Forecasting Local Inflation with Global Inflation: When Economic Theory Meets the Facts

Roberto Duncan
Ohio University

Enrique Martínez-García
Federal Reserve Bank of Dallas

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Motivation

- The idea that domestic inflation in a small open economy may depend on international conditions is not new.
- However, that is not necessarily the case for a large economy such as the US.
- Ciccarelli and Mojon (2010), Ferroni and Mojon (2014), among others, find that global inflation (captured by a factor component) can be useful in predicting the US inflation rate.
- We believe that this fact could be understood with a New Open Economy Macro (NOEM) model.
1. Introduction

What we do

- We provide a tractable framework to interpret the global determinants of local inflation: a NOEM model
- An *error correction mechanism* is derived from our model
- This mechanism pulls local inflation in line with global inflation and can be exploited for forecasting
- We show that the solution to our workhorse NOEM model can be approximated by a parsimonious VAR that we opt to estimate using Bayesian techniques.
What we find

- In general, our NOEM-BVAR produces mostly a lower RMSPE than its competitors
- In a number of interesting cases, the gains in smaller RMSPEs are statistically significant
- The NOEM-BVAR outperforms or at least shows a predictive ability similar to factor-augmented models for the case of the US
- The NOEM-BVAR produces success ratios that are comparable or higher than those of its competitors
- We view the proposed NOEM-BVAR model as an important benchmark for forecasting inflation across the world.
1. Introduction

On inflation forecasting with DSGE models

**Inflation forecasting with DSGE models**

- DSGE models have become an integral part of the toolkit for macroeconomic forecasting and policy analysis of many central banks.

- Unlike most of the existing DSGE model-based forecasting literature:
  - we adopt a stylized New Keynesian framework that emphasizes the role of global economic developments;
  - we derive a parsimonious forecasting model of inflation.
1. Introduction

2. The model

3. Empirical findings

4. Concluding remarks
2. The NOEM model

Main features and assumptions

The NOEM model

- Simple New Open Economy Macro (NOEM) model
  - similar to Martínez-García and Wynne (2010)
  - related to Clarida et al. (2002)

- Two-country DSGE model with
  - complete asset markets
  - monopolistic competition, price stickiness
  - linear-in-labor technologies
  - cashless economy, flexible exchange rates

- Equilibrium conditions are log-linearized around the steady state
The open-economy Phillips curves:

\[
\hat{\pi}_t \approx \beta E_t \hat{\pi}_{t+1} + [\phi_{1,1} \hat{x}_t + \phi_{1,2} \hat{x}^*_t] \\
\hat{\pi}^*_t \approx \beta E_t \hat{\pi}^*_{t+1} + [\phi_{2,1} \hat{x}_t + \phi_{2,2} \hat{x}^*_t]
\]

where

\(\hat{\pi}_t(\hat{\pi}^*_t)\) ≡ Home (Foreign) inflation (q-o-q changes in CPI)
\(\hat{x}_t(\hat{x}^*_t)\) ≡ Home (Foreign) output gaps
\(\phi_{i,j}\) ≡ composite parameters.
The open-economy dynamic IS equations:

\[ \phi_{3,1}E_t [\hat{x}_{t+1} - \hat{x}_t] \approx \phi_{3,2} [\hat{r}_t - \hat{r}_t] + \phi_{3,3} [\hat{r}^*_t - \hat{r}^*_t] \] \quad (3)

\[ \phi_{3,1}E_t [\hat{x}^*_{t+1} - \hat{x}^*_t] \approx \phi_{4,2} [\hat{r}_t - \hat{r}_t] + \phi_{4,3} [\hat{r}^*_t - \hat{r}^*_t] \] \quad (4)

where

\[ \hat{r}_t \equiv \hat{i}_t - E_t [\hat{\pi}_{t+1}] \equiv \text{Home country real interest rate} \]
\[ \hat{r}^*_t \equiv \hat{i}^*_t - E_t [\hat{\pi}^*_{t+1}] \equiv \text{Foreign country real interest rate} \]
\[ \hat{i}_t(\hat{i}^*_t) \equiv \text{Home (Foreign) short-term nominal interest rate} \]
\[ \hat{r}_t(\hat{r}^*_t) \equiv \text{Home (Foreign) natural real rates of interest} \]
\[ \phi_{i,j} \equiv \text{composite parameters} \]
2. The NOEM model

Loglinearized conditions

Home and Foreign potential outputs:

\[
\hat{\gamma}_t \approx \phi_{5,1} \hat{a}_t - \phi_{5,2} \hat{a}^*, \\
\hat{\gamma}^*_t \approx -\phi_{6,1} \hat{a}_t + \phi_{6,2} \hat{a}^*
\] (5) (6)

where

\( \hat{a}_t (\hat{a}^*_t) \equiv \text{Home (Foreign) productivity shock.} \)

\( \phi_{i,j} \equiv \text{composite parameters.} \)
2. The NOEM model

Loglinearized conditions

Home and Foreign natural rates of interest:

\[ \hat{r}_t \approx \phi_{7,1} \left( E_t \left[ \hat{y}_{t+1} \right] - \hat{y}_t \right) + \phi_{7,2} \left( E_t \left[ \hat{y}_{t+1}^* \right] - \hat{y}_t^* \right) \]  \hspace{1cm} (7)  

\[ \hat{r}_t^* \approx \phi_{8,1} \left( E_t \left[ \hat{y}_{t+1} \right] - \hat{y}_t \right) + \phi_{8,2} \left( E_t \left[ \hat{y}_{t+1}^* \right] - \hat{y}_t^* \right) \]  \hspace{1cm} (8)
Loglinearized conditions

Home and Foreign Taylor-type monetary policy rules:

\[
\hat{i}_t \approx \psi_\pi \hat{\pi}_t + \psi_x \hat{x}_t + \hat{m}_t \quad (9)
\]

\[
\hat{i}_t^* \approx \psi_\pi \hat{\pi}_t^* + \psi_x \hat{x}_t^* + \hat{m}_t^* \quad (10)
\]

where

\[
\hat{m}_t (\hat{m}_t^*) \equiv \text{Home (Foreign) monetary policy shock.}
\]
2. The NOEM model

Loglinearized conditions

The stochastic process for Home and Foreign monetary policy shocks:

\[
\begin{pmatrix}
\hat{m}_t \\
\hat{m}^*_t
\end{pmatrix}
\approx
\begin{pmatrix}
\delta_m & 0 \\
0 & \delta_m
\end{pmatrix}
\begin{pmatrix}
\hat{m}_{t-1} \\
\hat{m}^*_{t-1}
\end{pmatrix}
+
\begin{pmatrix}
\hat{\varepsilon}_t^m \\
\hat{\varepsilon}^*_t
\end{pmatrix}
\] (11)

\[
\begin{pmatrix}
\hat{\varepsilon}_t^m \\
\hat{\varepsilon}^*_t
\end{pmatrix}
\sim
\mathcal{N}
\left(
\begin{pmatrix}
0 \\
0
\end{pmatrix},
\begin{pmatrix}
\sigma^2_m & \rho_{m,m^*}\sigma^2_m \\
\rho_{m,m^*}\sigma^2_m & \sigma^2_m
\end{pmatrix}
\right)
\] (12)

The stochastic process for Home and Foreign aggregate productivity:

\[
\begin{pmatrix}
\hat{a}_t \\
\hat{a}^*_t
\end{pmatrix}
\approx
\begin{pmatrix}
\delta_a & 0 \\
0 & \delta_a
\end{pmatrix}
\begin{pmatrix}
\hat{a}_{t-1} \\
\hat{a}^*_{t-1}
\end{pmatrix}
+
\begin{pmatrix}
\hat{\varepsilon}_t^a \\
\hat{\varepsilon}^*_t
\end{pmatrix}
\] (13)

\[
\begin{pmatrix}
\hat{\varepsilon}_t^a \\
\hat{\varepsilon}^*_t
\end{pmatrix}
\sim
\mathcal{N}
\left(
\begin{pmatrix}
0 \\
0
\end{pmatrix},
\begin{pmatrix}
\sigma^2_a & \rho_{a,a^*}\sigma^2_a \\
\rho_{a,a^*}\sigma^2_a & \sigma^2_a
\end{pmatrix}
\right)
\] (14)
2. The NOEM model

Three key implications

Key implications

- The global economy
- The "error correction" representation
- The VAR solution
The global economy

The system that describes the world economy is

\[ \hat{\pi}_t^W \approx \beta \mathbb{E}_t \left[ \hat{\pi}^W_{t+1} \right] + \left( \frac{(1 - \alpha)(1 - \beta \alpha)}{\alpha} \right) (\varphi + \gamma) \hat{x}_t^W \]  
(15)

\[ \gamma \left( \mathbb{E}_t \left[ \hat{x}^W_{t+1} \right] - \hat{x}_t^W \right) \approx \left( \hat{i}_t^W - \mathbb{E}_t \left[ \hat{\pi}^W_{t+1} \right] \right) - \hat{r}_t^W \]  
(16)

\[ \hat{i}_t^W \approx \psi_{\pi} \hat{\pi}_t^W + \psi_x \hat{x}_t^W + \hat{m}_t^W \]  
(17)

where

\[ \hat{g}^W_t \equiv \frac{1}{2} \hat{g}_t + \frac{1}{2} \hat{g}_t^* \text{ for any } g = \{\pi, x, i, r, m\}. \]
The "error correction" representation

We can derive the following simple "error correction" representation for Home inflation relative to global inflation ($\hat{\pi}_t^W$):

$$\hat{\pi}_t = \hat{\pi}_t^W + \tilde{a}_{11} (\theta) (\hat{\pi}_{t-1} - \hat{\pi}_{t-1}^W) + \tilde{a}_{12} (\theta) (\hat{y}_{t-1} - \hat{y}_{t-1}^W) + \hat{\varepsilon}_{t}^{ec}$$  \hspace{1cm} (18)

where

$$\hat{\pi}_t^W \equiv \frac{1}{2} \hat{\pi}_t + \frac{1}{2} \hat{\pi}^*$$
$$\hat{y}_t^W \equiv \frac{1}{2} \hat{y}_t - 1 + \frac{1}{2} \hat{y}^*-1$$
$$\tilde{a}_{11}, \tilde{a}_{12} \equiv \text{composite parameters of } \theta \text{ (vector of structural parameters)}$$
$$\hat{\varepsilon}_{t}^{ec} \equiv \text{composite of the exogenous monetary and productivity innovations}.$$
2. The NOEM model

Intuition about the error correction mechanism

**Intuition**

A positive productivity shock in the rest of the world causes

- an increase in the external potential output
- lower external output gap and external inflation
- lower real exchange rate (foreign products become relatively cheaper)
- a substitution effect away from domestic goods
- domestic output and output gap fall
- domestic inflation decreases
2. The NOEM model

The VAR-type solution

We can simply recast the state-space solution of the NOEM model in terms of the vector of observables

$$\hat{Z}_t = (\hat{\pi}_t, \hat{\pi}_t^*, \hat{y}_t, \hat{y}_t^*)'$$

The full NOEM model solution takes the form of a VAR(1):

$$\hat{Z}_t = \tilde{A}(\theta) \hat{Z}_{t-1} + D(\theta) \hat{\varepsilon}_t$$

with

$$\hat{\varepsilon}_t = (\hat{\varepsilon}_t^a, \hat{\varepsilon}_t^{a*}, \hat{\varepsilon}_t^m, \hat{\varepsilon}_t^{m*})'.$$
3. Empirical findings

The forecasting exercise

- Horse race to forecast inflation, 15 competing models vs ours
- Quarter-on-quarter headline-CPI inflation rates ($\pi_t$)

$$\pi_t = 400 \ln(CPI_t/CPI_{t-1})$$

- End-of-quarter and seasonally-adjusted data for a sample of 17 OECD economies during the 1980Q1-2014Q4 period
3. Empirical findings

The forecasting exercise

- Pseudo out-of-sample forecasts are constructed by recursive estimation.
- The forecast horizons are \( h = \{1, 4, 8\} \) quarters.
- The training sample is 1980Q2-2008Q3.
- Aside from univariate specifications and frequentist techniques, we consider other elements and methods that have proved to be useful in inflation forecasting (Ferroni and Mojon, 2014):
  - Factor components (Stock and Watson, 2002, Ciccarelli and Mojon, 2010)
  - Phillips-curve-type features and commodity price indexes (Stock and Watson, 1999)
  - Bayesian vector autoregressions (Doan et al. 1984, Litterman 1986)
Competing models

1 Recursive autoregression, AR(p) model (RAR)

\[ M_1 : \pi_t = \phi_0 + \Phi(L)\pi_t + \epsilon_t \]

where \( \Phi(L) = \phi_1 L + \ldots + \phi_p L^p \) is a lag polynomial.

2 Direct forecast, AR(p) model (DAR)

\[ M_2 : \pi_{t+h} = \phi_{0,h} + \Phi(L,h)\pi_t + \epsilon_{t+h} \]

where \( \Phi(L,h) = \phi_{1,h} + \phi_{2,h} L + \ldots + \phi_{p,h} L^{p-1} \) is a lag polynomial for a given forecast horizon \( h \).
3. Empirical findings

Competing models

3 Random Walk (RW-AO)

\[ M_3 : \pi_{t+h} = \frac{1}{4} \sum_{i=1}^{4} \pi_{t+1-i} + \epsilon_{t+h} \]

4 AR(p) model with error correction (AR-EC)

\[ M_4 : \pi_{t+h} - \pi_t = \phi_{0,h} + \Phi(L, h) \Delta \pi_t + \epsilon_{t+h} \]
3. Empirical findings

Competing models

5 Factor-Augmented AR(p) model (FAR)

\[ M_5 : \pi_{t+h} = \phi_{0,h} + \Phi(L, h)\pi_t + \Theta(L, h)\hat{F}_t + \epsilon_{t+h} \]

where \( \hat{F}_t \) denotes an estimated static factor component of the inflation rates of the countries in the sample.

6 Factor-Augmented AR(p) model with error correction (FAR-EC)

\[ M_6 : \pi_{t+h} - \pi_t = \phi_{0,h} + \Phi(L, h)\Delta\pi_t + \Theta(L, h)\Delta\hat{F}_t + \epsilon_{t+h} \]

7 Factor-Augmented AR(p) model with idiosyncratic error correction term (FAR-IEC)

\[ M_7 : \pi_{t+h} - \pi_t = \phi_{0,h} + \Phi(L, h)\Delta\pi_t + \Theta(L, h)\Delta\hat{F}_t + \beta_h e_t + \epsilon_{t+h} \]

where \( e_t \) is the residual from regressing the country inflation to a measure of global inflation.
Augmented Phillips Curve

\[ M_8 : \pi_{t+h} = \phi_{0,h} + \Phi(L,h)\pi_t + A(L,h)\Delta IPI_t + B(L,h)\Delta M^2_t + \\
C(L,h)\Delta P_{t}^{Com} + \epsilon_{t+h} \]

where

\[ IPI \equiv \text{industrial production index}, \]
\[ P^{Com} \equiv \text{commodity price index (agricultural raw materials, beverages, metals and crude oil)} \]

Augmented Phillips Curve with error correction

\[ M_9 : \pi_{t+h} - \pi_t = \phi_{0,h} + \Phi(L,h)\Delta \pi_t + A(L,h)\Delta IPI_t + B(L,h)\Delta M^2_t + \\
C(L,h)\Delta P_{t}^{Com} + \epsilon_{t+h} \]
3. Empirical findings

Competing models

10 Bivariate BVAR (BVAR2-FP, BVAR2-MP).

\[ M_{10}, M_{11} : X_{t+h} = \Phi_{0,h} + \Phi(L,h)X_t + \epsilon_{t+h} \]

with \( X_t = (\pi_t, \hat{F}_t)' \), flat priors \((M_{10})\) and Minnesota priors \((M_{11})\).

11 Multivariate BVAR (BVAR4-FP, BVAR4-MP), with

\[ X_t = (\pi_t, \Delta IPI, \Delta M_2_t, \Delta P_{t}^{Com})' \]

using flat priors \((M_{12})\) and Minnesota priors \((M_{13})\).
3. Empirical findings

Competing models

Bivariate BVAR with commodity price indexes (BVAR2-COM, BVAR2-FCOM), with

\[ X_t = (\pi_t, \Delta P_{tCom})' \quad (M_{14}) \]

and

\[ X_t = (\pi_t, P_{tFCom})' \quad (M_{15}) \]

using flat priors, where

\[ P_{FCom} \equiv \text{MA-filtered commodity price index}. \]
3. Empirical findings

Our model

**NOEM-BVAR**

We follow a hybrid approach and estimate a 4-variable BVAR(1) of the NOEM model using flat priors with the following vector

$$Z_t = (\pi_t, \pi^*_t, y_t, y^*_t)'$$

where

$$\pi^* \equiv \text{rest-of-the-world inflation} \ (= (1/16) \sum_{i=1}^{16} \pi^*_i)$$

$$y \equiv \text{domestic HP-detrended real GDP}$$

$$y^* \equiv \text{rest-of-the-world HP-detrended real GDP} \ (= (1/16) \sum_{i=1}^{16} y^*_i)$$
3. Empirical findings

Predictive ability:

(1) RMSPE

- RMSPE for each country, model, and forecast horizon are calculated.
- We report the Theil-U statistic

\[ \text{Theil} - U = \frac{RMSPE_{NOEM-BVAR}}{RMSPE_i} \]

for \( i = 1, 2, \ldots, 15 \)

- Values less than one imply that the NOEM-BVAR has a lower RMSPE than does the competitive model.
- To assess the statistical significance of the difference of the Theils U-statistics from one, we use
  - Diebold-Mariano-West test
  - Clark and West (2007) if the models are nested
3. Empirical findings

Forecast evaluation

Medians of Relative RMSPEs (Full sample of countries)
Forecasting Local Inflation with Global Inflation: When Economic Theory Meets the Facts

3. Empirical findings

Forecast evaluation

Number of Cases with Relative $RMSPE < 1$

![Bar chart showing number of cases with relative RMSPE < 1 for various models and horizons.](chart.png)

- RAR
- DAR
- RW-AO
- AR-EC
- FAR
- FAR-EC
- FAR-IEC
- APC
- APC-EC
- BVAR2FP
- BVAR2MP
- BVAR4FP
- BVAR4MP
- BVAR2COM
- BVAR2SCOM

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</table>
3. Empirical findings

Forecast evaluation

Medians of Relative RMSPEs (US)

- RAR
- DAR
- RW-AO
- AR-EC
- FAR
- FAR-EC
- FAR-IEC
- APC
- APC-EC
- BVAR2FP
- BVAR2MP
- BVAR4FP
- BVAR4MP
- BVAR2COM
- BVAR2SCOM
## 3. Empirical findings

### Forecast evaluation

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<th>M₁/M₂</th>
<th>M₃</th>
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<th>M₅</th>
<th>M₆</th>
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<td>0.828</td>
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<td>0.924</td>
<td>0.780</td>
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**Full sample**

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<td>1.018</td>
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<td>1.018</td>
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**US**

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### 3. Empirical findings

#### Forecast evaluation

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### Eight-Quarter-Ahead RMSPE of the NOEM-BVAR Model Relative to Selected Benchmarks

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**US**

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Forecasting Local Inflation with Global Inflation: When Economic Theory Meets the Facts

3. Empirical findings

Forecast evaluation

Predictive ability: (2) success ratio

- An estimate of the probability that a given forecast correctly anticipates the **direction of change in inflation**

- Tossing a fair coin on a sufficiently long sample already predicts the direction of change correctly about 50% of the time

- So a model needs to attain a success ratio greater than 0.5 to provide an improvement in directional accuracy over pure chance

- Statistical significance of the directional accuracy relative to pure chance is assessed following Pesaran and Timmermann (2009).
### 3. Empirical findings

#### Forecast evaluation

**Success Ratios (Full sample)**

![Graph showing success ratios for various models including RAR, DAR, RW-AO, AR-EC, FAR, FAR-EC, FAR-IEC, APC, APC-EC, BVAR2FP, BVAR2MP, BVAR4FP, BVAR4MP, BVAR2COM, BVAR2SCOM, NOEM-BVAR at different forecast horizons (h=1, h=4, h=8).]
3. Empirical findings

Forecast evaluation

Number of Cases with Success Ratios > 0.5
3. Empirical findings

Forecast evaluation

Success Ratios (US economy)
### Directional Accuracy: Success Ratio of One-Quarter-Ahead Forecasts

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### Directional Accuracy: Success Ratio of Four-Quarter-Ahead Forecasts

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### Forecasting Local Inflation with Global Inflation: When Economic Theory Meets the Facts

#### 3. Empirical findings

#### Forecast evaluation

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Robustness checks

- RW-AO ($M_3$) $\succ$ driftless RW
- M2 $\succ$ M1 or M3
- $\succ$ NOEM-BVAR(2)
- $\sim$ BVAR(1), Normal-Wishart priors
- $\succ$ Unrestricted VARs
- $\sim$ GDP-weighted average of the inflation rates as proxy of global inflation ($M_7$) or rest-of-the-world inflation rate (NOEM-BVAR)
- $\sim$ Other detrending techniques
- Forecast averages.
4. Conclusions

Summary

- Unlike most of the existing DSGE-based forecasting models, we adopt a stylized parsimonious framework that emphasizes the role of openness in linking domestic economic developments to those of the rest of the world.

- This strategy gives us a forecasting model (the NOEM-BVAR) that mostly produces lower RMSPEs than its competitors.

- In a number of cases, these gains are statistically significant.

- It also produces success ratios generally above the 0.5 threshold and, often, statistically significant.

- The NOEM-BVAR outperforms, or shows similar predictive ability to, factor-augmented models in forecasting the U.S. inflation rate.