Macroeconometric forecasting using a cluster of dynamic factor models

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The Motivation

- The model (cluster) consists of sequentially linked, small-scale dynamic factor models
- The linkages are motivated by Granger causality tests
- The model combines the advantages of small factor models (soft indicators, mixed frequency) and large structural models (SNA coverage, disaggregation)
- The model uses monthly and quarterly frequency
- The specification of the dynamic factor models and their linkages focuses on forecasting performance
- The model can produce conditional forecasts that depend on exogenous assumptions and perform simulations

The Cluster DFM – Key facts

Data

- A rich data set comprising quarterly SNA series (1995-2019) and monthly indicators
- Year-on-year growth rates are less erratic and less seasonal
- Standardization reduces the number of parameters and stabilizes the covariances

The cluster

- Disaggregated GDP forecasts tend to be more accurate
- Unidirectional Granger-causal links improve the accuracy by up to 50 percent

A DFM estimated using the Kalman filter

- Missing observations
- Mixed-frequencies
- Conditional forecasts

SNA coverage

GDP (Production)	GDP (Expenditure)	GDP (Income)
Manufacturing VA	Private consumption	Labor income
Construction VA	Investment	Manufacturing
Services VA	Construction	Construction
	Equipment	Services
	Intangibles	Capital Income
	Exports	
	Goods	
	Services	
	Imports	
Residual	Residual	Residual

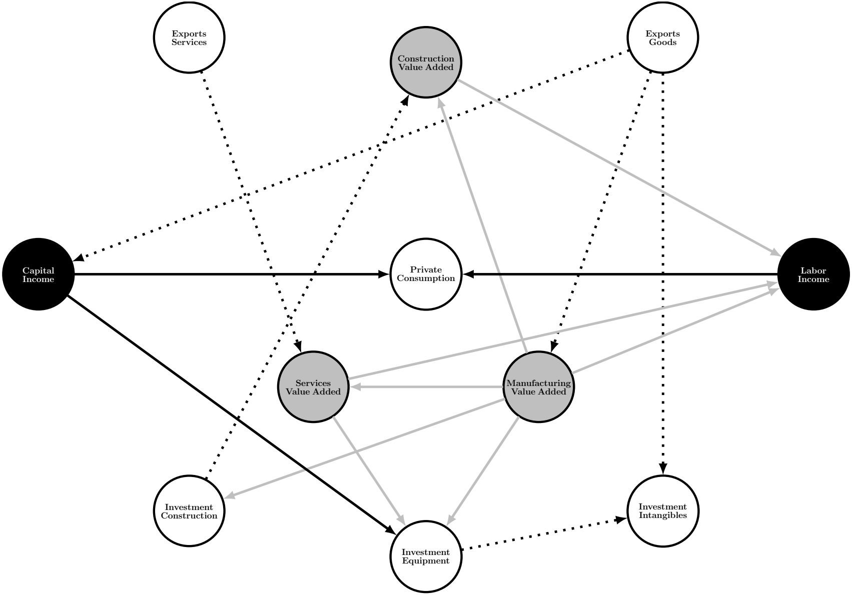
Identifying (W-Weak and S-Strong) Granger-causal links

From	To	Class.	Mult.	Nonlin.	Class.	Mult.	Nonlin.
Exports of goods	Invest. intangibles	S	S	S	S		W
Exports of goods	Manuf. VA	S			S	S	
Exports of goods	Capital income	S					
Exports of serv.	Serv. VA						
Invest. equipment	Invest. intangibles				S	S	
Invest. construct.	Construct. VA						
Manuf. VA	Invest. equipment	S		S	S		S
Manuf. VA	Invest. construct.	S	S	S	S	S	W
Manuf. VA	Construct. VA	W	S		W		
Manuf. VA	Serv. VA	S		S	S		S
Manuf. VA	Labor income			S			S
Construct. VA	Labor income	S		S			S
Serv. VA	Invest. equipment	S		W	S		
Serv. VA	Labor income			S			S
Labor income	Consumption		S				
Capital income	Invest. equipment	S		S	S		W
Capital income	Consumption					S	

Three distinct but complementary methods

- Classical bivariate Granger test based on a VAR with restrictions
- Multivariate test based on a high-dimensional VAR refined by sparsity-seeking regularization
- Bivariate test based on highly nonlinear View Adaptive Recurrent Neural Network (VA-RNN)

Granger-causal links



Behavioural and aggregator DFM

Granger-causal partition

Downstream DFMs forecast conditionally on the link variables from upstream DFMs.

$$\boldsymbol{x}_t^{(j)} = \begin{bmatrix} x_t^{(j)} \\ \boldsymbol{x}_t^{l} \\ \boldsymbol{x}_t \end{bmatrix} \qquad \begin{array}{l} \text{– target variable (quarterly)} \\ \text{– link variables (monthly or quarterly)} \\ \text{– other variables (monthly or quarterly).} \end{array}$$

Behavioural models are conventional DMFs

$$\boldsymbol{x}_t^{(j)} = \boldsymbol{\Lambda}(L)\mathbf{f}_t + \boldsymbol{D}(L)\boldsymbol{\epsilon}_t$$
$$(\boldsymbol{I} - \boldsymbol{\Phi}(L))\mathbf{f}_t = \boldsymbol{e}_t$$

Aggregator models take a weighted sum of components as key input

$$y_t = \sum_{i=1}^{r} \omega_i x_t^{(i)} + \theta(L)\eta_t$$
$$(1 - \varphi(L))(\eta_t - \mu) = \epsilon_t$$

Two DFMs as an example

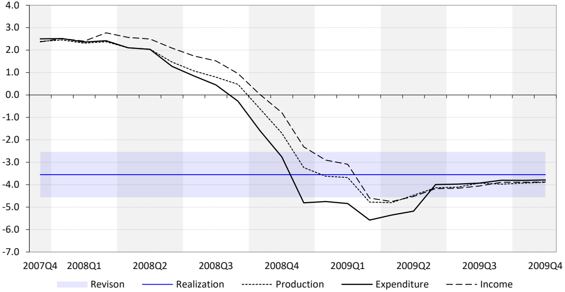
The DFM for goods exports and the DFM for the value added in the manufacturing sector.

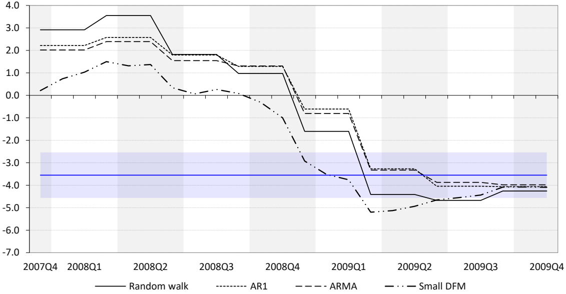
$$\boldsymbol{x}_t^{(\text{Exp of Goods})} = \begin{bmatrix} \text{Exp of Goods}_t \\ \\ \text{Truck Mileage}_t \\ \text{EU PMI}_t \\ \text{EU GDP}_t \\ \text{US GDP}_t \end{bmatrix} \qquad \boldsymbol{x}_t^{(\text{VA Manuf})} = \begin{bmatrix} \text{VA Manuf}_t \\ \\ \textbf{Exp of Goods}_t \\ \textbf{Truck Mileage}_t \\ \\ \text{Manuf Orders}_t \\ \text{Manuf Employment}_t \\ \text{Manuf Vacancies}_t \\ \text{Industr Prod}_t \\ \text{DE Manuf Conf}_t \end{bmatrix}$$

NRMSE by aggregator DFM (2007-2018)

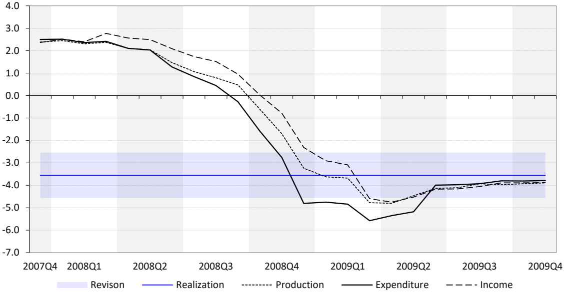
	3m(1q)	6m(2q)	9m(3q)	12m(4q)
Exports	0.36	0.65	0.91	1.14
Imports	0.52	0.79	1.04	1.26
Investment	0.85	0.90	1.02	1.15
Labor income	0.36	0.55	0.76	0.95
Employment	0.39	0.67	0.90	1.09
GDP deflator	0.57	0.73	0.76	0.76
GDP production	0.43	0.62	0.86	1.04
GDP expenditure	0.39	0.62	0.89	1.09
GDP income	0.50	0.70	0.90	1.03
GDP average	0.41	0.61	0.86	1.05
	Competing models			
GDP random walk	0.60	0.96	1.28	1.58
GDP AR(1)	0.58	0.87	1.09	1.27
GDP ARMA(2,1)	0.56	0.82	1.02	1.18
GDP Small DFM	0.50	0.76	0.96	1.14
GDP Large DFM	0.60	0.73	0.85	0.93
GDP MIDAS	0.49	0.79	0.99	1.12
	Error inflation without linkages			
GDP production	1.09	1.11	1.03	1.01
GDP expenditure	1.51	1.26	1.10	1.05
GDP income	1.08	1.14	1.11	1.07
GDP average	1.15	1.16	1.08	1.04

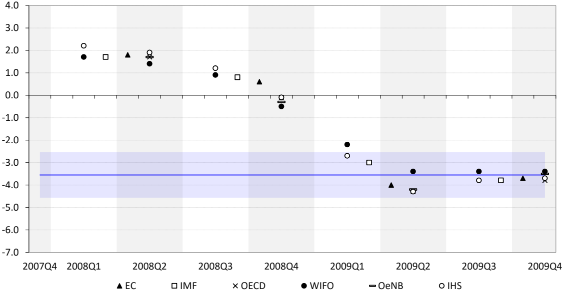
CDFM vs. competing models (2009)



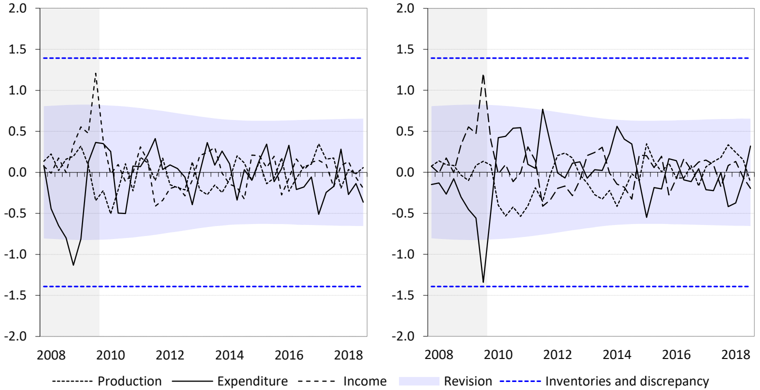


CDFM vs. experts (2009)





Discrepancies between the three GDPs



Conditional forecasting – Foreign GDP shock