PREDICTING DOWNTURNS IN THE US HOUSING MARKET: A BAYESIAN APPROACH

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Gupta and Das Predicting downturns in US housing market

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2 Models - VARs, BVARs and SBVARs

- Vector Autoregressive Models
- Bayesian Vector Autoregressive Models
- Spatial Bayesian Vector Autoregressive Models

Forecasting House Prices in the Twenty Largest US States

4 Results







- Models VARs, BVARs and SBVARs
 - Vector Autoregressive Models
 - Bayesian Vector Autoregressive Models
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- 3 Forecasting House Prices in the Twenty Largest US States
- 4 Results
- 5 Predicting the Downturns



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Background and Motivation

- Boom of the 1990s versus bust in the 2000s in the US housing market (NAR, 2006)
- House price significantly influence consumer expenditure → financial markets
- Role of asset prices in forecasting inflation (Stock and Watson, 2003)
- Questions that we are seeking answers to:
 - Is growth in house prices predictable?
 - Can simple VARs, and their variants, based on only *real house price growth*, give any indications?
 - Could these simple models have predicted the downturns in the US housing market?



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Vector Autoregressive Models Bayesian Vector Autoregressive Models Spatial Bayesian Vector Autoregressive Models



- Atheoretical but very useful for forecasting
- Unrestricted VAR (Sims, 1980)

$$\vec{y}_t = A_0 + A(L)\vec{y}_t + \vec{\epsilon}_t$$
, with $\vec{\epsilon}_t \sim N(0, \sigma^2 I_n)$

 \triangleright VARs use equal lag for all variables \rightarrow Many parameters to estimate (*overparametrization*)

✓ Option 1: Exclude insignificant lags



$$\vec{y}_t = A_0 + A(L)\vec{y}_t + \vec{\epsilon}_t$$
, with $\vec{\epsilon}_t \sim N(0, \sigma^2 I_n)$

\checkmark **Option 2**: Instead of eliminating insignificant lags, impose

restrictions on coefficients (Litterman, 1981; Doan et al, 1984)

- Coeff. of longer lags more likely to be near zero → Data can override this assumption
- In *ith* equation, for β_i of the lagged dependent variable, and β_i of any other variable:

$$eta_i \sim N(1, \sigma_{eta_i}^2), \ \ eta_j \sim N(0, \sigma_{eta_i}^2)$$

Minnesota prior





$$\vec{y}_t = A_0 + A(L)\vec{y}_t + \vec{\epsilon}_t$$
, with $\vec{\epsilon}_t \sim N(0, \sigma^2 I_n)$

 \checkmark **Option 3**: Generate the σ s in terms of few hyperparameters,

viz., w, d and a weight matrix f(i, j) (Doan et al, 1984)

Standard deviation of prior distribution of variable *j* in eq. *i* at lag *m* given as S₁(*i*, *j*, *m*) = [*w* × *g*(*m*) × *f*(*i*, *j*)]^{[∂]/_{∂i}}/_{∂i}

•
$$f(i,j) = 1$$
 if $i = j$, and k_{ij} otherwise $(0 \le k_{ij} \le 1)$

•
$$g(m) = m^{-d}, \ d > 0$$

- d is the decay parameter
- $\hat{\sigma}_i$ estimated s.e. of univariate autoregression of variable i
- w tightness parameter, s.d. on first own lag

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Minnesota Prior treats all variables in VAR, except for the first own-lag of the dependent, in identical manner

✓ **Option 4**: Construct weight matrix based on First-Order Spatial Contiguity (FOSC) (Lesage and Pan, 1995)

- Asymmetric F matrix
- Emphasize variables from neighbors
- 1 for neighbors, 0.1 for non-neighbors





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Data

• 20 largest US states (2000 census) considered:

Arizona (AZ), California (CA), Florida (FL), Georgia (GA), Illinois (IL), Indiana (IN), Massachusetts (MA), Maryland (MD), Michigan (MI), Missouri (MO), North Carolina (NC), New Jersey (NJ), New York (NY), Ohio (OH), Pennsylvania (PA), Tennessee (TN), Texas (TX), Virginia (VA), Washington (WA) and Wisconsin (WI)





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(OH), Pennsylvania (PA), Tennessee (TN), Texas (TX), Virginia (VA), Washington (WA) and Wisconsin (WI)

Real house price growth obtained from

- Nominal house price data
- Conventional Mortgage House Price Index (CMHPI)
- Personal Consumption Expenditure (PCE)
- Quarterly data from 1976:Q1 to 1994:Q4
- Sources: Freddie Mac, Bureau of Economic Analysis



The FOSC F matrix

F

	1	1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
	1	1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
	0.1	0.1	1	1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
	0.1	0.1	1	1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
	0.1	0.1	0.1	0.1	1	1	0.1	0.1	1	1	0.1	0.1	0.1	0.1
	0.1	0.1	0.1	0.1	1	1	0.1	0.1	1	0.1	0.1	0.1	0.1	1
	0.1	0.1	0.1	0.1	0.1	0.1	1	0.1	0.1	0.1	0.1	0.1	1	0.1
	0.1	0.1	0.1	0.1	0.1	0.1	1	1	0.1	0.1	0.1	0.1	0.1	0.1
	0.1	0.1	0.1	0.1	1	1	0.1	0.1	1	0.1	0.1	0.1	0.1	1
=	0.1	0.1	0.1	0.1	1	0.1	0.1	0.1	0.1	1	0.1	0.1	0.1	0.1
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1	0.1	0.1	0.1
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1	1	0.1
	0.1	0.1	0.1	0.1	0.1	0.1	1	0.1	0.1	0.1	0.1	1	1	0.1
	0.1	0.1	0.1	0.1	0.1	1	0.1	0.1	1	0.1	0.1	0.1	0.1	1
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1	0.1	0.1	0.1	1	1	1
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1	1	0.1	0.1	0.1
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1	0.1	0.1	1	0.1	0.1	0.1
	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
	0.1	0.1	0.1	0.1	1	0.1	0.1	0.1	1	0.1	0.1	0.1	0.1	0.1

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- Out-of-sample forecast for 1995:Q1 to 2006:Q4
 - Marked difference in house price growth in the US from mid 1990s (Rapach and Strauss, 2007, 2008)
- 'Optimal' model selected based on lowest average RMSE in the period 1995:Q1 to 2006:Q4
- 2 lags for each variable ¹
- RATS Econometrics Software²



Models Compared

Univariate and Multivariate

VAR

SBVAR





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Background and Motivation Models - VARs, BVARs and SBVARs Forecasting House Prices in the Twenty Largest US States

Results

Predicting the Downturns

Table1. One-to -Four- Quarters-Ahead Average RMSEs (2001:01-2006:04)

	Models												
	VAR		BVAR1		BVAR2		BVAR3		BVAR4		BVAR5		SBVAR
States	UV	MV	UV	MV	UV	MV	UV	MV	UV	MV	UV	MV	
AZ	9.2	8.9	9.0	8.3	8.8	8.5	7.9	8.1	7.9	8.6	8.8	8.1	8.4
CA	7.0	7.4	7.0	6.9	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	6.9
FL	8.3	7.9	8.2	7.3	8.4	7.6	7.9	7.5	8.4	8.0	9.0	7.9	7.9
GA	3.4	3.4	3.3	3.2	3.3	3.2	2.9	2.9	2.9	3.2	3.3	2.9	2.9
IL	3.0	4.1	3.0	3.2	3.0	3.2	2.9	3.2	3.0	3.2	3.1	3.3	3.0
IN	2.3	2.7	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.3	2.3	2.3	2.2
MA	4.6	5.3	4.6	4.6	4.6	4.7	4.7	4.6	4.7	4.7	4.7	4.7	4.7
MD	6.0	5.9	6.0	5.8	6.2	5.9	5.9	5.8	6.0	6.0	6.4	5.8	5.8
MI	3.3	3.7	3.3	2.9	3.3	3.2	3.1	3.0	3.2	3.4	3.5	3.2	3.3
MO	3.4	4.3	3.4	3.1	3.4	3.2	3.4	3.7	3.4	3.4	3.4	3.8	3.6
NC	2.6	2.7	2.6	2.6	2.6	2.6	2.4	2.4	2.5	2.7	2.7	2.5	2.4
NJ	5.5	5.8	5.5	5.5	5.6	5.4	5.4	5.4	5.4	5.4	5.6	5.4	5.4
NY	5.7	6.8	5.6	5.5	5.6	5.4	5.4	5.4	5.4	5.4	5.7	5.4	5.2
ОН	2.3	2.6	2.3	2.1	2.3	2.2	2.2	2.1	2.3	2.2	2.3	2.2	2.1
PA	4.7	4.4	4.7	3.9	4.5	3.8	4.2	4.0	4.1	3.9	4.5	4.0	3.8
TN	3.2	4.0	3.1	3.3	3.1	3.2	2.8	3.0	2.9	3.3	3.1	3.0	2.9
тх	3.3	3.4	3.3	3.3	3.2	3.4	3.0	3.3	3.0	3.5	3.3	3.4	3.1
VA	5.7	5.5	5.7	5.1	5.7	5.1	5.1	4.9	5.2	5.2	5.8	4.9	5.0
WA	4.1	4.4	4.0	3.8	4.0	3.8	3.8	3.7	3.7	3.9	4.0	3.8	3.8
WI	3.6	4.6	3.6	3.5	3.6	3.5	3.5	3.6	3.6	3.6	3.6	3.6	3.5

UV(Univariate); MV(Multivariate);

BVAR1(w=0.3,d=0.5); BVAR2(w=0.2,d=1.0); BVAR3(w=0.1,d=1.0); BVAR4(w=0.2,d=2.0), BVAR5(w=0.1,d=2.0)





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Predicting the Downturns

For the period 2007:Q1 to 2008:Q1

- In 19 of the 20 states, some Bayesian model outperforms
- Use 'optimal' model to predict downturn for each state
- For 18 of the 20 states, corresponding 'optimal' model could predict the downturn





For the period 2007:Q1 to 2008:Q1

- Use 'optimal' model to predict downturn for each state
- For 18 of the 20 states, corresponding 'optimal' model predicted the downturn
- However, they tend to under predict the downturn
- ⇒ Just lagged values of house price not enough
 ⇒ information on other fundamentals needed
- None the less, the Bayesian models give useful preliminary indications of downturn
- Immense importance to policy makers (Del Negro, 1999)

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Concluding Remarks

- Bayesian methods influenced by choice of prior
- None-the-less, their importance cannot be disregarded
 - In light of current exercise
 - Existing other literature ³
- Way forward: Try other large scale Bayesian models that incorporate other potential fundamentals.

³Amirizadeh and Todd (1984), Kuprianov and Lupoletti (1984), Hoen *et al.* (1984), Hoen and Balazsy (1986, Silk Kinal and Ratner (1986), LeSage (1990), Gruben and Hayes (1991), Shoesmith (1992, 1995), Dua *et al.* (1999), where the two terms Gupta (2006, 2007), Liu and Gupta (2007), Zita and Gupta (2007), Banerji *et al.* (2008), Das *et al.* (2008), Gupta *et al.* (2008)