COMPARISON OF FORECASTING PERFORMANCE OF DSGE AND VAR MODELS: THE CASE OF PAKISTAN

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PRESENTATION OUTLINE

1. Introduction and motivation
2. Literature Review
3. Models
4. Estimation of Models
5. Forecast Evaluation
6. Conclusion and Policy Implications
1. Introduction and Motivation
INTRODUCTION AND MOTIVATION

- Policy transmission lag and forward looking policy analysis

- Reliable forecasts of macro variables—an indispensable ingredient of forward looking policy analysis

So....

- Research related to macro forecasting has direct relevance for macro policy making.
DIFFERENT MODELS FOR FORECASTING AND POLICY ANALYSIS

1. Single equation models
   - Univariate (ARIMA)
   - Structural models

2. Multiple equations models
   - Macroeconometric models
   - Vector autoregressive (VAR) models
   - Dynamic Stochastic General Equilibrium (DSGE) models

Weaknesses
- Cannot capture all important dynamic relationships in data
- Endogeneity
- Lucas Critique
- Lucas Critique, Degrees of freedom, lack of consistent time series, lack economic theory.
- Poor data fit and forecasting power (Pagan 2003))
DILEMMA OF INITIAL DSGE/RBC MODELS

- Rich in terms of economic theory
  - Micro foundations,
  - Rational expectations,
  - Policy rules (e.g. Taylor rule)
  - Overcome Lucas Critique

.....but still poor in terms of data fitting and forecasting

- Tradeoff between theoretical rigor and data fit.

- Reason: Incomplete modeling of real and nominal frictions
Break through---New Generation of DSGE Models

- New Generation of DSGE Models pioneered by Christiano et al. (2005)
- Nominal and real frictions to capture micro foundations of inertia in macro data
  - Price rigidity
  - Wage rigidity
  - Inflation indexation
  - Investment adjustment costs
  - Variable capacity utilization
  - Consumption habit formation
- Adolfson et al. (2005) “No tension between rigor and fit”

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Forecasting accuracy vs. richness in economic theory
Source: IMF Capacity Building Institute Slides
2. LITERATURE REVIEW

International literature
Pakistan related literature
MAIN THEME OF LITERATURE REVIEW

- Out-of-sample forecasting power of the DSGE models against different competing models such as structural VAR, BVAR and judgmental forecasts.
INTERNATIONAL LITERATURE

- **Smets and Wouter (2007)**
  Construct, estimate and compare forecasting power of a closed economy DSGE model against BVAR for USA economy.
  **Conclusion:** DSGE forecasts are as good as BVAR forecasts.

- **Edge et al. (2010)**
  Forecasting performance comparison of estimated DSGE models using real time data with judgmental forecasts provided by Federal Reserve Staff and BVAR models.
  **Conclusion:** DSGE models provide competitive forecasts and they should be part of central bank’s monetary policy analysis toolkit.
PAKISTAN RELATED LITERATURE

Almost all studies employing DSGE framework have done so to analyze certain macro issues rather than forecasting and policy analysis.

- **Haider and Khan (2008)**
  Provide Bayesian estimation and interpretation of estimated parameters.

- **Choudhary and Malik (2012)**
  Analyze consequences of fiscal dominance for conduct of monetary policy in Pakistan.

- **Ahmad et al. (2012)**
  Analyze consequences of informal sector for conduct of monetary and fiscal policies.

- **Choudhary and Pasha (2013)**
  Analyze FDI shocks.

- **Rehman et al. (2017)**
  Analyze effects of workers’ remittances for macro outcomes.
CONTRIBUTION

- To our knowledge, there is not a single published paper that has evaluated forecasting performance of an estimated DSGE model for Pakistan data.

- This paper tries to fill this gap by estimation and then comparison of forecasting performance of a DSGE model.
3. Models

- DSGE Model
- VARX Model
- BVAR Model
- BVARX Model
DSGE Model

- A variant of Adolfson et al. (2007)*
- Justification for using Adolfson et al. (2007):
  1. Nominal and real frictions
  2. Small open economy model and can analyze international trade flows and exchange rate
  3. Corner stone of many central banks' DSGE models (Wieland et al. (2012))
  4. Incorporates different types of taxes and can be used quite efficiently for fiscal policy analysis as well

VARX MODEL

- **Reduced form VAR:** An economic variable depends upon its own and, other variables' lagged values.

- **VARX:** VAR with exogenous variables.

\[ y_t = \sum_{l=1}^{L} A_l y_{t-1} + \sum_{m=0}^{M} B_m x_{t-m} + \varepsilon_t \]

- Variables to be included:
  - **Endogenous:**
    \[ y_t = [\Delta GDP_t \quad \pi_t \quad \Delta S_t \quad i_t ]' \]
  - **Exogenous:**
    \[ x_t = [\alpha \quad \Delta GDP_{t}^{USA} \quad \pi_{t}^{USA} \quad i_{t}^{USA} ]' \]

- Lags: AIC and SC both suggest 1 lag.
BAYESIAN VAR MODEL

- Over-parameterization of VAR models erodes forecasting power.
- Moreover, time series macro data could be either scarce or irrelevant (Litterman (1986))
- Solution to the problem: Bayesian estimation approach
- Application of prior knowledge in the form of parameters prior distributions
- Minnesota Priors for BVAR
4. Estimation of Models

Data
Estimation of DSGE
Estimation of VARX
Estimation of BVAR and BVARX
## DATA

<table>
<thead>
<tr>
<th>Sr. #</th>
<th>Data Series Description</th>
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<th>Source</th>
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<td>Real GDP at constant factor cost</td>
<td>Million</td>
<td>Nadim Hanif et al. (2013)</td>
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<td>PKR</td>
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<td>2</td>
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<td>PKR/USD</td>
<td>SBP</td>
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<td>CPI</td>
<td>Index</td>
<td>SBP</td>
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<td>4</td>
<td>Pakistan Population</td>
<td>Million</td>
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<td>5</td>
<td>Call Money Rate</td>
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<td>SBP</td>
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<tr>
<td>6</td>
<td>USA Real GDP</td>
<td>Billion USD</td>
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<td>7</td>
<td>USA 3-Months T-Bill Rate</td>
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<td>USA CPI</td>
<td>Index</td>
<td>IFS IMF</td>
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</table>
ESTIMATION OF DSGE MODEL

- Combination of Calibration and Bayesian MLE method.
- Calibration: use of micro studies, long term data and literature to parameterize the model coefficients.
**Bayesian MLE**

- Most of the variables used in DSGE model cannot be observed directly e.g. marginal cost, expected inflation and marginal rate of substitution and capital stock etc.
- Rational expectation solution of DSGE model is obtained where state variables are expressed as function of lagged states and shocks (state equation).
- Kalman Filter is used to relate these unobserved (latent) variables to observed variables (measurement equation).
STATE SPACE REPRESENTATION AND MEASUREMENT EQUATION

- State equation
  \[ X_t = RX_{t-1} + S\epsilon_t \]

- Measurement equation
  \[ X_{t}^{obs} = \Gamma + VX_t + e_t \]

\[
X_{t}^{obs} = \begin{bmatrix}
\hat{y}_{t}^{obs} \\
\hat{\pi}_{t}^{obs} \\
\Delta S_{t}^{obs} \\
R_{t}^{obs} \\
\hat{y}_{t}^{obs} \\
\pi_{t}^{USA,obs} \\
R_{t}^{USA,obs}
\end{bmatrix} = \begin{bmatrix}
100(\mu_{Z}^4 - 1) + 400(\hat{y}_{t} - \hat{y}_{t-1}) \\
100(\pi^4 - 1) + 400\pi_t \\
\Delta S + 100\Delta S_t \\
100(\pi^4 - 1) + 400\hat{R}_t \\
100(\mu_{Z}^* - 1) + 400(\hat{y}_{t}^{USA} - \hat{y}_{t-1}^{USA}) \\
100(\pi^{USA}_t^4 - 1) + 400\pi^{USA}_t \\
100(\pi^{USA}_t^4 - 1) + 400\hat{R}_t^{USA}
\end{bmatrix} = \Gamma + VX_t
\]
SHOCKS IN DSGE MODEL

1. Total Factor Productivity Shock
2. Fiscal Spending Shock
3. Monetary Policy Shock (through interest rate)
4. Foreign Exchange Risk Premium Shock
5. Foreign Inflation Shock
6. Foreign Demand Shock
7. Foreign interest rate
5. **Forecast Evaluation**

Forecast Evaluation over Different Forecast Horizons

Forecast Evaluation over Time
RECURSIVE FORECASTING AND PARAMETERS UPDATION

- Our objective is to obtain expanding window recursive forecast.
- We initially estimate models for sample period 1980Q4-2008Q4 and obtain forecast for 2009Q1-2010Q4.
- Sequentially adding one observation to estimation data, we forecast 8-quarter 23 windows of out-of-sample forecasts.
FORECAST ERRORS MATRIX

- 23 forecasting windows
- 8-quarter forecast horizon
- 4 models
- 4 variables

We have 16 (8x23) matrices of forecast errors.

Table C1: Forecast Errors for GDP Growth (VARX Model)

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</table>
FORECAST ERROR STATISTICS

- Average amount of over prediction or under prediction
  \[
  \text{Bias} = \frac{1}{f} \sum_{t=1}^{f} (FE_t)
  \]

- Standard deviation of forecast error
  \[
  \text{RMSE} = \sqrt{\frac{1}{f} \sum_{t=1}^{f} (FE_t)^2}
  \]

- Both of these stats have been computed over:
  - Different forecast horizons
  - Different forecasting windows (over time)
FORECASTING PERFORMANCE OVER DIFFERENT FORECAST HORIZONS

<table>
<thead>
<tr>
<th>GDP Growth (Annual %)</th>
<th>RMSE</th>
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<tbody>
<tr>
<td>DSGE</td>
<td>VARX</td>
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<table>
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FORECASTING PERFORMANCE OVER DIFFERENT FORECAST HORIZONS

<table>
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<th>RMSE</th>
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<td>DSGE</td>
<td>VARX</td>
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<tr>
<td>Change in ER (Annual %)</td>
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<tr>
<td>DSGE</td>
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FORECASTING PERFORMANCE OVER DIFFERENT TIME PERIODS
Forecasting Performance over Different Time Periods

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<tr>
<td><strong>CPI Inflation (Annual %)</strong></td>
<td>![Graph]</td>
<td>![Graph]</td>
</tr>
<tr>
<td><strong>Change in ER (Annual %)</strong></td>
<td>![Graph]</td>
<td>![Graph]</td>
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</tbody>
</table>
6. Conclusion and Policy Implications

Conclusion
Policy Implications
CONCLUSION

- In general, VAR models provide better forecasts than DSGE model.
- For GDP growth, call money rate and inflation, forecasting performance of DSGE model was quite close.
- For exchange rate, DSGE forecasts provide relatively larger positive bias and RMSEs.
- Positive bias in exchange rate indicates over-valued local currency.
POLICY IMPLICATIONS

- Better forecast, better forward looking policy.

- Forecast errors can be used to compute deviations from equilibrium values e.g.
  - Exchange rate forecast error: ER misalignment
  - Interest rate forecast error: Interest rate gap
  - GDP forecast error: Output gap

- Estimated models could be used for a wide range of policy experiments by utilizing IRF’s, variance decompositions and shock decompositions.
LIFE OF A “PROFESSIONAL FORECASTER”...

Source: IMF Capacity Development Institute
THANK YOU!
REFERENCES


