The transmission of shocks across sectors and the dynamics of sectoral prices

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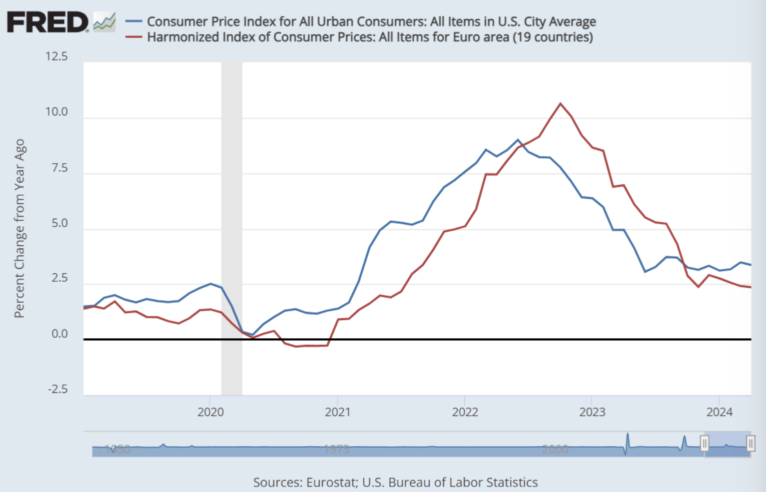
The 2021-2023 inflation surge



Why?

- demand > supply (Covid reopening, fiscal stimuli, ...)
- supply chain disruptions (semi-conductors, shipping, ...)
- pricing chain spillovers or "pipeline pressures"

Pricing chain spillovers

Pricing chain spillovers or "pipeline pressures": shocks originating in individual sectors cascade through the production network and impact other sectors.

Existence of pricing chain spillovers as channel of headline inflation

$\Rightarrow$ *the production network should matter for prices dynamics !*

This paper:

- Does the **production network matter** for the dynamics of sectoral prices and headline inflation ?
- If yes, how does it shape the degree of **pass-through and persistence** of sectoral and aggregate shocks to the prices in different sectors as well as to headline inflation ?

Studying the dynamics of sectoral prices

1. **Traditionally**: dynamic factor models (DFMs) that decompose sectoral inflation into
    - a *common component*
    - an *idiosyncratic component*

⇒ See Altissimo et al., 2006, Maćkowiak et al., 2009, Boivin et al., 2009.

⇒ Unable to disentangle sectoral shocks spilling over to other sectors from aggregate shocks.

2. **New**: multi-sector dynamic stochastic general equilibrium models (DSGEs)

⇒ See Smets et al., 2019, Carvalho et al., 2021, Pasten et al., 2021, Rubbo, 2023.

⇒ Formally describe/quantify how sectoral prices shocks spill over to other sectoral prices.

⇒ Results rely on strongly structural models.

Studying the dynamics of sectoral prices

Our approach: a hierarchical Bayesian vector autoregression (BVAR) with **prior that incorporates information from the Input-Output (IO) matrix** to structure the long-run relationships between sectoral prices.

- Giannone et al., 2019 incorporates in the hierarchical BVAR model a family of priors that provide guidance on the joint dynamics of the time series in the long run. (details on hierarchical BVARs)
- **Idea:** incorporate beliefs about the dynamics of sectoral prices.

  What structural information do we have ?

  - Input-Output matrix *IO*
    $\rightarrow$ gives for each sector the share of intermediate goods from all other sectors

Example Input-Output matrix

Table: Example Input-Output matrix

	Agriculture and forestry	Oil and gas extraction	Mining except oil and gas	Support activities for mining	...
Agriculture and forestry	0.35	0	0.01	0	...
Oil and gas extraction	0	0.21	0	0.05	...
Mining except oil and gas	0	0.01	0.1	0.02	...
Support activities for mining	0	0.01	0	0.01	...
...	...	...	...	...	...

A hierarchical BVAR with priors for the long run (PLR)

VECM representation of the VAR

$$\Delta y_t = c + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + e_t$$

Giannone et al., 2019 aim to elicit a prior for the Π matrix that is centered around zero but has covariance matrix guided by economic theory. Rewrite the model as:

$$\Delta y_t = c + \underbrace{\Lambda \tilde{y}_{t-1}}_{=\Pi H^{-1} H y_{t-1}} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + e_t$$

where :

- $\tilde{y}_{t-1} = H y_{t-1}$: $n \times 1$ vector of linearly independent combinations of the variables y_{t-1}
- $\Lambda = \Pi H^{-1}$: $n \times n$ matrix capturing the effects of the linear combinations on Δy_t

A hierarchical BVAR with priors for the long run (PLR)

Giannone et al., 2019 propose a specific *a priori* distribution for the columns of the Λ matrix:

$$\Lambda_{\cdot i} | H_{i\cdot}, \Sigma \sim N(0, \tilde{\phi}_i(H_{i\cdot})\Sigma)$$

The proposed reference value for $\tilde{\phi}_i(H_{i\cdot})$ is the following:

$$\tilde{\phi}_i(H_{i\cdot}) \sim \frac{\phi_i^2}{(H_{i\cdot}\bar{Y}_0)^2}$$

- ϕ_i is a scalar hyperparameter
- $\bar{Y}_0$ is a column vector containing the average of the initial p observations

This prior can be implemented by dummy observations $\Rightarrow$ possible to optimize the ϕ_i hyperparameters by maximizing the marginal likelihood.

A hierarchical BVAR with priors for the long run (PLR)

Q: Is it possible to use the production structure to construct an economically grounded H matrix that allows for a better estimation of cointegration relationships between sectoral PPIs?

R: Let's use the Input-Output matrix to construct *economically meaningful* linear combinations of sectoral price indices

$$\tilde{Y}_t = \underbrace{\begin{pmatrix} \underbrace{\textbf{IO}}_{35\times35} & \cdots \\ \cdots & \cdots \end{pmatrix}}_{H} \times \underbrace{\begin{pmatrix} \textbf{35 sectoral prices}_t \\ \cdots \end{pmatrix}}_{Y_t}$$

Why does it make sense?

Intuition: sectors that are strongly linked through the IO matrix should share common trends.

A hierarchical BVAR with priors for the long run (PLR)

Why does it make sense?

Long Run Prior BVAR (with IO) ***on prices*** $\Leftrightarrow$ Minnesota BVAR on ***average input cost***

- The random walk prior is imposed on "input costs" rather than final producer price (which contains markups, etc.)
- Aggregation smooths high-frequency noise : "input cost" is more persistent (so last period is a strong predictor, closer to the Minnesota prior)
- Y_t contains log price indices $\Rightarrow$ $\tilde{Y}_t$ is actually a cost-weighted average of log prices but:
  - mean of log prices $\Leftrightarrow$ log of geometric mean (standard in index number theory)
  - matches log-linearized CES price aggregators found in multi-sector DSGE models

Data, identification and validation of the model

Monthly data on the U.S. economy from January 2004 to December 2024:

- 35 sectoral PPI - Bureau of Labor Statistics (BLS, NAICS classification)
- 7 additional variables
  - Industrial Production, CPI, Real oil price (WTI), Real cereals price, Excess bond premium, Michigan inflation expectation, Shadow rate.

$\Rightarrow$ Input-Output matrix comes from the Bureau of Economic Analysis

$\Rightarrow$ Data is log-transformed except

- Headline CPI that is expressed as annualized inflation
- Excess bond premium, Michigan inflation expectation and Shadow rate (no transformation)

Data, identification and validation of the model

Long run prior H matrix:

$$\tilde{Y}_t = \underbrace{\begin{pmatrix} \underbrace{\mathbf{IO}}_{35\times 35} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ \mathbf{0} & 0 & -1 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}}_{H} \times \underbrace{\begin{pmatrix} \textbf{35 sectoral prices}_t \\ \text{industrial production}_t \\ \text{headline inflation } \pi_t \\ \text{oil price}_t \\ \text{cereals price}_t \\ \text{inflation expectations}_t \\ \text{excess bond premium}_t \\ \text{shadow rate}_t \end{pmatrix}}_{Y_t}$$

Identification: achieved via external / internal instruments

- Oil price surprises: from Känzig, 2021
- Monetary policy surprises: from Bauer and Swanson, 2023
- Cereal price shock: from Jo and Adjemian, 2023

Forecasting headline CPI

Validation of the model ?

Pseudo real-time forecast for headline CPI and comparison with the CPI forecast of the Survey of Professional Forecasters. The models are :

1. MN: Minnesota BVAR
2. MN-C: Minnesota BVAR + Covid-19 correction
3. LR: Minnesota BVAR + Covid-19 correction + PLR reduced (two last lines of the H matrix defined above)
4. LR-IO: Minnesota BVAR + Covid-19 correction PLR with IO

Forecasting headline CPI

		Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf)			
	rmse(spf)	MN/spf	MN-C/spf	LR/spf	LR-IO/spf
h=0Q	0.3721	1.6367	1.3600	1.2662	1.2102
h=1Q	0.6144	**1.5524**	**1.4191**	**1.3670**	1.4504
h=2Q	0.6665	**1.6776**	**1.4471**	**1.3468**	1.2741
h=3Q	0.6811	**1.6968**	**1.3778**	1.3026	1.0678
h=4Q	0.6815	**2.0848**	**1.6840**	**1.5862**	0.9978

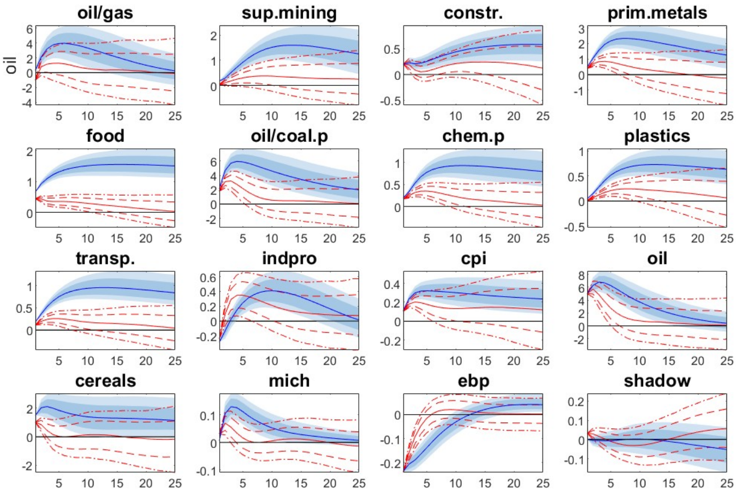
Table: SPF RMSE and RMSE ratios for CPI forecasts: benchmarks (MN, MN-C, LR) and LR-IO BVAR(2) models. Entries in bold are significantly different from SPF forecasts at the 5% level (Diebold–Mariano test). Full evaluation sample : 2018Q1 up to 2024Q4.

Forecasting headline CPI

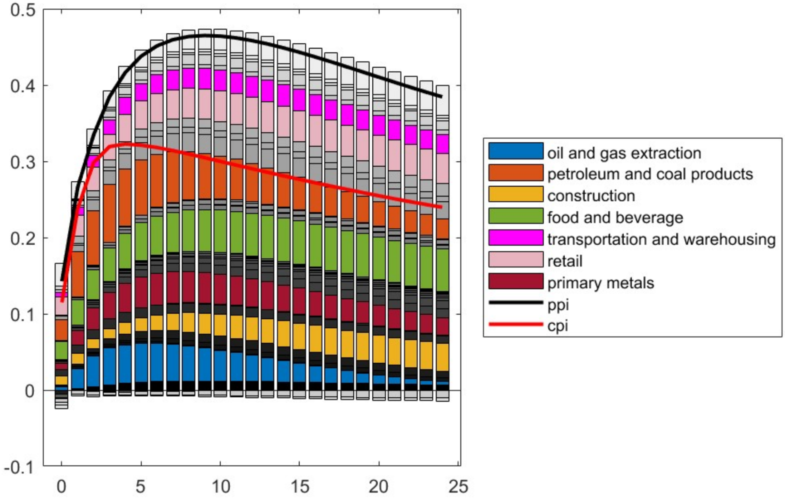
		Ratios rmse(BVARs) / rmse(spf) ($< 1 \rightarrow$ better than spf)			
	rmse(spf)	MN/spf	MN-C/spf	LR/spf	LR-IO/spf
h=0Q	0.5640	0.8292	0.8424	0.7867	0.5853
h=1Q	0.9177	1.4015	1.2580	1.4307	0.9754
h=2Q	0.9119	1.1616	1.0198	1.1008	0.9700
h=3Q	0.9255	1.1059	0.9713	0.9492	0.9189
h=4Q	0.8972	**1.5594**	**1.5597**	1.3621	0.9834

Table: SPF RMSE and RMSE ratios for CPI forecasts: benchmarks (MN, MN-C, LR) and LR-IO BVAR(2) models. Entries in bold are significantly different from SPF forecasts at the 5% level (Diebold–Mariano test). Shorter evaluation sample : 2018Q1 up to 2021Q2.

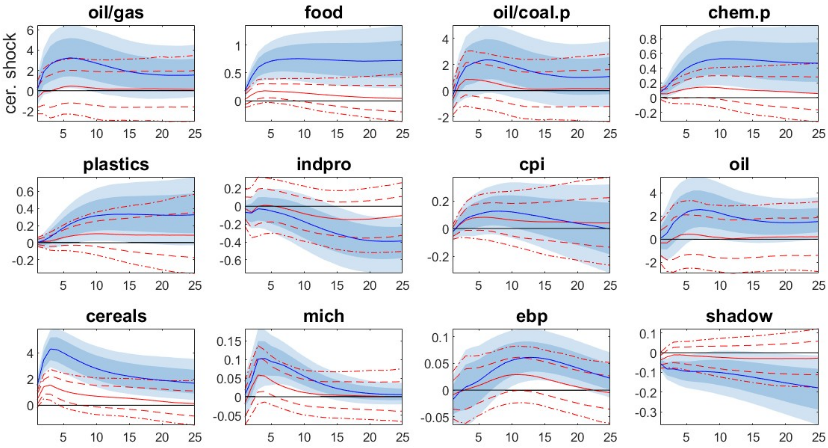
Oil price shock - BVAR(2)-IO IRFS



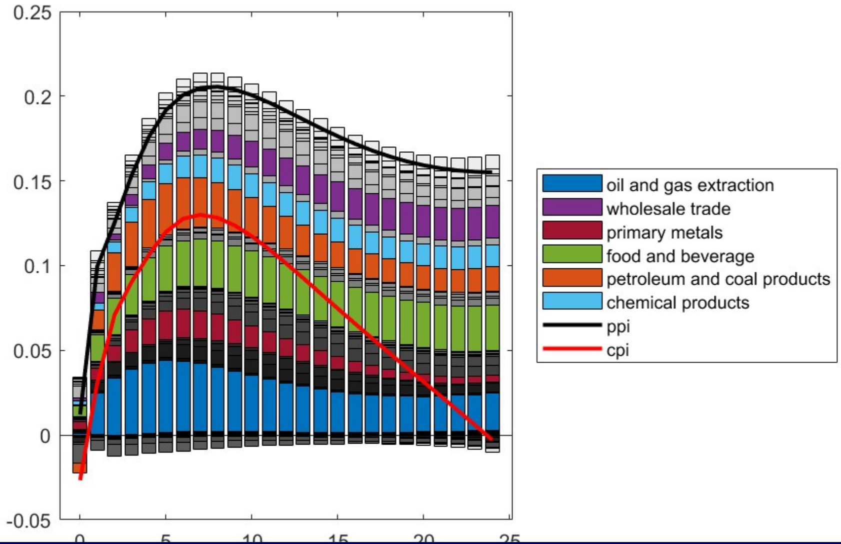
Oil price shock - BVAR(2)-IO Contributions



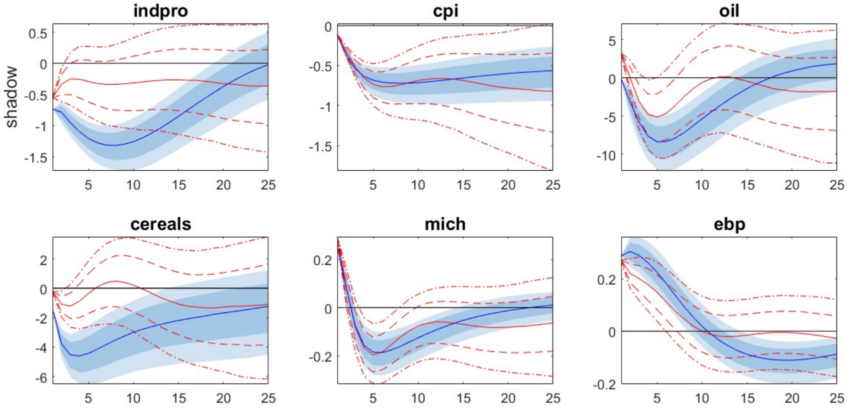
Cereal price shock - BVAR(2)-IO IRFS



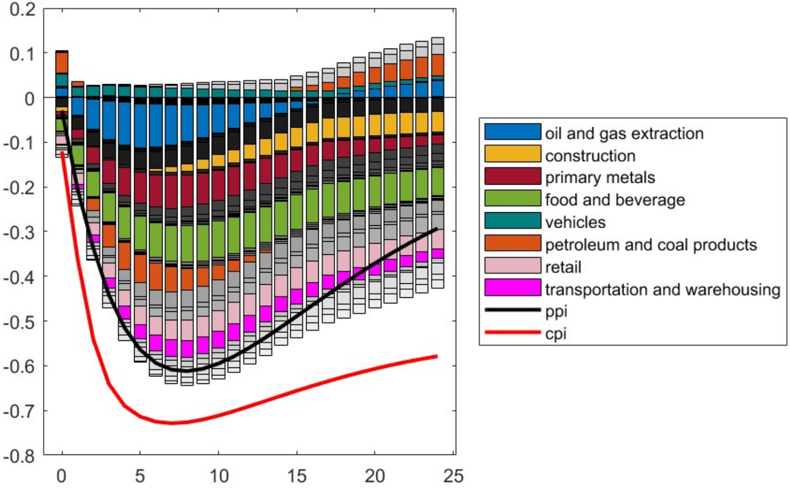
Cereal price shock - BVAR(2)-IO Contributions



Monetary policy shock - BVAR(2)-IO IRFS



Monetary policy shock - BVAR(2)-IO Contributions



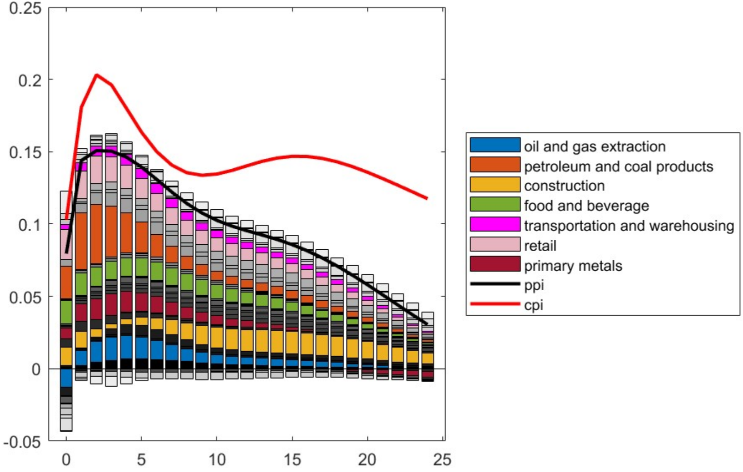
Conclusion

- The sectoral links represented by the input-output matrix or investment flows help to model the dynamics of sectoral prices.
- The disaggregated model shows how sectoral prices respond to shocks.
- It could help inform monetary decisions: should we target specific sectors?

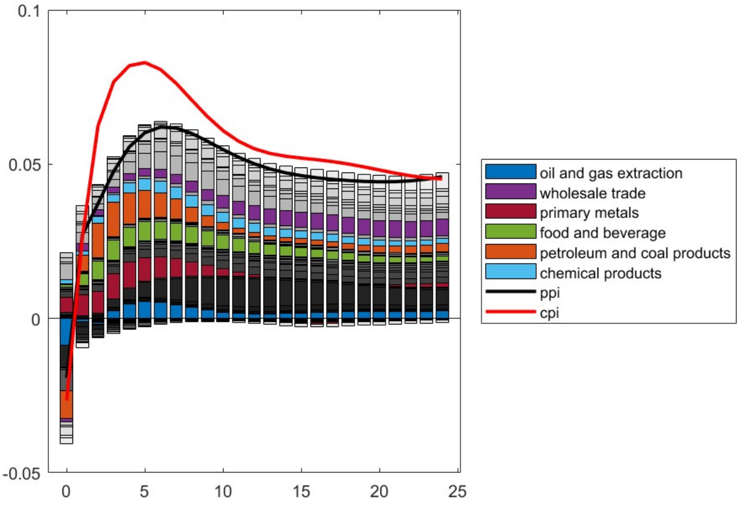
Thank you!
All comments and suggestions will help

Appendix slides BVAR-MN - OIL Contributions

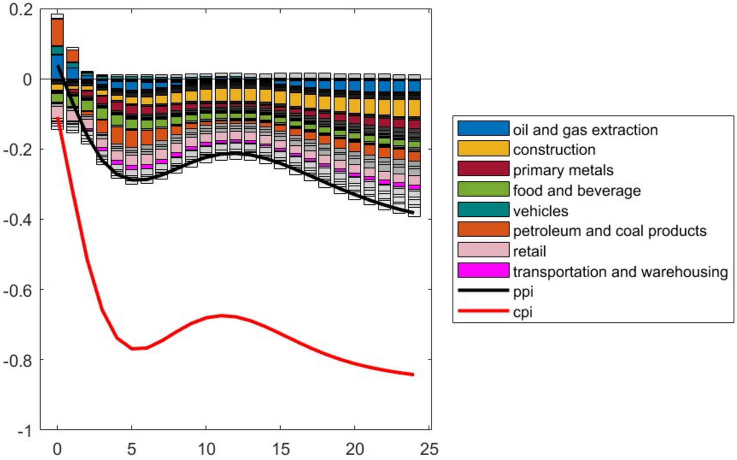
(back)



Appendix slides - BVAR-MN - CER Contributions



Appendix slides - BVAR-MN - MP Contributions



Appendix slides - A hierarchical BVAR

(back) We model sectoral prices dynamics with a hierarchical Bayesian vector autoregression (BVAR) adopting the approach of Giannone et al., 2015 to which we then add a prior that governs long-run cointegration relationships between variables as in Giannone et al., 2019.

Let Y_t represent the N-dimensional vector of (transformed) variables, the reduced-form VAR model writes as

$$Y_t = a + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + e_t \quad (1)$$

where

- A_p is the p-th lag coefficient matrix
- $e_t \sim N(0, \Sigma)$

Appendix slides - A hierarchical BVAR

The Normal-Inverse Wishart prior: let $\beta = vec([a, A_1, ..., A_p]')$,

$$\begin{aligned} \Sigma &\sim IW(\Phi, d) \\ \beta|\Sigma &\sim N(b, \Sigma \otimes \Omega) \end{aligned} \tag{2}$$

- degrees of freedom d fixed to $N + 2$
- scale matrix Φ assumed diagonal with diagonal $\phi_{N\times 1}$ treated as a hyperparameter
- $\mathbb{E}[(A_s)_{ij}|\Sigma] = \begin{cases} 1 \text{ if } i = j \text{ and } s = 1 \\ 0 \text{ otherwise} \end{cases}$
- $cov[(A_s)_{ij}, (A_r)_{hm}|\Sigma] = \begin{cases} \lambda^2 \frac{\Sigma_{ih}}{s^2\phi_j} \text{ if } m = j \text{ and } s = r \\ 0 \text{ otherwise} \end{cases}$ with hyperparameter λ

Appendix slides - An addition: take Covid-19 into account

Building on Giannone et al., 2015, Lenza and Primiceri, 2022 propose to explicitly model the surge in shock volatility during the pandemic.

The standard VAR becomes :

$$Y_t = a + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + s_t e_t \tag{3}$$

Letting $t* =$ March 2020 and $[s_0, s_1, s_2, \rho]$ be a vector of unknown coefficients,

- $s_{t<t*} = 1$
- $s_{t*} = s_0$
- $s_{t*+1} = s_1$
- $s_{t*+2} = s_2$
- $s_{t*+j} = 1 + (s_2 - 1)\rho^{j-2}$