THE BLESSING OF DIMENSIONALITY IN FORECASTING REAL HOUSE PRICE GROWTH IN THE NINE CENSUS DIVISIONS OF THE US

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Main question

Is the wealth of information contained in 126 monthly series more useful in forecasting regional real house price growth rate for the 9 census divisions of the US?

- Why is forecasting real house price growth important?
  - Asset prices help to forecast both inflation and output
  - Models that forecast real house price inflation can be indicative of overall inflation
    (Forni et al., 2003; Stock and Watson, 2003; Gupta and Das, 2008a,b; Das et al., 2008a,b)

- Why use large scale models?
  - Large number of economic indicators help in predicting real house price growth
    (Cho, 1996; Abraham and Hendershott, 1996; Rapach and Strauss, 2007, 2008)

- Why use regional data?
  - Segmented nature of the housing market
  - Non-uniform economic conditions across regions
    (Carlino and DeFina, 1998, 1999; Burger and van Rensburg, 2008; Gupta and Das 2008a; Vargas-Silva 2008a,b)
Our previous work


Unrestricted classical Vector Autoregressive (VAR) model (*Sims, 1980*)

**Model**

- $y_t = C + A(L)y_t + \epsilon_t$, where $A(L)$ is a $n \times n$ polynomial matrix in the backshift operator $L$ with lag $p$
- *at theoretical* though particularly useful for forecasting
- Equal lag length for all variables
- Many parameters to estimate
- Possible large out-of-sample forecast errors

**Solution**

- Exclude insignificant lags
- Specify unequal number of lags for different equations
Bayesian Vector Autoregressive (BVAR)

- An alternative to overcome overparameterization

- Instead of eliminating longer lags, impose restrictions on these coeff. → more likely to be near zero than the coeff. on shorter lags

- If strong effects exist from less important variables, data can override this assumption

- Restrictions: normal prior distributions with zero means and small standard deviations for all coeff. One Exception: coeff. on the first own lag of a variable has a mean of 1

- Popularly referred to as the *Minnesota Prior*
Minnesota Prior

Notationally,
- \( \beta_i \sim N(1, \sigma_{\beta_i}^2) \) and \( \beta_j \sim N(0, \sigma_{\beta_j}^2) \)
- To circumvent overparametrization, Doan et al (1984) suggest a formula to generate standard deviations (s.d.) as a function of a few hyperparameters: \( w, d \) and a weighting matrix \( f(i, j) \)
- s.d. of variable \( j \) in equation \( i \) and lag \( m \) is given as

\[
\sigma_{ijm} = \left\{ w \times m^{-d} \times f(i, j) \right\} \times \frac{\hat{\sigma}_j}{\hat{\sigma}_i}
\]

\( \hat{\sigma}_i \): Standard error of univariate autoregression for variable \( i \)

\( w \): Overall tightness

\( d \): Decay factor

\( f(i, j) \): Tightness of variable \( j \) in equation \( i \) relative to variable \( i \)

\( f(i, j) = 1 \) if \( i = j \) and \( k_{ij} \) otherwise; \( 0 \leq k_{ij} \leq 1 \), and; \( d > 0 \).
Dynamic Factor Model

- Can cope with many variables without running into degrees of freedom problems

- Common factors can affect variables not only contemporaneously, but also with lags

- Advantage over VAR models where one chooses variables
Dynamic Factor Model

- Each time series represented as sum of two latent components: common (capturing multivariate correlation) and idiosyncratic
- Let $X_t = (x_{1t}, \ldots, x_{nt})'$ be a standardized stationary process
- In terms of a DFM, $X_t$ can be written as:

\[ X_t = B(L)f_t + \xi_t \quad (1) \]
\[ = \Delta F_t + \xi_t \quad (2) \]

- $B(L) = B_0 + B_1 L + \ldots + B_s L^s$ a $n \times q$ matrix of factor loadings of order $s$
- $f_t$ is a $q \times 1$ vector of dynamic components
- $F_t$ is the $r = q(s + 1) \times 1$ vector of static factors, i.e., $F_t = (f_t', f_{t-1}', \ldots, f_{t-s}')$
- $\Delta$ is the matrix of factor loadings
Dynamic Factor Model

Determination of number of dynamic factors

- Informal criteria based on prop. of variance explained
  (Bai and Ng, 2005; Stock and Watson, 2005)

- Principle component  (Forni et al, 2004)

Estimation of dynamic factors - Frequency domain

(Forni et al, 2000, 2002)

- Spectral density matrix of $X_t$ decomposed as
  $\Sigma(\theta) = \Sigma_\chi(\theta) + \Sigma_\xi(\theta), \ -\pi < \theta < \pi$
  - Rank of $\Sigma_\chi(\theta) = q$, is the number of dynamic factors

- Covariance of $X_t$ can be decomposed as $\Gamma_k = \Gamma_k^\chi + \Gamma_k^\xi$
  - Rank of $\Gamma_k^\chi = r$, the number of static factors
DFM specifications considered

- **UFAVAR**: includes one of the variables of interest and the obtained number of common static factors;
- **MFAVAR**: includes all the nine real house price growth rates and the common static factors;
- **UBFAVAR**: uses one of the variables of interest and the common static factors, and which, in turn, are estimated based on Bayesian restrictions discussed in the previous subsection;
- **MBFAVAR**: with a specification similar to the MFAVAR, except that the current model applies Bayesian restrictions on lag of the variables based on the Minnesota prior.
Motivation

Models

Data

Results

Conclusion

US Census Regions and Divisions
Forecast period
Variables

Outline

1. Motivation

2. Models

3. Data

4. Results

5. Conclusion
The bureau recognizes four census regions:

- Further organizes them into nine divisions.
- For the presentation of data:
  - *Not to be construed as necessarily being grouped owing to any geographical, historical, or cultural bonds.*

### US Census Regions and Divisions

**Forecast period**

**Variables**

<table>
<thead>
<tr>
<th>Region 1: Northeast</th>
<th>Region 2: Midwest*</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Division 1:</strong> New England</td>
<td><strong>Division 2:</strong> Middle Atlantic</td>
</tr>
<tr>
<td>Connecticut (59)</td>
<td>New Jersey (34)</td>
</tr>
<tr>
<td>Maine (23)</td>
<td>New York (36)</td>
</tr>
<tr>
<td>Massachusetts (25)</td>
<td>Pennsylvania (42)</td>
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<tr>
<td>New Hampshire (33)</td>
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<td>Rhode Island (44)</td>
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<tr>
<td>Vermont (50)</td>
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<table>
<thead>
<tr>
<th>Region 2: Midwest*</th>
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</thead>
<tbody>
<tr>
<td><strong>Division 3:</strong> East North Central</td>
</tr>
<tr>
<td>Delaware (19)</td>
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<tr>
<td>District of Columbia (11)</td>
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<tr>
<td>Florida (12)</td>
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<tr>
<td>Georgia (13)</td>
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<tr>
<td>Maryland (24)</td>
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<tr>
<td>North Carolina (37)</td>
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<tr>
<td>South Carolina (45)</td>
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<tr>
<td>Virginia (51)</td>
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<tr>
<td>West Virginia (54)</td>
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<tr>
<td><strong>Division 4:</strong> West North Central</td>
</tr>
<tr>
<td>Iowa (19)</td>
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<tr>
<td>Kansas (20)</td>
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<tr>
<td>Minnesota (27)</td>
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<tr>
<td>Missouri (29)</td>
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<tr>
<td>Nebraska (31)</td>
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<tr>
<td>North Dakota (38)</td>
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<tr>
<td>South Dakota (46)</td>
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</tbody>
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<tr>
<th>Region 3: South</th>
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<tbody>
<tr>
<td><strong>Division 5:</strong> South Atlantic</td>
</tr>
<tr>
<td>Arkansas (05)</td>
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<td>Louisiana (22)</td>
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<tr>
<td>Oklahoma (46)</td>
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<tr>
<td>Texas (48)</td>
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<tr>
<td><strong>Division 6:</strong> East South Central</td>
</tr>
<tr>
<td>Alabama (01)</td>
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<td>Kentucky (21)</td>
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<td>Mississippi (28)</td>
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<td>Tennessee (47)</td>
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<tr>
<td><strong>Division 7:</strong> West South Central</td>
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<tr>
<td>Alaska (02)</td>
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<td>California (08)</td>
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<td>Hawaii (15)</td>
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<td>Oregon (41)</td>
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<td>Washington (53)</td>
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<tr>
<th>Region 4: West</th>
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<tbody>
<tr>
<td><strong>Division 8:</strong> Mountain</td>
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<tr>
<td>Arizona (04)</td>
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<td>Colorado (06)</td>
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<td>Idaho (16)</td>
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<tr>
<td>New Mexico (30)</td>
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<td><strong>Division 9:</strong> Pacific</td>
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<td>Montana (30)</td>
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<td>Utah (49)</td>
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<td>Nevada (52)</td>
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<tr>
<td>Wyoming (56)</td>
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<td><strong>Division 10:</strong> Mountain</td>
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<tr>
<td><strong>Division 11:</strong> Pacific</td>
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*Prior to June 1994, the Midwest Region was designated as the North Central Region.*
In-sample analyses period: 1991(02) to 2000(12)
Out-of-sample forecast evaluation period: 2001(01) to 2005(06)
Out-of-sample forecast is done for one to twelve months ahead
Choice of 2001:01 as the onset of forecast horizon motivated from Iacoviello and Neri (2008)
Small-scale VARs, both the classical and Bayesian variants
– Only the nine variables of interest, namely, real house price growth rates of the nine census divisions of the US

Large-scale BVARs and the DFM:
– Based on 126 monthly series (9 + 1 + 116).

The nominal house price figures for these nine US census divisions and for the whole of US were obtained from the Office of Federal Housing Enterprise Oversight (OFEO), and were converted to their real counterpart by dividing them with the personal consumption expenditure deflator.
Remaining 116 variables from dataset of Boivin et al. (2008) which contains a broad range of macroeconomic variables such as industrial production, income, employment and unemployment, housing starts, inventories and orders, stock prices, exchange rates, interest rates, money aggregates, consumer prices, producer prices, earnings, and consumption expenditure.

Balanced panel of 126 monthly series from 1991:02-2005:06

All data transformed to induce stationarity.
1 Motivation
2 Models
3 Data
4 Results
5 Conclusion
‘optimal’ model based on minimum average RMSE for real house price growth rate
‘optimal’ model based on minimum average RMSE for real house price growth rate

- For all the 9 census divisions, some large model outperforms small-scale models
  - UVFAVAR for East South Central and West South Central, UVBFAVAR \((w=0.1, d=2)\) for East North Central and Mountain, LBVAR \((w=0.1, d=1)\) for Middle Atlantic, MVBFAVAR \((w=0.2, d=2)\) for New England, MVBFAVAR \((w=0.1, d=2)\) for South Atlantic and West North Central, and MVFAVAR for Pacific

- Even the second-best performing model are large-scale in nature
  - barring West South Central for which the SBVAR \((w=0.1, d=1)\) comes second

- There always exists at least one small-scale model that outperforms the large-scale BVAR
  - exceptions being Middle Atlantic under \(w=0.3, d=0.5, w=0.2, d=1, w=0.1, d=1\) and \(w=0.1, d=\)
Outline

1. Motivation
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FAVARs, in their various forms, are standout performers.

Data rich environment of the FAVAR models that include a wide range of macroeconomic series of the US economy, besides the house price growth rates of the census divisions, more informative when forecasting the house price growth rate of the nine census regions.

Role of fundamentals in affecting the housing market cannot be underestimated.
First - detailed look at the factors to determine the dominant macroeconomic variables that comprise these factors;

Second - incorporate role of the house price growth rate of the neighboring division(s) in the forecasting process of a particular census division, by developing spatial versions of the above models.