Nowcasting the Czech Trade Balance

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Research Open Day

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The views expressed herein are those of the authors and do not necessarily reflect the view of the Czech National Bank

Road Map

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- **Motivation**
- **Data & Stylized Facts**
- **Description of Methods**
- **Results & Conclusions**

Motivation

⇒ There is evidence that real time information improves forecasting with structural models

⇒ It usually focuses on GDP, including CNB research …

- Arnoštová, K., Havrlant, D., Růžička, L., & Tóth, P. (2011). Short-Term Forecasting of Czech Quarterly GDP Using Monthly Indicators. *Finance a Úvěr–Czech Journal of Economics and Finance*, 6, 566-583
- Michal Franta, David Havrlant, Marek Rusnák (2014). Forecasting Czech GDP Using Mixed-Frequency Data Models, CNB WP 8/2014
- Marek Rusnák (2013). Nowcasting Czech GDP in Real Time, CNB WP 6/2013

⇒ To our knowledge there is no nowcast model for Czech trade

⇒ We aim at filling this gap

Data: forecasted variables

- We aim at nowcasting of the following 8 time series:
  - Monthly frequency (4 series):
    - growth rates of export and import (values)
    - growth rates of export and import prices
  - Quarterly frequency:
    - Real and nominal export and import (national account)

- Data transformations:
  - We chose to represent our results using yearly growth rates

- Our Data sample starts after the Czech Republic joined the E.U.
  - To avoid a clear structural break in export and import series

Data: Indicators

- We have collected a large number of indicators that can help in forecasting the variables of interests

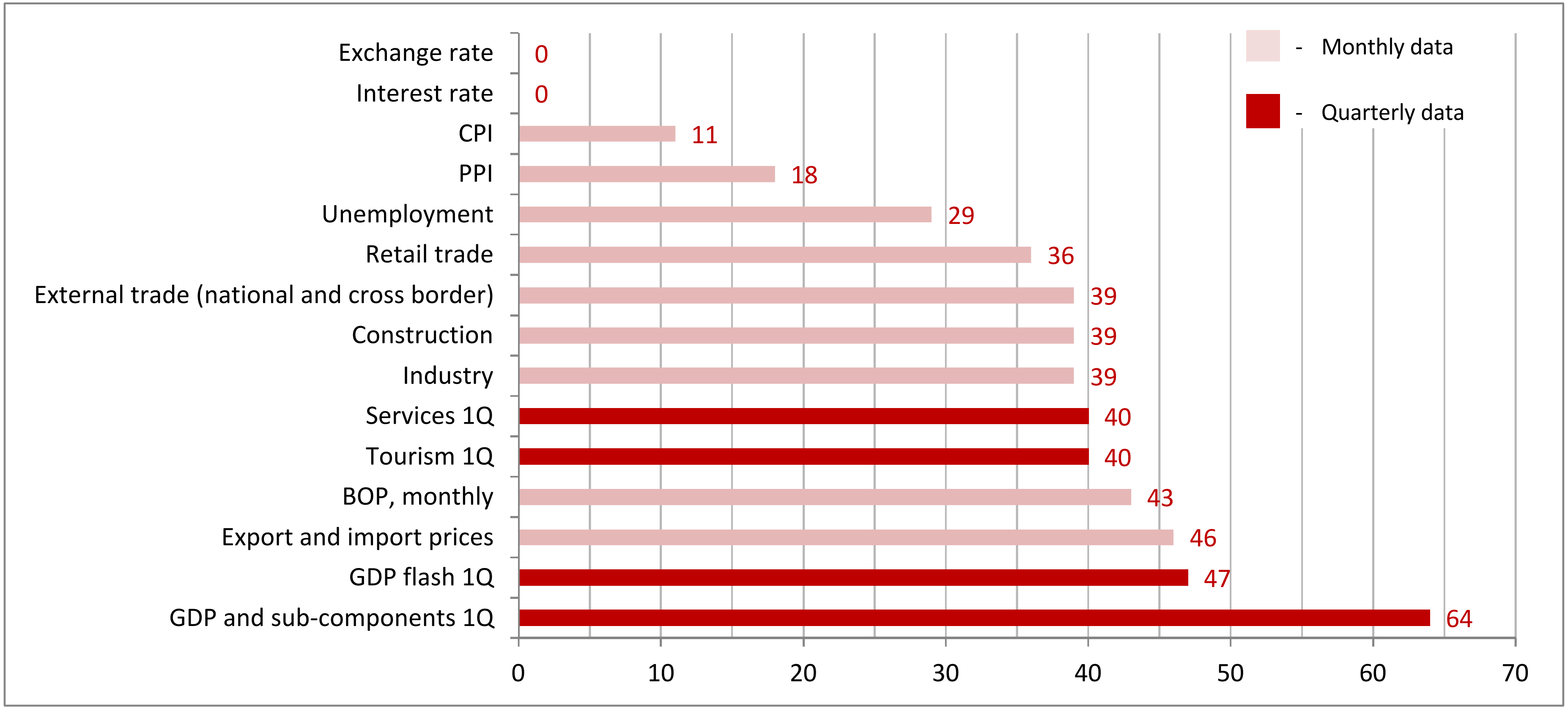
1. Variables describing historical development:
   Foreign (mainly German, but also US and EA) and Czech

2. Leading indicators

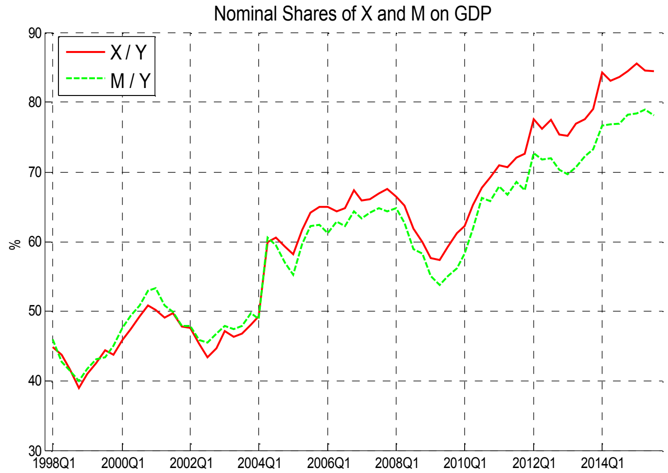
3. Financial variables
   - Commodity prices
   - Exchange rates

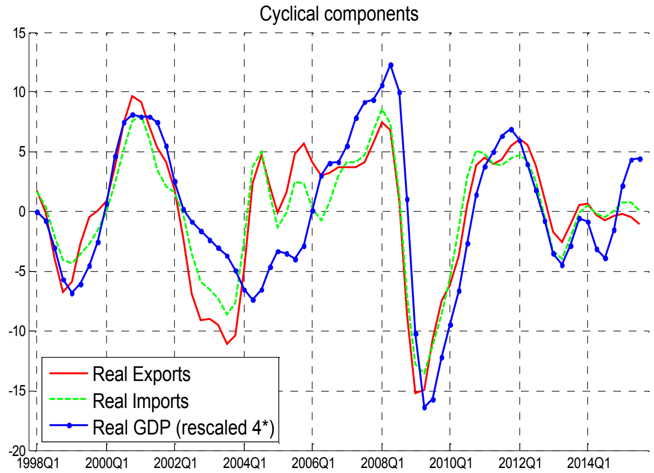
Export and import data are the most affected by publication delay.

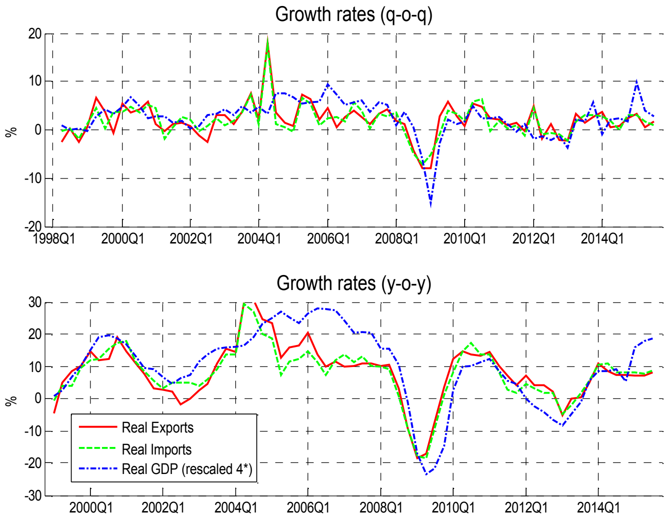
Publication delay for selected March 2016 data for the Czech Republic
Number of days

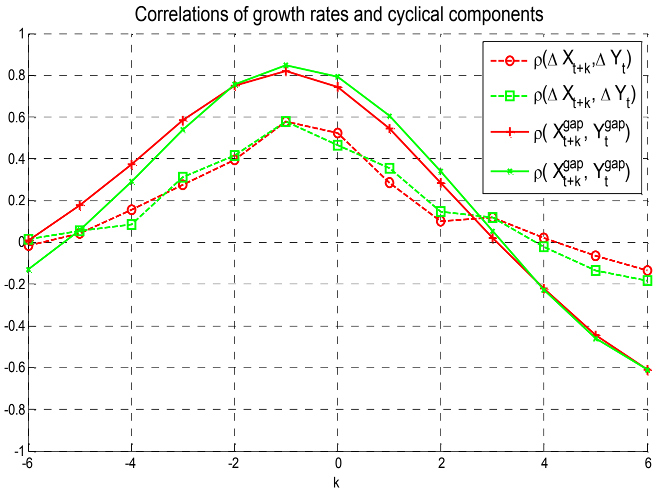


Some stylized facts about Czech trade: trends & cycles









Czech Trade is aligned with Cyclical Position of the EA

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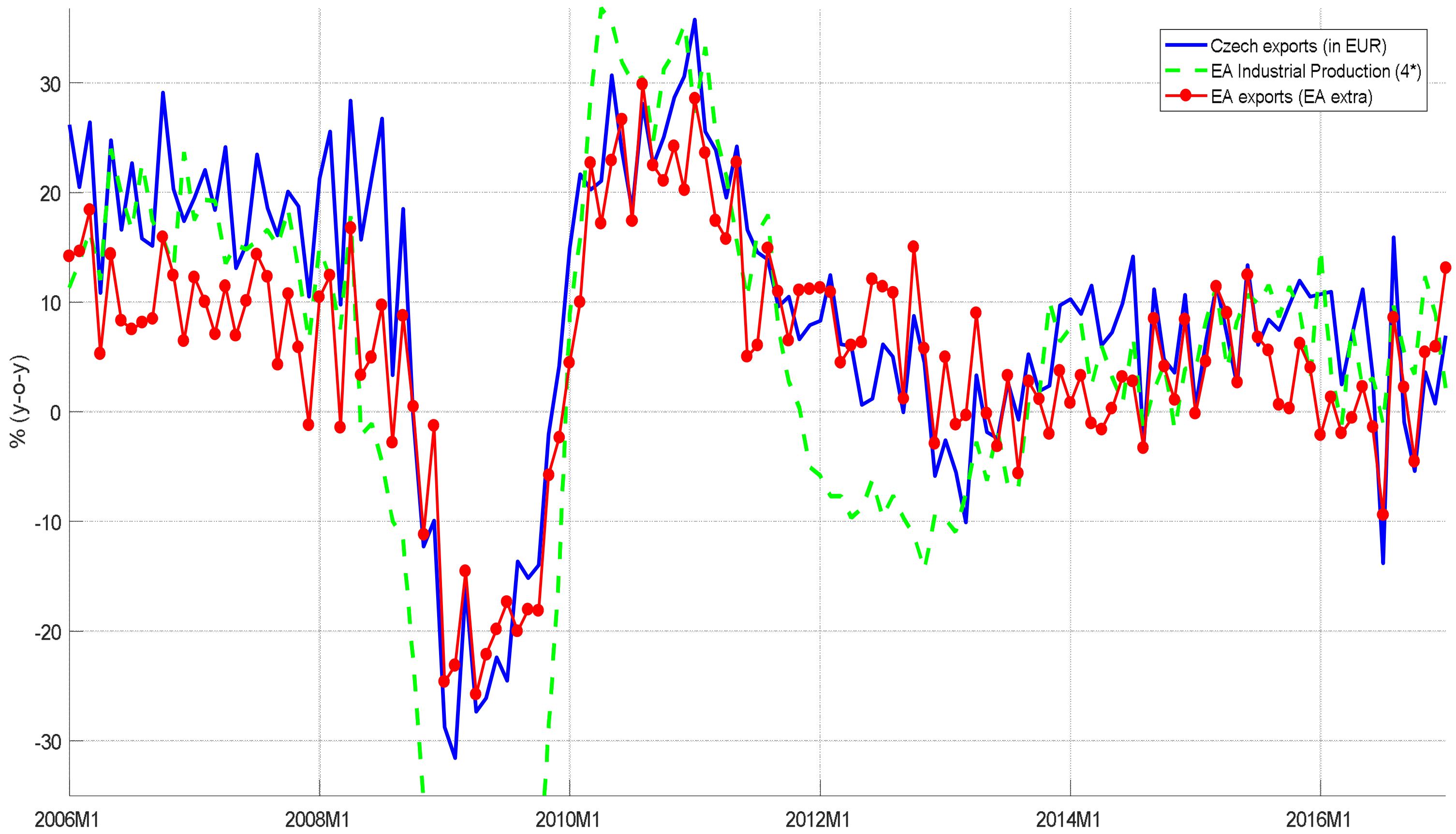


- **The alignment is strong especially for exports and investments**
  - **CZ exports are part of the Global Value Chains**

Methods Considered

- Univariate techniques:
    - Random walk and unconditional mean
    - Exponential smoothing
    - Univariate AR processes of various lags
        - Including Bayesian and TV variants
- Dimension-reduction Techniques:
    - Principal component regression
    - Partial least squares
- Elastic net regression
- Dynamic Factor Model

Univariate Techniques

- **Trade values:**
  - AR(4) to AR(6) clearly outperform other univariate models
  - Time-varying methods do not improve over the constant parameter AR models

- **Import and export price growth**
  - AR(1) or a variant of exponential smoothing is the best model
  - Very similar to random walk prediction
  - For backcast and nowcast of trade prices (unlike values), the random walk is a benchmark hard to beat

Principal Component Regression

The forecasting regressions

$$y_{t+k|t} = \Lambda_t \beta_k + \varrho y_t,$$

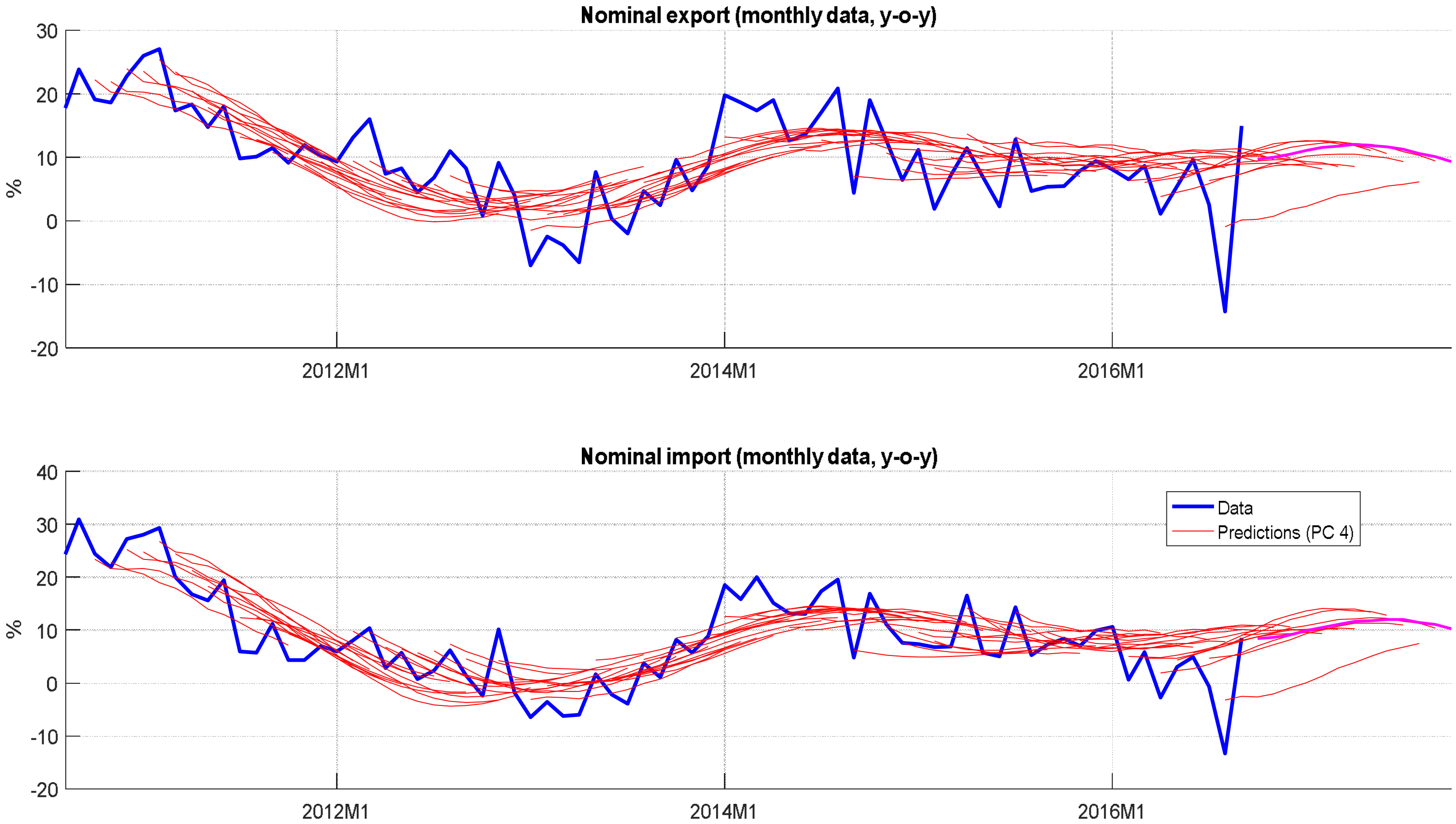
where Λ_t is the vector of principal components, i.e. a low dimensional object that spans the variability in data.

- By means of an EM algorithm, the PC can be adapted to missing data
- using a MIDAS framework, it can be adapted to mixed frequency data

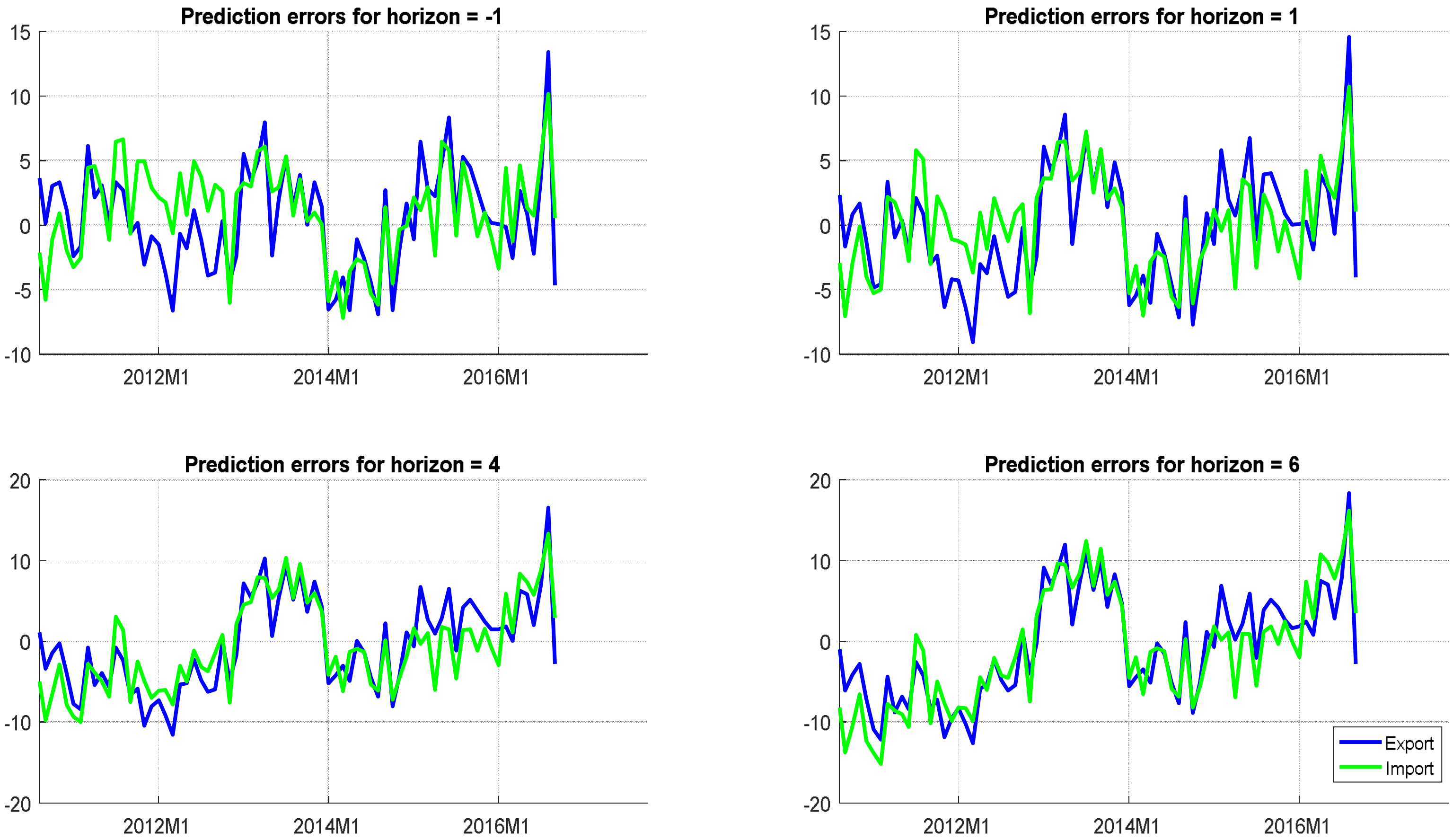
We evaluate the forecasting properties for various number of principal components and also consider limited time variation in loadings β_k

- The best number of principal components is 4
- Little reason for time variation (even for in-sample evaluation)

Principal Component Regression: Forecast



Principal Component Regression: Forecast Errors



Forecast errors of exports and imports are strongly correlated

Elastic Net Regression

- This is another regularization technique.

$$y_{t+k|t} = X_t \beta_k$$

- All coefficients are shrunk to zero (λ_2) and some are set to zero by soft thersholding (λ_1)

$$\beta = argmin\{\sum_i (Y_i - \sum_l X_{il}\beta_l)^2 - \lambda_1 \sum_l |\beta_l| - \lambda_2 \sum_l \beta_l^2\},$$

- The two constants (λ_1) and (λ_2) are estimated by cross-validation:
  - Separately for each time horizon and each variable of interest

Elastic Net Regression: Important Predictors

- Predictors selected by elastic net widely differ across variables and horizons:

- **Exports and Imports**:
  - For backcast, own lags tend to dominate
  - For nowcast, the new orders (domestic and foreign) and sentiment (German) dominate
  - For short-term fcast, also domestic variables (labor market) enter

Price Indexes

  - For backcast, nowcast and short-term fcast a bunch of domestic and foreign variables (commodity prices, senitiments, new orders, …) are important
  - Not only costs, but also cyclical variables play a role

Elastic Net Regression: Forecast /1

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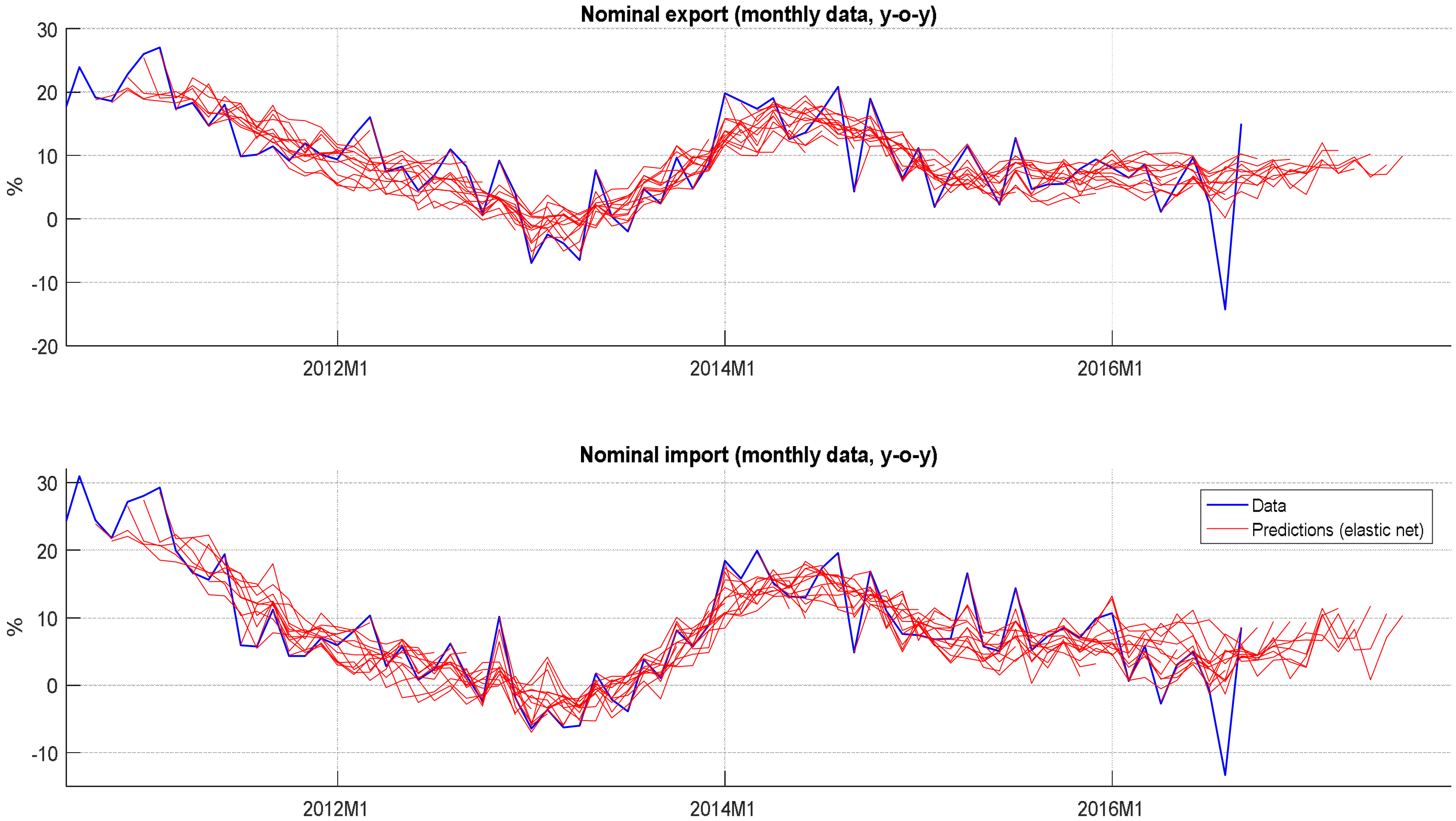
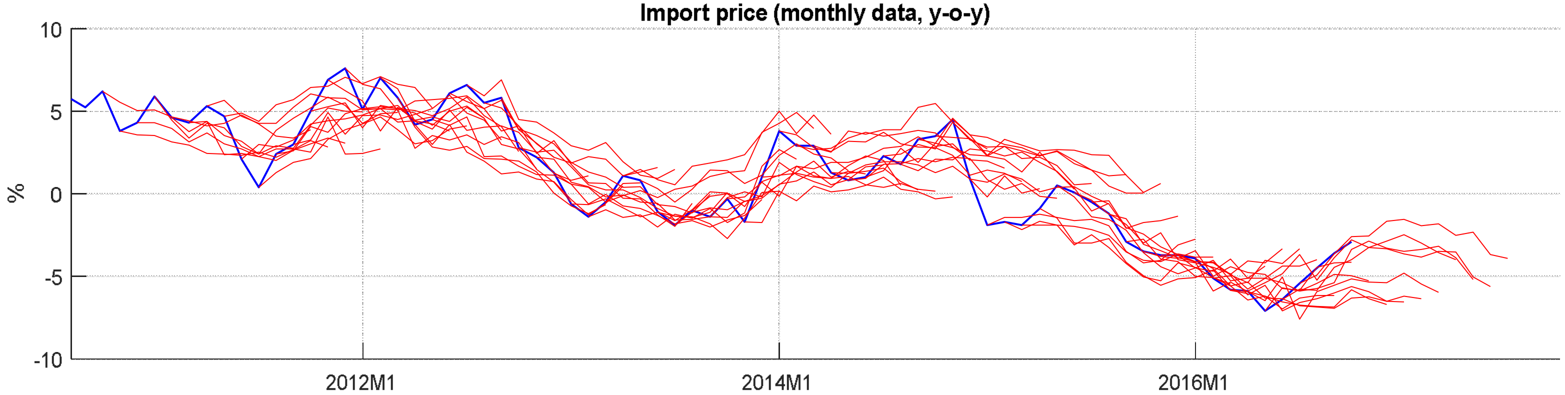
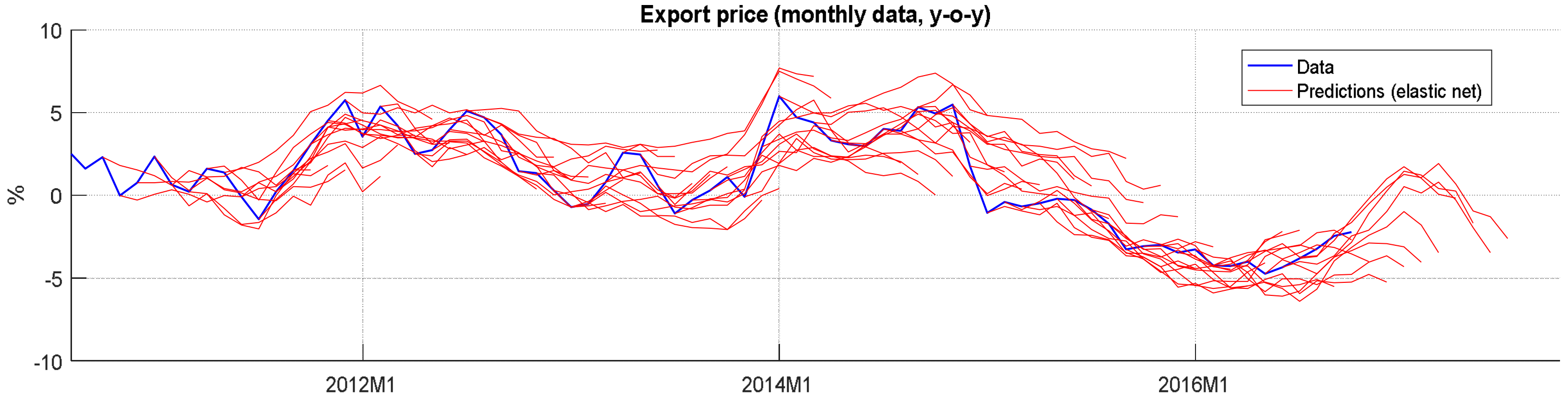
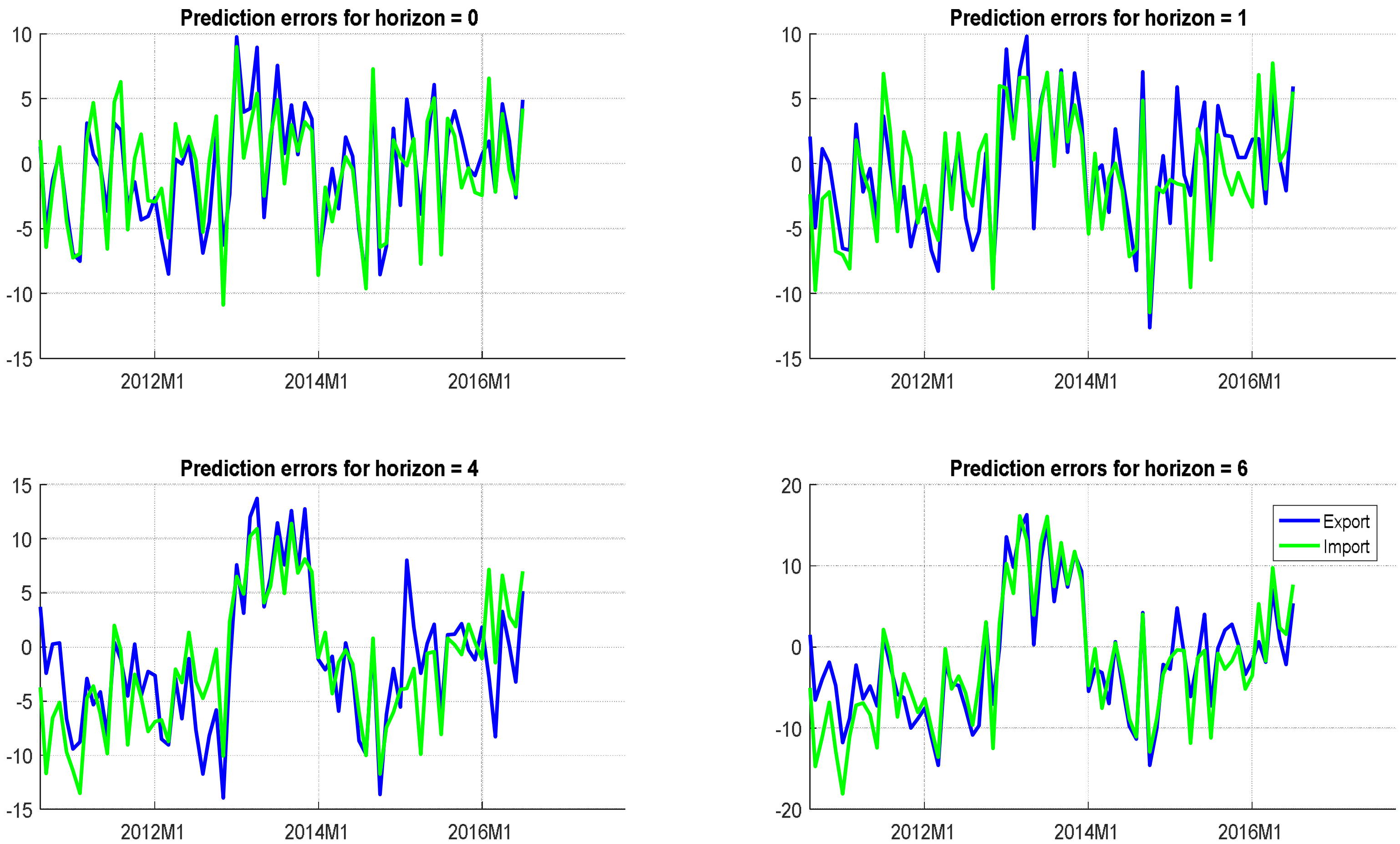


Elastic Net Regression: Forecast /2





Prediction errors are correlated



Export and import forecast errors are strongly correlated

Dynamic Factor Model

The Dynamic Factor Model is casted in the state space form.

- The state equation:

$$f_t = A_1 f_{t-1} + \cdots + A_k f_{t-k} + \varepsilon_t.$$

- The observation equation:

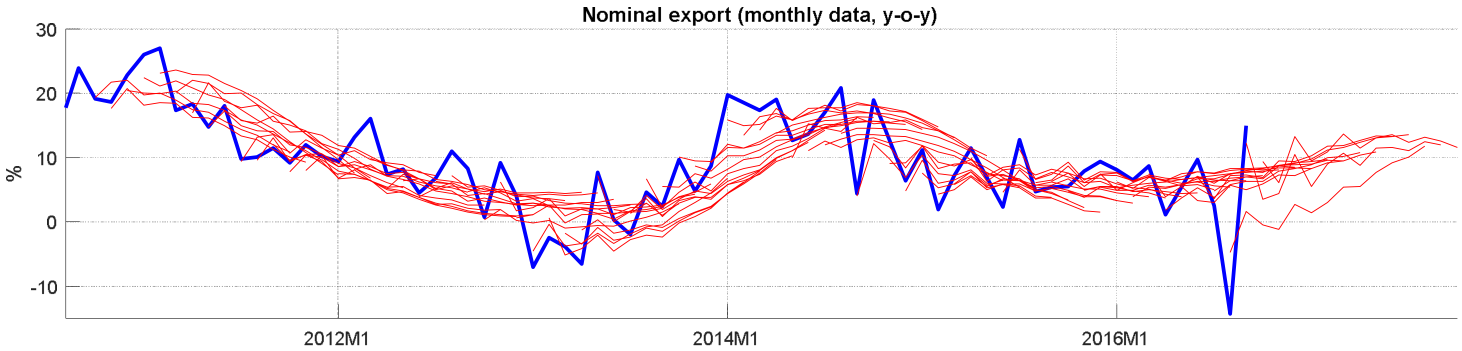
$$y_t^m = D + C_0 f_t + \cdots + C_L f_{t-L} + v_t^m.$$

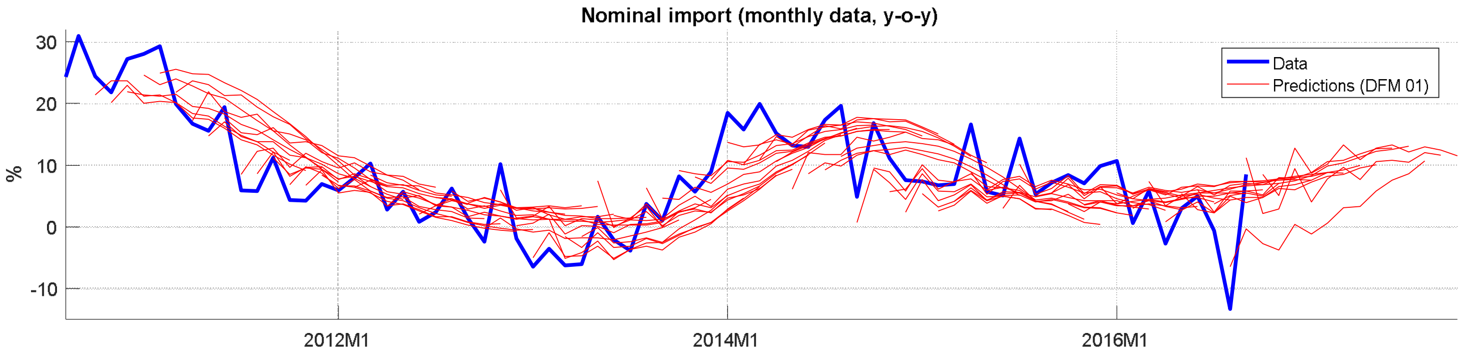
If coefficients $\{A_i\}_{i=1}^{k}, D, \{C_j\}_{j=0}^{l}$ are known, prediction can be done by the Kalman filter

- The Kalman filter machinery easily deals with missing observations
- Also, judgments can be easily incorporated

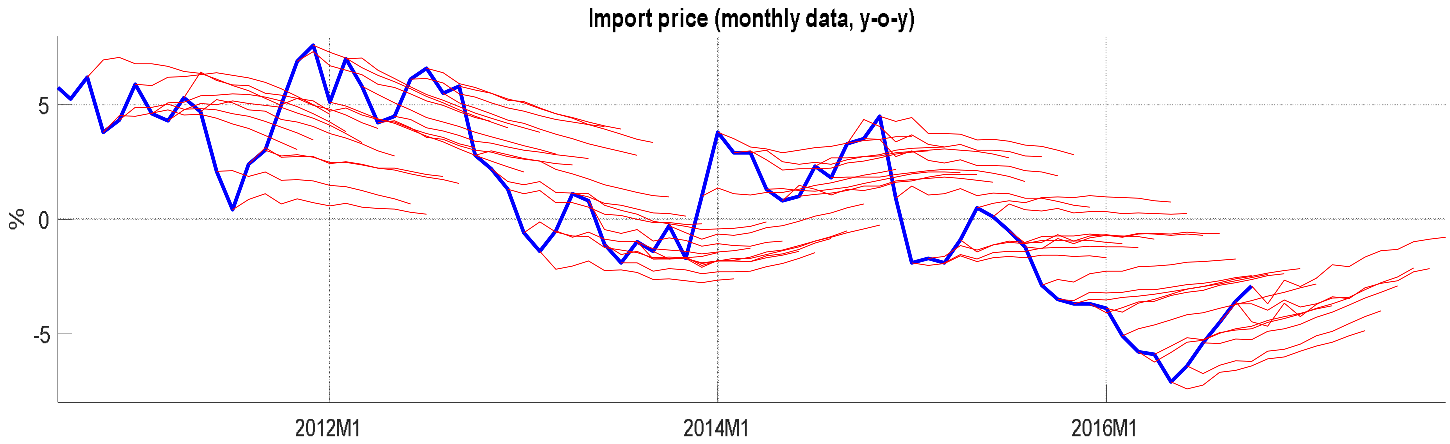
Estimation: two stage approach by DOZ, GIANNONE & REICHLIN (2011)

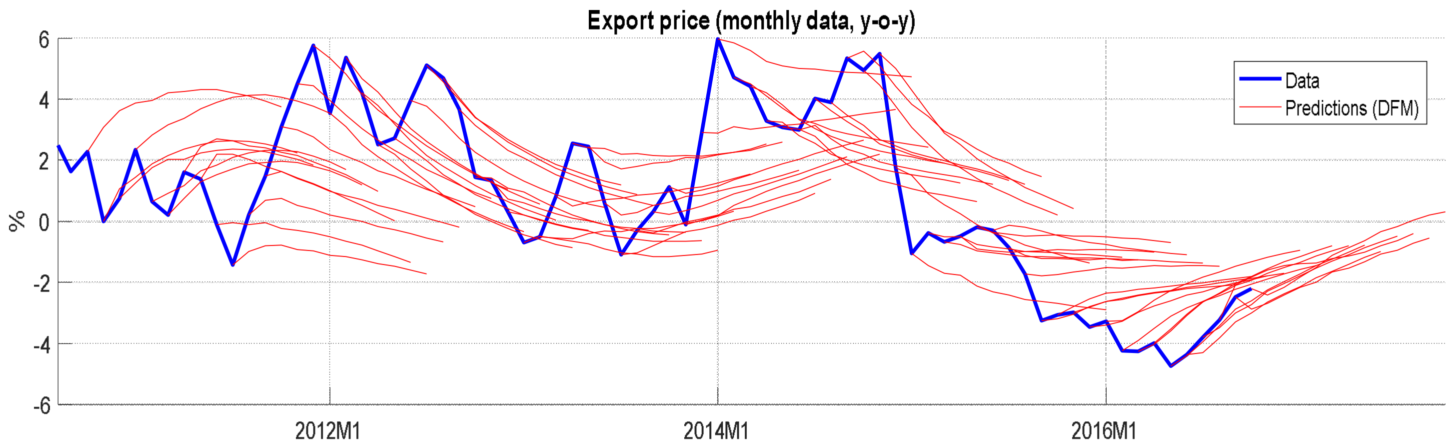
Dynamic Factor Model: Forecast of Volumes



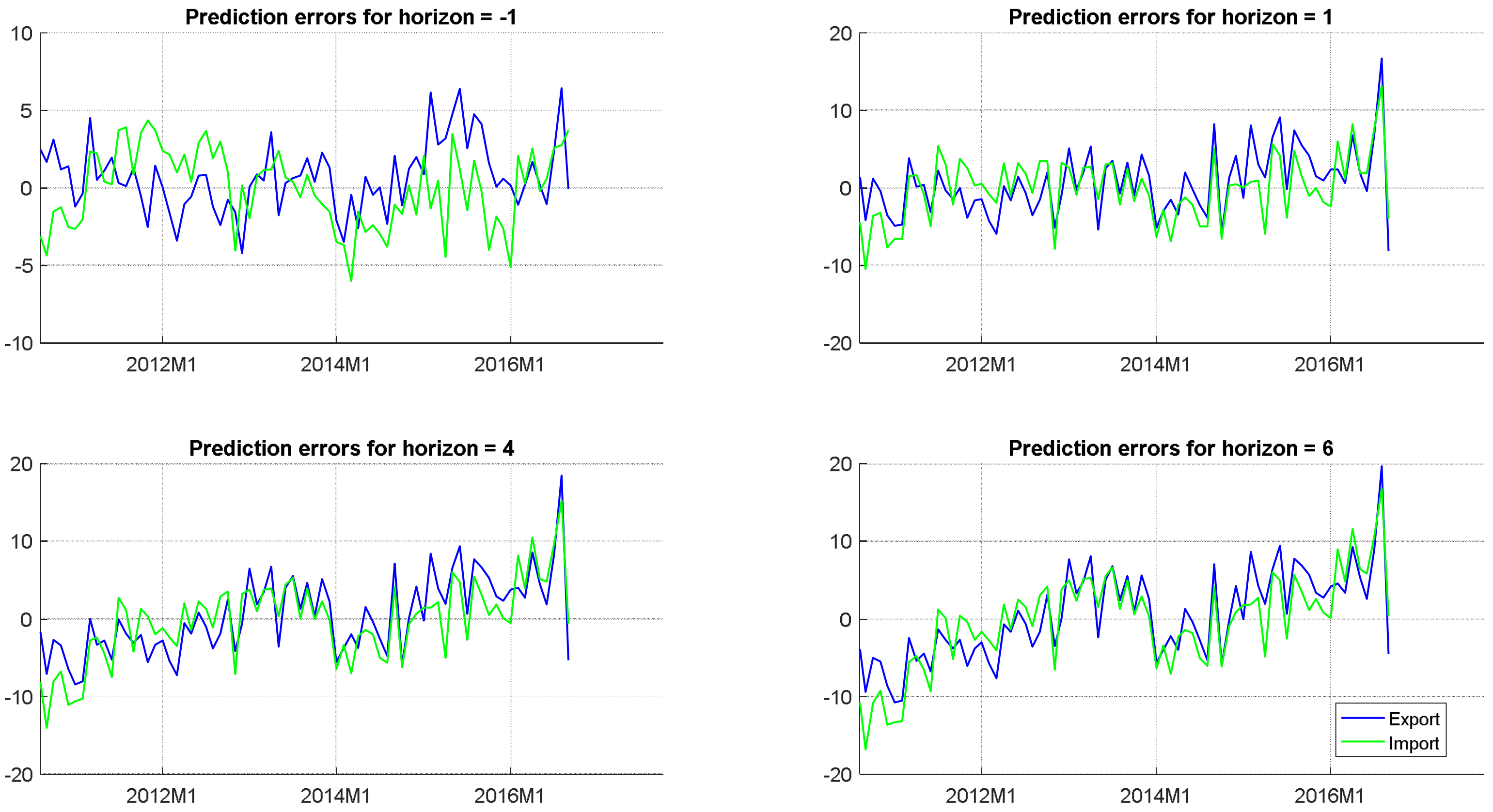


Dynamic Factor Model: Forecasting of Prices





Dynamic Factor Model: Forecast Errors



- Unlike Elastic Net, fcast errors are not correlated for short horizons
- DFM fcast errors uncorrelated with PC/ elastic net fcast errors

Forecasts Comparisons: Trade Volumes

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	-1	0	1	2	3	4	5	6	7	8	9
Export (nominal, yearly growth rates), monthly data											
Unconditional mean	6.58	6.65	6.69	6.72	6.59	6.53	6.51	6.38	6.32	6.26	6.11
Random walk	5.09	5.41	4.92	6.25	6.44	6.40	7.64	7.53	7.91	8.86	8.89
AR model (4)	**4.20**	**4.51**	4.69	5.27	5.57	5.57	6.15	6.16	6.46	6.93	6.96
PCA (4)	4.60	4.81	4.86	5.49	5.51	5.87	6.04	6.04	6.14	6.15	6.03
Elastic Net	4.57	4.54	**4.63**	**4.48**	**4.88**	**4.88**	**5.05**	**4.91**	**5.19**	**5.17**	**4.83**
DFM	4.31	4.63	4.94	5.67	6.03	6.52	7.04	7.24	7.54	7.78	7.80
PLS (3)	8.06	8.19	8.54	8.87	8.92	9.34	9.31	9.42	9.40	10.02	10.06
Import (nominal, yearly growth rates), monthly data											
Unconditional mean	7.59	7.71	7.71	7.74	7.59	7.39	7.27	7.02	6.85	6.72	6.50
Random walk	5.05	5.51	5.34	6.93	7.18	7.13	8.77	8.67	9.00	10.33	10.20
AR model (6)	4.39	4.68	4.76	5.70	5.80	5.88	6.27	5.84	6.31	6.87	6.51
PCA (4)	**4.33**	**4.39**	**4.44**	5.04	5.19	5.47	5.78	5.79	6.01	6.05	5.98
Elastic Net	4.62	4.67	4.73	**4.48**	**4.82**	**5.03**	**5.12**	**4.80**	**4.89**	**4.94**	**5.20**
DFM	4.38	4.72	5.09	5.80	6.25	6.89	7.43	7.57	8.08	8.46	8.50
PLS (3)	7.23	7.31	7.60	8.02	8.41	9.06	9.33	9.67	10.13	10.70	10.84

Forecast Comparison: Prices Indexes

Export prices (yearly change)											
Unconditional mean	2.85	2.82	2.83	2.86	2.90	2.91	2.92	2.93	2.94	2.98	3.01
Random walk	1.12	1.64	2.00	2.31	2.45	2.51	2.59	2.69	2.92	3.27	3.58
AR model (1)	**1.09**	**1.59**	1.92	2.20	2.34	2.41	2.52	2.61	2.72	2.89	3.05
PCA (4)	1.70	1.95	2.09	2.17	2.15	2.11	2.07	2.05	2.07	2.03	2.00
Elastic Net	1.62	1.65	**1.67**	**1.66**	**1.85**	**1.80**	**1.72**	**1.64**	**1.66**	**1.65**	**1.61**
DFM	1.32	1.73	2.08	2.23	2.34	2.45	2.54	2.58	2.62	2.66	2.68
PLS (3)	1.59	1.87	1.97	2.17	2.35	2.68	2.76	3.07	3.32	3.64	3.68
Import prices (yearly change), monthly data											
Unconditional mean	3.58	3.60	3.68	3.75	3.77	3.76	3.74	3.72	3.69	3.68	3.67
Random walk	1.22	1.81	2.30	2.64	2.76	2.82	2.84	2.96	3.18	3.46	3.83
Local level model	**1.20**	1.81	2.32	2.68	2.81	2.88	2.88	2.98	3.16	3.41	3.82
PCA (4)	1.70	1.95	2.09	2.17	2.15	2.11	2.07	2.05	2.07	2.03	2.00
Elastic Net	1.56	**1.61**	**1.64**	**1.69**	**1.77**	**1.79**	**1.73**	**1.65**	**1.60**	**1.61**	**1.64**
DFM	1.32	1.73	2.08	2.23	2.34	2.45	2.54	2.58	2.62	2.66	2.68
PLS (3)	1.59	1.87	1.97	2.17	2.35	2.68	2.76	3.07	3.32	3.64	3.68
Effective foreign PPI (yearly change)											
Unconditional mean	2.88	2.89	2.91	2.96	3.02	3.08	3.13	3.19	3.23	3.28	3.33
Random walk	**0.38**	**0.66**	0.89	1.08	1.22	1.34	1.46	1.58	1.73	1.88	2.04
AR (1)	0.39	0.66	**0.89**	1.07	1.21	1.33	1.43	1.55	1.69	1.83	1.96
PCA (4)	0.68	0.80	0.96	1.17	1.36	1.59	1.78	1.96	2.10	2.22	2.32
Elastic Net	0.87	0.78	0.90	**0.94**	**1.01**	**1.04**	**1.02**	**1.07**	**1.05**	**1.09**	**1.09**
PLS (5)	1.11	1.33	1.54	1.82	2.12	2.48	2.69	2.89	3.08	3.15	3.21

Conclusions

- There are methods that can improve over univariate benchmark for **import and export growths**
  - At lower horizons, the PC regression is a very good predictor
  - At longer horizons, the elastic net regression is a clear winner
- **Import and export prices**
  - We were unable to find a method that would beat the univariate benchmarks for short horizons, however the DFM could be competitive
  - For longer horizons, the elastic net regression is a clear winner

Thank you for your attention

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