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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• New Keynesian DSGE’s, though, grew out of SVAR modeling of monetary policy. There were some well understood patterns in the data that Christiano, Eichenbaum and Evans calibrated to in generating the empirical New Keynesian framework.
• 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.
Challenges in establishing the statistical regularities: Identification

- Identification problems are at least as bad as the problem of separating the Fisher equation from the Taylor rule that was more or less solved in the monetary VAR literature.
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- But across countries or long historical periods credit expansion clearly goes with economic growth.

- This creates a static positive correlation similar to the static positive correlation of interest rates and prices.
• 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.

• Reliably extracting a negative effect of credit expansion on growth, if it exists at all, requires multiple equation methods, just as did extracting a negative effect of monetary contraction on growth.
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• Financial variables often have much fatter-tailed innovation distributions than typical non-financial macro time series.

• It’s not clear how to measure financial stress. Many of the candidate measures have relatively brief histories.
What we need

• A time series modeling framework that allows for non-normality, regime-switches in variances and coefficients, nonlinearity, proper modeling of the zero-lower bound, convincing identification of policy shocks and financial friction shocks.
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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.
Our approach and objectives in this paper

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• 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

\[ A(L)y_t = \Lambda(s_t)\varepsilon_t \]
\[ \Lambda(s_t) \text{ diagonal, with } \lambda(s_t) \text{ on diagonal} \]
\[ \lambda(1) = 1 \]

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 $\Lambda_t$ 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.
Others, maybe Rigabon initially, have noticed this before. (Also, see my “Comparison of Interwar and Postwar Business Cycles” _AER_ paper.)
Identification proof

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

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

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

<table>
<thead>
<tr>
<th>Series</th>
<th>Reporter</th>
<th>Source</th>
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<tr>
<td>$Y$</td>
<td>Industrial production</td>
<td>Fed. Reserve</td>
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<tr>
<td>$P_{CS}$</td>
<td>PCE deflator</td>
<td>NIPA</td>
</tr>
<tr>
<td>$M$</td>
<td>M1</td>
<td>Fed. Reserve</td>
</tr>
<tr>
<td>$R_{FF}$</td>
<td>Effective FFR</td>
<td>Fed. Reserve</td>
</tr>
<tr>
<td>$P_{CM}$</td>
<td>Monthly average of spot index</td>
<td>CRB/BLS</td>
</tr>
<tr>
<td>$T$</td>
<td>10-year constant maturity rate minus 3-month secondary market Treasury rate</td>
<td>Fed. Reserve</td>
</tr>
<tr>
<td>$B$</td>
<td>GZ bond spread</td>
<td></td>
</tr>
<tr>
<td>$R_{IB}$</td>
<td>3-month London Eurodollar rate minus 3-month secondary market Treasury rate</td>
<td>Fed. Reserve</td>
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</tbody>
</table>
Results from two branches

• Branch 1: $A_0$ restricted to have unit diagonal, $\lambda(1)$ unconstrained, therefore prior not permutation-neutral and possibly unintentionally dogmatic. 82 free parameters in $A_0, \Lambda()$

• However, for this model, posterior simulations are complete, allowing error bands on impulse responses.

• Branch 2: model as described above, but with converged posterior mode only, no posterior draws. 104 free parameters. Broadly similar results.
Dates

- Ten lags of all series at the monthly frequency.
- Period: November 1973 to December 2012
- “Minnesota prior” dummy observations pulling toward persistence.
- Normal prior on $A_0$, priors on $\lambda$'s keeping them away from zero.
Current IRF’s
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.
## Restrictions on $A_0$ in branch 1

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<tr>
<th></th>
<th>$Y$</th>
<th>$P_{CS}$</th>
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<th>$R_{FF}$</th>
<th>$P_{CM}$</th>
<th>$T$</th>
<th>$B$</th>
<th>$R_{IB}$</th>
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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.
## Pattern of time variation in the variances

<table>
<thead>
<tr>
<th>Shock name</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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<tbody>
<tr>
<td>Demand</td>
<td>1.00</td>
<td>0.96</td>
<td>0.72</td>
<td>0.65</td>
<td>1.19</td>
<td>0.61</td>
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<tr>
<td>P</td>
<td>1.00</td>
<td>1.03</td>
<td>1.07</td>
<td>1.09</td>
<td>1.28</td>
<td>0.57</td>
</tr>
<tr>
<td>Trns Tech</td>
<td>1.00</td>
<td>1.07</td>
<td>0.86</td>
<td>1.25</td>
<td>2.15</td>
<td>1.95</td>
</tr>
<tr>
<td>M policy</td>
<td>1.00</td>
<td>2.81</td>
<td>0.69</td>
<td>0.27</td>
<td>0.51</td>
<td>0.04</td>
</tr>
<tr>
<td>Bond Market</td>
<td>1.00</td>
<td>0.57</td>
<td>0.67</td>
<td>0.83</td>
<td>2.56</td>
<td>1.05</td>
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<tr>
<td>Interbank</td>
<td>1.00</td>
<td>1.16</td>
<td>0.54</td>
<td>0.35</td>
<td>1.43</td>
<td>0.11</td>
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<tr>
<td>Supply</td>
<td>1.00</td>
<td>0.68</td>
<td>0.67</td>
<td>0.69</td>
<td>1.14</td>
<td>0.77</td>
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<tr>
<td>Term premium</td>
<td>1.00</td>
<td>1.69</td>
<td>0.86</td>
<td>0.63</td>
<td>1.08</td>
<td>0.61</td>
</tr>
</tbody>
</table>
Posterior mode of $A_0$

<table>
<thead>
<tr>
<th>INDPRO</th>
<th>PCEPI</th>
<th>M1SL</th>
<th>FEDFUNDS</th>
<th>PSCCOM</th>
<th>GS10_TB3MS</th>
<th>gzspr_nf</th>
<th>MED3_TB3MS</th>
</tr>
</thead>
<tbody>
<tr>
<td>123.19</td>
<td>-7.19</td>
<td>5.86</td>
<td>-34.33</td>
<td>13.28</td>
<td>5.47</td>
<td>-37.53</td>
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<tr>
<td>11.23</td>
<td>626.64</td>
<td>-5.44</td>
<td>50.67</td>
<td>-13.13</td>
<td>93.77</td>
<td>86.57</td>
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</tr>
<tr>
<td>1.69</td>
<td>69.86</td>
<td>210.52</td>
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<td>-3.70</td>
<td>-49.73</td>
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<td>-2.43</td>
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<td>-0.57</td>
<td>199.37</td>
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<td>-10.84</td>
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<td>35.35</td>
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<td>-2.23</td>
<td>-8.98</td>
<td>16.52</td>
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<tr>
<td>-3.78</td>
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<td>1.13</td>
<td>-82.78</td>
<td>1.38</td>
<td>-22.97</td>
<td>-29.56</td>
<td>266.86</td>
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<td>45.37</td>
<td>-55.67</td>
<td>3.59</td>
<td>28.73</td>
<td>-38.45</td>
<td>51.81</td>
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<td>20.85</td>
<td>101.54</td>
<td>-13.36</td>
<td>-194.88</td>
<td>-0.45</td>
<td>-368.22</td>
<td>-99.03</td>
<td>147.52</td>
</tr>
</tbody>
</table>
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 $A_0$, 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.
Conclusions

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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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• Evidence for improved fit from including financial stress was weaker before the crisis, but

• the model’s dynamics are quite similar if estimated from the shorter sample.

• Debt, deficits, and fiscal policy are not integrated into the model.

• Should model the regime switches rather than treat them as exogenous.