Online Appendix to 'Disentangling Covid-19, Economic Mobility, and Containment Policy Shocks'

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A Data

This section describes the data. All data refer to the calendar daily frequency and are downloaded through Macrobond. The countries in the analysis are Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Colombia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Russia, Saudi Arabia, Slovenia, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Arab Emirates, United Kingdom and United States.

Variable	**Definition, transformation, original source, mnemonic**
Containment policy index	Unweighted average of containment and closure policy indices of the Oxford COVID-19 Government Response Tracker, which systematically collects information on several different common policy responses that governments have taken to respond to the pandemic, source University of Oxford, logarithm. *Record closings of schools and universities*, Ordinal scale, 0 - No Measures 1 - Recommend Not Leaving House 2 - Require Not Leaving House with Exceptions for Daily Exercise, Grocery Shopping & Essential Trips 3 - Require Not Leaving House with Minimal Exceptions (E.G. Allowed to Leave Only Once Every Few Days, or Only One Person Can Leave at a Time) No Data - Blank, standardized, oxf_deu_c1, all mnemonics for University of Oxford data are listed for Germany, for other countries just replace *deu* for Macrobond-Oxford country code or click on 'Series list' and than right mouse-click on series and select 'Change region and duplicate...' *Record closings of workplaces*, Ordinal scale, 0 - no measures 1 - recommend closing (or recommend work from home) 2 - require closing (or work from home) for some sectors or categories of workers 3 - require closing (or work from home) for all-but-essential workplaces (eg grocery stores, doctors) Blank - no data, standardized, oxf_deu_c2 *Record cancelling public events*, Ordinal scale, 0 - no measures 1 - recommend cancelling 2 - require cancelling Blank - no data, standardized, oxf_deu_c3 *Record limits on private gatherings*, Ordinal scale, 0 - no restrictions 1 - restrictions on very large gatherings (the limit is above 1000 people) 2 - restrictions on gatherings between 101-1000 people 3 - restrictions on gatherings between 11-100 people 4 - restrictions on gatherings of 10 people or less Blank - no data, standardized, oxf_deu_c4 *Record closing of public transport*, Ordinal scale, 0 - no measures 1 - recommend closing (or significantly reduce volume/route/means of transport available) 2 - require closing (or prohibit most citizens from using it) Blank - no data, standardized, oxf_deu_c5 *Record orders to shelter-in-place and otherwise confine to the home*, Ordinal scale, 0 - no measures 1 - recommend not leaving house 2 - require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips 3 - require not leaving house with minimal exceptions (eg allowed to leave once a week, or only one person can leave at a time, etc) Blank - no data, standardized, oxf_deu_c6 *Record restrictions on internal movement between cities/regions*, Ordinal scale, 0 - no measures 1 - recommend not to travel between regions/cities 2 - internal movement restrictions in place Blank - no data, standardized, oxf_deu_c7
Covid-19 cumulative deaths	Coronavirus Disease (COVID-19) Pandemic, Total Deaths, Aggregate, Stock, World Health Organization, logarithm, *whocovid19_deaths_de*, , all mnemonics for WHO data are listed for Germany, for other countries just replace *de* with Macrobond-WHO country code
Covid-19 cumulative cases	Coronavirus Disease (COVID-19) Pandemic, Confirmed Cases, Aggregate, Stock, Confirmed cases include both laboratory confirmed and clinically diagnosed cases, World Health Organization, logarithm, *whocovid19_de*
Total tests	Novel Coronavirus (COVID-19), Total Tests Performed, source: Our World in Data, logarithm, *owidtestcovid_de*, for other countries replace *de* for Macrobond-Our World in Data country code

Economic mobility index	Unweighted average of economic activity related mobility indices. These show how visits and length of stay at different places change compared to a baseline. These changes are calculated using the same kind of aggregated and anonymized data used to show popular times for places in Google Maps. Changes for each day are compared to a baseline value for that day of the week. The baseline is the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. The data start on February 15, 2020. We set earlier observations to zero in line with the baseline for computing the changes afterwards, source Google *Mobility, Workplaces*, Length of Stay, The Whole Country, Compared to Baseline. Mobility trends for places of work. 7-day trailing moving average, *googledemo1571*, all mnemonics for Google Mobility data are listed for Germany, for other countries just replace the numeric country code (first 2 of the 4 digits) toward the end of the Macrobond mnemonic *Mobility, Transit Stations*, Length of Stay, The Whole Country, Compared to Baseline. Mobility trends for places like public transport hubs such as subway, bus, and train stations. 7-day trailing moving average, *googledemo1570* *Mobility, Retail & Recreation*, Length of Stay, The Whole Country, Compared to Baseline. Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. 7-day trailing moving average, *googledemo1567*
Real GDP	World Bank, Global Economic Monitor, Gross Domestic Product, SA, constant USD, *denygdpmktpsakdgemquar*, the mnemonics for World Bank data are for Germany, for other countries just replace *de* at the start of the mnemonic for the respective Macrobond-World Bank country code
Unemployment rate	World Bank, Global Economic Monitor, Unemployment, Rate in %, *deunempsagemmonth*
Stock prices small firms	Equity Indices, MSCI, Small Cap, Index, Total Return, Local Currency, source MSCI, logarithm, *msci_106214g* , for other countries replace the last 2 of the 6 digits with the Macrobond-MSCI country code
Stock prices large firms	Equity Indices, MSCI, Large Cap, Index, Total Return, Local Currency, source MSCI, logarithm, *msci_650019g*, for other countries replace the last 2 of the 6 digits with the Macrobond-MSCI country code
Weekly Economic Index	Leading Indicators, Federal Reserve Bank of New York, Weekly Economic Index (WEI), Index, Lewis et al. (2020), *ussurv01117*

B Supplementary material for main model

B.1 Economic mobility and economic activity

This subsection documents a significant and stable relation between economic mobility and economic activity. First, we collect data on real, seasonally adjusted GDP for the 44 countries in the sample. We compute the percentage GDP loss for each quarter 2020Q1-Q3 relative to real GDP in 2019Q4. Furthermore, we average the three mobility indices that enter the economic mobility index (retail, transit stations, and workplaces) within quarter to have the same frequency as the GDP data. Table B.2 shows strong positive correlations of the GDP loss with the mobility indices of 0.67-0.77.

	Retail	Transit stations	Workplace	Economic mobility
GDP loss	0.67	0.72	0.68	0.77

Table B.2: Correlation between real GDP loss and economic mobility indices.

Table B.3 shows that these positive relations are also highly significant. The R^2s are between 0.45 for the retail mobility index and 0.60 for the aggregate economic mobility index. All the coefficients on the mobility indices are statistically significant at the 1% level. The index for workplace mobility has the highest association, with point estimate of 0.36. The point estimate for the aggregate economic mobility index of 0.34 implies that one percentage point less economic mobility is associated with a real GDP loss of 0.34%.

Dependent variable:	GDP loss			
Retail mobility	0.23			
	(0.02)			
Transit stations mobility		0.26		
		(0.02)		
Workplace mobility			0.36	
			(0.03)	
Economic mobility				0.34
				(0.02)
Constant	0.03	1.75	2.65	3.08
	(0.69)	(0.75)	(0.88)	(0.73)
Observations	131	131	131	131
R^2	0.45	0.51	0.47	0.60

Table B.3: Regression of real GDP loss on mobility indices. *Note:* Standard errors in parentheses.

Table B.4 shows that these relationships are relatively stable over time. We augment the previous regressions with two interaction variables that multiply the mobility indices, one at a time, with dummy variables for 2020Q2 and 2020Q3. While the baseline coefficient on the level of each index remains significant at the 5% level in all cases, none of the interaction variables are significant at that level. This suggests that the relationship between the GDP loss and the mobility indices is stable in the sample, despite a likely shift to work from home and e-commerce during the pandemic.

Dependent variable:	GDP loss			
Explanatory:	Retail	Transit	Workplace	Econ. mobility
Level	0.14	0.16	0.12	0.18
	(0.07)	(0.07)	(0.08)	(0.08)
Level*2020Q2	0.09	0.05	0.18	0.15
	(0.08)	(0.08)	(0.09)	(0.09)
Level*2020Q3	-0.07	-0.03	0.02	-0.02
	(0.08)	(0.08)	(0.11)	(0.09)
Observations	131	131	131	131
R^2	0.64	0.65	0.61	0.69

Table B.4: Regression of real GDP loss on mobility indices and interactions with quarter dummies. *Note:* Standard errors in parentheses.

As an alternative measure of economic activity that is available at the monthly frequency, we collect data on unemployment rates for all countries in the sample. Table B.5

shows that the mobility indices are strongly negatively correlated with the unemployment rate. All point estimates are statistically significant at the 1% level. The point estimate on the aggregate mobility index of –0.05 suggests that, on average, one percentage point less economic mobility is associated with +0.05 percentage points in the unemployment rate.

Dependent variable:	Unemployment rate (in %)			
	(1)	(2)	(3)	(4)
Retail mobility	-0.04			
	(0.01)			
Transit stations mobility		-0.04		
		(0.01)		
Workplace mobility			-0.05	
			(0.01)	
Economic mobility				-0.05
				(0.01)
Constant	6.27	6.21	6.07	6.04
	(0.27)	(0.30)	(0.33)	(0.31)
Observations	369	369	369	369
R^2	0.06	0.05	0.05	0.06

Table B.5: Regression of unemployment rate on mobility indices. *Note:* Standard errors in parentheses.

To assess the stability of the relationship between the unemployment rate and economic mobility over time, we estimate rolling regressions. We use a moving window of three months, which we shift forward by one month. The sample is 2020M1-2020M9. Thus, we use the first quarter 2020 as a reference period. Figure B.1 plots the estimated point estimates (dots) and their 90% confidence intervals (vertical lines). The figure suggests that the elasticity between the unemployment rate and the economic mobility index is relatively stable over time. The confidence intervals all overlap.

As final analyses, we use two activity measures that are available at the weekly and daily frequency, respectively, but only for the U.S. First, we employ the Weekly Economic Index of Lewis et al. (2020) and conduct rolling regressions of this index on the economic mobility index. We use a moving window of 13 weeks, which we shift forward by one week. Figure B.2 shows a positive and mostly statistically significant relationship between the two activity measures throughout the sample. There is a small dip in the point estimate in June 2020, but generally the upper and lower bounds overlap, suggesting that the relation is stable.

Second, we use the Mobility and Engagement Index of Atkinson et al. (2020), which is available at the daily frequency. Figure B.3 shows a strong and highly statistically significant relation between this activity measure and the economic mobility index. The elasticity increases through the sample from 1.9 to 2.4.

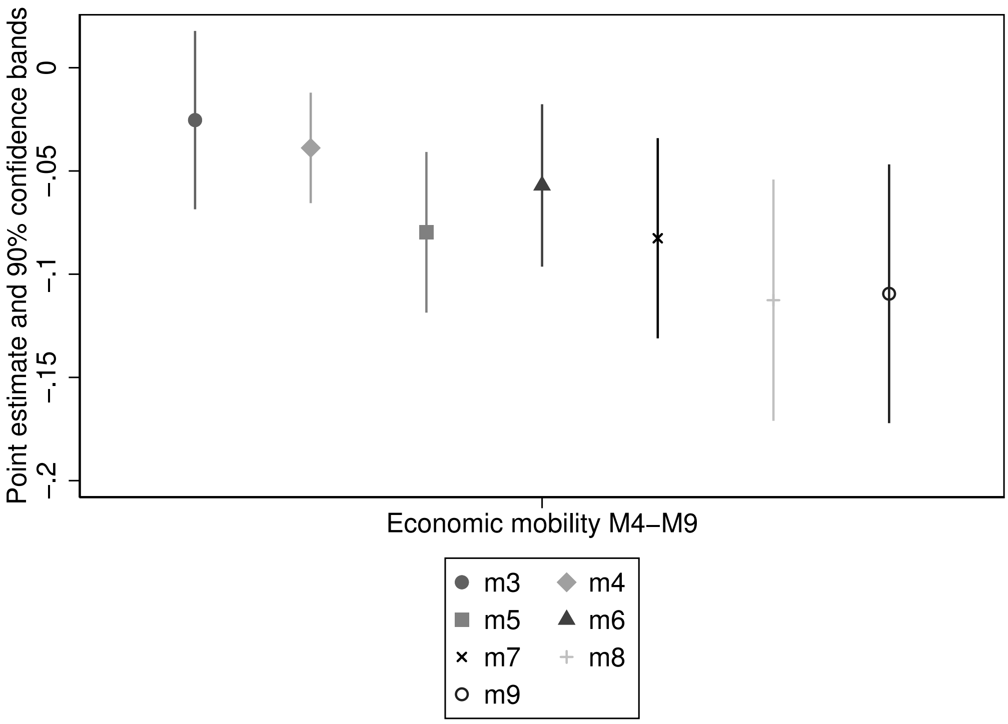

Figure B.1: Rolling regression estimates of unemployment rate on economic mobility. *Notes:* The figure shows the point estimate and the 90% confidence interval for rolling regressions of the unemployment rate on the economic mobility index for the months 2020M1-2020M9 with window of 3 months and step size of 1 month.

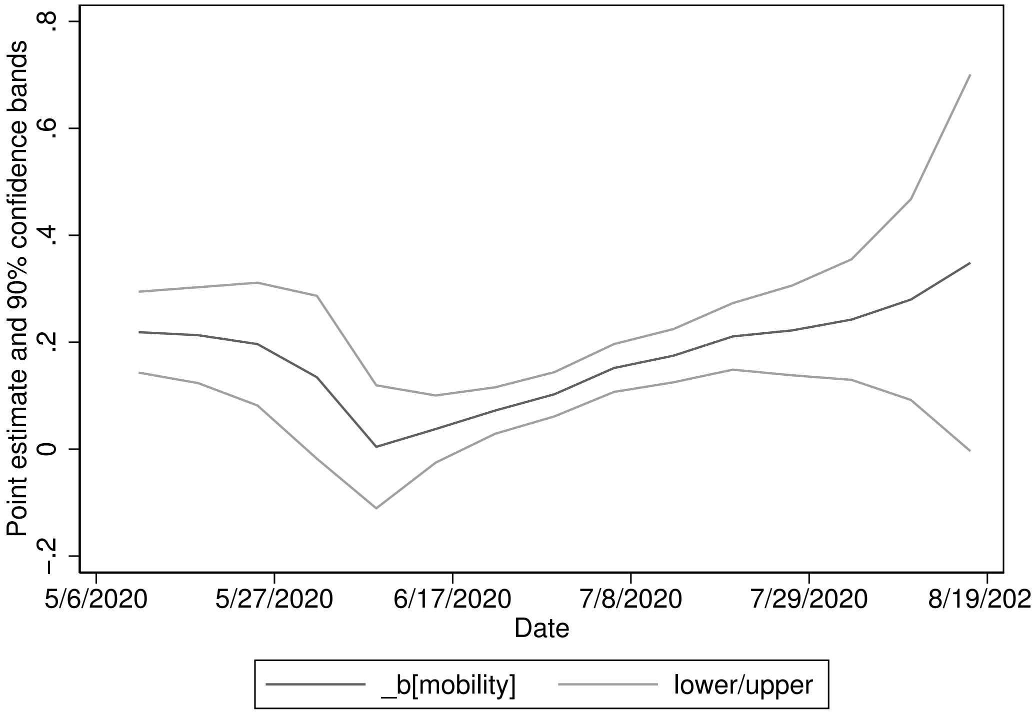

Figure B.2: Rolling regression estimates of Weekly Economic Index on economic mobility index. *Notes:* The figure shows the point estimate and the 90% confidence interval from rolling regressions of the Weekly Economic Index on the economic mobility index for the weeks 2020W1-2020W28 with moving window of 13 weeks and step size of 1 week.

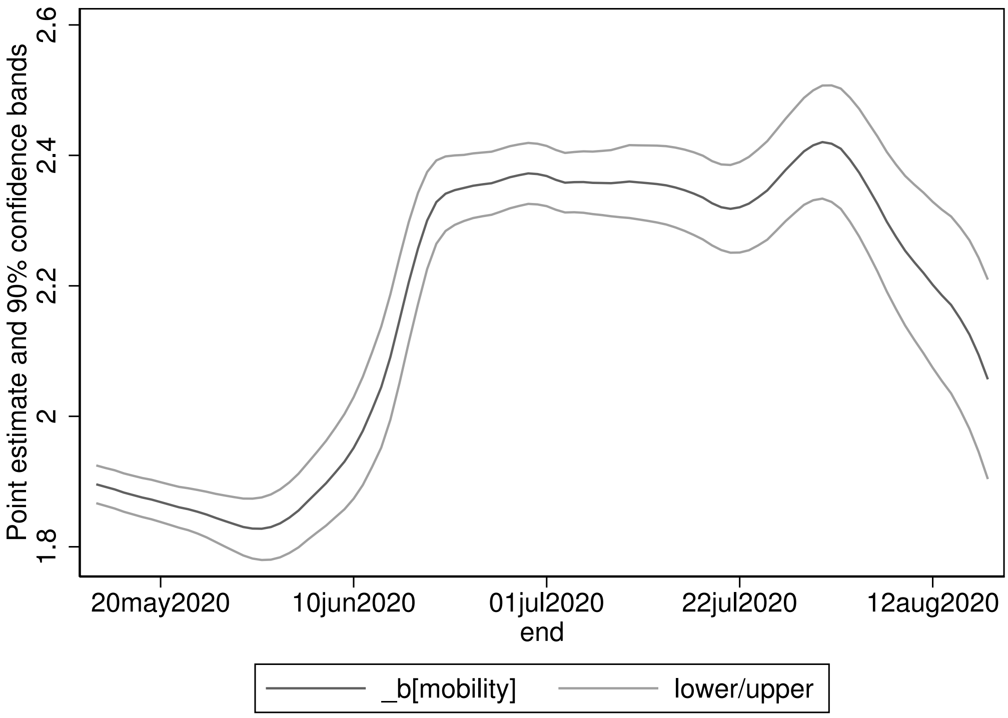

Figure B.3: Rolling regression estimates of Mobility and Engagement Index on economic mobility index. *Notes:* The figure shows the point estimate and the 90% confidence interval from rolling regressions of the Mobility and Engagement Index on the economic mobility index over the sample February 14, 2020 until August 19, 2020 with moving window of 90 days and step size of 1 day.

B.2 Algorithm

Stacking the model in equation (2) over T time periods gives

$$\mathbf{Y} = \mathbf{A}\mathbf{X} + \mathbf{U} \tag{1}$$

with $Y = (\mathbf{Y}_1, \ldots, \mathbf{Y}_T)$, $\mathbf{X} = (\mathbf{X}_1, \ldots, \mathbf{X}_T)$ and $\mathbf{U} = (\mathbf{U}_1, \ldots, \mathbf{U}_T)$. The posterior distribution of Σ is given by

$$\begin{aligned} \Sigma|\mathbf{Y} &\sim \mathcal{IW}(\bar{S}, \bar{s}) \\ \bar{S} &= S_0 + (\mathbf{Y} - \mathbf{A}\mathbf{X})(\mathbf{Y} - \mathbf{A}\mathbf{X})' \\ \bar{s} &= NT + s_0 \end{aligned} \tag{2}$$

where the prior distributions is $\Sigma \sim \mathcal{IW}(S_0, s_0)$. The posterior of $\mathbf{A}$ is normal:

$$\begin{aligned} \text{vec}(\mathbf{A})|\Sigma, \mathbf{Y} &\sim \mathcal{N}(\bar{\mu}, \bar{V}) \\ \bar{\mu} &= \bar{V}^{-1}\left[(\mathbf{X} \otimes \Sigma^{-1})\text{vec}(\mathbf{Y})\right] \\ \bar{V} &= \left[V_0^{-1} + (\mathbf{X}\mathbf{X}' \otimes \Sigma^{-1})\right]^{-1} \end{aligned} \tag{3}$$

with prior distribution $\text{vec}(\mathbf{A}) \sim \mathcal{N}(\mathbf{0}_{K(Kp+N+M)}, V_0)$. We chose the following prior parameters: $S_0 = I, s_0 = K$, and $V_0 = 10I$.

To obtain draws of Σ, $\mathbf{A}$ and $\mathbf{Q}$ from the uniform-normal-inverse-Wishart posterior conditional on the traditional sign and narrative sign restrictions, we use the algorithm of Antolín-Díaz and Rubio-Ramírez (2018). The algorithm has the following steps:

Step 1 Draw Σ and $\mathbf{A}$ from the posterior distributions given in equations (2) and (3).

Step 2 Draw an orthogonal matrix $\mathbf{Q}$ that satisfies the exclusion restrictions with the following steps for each $j = 1, \ldots, K$:

Step 2.1 Draw x_j from a standard normal distribution and set $\tilde{x}_j = x_j / \|x_j\|$

Step 2.2 Set $q_j = K_j \tilde{x}_j$ where K_j is a matrix whose columns form an orthonormal basis of the null space of the matrix $M_j = (q_1, \ldots, q_{j-1}, \mathbf{L})'$. Set $\mathbf{Q} = (q_1, \ldots, q_K)$.

Step 3 Calculate the structural parameters $(\mathbf{B}_0, \mathbf{B})$ by $\mathbf{B}_0 = (\text{chol}(\Sigma)\mathbf{Q})^{-1}$ and $\mathbf{B} = \mathbf{B}_0\mathbf{A}$. Re-calculate $\mathbf{L}$ with $L_0\mathbf{Q}$.

Step 4 If $(\mathbf{B}_0, \mathbf{B})$ satisfy the sign restrictions $S_j\mathbf{L}e_j > 0$ for $j = 1, \ldots, K$ and the narrative sign restrictions $e_j'\boldsymbol{\epsilon}_{lt} > 0$ or $e_j'\boldsymbol{\epsilon}_{lt} < 0$ for $l \in C_j^r$, $t \in T_j^r$, compute an importance weight, w, by

Step 4a Simulate *ndraws*=5000 independent draws of $\boldsymbol{\epsilon}_{it}$ and check whether the narrative sign restrictions are satisfied.

Step 4b Calculate the weight w as 1/proportion of *ndraws* that satisfy the restriction.

Otherwise, discard the draw.

Step 5 Repeat Step 1 to 4 until the required number of draws is obtained.

Step 6 Re-sample with replacement the required number of draws using the importance weights and calculate the impulse response functions for each draw based on $\mathbf{B}, \mathbf{Q}$ and Σ.

B.3 Robust prior

Sampling $\mathbf{Q}$ introduces a second source of randomness purely due to the random number generator as opposed to sampling uncertainty driven by the finite number of observations. The prior on $\mathbf{Q}$ is not agnostic in all dimensions as shown by Baumeister and Hamilton (2015, 2018, 2020). The prior distribution on the rotation matrix $\mathbf{Q}$ can be informative for the posterior inference. This prior on the structural parameters given the reduced form parameters is not updated by the data. Giacomini and Kitagawa (2021) suggest to specify for set identified models multiple prior distributions on the structural parameters given one prior on the reduced form parameters. This robust prior approach of Giacomini and Kitagawa (2021) thus avoids specifying a specific pior on the rotation matrix. To capture the induced information of this class of priors, they suggest to report additionally to the standard posterior inference the lower and upper bounds of posterior means of the object of interest (in our cases the impulse response functions) using multiple priors on $\mathbf{Q}$. To obtain these bounds we extend our algorithm by an additional step following the suggested Algorithm 2 in Giacomini and Kitagawa (2021) and Algorithm 1 in Giacomini, Kitagawa and Read (2021):

Step 4.1 Repeat Step 2 to Step 4 until M draws of $\mathbf{Q}$ are obtained.

We then calculate the lower and upper bounds of the identified set for each reduced form draw as the minimum and maximum impulse responses of all $\mathbf{Q}$ draws. The posterior medians of the bounds are given by the average of the bounds over all draws from the reduced form. We set M to 100 which leaves us with 225 accepted draws. If we do not obtain a $\mathbf{Q}$ draw after 1,000,000 repetitions that satisfies the identifying restrictions, we discard the reduced form draw. We stick to the relative small number of M due to the computational time needed.

Figure B.4 shows the responses to incidence, mobility and containment policy shocks using multiple prior distributions implemented as outlined for narrative sign restrictions in

Giacomini et al. (2021). The solid lines give the median response of the baseline model, the dashed-dotted lines are the lower and upper bounds of the set of posterior median responses. The lower and upper bounds are closely in line with the 90% reported credible set. In general, if the median response based on one uniform prior is significantly positive (negative) also the lower and upper bounds are positive (negative). Thus, choosing an uniform prior for $\mathbf{Q}$ increases the uncertainty but does not seem to have a great impact on the main findings. However, since the lower and upper bounds are approximated at each draw of the reduced form parameters by a Monte Carlo simulation, relying on a relatively small M leads to an approximation bias (Giacomini and Kitagawa, 2021).

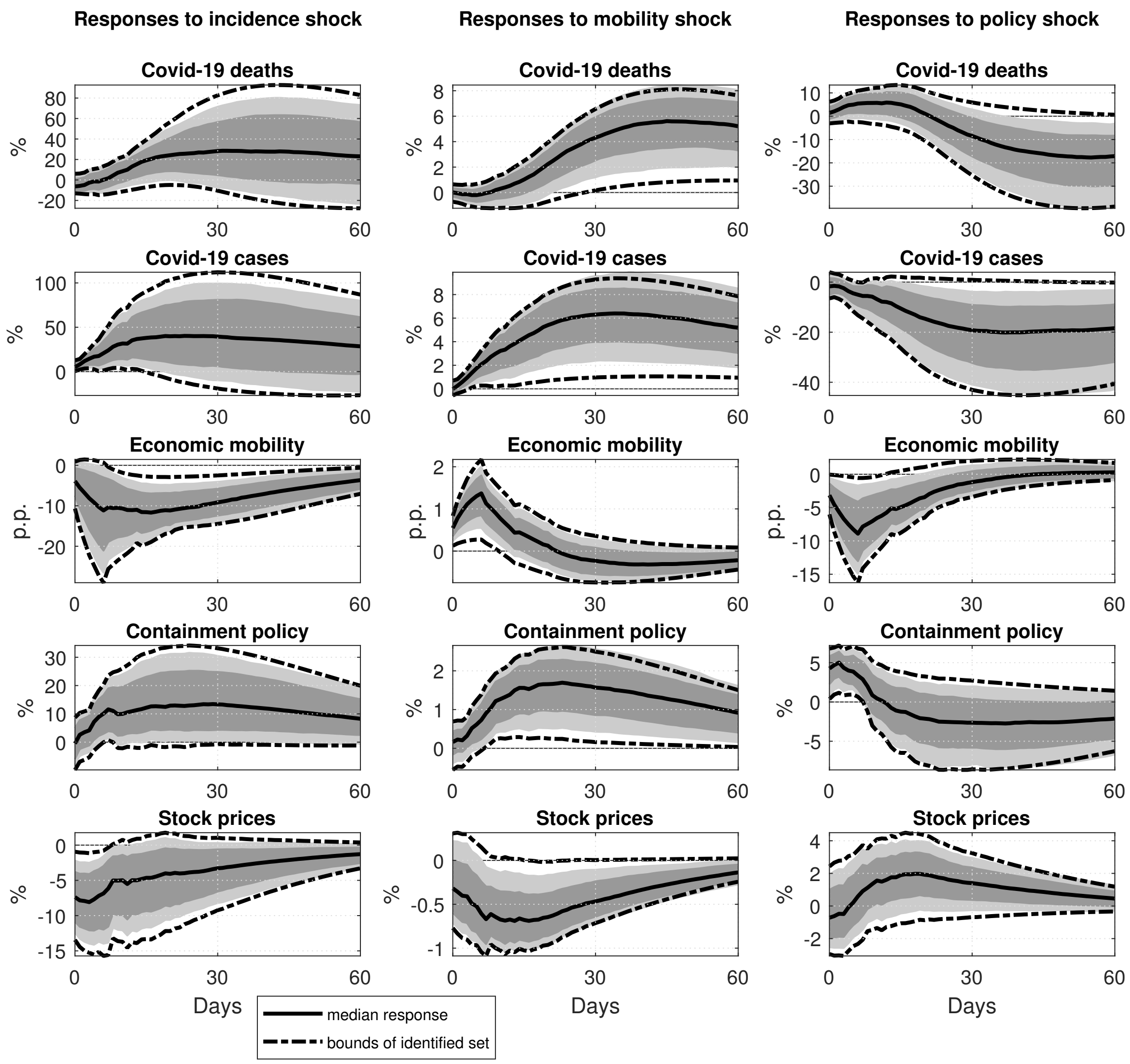

Figure B.4: The dynamic effects of incidence, mobility and containment policy shocks based on robust Bayesian approach. *Notes:* The figure shows the median response of the baseline specification (solid lines) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column), and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas, respectively). The dashed-dotted lines are the lower and upper bound of the identified set (posterior medians). The shocks are normalized to be positive and have size of one standard deviation.

B.4 Comparison identification

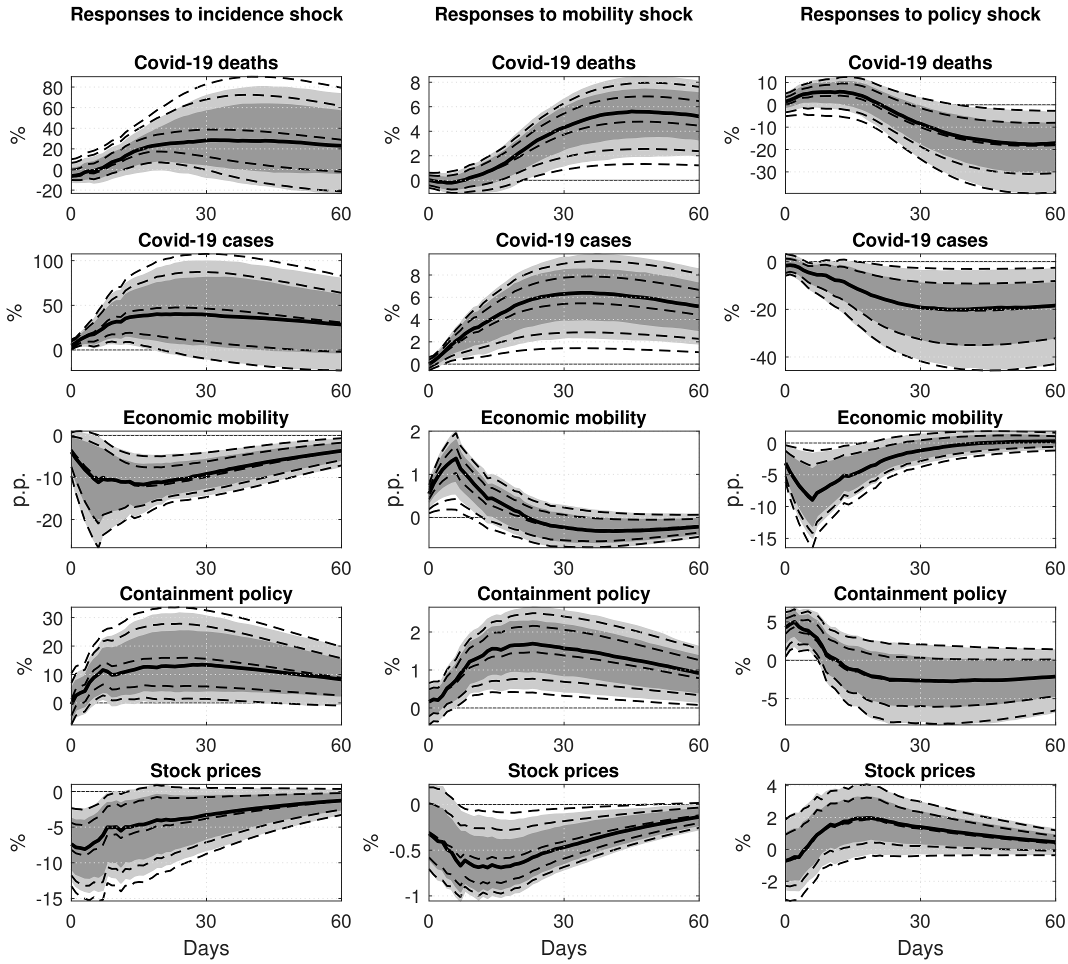

Figure B.5: Comparison of impulse responses for different identification strategies. *Notes:* The figure shows the responses of the endogenous variables (in rows) to an incidence shock (first column), to an economic mobility shock (middle column), and to a containment policy shock (right column) over 60 days. The solid line and the shaded areas refer to the median estimate and 68% and 90% credible sets, respectively, of the baseline model identified with traditional and narrative sign restrictions. The dashed lines refer to a model identified with traditional sign restrictions only, that is, without narrative restrictions. The shocks are normalized to the standard deviation of the shocks in the model identified with both traditional and narrative sign restrictions.

C Supplementary material for alternative models

C.1 Further subgroup analysis

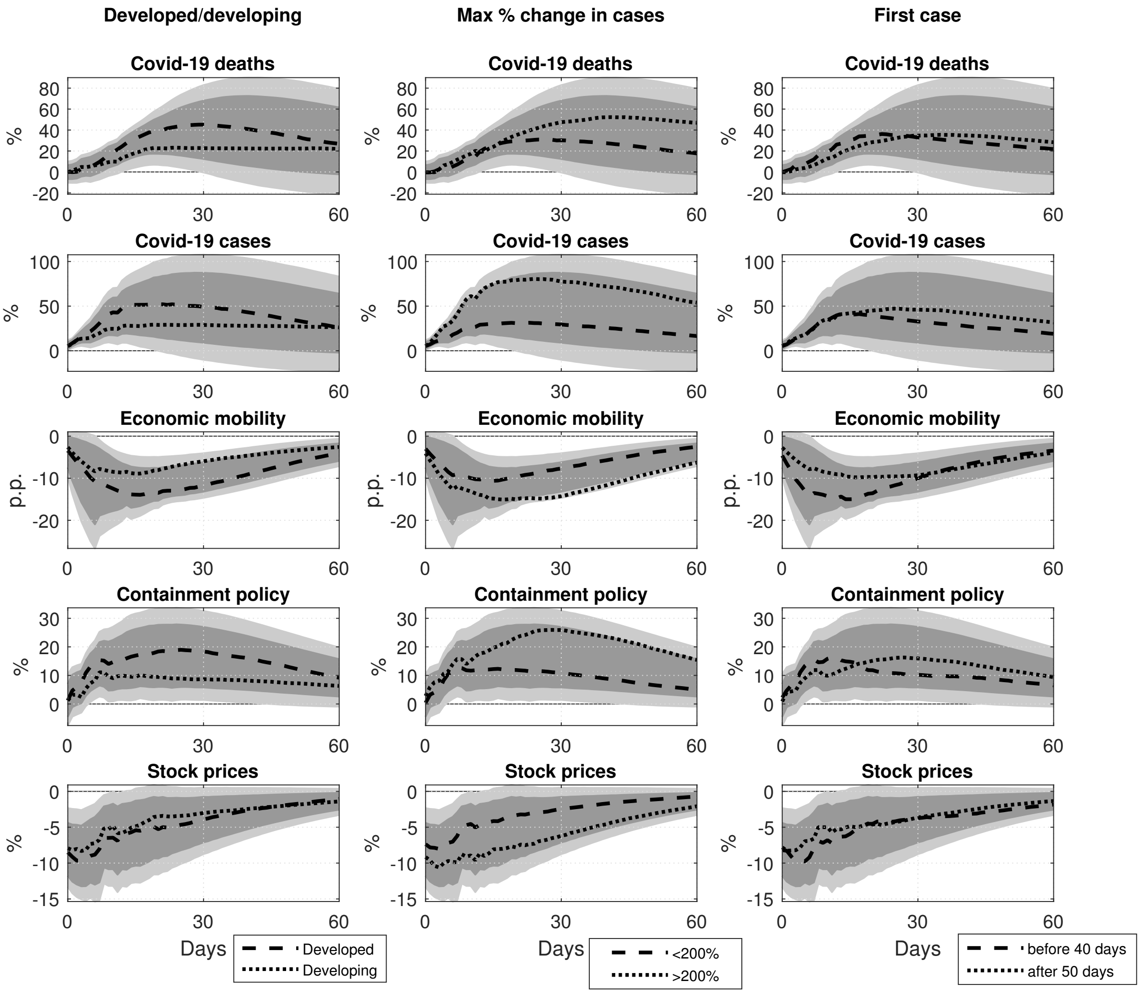

Figure C.6: The effects of incidence shocks in countries grouped by level of development or pandemic timing. *Notes:* The figure shows the median responses of the endogenous variables (in rows) to an incidence shock over 60 days for developed and developing countries (left column), for countries in which the maximum daily increase in cases is $\leq 200\%$ and for those where it is $> 200\%$ (middle column), and for countries where the first case occurs within the first 40 days of the sample and where it occurs after the first 50 days (right column), along with 68% and 90% credible sets of the pooled model (dark and light shaded areas, respectively). The shocks are normalized to the standard deviation of incidence shocks in the baseline specification.

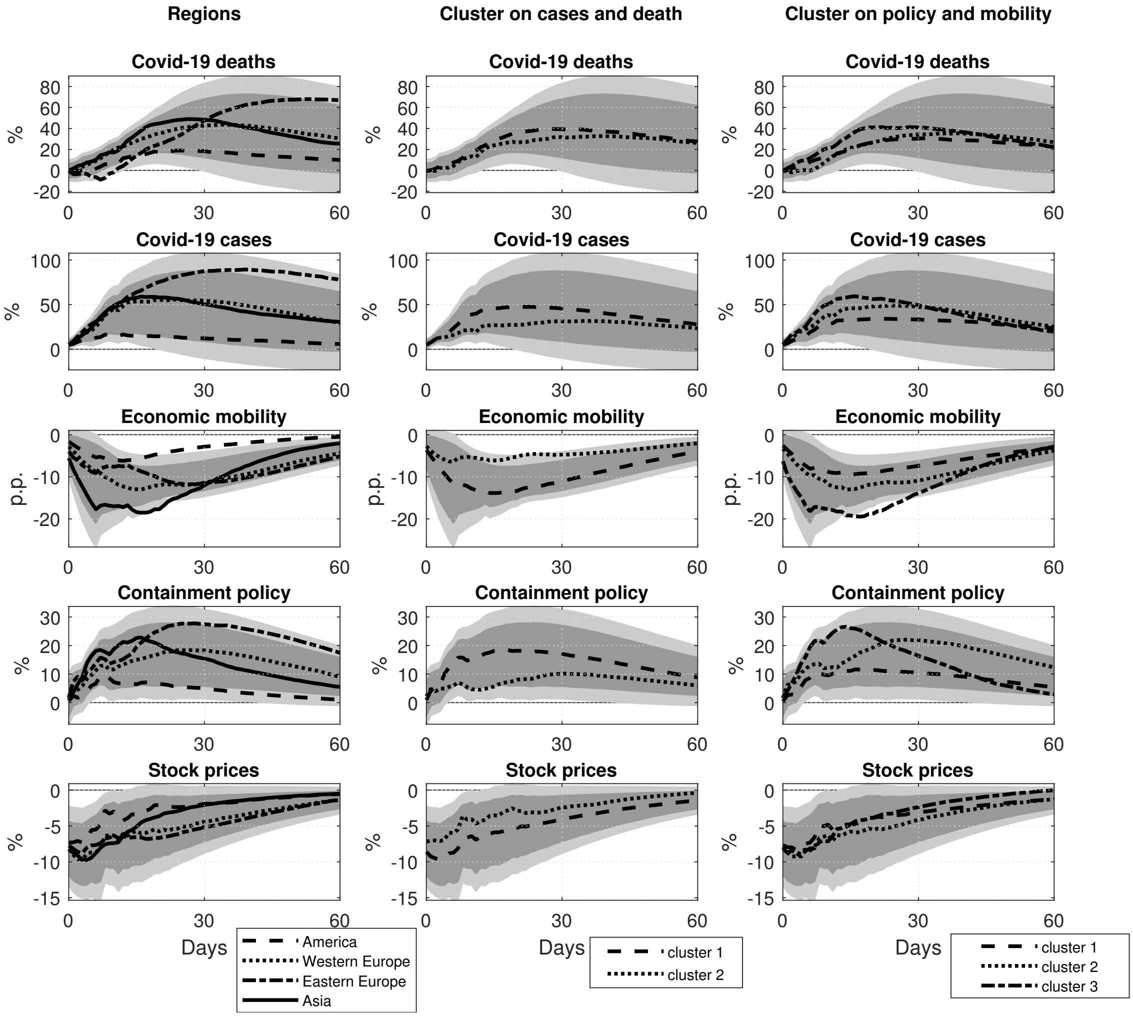

Figure C.7: The effects of incidence shocks for countries grouped by region or severity of pandemic. *Notes:* The figure shows the median responses of the endogenous variables to an incidence shock over 60 days for geographic regions (left column), for countries clustered along the percentage of Covid-19 cases and deaths in the population (middle column), and for countries clustered on the level of the mobility and stringency index at the end of the sample (right column), along with 68% and 90% credible sets of the pooled model (dark and light shaded areas, respectively). The shocks are normalized to the standard deviation of incidence shocks in the baseline specification.

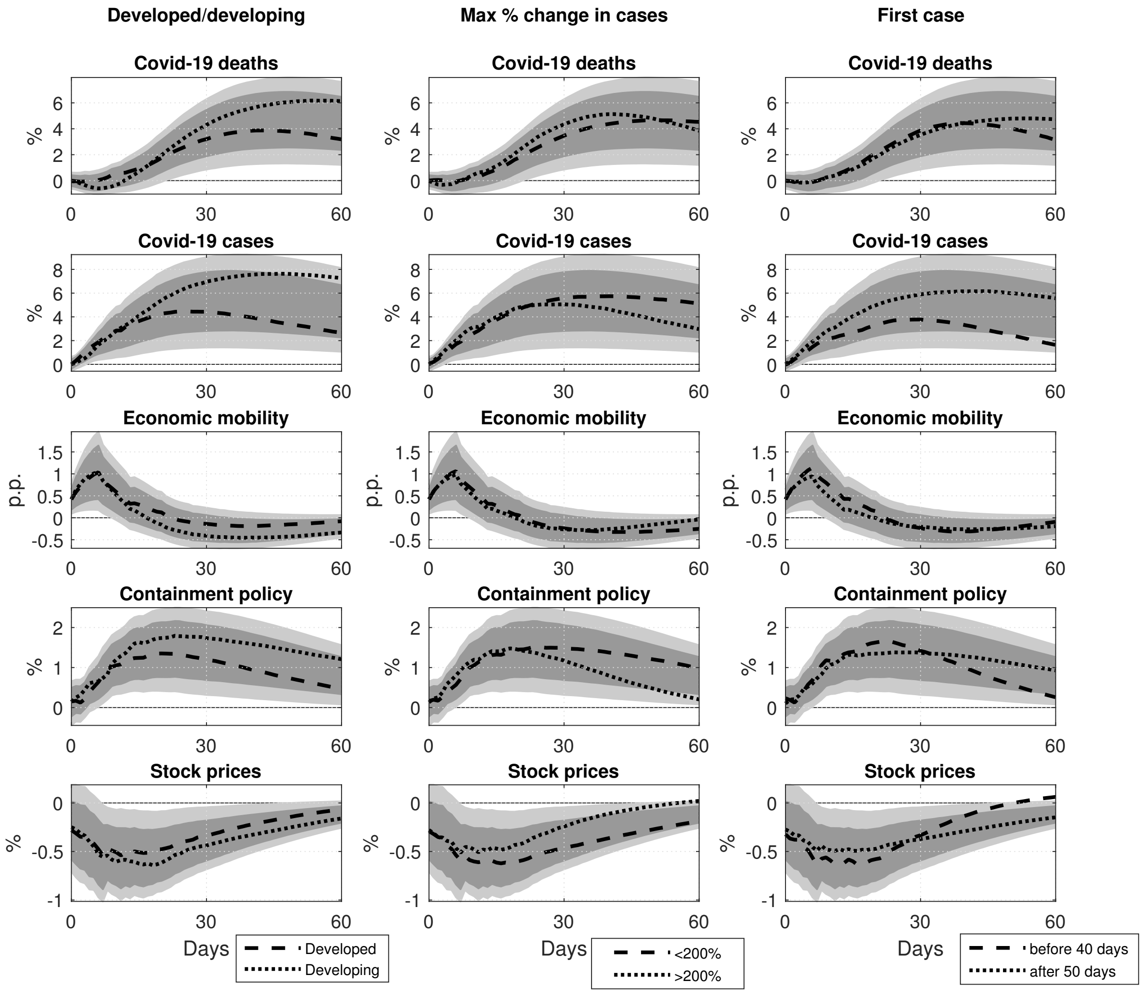

Figure C.8: The effects of economic mobility shocks in countries grouped by level of development or pandemic timing. *Notes:* The figure shows the median responses of the endogenous variables (in rows) to an economic mobility shock over 60 days for developed and developing countries (left column), for countries in which the maximum daily increase in cases is $\leq 200\%$ and for those where it is $> 200\%$ (middle column), and for countries where the first case occurs within the first 40 days of the sample and where it occurs after the first 50 days (right column), along with 68% and 90% credible sets of the pooled model (dark and light shaded areas, respectively). The shocks are normalized to the standard deviation of economic mobility shocks in the baseline specification.

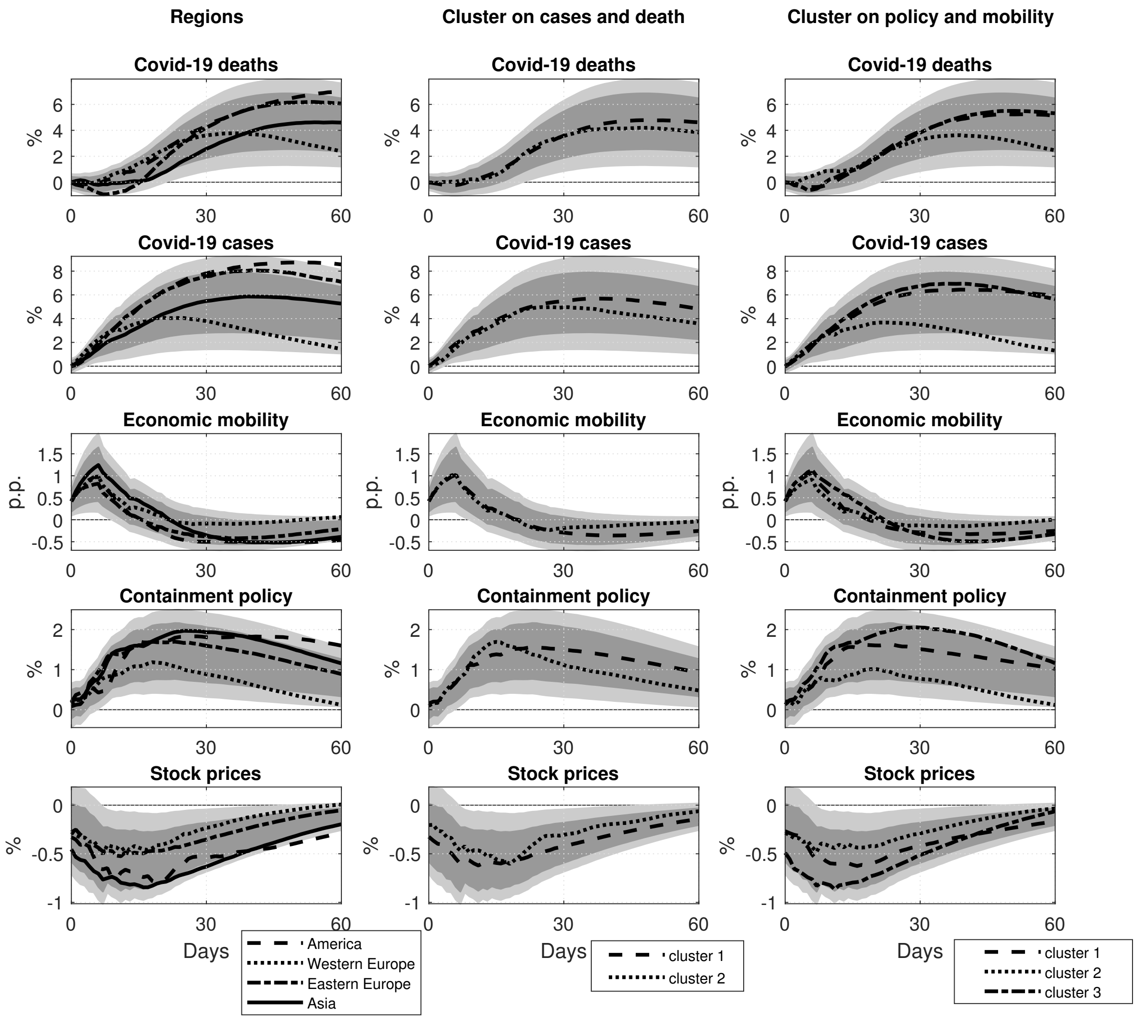

Figure C.9: The effects of economic mobility shocks for countries grouped by region or severity of pandemic. *Notes:* The figure shows the median responses of the endogenous variables to an economic mobility shock over 60 days for geographic regions (left column), for countries clustered along the percentage of Covid-19 cases and deaths in the population (middle column), and for countries clustered on the level of the mobility and stringency index at the end of the sample (right column), along with 68% and 90% credible sets of the pooled model (dark and light shaded areas, respectively). The shocks are normalized to the standard deviation of economic mobility shocks in the baseline specification.

In Figures C.10-C.12, we study whether the effects depend on the level of volatility. We split the data into volatility regimes according to three different criteria. The first two separate the data along the cross-section, the last along the time dimension. In all cases, we standardize the data for comparison. We also estimate a pooled model on the standardized data and show the credible sets as shaded areas in the figures as a reference. In the first column, we sort countries based on the summed median variances of the reduced form errors. We form two volatility groups, splitting the countries at the median summed variance. In the second column, we use k-means clustering based on the variances of all reduced from residuals. The data suggest three volatility clusters, with Taiwan building an own cluster. We attribute it to the high volatility cluster. In the third column, we separate time periods of low and high volatility. We calculate rolling standard deviations of the mean (across countries) reduced form residuals for each variable using a window of 30 days. For each day, we check whether more than three variables have values above the mean standard deviation plus one standard deviation (Rigobon and Sack, 2003). In that case, we classify the day into the high volatility regime, otherwise into the low volatility regime. For each regime, we recompute the reduced form error covariance matrix but use the pooled autoregressive component of the model to avoid breaks in the lag structure. Overall, the effects of the structural shocks are similar across volatility regimes and to the baseline estimates.

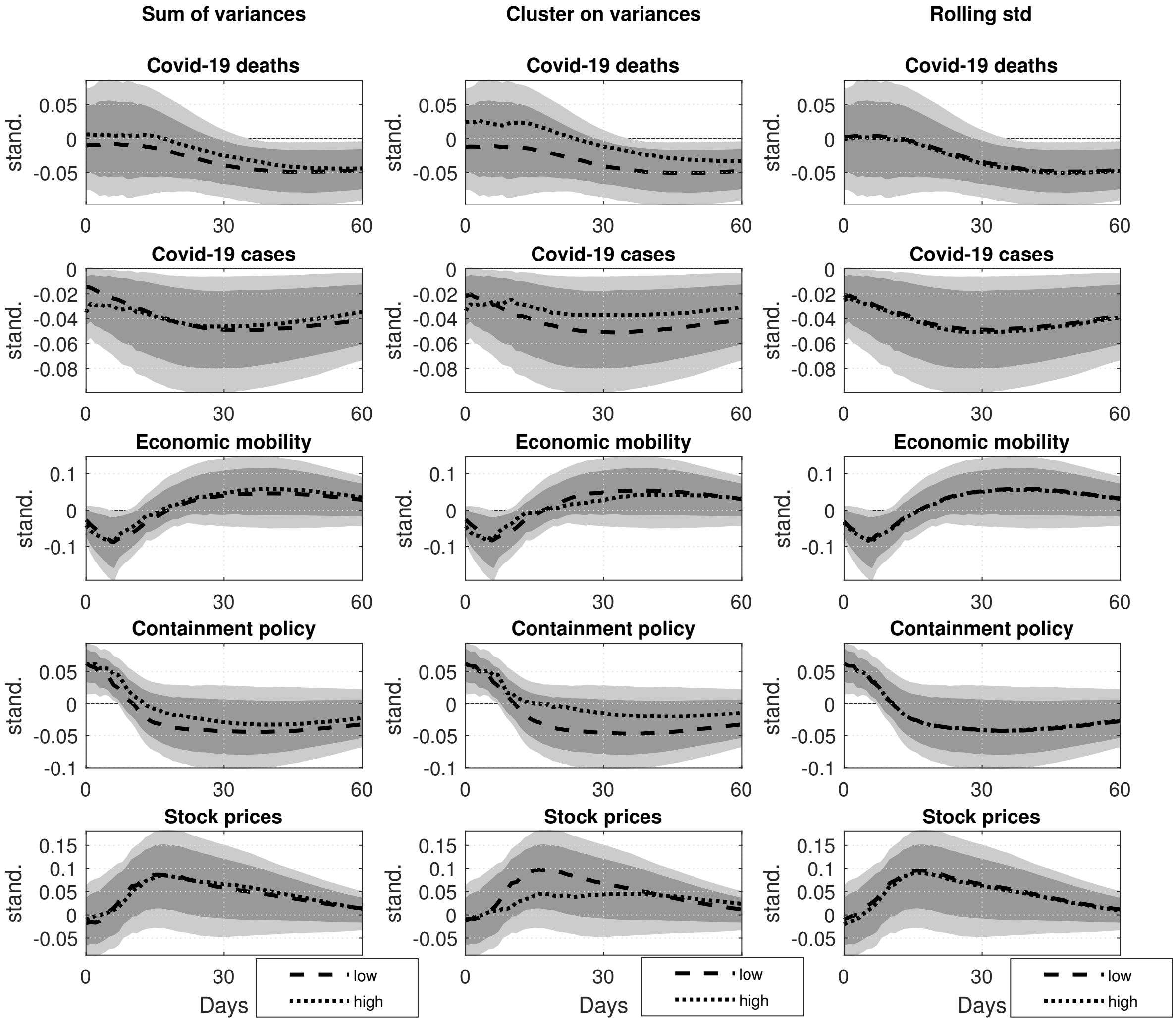

Figure C.10: The effects of containment policy shocks for countries grouped by volatility. *Notes:* The figure shows the median responses of the endogenous variables (in rows) to a containment policy shock over 60 days for low volatility regimes (dashed lines) and high volatility regimes (dotted lines). The grouping is based on the summed variance over all variables (left column), on clustering by the variances of all variables (middle column), on periods split according to the rolling standard deviations of reduced form residuals (right column), along with 68% and 90% credible sets of the pooled model (dark and light shaded areas, respectively). The shocks are normalized to the standard deviation of containment policy shocks in the baseline specification.

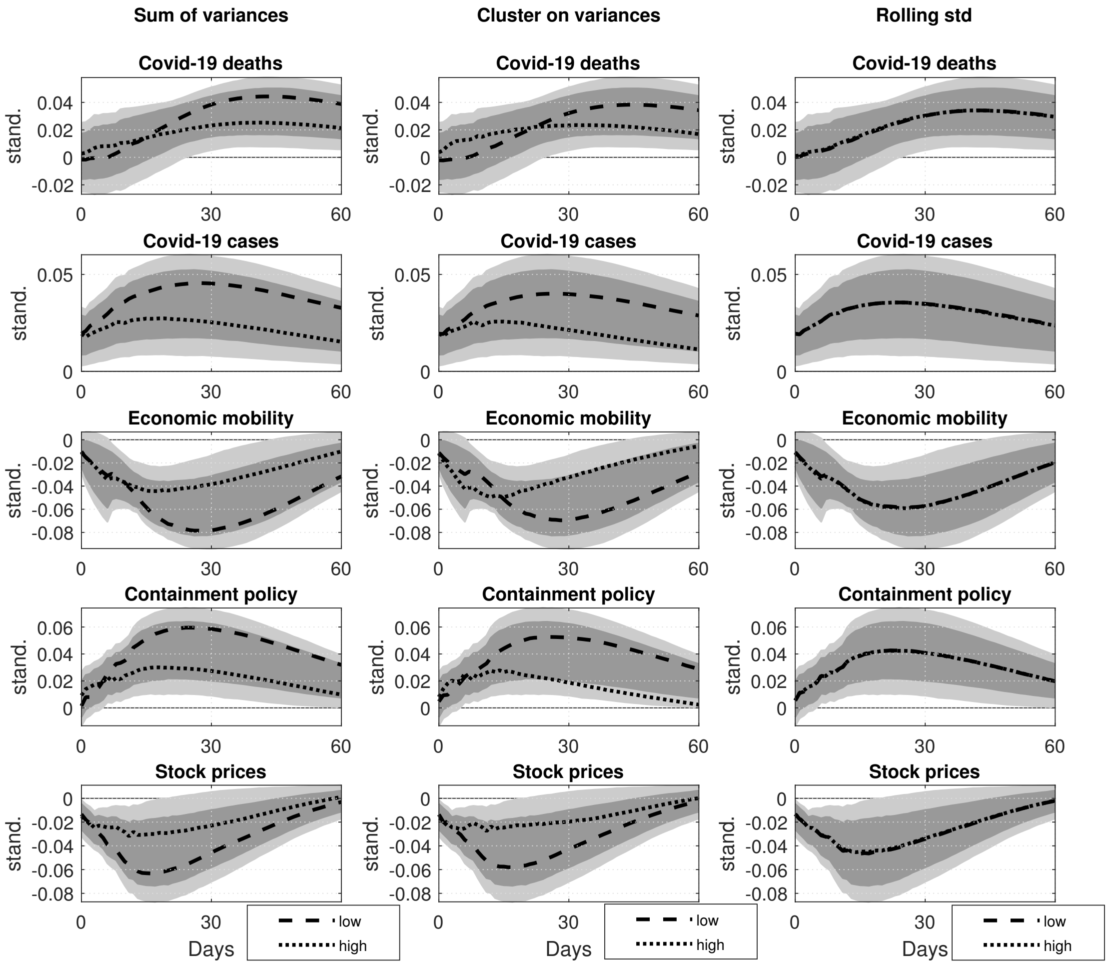

Figure C.11: The effects of incidence shocks for countries grouped by volatility. *Notes:* The figure shows the median responses of the endogenous variables (in rows) to an incidence shock over 60 days for low volatility regimes (dashed lines) and high volatility regimes (dotted lines). The grouping is based on the summed variance over all variables (left column), on clustering by the variances of all variables (middle column), on periods split according to the rolling standard deviations of reduced form residuals (right column), along with 68% and 90% credible sets of the pooled model (dark and light shaded areas, respectively). The shocks are normalized to the standard deviation of incidence shocks in the baseline specification.

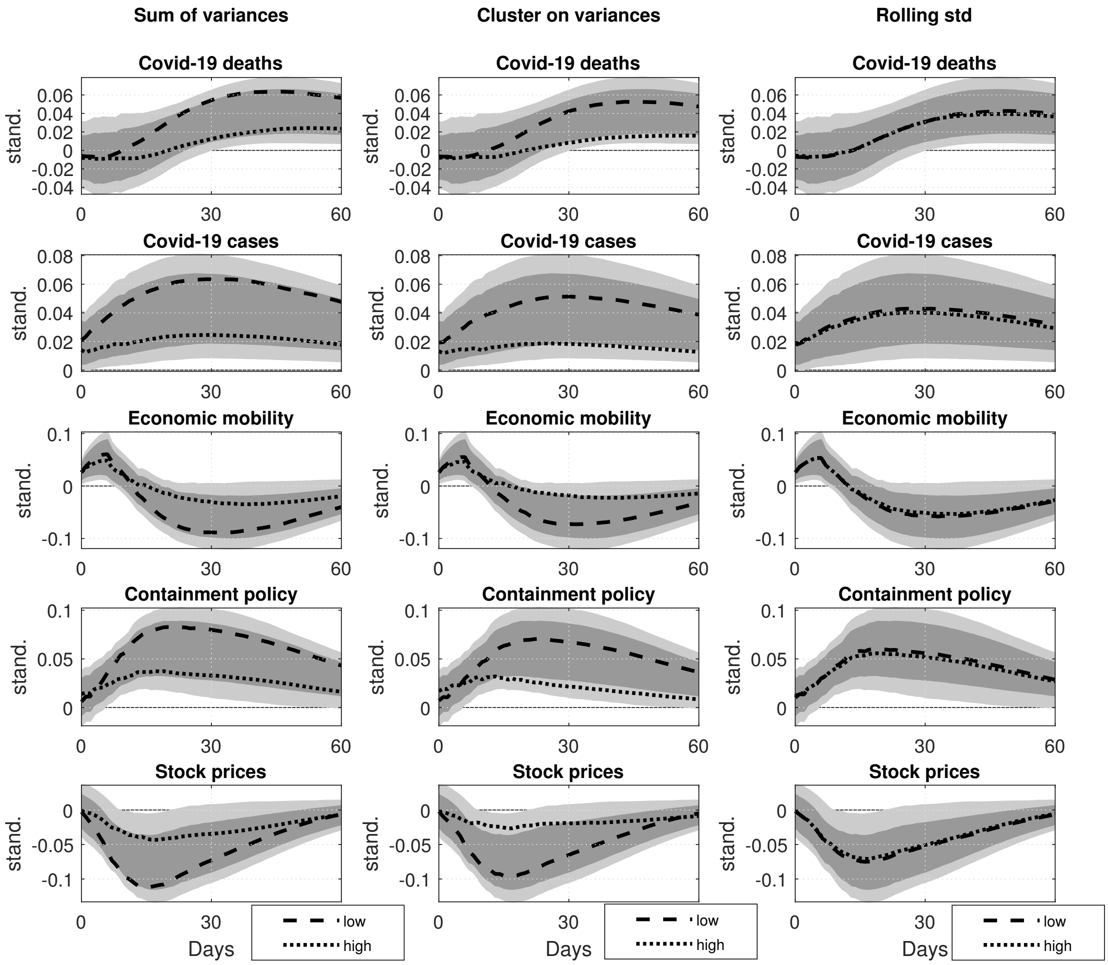

Figure C.12: The effects of economic mobility shocks for countries grouped by volatility. *Notes:* The figure shows the median responses of the endogenous variables (in rows) to an economic mobility shock over 60 days for low volatility regimes (dashed lines) and high volatility regimes (dotted lines). The grouping is based on the summed variance over all variables (left column), on clustering by the variances of all variables (middle column), on periods split according to the rolling standard deviations of reduced form residuals (right column), along with 68% and 90% credible sets of the pooled model (dark and light shaded areas, respectively). The shocks are normalized to the standard deviation of economic mobility shocks in the baseline specification.

C.2 Supplementary material measurement error analysis

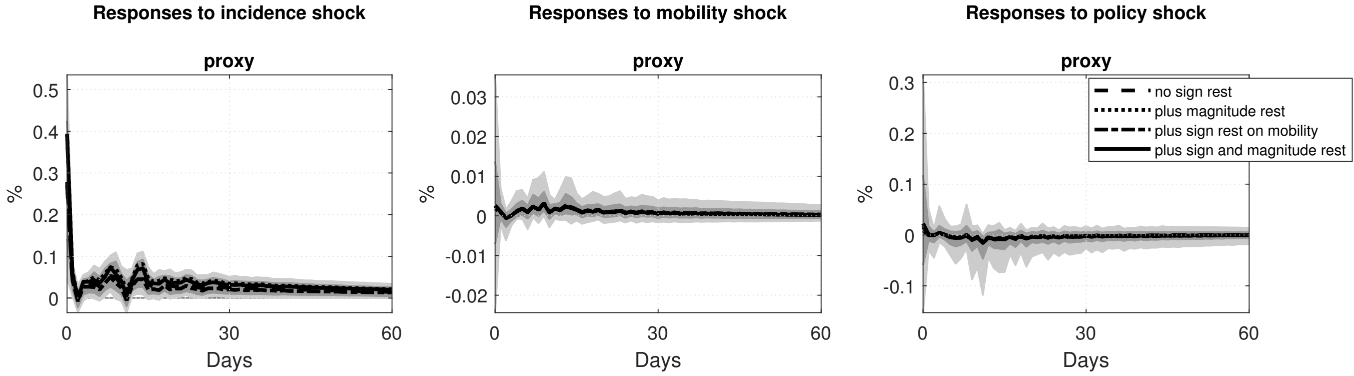

Figure C.13: The response of the proxy to the structural shocks. *Notes:* The figure shows the median responses of the proxy to an incidence shock (left panel), economic mobility shock (middle panel), and containment policy shock (right panel) over 60 days for four different proxy-SVAR models, along with 68% and 90% credible sets.

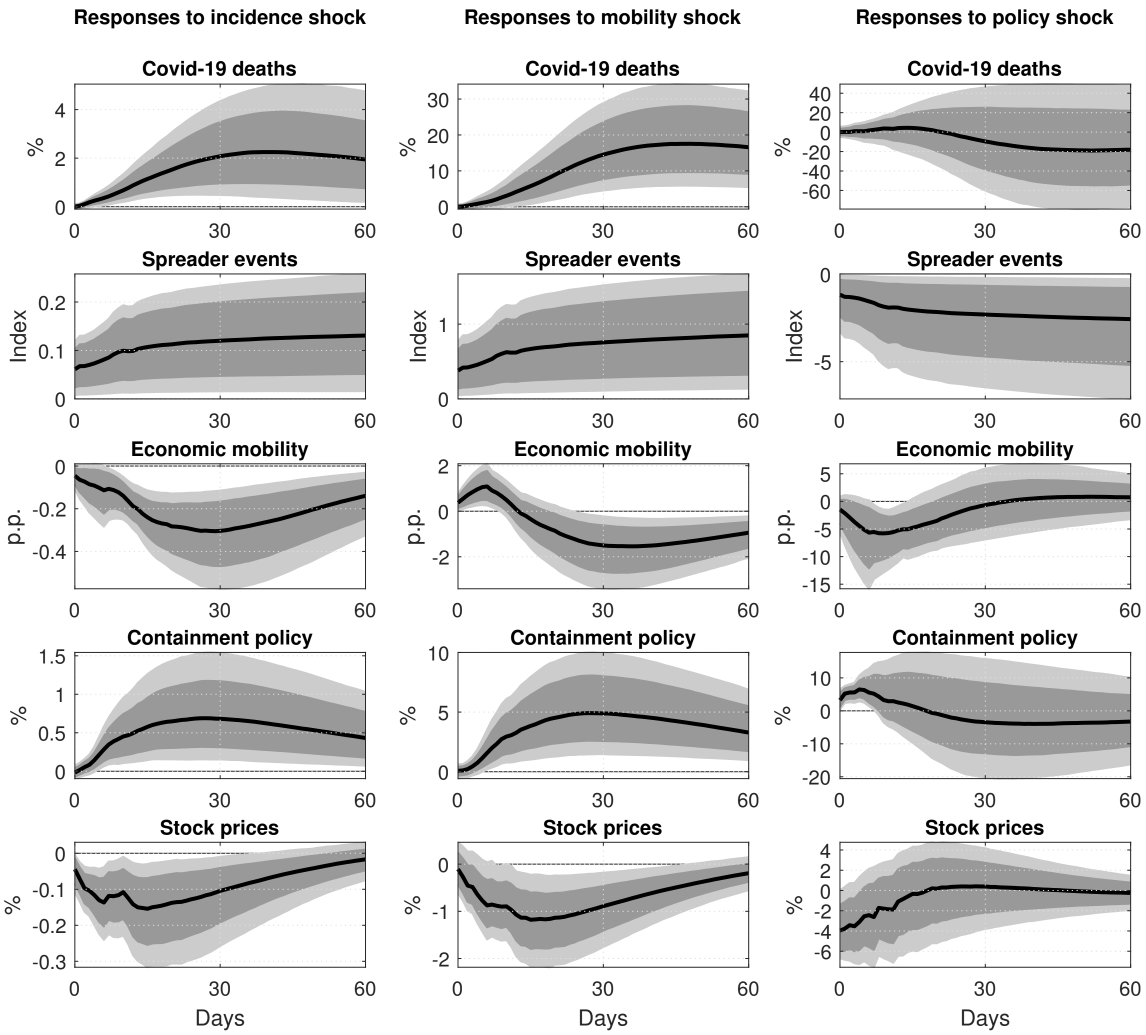

Figure C.14: The dynamic effects of incidence, economic mobility, and containment policy shocks for a model with an indicator variable for Covid-19 cases. *Notes:* The figure shows the median response (solid lines) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column), and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas, respectively). The shocks are normalized to be positive and have size of one standard deviation.

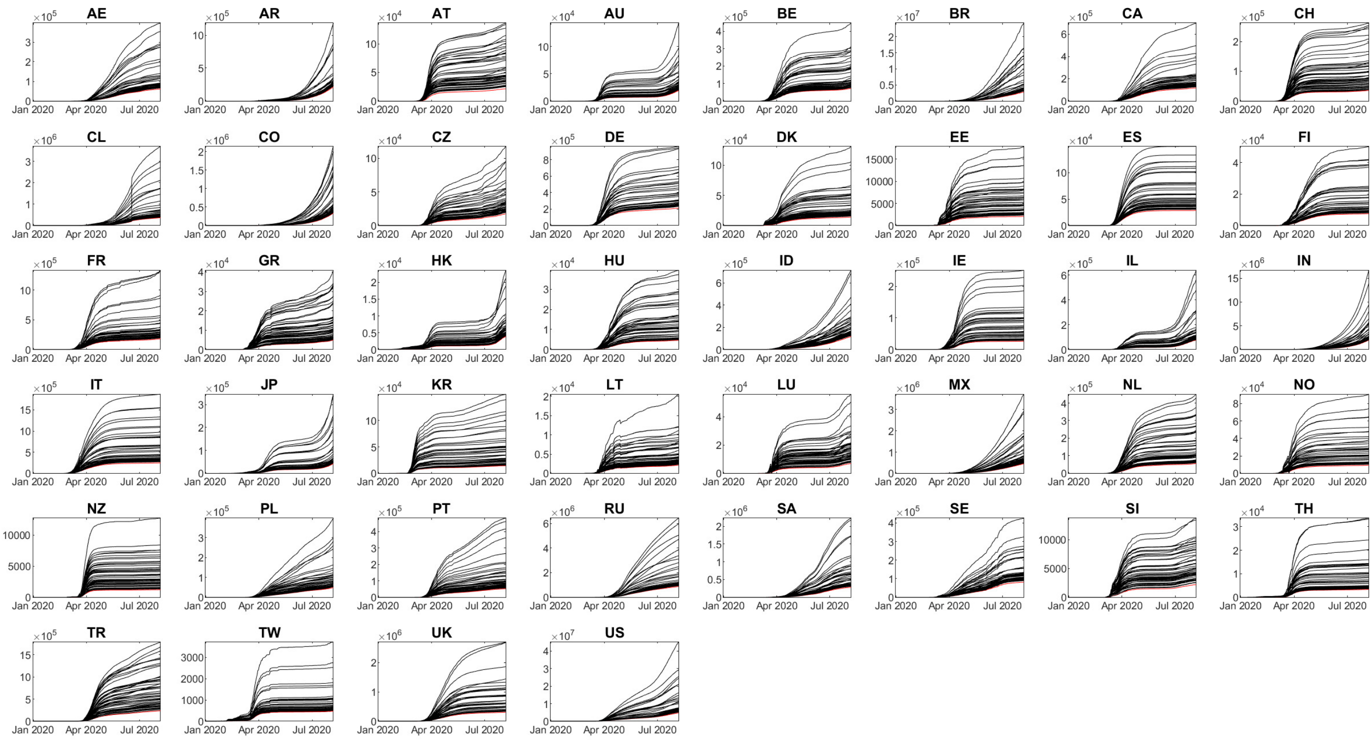

Figure C.15: Simulated data on cumulative cases. *Notes:* The figure shows the 50 simulated time series for cumulative cases for all countries in the sample.

Table C.6: Parameter specifications

	I	II	III	IV	V
μ	$U(0, 0.2)$	$U(0, 0.05)$	$U(0, 0.2)$	$U(0, 0.2)$	$U(0, a_1)$, $a_1 \sim U(0.01, 0.2)$
δ	$Beta(1, 20)$	$Beta(1, 20)$	0.05	$Beta(2, 5)$	$Beta(a_2, a_3)$, $a_2 = 1$, $a_3 \sim U(2, 20)$
v_t	$\mathcal{N}(0, 0.1)$	$\mathcal{N}(0, 0.1)$	$\mathcal{N}(0, 0.1)$	$\mathcal{N}(0, 0.5)$	$\mathcal{N}(0, a_4)$, $1/a_4 \sim G(10, 0.5)$
$\rho_{initial}$	$U(1, 10)$	$U(1, 5)$	$U(1, 10)$	$U(1, 10)$	$U(1, a_5)$, $a_5 \sim U(5, 20)$

We verify the robustness of the simulation results by using four alternative parameter specifications. Table C.6 gives the parameter choices. In the main text, we use specification I. Specification II allows for less misreporting (5%) and lower initial ρ. The latter implies that the true cases are 1 to 6 times higher. We fix δ at 0.05 in specification III. Thus, the persistence decreases over time by the same amount plus the additional randomness through v_t. We allow for a higher variability in the persistence measure in specification IV. We draw δ from a Beta distribution shifted away from zero with mean 0.29. We also specify a larger variance for v_t (0.5). Specification V introduces hierarchical prior distributions for the hyperparameters. We allow for misreporting between zero and 1% to 20%. The persistence parameter δ is drawn from a Beta distribution with parameters 1 and a draw from a uniform distribution ranging from 2 to 20. We allow for additional randomness by drawing the error term v_t from a normal distribution with the precision following a gamma distribution, where the parameters are set such that the mean of the distribution is 0.1. The initial parameter ρ ranges between 1 and 5 to 20. For specification II to V, we occasionally obtain negative values for cases, which we then set to the previous positive value.

The solid lines in Figures C.16-C.19 plot the median impulse responses for the four alternative specifications. The each 50 lines show no remarkable differences across the alternative parameter settings and relative to the baseline estimates.

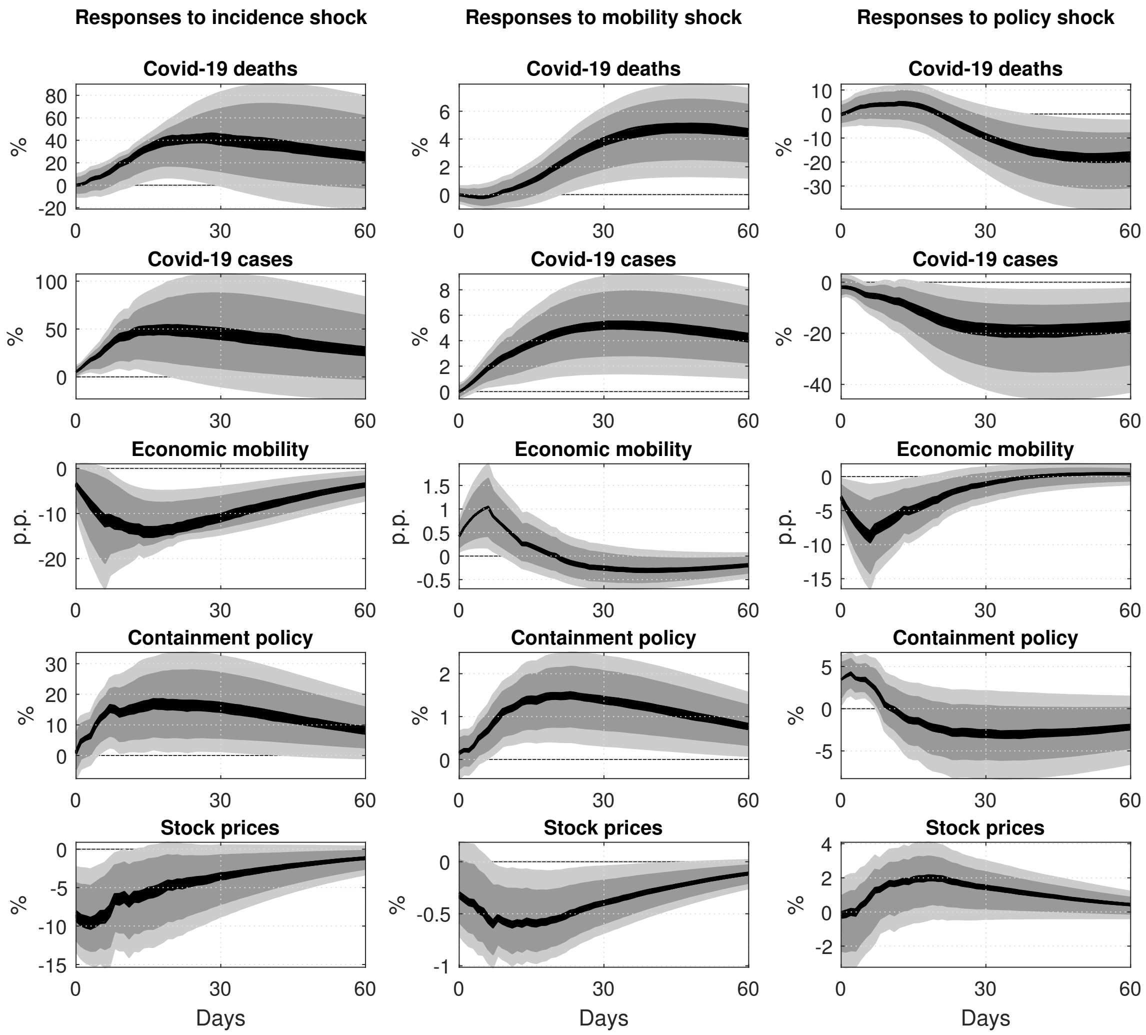

Figure C.16: The dynamic effects of incidence, economic mobility and containment policy shocks using simulated cases data - Specification II. *Notes:* The figure shows the median responses of the endogenous variables to an incidence shock (left column), a mobility shock (middle column), and a containment policy shock (right column) over 60 days for 50 simulated cases data, along with 68% and 90% credible sets of the baseline model (shaded areas). The shocks are standardized to the impact effect on containment policy in the baseline model.

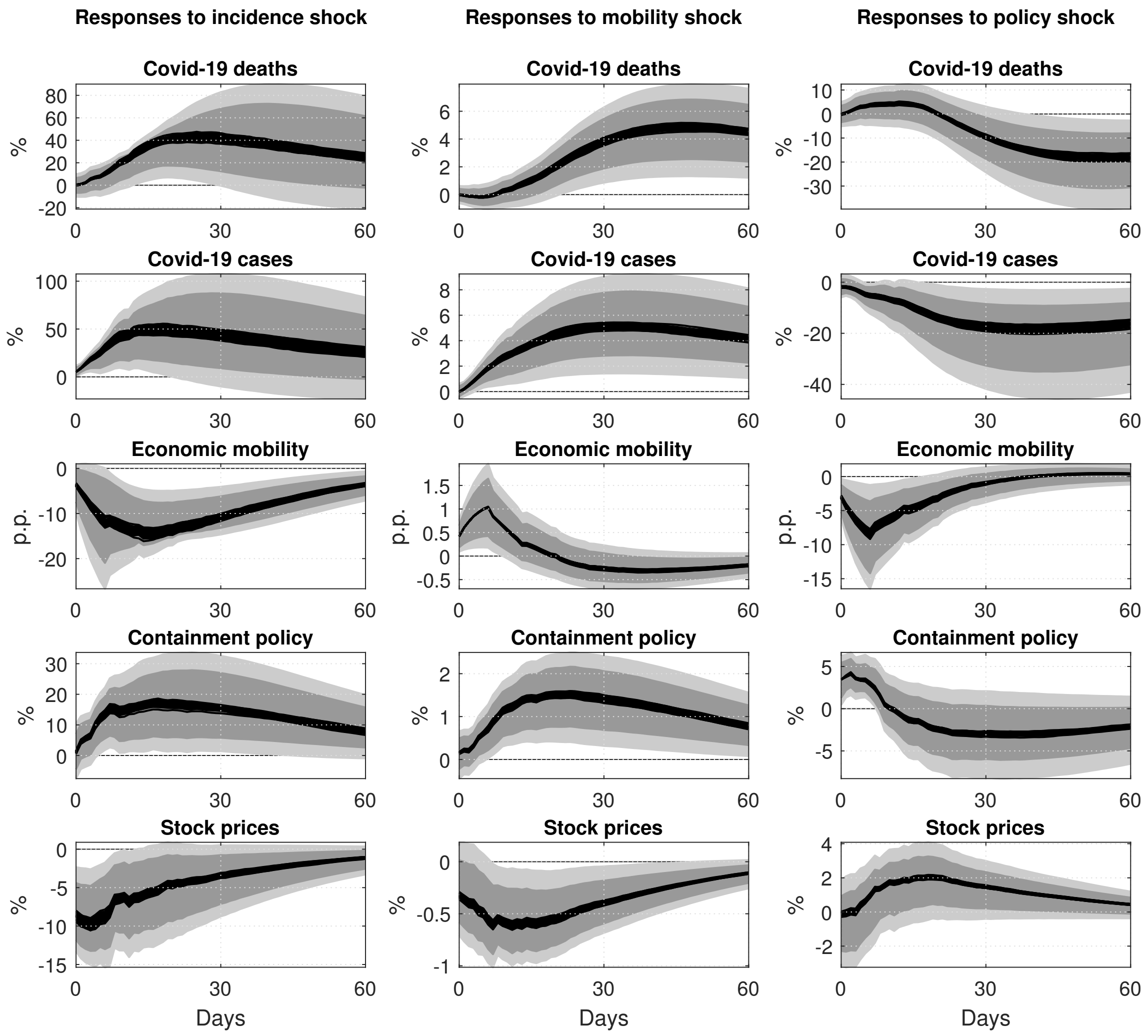

Figure C.17: The dynamic effects of incidence, economic mobility and containment policy shocks using simulated cases data - Specification III. *Notes:* The figure shows the median responses of the endogenous variables to an incidence shock (left column), a mobility shock (middle column), and a containment policy shock (right column) over 60 days for 50 simulated cases data, along with 68% and 90% credible sets of the baseline model (shaded areas). The shocks are standardized to the impact effect on containment policy in the baseline model.

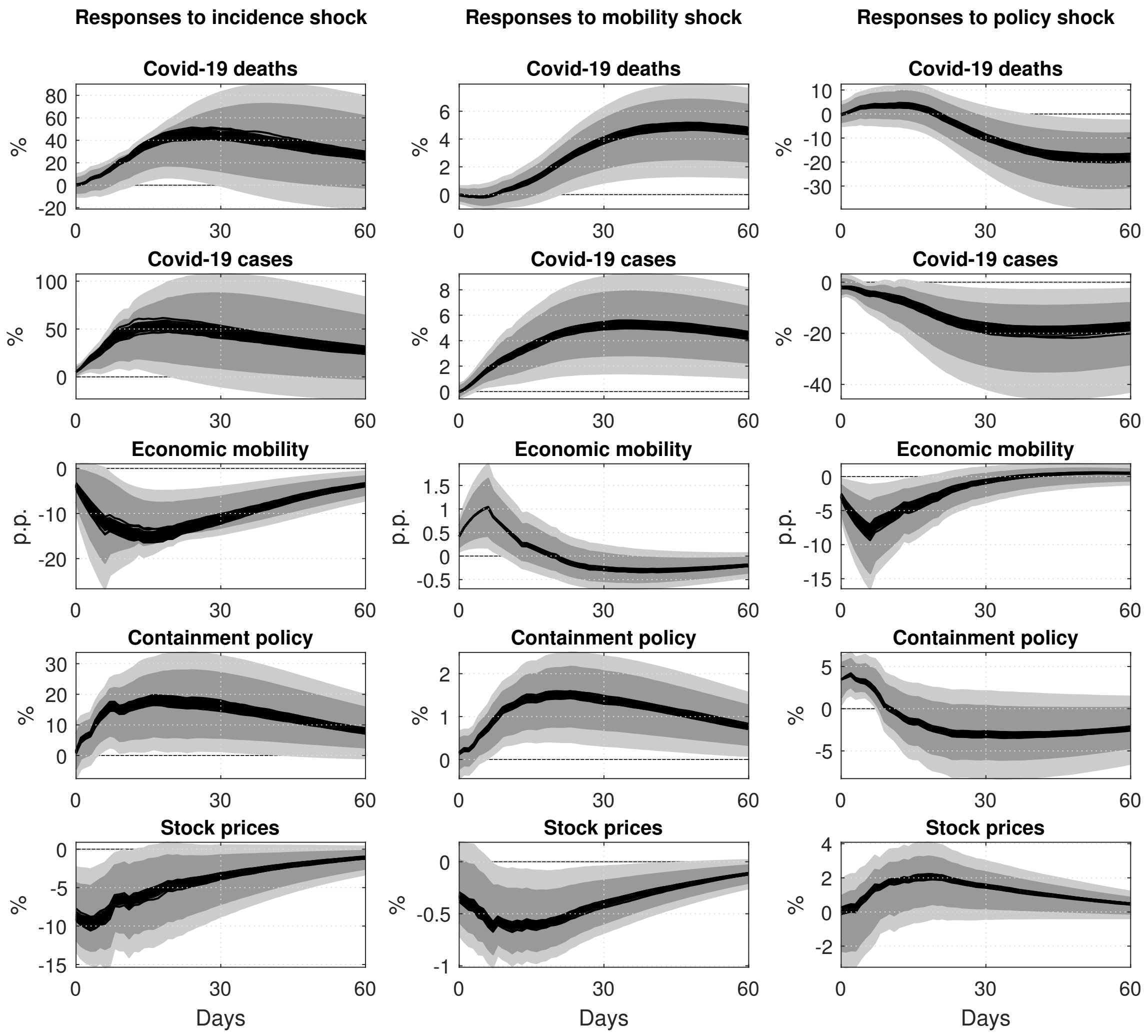

Figure C.18: The dynamic effects of incidence, economic mobility and containment policy shocks using simulated cases data - Specification IV. *Notes:* The figure shows the median responses of the endogenous variables to an incidence shock (left column), a mobility shock (middle column), and a containment policy shock (right column) over 60 days for 50 simulated cases data, along with 68% and 90% credible sets of the baseline model (shaded areas). The shocks are standardized to the impact effect on containment policy in the baseline model.

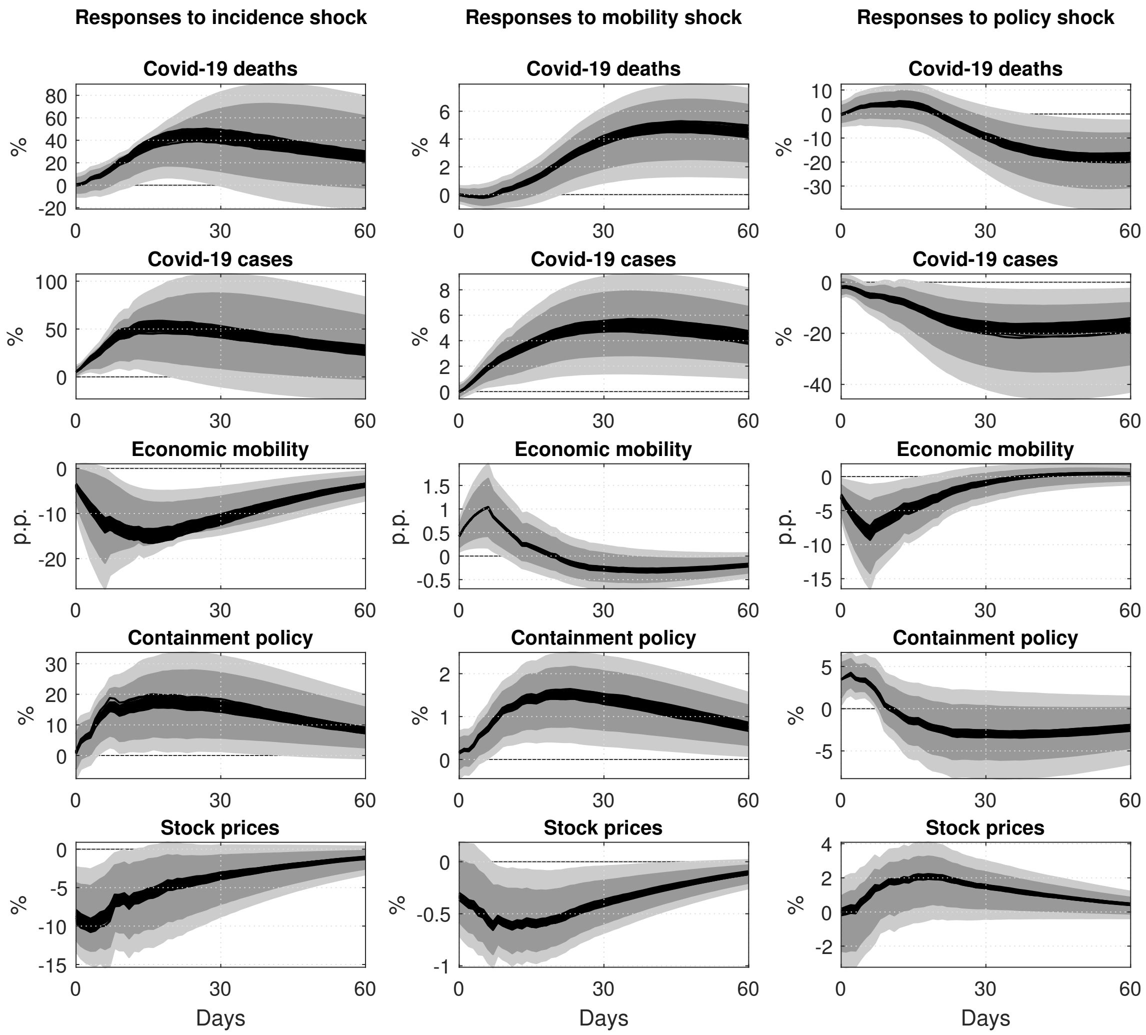

Figure C.19: The dynamic effects of incidence, economic mobility and containment policy shocks using simulated cases data - Specification V. *Notes:* The figure shows the median responses of the endogenous variables to an incidence shock (left column), a mobility shock (middle column), and a containment policy shock (right column) over 60 days for 50 simulated cases data, along with 68% and 90% credible sets of a baseline model (shaded areas). The shocks are standardized to the impact effect on containment policy in the baseline model.

D Further sensitivity tests

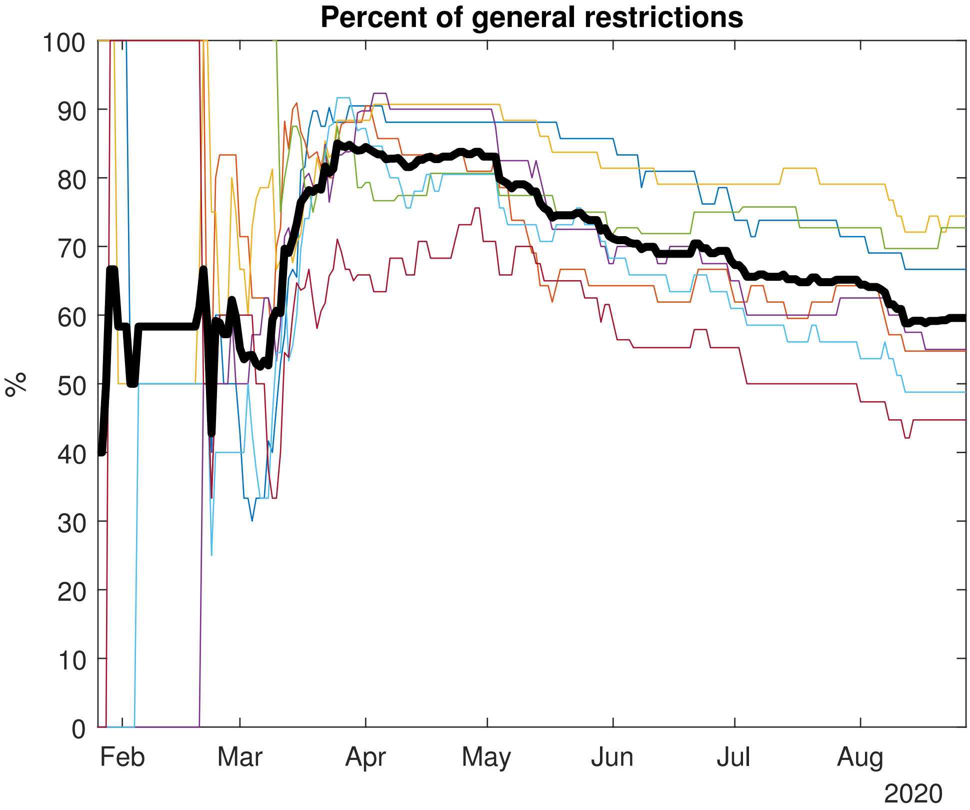

Figure D.20: Percent of general containment policies. *Notes:* The figure shows the mean percent of containment measures that are nation wide for different subindices (thin colored lines) and the mean over these (thick black line).

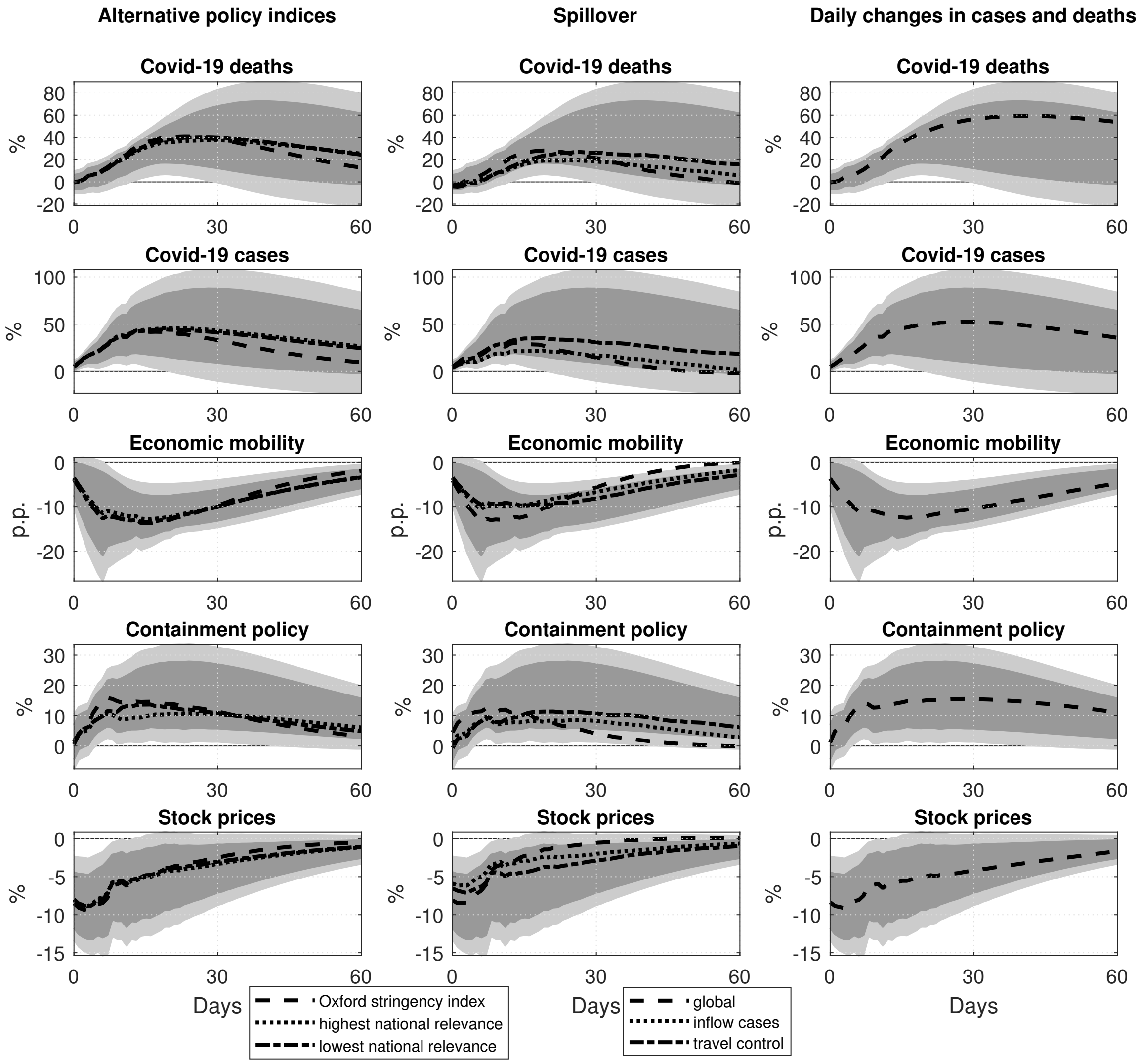

Figure D.21: The effects of incidence shocks using alternative policy indices, spillover variables, and log changes in cases and deaths. *Notes:* The figure shows the median responses of the endogenous variables to a containment policy shock over 60 days for alternative policy indices (left column), for models including spillover variables (middle column), and using log changes in cases and deaths (right column), along with 68% and 90% credible sets of the pooled model (dark and light shaded areas, respectively). The shocks are normalized to the standard deviation of containment policy shocks in the baseline specification.

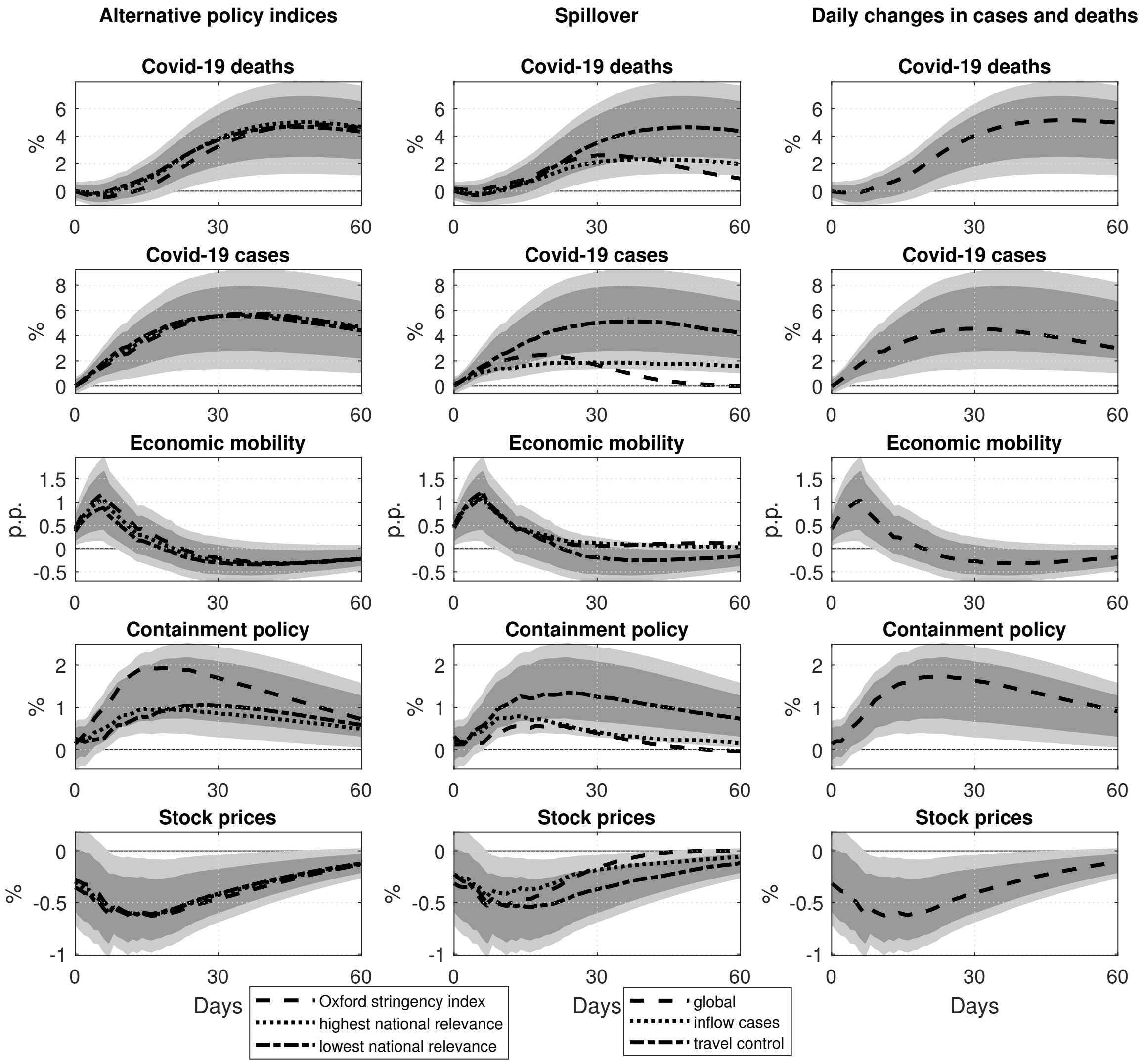

Figure D.22: The effects of mobility shocks using alternative policy indices, spillover variables, and log changes in cases and deaths. *Notes:* The figure shows the median responses of the endogenous variables to a containment policy shock over 60 days for alternative policy indices (left column), for models including spillover variables (middle column), and using log changes in cases and deaths (right column), along with 68% and 90% credible sets of the pooled model (dark and light shaded areas, respectively). The shocks are normalized to the standard deviation of containment policy shocks in the baseline specification.

This section presents further robustness analysis for the baseline model. All graphs below show the impulse responses to positive incidence, economic mobility and containment policy shocks of one standard deviation based on the benchmark specification. Solid lines are the median estimate and shaded areas are the credible sets. In addition, each figure shows the estimates from an alternative specification using dashed lines. We change either the reduced form model or the identification strategy. All in all, the figures show that the main results hold.

First, Figure D.23 shows the impulse response for a model including a linear trend and, second, Figure D.24 including a quadratic trend. Third, Figure D.25 presents the responses for a model including 7 lags. Fourth, Figure D.26 shows results for a model with 21 lags. Fifth, Figure D.27 summarizes the estimates for a model without weekday dummies. Sixth, Figure D.28 shows the impulse responses when using the mobility index for workplaces. Seventh, Figure D.29 gives the impulse response functions for a model including as an alternative measure for stock prices the MSCI large cap indices. This model does not include AT and NZ due to data availability. Eighth, the responses for a model additionally including a variable on total tests performed are given in Figure D.30. We include total tests as last variable.

Figure D.31 shows country-specific responses to incidence, mobility and containment policy shocks. We implement a partial pooling approach allowing for heterogeneity across countries in autoregressive parameters and the error covariance matrices. Similar to Canova and Ciccarelli (2013) and Jarociński (2010), we estimate SVAR models for each country using the following prior specifications for country i:

$$a_i|\Sigma_i, \sigma_v \sim \mathcal{N}(\bar{a}, \Sigma_i \otimes \sigma_v I_{Kp+1+M}), \quad \Sigma_i \sim IW(I_K, K), \quad \sigma_v \sim IG(2, 0.005)$$

where a_i denotes the $(K^2p+K+KM)\times 1$-dimensional vector of country-specific autoregressive coefficients and $\bar{a}$ denotes the $(K^2p+K+KM)\times 1$-dimensional vector of homogeneous autoregressive coefficients estimated with the fixed effect PVAR model. That way we allow for heterogeneity across countries centered around the homogeneous coefficients $\bar{a}$ where σ_v determines the shrinkage towards common coefficients. We use a Gibbs sampler to sample from the following posterior distributions:

$$\begin{aligned}
a_i|Y_i, \Sigma_i, \sigma_v &\sim \mathcal{N}(\tilde{a}, \tilde{V}_a) \\
\tilde{a} &= \tilde{V}_a^{-1}[(X_i X_i \otimes \Sigma_i^{-1}) vec(Y_i) + (1/\sigma_v)\bar{a}] \\
\tilde{V}_a &= [X_i X_i' \otimes \Sigma_i^{-1} + (1/\sigma_v) I]^{-1} \\
\Sigma_i|Y_i, a_i &\sim IW(I_K + (Y_i - A_i X_i)(Y_i - A_i X_i)', K + T) \\
\sigma_v|Y_i, a_i &\sim IG(2 + 0.5(K^2p + K + KM), 0.005 + 0.5 \sum((a_i - \bar{a})(a_i - \bar{a}))
\end{aligned}$$

Details on the posterior distributions can be found in Canova and Ciccarelli (2013) and

Jarociński (2010). The majority of country-specific responses lies within the credible sets of the pooled model. The variation in responses across countries is limited, backing the homogeneity assumption of the baseline model. The response which is almost always outside the credible sets belongs to Columbia. In general, the limited number of observations for the epidemiological variables per country can lead to rather extreme reactions. The responses of the pooled estimator and the average over the country-specific responses are well aligned.

The next specifications alter the identification. Figure D.32 shows the estimates for a model setting restrictions on horizon 0 and 14. Figure D.33 gives the responses for a model with no sign restriction on the reaction of stock prices to incidence shocks. The last three figures presents impulse response functions for a model without restricting the response of containment policy at horizon 7 to incidence shocks, Figure D.34, to mobility shocks, Figure D.35, and to incidence, mobility, and containment policy shocks, Figure D.36.

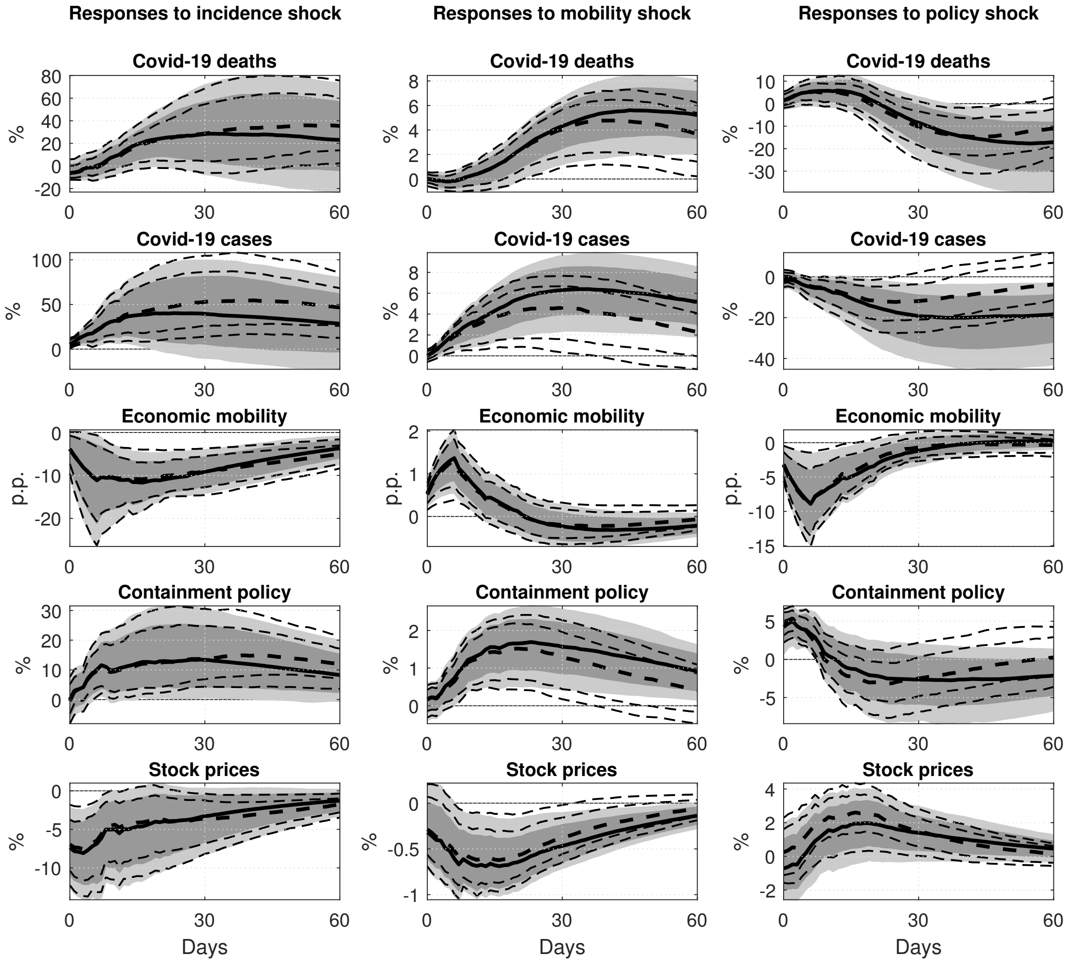

Figure D.23: The effects of incidence, economic mobility and containment policy shocks with linear trend. *Notes:* The figure shows the median response (solid lines for the benchmark model and bold dashed lines for the model with linear trend) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas/dashed lines, respectively). The shocks are normalized to be positive and have size of one standard deviation.

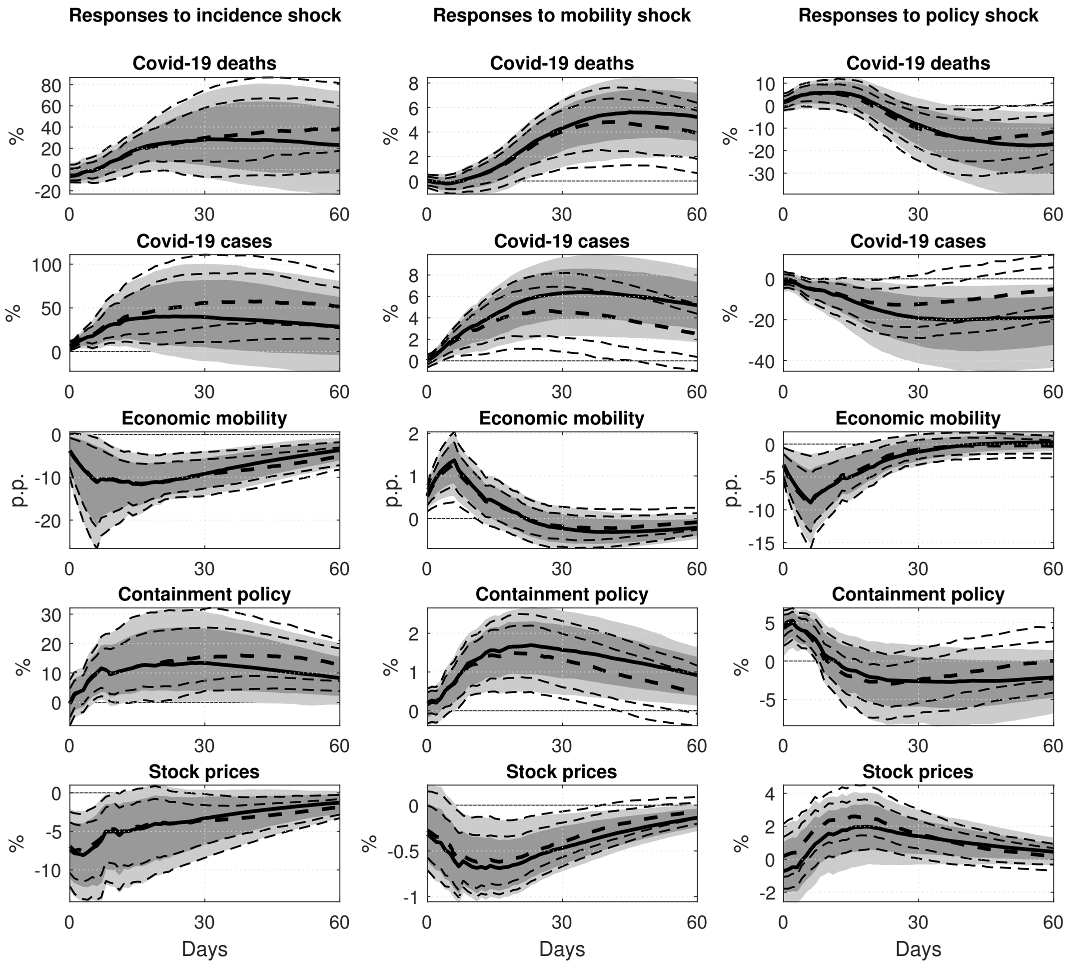

Figure D.24: The effects of incidence, economic mobility and containment policy shocks with quadratic trend. *Notes:* The figure shows the median response (solid lines for the benchmark model and bold dashed lines for the model with linear trend) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas/dashed lines, respectively). The shocks are normalized to be positive and have size of one standard deviation.

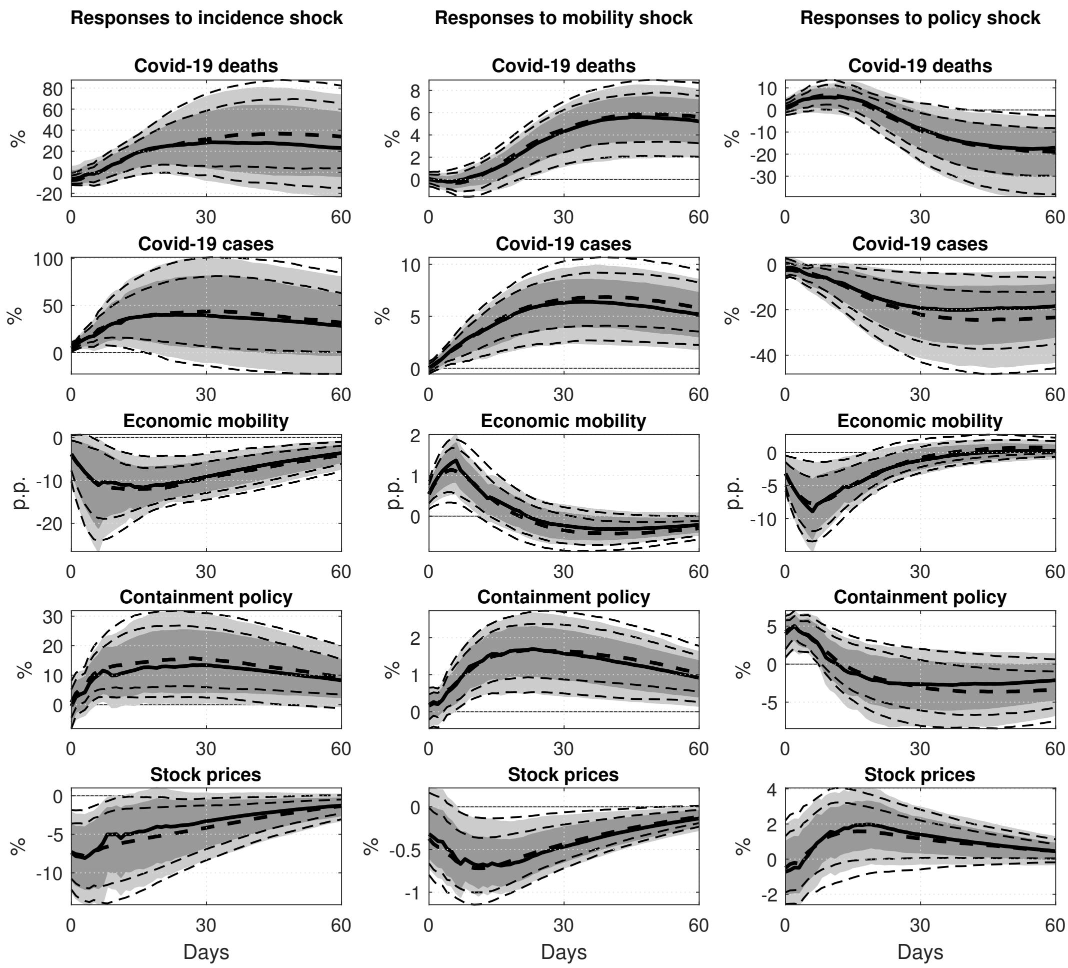

Figure D.25: The dynamic effects of incidence, economic mobility and containment policy shocks with 7 lags. *Notes:* The figure shows the median response (solid lines for the benchmark model and bold dashed lines for a model with 7 lags) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas/dashed lines, respectively). The shocks are normalized to be positive and have size of one standard deviation.

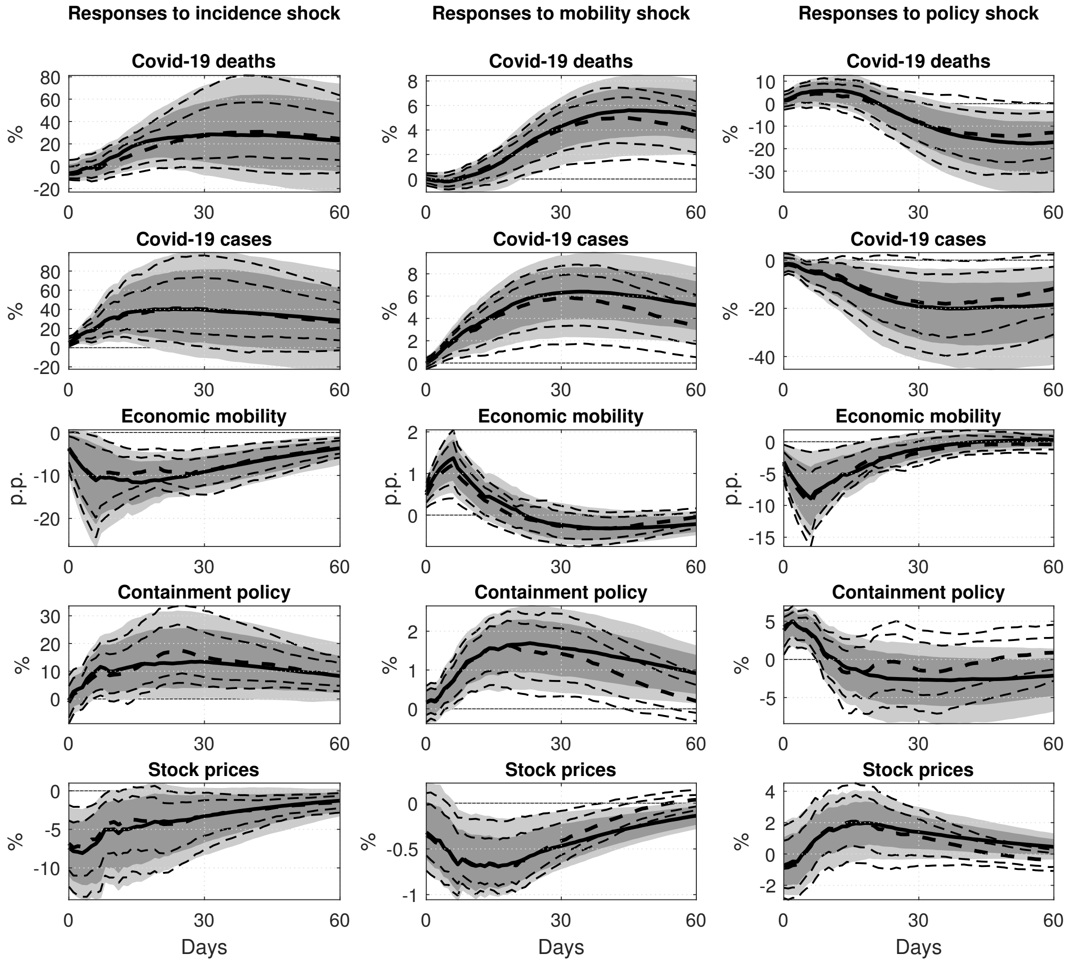

Figure D.26: The dynamic effects of incidence, economic mobility and containment policy shocks with 21 lags. *Notes:* The figure shows the median response (solid lines for the benchmark model and bold dashed lines for a model with 21 lags) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas/dashed lines, respectively). The shocks are normalized to be positive and have size of one standard deviation.

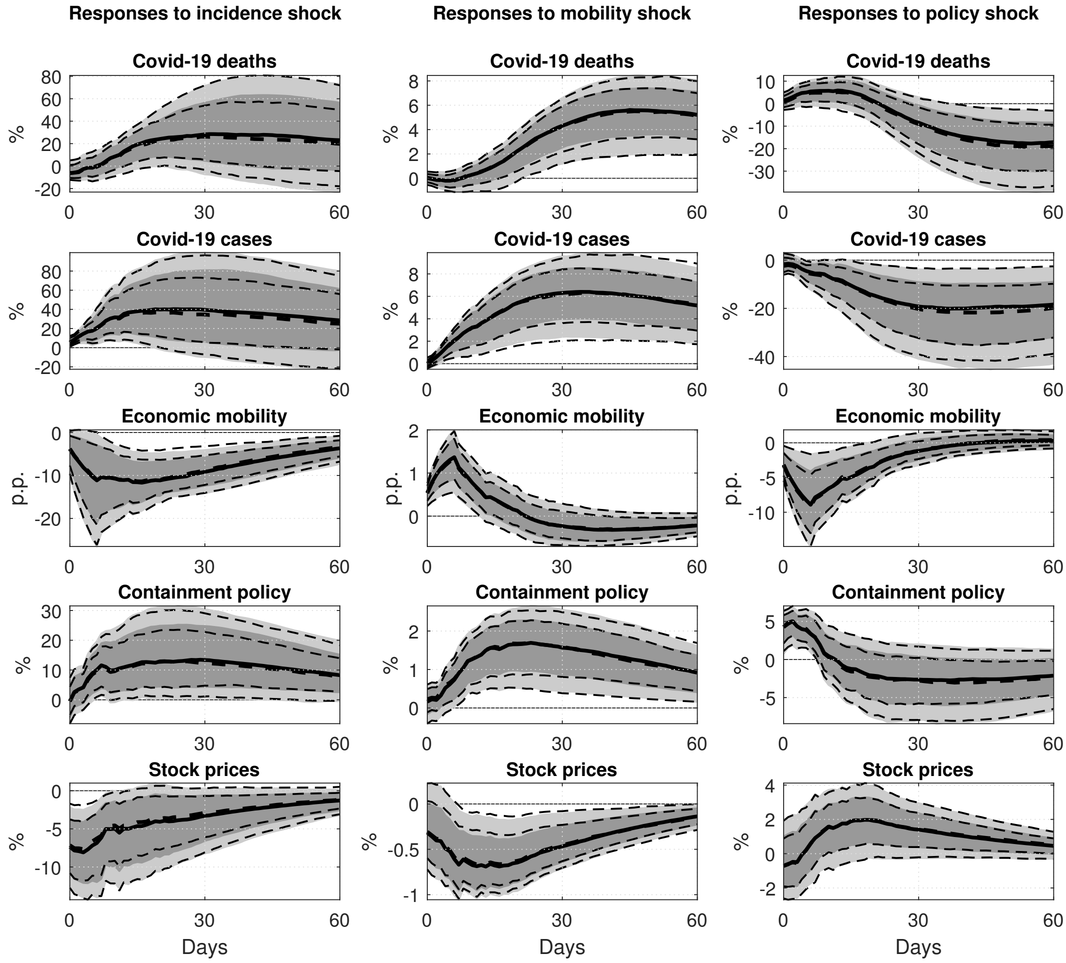

Figure D.27: The dynamic effects of incidence, economic mobility and containment policy shocks excluding weekday dummies. *Notes:* The figure shows the median response (solid lines for the benchmark model and bold dashed lines for the model of the sensitivity analysis) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas/dashed lines, respectively). The shocks are normalized to be positive and have size of one standard deviation.

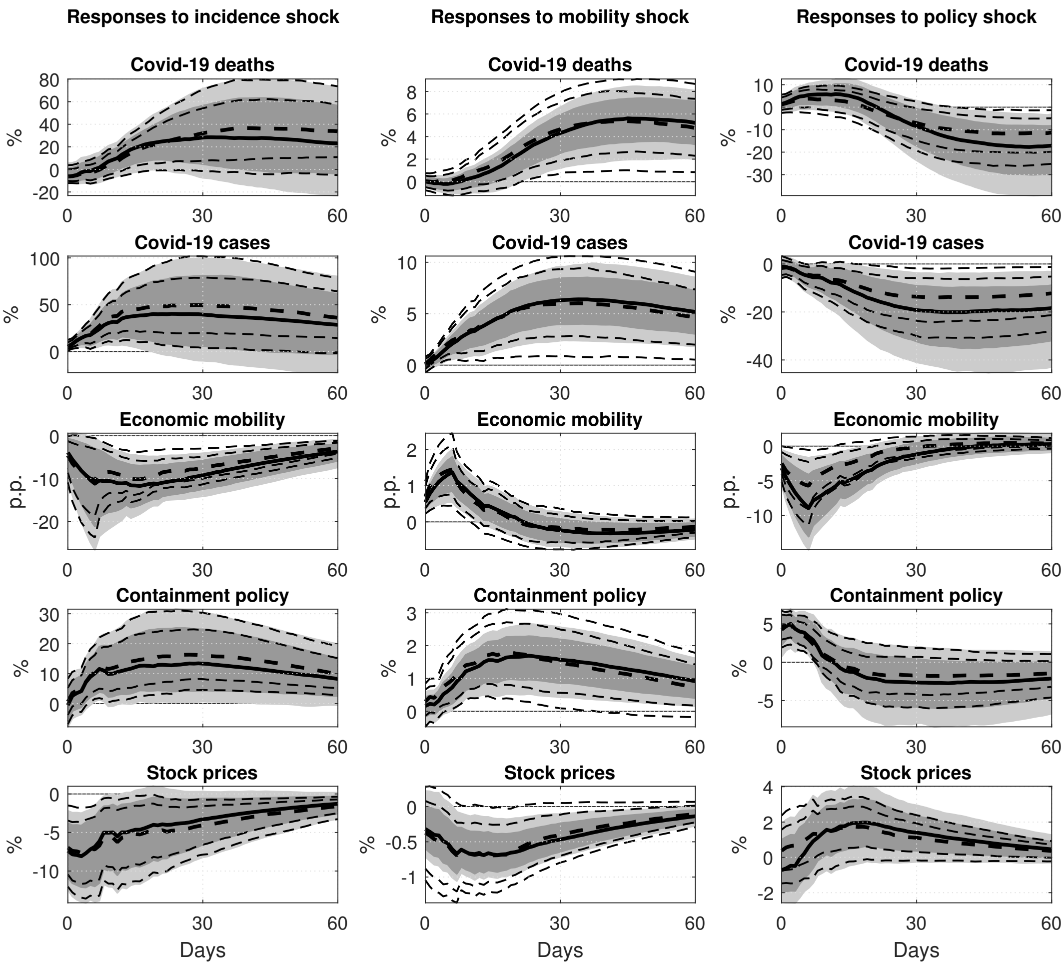

Figure D.28: The dynamic effects of incidence, economic mobility and containment policy shocks with alternative mobility index. *Notes:* The figure shows the median response (solid lines for the benchmark model and bold dashed lines for the model of the sensitivity analysis) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas/dashed lines, respectively). The shocks are normalized to be positive and have size of one standard deviation.

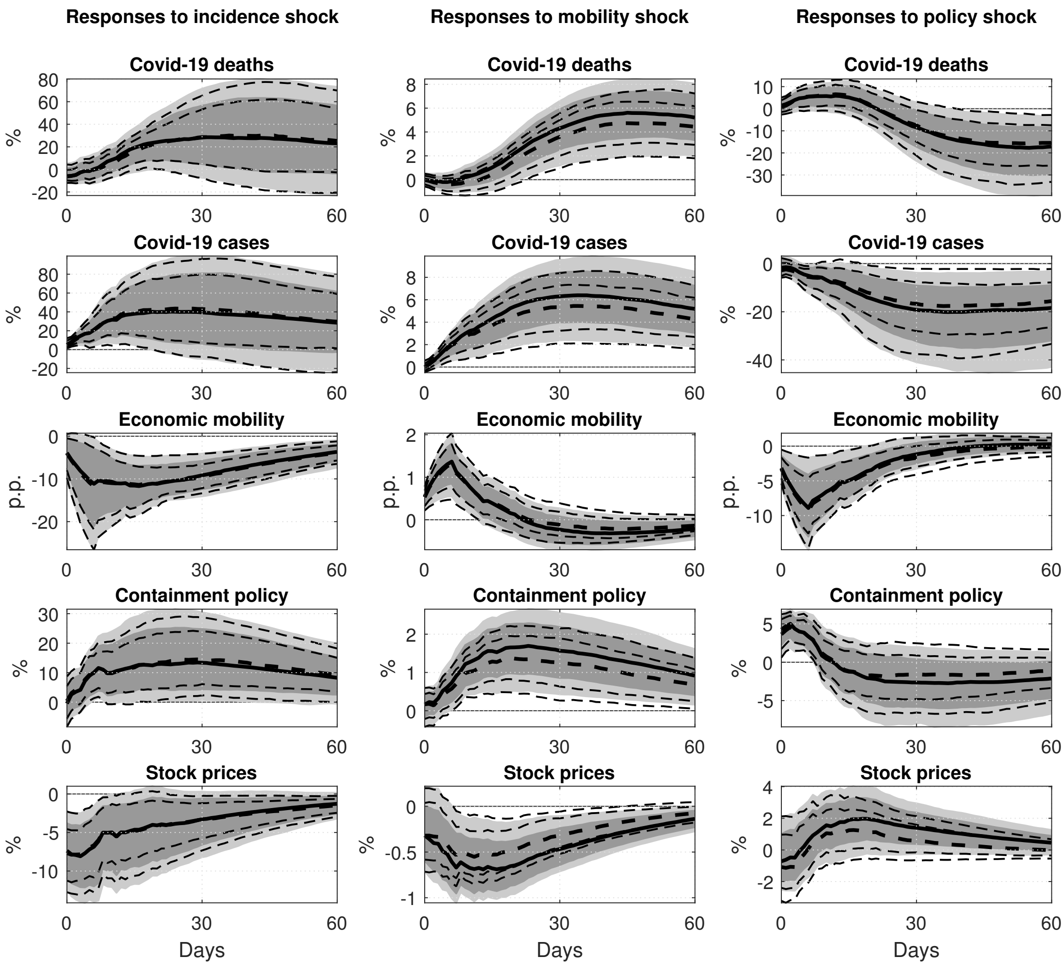

Figure D.29: The dynamic effects of incidence, economic mobility and containment policy shocks including alternative stock prices (large cap). *Notes:* The figure shows the median response (solid lines for the benchmark model and bold dashed lines for the model of the sensitivity analysis) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas/dashed lines, respectively). The shocks are normalized to be positive and have size of one standard deviation.

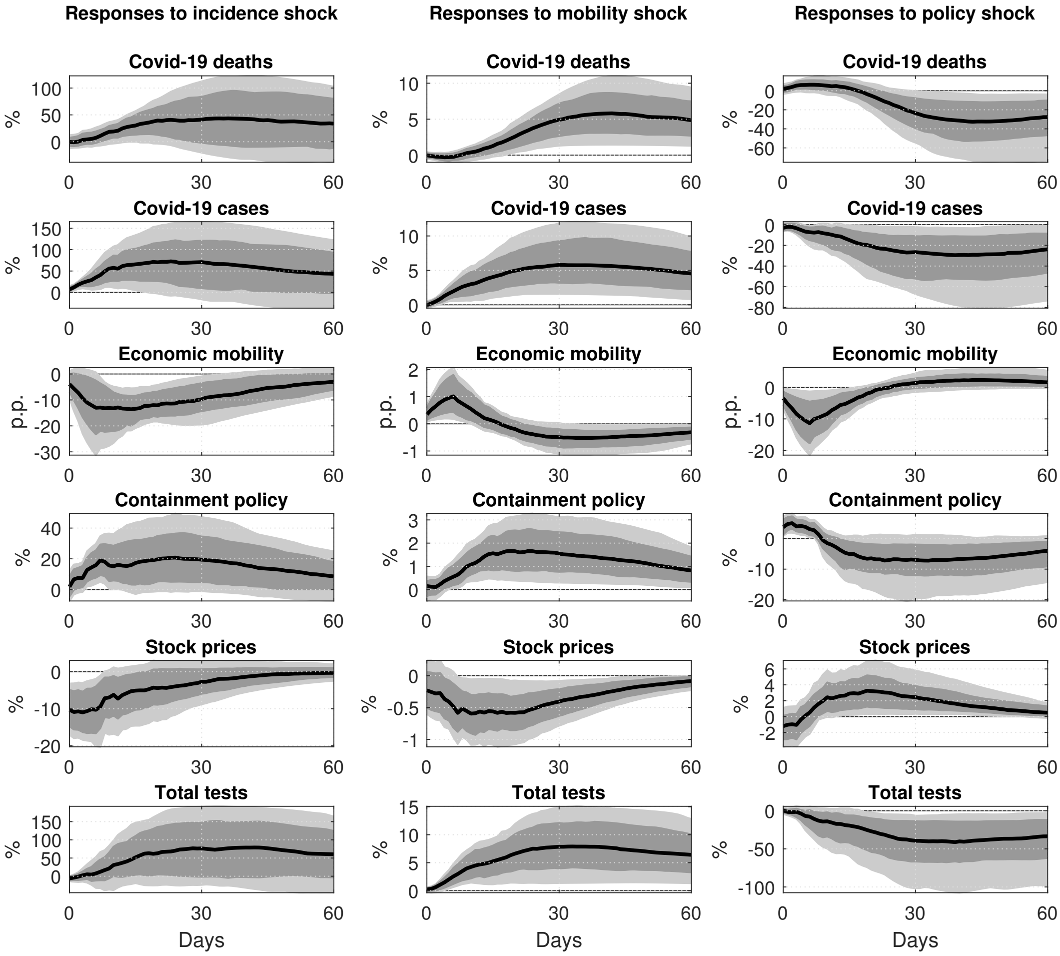

Figure D.30: The dynamic effects of incidence, economic mobility and containment policy shocks including additionally total tests. *Notes:* The figure shows the median response (solid lines for the model of the sensitivity analysis) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas, respectively). The shocks are normalized to be positive and have size of one standard deviation.

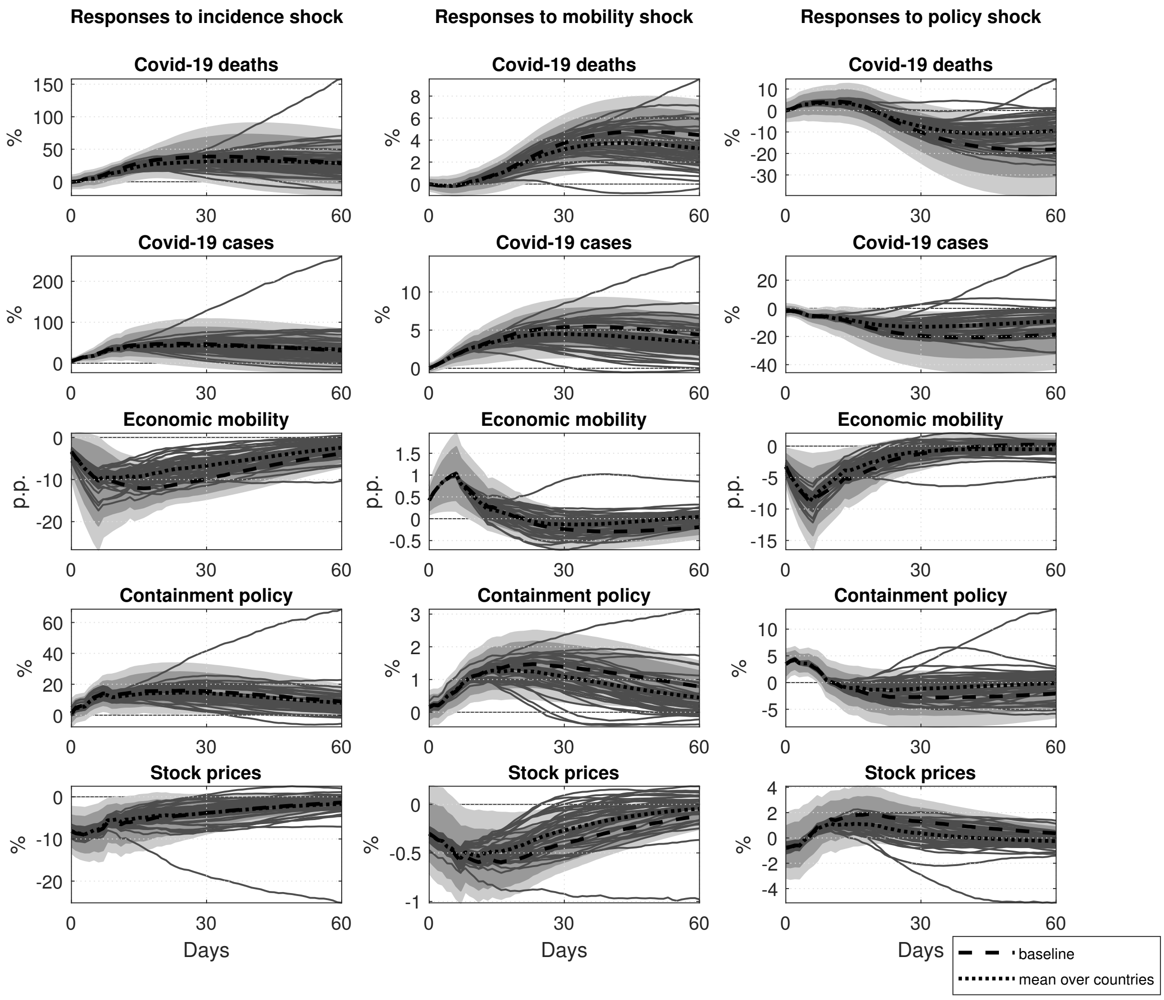

Figure D.31: The dynamic effects of incidence, economic mobility, and containment policy shocks with partial pooling. *Notes:* The figure shows the median response (thick dashed lines) and 68% and 90% credible sets (shaded areas) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, for a fully pooled model. The thin solid lines show the country-specific estimates from partial pooling and the thick dotted line the median of these. All models are identified with sign restrictions. The shocks are normalized to be positive and have size of one standard deviation.

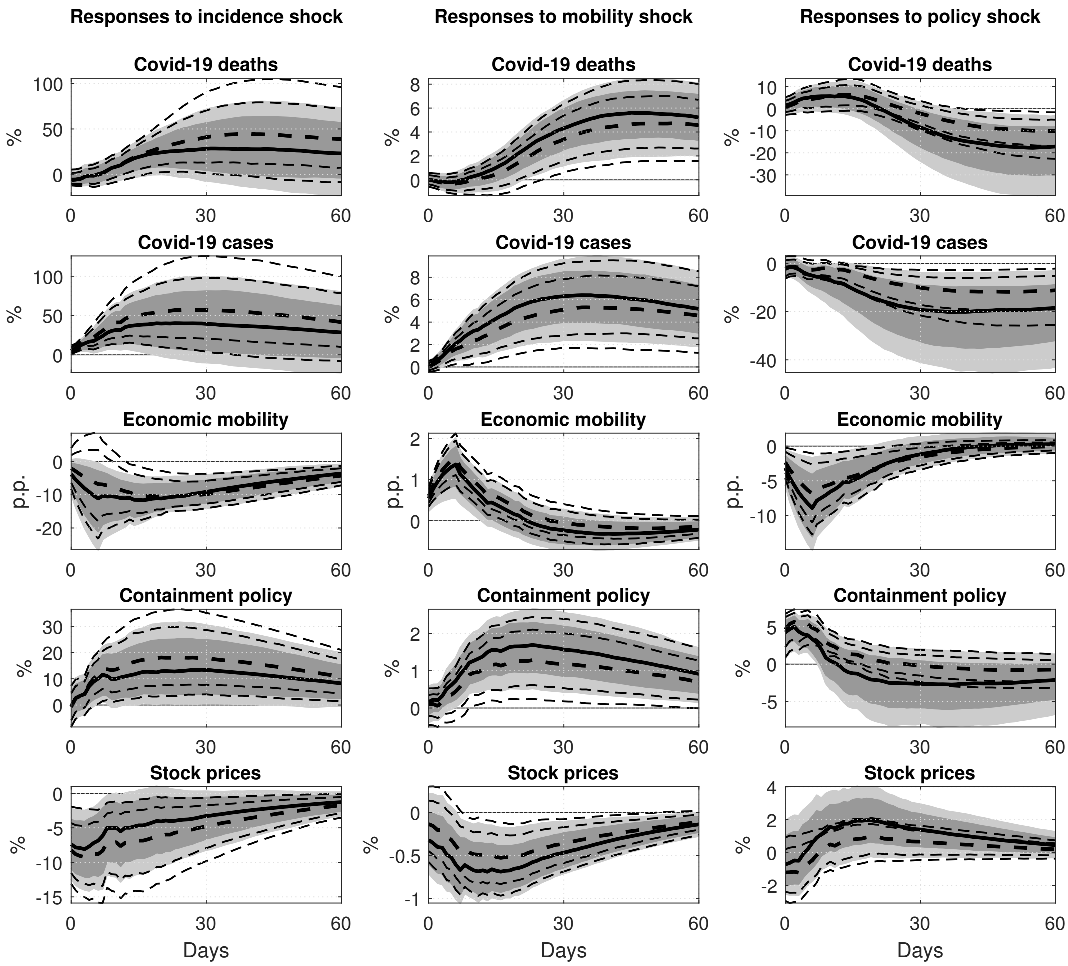

Figure D.32: The dynamic effects of incidence, economic mobility and containment policy shocks with restrictions on horizon 0 and 14. *Notes:* The figure shows the median response (solid lines for the benchmark model and bold dashed lines for the model with alternative identification horizon) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas/dashed lines, respectively). The shocks are normalized to be positive and have size of one standard deviation.

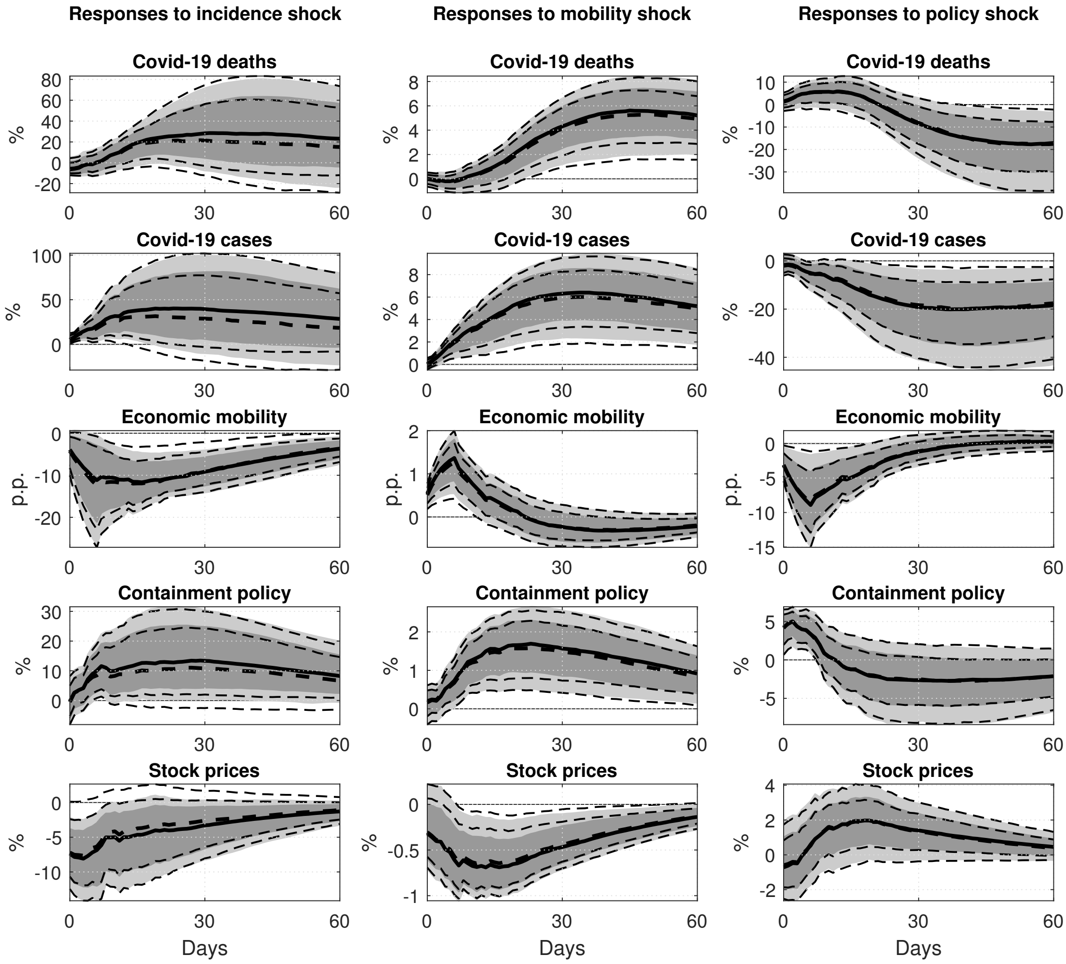

Figure D.33: The dynamic effects of incidence, economic mobility and containment policy shocks with no sign restriction on the reaction of stock prices to incidence shocks. *Notes:* The figure shows the median response (solid lines for the benchmark model and bold dashed lines for the model with alternative identification horizon) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas/dashed lines, respectively). The shocks are normalized to be positive and have size of one standard deviation.

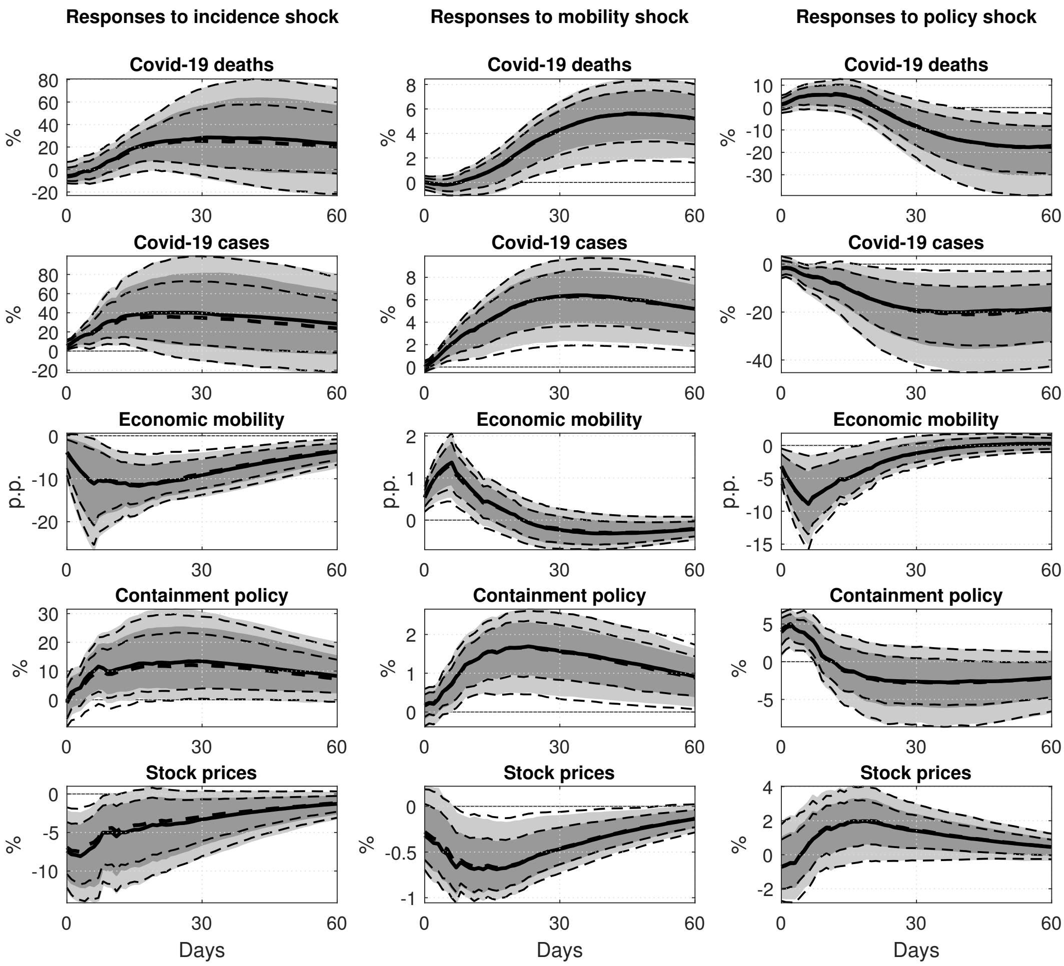

Figure D.34: The dynamic effects of incidence, economic mobility and containment policy shocks without restricting the response of containment policy to incidence shocks. *Notes:* The figure shows the median response (solid lines for the benchmark model and bold dashed lines for the model with alternative identification horizon) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas/dashed lines, respectively). The shocks are normalized to be positive and have size of one standard deviation.

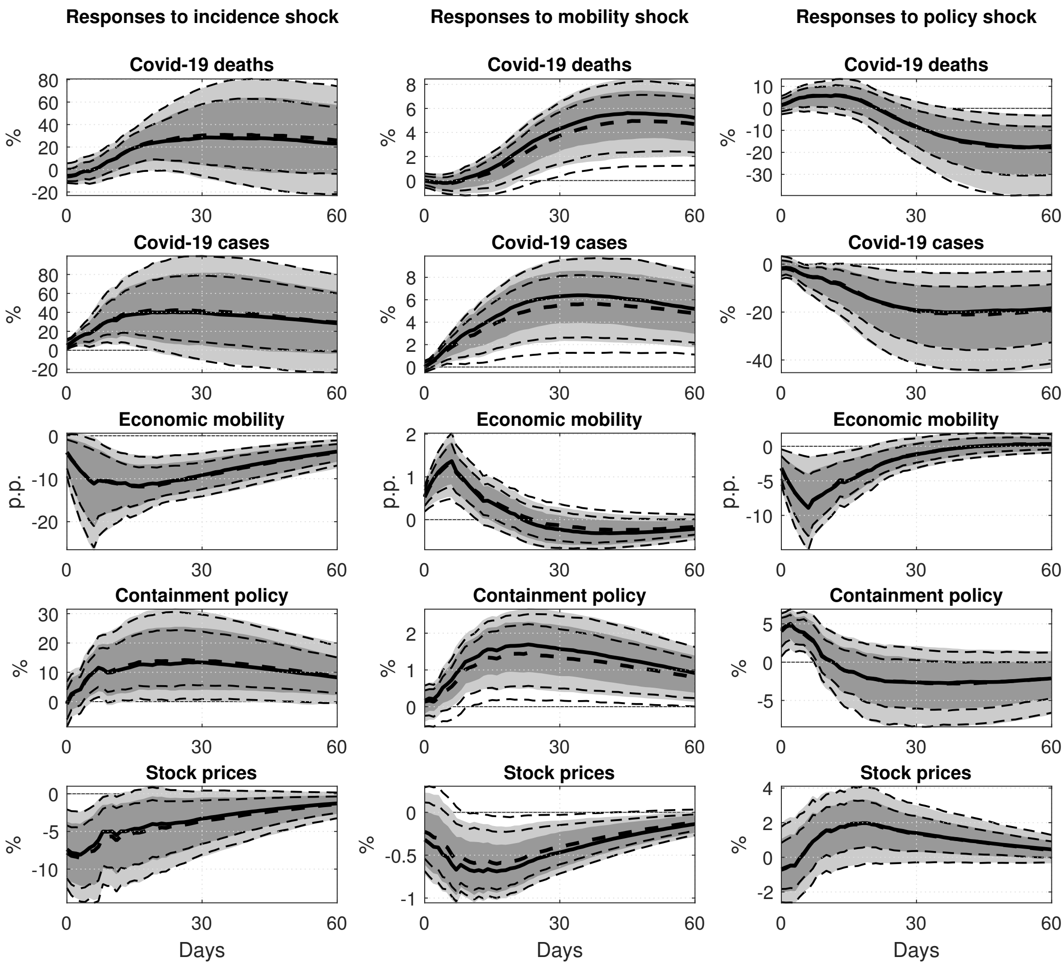

Figure D.35: The dynamic effects of incidence, economic mobility and containment policy shocks without restricting the response of containment policy to mobility shocks. *Notes:* The figure shows the median response (solid lines for the benchmark model and bold dashed lines for the model with alternative identification horizon) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas/dashed lines, respectively). The shocks are normalized to be positive and have size of one standard deviation.

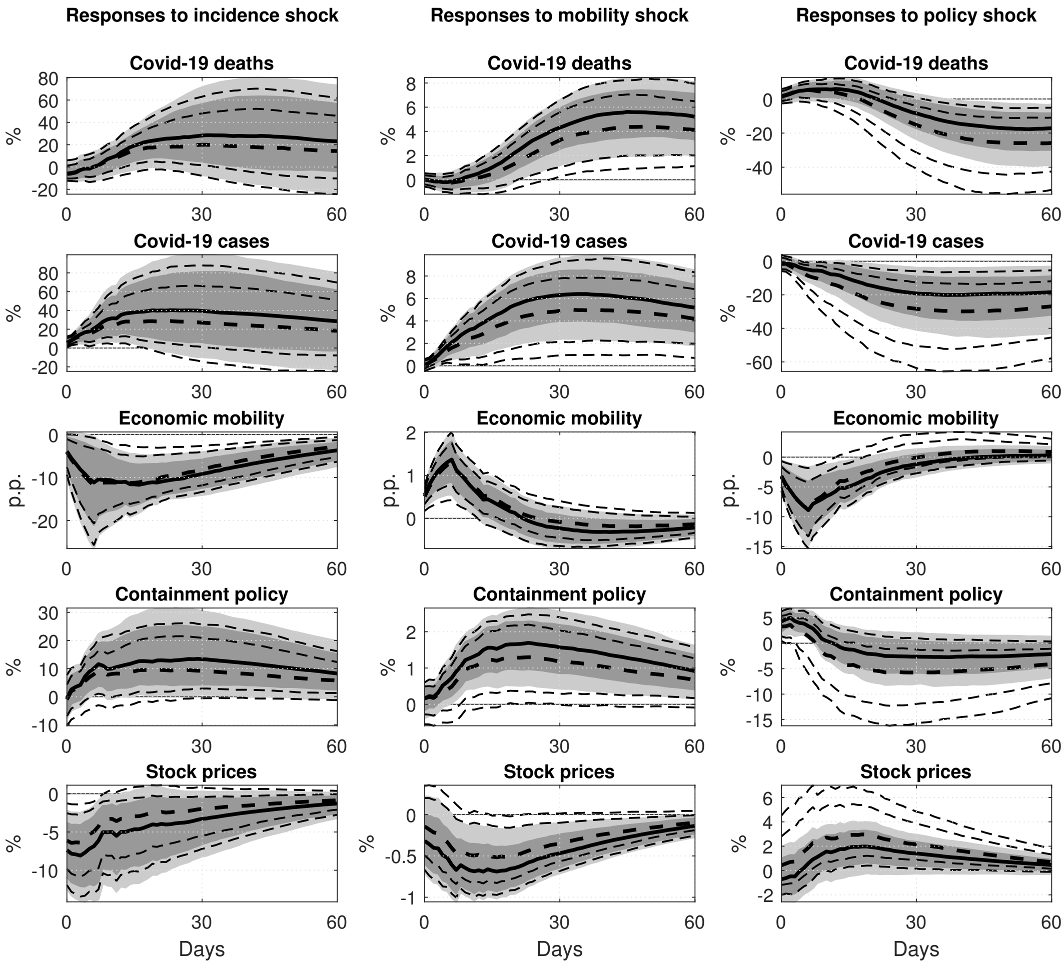

Figure D.36: The dynamic effects of incidence, economic mobility and containment policy shocks without restricting the response of containment policy to incidence, mobility, and containment policy shocks. *Notes:* The figure shows the median response (solid lines for the benchmark model and bold dashed lines for the model with alternative identification horizon) of the endogenous variables to an incidence shock (first column), a mobility shock (middle column) and a containment policy shock (right column) over 60 days, along with 68% and 90% credible sets (dark and light shaded areas/dashed lines, respectively). The shocks are normalized to be positive and have size of one standard deviation.

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