



Business Cycles and Health Dynamics during the Covid-19 Pandemic. A Scandinavian Perspective

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- How did the increase in the number of Covid infected and the subsequent containment measures affect the (Norwegian) economy?
- How much of the evolution of the pandemic was driven by the containment policies versus people taking voluntary precautionary actions?
- What is the health/economy trade-off of tightening containment policies?
- Counterfactuals: What would the effect be on Norwegian health outcomes if they had instead followed Swedish containment policies?

Despite intense research efforts, surprisingly little consensus on these types of questions

From the health perspective:

- Early studies using epidemiological models, e.g., [Ferguson et al. \(2020\)](#), predicted that a suppression strategy using strict Non-Pharmaceutical Interventions (NPI) would reduce Covid-19 mortality by up to 99%, justifying the more direct negative economic costs
- Later studies, incorporating endogenous and voluntary precautionary behavioral changes, find that these actions matter far more than publicly enforced NPI policies, see [Herby et al. \(2022\)](#)

From the economy perspective:

- Using panel data pooling estimates across 60 countries, [Deb et al. \(2020\)](#) argue that strict NPI policies have had, on average, a very large impact on economic activity
- In contrast, [Sheridan et al. \(2020\)](#), focusing on Denmark relative to Sweden using credit card transaction data, suggests that most of the economic contraction during the spring of 2020 occurred regardless of social distancing laws
- These opposing conclusions have direct implication for how we consider the effect of policy and overall dynamics between economic and health outcomes during the pandemic

At least three challenges can explain lack of consensus

1. Cross sectional studies

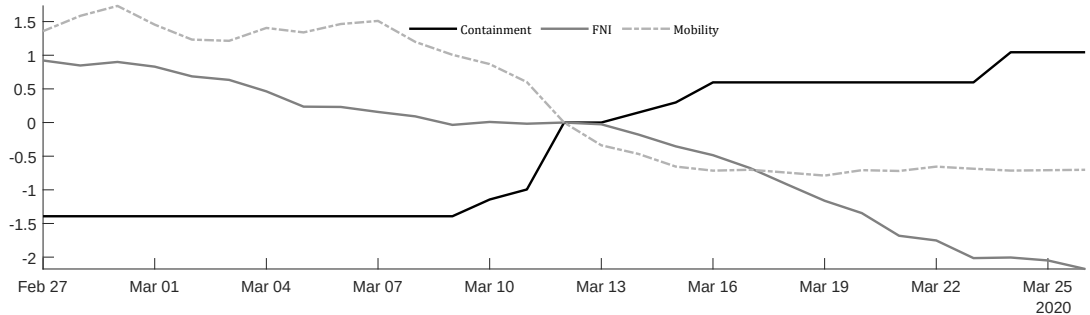
- Looking at average responses across potentially very different countries might yield estimates that are not representative

2. Missing observations, measurement errors and biases

- Oxford COVID-19 Government Response Tracker (OxCGRT) indexes are likely subject to biases

3. Simultaneity

- Health and economics affect each other. Calls for general, and not partial, equilibrium analysis
- Spring 2020, events happened fast. Using conventional economic data, available at a weekly or monthly frequency, makes identification of the underlying drivers challenging



- Analyze **joint daily dynamics** between NPI, business cycles and health variables during the pandemic using a Structural Vector Autoregressive (SVAR) model
- Assume variation in the underlying data can be approximated by four main drivers and use sign restrictions to identify; (i) **surprises in infection rates**, (ii) **containment measures**, and **precautionary actions** via (iii) news or (iv) contemporaneous mobility changes
- Reduced rank treatment of the stochastic elements facilitates identification and incorporates **measurement errors** in the underlying data, cf. [Korobilis \(2022\)](#)
- A horseshoe prior ([Carvalho et al. \(2010\)](#)) is used to allow for a rich set of lags and enforce sparsity on system

- Large measurement errors in standard policy indexes
- Clear health-economy trade-offs
- Large degree of forward looking behavior in policy
- Counterfactuals using SIR framework and simulating Norway as Sweden indicate that Norway's stricter measures likely lowered GDP by roughly 1.2% (about 10 billion NOK) but prevented far greater health losses, implying an output cost per life saved between 15 and 50 million NOK depending on the assumed infection fatality rate.

- Among the first to estimate a system where the dynamics of health and economic outcomes are modeled jointly using daily data.
- Early influential papers in the economic literature used theoretical models to cast light on the important endogeneity issue ([Eichenbaum et al., 2021](#); [McKibbin and Fernando, 2021](#); [Alvarez et al., 2021](#); [Berger et al., 2020](#); [Jones et al., 2020](#)), but empirical estimates have been lacking.
- Contributes to the epidemiological literature, by being able to decompose the time-varying reproduction number into contributions stemming from either NPI policies or precautionary actions

1. Addressing the challenges:
 - Daily measures of economic activity: FNI
 - Measurement errors in the containment policy data: Manual corrections
 - Joint dynamics and simultaneity: SVAR
2. Results: impulse responses and variance decompositions
3. Use the estimated model to conduct a series of counterfactual experiments, e.g. the Norwegian versus Swedish experience

- Key to our analysis is the usage of a high frequency business cycle indicator for Norway
- The daily business cycle index is labeled FNI and sourced from <https://www.retriever.no/fni/>.
- This index builds on [Thorsrud \(2018\)](#), and is updated approximately one time per month. The index is constructed by first decomposing Norwegian business news, sampled from Norway's major news outlets, into topics using a Latent Dirichlet Allocation (LDA) model

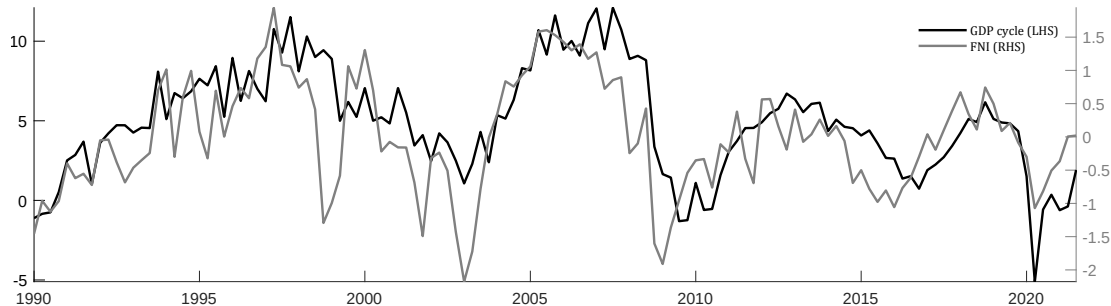


Figure. FNI and GDP cycle. The GDP cycle is computed using the eight quarter difference in GDP, i.e., $GDP_t - GDP_{t-8}$, which in practice is very similar to the trend-cycle filter suggested by [Hamilton \(2018\)](#).

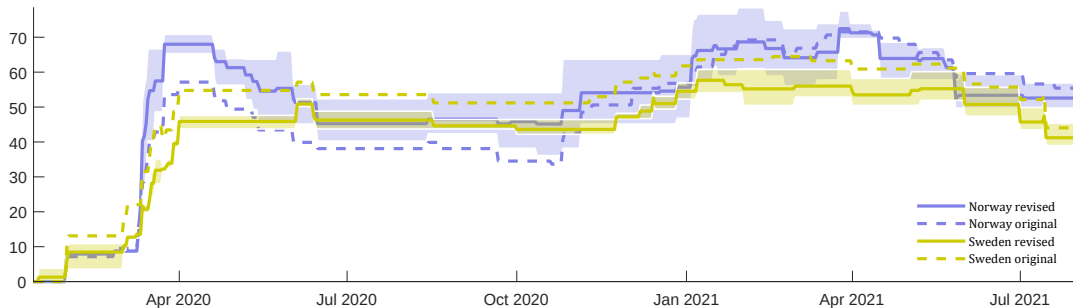
Table. Regression Table. Dep. var: Δ Quarterly GDP:

Independent variables	(1)	(2)	(3)	(4)
Quarterly Financial News Index	0.52** (0.11)			0.7**
Quarterly Electricity Consumption		0.002** (0.00)		0.0001
Quarterly No2 emissions			0.01** (0.002)	0.009
No. obs	120	96	48	48
R^2	0.15	0.32	0.26	0.53

- The FNI index provides a better description of aggregate economic activity in Norway than other high-frequency measures sometimes used in the Covid-literature to approximate economic activity

- To measure the effects of NPI policies on health and economic outcomes during Covid-19, one of the most widely used data sets is the Oxford Covid-19 Government Response Tracker (OxCGRT)
- OxCGRT is constructed and updated by a team of researchers and volunteers at the University of Oxford ([Hale et al., 2021](#)), and contains a systematic set of 23 daily response indicators, for more than 180 countries, starting 1. January 2020
- Indicators describe the evolution in restrictions on for example travel, schools and gatherings, but also report on variables such as health care facilities and economic relief packages
- We use the containment and health index (CON), which is an aggregated measure of containment and closure policies such as school closures and travel restrictions, and health system policies, such as facial coverings or testing policies

- Despite a well documented code-book, errors and revisions to the OxCGRT indicators can happen
- Two observations stand out
 1. Although it is commonly believed that Sweden had much less stringent containment policies than, e.g., Norway, in the beginning of the pandemic, this is not the impression displayed in raw data
 2. Compared to the versions of the index provided for Sweden in the spring of 2020, the numbers have changed, and comparing the indicators reported in different papers, find discrepancies



Following [Korobilis \(2022\)](#), the reduced-form vector autoregressive (VAR) model we consider can be written as:

$$\mathbf{y}_t = \Phi \mathbf{x}_t + \boldsymbol{\varepsilon}_t \quad (1)$$

with

$$\boldsymbol{\varepsilon}_t = \Lambda \mathbf{f}_t + \mathbf{v}_t \quad (2)$$

where $\mathbf{y}_t$ is vector of observed variables, $\mathbf{x}_t = (1, \mathbf{y}'_{t-1}, \dots, \mathbf{y}'_{t-p})'$ a vector containing a constant and p lags of $\mathbf{y}$, Φ is a matrix of coefficients, and $\boldsymbol{\varepsilon}_t$ is a vector of disturbances. Here Λ is a matrix of factor loadings, $\mathbf{f}_t$ is a vector of common factors, and $\mathbf{v}_t$ is a vector of idiosyncratic shocks, with covariance matrix Σ , being diagonal

It then follows that

$$\text{cov}(\epsilon_t | \Lambda, \Sigma) = \Omega = \Lambda \Lambda' + \Sigma \quad (3)$$

The reduced-rank structural VAR (SVAR) representation of this model is obtained by combining (1) and (2), and multiplying the reduced-form VAR with the generalized inverse of Λ . This gives

$$A_1 y_t \approx B_1 x_t + f_t \quad (4)$$

where the SVAR matrix A_1 equals the generalized inverse of Λ , and v_t is treated as a residual or noise shock with no structural interpretation. Two attractive features:

1. Can project n shocks into r structural shocks, where n is relatively large to capture the joint dynamics between the endogenous variables, and $r < n$. Dimensionality reduction helps in terms of specifying the identification restrictions as well as estimating the system
2. The model incorporates potential measurement errors in the underlying data through the idiosyncratic error term $\mathbf{v}_t$

Assuming invertability, and using the VMA representation of the VAR, the structural impulse response function on impact is

$$\frac{\partial \mathbf{y}_t}{\partial \mathbf{f}_t} = \mathbf{\Lambda} \quad (5)$$

Thus, parametric restrictions on $\mathbf{\Lambda}$ correspond to structural restrictions on the impact impulse response functions, as in conventionally used SVAR models

- We include 4 variables directly related to health outcomes, 5 financial and 4 mobility variables, to better capture rapid changes in expectations and agent's behavior, and 3 macroeconomic indicators. Together with the FNI and CON indexes, this results in a system of $n = 18$ variables in total.
- To ensure that we estimate the model by drawing from a stationary posterior, all non-stationary variables are first differenced prior to estimation.
- Many series have clear day-of-the-week effects, e.g. number of confirmed infected is typically much higher following weekends than on other days of the week. We apply a simple seasonal filter on the data prior to estimation.
- We consider the sample 17th January 2020 to 30th June 2021. This covers the three infection waves.

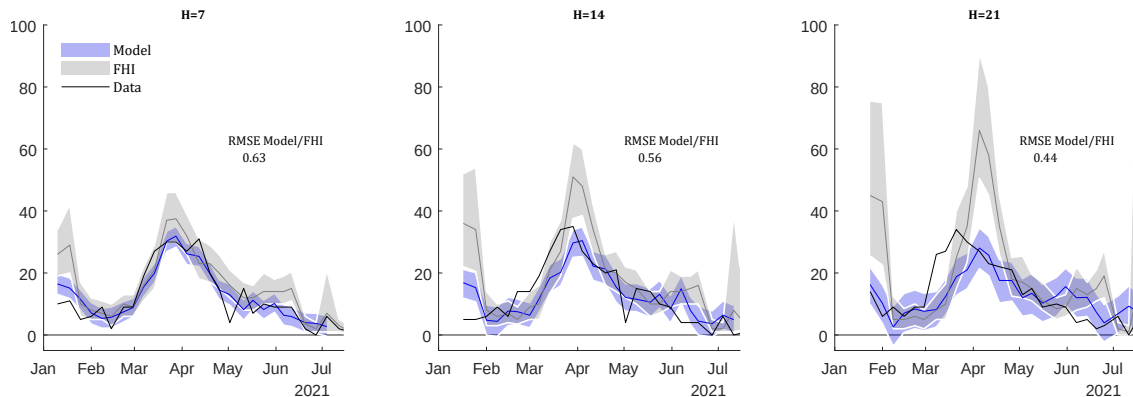
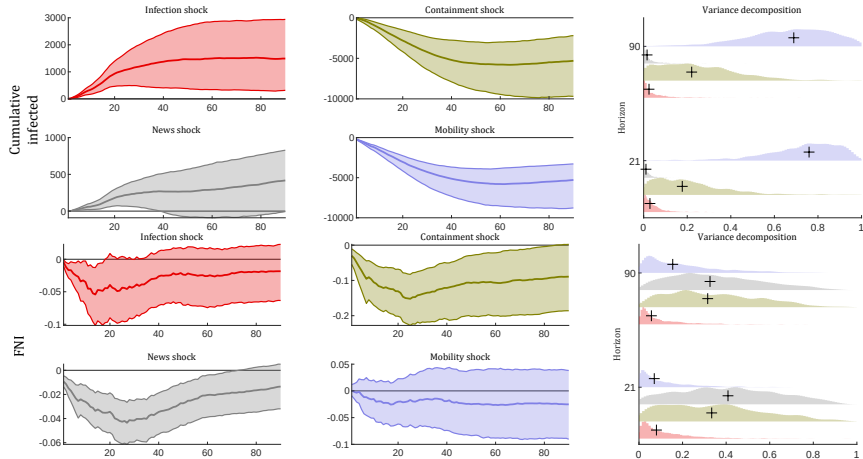


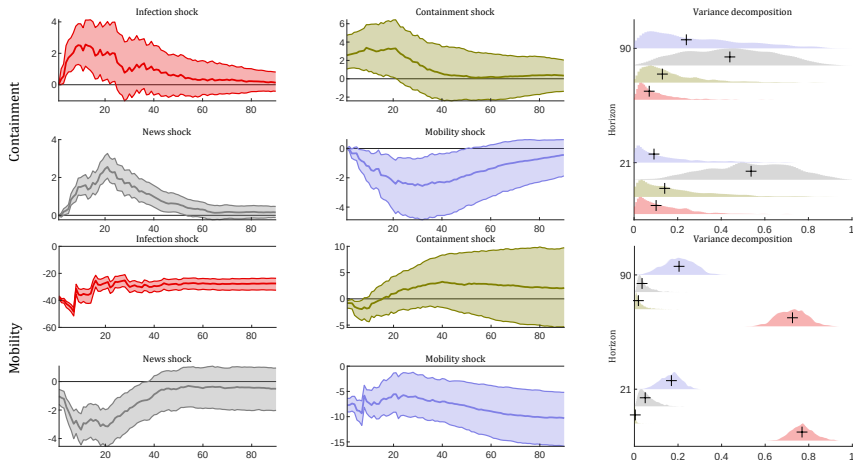
Figure. Predictive evaluation. The graphs report the predicted number of new hospitalizations (due to COVID-19) for three different forecasting horizons; one, two, and three weeks. The point estimates are reported together with 68% posterior probability bands. The alternative predictions were produced in real-time by the FHI.

- The proposed model does a reasonably good job at describing the evolution of the health outcomes in the model.

- Unpredictable variation in data is approximated by four main drivers/shocks during the first three waves of the pandemic
- Shocks are identified with sign restrictions
 1. **Infection shock:** Captures unexpected changes in the number of new infections, due to, e.g., sudden increase in infected, super spreader events, mutations, etc.
 2. **Containment shock:** Containment policies that were stronger or weaker than expected.
 3. **Precautionary shocks:**
 - ▶ News, i.e., that the agents in the economy receive unexpected information today about future economic prospects
 - ▶ Contemporaneous mobility shock

Block	Variables	COVID-19	Policy	Shocks	Precautionary
		Infection	Containment	News (Anticipatory)	Mobility (Instantaneous)
Fast-moving health	New COVID-19 cases	+	-	0	-
	Share positive	+	-	0	-
Policy	Containment Health index	0	+	0	0
	Economic support index	0	na	0	0
Economy	FNI	-	-	-	na
	Interest rate	-	-	-	na
	Stock market index	-	-	-	na
	Spread	-	-	-	na
	Exchange rate	+	+	+	na
	Realized volatility	+	na	+	na
	Oil price	0	0	na	0
Mobility	Transit mobility index	-	-	-	-
	Dom. and int. flights	-	-	-	-
	Walking mobility index	-	-	-	-
	Driving mobility index	-	-	-	-
Slow-moving	New hospitalizations	0	0	0	0
	New dead	0	0	0	0
	New unemp. benefit app.	0	0	0	0





1. What would infection rates have been without (systematic) NPI policies?
2. How would the pandemic have evolved if Norway had followed Swedish policies?

- The VAR model in itself is inappropriate for these types of experiments, as the estimated model parameters and shocks reflect systematic and unexpected policies and actions relative to a constant steady-state. This includes NPI policies.
- We use a simple epidemiological compartment model which frequently has been used to inform policymakers and health authorities during the Covid-19 pandemic.
- The conventional usage of this type of models assume that the (important) reproduction number often is kept constant.
- Instead, we use the SVAR machinery to compute time-varying reproduction numbers reflecting (endogenous) changes in policy or behavior following disease outbreaks and feed these into the compartment model simulations.

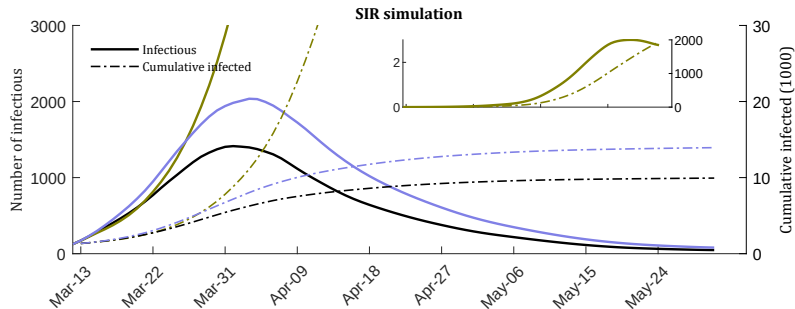
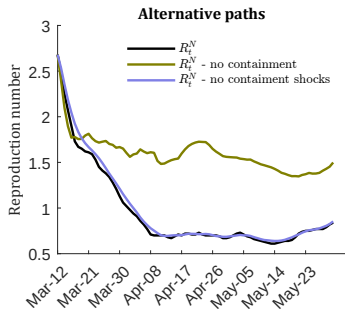


Figure. SIR simulations. Left: R_t^N (Arroyo-Marioli et al., 2021) together with two simulated alternatives - without containment shocks and without the systematic containment rule. Right: SIR-implied pandemic curves.

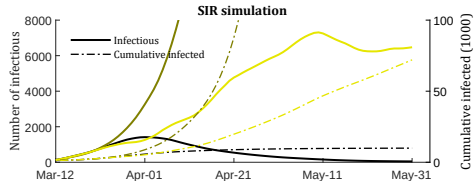
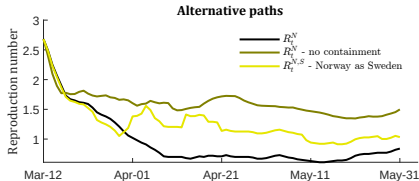
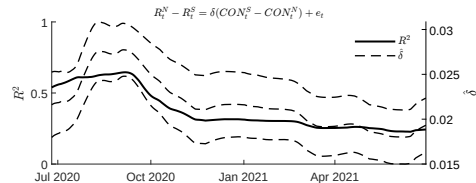
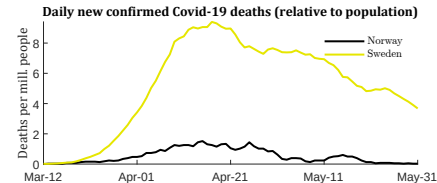


Figure. Norway as Sweden. Upper left: Daily new confirmed COVID-19 deaths (relative to population). Upper right: $\hat{\delta}$, with 95% confidence bands, and R^2 from equation (??) as the sample expands. Lower left: R_t^N , the *Laissez-faire* path, and $\hat{R}_t^{N,S}$. Lower right: SIR-implied pandemic curves.

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- Find that:
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Thank you

Comments and questions welcome.

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