



Forecasting Retail Credit Market Conditions

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Forecasting Retail Credit Market Conditions

Agenda

- On-going project to implement Vector Autoregression models for forecasting retail credit conditions in UK and to establish robust links to macroeconomic conditions for forecasting (both economic and credit conditions) and stress testing
- Background:
 - ▶ Expect range of strong two-way linkages between macroeconomic conditions and credit markets
 - ▶ Combined system modelling uses:
 - Large-scale structural macroeconomic models
 - (Relatively) smaller econometric models generally in Vector Autoregressive (VAR) form
 - ▶ VARs are routine in empirical macroeconomics and suggest efficient approach for modelling economic-credit interactions
 - ▶ Limitations of standard VARs constrain effectiveness for forecasting and simulation / policy assessment. More recent developments extend VAR analysis to:
 - Include richer information on economic conditions
 - Allow for time-varying dynamics



Forecasting Credit Market Conditions

Outline of the Project

Phase 1: Public Domain Data

- Improve forecasts for market-level indicators of credit market conditions focused on retail credit:
 - ▶ Lending volumes (stock, gross and net new lending) → Financial planning, Basel III liquidity
 - ▶ Retail interest rates → Loss forecasting
 - ▶ Loan performance measures (write off rates) → Systemic risk assessment, stress testing
- Better integration of macroeconomic and credit market forecast/scenario models → Systemic risk assessment, stress testing

Phase 2: Bureau Data

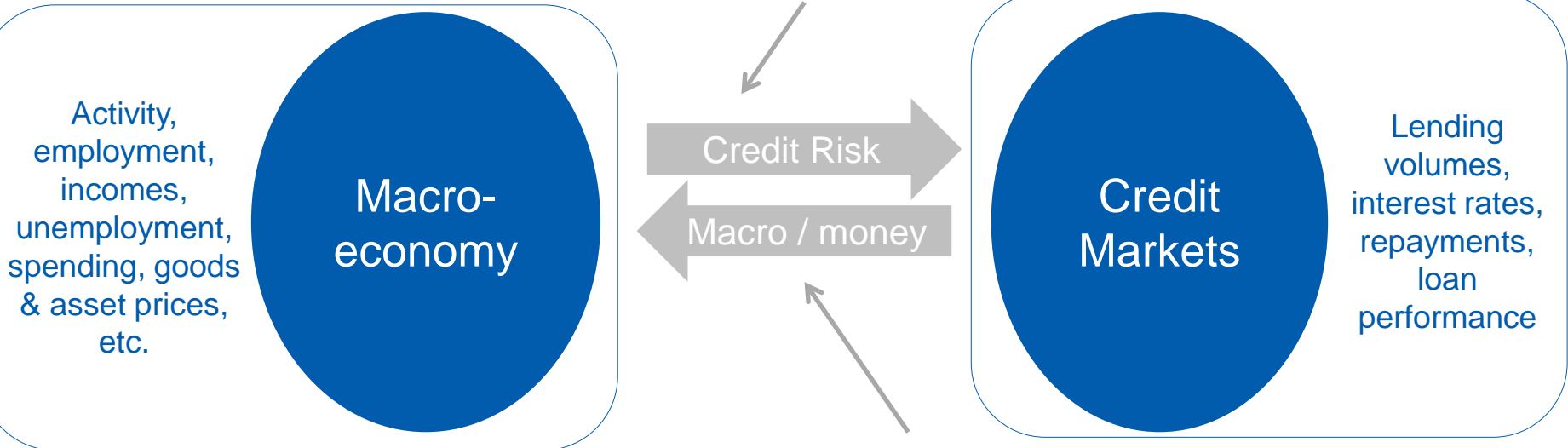
- More granular and/or targeted credit forecasts → As above
- Lender-specific forecasts / scenarios
- Benchmarking



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Credit-Economy Linkages

Expanding literature shows impacts from macroeconomic conditions to retail credit markets; Basel II / III; IFRS9



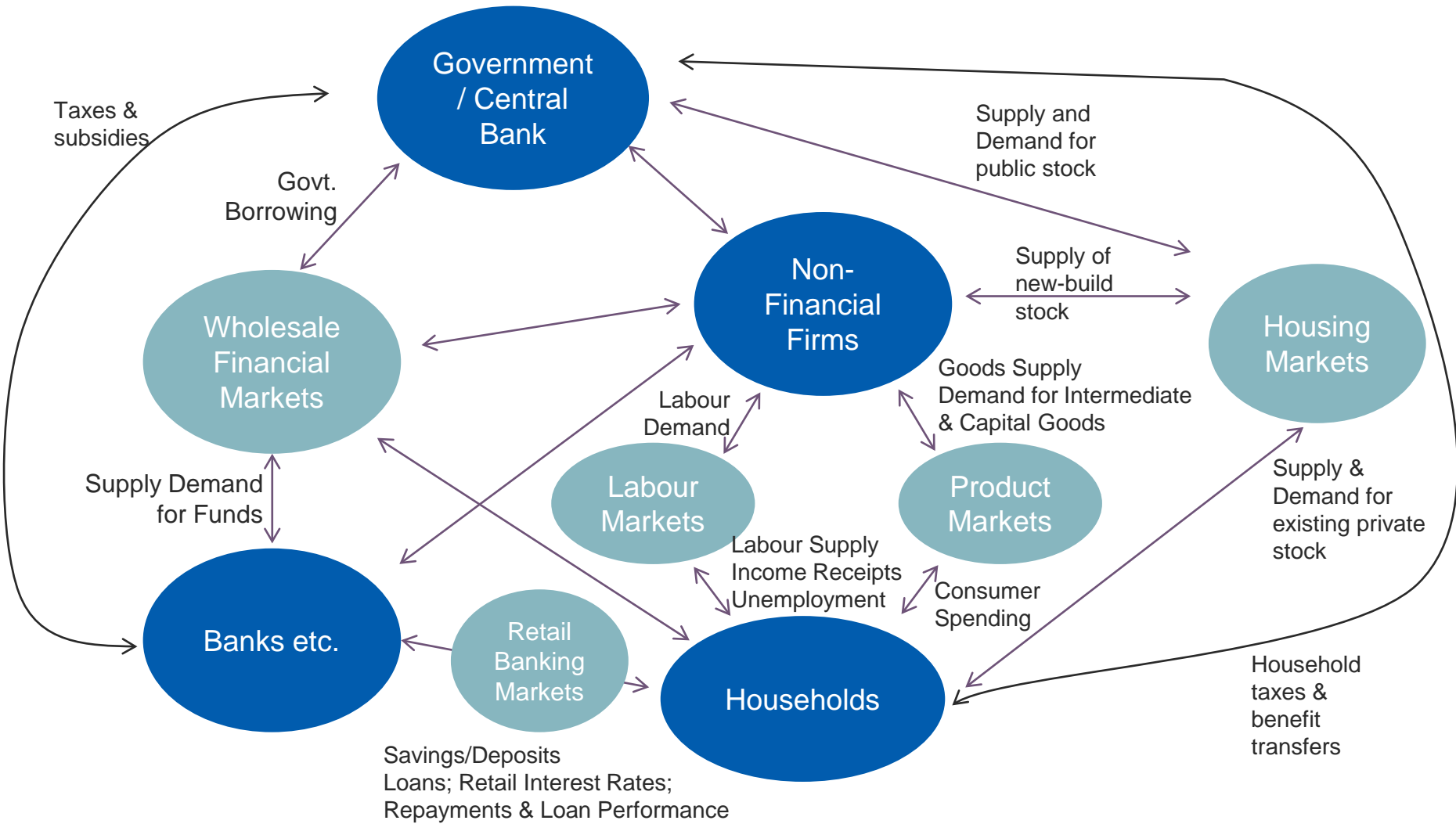
Stiglitz & Weiss (1981): Equilibrium credit rationing; Mankiw (1986): Inefficient & precarious credit market equilibrium; Bernanke (1983): Banking crises disrupt efficiency of credit allocation process and increase costs of credit intermediation – adversely impacting aggregate demand and economic activity; Bernanke, Getler & Gilchrist (1999): financial accelerator’: endogenous developments in credit markets work to propagate and amplify shocks to the macroeconomy.

“[D]eteriorating credit-market conditions – sharp increases in insolvencies and bankruptcies, rising real debt burdens, collapsing asset prices, and bank failures – are not simply passive reflections of a declining real economy but are in themselves a major factor depressing economic activity.”



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Credit-Economy Linkages





Forecasting Retail Credit Market Conditions Vector Autoregression (VAR) Model

- Simple VAR(p) Model:

$$y_t = \alpha_0 + \sum_{j=1}^p A_j y_{t-j} + \varepsilon_t = X_t \theta + \varepsilon_t$$

y_t is an $M \times 1$ vector containing observations on M time series variables

α_0 is an $M \times 1$ vector of (time-invariant) intercepts

A_j in an $M \times M$ matrix of (time-invariant) coefficients

ε_t is an $M \times 1$ vector of errors assumed *i.i.d.* $N(\mathbf{0}, \Sigma)$

Can be extended to include additional exogenous variables. Given sufficient data VAR can be estimated by equation-by-equation ordinary least squares.

However:

- Model contains $M \cdot (1 + Mp)$ parameters to be estimated (α_0, A_j, Σ): e.g. $M = 5, p = 4$ implies 105 parameters to estimate. Larger models may overwhelm available time series.
- Assumption of fixed parameters implausible over long time periods given structural changes in the economy.



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VAR Variables & Dimensions

- 'Exogenous' variables: Extend VAR system to include additional variables treated as exogenous:

$$y_t = X_t\theta + Z_t\varphi + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma)$$

- Classical & Bayesian variable selection/shrinkage methods for larger endogenous VAR systems
- Factor Augmented VARs (FAVARs): Additional variables may be unobserved factors summarizing multiple macroeconomic time series rather than individual variables

$$y_t = X_t\theta + F_t\omega + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma)$$

$$F_t = \gamma F_{t-1} + \eta_t$$

- Several papers show improved forecast performance from large scale (FA)VARs including tens or even hundreds of dependent variables (however most recent evidence is ambiguous on this).



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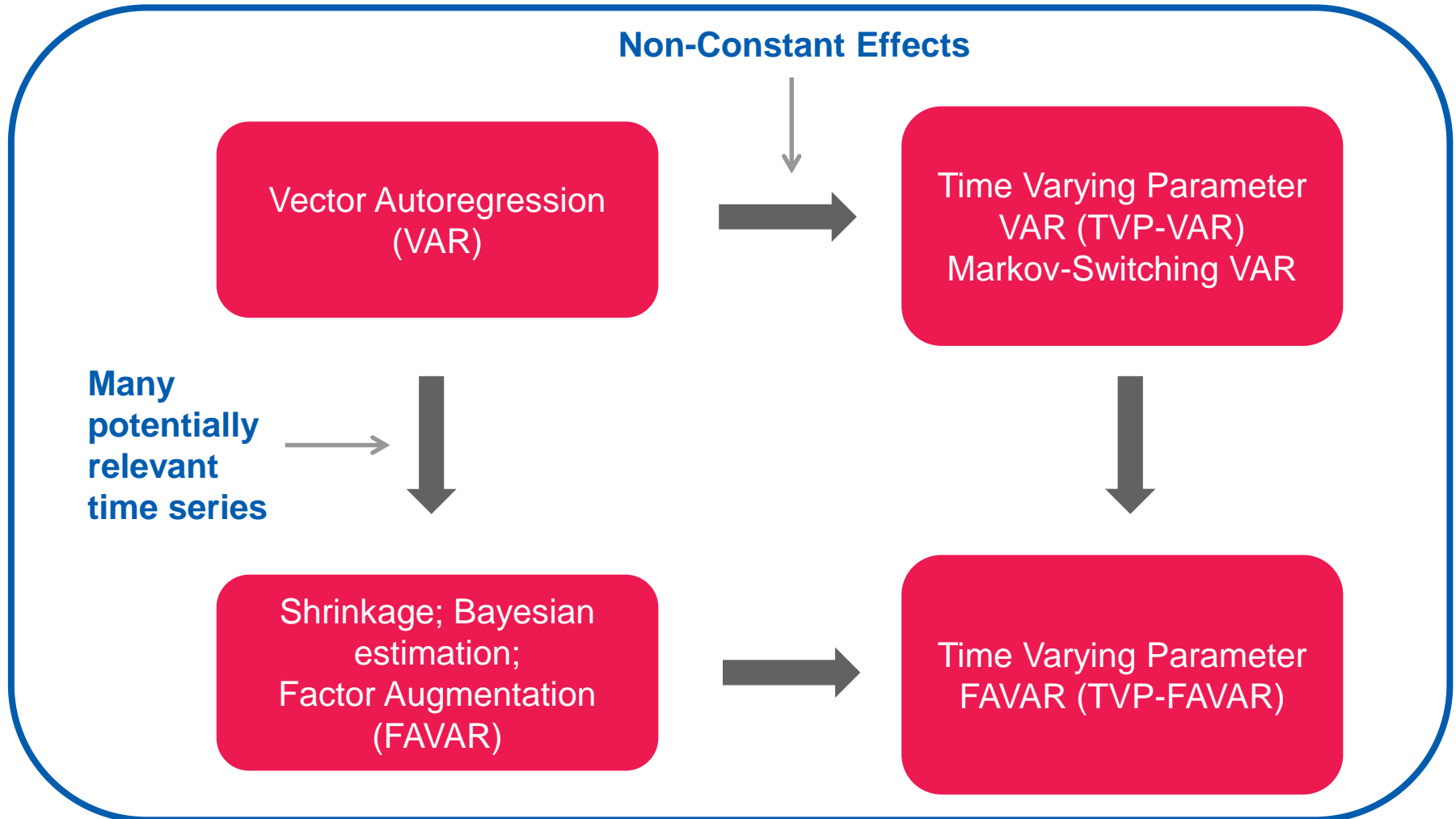
Time invariance

- Standard VAR model assumes parameters of the system are invariant over time
- Economic theory and evidence related to:
 - Non-constant coefficients:
 - Evolution of credit markets: lender and borrower behaviours
 - Regime shifts:
 - Changes in policy regimes
 - Endogenous credit/macroeconomic regime shifts
- Suggests value from extended models which allow for time-varying parameters or regime shifts
 - Shifts in intercepts
 - Coefficients in the A matrix?
 - Distribution of 'errors'



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Extended VAR-type models





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VAR Applications to Macroeconomics & Credit

- Standard VARs: Many, many applications in empirical macroeconomics
- Factors & FAVAR:
 - ▶ Many studies suggest macroeconomic movements can be summarized by small number of factors;
 - ▶ Frequent applications of factor augmented regressions and FAVARs in macroeconomics and particularly in monetary economics. Mainly focused on simulation/policy
 - Sims & Sargent (1977); Stock & Watson (1999, 2002, 2005); Giannone, Reichlin & Sala (2004); Bernanke & Boivin (2003); Bernanke, Boivin & Elias (2005).
- Time Variation:
 - Continuously evolving parameters: Cogley & Sargent (2000, 2001, 2005); Del Negro & Otrok (2008)
 - Regime shifts: Sims & Zha (2006);



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VAR Estimation

▪ Classical

- ▶ Small scale VARs efficiently estimated by OLS
 - ▶ More general specifications formulated as 'state-space' models and estimating using Kalman filtering and MLE
 - ▶ Factor-Augmented VARs:
 - State-space formulation
 - ▲ 2 step process based on principal components with bootstrapping for coefficient confidence intervals
 - ▶ Time varying coefficients:
 - Kalman filter/MLE for state-space formulation
- Relatively easily implemented in standard statistical/econometrics software

▪ Bayesian

- ▶ Some variants allow MLE estimation for natural conjugate priors
 - ▶ Generally requires numerical simulation
 - Markov-Chain Monte Carlo / Gibbs sampling / Metropolis-Hastings
- MCMC methods are very flexible to alternative model specifications
- Naturally supports shrinkage; probabilistic forecasting; model averaging
- Tolerant of untidy data structures (mixed frequencies; sample periods; gaps in data).
- Becoming popular for 'nowcasting'
- Python / R , etc. packages emerging but Implementation can be challenging!
- Koop & Korobilis (2010) gives useful summary.



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UK Data

- Sources:

- ▶ Credit market data: From Bank of England, Several hundred time series variables at monthly or quarterly frequency related to money markets and credit. We focus on retail lending to households: volumes; interest rates; write offs
- ▶ Comprehensive databanks of several hundred UK time series (mainly from ONS) related to economic activity; labour market conditions; asset prices; household finances; consumer behaviour (mainly quarterly but some monthly)

- Working Dataset:

- ▶ Core set of credit data for total, secured, unsecured retail lending to households (volumes, rates, write offs)
- ▶ Core set of economic metrics related to activity, unemployment, market interest rates
- ▶ Extended set of economic metrics for house prices, equity prices, labour market conditions, household incomes, consumer behaviour – either directly or via FAVAR approach



Forecasting Retail Credit Market Conditions

Illustration: Economic & Credit Data

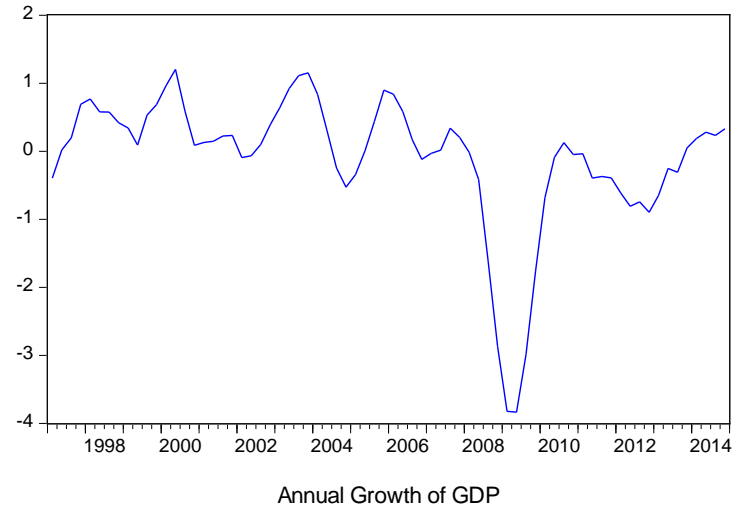
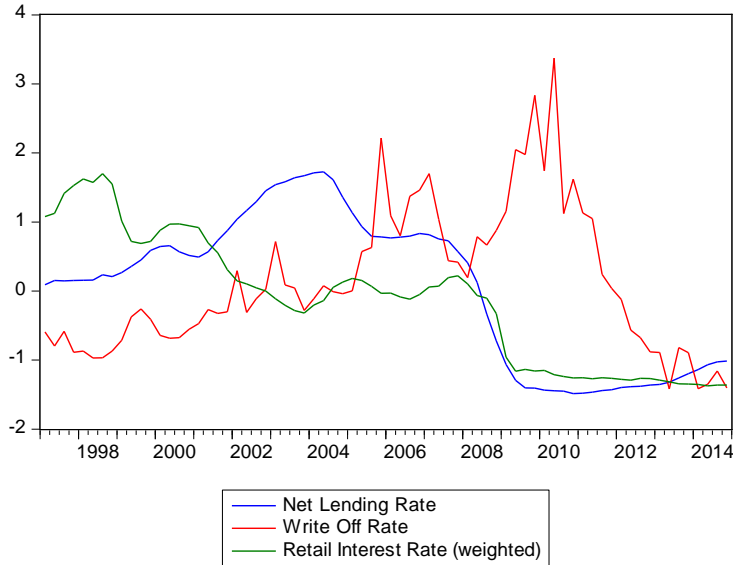
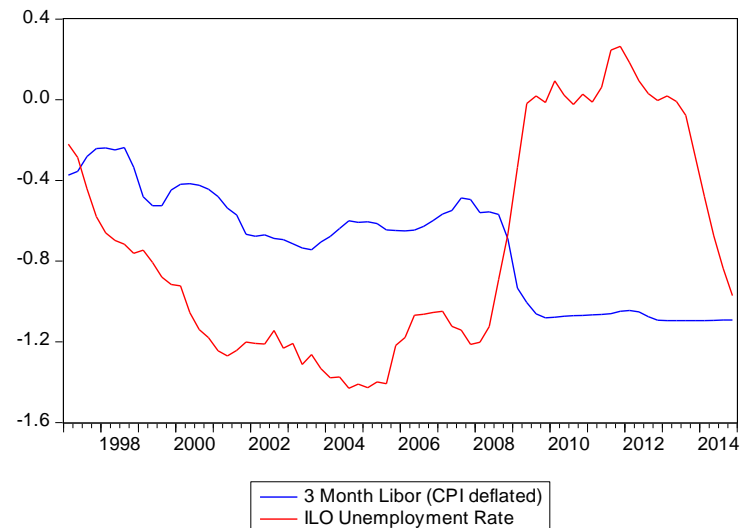


Illustration based on models for all lending to UK households:
Core Credit Data – Net Lending;
Retail Interest Rates; Write Offs
Core Economic Data: GDP growth;
Unemployment; Market Interest Rates (3m)



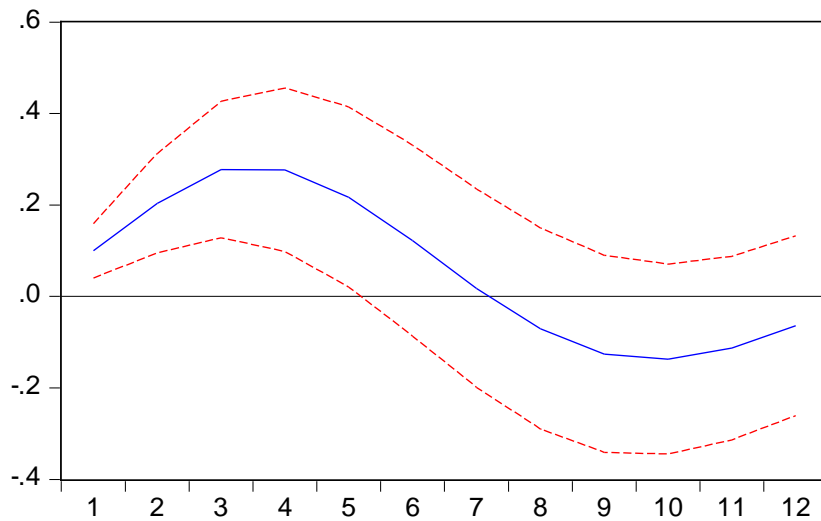


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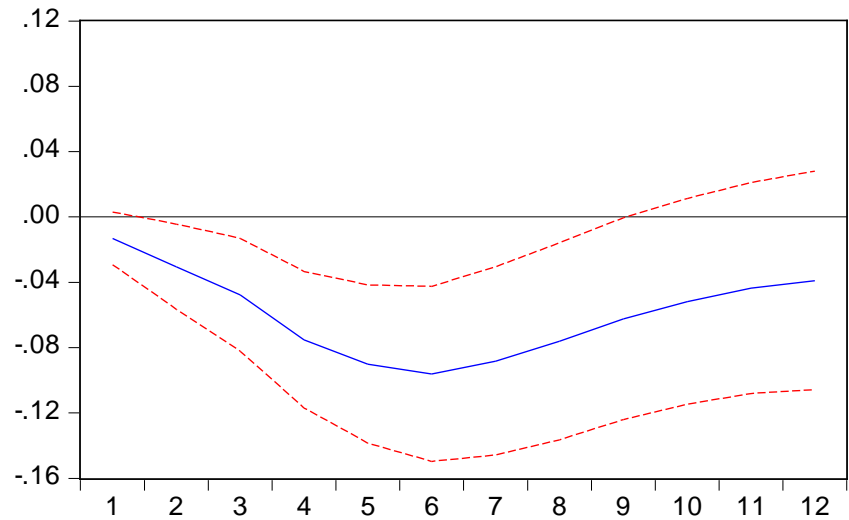
Illustration: Credit impacts on macroeconomy

Response to Cholesky One S.D. Innovations ± 2 S.E.

Response of GDP Growth to Net Lending Rate



Response of Unemployment Rate to Net Lending Rate

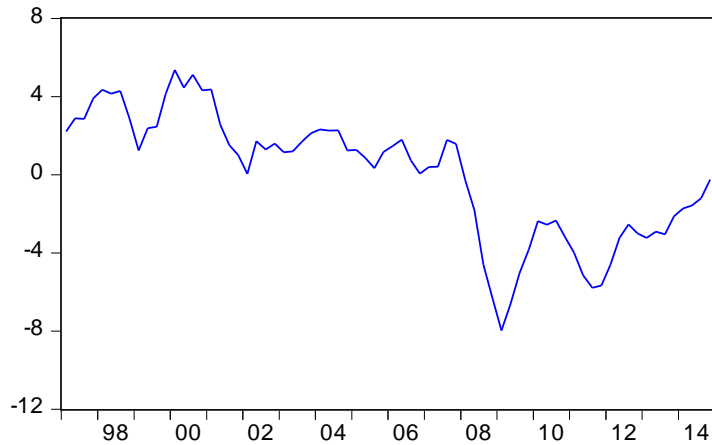




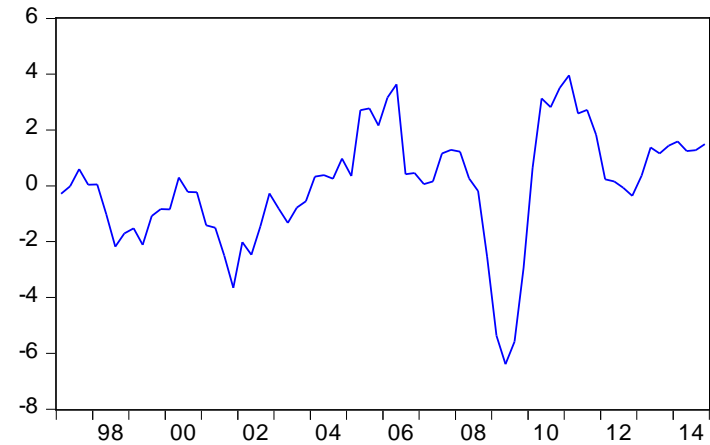
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Illustration: Principal Components for FAVAR

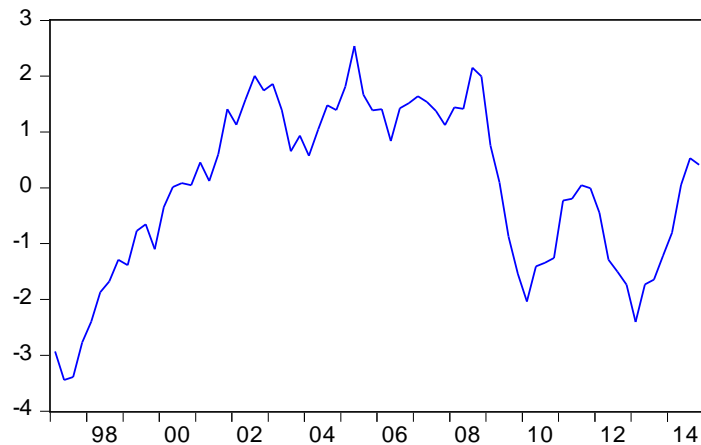
PC1



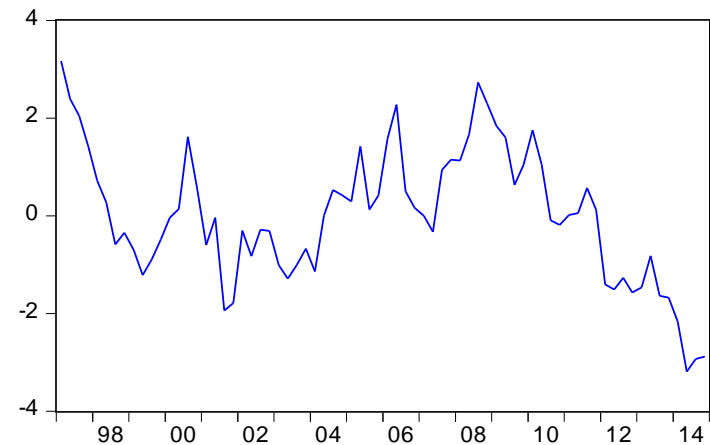
PC2



PC3



PC4





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Illustration: Forecast Accuracy

Forecast Errors vs ARMA

	Mean Absolute Forecast Error				Root Mean Squared Error			
	Forecast Horizon (n-step)							
	1	2	4	8	1	2	4	8
Net Lending								
Credit Only VAR	93%	91%	89%	80%	90%	89%	87%	83%
Credit & Macro VAR	84%	82%	79%	70%	85%	84%	82%	74%
FAVAR	85%	81%	78%	63%	80%	78%	75%	65%
Retail Interest Rate								
Credit Only VAR	95%	93%	94%	96%	97%	96%	95%	92%
Credit & Macro VAR	90%	88%	85%	82%	88%	86%	82%	79%
FAVAR	87%	81%	76%	72%	87%	83%	76%	65%
Write Off Rate								
Credit Only VAR	99%	97%	92%	93%	100%	98%	96%	94%
Credit & Macro VAR	99%	99%	94%	95%	100%	98%	96%	90%
FAVAR	104%	99%	91%	84%	102%	98%	93%	85%



Forecasting Retail Credit Market Conditions In Progress/To Do

Public Domain Data:

- Bayesian estimation/shrinkage/FAVAR for larger systems
- Mixed frequency and sample period data
- Time variation and regime shifts

Bureau Data:

- Further disaggregation for lending volumes and interest rates:
 - ▶ Products
 - ▶ Risk groups
 - ▶ Socio-demographics
- Alternative loan performance metrics



Conclusions

- VAR models provide efficient method for modelling systems for forecasting and simulation analysis
- Applications to monetary macroeconomics widespread; growing applications to credit markets but limited on retail credit market conditions
- Initial results show VAR models can provide (at least) a useful complement to forecasting using large-scale structural macroeconomic models
- Models including macroeconomic and credit variables improve forecast accuracy for both, relative to simpler time series approaches
- Larger systems/Factor Augmentation appear to improve accuracy further
- Some evidence in literature and preliminary results of time-varying structures – require further investigation.
- Future work to focus on:
 - ▶ implementing flexible Bayesian methods to incorporate more comprehensive information for short-term forecasting/'nowcasting'
 - ▶ Connecting public-domain and bureau-data based models to allow more comprehensive and granular forecasting.