Macroeconomic Forecasts for China[1]

Chun Chang[a] Patrick Higgins[b] Tao Zha[c] Karen Zhong[d]

[a]SAIF, Jiaotong University
[b]FRB Atlanta
[c]FRB Atlanta, Emory University, and NBER
[d]SAIF, Jiaotong University

Fudan University
May 25, 2015

China's macroeconomy

- Growth and cyclical fluctuations (especially after 2008) depend largely on China's macroeconomic policies.
- Wen (2015) provides a unique historical perspective of China's rapid growth.
- Consistent with Wen (2015), Chang et al. (2015) provide both a theoretical framework and empirical evidence to show how China's macroeconomic performance depends crucially on its macroeconomic policies for the past two decades.
- In particular, policies for promoting investment in China's heavy industry constitute a driving force behind both growth and cyclical fluctuations.
- The question of where China's growth will be headed in both short and long terms has been a hotly contested policy issue for policymakers and researchers alike.

What's lacking?

- Yet, there is no systematic quantitative analysis of out-of-sample evaluation of a predicting performance of China's macroeconomy.
- Two main problems:
  (1) Data problems. Quarterly or monthly macroeconomic time series are only unavailable and the quality is arguably poor.
  (2) Given the macroeconomic time series, there are no systematic studies of macroeconomic forecasting usable for policy analysis.
- In this context, monthly macroeconomic time series are most important for timely policy projections as a key part of the regular policymaking procedure.

What're the solutions?

- Problem (1) has been a continuing problem for Chang et al. (2015) and Higgins and Zha (2015) take a systematic approach to constructing a core set of higher-frequency macroeconomic time series.
- This effort will continue for many years to come; it would be naive to think that the problem can be resolved overnight or there is some absolutely authoritative source of *quality* data.
- Given the constructed time series, however, Problem (2) can be solved by using the most reliable and sophisticated econometric methodology as well as scientific evaluation procedures.
- In this paper we focus on solving Problem (2):
  - As progress in solving Problem (1) continues, the solution to Problem (2) will improve systematically.
  - We use the VAR methodology eloquently advocated by the seminal works of Christiano, Eichenbaum, and Evans (1999) and Christiano, Eichenbaum, and Evans (2005).

Monthly data (seasonally adjusted)

Seven variables:

- Interpolated real value-added GDP (log).
- Real retail sales of consumer goods (log).
- Real fixed-asset investment (log).
- M2 (log).
- CPI (log).
- Net exports as percent of GDP.
- 7-day repo rate (percent) or 1-year deposit rate (percent).

Introduction to conditional forecasts

- Often, policymakers and analysts would like to know what would happen to the economy if different scenarios in the future are contemplated.
- There are two kinds of conditions imposed on future paths (Doan, Litterman, and Sims, 1984; Waggoner and Zha, 1999).
  - First kind: conditions are imposed on the future values of *endogenous* variables such as the interest rate and investment.
  - Second kind: conditions are imposed on sequences of structural shocks in the future.
- We begin with constant-parameter VARs:

$$y_t' A_0 = \sum_{\ell=1}^{p} y_{t-\ell}' A_\ell + C' + \varepsilon_t' \text{ for } 1 \leq t \leq T,$$

  where C is an $n \times 1$ vector of intercept terms and ε_t is an $n \times 1$ vector of random shocks with standard normal distribution (i.e., zero mean and unit variance).
- Denote all the parameters by a vector called a.

Unconditional forecasts

- The reduced form is

$$y_t = \sum_{\ell=1}^{p} y'_{t-\ell} B_\ell + c' + \varepsilon'_t A_0^{-1},\ B_\ell = A_\ell A_0^{-1},\ c' = C' A_0^{-1}.$$

- With the data up to T, the h-step forecast is

$$y_{T+h} = \underbrace{c' K_{h-1} + \sum_{\ell=1}^{p} y'_{T+1-\ell} N_{\ell,h}}_{y^u_{T+h}(a):\ \text{unconditional forecast}} + \underbrace{\sum_{k=1}^{h} \varepsilon'_{T+k} M_{h-k}}_{\text{cumulative responses}}, \quad (1)$$

$$B_k = 0 \text{ for } k > p;$$

$$K_0 = I,\ K_i = I + \sum_{k=1}^{i} K_{i-k} B_k, \quad i = 1, 2, 3, \ldots;$$

$$N_{\ell,1} = B_\ell,\ N_{\ell,h} = \sum_{k=1}^{h-1} N_{\ell,h-k} B_k + B_{h+\ell-1},\ \ell = 1, \ldots, p; h = 2, 3, \ldots;$$

$$M_0 = A_0^{-1},\ M_i = \sum_{k=1}^{i} M_{i-k} B_k,\ i = 1, 2, \ldots.$$

One condition on the i^{th} variable

- Denote the unconditional forecast of the i^{th} variable by $y^u_{T+h}(a)$ by $y^u_{T+h,i}(a)$.
- Consider a condition that restrains the i^{th} value of y_{T+h}, denoted by $y_{T+h,i}$, at the value $y^*_{T+h,i}$.
- Given the parameter vector a, this condition amounts to the restrictions on the independent shocks

$$\sum_{k=1}^{h} \varepsilon'_{T+k} \underbrace{M_{h-k}(:,i)}_{R^i_k(a)} = \underbrace{y^*_{T+h,i} - y^u_{T+h,i}(a)}_{r(a)'} . \qquad (2)$$

- In general, let $R(a)$ be a vector stacking $R^i_k(a)$ for all k and i.
- Rewrite the above condition in the following general form:

$$\underset{1\times hn}{R(a)'} \underset{hn\times 1}{\varepsilon} = \underset{1\times 1}{r(a)}.$$

Multiple conditions

- Suppose we have multiple conditions on various variables or in different horizons.
- We represent these conditions by q constrained values in the form of the vector $r(a)$.
- The constraints can now be represented as

$$\underset{q\times hn}{R(a)'}\underset{hn\times 1}{\varepsilon}=\underset{q\times 1}{r(a)}. \tag{3}$$

- Given the parameter vector a, these constraints amount to restricting the values of independent shocks.
- Thus, they encompass the second kind of restrictions—those directly imposed on independent shocks, where $R(a)$ and $r(a)$ may not depend on the values of parameters a.
- Both kinds of restrictions can be expressed by the same form as (3).

Point conditional forecast

- Given the values of a (e.g., the maximum likelihood or posterior mode estimate), the constraints (3) imply the normal distribution of the $nh \times 1$ vector ε of the following form

$$p\left(\varepsilon | a, R(a)'\varepsilon = r(a)\right) = \varphi\Big(R(a)\left(R(a)'R(a)\right)^{-1} r(a), \\ I - R(a)\left(R(a)'R(a)\right)^{-1} R(a)'\Big). \quad (4)$$

- The mode (the most likely) path of the constrained shocks is

$$R(a)\left(R(a)'R(a)\right)^{-1} r(a). \quad (5)$$

- It follows from (1) that the point conditional forecast is

$$y^{c}_{T+h}(a) = y^{u}_{T+h}(a) + \sum_{k=1}^{h} \varepsilon'_{T+k} M_{h-k}, \quad (6)$$

where the values of ε_{T+k} are computed from (5).

Competing models

- The standard VAR model (e.g., with no prior).
- The widely-used BVAR model with the Minnesota prior (Litterman, 1986).
- The gold-standard random-walk forecasting model (the percent change of the current month value over the value 12 months earlier)—Atkeson and Ohanian (2001).
- The BVAR model with the Sims and Zha (1998) prior. The standard monthly prior setting is documented in Zha (1998).

Out-of-sample forecasts

- For each month from 2005:12 to 2014:11, we fit the three VARs to the data up to that month and generate out-of-sample point forecasts for next four calendar years.
- The gold-standard random-walk forecasting model: for each month t from 2005:12 to 2014:11, the growth rates of the i^{th} variable for the next four calendar years are generated by the formula

$$100 * \exp\left\{\log y_t^i - \log y_{t-12}^i\right\}.$$

- AR(1), AR(6), and AR(12) models with and without trend:

$$x_t = \alpha + \beta t + \sum_{i=1}^{p} \gamma_i x_{t-i} + u_t,$$

where $p = 1, 6, 12$ and $\beta = 0$ if the trend is not allowed.

A horse race among models: a RMSE analysis (%)

Out-of-sample periods	Forecasting GDP growth: years ahead 1st year	2nd year	3rd year	4th year
	The Sims and Zha (1998) prior			
2006-2014	0.9627	2.7835	3.5608	4.3082
2007-2014	0.9820	2.7404	3.8084	4.6449
2008-2014	0.9865	2.5370	3.6645	4.9107
2009-2014	0.9453	2.6680	4.0453	5.6190
2010-2014	0.8879	1.5117	2.6302	3.0021
2011-2014	0.9281	1.3281	1.8140	1.6953
	The Minnesota prior			
2006-2014	0.9622	3.1509	4.5480	5.5409
2007-2014	1.0022	3.1852	4.7782	5.7415
2008-2014	1.0156	3.2193	4.7919	6.1048
2009-2014	0.9839	3.1454	5.0008	6.5999
2010-2014	0.8801	1.6954	3.6117	5.0328
2011-2014	0.9441	1.4520	2.2544	4.0835
	No prior			
2009-2014	0.5067	2.2184	6.3077	11.5883
2010-2014	0.4555	2.1819	6.6204	12.7502
2011-2014	0.4683	1.4950	6.4120	17.0510

A horse race among models: a RMSE analysis (%)

Out-of-sample	Forecasting GDP growth: years ahead			
periods	1st year	2nd year	3rd year	4th year
The Sims and Zha (1998) prior				
2006-2014	0.9627	2.7835	3.5608	4.3082
2007-2014	0.9820	2.7404	3.8084	4.6449
2008-2014	0.9865	2.5370	3.6645	4.9107
2009-2014	0.9453	2.6680	4.0453	5.6190
2010-2014	0.8879	1.5117	2.6302	3.0021
2011-2014	0.9281	1.3281	1.8140	1.6953
The gold-standard random walk				
2006-2014	1.5215	2.5766	3.0574	2.9604
2007-2014	1.5698	2.6614	3.0566	2.7514
2008-2014	1.6290	2.2092	2.3641	2.5056
2009-2014	1.6171	2.2332	2.5033	2.7060
2010-2014	1.5481	2.0664	2.6257	2.9521
2011-2014	1.5784	2.1141	2.1273	2.3276

A horse race among models: a RMSE analysis (%)

Out-of-sample periods	Forecasting GDP growth: years ahead 1st year	2nd year	3rd year	4th year
	The Sims and Zha (1998) prior			
2006-2014	0.9627	2.7835	3.5608	4.3082
2007-2014	0.9820	2.7404	3.8084	4.6449
2008-2014	0.9865	2.5370	3.6645	4.9107
2009-2014	0.9453	2.6680	4.0453	5.6190
2010-2014	0.8879	1.5117	2.6302	3.0021
2011-2014	0.9281	1.3281	1.8140	1.6953
	AR(1) without trend			
2006-2014	1.1116	2.7687	3.7531	4.5931
2007-2014	1.1147	2.8377	3.8635	4.6186
2008-2014	1.1704	2.6108	3.3448	4.5213
2009-2014	1.1042	2.3198	3.4319	4.4393
2010-2014	1.0960	2.5003	3.6996	4.3759
2011-2014	1.2046	2.6592	3.4367	4.2407
	AR(1) with trend			
2006-2014	1.4505	3.2077	2.1081	2.1962
2007-2014	1.3264	2.5144	2.2670	2.3893
2008-2014	1.2140	2.6779	2.4641	2.6540
2009-2014	1.2965	2.9196	2.7467	3.0076
2010-2014	1.3504	3.2630	3.1286	3.1016
2011-2014	1.5085	3.7408	3.2773	3.2610
	AR(6) without trend			
2006-2014	0.9915	3.0619	4.2376	5.2534
2007-2014	1.0349	3.2199	4.3141	5.2192
2008-2014	1.0858	2.9595	3.7176	5.0314
2009-2014	0.8830	2.5484	3.7027	4.7670
2010-2014	0.8925	2.7476	3.9725	4.6977
2011-2014	0.9512	2.8980	3.6840	4.5163

A horse race among models: a RMSE analysis (%)

Out-of-sample periods	Forecasting GDP growth: years ahead 1st year	2nd year	3rd year	4th year
The Sims and Zha (1998) prior				
2006-2014	0.9627	2.7835	3.5608	4.3082
2007-2014	0.9820	2.7404	3.8084	4.6449
2008-2014	0.9865	2.5370	3.6645	4.9107
2009-2014	0.9453	2.6680	4.0453	5.6190
2010-2014	0.8879	1.5117	2.6302	3.0021
2011-2014	0.9281	1.3281	1.8140	1.6953
AR(6) with trend				
2006-2014	1.0275	3.1952	4.2308	5.0595
2007-2014	1.0585	3.3350	4.3353	5.0451
2008-2014	1.0987	2.8695	3.0928	3.7092
2009-2014	0.9631	2.6738	3.2109	3.5953
2010-2014	0.9929	2.9559	3.5716	3.6287
2011-2014	1.0916	3.2887	3.6077	3.7132
AR(12) without trend				
2006-2014	1.2304	3.4892	4.6854	5.9228
2007-2014	1.2947	3.6969	4.7762	5.9212
2008-2014	1.3757	3.4845	4.2525	5.8114
2009-2014	0.9833	2.8983	4.0871	5.3059
2010-2014	0.9930	3.0720	4.2898	5.1203
2011-2014	1.0601	3.1852	3.9799	4.9121
AR(12) with trend				
2006-2014	1.3138	3.8272	5.2329	6.7982
2007-2014	1.3839	4.0799	5.2025	6.5093
2008-2014	1.4701	3.5593	3.7030	4.7119
2009-2014	1.0972	3.1028	3.4418	3.8154
2010-2014	1.1530	3.4174	3.7921	3.8188
2011-2014	1.2670	3.7772	3.8297	3.8791

A horse race among models: a RMSE analysis (%)

Out-of-sample periods	Forecasting inflation: years ahead 1st year	2nd year	3rd year	4th year
The Sims and Zha (1998) prior				
2006-2014	0.6624	2.4695	2.7009	1.5465
2007-2014	0.7008	2.4117	2.3832	1.3118
2008-2014	0.5962	2.3982	1.3490	1.1902
2009-2014	0.4306	1.6037	1.3918	0.3922
2010-2014	0.2696	1.5966	0.4438	0.3126
2011-2014	0.1826	0.7512	0.4721	0.3025
The Minnesota prior				
2006-2014	0.7791	2.8061	3.1783	2.4785
2007-2014	0.8199	2.8623	3.2702	1.9194
2008-2014	0.7966	3.0126	2.0945	1.6691
2009-2014	0.7254	2.8438	2.2968	1.8795
2010-2014	0.6426	2.9969	1.6410	1.7239
2011-2014	0.3453	1.3082	1.0259	1.1645
No prior				
2009-2014	1.1995	5.3425	6.8691	9.5311
2010-2014	1.2733	5.6335	7.3533	11.2280
2011-2014	1.1440	5.5709	8.5032	15.2425

A horse race among models: a RMSE analysis (%)

Out-of-sample periods	Forecasting inflation: years ahead 1st year	2nd year	3rd year	4th year
	The Sims and Zha (1998) prior			
2006-2014	0.6624	2.4695	2.7009	1.5465
2007-2014	0.7008	2.4117	2.3832	1.3118
2008-2014	0.5962	2.3982	1.3490	1.1902
2009-2014	0.4306	1.6037	1.3918	0.3922
2010-2014	0.2696	1.5966	0.4438	0.3126
2011-2014	0.1826	0.7512	0.4721	0.3025
	The gold-standard random walk			
2006-2014	1.0798	3.6183	4.0728	2.5973
2007-2014	1.1410	3.6666	4.0171	2.6546
2008-2014	1.0316	3.8553	3.6495	2.7651
2009-2014	0.7687	2.6296	3.6205	2.9518
2010-2014	0.7331	2.1385	2.0012	2.6391
2011-2014	0.6634	1.8855	2.3496	3.5950

A horse race among models: a RMSE analysis (%)

Out-of-sample periods	Forecasting inflation: years ahead 1st year	2nd year	3rd year	4th year
	The Sims and Zha (1998) prior			
2006-2014	0.6624	2.4695	2.7009	1.5465
2007-2014	0.7008	2.4117	2.3832	1.3118
2008-2014	0.5962	2.3982	1.3490	1.1902
2009-2014	0.4306	1.6037	1.3918	0.3922
2010-2014	0.2696	1.5966	0.4438	0.3126
2011-2014	0.1826	0.7512	0.4721	0.3025
	AR(1) without trend			
2006-2014	0.8874	4.2202	6.3925	9.6557
2007-2014	0.9376	4.3337	6.6851	10.5059
2008-2014	0.8987	4.5958	6.2705	10.8102
2009-2014	0.5551	2.0705	2.9151	3.7396
2010-2014	0.5296	2.2975	3.2115	4.3367
2011-2014	0.5708	2.4274	3.7548	5.6556
	AR(1) with trend			
2006-2014	0.7208	2.9996	3.3164	2.8151
2007-2014	0.7611	3.0726	3.3183	2.6557
2008-2014	0.6861	3.2020	2.7202	2.6809
2009-2014	0.4574	1.4014	1.6113	1.4260
2010-2014	0.4076	1.5576	1.4158	1.6152
2011-2014	0.4277	1.3321	1.6398	2.1021
	AR(6) without trend			
2006-2014	0.8435	4.0064	5.8723	7.7860
2007-2014	0.8813	3.9782	5.9154	8.5143
2008-2014	0.8455	4.1623	5.3440	8.4611
2009-2014	0.4935	2.1834	2.8960	2.4512
2010-2014	0.3421	1.9232	1.8680	2.6878
2011-2014	0.3068	1.5682	2.1442	3.5891

A horse race among models: a RMSE analysis (%)

Out-of-sample	Forecasting inflation: years ahead			
periods	1st year	2nd year	3rd year	4th year
	The Sims and Zha (1998) prior			
2006-2014	0.6624	2.4695	2.7009	1.5465
2007-2014	0.7008	2.4117	2.3832	1.3118
2008-2014	0.5962	2.3982	1.3490	1.1902
2009-2014	0.4306	1.6037	1.3918	0.3922
2010-2014	0.2696	1.5966	0.4438	0.3126
2011-2014	0.1826	0.7512	0.4721	0.3025
	AR(6) with trend			
2006-2014	0.6669	2.8028	2.9332	1.9424
2007-2014	0.7052	2.8115	2.7746	1.6684
2008-2014	0.5911	2.8696	2.2300	1.6898
2009-2014	0.3260	1.3875	1.5660	0.5156
2010-2014	0.3220	1.4250	0.5194	0.6285
2011-2014	0.2934	0.6890	0.6269	0.8845
	AR(12) without trend			
2006-2014	0.9915	4.3434	6.3054	7.6057
2007-2014	1.0361	4.2989	6.2607	8.3293
2008-2014	1.0173	4.5011	5.6451	8.0674
2009-2014	0.6993	2.7799	3.5740	2.7211
2010-2014	0.3142	1.8396	1.7961	2.6308
2011-2014	0.2873	1.5130	2.0388	3.4780
	AR(12) with trend			
2006-2014	0.7460	2.9028	3.0477	2.0165
2007-2014	0.7882	2.8553	2.7924	1.9218
2008-2014	0.6930	2.9022	2.2302	1.9543
2009-2014	0.4041	1.3535	1.4522	0.5047
2010-2014	0.3005	1.3628	0.4844	0.6164
2011-2014	0.2792	0.5932	0.5920	0.8616

Real-time out-of-sample forecasts

- Sample: from 2000:1 to 2014:12.
- Lags: 13.
- Conditions: $\log \mathrm{M2}$ and $\log \mathrm{CPI}$ in January, 2015; Repo rate in January and February, 2015.
- Prior: $\mu_1 = 0.8, \mu_2 = 0.5, \mu_3 = 0.5, \mu_4 = 1.2, \mu_5 = \mu_6 = 5$.
- Slightly different from the standard prior setting, but will use the standard one in the next revision.

Density conditional forecast

The Gibbs algorithm from Waggoner and Zha (1999):

(a) Initialize $a^{(0)}$ (e.g., the maximum likelihood or posterior mode estimate). For $i = 1, 2, \ldots, N_1 + N_2$, we loop through i as follows.

(b) Draw ε from the normal distribution that satisfies the constraints (i.e., (4)) and then generate $y^c_{T+1}\left(a^{(i-1)}\right), \ldots, y^c_{T+h}\left(a^{(i-1)}\right)$ from (6).

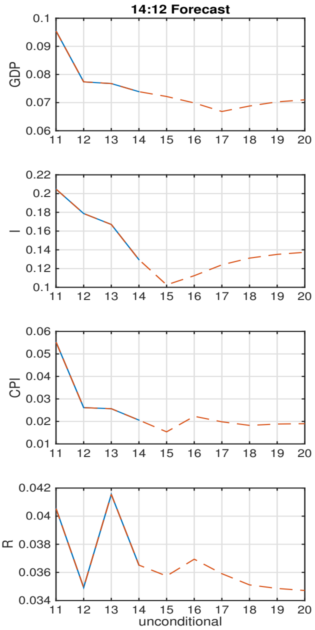
(c) Generate $a^{(i)}$ from $p\left(a \mid Y_T, y^c_{T+1}\left(a^{(i-1)}\right), \ldots, y^c_{T+h}\left(a^{(i-1)}\right)\right)$.

(d) Use the newly sampled $a^{(i)}$ to reset $a^{(i-1)} = a^{(i)}$ and repeat steps (b) and (c).

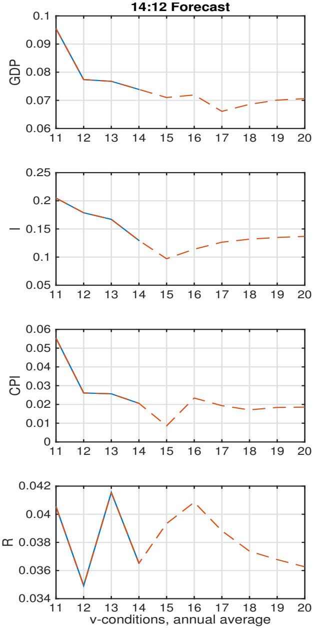
(e) Keep the last N_2 draws.

Snapshot of forecasts made at 2010:12—turning point

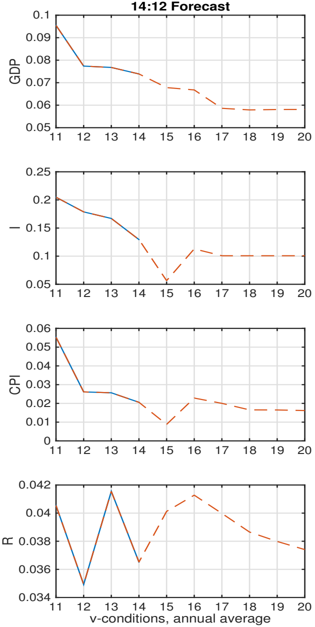
Actual data					
Year	GDP	C	I	M2	CPI
2009	8.95	15.45	31.36	26.45	-0.72
2010	10.74	23.32	20.58	20.67	3.17
2011	9.54	17.11	20.47	15.61	5.53
2012	7.73	14.49	17.87	17.24	2.61
2013	7.67	13.13	16.70	14.84	2.56
2014	7.38	11.98	12.95	12.74	2.05
Forecasts (out-of-sample)					
2011	8.54	19.18	20.03	14.49	5.59
2012	7.38	15.63	22.01	14.63	1.66
2013	9.18	14.17	22.09	17.40	1.25
2014	9.37	15.67	21.66	15.77	2.47



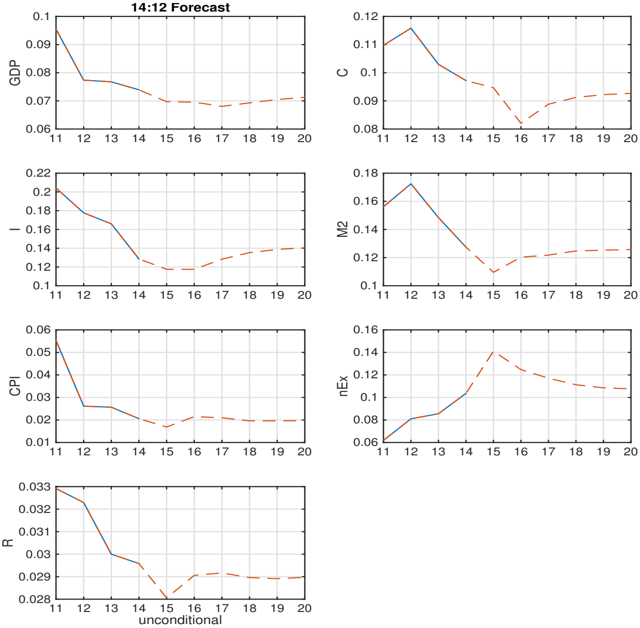
Unconditional forecasts.



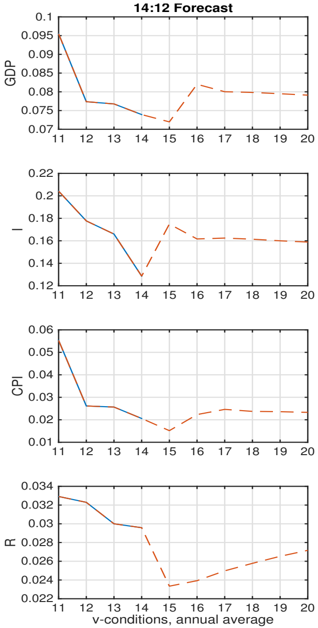
Forecasts conditional on M2 (2015:1), CPI (2015:1), and Repo (2015:1-2015:2).



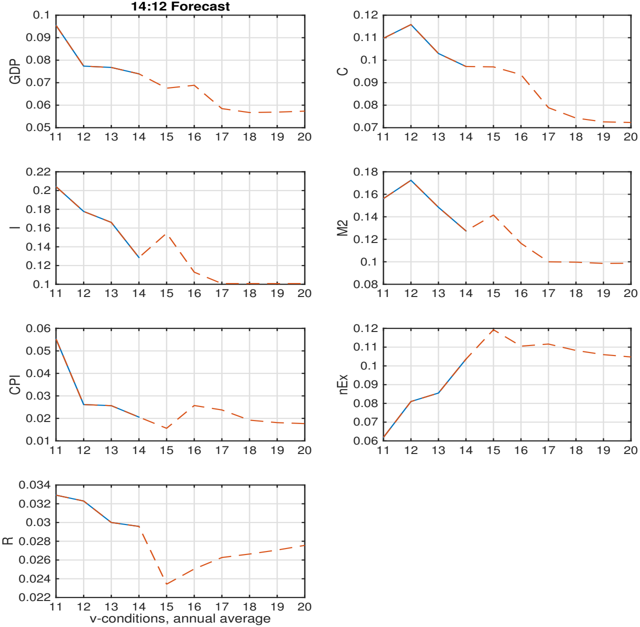
Policy projections: conditional on M2 (2015:1), CPI (2015:1), Repo (2015:1-2015:2), and counterfactual values I (2015:1-2020:12, growth rate is the average of 2014; then 2016:1-end of periods is set to be 10% annually on average).



Unconditional forecasts with the 1-yr deposit rate.



Forecasts (with the 1-yr deposit rate) conditional on M2 (2015:1), CPI (2015:1), and Repo (2015:1-2015:2).



Policy projections (with the 1-yr deposit rate): conditional on M2 (2015:1), CPI (2015:1), Repo (2015:1-2015:2), and counterfactual values I (2015:1-2020:12, growth rate is the average of 2014; then 2016:1-end of periods is set to be 10% annually on average).

Key implications

- As one can infer from the previous results, contrary to the common belief based from the robust studies on the U.S. and European economies, the impact of the interest rate on the aggregate economy is either insignificant or unrealistic.
- Instead, China's investment policy backed by credit (money supply) has a much larger impact on the aggregate economy.
- What do these findings teach us?
  - Macroeconomic analysis directly borrowed from the U.S. models (such as the DSGE analysis) would miss the boat when analyzing China's macroeconomy.
  - The basic facts about China's macroeconomy need to be understood and taken into account before embarking on a new analysis based on plain vanilla macro models.

Future research

- The Chinese economy and monetary policy have reached a stage mature enough for more rigorous empirical macroeconomic analysis comparable to the international standards.
- Significant progress in such an analysis has, no doubt, its first-order benefits to the stabilization of international economies.
- In light of our analysis, specifically, the following development is welcome:
  - Markov-switching BVAR taking account of stochastic volatility.
  - Mixed-frequency BVAR incorporating weekly or daily financial variables.
  - DSGE models accounting for the basic facts documented by Chang et al. (2015).

References I

Atkeson, Andrew and Lee E. Ohanian (2001). "Are Phillips Curves Useful for Forecasting Inflation?" In: *Quarterly Review* 25.1, pp. 2–11.

Chang, Chun et al. (2015). "Trends and Cycles in China's Macroeconomy". In: *NBER Macroeconomics Annual* 30.

Christiano, Lawrence J., Martin S. Eichenbaum, and Charles L. Evans (1999). "Monetary Policy Shocks: What Have We Learned and To What End?" In: *Handbook of Macroeconomics*. Ed. by John B. Taylor and Michael Woodford. Vol. 1A. Amsterdam, Holland: North-Holland, pp. 65–148.

– (2005). "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy". In: *Journal of Political Economy* 113, pp. 1–45.

Doan, Thomas, Robert B. Litterman, and Christopher A. Sims (1984). "Forecasting and Conditional Projection Using Realistic Prior Distributions". In: *Econometric Reviews* 3.1, pp. 1–100.

References II

Higgins, Patrick C. and Tao Zha (2015). "China's Macroeconomic Time Series: Methods and Implications". Unpublished Manuscript, Federal Reserve Bank of Atlanta.

Litterman, Robert B. (1986). "Forecasting with Bayesian Vector Autoregressions — Five Years of Experience". In: *Journal of Business and Economic Statistics* 4, pp. 25–38.

Sims, Christopher A. and Tao Zha (1998). "Bayesian Methods for Dynamic Multivariate Models". In: *International Economic Review* 39.4, pp. 949–968.

Waggoner, Daniel F. and Tao Zha (1999). "Conditional Forecasts in Dynamic Multivariate Models". In: *The Review of Economics and Statistics* 81.4, pp. 639–651.

Wen, Yi (2015). "The Making of an Economic Superpower—Unlocking China's Secret of Rapid Industrialization". Federal Reserve Bank of St. Louis Working Paper 2015-006B.

References III

Zha, Tao (1998). "A Dynamic Multivariate Model for Use in Formulating Policy". In: *Federal Reserve Bank of Atlanta Economic Review* 83.1. First Quarter, pp. 16–29.