Using Financial Data in Macroeconomic Models

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Apologies

- A tremendous amount of computation, but not yet much paper-writing, underly this presentation.

- My co-authors have seen some of the results I'll present, but not all, so are not responsible for errors or omissions.

Structural VAR modeling of financial/real interactions?

- That, since 2008-9, economists and policy-makers are interested in quantitative modeling of the interaction of the financial sector and the rest of the economy goes without saying.

- Even before 2008, theorists had produced models in which financial frictions mattered, and New Keynesian empirical modelers had tried incorporating such frictions in estimated models. (Kiyotaki-Moore, Bernanke-Gertler-Gilchrist)

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- Though BGG found large effects of financial friction shocks, they did not emphasize this result in their paper, probably in part because people did not think of the effects of financial friction shocks as an established empirical regularity that needed explanation.

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- It's not clear how to measure financial stress. Many of the candidate measures have relatively brief histories.

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- Also, these elements interact. Time-varying variances may be the source of apparent non-normality. Tightly constrained dynamics in variance regime switches may make nonlinearity and coefficient regime switches pick up explanatory power, and vice versa.

- The questions of "time variation of coefficients vs. variances", or "fat tails vs. heteroskedasticity" are artificial.

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- In most countries and time periods, positive innovations in credit to gdp predict persistent increased gdp growth in simple time series models.
- Monetary policy contraction probably increases at least some measures of financial stress, creating a source of spurious results in modeling the impact of financial stress itself.

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- In particular, we are open to the idea that financial stress is not one-dimensional.
- We allow for regime-switching in variances of structural shocks, since time-varying variances of innovations in financial variables, and of the federal funds rate, are obviously important.
- Allowing for time-varying variances of structural shocks aids identification, and we want to exploit that possibility.

Our model

$$A(L)y_t = \Lambda(s_t)\varepsilon_t$$

$$\Lambda(s_t) \text{ diagonal}$$

$$\text{diagonal}(A_0) \equiv 1$$

The states s_t change at exogenously specified times and do not repeat (i.e.. not Markov-switching), to allow handling of a larger model.

Identification

- If s_t changes at least once, and if all the diagonal elements of Λ_t differ across states by different factors, then A_0 is identified up to a permutation of its rows.

- That is, if we can distinguish the shocks by looking at their impulse responses or by looking at the coefficients in A, we can achieve identification without any formal restrictions at all.

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- Of course this may be too good to be true. It remains to be seen how well it works in practice.

Identification proof

$$\Sigma_1 = A^{-1}\Lambda_1(A')^{-1}\,, \qquad \Sigma_2 = A^{-1}\Lambda_2(A')^{-1}$$
$$\therefore \Sigma_1^{-1}\Sigma_2 = A'\Lambda_1^{-1}\Lambda_2(A')^{-1}$$

This last matrix has the columns of A' as eigenvectors and the diagonal of $\Lambda_1^{-1}\Lambda_2$ as eigenvalues. As long as the diagonal elements of $\Lambda_1^{-1}\Lambda_2$ are all distinct, the columns of A' (rows of A) are uniquely determined up to their ordering.

Data

	Series	Reporter	Source
Y	Industrial production	Fed. Reserve	FRED
P_{CS}	PCE deflator	NIPA	FRED
M	M1	Fed. Reserve	FRED
R_{FF}	Effective FFR	Fed. Reserve	FRED
P_{CM}	Monthly average of spot index	CRB/BLS	IHS
T	10-year constant maturity rate minus 3-month secondary market Treasury rate	Fed. Reserve	FRED
B	GZ bond spread		
R_{IB}	3-month London Eurodollar rate minus 3-month secondary market Treasury rate	Fed. Reserve	FRED

Restrictions on A_0

	Y	P_{CS}	M	R_{FF}	P_{CM}	T	B	R_{IB}
Output	○							
	●	○						
Financial	●	●	○	●	●	●	●	●
	●	●	●	○	●	●	●	●
	●	●	●	●	○	●	●	●
	●	●	●	●	●	○	●	●
	●	●	●	●	●	●	○	●
	●	●	●	●	●	●	●	○

This is just a block triangularity restriction, saying output and and consumer prices do not respond to other variables within the period. Clearly not enough by themselves to produce identification.

Dates

- Ten lags of all series at the monthly frequency.
- Period: November 1973 to December 2012
- s_t step shifts: October 1979, January 1983, January 1990, January 2008, and January 2011.

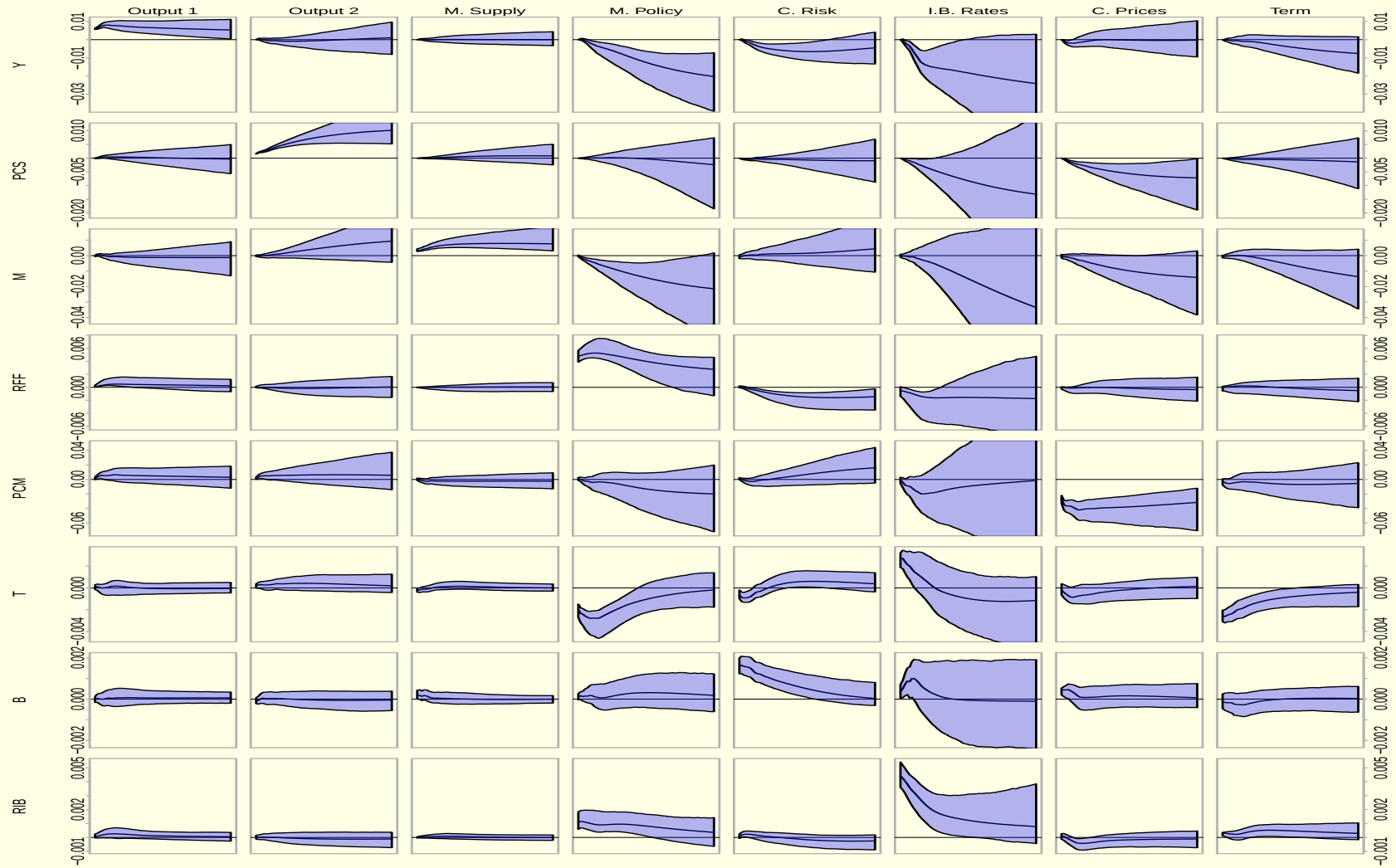
Comparison to Hubrich-Tetlow

- Their model (Financial Stress and Economic Dynamics: the Transmission of Crises, 9/2014) is also a structural VAR with regime switches, combining financial and traditional macro variables.
- They allow both coefficients ($A(L)$) and structural shock variances to change with "regime", while we allow only structural variance shifts.
- They model stochastic switches, and regimes recur, whereas we just fix six regime periods.
- They use a single index of fiscal stress, whereas we are exploring the need for multi-dimensional measures of it.

- Their data goes back only to 1988, while we use the late 70's and early 80's for estimation.

- They use a strictly triangular pattern of identifying restrictions on A_0, and A_0's are allowed to change, so there is very little identification power coming from the time-varying variances. If true A_0 is not triangular, variance changes get forced onto coefficient changes. Of course reverse is true for our paper.

- They use differenced data. This is unnecessary since their inference framework is Bayesian and is in tension with use of the usual Minnesota prior.


Output 1
Output 2
M. Supply
M. Policy
C. Risk
I.B. Rates
C. Prices
Term
Y
PCS
M
RFF
PCM
T
B
RIB

Pattern of time variation in the variances

	1	2	3	4	5	6
M. Demand	1.000	3.311	1.805	3.404	26.515	5.194
M. Policy	1.000	15.793	0.511	0.112	0.368	0.002
C. Risk	1.000	0.507	0.737	0.973	14.367	0.516
I.B. Rates	1.000	1.223	0.262	0.097	2.503	0.008
C. Prices	1.000	0.481	0.452	0.357	2.850	0.436
Term	1.000	4.069	0.620	0.384	2.862	0.173

Posterior mode of A_0

	Y	P_{CS}	M	R_{FF}	P_{CM}	T	B	R_{IB}
Output 1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Output 2	0.0040	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
M Demand	0.0330	0.1180	1.0000	−0.0820	−0.0070	−0.2340	0.3490	0.0840
M Policy	−0.0160	−0.0020	−0.0020	1.0000	−0.0010	0.0110	−0.0030	0.1090
C. Risk	−0.0013	0.0358	−0.0564	−0.0479	0.0177	−0.0662	1.0000	−0.0415
I.B. Rates	−0.0127	−0.0274	0.0058	−0.1776	0.0028	0.1161	0.0010	1.0000
Cm Prices	0.1720	0.7280	−0.0080	0.5090	−0.6780	0.6640	1.0000	−0.6030
Term	0.0147	0.0943	−0.0307	−0.5366	0.0035	−1.0000	−0.4570	0.5896

Monetary policy contemporaneous coefficient distribution

	Y	P_{CS}	M	P_{CM}	T	B	R_{IB}
2.5%	0.06000	0.11426	0.01078	0.01062	0.20566	0.21018	0.01470
16%	0.04428	0.06737	0.00492	0.00605	0.10382	0.12561	−0.07051
50%	0.02906	0.02412	−0.00130	0.00233	0.02866	0.04690	−0.16937
84%	0.01662	−0.02137	−0.00860	−0.00087	−0.02154	−0.00341	−0.28848
97.5%	0.00596	−0.06379	−0.01888	−0.00375	−0.06409	−0.04209	−0.44660

Do the spread variables have predictive value for the others?

We use the posterior covariance of matrix of the reduced form coefficients, conditional on the posterior modal $A0$, to construct a chi-squared statistic for comparing the equations for the first 4 or 5 variables with versions of them that exclude the remaining variables.

- At conventional significance levels, these chi-squared statistics favor the unrestricted model.

- Posterior odds (from the conditional posterior) favor the restricted model. Same idea as Schwarz criterion.

- However, none of these measures captures what we would like. Posterior odds on the restricted model, calculated this way from the prior density, would strongly favor the restricted model. Should calculate the ratio.

Pre-2008 fit

- Estimated impulse response functions are very similar to what emerges from the full sample.
- Chi-squared statistics favor the restricted model with the shorter sample.
- The implication is that the potential importance of financial stress was there in the data pre-2008, but that the penalty in fit and forecasting performance from ignoring it before then was modest.

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- Financial variables play a big role in system dynamics, probably have aided in identifying monetary policy.
- Identification via heteroskedasticity seems to have worked surprisingly well.
- No formal comparison here to models with time varying coefficients as well. We should at least try identifying monetary policy as fixed at the ZLB in the last part of the sample.

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- the model's dynamics are quite similar if estimated from the shorter sample.
- Neither in this paper, nor in most of the conference papers (Schorfheide excepted), is debt, deficits, and fiscal policy integrated into the modeling. Are we setting ourselves up for the next round of post-crisis $mea\ culpas$ for having not paid sufficient attention to a factor that turns out to be of huge importance?