop obvious tax havens such as the British Virgin Islands, Jersey or Bermuda, which often appear in the list of FDI sources but from which we do not expect meaningful spillover effects.

The empirical estimates are shown in Figures (14) to (16). Again, the sign and the strength of lockdown spillovers remain largely unchanged compared to the baseline findings using export weights. For FDI weights, we find that the responses of emissions and mobility are stronger in country group I compared to country group II. Mobility in country group I falls by one percent, while mobility in group II drops by 0.6%.

As discussed in the introduction, the pandemic is threatening highly integrated global value chains. In the long run, a lockdown abroad could contribute to a reshoring of production capacity and a dismantling of global value chains. In the short run, a tighter lockdown in countries from which intermediate products are sourced could adversely affect domestic economic activity. In the previous section, we used export weights to construct foreign lockdown shocks. To account for the role of global value chains, we now employ a third set of alternative weights, which reflect the participation of a country's industries in global value chains. We use the OECD's Trade in Value Added (TiVA) database and collect the foreign value-added share in gross exports for total industries.[13]

For each country, we exclude the domestic source of value-added and obtain the top ten foreign source countries as well as these countries' share of value-added in exports. These shares are our alternative country weights. A drawback of these weights is their time coverage: at the time of writing, the most recent version of the TiVA database, i.e. the 2018 update, covers trade until 2015 only. Hence, our weights reflect the connections through global value chains as of 2015.

The resulting impulse response functions for the final set of alternative weights are reported in Figures (17) to (19). Again, we find that the results remain remarkably similar to our baseline findings. For value-added weights, the responses to the foreign lockdown shock in the subsets of countries, e.g. Figures (18) and (19), exhibit the same patterns as in the other specifications.

Overall, we can conclude that the sign and the strength of lockdown spillovers remain robust with respect to the weights used in the calculation of foreign lockdown shocks.

6 The response to lockdown shocks in the US and China

For each of our sample countries, the US and China are key export destinations as well as source countries of foreign direct investment. In this section, we study the effects of lockdown shock in these two large open economies. Again, we estimate panel local projections but replace the weighted foreign shock, $\varepsilon_{i,t}^{for}$, by the shock in the US and in China, ε_t^{US} and ε_t^{China}. Thus, our estimated model becomes

$$y_{i,t+h} = \alpha_{i,h} + \beta_h^{dom}\varepsilon_{i,t}^{dom} + \beta_h^{US}\varepsilon_t^{US} + \beta_h^{China}\varepsilon_t^{China} + \gamma_{i,h}\boldsymbol{X}_{i,t} + u_{i,t+h} \tag{5}$$

We are particularly interested in the estimates of β_h^{US} and β_h^{China}. To control for economic support packages, the vector of control variable now includes the economic support indices for the US and China.

The estimated response coefficients for the full sample and the two groups of countries are shown in Figures (20) to (25). A US lockdown shock lowers stock market valuations and effective exchange rates, reduces emissions and curbs mobility. All of these effects are

[13] The TiVA database is available at https://www.oecd.org/industry/ind/measuring-trade-in-value-added.htm.

highly significant. The response of exports, in contrast, is inconclusive. These results remain unchanged if we narrow the sample to the set of advanced small-open economies (group I). For the group of Asian economies, see Figure (22), the responses of effective exchange rates and emissions are much weaker and remain insignificant.

A Chinese lockdown shock, as shown in Figures (23) to (25), has a significantly negative effect on the exchange rate, the level of emissions and the level of exports, while the responses of the other variables remain mostly ambiguous.

Let us compare the responses in group I between a shock originating in the US, Figure (21), and a shock originating in China, see Figure (24). After a US lockdown shock, the response of the domestic currency remains inconclusive. A Chinese lockdown shock, in contrast, triggers an appreciation of the domestic currency. Likewise, imports tend to increase after a US shock but tend to fall after a lockdown is imposed in China. Emissions fall by one percent after the US lockdown shock, but only 0.7% after the Chinese shock. Group II also exhibits differences in the responses between shocks originating in the US and China, respectively. The stock market valuation falls after a US shock but increases after a Chinese lockdown. Emissions remain more or less unchanged if the shock originates in the US, but strongly fall after the shock originating in China. Hence, the advanced small open economies in the sample are particularly exposed to the US lockdown. A comparison of export shares across groups corroborates this notion. For the group of advanced small open economies, the average share of exports to the US is 25%, while the share of exports to China is 20%. For the group of emerging Asian economies, the difference is even more pronounced. The average weight on the US is 14%, while the average export share to China is 31%.

7 Trade intensity and the strength of spillovers

In our baseline model, the estimate of the spillover-coefficient is restricted to be identical across sample countries. Hence, we cannot shed light on the nature of cross-country heterogeneity in the exposure to shocks. One key determinant of the intensity of spillovers should be the relevance of the export sector for domestic activity. We now modify the model in order to assess whether countries with a larger share of exports in GDP experience stronger spillovers.

For each sample country, we compute the ratio of exports to the top-ten export destinations to GDP. Since we use the export shares from the construction of foreign lockdown shocks, which are based on 2018 trade data, we divide the sum of exports to the top-ten destinations by GDP for 2018. The resulting export shares, S_i^{exp}, vary between 0.11 (Japan) and 1.28 (Hong Kong SAR). We augment the regression model and include an interaction between the export share and the foreign lockdown shock,

$$y_{i,t+h} = \alpha_{i,h} + \beta_h^{dom}\varepsilon_{i,t}^{dom} + \beta_h^{for}\varepsilon_{i,t}^{for} + \beta_h^{interact}S_i^{exp}\varepsilon_{i,t}^{for} + \gamma_h \boldsymbol{X}_{i,t} + \delta_{i,h}t + u_{i,t+h}\,. \quad (6)$$

As spillovers were more pronounced during the first part of the sample and weaker thereafter, we estimate equation (6) for two subsamples, the first wave between February and the end of June 2020 and the remaining part of the sample between July 2020 and April 2021.

The estimated coefficient on the interaction term, $\beta_h^{interact}$, is shown in Figure (26). In the first subsample, we find a significantly negative coefficient on the interaction term for stock prices, mobility and exports. The coefficient for emissions is volatile over the prediction horizon, but also negative on average over the horizon. Hence, countries with a larger ratio of exports to GDP are particularly exposed to adverse lockdown spillovers from abroad. In the second subsample, the coefficient remains negative for emissions and mobility. A foreign lockdown reduces emissions and mobility more strongly for countries with a larger volume of exports relative to GDP.

8 Alternative specifications

In a first alternative set-up, we go back to the first-stage regressions. The baseline series of lockdown shocks are the residuals from a regression of the country-specific stringency index on its own lags, a time trend and the weighted average of the number of new infections. However, policymakers could also respond to the extent of mobility when imposing lockdowns. Hence, the Google mobility indicator introduced before should enter the first-stage as a regressor. We re-run the first-stage regression including mobility and estimate the impulse responses following foreign lockdown shocks based on these modified shocks. Figure (27) shows the results. The impulse responses remain broadly unchanged compared to Figure (5). The only noticeable difference is that the drop of mobility is smaller compared to the baseline findings.

Finally, we revisit the estimation methodology. In the baseline model, we estimate a pooled fixed effects specification. Pesaran and Smith (1995) show that the estimated slope coefficients could be biased if there is cross-sectional heterogeneity. They introduce the mean group estimator to address this shortcoming. The estimator is essentially the average across the estimated country-specific slope coefficients. Figure (28) reports the impulse response functions obtained from the mean group estimator. There is no substantial difference in the responses compared to the baseline results in Figure (5).

9 Conclusions

Integrated economies are exposed to the economic consequences of lockdowns imposed in the rest of the world. Hence, lockdowns can have cross-border effects. In this paper, we estimate the nature of these spillovers for a panel of 13 small open economies. We obtain two key findings:

First, lockdown shocks originating abroad significantly reduce economic activity at home. In particular, stock returns fall, the currency depreciates, the levels of NO_2 emissions and exports fall and the mobility of persons drops. These findings are robust with respect to the construction of foreign lockdown shocks. The literature typically focuses on spillovers of monetary and fiscal policy. One lesson from this paper is that lockdowns are a separate source of spillovers to the domestic economy. Since the estimated model is linear, these findings equally apply to the relaxation of restrictions: lifting the lockdown abroad is expansionary for the domestic economy.

Second, lockdown spillovers can have a larger impact on the domestic economy than domestic lockdown shocks. Some sectors of open economy heavily rely on foreign export markets. For these firms, a foreign lockdown might be more restrictive than a lockdown at home. As a result, variables such as emissions and mobility respond more strongly to foreign lockdown shocks compared to domestic ones.

In principle, the existence of spillovers, e.g. in the realm of monetary and fiscal policy, calls for a role of coordinating policies across countries. In contrast to macroeconomic policy, non-pharmaceutical interventions have often been introduced on very short notice leaving very little room for international consultations. In addition, the nature of the pandemic threat precludes negotiations with other governments or even a postponement of lockdowns by a few days. This is the main difference with respect to monetary and fiscal policy spillovers. The best policy response to reduce the exposure to lockdown spillovers is to diversify export markets and contain the complexity of global value chains.[14]

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[14] See Baldwin and Freeman (2021) for a survey of policy implications that arise from the propagation of shocks through global value chains.

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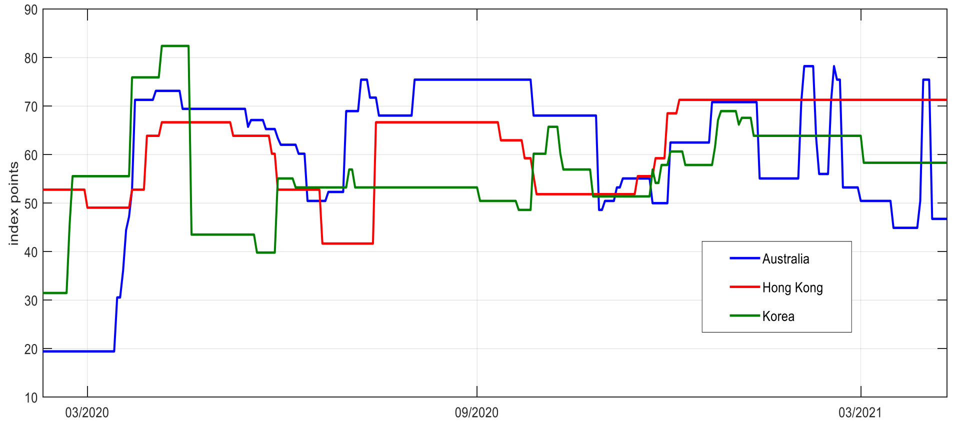
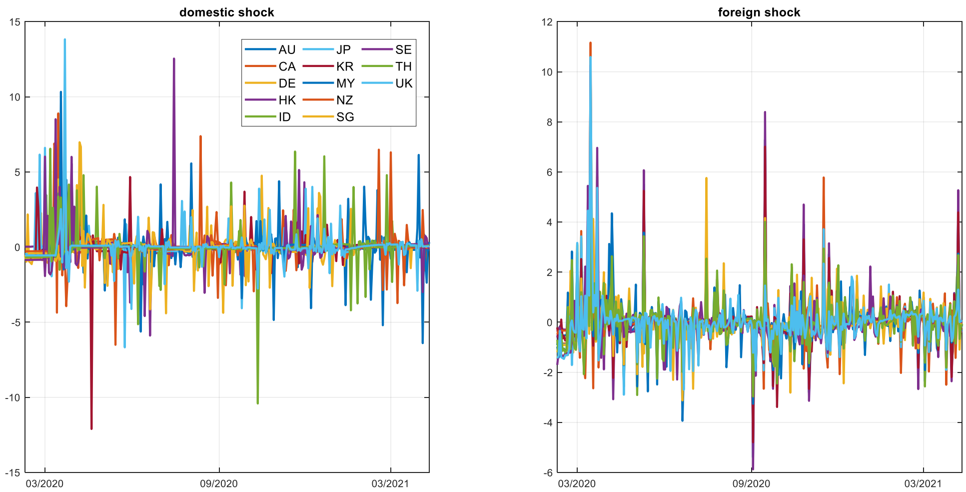
Figure 1: Stringency index for three sample countries



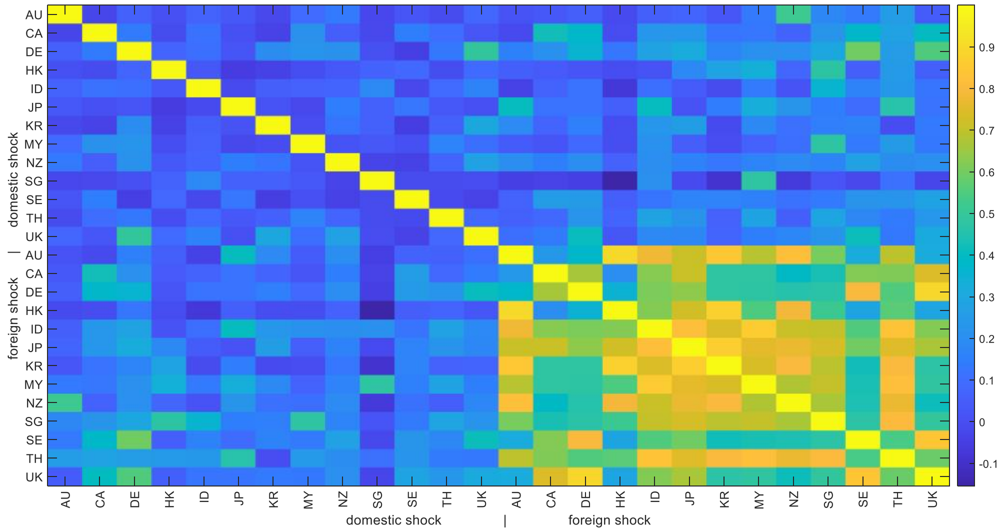
Notes: The figure shows the level of the stringency index for Australia, Hong Kong SAR and Korea.

Figure 2: Domestic and foreign lockdown shocks



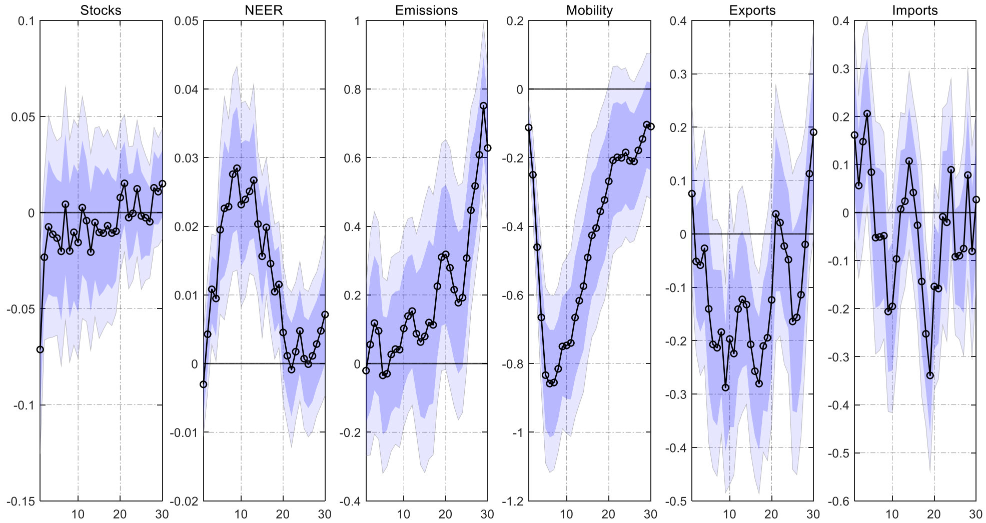
Notes: The figures show the domestic and foreign lockdown shocks. The domestic shock is the residual of a regression of the stringency index on lags of itself, a time trend and the number of new infections. The foreign shock for country *i* is the weighted average of the domestic shocks in country *i*'s ten most important export markets. All shocks are standardized.

Figure 3: Correlation between domestic and foreign lockdown shocks



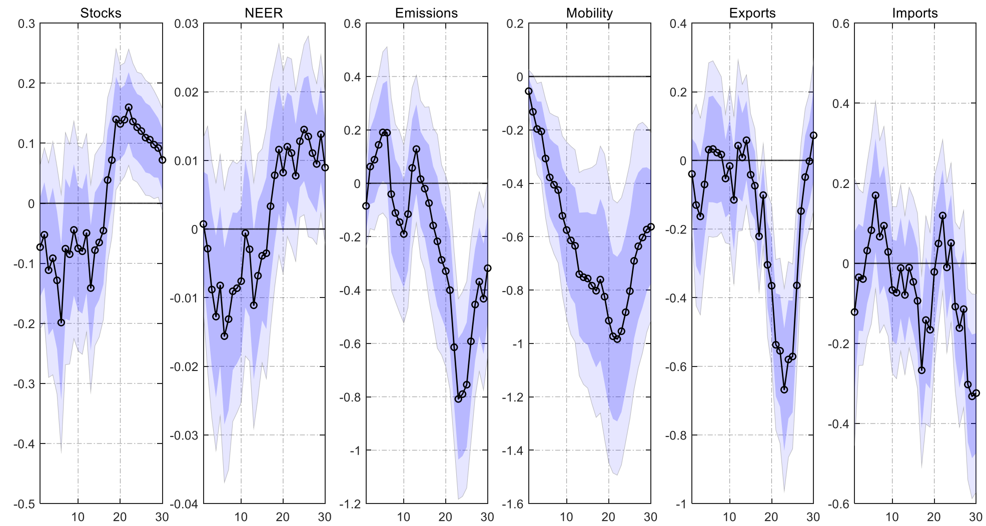
Notes: The figure shows the contemporaneous correlation across domestic and foreign lockdown shocks.

Figure 4: Response to domestic lockdown shock



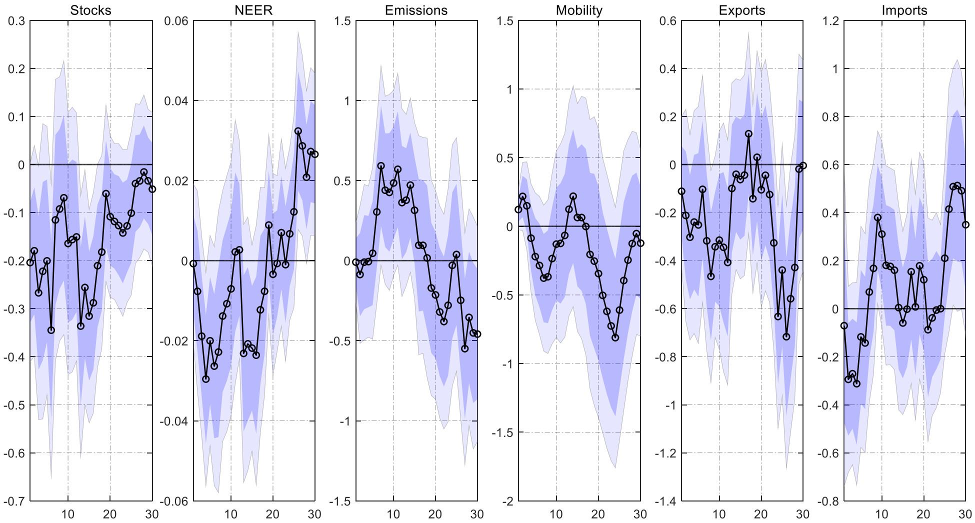
Notes: The figure shows the estimated β_h^{dom} from panel local projections for all countries as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 5: Response to foreign lockdown shock



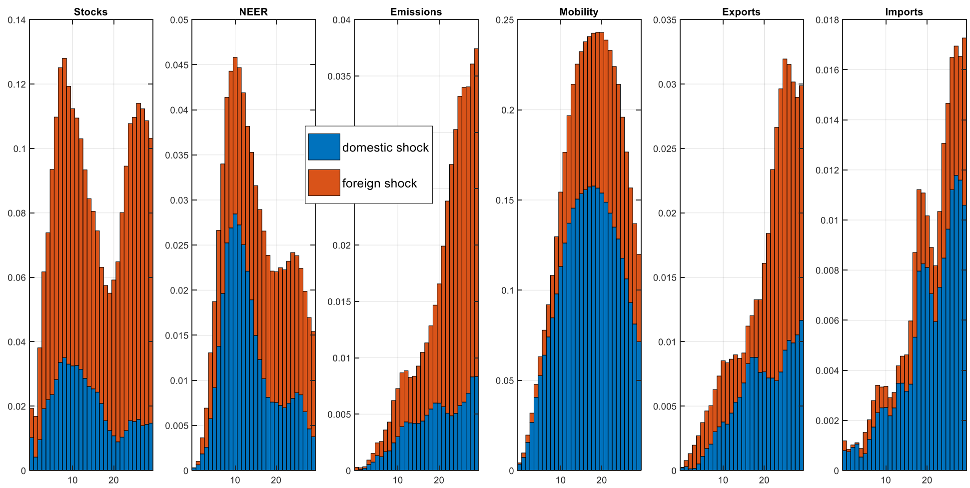
Notes: The figure shows the estimated β_h^{for} from panel local projections for all countries as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 6: Response to foreign lockdown shock across subsamples



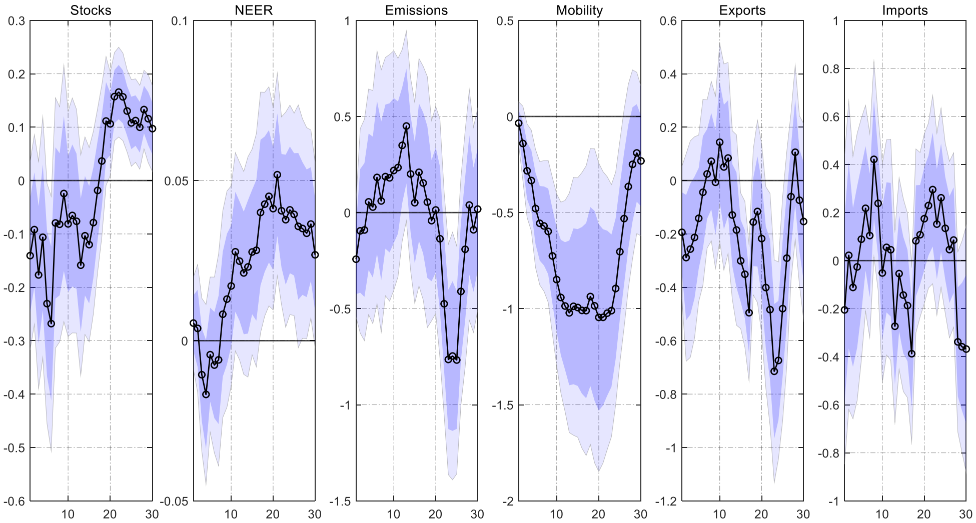
Notes: The figure shows the estimated $\beta_h^{for,1st}$ from panel local projections for all countries as a function of h (black, circled line), i.e. the coefficient on the interaction term between the foreign lockdown shock and the dummy for the first subsample between February and June 2020. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 7: Contributions of lockdown shocks



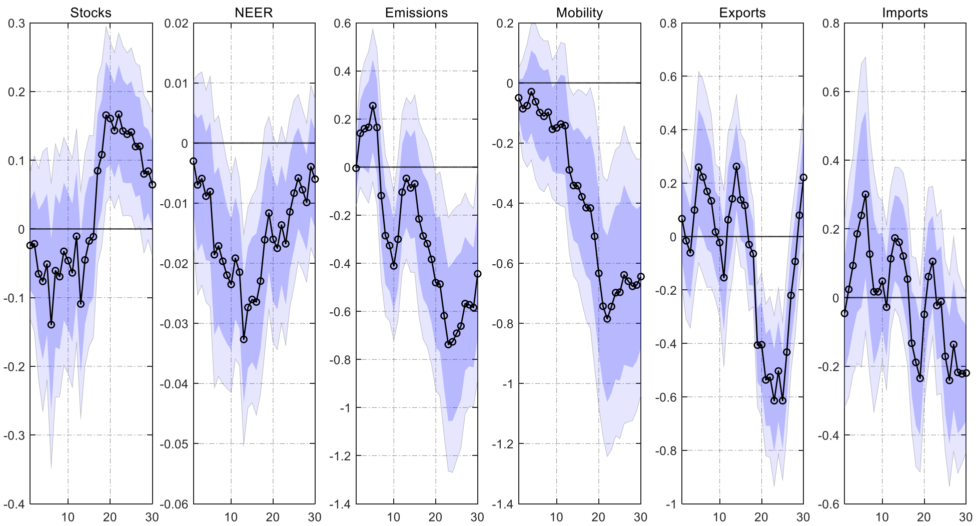
Notes: The figure shows the contribution of the domestic and foreign lockdown shocks to the forecast error variance of the dependent variables. The analysis follows Gorodnichenko and Lee (2020).

Figure 8: Response of group I to foreign lockdown shock



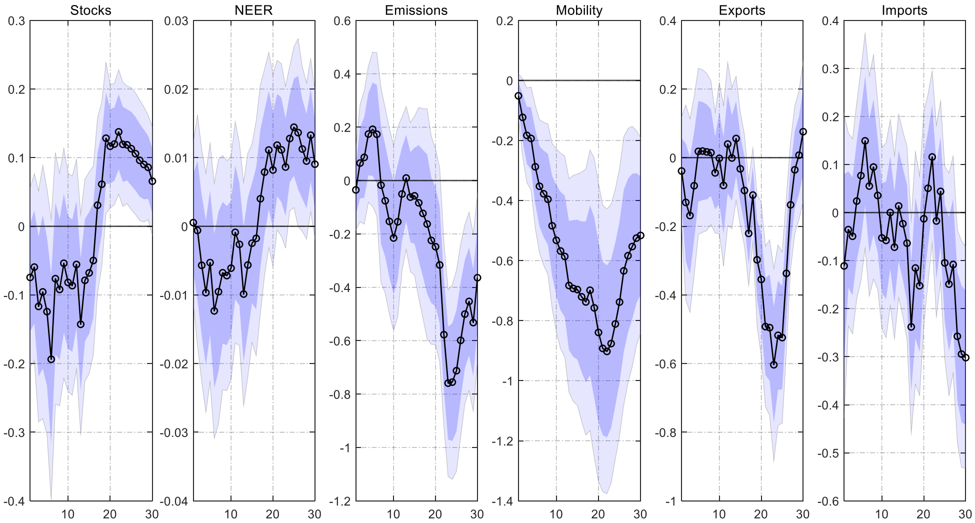
Notes: The figure shows the estimated β_h^{for} from panel local projections for group I as a function of *h* (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 9: Response of group II to foreign lockdown shock



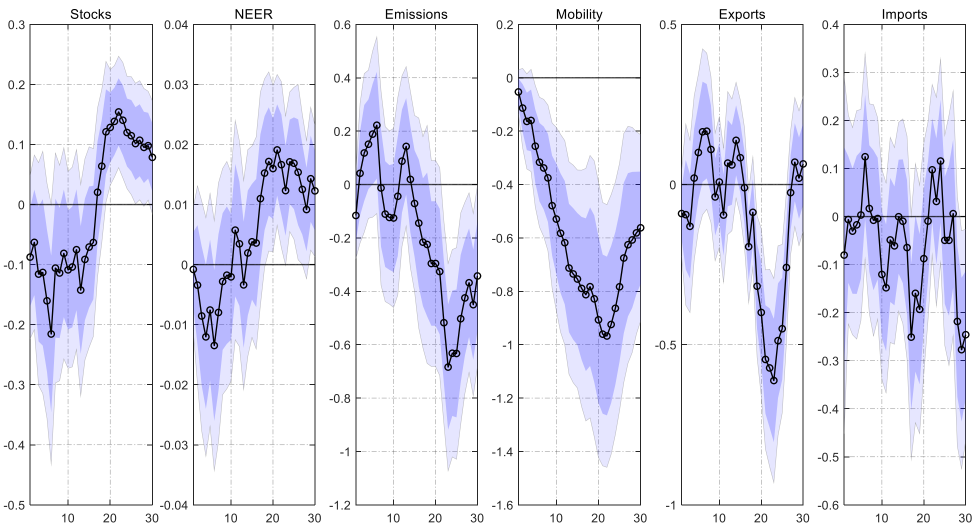
Notes: The figure shows the estimated β_h^{for} from panel local projections for group II as a function of *h* (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 10: Response to foreign lockdown shock including China



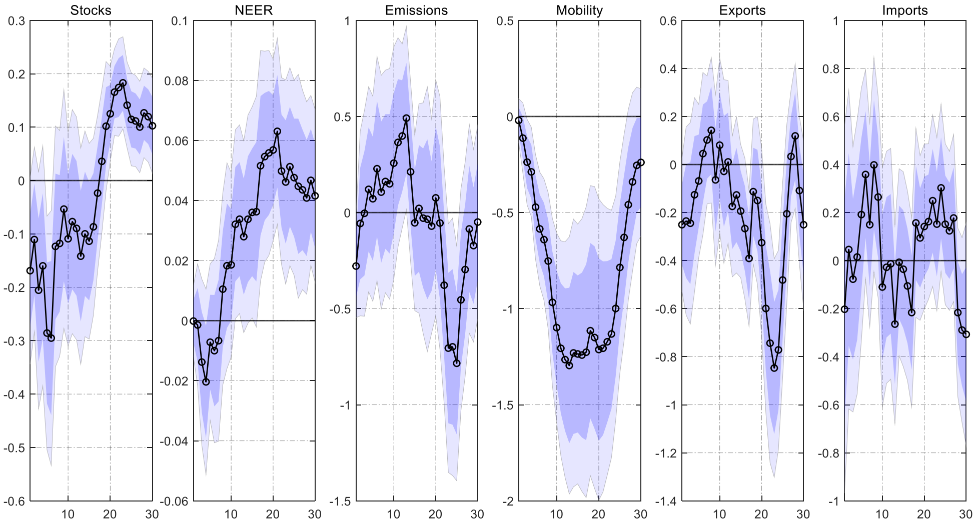
Notes: The figure shows the estimated β_h^{for} from panel local projections for all countries including China as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 11: Response to foreign lockdown shock (import weighted)



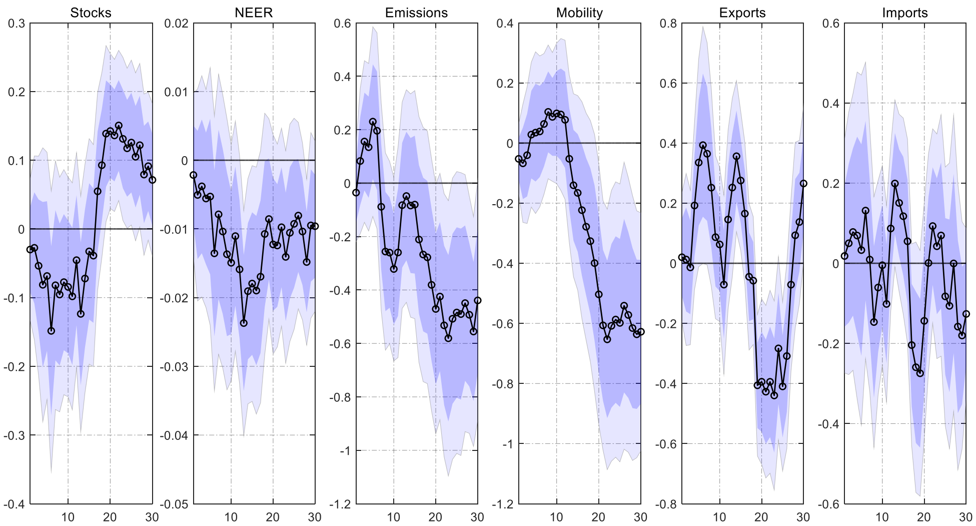
Notes: The figure shows the estimated β_h^{for} from panel local projections for all countries as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 12: Response of group I to foreign lockdown shock (import weighted)



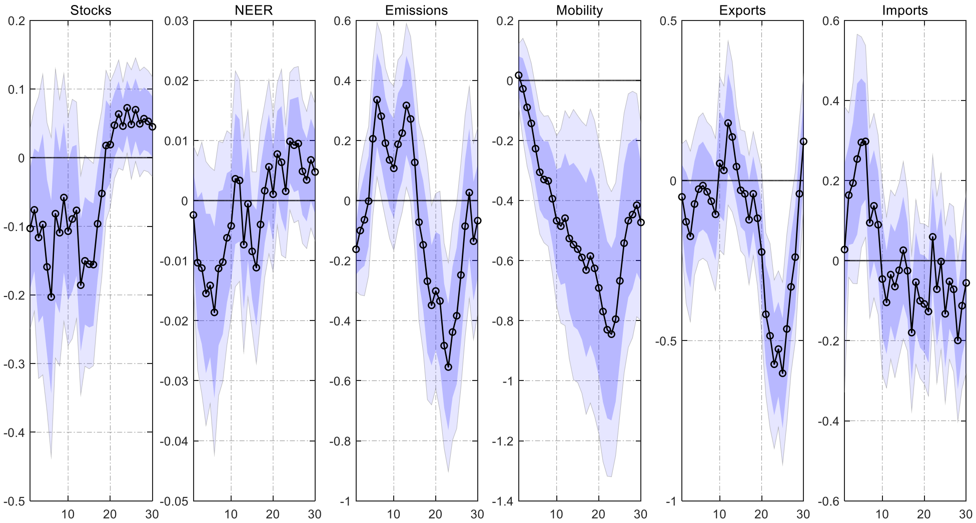
Notes: The figure shows the estimated β_h^{for} from panel local projections for group I as a function of *h* (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 13: Response of group II to foreign lockdown shock (import weighted)



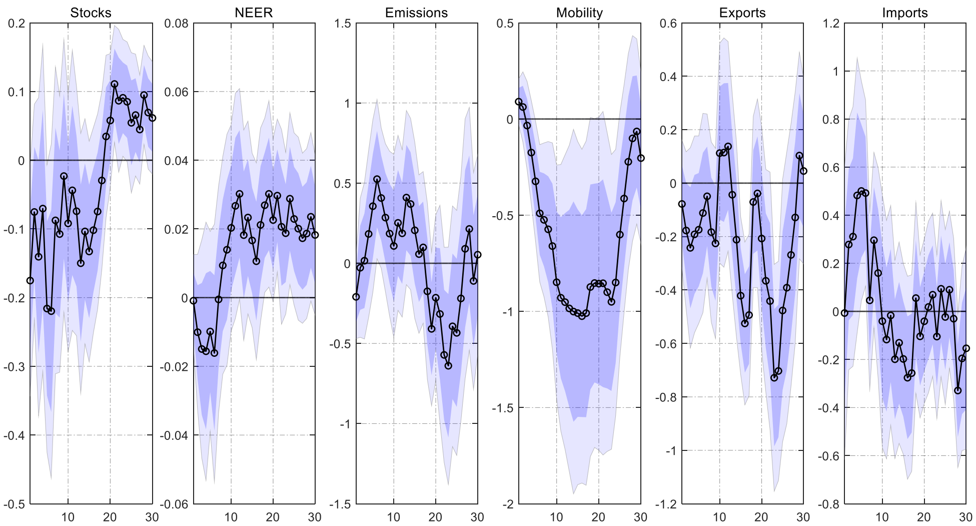
Notes: The figure shows the estimated β_h^{for} from panel local projections for group II as a function of *h* (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 14: Response to foreign lockdown shock (FDI weighted)



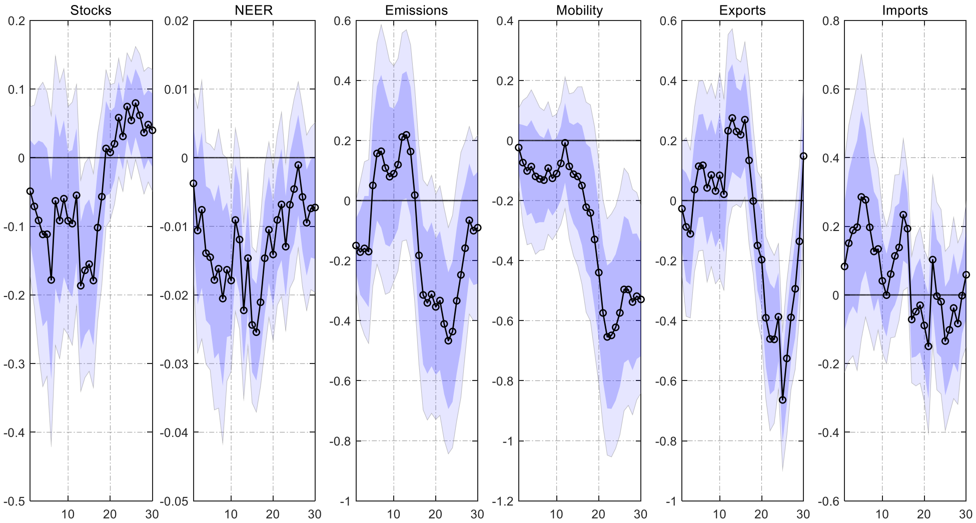
Notes: The figure shows the estimated β_h^{for} from panel local projections for all countries as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 15: Response of group I to foreign lockdown shock (FDI weighted)



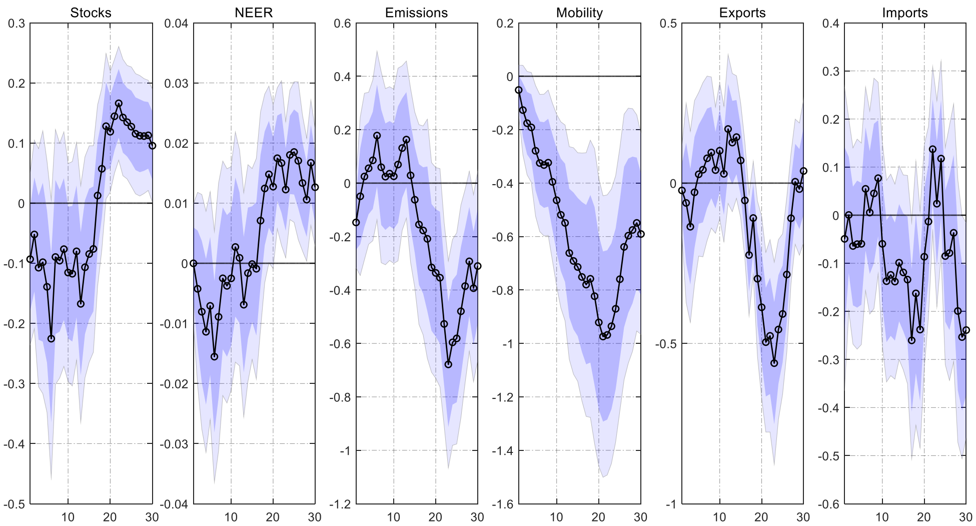
Notes: The figure shows the estimated β_h^{for} from panel local projections for group I as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 16: Response of group II to foreign lockdown shock (FDI weighted)



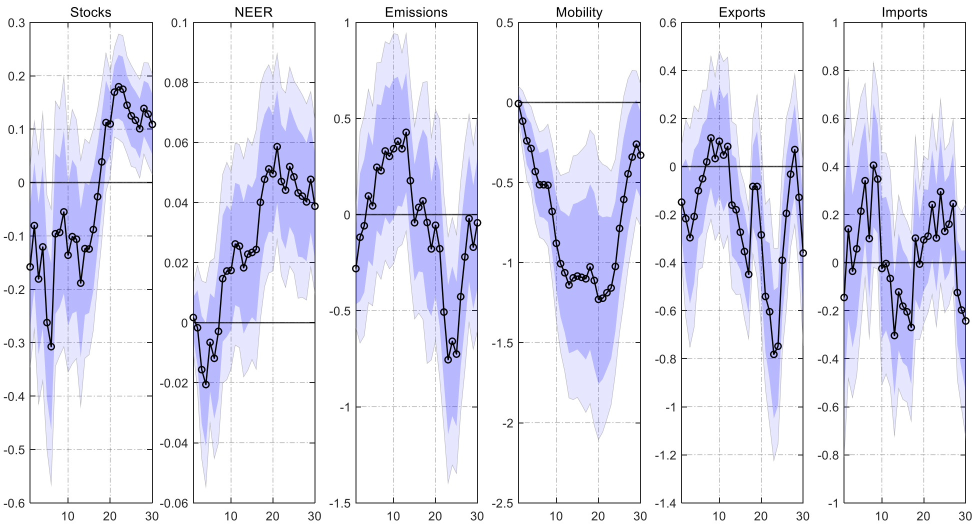
Notes: The figure shows the estimated β_h^{for} from panel local projections for group II as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 17: Response to foreign lockdown shock (VA weighted)



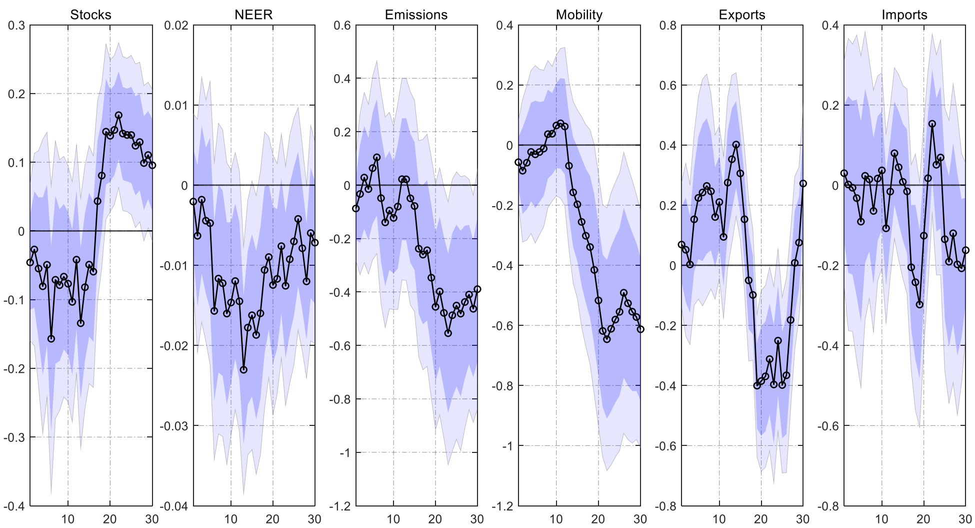
Notes: The figure shows the estimated β_h^{for} from panel local projections for all countries as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 18: Response of group I to foreign lockdown shock (VA weighted)



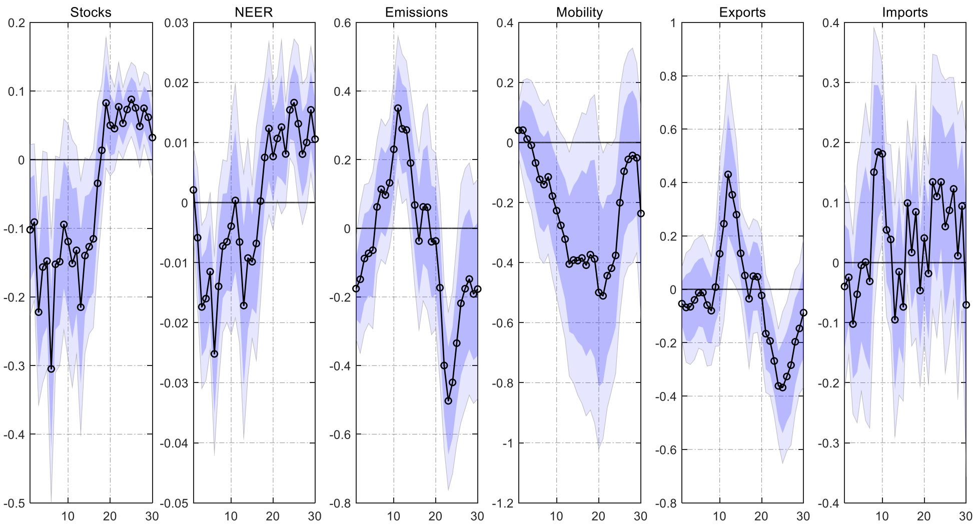
Notes: The figure shows the estimated β_h^{for} from panel local projections for group I as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 19: Response of group II to foreign lockdown shock (VA weighted)



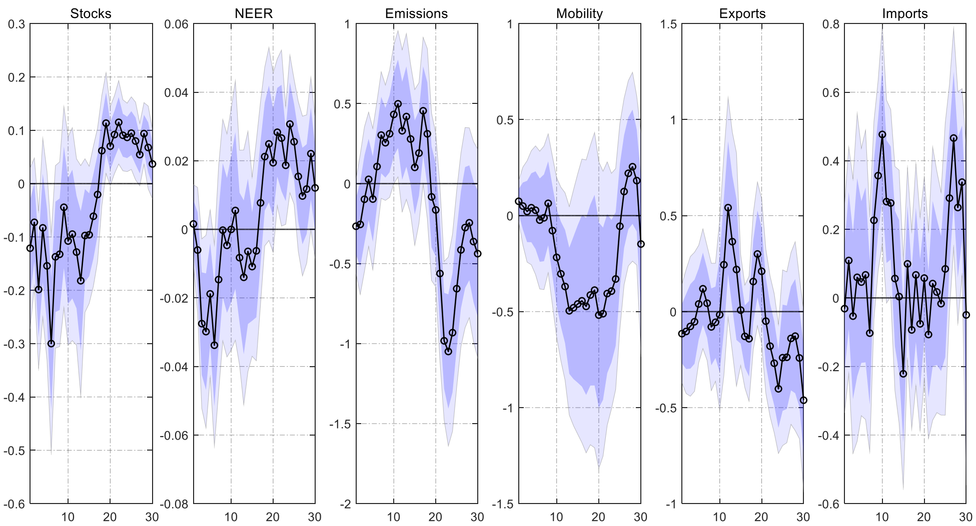
Notes: The figure shows the estimated β_h^{for} from panel local projections for group II as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 20: Response to US lockdown shock



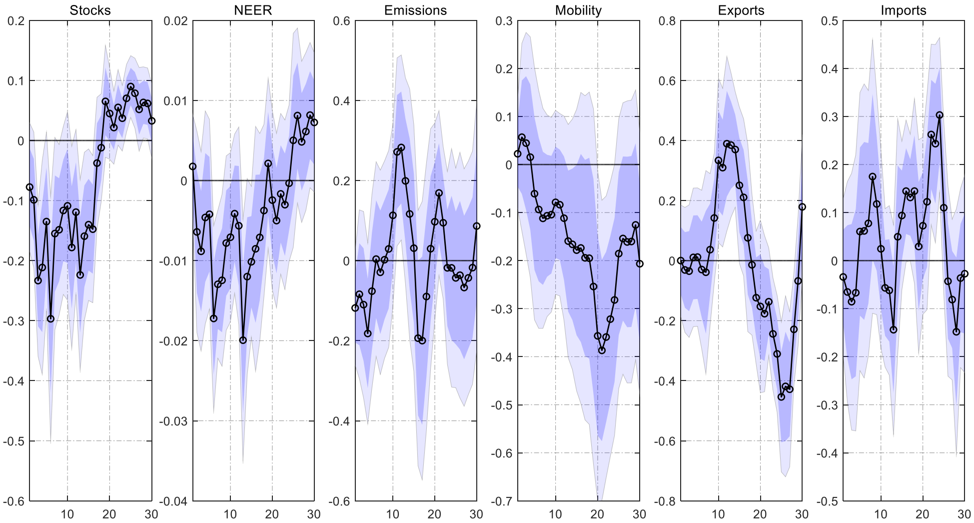
Notes: The figure shows the estimated β_h^{US} from panel local projections for all countries as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 21: Response of group I to US lockdown shock



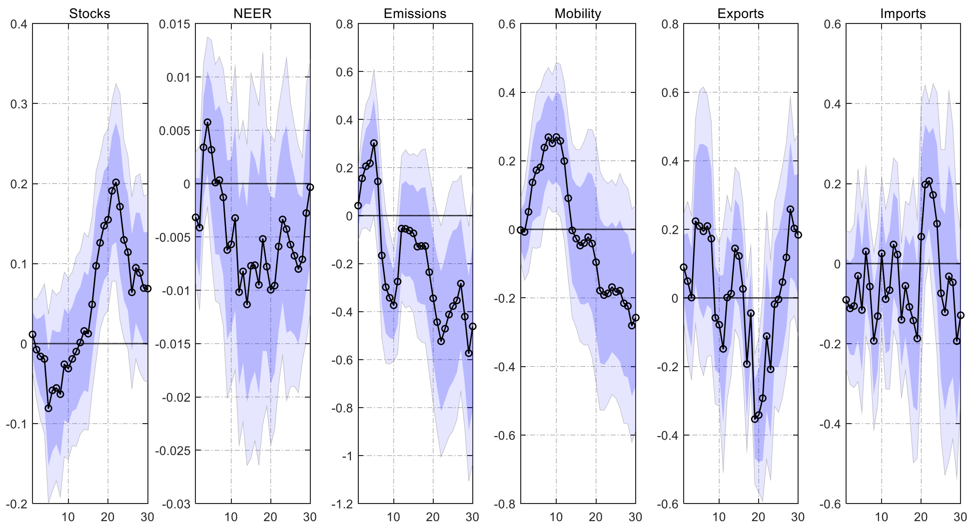
Notes: The figure shows the estimated β_h^{US} from panel local projections for group I as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 22: Response of group II to US lockdown shock



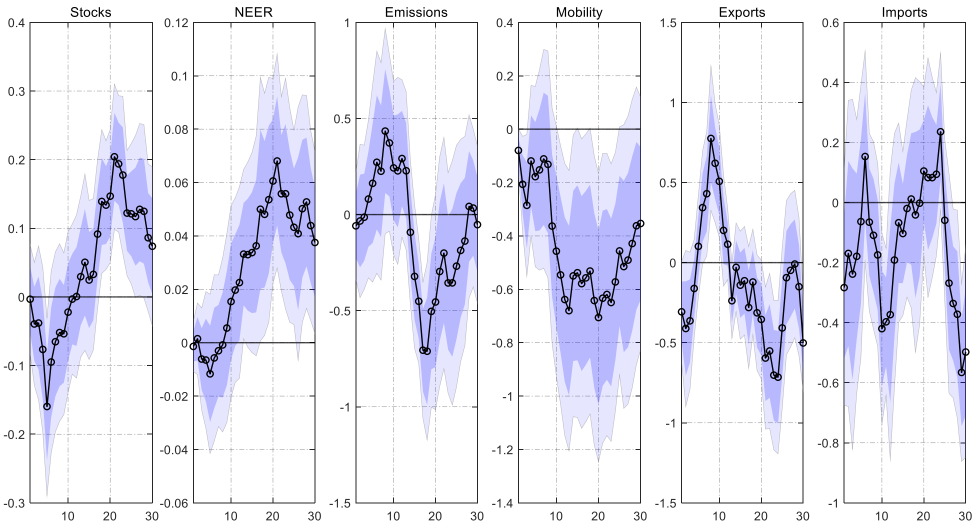
Notes: The figure shows the estimated β_h^{US} from panel local projections for group II as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 23: Response to Chinese lockdown shock



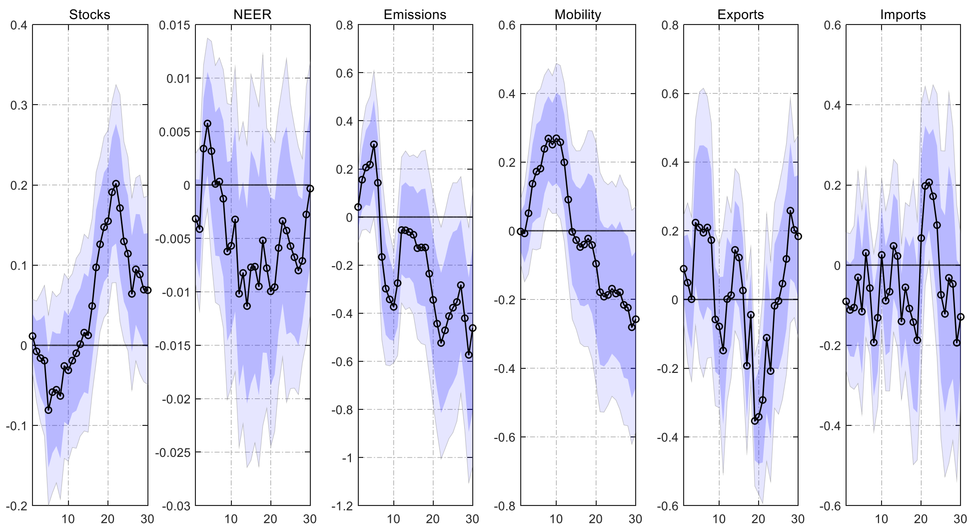
Notes: The figure shows the estimated β_h^{China} from panel local projections for all countries as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 24: Response of group I to Chinese lockdown shock



Notes: The figure shows the estimated β_h^{China} from panel local projections for group I as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

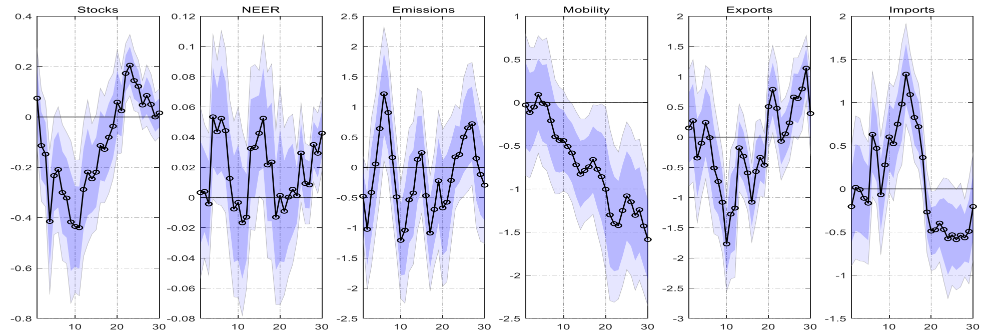
Figure 25: Response of group II to Chinese lockdown shock



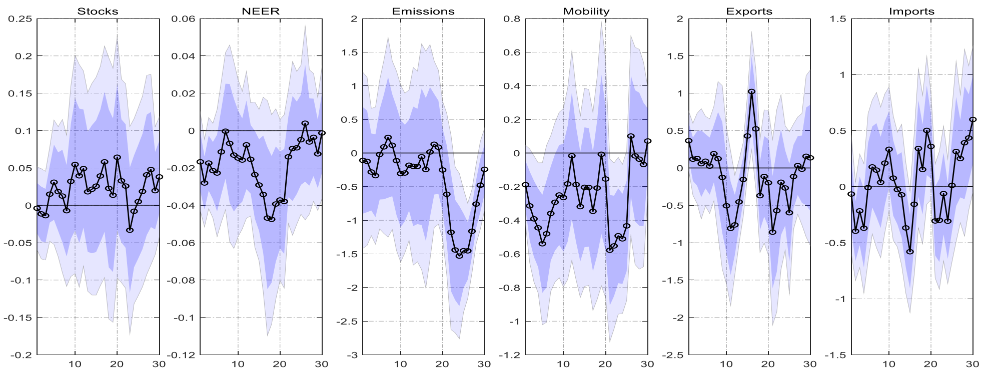
Notes: The figure shows the estimated β_h^{China} from panel local projections for group II as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 26: Interaction of foreign lockdown shock with export share

(a) February – June 2020

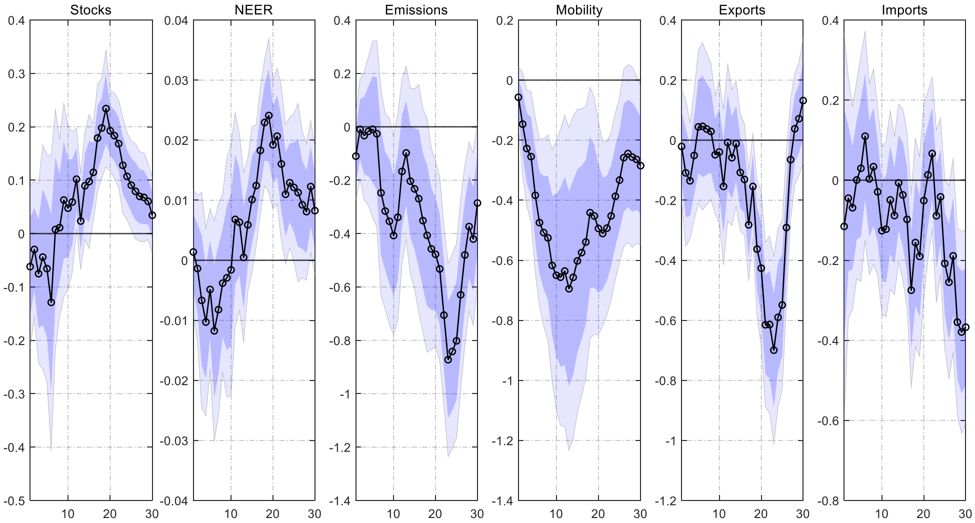


(b) July 2020 – April 2021



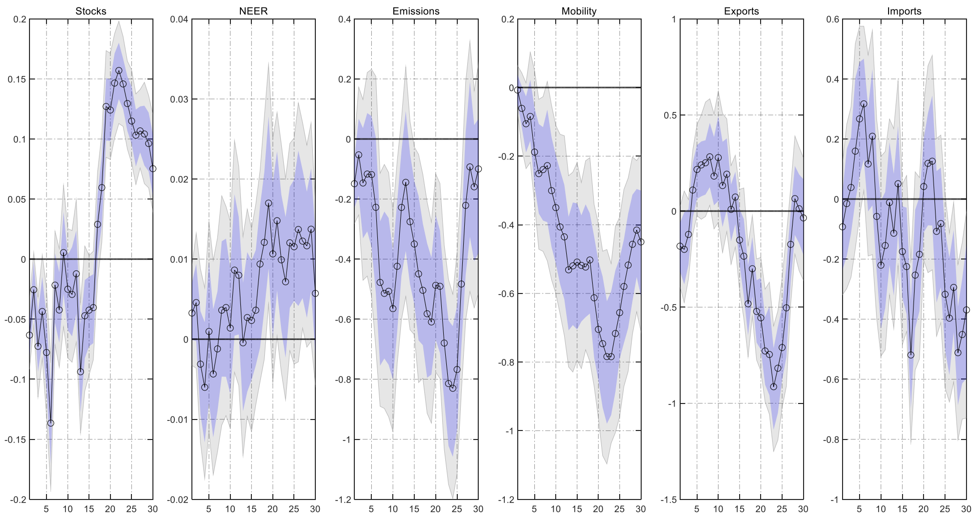
Notes: The figure shows the estimated $\beta_h^{interact}$ from panel local projections for all countries as a function of h (black, circled line), i.e. the coefficient on the interaction term between the foreign lockdown shock and the dummy for the export share. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 27: Response to foreign lockdown shock (mobility included in the derivation of shocks)



Notes: The figure shows the estimated β_h^{for} from panel local projections for all countries as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The shocks are derived from a first-stage regression including measures of personal mobility. The light (dark) blue areas are 90% (68%) confidence bands constructed from Driscoll-Kraay standard errors.

Figure 28: Response to foreign lockdown shock (mean group estimator)



Notes: The figure shows the estimated β_h^{for} from panel local projections with the mean group estimator for all countries as a function of h (black, circled line), i.e. the response to a domestic lockdown shock. The light (dark) blue areas are 90% (68%) bootstrapped confidence bands.