Program

Dynamic Factor Models

Prof. Mark Watson
Oct 22–23–24, 2018
Auditorium Central Bank of Chile

Monday, Oct 22

09:30 - 09:35	Welcome words
09:35 - 10:50	Session 1
10:50 - 11:00	Coffee Break
11:00 - 12:30	Session 2

Tuesday, Oct 23

09:30 - 10:45	Session 1
10:45 - 11:00	Coffee Break
11:00 - 12:00	Session 2

Wednesday, Oct 24

09:30 - 10:45	Session 1
10:45 - 11:00	Coffee Break
11:00 - 12:00	Session 2

Structural VARs and Dynamic Factor Models in Macroeconomics
Central Bank of Chile, October 22-24, 2018

This course will work through the recent Stock-Watson *Handbook of Macroeconomics* chapter of the same title as this course. Software (in Matlab) will be provided to carry out empirical analysis.

The chapter's abstract:

"This chapter provides an overview of and user's guide to dynamic factor models (DFMs), their estimation, and their uses in empirical macroeconomics. It also surveys recent developments in methods for identifying and estimating SVARs, an area that has seen important developments over the past 15 years. The chapter begins by introducing DFMs and the associated statistical tools, both parametric (state-space forms) and nonparametric (principal components and related methods). After reviewing two mature applications of DFMs, forecasting and macroeconomic monitoring, the chapter lays out the use of DFMs for analysis of structural shocks, a special case of which is factor-augmented vector autoregressions (FAVARs). A main focus of the chapter is how to extend methods for identifying shocks in structural vector autoregression (SVAR) to structural DFMs. The chapter provides a unification of SVARs, FAVARs, and structural DFMs and shows both in theory and through an empirical application to oil shocks how the same identification strategies can be applied to each type of model."

Dynamic Factor Models, Factor Augmented VARs, and SVARs in Macroeconomics

Mark Watson
Princeton University

Central Bank of Chile
October 22-24, 2018

Reference: Stock, James H. and Mark W. Watson (2016)
Handbook of Macroeconomics, Vol 2. chapter

Outline

Monday: Dynamic Factor Models – Part 1

Tuesday: Dynamic Factor Models – Part 2
SVARs – Part 1

Wednesday: SVARs – Part 2
FAVAR/SDFM

Historical Evolution of DFMs

I. Factor Analysis

- Spearman (1904)
- Lawley (1940), Joreskög (1967) … Lawley and Maxwell (1971)

Spearman's problem:

Data: X_{ij}, $i = 1, \ldots, N$ (individuals)

and $j = 1, \ldots n$ (measurements for each individual)

$$X_i = \begin{pmatrix} X_{i1} \\ X_{i2} \\ \vdots \\ X_{in} \end{pmatrix} \text{ and } \Sigma_{XX} = \mathrm{cov}(X_i)$$

How can we measure 'intelligence'?

"GENERAL INTELLIGENCE," OBJECTIVELY DETERMINED AND MEASURED.

By C. SPEARMAN.

TABLE OF CONTENTS.

Experimental Series IV.

High Class Preparatory School for Boys.

A. **Original Data.**

Age		Pitch	Place in School (*before modification to eliminate Age*).												Music
			Classics			French			English			Mathem.			
Years	Months	Discrim. Thres. in 1/3 v. d., October, 1902	Xmas, 1902	Easter, 1903	July, 1903	Xmas, 1902	Easter, 1903	July, 1903	Xmas, 1902	Easter, 1903	July, 1903	Xmas, 1902	Easter, 1903	July, 1903	Ranked by Music Master
12	6	2	8	7	4	5	3	3	4	3	3	4	2	3	8
12	4	3	11	12	10	13	13	10	13	13	11	12	13	11	9
9	8	3	19	18	15	21	19	16	23	21	18	21	19	17	6
13	7	4	2	2	1	2	2	1	2	2	1	7	7	7	3
10	4	4	21		19	22		23	22		20	21		24	16
10	7	4	23	23	22	26	23	22	28	25	23	29	25	23	1
13	6	5	3			3			3			3			21
11	10	5	6	4	3	7	6	5	6	6	2	9	8	6	
10	1	5	29	26	24	23	25	21	27	26	22	25	23	19	7
11	1	6	20	20	18	20	21	18	21	20	19	17	16	15	14
13	4	7	1	1		1	1		1	1		1	1		5
10	6	7	26	24	21	27	16	13	26	19	17	22	18	16	11
12	3	7	18	17	16	17	20	19	25	23	21	19	17	14	20
13	1	8	5	5	5	4	4	2	5	8	5	5	4	1	4
11	1	10	22	19	17	19	18	17	20	17	15	23	21	21	18
9	9	10	33	29	27	33	29	27	33	27	27	32	29	27	17
10	4	11	28	25	23	30	27	24	18	18	13	30	27	22	
13	0	11	4	3	2	6	5	4	7	4	4	2	3	4	
10	2	11	7	6	6	12	7	6	8	5	8	11	9	8	
13	0	11	12	11	11	11	11	12	15	16	16	6	5	2	12
12	0	11	17	16		16	15		24	22		24	24		15
12	11	12	9	8	7	8	8	7	9	7	7	14	12	12	
13	1	14	10	9	8	10	9	8	11	10	9	10	10	9	13
10	4	14	27	21	14	24	22	15	17	11	10	26	20	18	2
10	1	15	24	22	20	18	17	14	29	24	24	18	15	13	
12	6	15	14	13	12	15	14	11	10	9	6	8	6	5	10
10	8	15	30	27		29	26		30	29		28	26		
12	8	18	16	15	13	25	24	20	14	14	12	20	21	20	19
9	5	20	32		25	31		25	32		26	33		26	
11	2	24	15	14	9	14	12	9	16	15	14	13	11	10	
10	9	50	25			28			19			15			
10	11	> 60	31	28	26	32	28	26	31	28	25	31	28	25	22
13	7	> 60	13	10		9	10		12	12		16	14		

Factor Model

$$X_{ij} = \lambda_j f_i + e_{ij} \text{ or}$$

$$X_i = \lambda f_i + e_i$$

$$\Sigma_{XX} = \sigma_f^2 \lambda\lambda' + \Sigma_{ee} \text{ with } \Sigma_{ee} \text{ diagonal}$$

$$X_i = \lambda f_i + e_i$$

$$\Sigma_{XX} = \sigma_f^2\ \lambda\lambda' + \Sigma_{ee} \text{ with } \Sigma_{ee} \text{ diagonal}$$

Issues:

(1) Estimation of parameters (σ_f^2, λ, $\sigma_{e_i}^2$)   (Lawley: Gaussian MLE)

(2) Estimation of $f_i \mid X_i$, (σ_f^2, λ, $\sigma_{e_i}^2$): 'reverse regression'

$$(X_i \mid f_i) \sim \mathrm{N}(\lambda f_i, \Sigma_{ee}) \text{ and } f_i \sim \mathrm{N}(0, \sigma_f^2)$$

$$\Rightarrow f_i \mid X_i \sim \mathrm{N}(\beta' X_i\,,\ \sigma_{f|Y}^2)$$

$$\text{with } \beta = \Sigma_{YY}^{-1}\Sigma_{Yf} = \left(\sigma_f^2 \lambda\lambda' + \Sigma_{ee}\right)^{-1} \lambda\sigma_f^2$$

$$\sigma_{f|Y}^2 = \sigma_f^2 - \sigma_f^2\lambda'\left(\sigma_f^2\lambda\lambda' + \Sigma_{ee}\right)^{-1}\lambda\sigma_f^2$$

Historical Evolution of DFMs:

2a: Replace covariance matrices with spectral density matrices. (Geweke (1977), Sargent and Sims (1977), Brillinger (1975)).

$$X_i = \lambda f_i + e_i$$

$$\Sigma_{XX} = \sigma_f^2 \lambda\lambda' + \Sigma_{ee} \text{ with } \Sigma_{ee} \text{ diagonal}$$

becomes

$$X_t = \lambda(\mathrm{L})f_t + e_t$$

$$S_{XX}(\omega) = s_f^2(\omega)\ \lambda(\mathrm{e}^{-\mathrm{i}\omega})\lambda(\mathrm{e}^{\mathrm{i}\omega})' + S_{ee}(\omega) \text{ with } S_{ee}(\omega) \text{ diagonal}$$

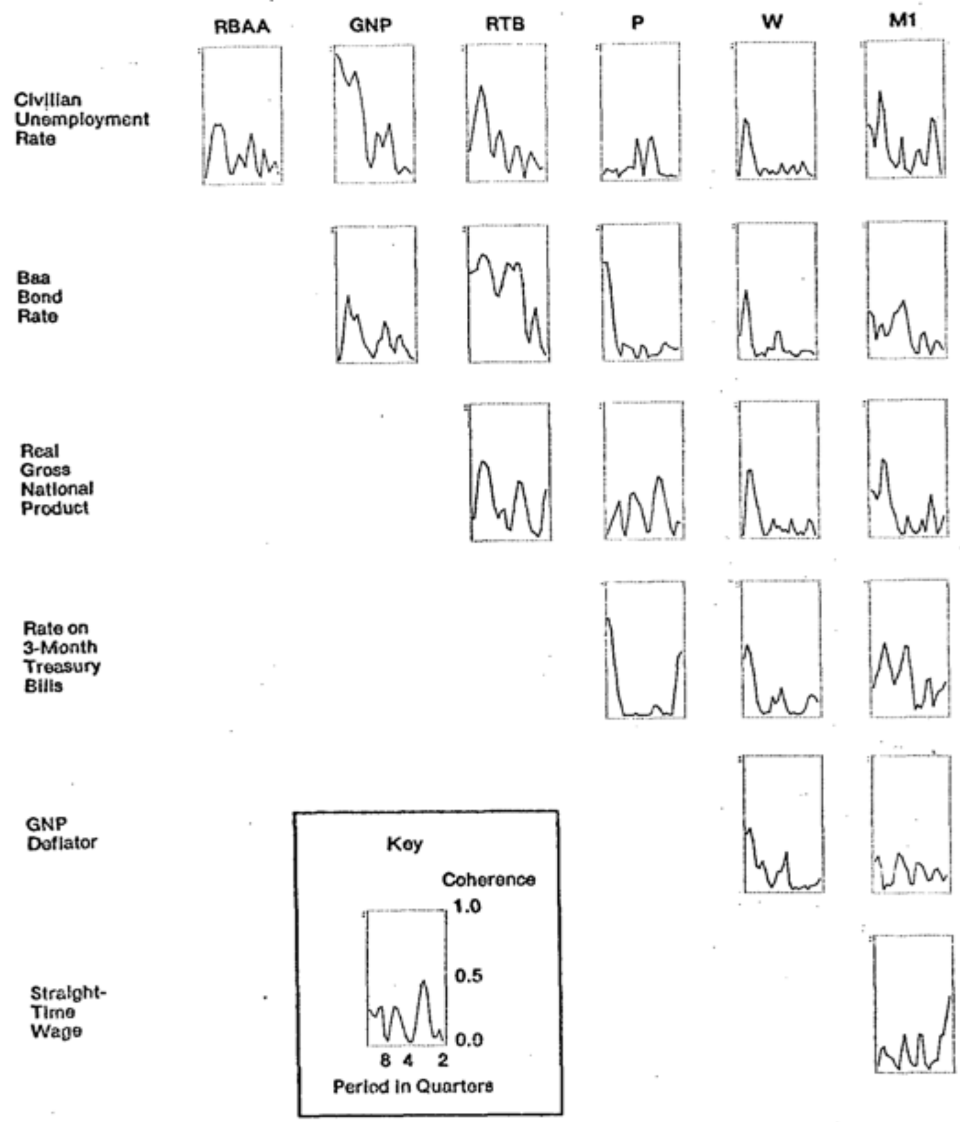
Business Cycle Modeling Without Pretending to Have Too Much A Priori Economic Theory

Thomas J. Sargent
Christopher A. Sims

Revised, January 1977

Paper prepared for seminar on New Methods in Business Cycle Research, Federal Reserve Bank of Minneapolis, November 13-14, 1975. The views expressed herein are solely those of the authors and do not necessarily represent the views of the Federal Reserve Bank of Minneapolis or the Federal Reserve System. John Geweke adapted the maximum likelihood factor analysis algorithm for application to the frequency domain factory model and wrote a computer program for estimating and testing the one-index model. Paul Anderson extended that program to handle k noises and performed all the frequency domain calculations in this paper. Salih Neftci carried out the calculations for the observable index model. John Geweke's contribution in developing the factor analysis algorithm and in formulating the unobservable index model were enough for him to qualify as a coauthor of this paper.

Table 1 — GRAPHS OF COHERENCE OF ECONOMIC VARIABLES



Sargent and Sims used various subsets of 14 variables: long rate, short rate, GNP, prices, wages, money supply, government purchases, government deficit, unemployment rate, residential construction, inventories, plant and equip investment, consumption, corporate profits.

$$X_t = \lambda(\mathrm{L})f_t + e_t$$

$$S_{XX}(\omega) = s_f^2(\omega)\ \lambda(\mathrm{e}^{-\mathrm{i}\omega})(\mathrm{e}^{\mathrm{i}\omega})\lambda' + S_{ee}(\omega) \text{ with } S_{ee}(\omega) \text{ diagonal}$$

Issues:

(1) Estimation of parameters ($s_f^2(\omega)$, $\lambda(\mathrm{e}^{-\mathrm{i}\omega})$, $S_{ee}(\omega)$) (Local Gaussian MLE, frequency by frequency)

(2) Estimation of $f(\omega) \mid X(\omega)$: can use 'reverse regression'

New issues: Converting frequency domain back to time domain. Leads/lags. Constraints across frequencies.

Table 12 Set 4

PROP OF VAR EXPLAINED BY 1 COMMON FACTORS

FREQUENCY	VAR. NO. 1	VAR. NO. 2	VAR. NO. 3	VAR. NO. 4	VAR. NO. 5	VAR. NO. 6	VAR. NO. 7	VAR. NO. 8	VAR. NO. 9
	UNEMP.RT	LREALGNP	LGNPDEFL	LM1	LRES CONST	DLINVENT	LPL.EQPT	LCONS	LCORP.IVA
.1200PI	.84977	.93613	.21773	.28148	.26281	.54252	.68492	.12651	.89845
.3500PI	.43539	.91708	.97035E-01	.51548E-01	.80182E-01	.55580	.64565	.73225E-01	.87726
.6400PI	.55832	.73002	.24552	.73328E-01	.28865E-01	.21120	.28034	.10498E-01	.67750
.8600PI	.82680E-01	.25349	.29783	.31570E-01	.18589	.36609E-01	1.0000	.65040E-02	.25051
OVERALL	.82831	.93171	.21507	.27275	.21453	.53089	.67412	.85918E-01	.89032

PROP OF VAR EXPLAINED BY 2 COMMON FACTORS

FREQUENCY	VAR. NO. 1	VAR. NO. 2	VAR. NO. 3	VAR. NO. 4	VAR. NO. 5	VAR. NO. 6	VAR. NO. 7	VAR. NO. 8	VAR. NO. 9
	UNEMP RT	LREALGNP	LGNPDEFL	LM1	LRES CONST	DLINVENT	LPL.EQPT	LCONS	LCORP.IVA
.1200PI	.97520	.93926	1.0000	.37270	.26820	.84758	.73196	.17193	.51112
.3500PI	.67835	1.0000	.43216	.79475E-01	.13698	.53886	.68603	.77118E-01	1.0000
.6400PI	.55357	.81562	.54733	.37229	.11346	.69574	1.0000	.29553E-01	.94345
.8600PI	.89870E-01	.72358	1.0000	.19129	.50046E-01	.51306	.56072	[illegible]	.86558
OVERALL	.86352	.93908	.98189	.36266	.22583	.83306	.77543	.11191	.91369

2b: Use linear state-space models: (e.g., Engle and Watson (1981))

$$X_t = \lambda(\mathrm{L})f_t + e_t \text{ and } \phi(\mathrm{L})f_t = \eta_t$$

$$X_t = \begin{pmatrix} \lambda_0 & \lambda_1 & \cdots & \lambda_k \end{pmatrix} \begin{pmatrix} f_t \\ f_{t-1} \\ \vdots \\ f_{t-k} \end{pmatrix} + e_t$$

$$\begin{pmatrix} f_t \\ f_{t-1} \\ \vdots \\ f_{t-k} \end{pmatrix} = \begin{bmatrix} \phi_1 & \phi_2 & \cdots & \phi_{k+1} \\ 1 & 0 & \cdots & 0 \\ & \ddots & \ddots & \\ & & 1 & 0 \end{bmatrix} \begin{pmatrix} f_{t-1} \\ f_{t-2} \\ \vdots \\ f_{t-k-1} \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \eta_t$$

or

$$X_t = \Lambda F_t + e_t$$
$$F_t = \Phi F_{t-1} + \mathrm{G}\eta_t$$

(More generally F equation can be VAR(p))

Issues:

(1) Estimation of parameters (Λ, σ_η^2, Φ, Σ_{ee}) (Gaussian MLE using prediction-error decomposition from Kalman filter)

(2) Estimation of $f_t \mid \left\{X_j\right\}_{j=1}^{T}$: 'reverse regression' computed using Kalman smoother.

New issues:

(a) State-space modeling afforded lots of flexibility.

(b) MLE hard when X_t is high dimensional.

A One-Factor Multivariate Time Series Model of Metropolitan Wage Rates

ROBERT ENGLE and MARK WATSON*

The paper formulates and estimates a single-factor multivariate time series model. The model is a dynamic generalization of the multiple indicator (or factor analysis) model. It is shown to be a special case of the general state space model and can be estimated by maximum likelihood methods using the Kalman filter algorithm. The model is used to obtain estimates of the unobserved metropolitan wage rate for Los Angeles, based on observations of sectoral wages within the Standard Metropolitan Statistical Area. Hypothesis tests, model diagnostics, and out-of-sample forecasts are used to evaluate the model.

KEY WORDS: State space model; Dynamic factor analysis; Kalman filter; Method of scoring; Unobserved component estimation.

1. INTRODUCTION

Much of the growth and decline of regional economies can be attributed to changes in comparative advantage, and the single most important component of this comparative advantage is probably wage rates. Therefore, considerable interest centers on the measurement of local wage rates and on the determinants of their movements. Because a region within a national economy can be thought of as a very open economy, there are strong economic pressures for wages to equalize between regions, both through commodity trade which tends to equate factor prices and through regional migration of labor and capital. For further discussion of these issues, see Engle (1974).

The measurement of a regional wage rate and its determinants is complicated by the differing wage in different industries and by differing skill mixes in different industries. In this article a statistical technique will be employed to separate movements in a metropolitan wage rate into a national industrial component, a metropolitan area-wide component, and a local industry specific component. For example, the wage rate in contract construction in Los Angeles will be decomposed into one component determined by the wage rate in contract construction in the United States, a second determined by the overall wage rate in Los Angeles, and a third resulting from factors particular to Los Angeles contract construction.

There are good economic reasons for expecting each of these components to be important. The national component measures not only changes in the U.S. economy as a whole through inflation and business cycles, but also measures changes in technology, changes in preferences, changes in the supply or demand for the output of the industry nationally, and collective bargaining outcomes that may affect industrial wages for a broad geographical region. The metropolitan component reflects the demand and supply of labor in the metropolitan labor market. Presumably, no industry can avoid the effect of the local labor market entirely, but some may be more strongly influenced than others. This component would reflect migration patterns of capital and labor, the cost of living in the region, and the tightness of the local labor market. The specific effect is the remainder which measures situations peculiar to this industry and region. By definition, the three effects are independent.

To illustrate the problem, consider the least squares regression of the log of the wage rate in industry i in Los Angeles, w_{it}, on the log of the national wage rate in this industry, n_{it}, using annual data. The residuals from this regression are composed of metropolitan effects and local industry specific effects. The metropolitan effects are common to each industry and therefore produce correlation across industries while the specific effects are by definition independent of other industries. In Table 1, these regressions and residual correlations are presented; the large cross-sectional correlations suggest the importance of the metropolitan effect. A factor analysis of these residual correlations indicates that one factor could explain 70 percent of the variance.

Because the data are a time series of cross-sections, the dynamic effects must also be considered and standard factor analysis is not appropriate. The first-order lagged correlation matrix, also presented in Table 1, shows the importance of the dynamics in the data set. Cross-correlations between sectors must result from serial correlation in the metropolitan component, while autocorrelations could arise from serial correlation in the specific effect. The frequency domain version of factor analysis of Geweke (1977) and Geweke and Singleton (1981) can

* Robert Engle is Professor, Department of Economics, University of California at San Diego, La Jolla, CA 92093. Mark Watson is Assistant Professor, Department of Economics, Harvard University, Cambridge, MA 02138. This research was supported by NSF grant SOC 77-07166. The authors are indebted to Clive W. J. Granger, David Lilien, Adrian Pagan, and Andrew Harvey for useful comments, suggestions, and encouragement at various stages of the research. The authors alone take credit for any remaining errors.

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Applications Section

Table 3. Dynamic Factor Analysis (Model B)[a]

Where $m_t = \phi_1 m_{t-1} + \phi_2 m_{t-2} + v_{1t}$

$w_{it} = \alpha_i m_t + \beta_i n_{it} + e_{it}$ For sectors $i = 1, \ldots, 5$

$e_{it} = \rho_i e_{it-1} + v_{i+1t}$

Sector	α	β	ρ	$\sigma^2 \times 10^4$	SE
Contract construction	1.	.874	.628	.598	.008
		(.078)	(.389)	(.329)	
Durable manufactures	.549	.786	.742	.835	.009
	(.090)	(.053)	(.155)	(.266)	
Nondurable manufactures	.380	.786	.898	.466	.007
	(.091)	(.040)	(.107)	(.149)	
Wholesale trade	.302	.959	.519	1.191	.011
	(.075)	(.032)	(.227)	(.352)	
Retail trade	.663	.810	.340	.941	.010
	(.070)	(.059)	(.289)	(.343)	

	ϕ_1	ϕ_2	$\sigma^2 \times 10^4$	σ_{v1}
Metropolitan component	1.606	−.619	1.229	.011
	(.125)	(.145)	(.585)	

[a] Standard errors are in parentheses.

Some Jargon:

$X_t = \lambda(\mathrm{L})f_t + e_t$ and $\phi(\mathrm{L})f_t = \eta_t$: *Dynamic form of DFM*

stacked version

$X_t = \Lambda F_t + u_t$ and $F_t = \Phi F_{t-1} + \mathrm{G}\eta_t$: *Static form of DFM*

Example: “Improving GDP Measurement: A Measurement-Error Perspective” Aruoba, Diebold, Nalewaik, Schorfheide, Song (2016)

S.B. Aruoba et al. / Journal of Econometrics 191 (2016) 384–397 387

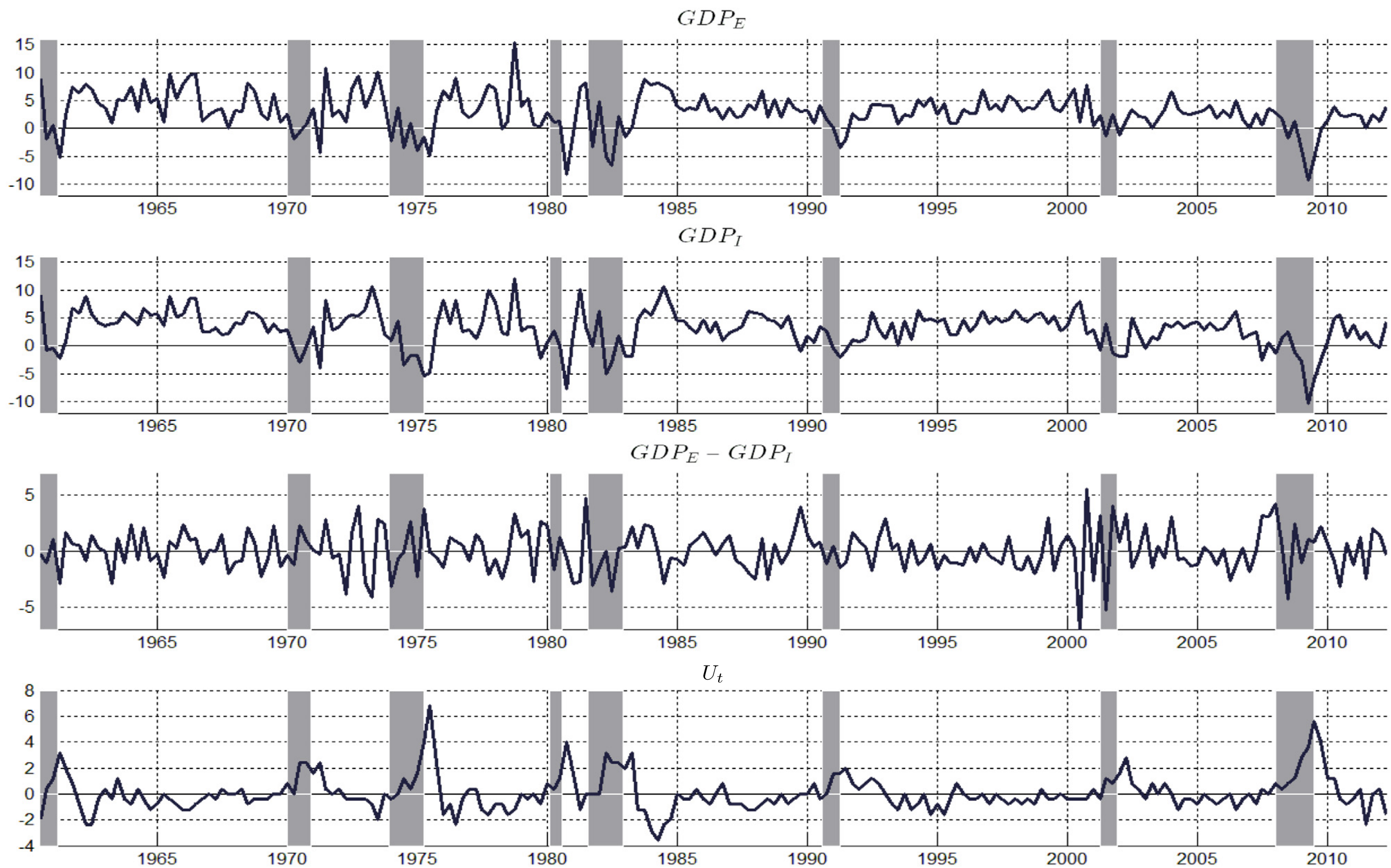


Fig. 1. *GDP* and unemployment data. GDP_E and GDP_I are in growth rates and U_t is in changes. All are measured in annualized percent.

$$\begin{bmatrix} GDP_{Et} \\ GDP_{It} \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} GDP_t + \begin{bmatrix} \varepsilon_{Et} \\ \varepsilon_{It} \end{bmatrix}$$

$$GDP_t = \alpha + \rho GDP_{t-1} + \varepsilon_{Gt}$$

$$\text{var}\begin{bmatrix} \varepsilon_g \\ \varepsilon_E \\ \varepsilon_I \end{bmatrix} = \Sigma = \begin{bmatrix} \sigma_{GG} & 0 & 0 \\ & \sigma_{EE} & \sigma_{EI} \\ & & \sigma_{II} \end{bmatrix} \text{ (identification issues)}$$

Results:

For the 2-equation model with Σ block-diagonal, we have

$$GDP_t = \underset{[2.77,3.34]}{3.06}(1-0.62) + \underset{[0.57,0.68]}{0.62} GDP_{t-1} + \epsilon_{Gt}, \tag{12}$$

$$\Sigma = \begin{bmatrix} \underset{[4.39,5.95]}{5.17} & 0 & 0 \\ 0 & \underset{[3.34,4.48]}{3.86} & \underset{[0.96,1.95]}{1.43} \\ 0 & \underset{[0.96,1.95]}{1.43} & \underset{[2.25,3.22]}{2.70} \end{bmatrix}. \tag{13}$$

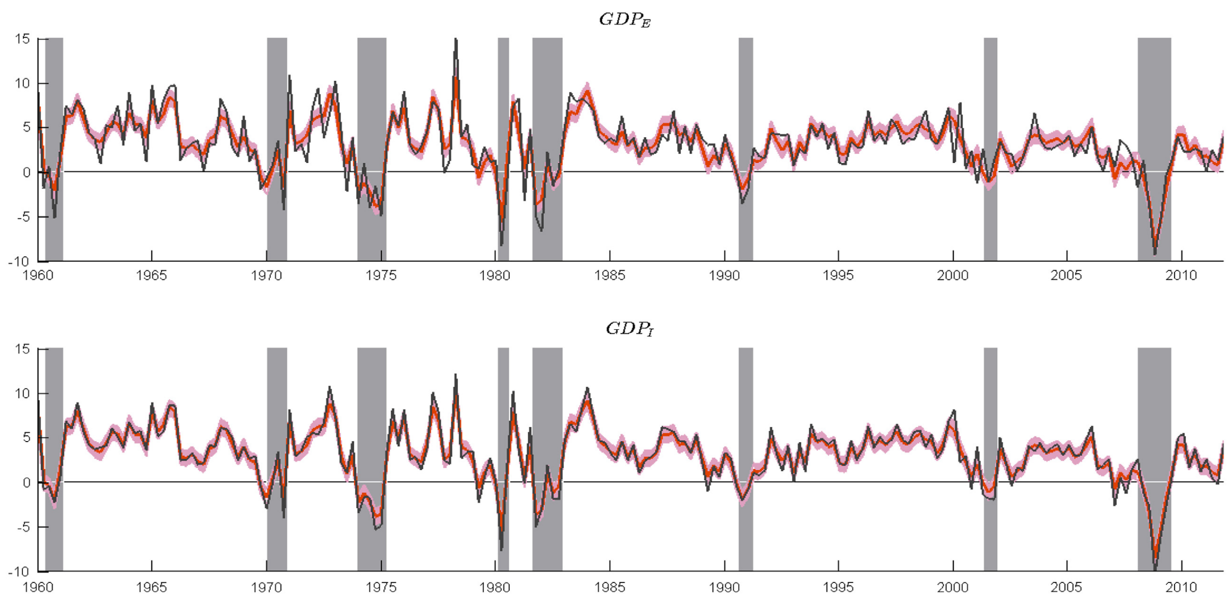
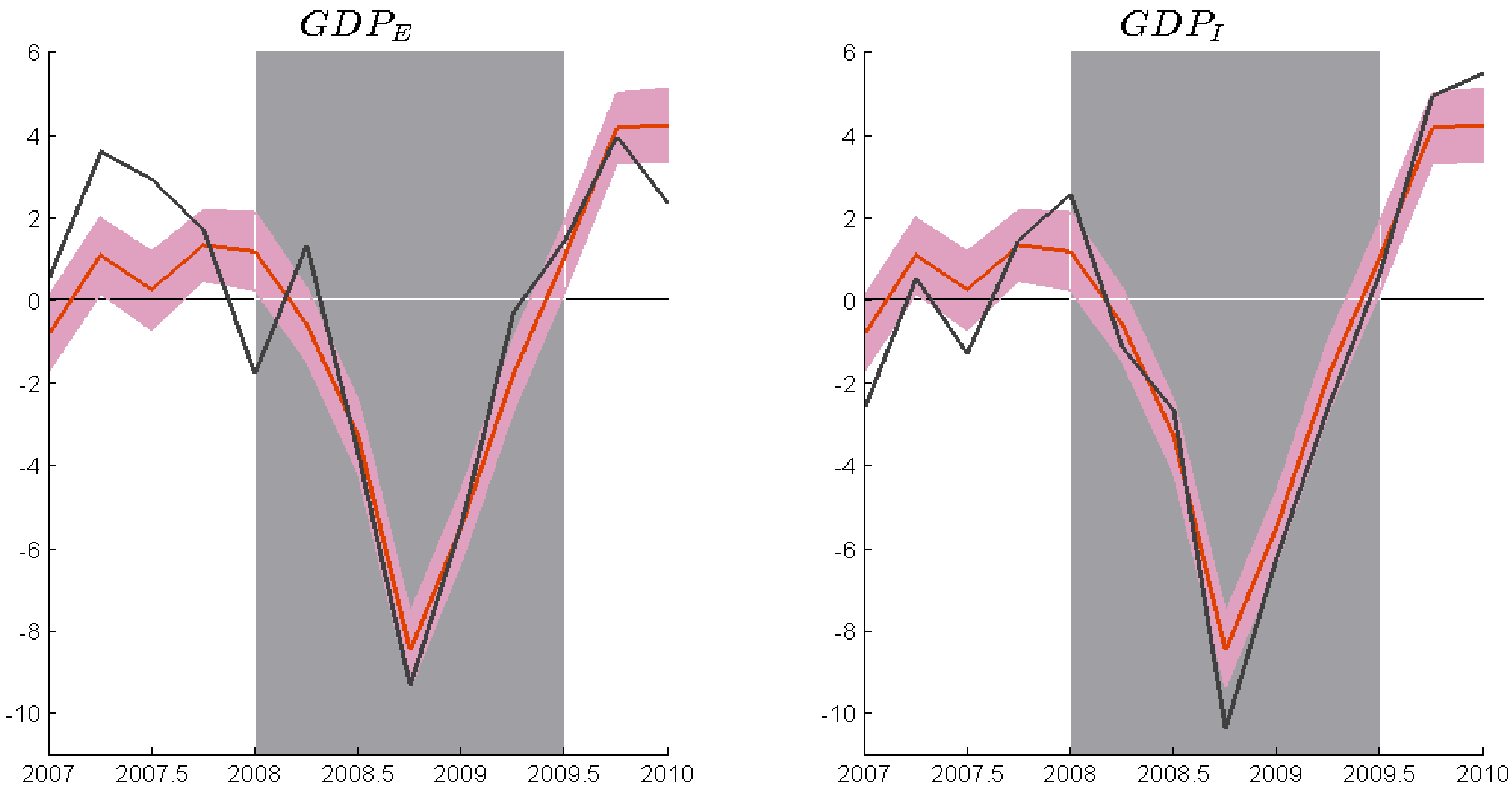


Fig. 3. *GDP* sample paths, 1960Q1–2011Q4. In each panel we show the sample path of GDP_M (light color) together with posterior interquartile range with shading and we show one of the competitor series (dark color). For GDP_M we use our benchmark estimate from the 2-equation model with $\zeta = 0.80$.

Figure 4: GDP Sample Paths, 2007Q1-2009Q4



Historical Evolution of DFMs:

3. Large-n approximations. Connor and Karijczyk (1986), Chamberlain and Rothschild (1983), Forni and Reichlin (1998), Stock and Watson (2002), …

Large n ... from curse to blessing: *An example following Forni and Reichlin (1998)*. Suppose f_t is scalar and $\lambda(L) = \lambda$ ("no lags in the factor loadings"), so

$$X_{it} = \lambda_i f_t + e_{it} \quad \text{for } i = 1, \ldots n$$

Then:
$$\frac{1}{n}\sum_{i=1}^{n} X_{it} = \frac{1}{n}\sum_{i=1}^{n}(\lambda_i f_t + e_{it}) = \left(\frac{1}{n}\sum_{i=1}^{n}\lambda_i\right) f_t + \frac{1}{n}\sum_{i=1}^{n} e_{it}$$

If the errors e_{it} have limited dependence across series, then as n gets large,

$$\frac{1}{n}\sum_{i=1}^{n} X_{it} \xrightarrow{p} \bar{\lambda} f_t$$

Large n lets us recover f_t up to a scale factor.

A “least squares” reason to use the sample mean.

Consider

$$\min_{\{f_t\},\{\lambda_i\}} \sum_{i,t} (X_{it} - \lambda_i f_t)^2 \quad \text{subject to } \bar{\lambda} = 1$$

Yields: $\hat{f}_t = \frac{1}{n}\sum_{i=1}^{n} X_{it}$

(Other normalizations: $T^{-1}\sum_{t=1}^{T} f_t^2 = 1$)

Multivariate Problem: $X_{it} = \lambda_i' F_t + e_{it}$, where λ_i' is i^{th} row of Λ.

$$\min_{\{f_t\},\{\lambda_i\}} \sum_{i,t} (X_{it} - \lambda_i' F_t)^2 \text{ subject } T^{-1} \sum_{t=1}^{T} F_t F_t' = \Gamma \text{ (diagonal, with } \gamma_i \geq \gamma_{i+1})$$

Yields: $\hat{F}_t$ as the principal components (PC) of X_t, (i.e., the linear combinations of X_t with the largest variance).

Odds and ends:

Missing data

Weighted least squares

…

More generally

$X_t = \lambda(L)f_t + e_t$ and $\phi(L)f_t = \eta_t \Rightarrow X_t = \Lambda F_t + e_t$ and $\Phi(L)F_t = G\eta_t$

So Principal Components (PC) can be used to estimate F in DFM.

A simple 2-step estimation problem:

(1) Estimate F_t by PC

(2) Estimate λ_i and var(e_{it}) from regression of X_{it} onto $\hat{F}_t$.

(3) Estimate dynamic equation for F using VAR with $\hat{F}_t$ replacing F.

Some results about these simple 2-step estimators when n and T are large:

Results for the exact static factor model:

Connor and Korajczyk (1986): consistency in the exact static FM with T fixed, $n \to \infty$.

Selected results for the approximate DFM: $X_t = \Lambda F_t + e_t$

Typical conditions (Stock-Watson (2002), Bai-Ng (2002, 2006)):

(a) $\frac{1}{T}\sum_{i=1}^{T} F_t F_t' \xrightarrow{p} \Sigma_F$ (stationary factors)

(b) $\Lambda'\Lambda/n \to$ (or $\xrightarrow{p}$) Σ_Λ Full rank factor loadings

(c) e_{it} are weakly dependent over time and across series

(d) F, e are uncorrelated at all leads and lags

Selected results for the approximate DFM, ctd.

Stock and Watson (2002a)

- consistency in the approximate DFM, n, $T \to \infty$.
- justify using $\hat{F}_t$ as a regressor (no errors-in-variable bias. etc.)
- oracle property for forecasts

Bai and Ng (2006)

- $N^2/T \to \infty$
- asymptotic normality of PC estimator of the common component at rate min($n^{1/2}$, $T^{1/2}$) in approximate DFM. These can be used to compute confidence sets for $F_{t.}$
- Similar results are rates for the two estimators of Λ, Φ, Σ_{ee} and $\Sigma_{\eta\eta}$.

Historical Evolution of DFMs:

An issue in PC estimates of DFMs: F_t is estimated using averages of X_t. This ignores information in leads and lags of X that would be utilized using optimal estimator (Kalman smoother).

4. Hybrid estimators: Use PCs to get first-round estimates of Λ, Φ, Σ_{ee} and $\Sigma_{\eta\eta}$, then use Kalman smoother to get estimates of F, or do MLE using these as initial guesses of parameters. (Doz, Giannone, Reichlin (2011, 2012).)

Example: Nowcasting (Good reference: Banbura, Giannoni, Modugno, and Reichlin (2013).)

- Problem: y_t is a variable of interest (e.g., GDP growth rate in quarter t). It is available with a lag (say in t+1 or t+2). X_t is a vector of variables that are measured *during* period t (and perhaps earlier). How do you guess the value of y_t given the X data that has been revealed.

- 'Solution': Suppose X_{t_1} denotes the information known at time t_1. Then best guess of y_t is $E(y_t|\ X_{t_1})$.
  - But how do you compute $E(y_t|\ X_{t_1})$?
  - How do you update the estimate as another element of X_t is revealed?

Giannone, Reichlin, et al modeling approach:

$$\begin{bmatrix} y_t \\ X_{1t} \\ \vdots \\ X_{nt} \end{bmatrix} = \begin{bmatrix} \lambda_y \\ \lambda_1 \\ \vdots \\ \lambda_n \end{bmatrix} F_t + \begin{bmatrix} e_{yt} \\ e_{1t} \\ \vdots \\ e_{nt} \end{bmatrix}$$

$$\Phi(\mathrm{L})F_t = \eta_t$$

- $\mathrm{E}(y_t | X_{t_1}) = \lambda_y \times \mathrm{E}(F_t \mid X_{t_1})$
- $\mathrm{E}(F_t \mid X_{t_1})$ computed by Kalman filter

(Lots of details left out)

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Nowcasting Report

We're sharing the MATLAB code for our nowcasting model on GitHub. Learn more on our blog.

OVERVIEW | NOWCAST | METHODOLOGY | FAQS

Oct 19, 2018: New York Fed Staff Nowcast

- The New York Fed Staff Nowcast stands at 2.1% for 2018:Q3 and 2.4% for 2018:Q4.

MORE

2018:Q4 | **2018:Q3** | 2018:Q2 | 2018:Q1

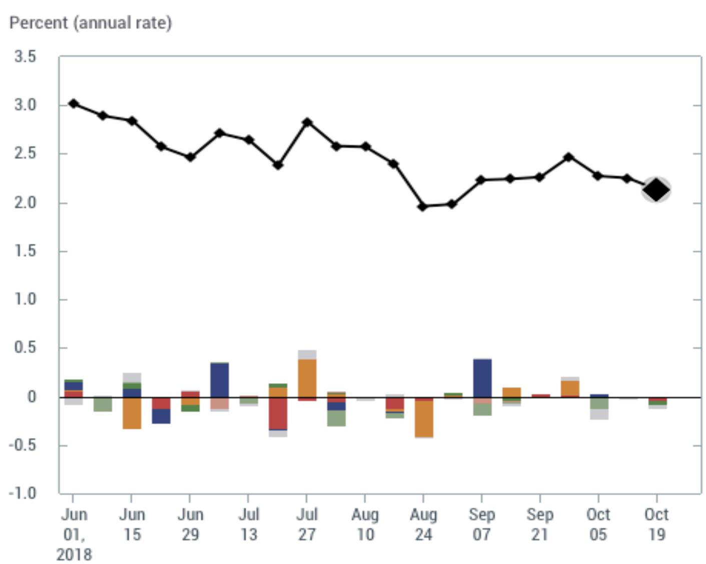
Last Release 11:15am EST Oct 19, 2018

ARCHIVE LAYOUT

◆ The New York Fed Staff Nowcast ○ Advance GDP estimate □ Latest GDP estimate

Housing and construction, Manufacturing, Surveys, Retail and consumption, Income, Labor, International trade, Others

Expand



Data Flow (Oct 19, 2018)

Model Update	Release Date	Data Series	Actual	Impact	Nowcast GDP Growth
Oct 19					2.13
	8:30AM Oct 18	Philadelphia Fed Mfg. Business Outlook: Current activity	22.20	0.00	
	8:30AM Oct 17	Building permits	-8.00	-0.01	
	8:30AM Oct 17	Housing starts	-5.28	-0.02	
	10:00AM Oct 16	JOLTS: Total job openings	59.00	-0.00	
	9:20AM Oct 16	Capacity utilization	0.05	-0.01	
	9:20AM Oct 16	Industrial production index	0.25	0.01	
	8:30AM Oct 15	Retail sales and food services	0.10	-0.05	
	8:30AM Oct 15	Empire State Mfg. Survey: General business conditions	21.10	0.00	
		Data revisions		-0.03	
Oct 12					2.25

Source: Authors' calculations, based on data accessed through Haver Analytics.

Notes: We start reporting the nowcast for a reference quarter about one month before the quarter begins; we stop updating it about one month after

2.1 | Nowcast Detail

Housing and construction · Manufacturing · Surveys · Retail and consumption · Income · Labor · International trade · Others

Update	Release Date	Data Series	Reference Period	Units	Forecast	Actual	Weight	Impact	Nowcast GDP Growth
					[a]	[b]	[c]	$[c(b-a)]$	
Sep 21									**2.66**
	10:00 AM Sep 26	New single family houses sold	Aug	MoM % chg.	0.236	3.45	0.008	0.025	
	8:30 AM Sep 27	Manufacturers' new orders: Durable goods	Aug	MoM % chg.	1.39	4.45	0.017	0.051	
	8:30 AM Sep 27	Merchant wholesalers: Inventories: Total	Aug	MoM % chg.	0.751	0.818	-0.078	-0.005	
	8:30 AM Sep 27	Manufacturers' shipments: Durable goods	Aug	MoM % chg.	0.730	0.753	0.106	0.002	
	8:30 AM Sep 27	Mfrs.' unfilled orders: All manufacturing industries	Aug	MoM % chg.	0.600	0.892	-0.008	-0.002	
	8:30 AM Sep 27	Manufacturers' inventories: Durable goods	Aug	MoM % chg.	0.693	-0.351	-0.185	0.194	
	8:30 AM Sep 28	Real disposable personal income	Aug	MoM % chg.	0.216	0.221	0.019	0.000	
	8:30 AM Sep 28	PCE less food and energy: Chain price index	Aug	MoM % chg.	0.157	0.037	0.293	-0.035	
	8:30 AM Sep 28	PCE: Chain price index	Aug	MoM % chg.	0.186	0.108	0.178	-0.014	
	8:40 AM Sep 28	Real personal consumption expenditures	Aug	MoM % chg.	0.229	0.222	0.270	-0.002	
		Data revisions						0.046	
Sep 28									**2.92**
	10:00 AM Oct 01	Value of construction put in place	Aug	MoM % chg.	0.379	0.080	0.027	-0.008	
	10:00 AM Oct 01	ISM mfg.: PMI composite index	Sep	Index	59.1	59.8	0.116	0.078	
	10:00 AM Oct 01	ISM mfg.: Prices index	Sep	Index	70.3	66.9	0.020	-0.068	
	10:00 AM Oct 01	ISM mfg.: Employment index	Sep	Index	57.3	58.8	0.053	0.079	
	8:05 AM Oct 03	ADP nonfarm private payroll employment	Sep	Level chg. (thousands)	177.4	229.0	1.358*	0.070	
	10:00 AM Oct 03	ISM nonmanufacturing: NMI composite index	Sep	Index	58.3	61.6	0.020	0.065	
	10:00 AM Oct 04	Inventories: Total business	Aug	MoM % chg.	0.397	0.479	-0.010	-0.001	
	8:30 AM Oct 05	All employees: Total nonfarm	Sep	Level chg. (thousands)	225.2	134.0	0.652*	-0.059	
	8:30 AM Oct 05	Civilian unemployment rate	Sep	Ppt. chg.	-0.084	-0.200	-0.186	0.022	
	8:30 AM Oct 05	Exports: Goods and services	Aug	MoM % chg.	1.30	-0.792	0.066	-0.138	
	8:30 AM Oct 05	Imports: Goods and services	Aug	MoM % chg.	1.00	0.586	0.050	-0.021	
		Data revisions						0.017	
		Parameter revisions						-0.153	
Oct 05									**2.80**
	8:30 AM Oct 10	PPI: Final demand	Sep	MoM % chg.	0.150	0.172	0.173	0.004	
	8:30 AM Oct 11	CPI-U: All items	Sep	MoM % chg.	0.229	0.059	0.151	-0.026	
	8:30 AM Oct 11	CPI-U: All items less food and energy	Sep	MoM % chg.	0.140	0.116	0.173	-0.004	
	8:30 AM Oct 12	Import price index	Sep	MoM % chg.	-0.039	0.470	0.045	0.023	
	8:30 AM Oct 12	Export price index	Sep	MoM % chg.	0.133	0.000	0.078	-0.010	
		Data revisions						-0.012	
Oct 12									**2.77**
	8:30 AM Oct 15	Empire State Mfg. Survey: General business conditions	Oct	Index	20.7	21.1	0.017	0.006	
	8:30 AM Oct 15	Retail sales and food services	Sep	MoM % chg.	0.560	0.104	0.353	-0.161	
	9:20 AM Oct 16	Industrial production index	Sep	MoM % chg.	0.182	0.252	0.399	0.028	
	9:20 AM Oct 16	Capacity utilization	Sep	Ppt. chg.	0.106	0.052	0.520	-0.028	
	10:00 AM Oct 16	JOLTS: Job openings: Total	Aug	Level chg. (thousands)	8.42	59.0	-0.048*	-0.002	
	8:30 AM Oct 17	Housing starts	Sep	MoM % chg.	-2.37	-5.28	0.018	-0.051	
	8:30 AM Oct 17	Building permits	Sep	Level chg. (thousands)	13.5	-8.00	0.002	-0.046	
	8:30 AM Oct 18	Phila. Fed Mfg. business outlook: Current activity	Oct	Index	26.4	22.2	0.012	-0.049	
		Data revisions						-0.042	
Oct 19									**2.43**

Source: Authors' calculations, based on data accessed through Haver Analytics.
Notes: MoM % chg. indicates month over month percentage change. QoQ % chg. indicates quarter over quarter percentage change. The weights with the asterisk are multiplied by 1,000 for legibility.

Historical Evolution of DFMs:

Issue: Many parameters in DFM. Shrinkage might be useful.

5. Bayes estimators (Kim and Nelson (1998), Otrok and Whiteman (1998))

$$X_t = \Lambda F_t + e_t \quad \text{and} \quad \Phi(\mathrm{L})F_t = \mathrm{G}\eta_t$$

Model is particularly amenable to MCMC methods:

(i) $(\Lambda, \Sigma_{ee}, \Phi, \Sigma_{\eta\eta} \mid \{X_t, F_t\})$: Linear regression problem

(ii) $(\{F_t\} \mid \{X_t\}, \Lambda, \Sigma_{ee}, \Phi, \Sigma_{\eta\eta})$: Linear signal extraction problem

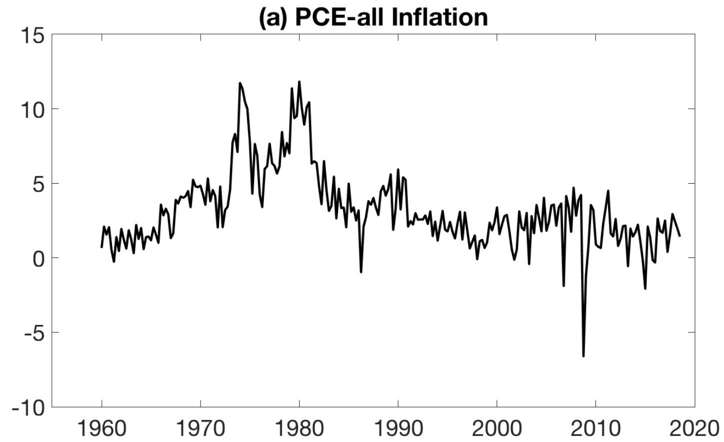
$$X_t = \Lambda F_t + e_t \text{ and } \Phi(\mathrm{L})F_t = \mathrm{G}\eta_t$$

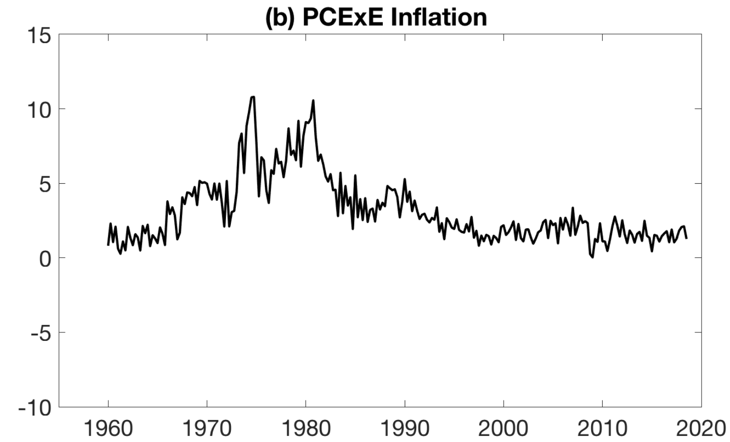
Generalizations (see paper for references):

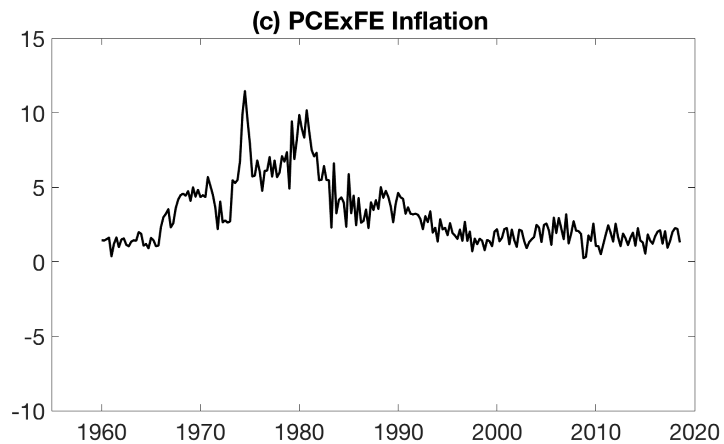
(1) Serial correlation in e
(2) Additional regressors in either equation
(3) Constraints on Λ ('sparsity')
(4) (Limited) cross-correlation between elements of e.
(5) Non-linearities and non-Gaussian evolution.

… many more.

Example (Non-linear and non-Gaussian): Stock and Watson (2016) 'Core Inflation and Trend Inflation' and earlier (2007) paper.







Unobserved Components Model with Stochastic Volatility and Outliers.

$$\boldsymbol{\pi_t = \tau_t + \varepsilon_t}$$

$$\tau_t = \tau_{t-1} + \sigma_{\Delta\tau,t} \times \eta_{\tau,t}$$

$$\varepsilon_t = \sigma_{\varepsilon,t} \times s_t \times \eta_{\varepsilon,t}$$

$$\Delta\ln(\sigma^2_{\varepsilon,t}) = \gamma_\varepsilon \nu_{\varepsilon,t}$$

$$\Delta\ln(\sigma^2_{\Delta\tau,t}) = \gamma_{\Delta\tau} \nu_{\Delta\tau,t}$$

$(\eta_\varepsilon, \eta_\tau, \nu_\varepsilon, \nu_{\Delta\tau})$ are iid $N(0, I_4)$

s_t = i.i.d. multinomial with values 1, 5, 10
and probability 0.975, 1/60, and 1/120

- Kim-Shephard-Chib (1998) approximate model for stochastic volatility:

Let $x_t = \sigma_t \eta_t$ and $\ln(\sigma_t^2) = \ln(\sigma_{t-1}^2) + \gamma \nu_t$ with $(\eta_t, \nu_t) \sim \text{iidN}(0, I_2)$.

Then $\ln(x_t^2) = \ln(\sigma_t^2) + \ln(\eta_t^2)$, where $\eta_t \sim N(0,1)$ so $\ln(\eta_t^2) \sim \ln(\chi_1^2)$

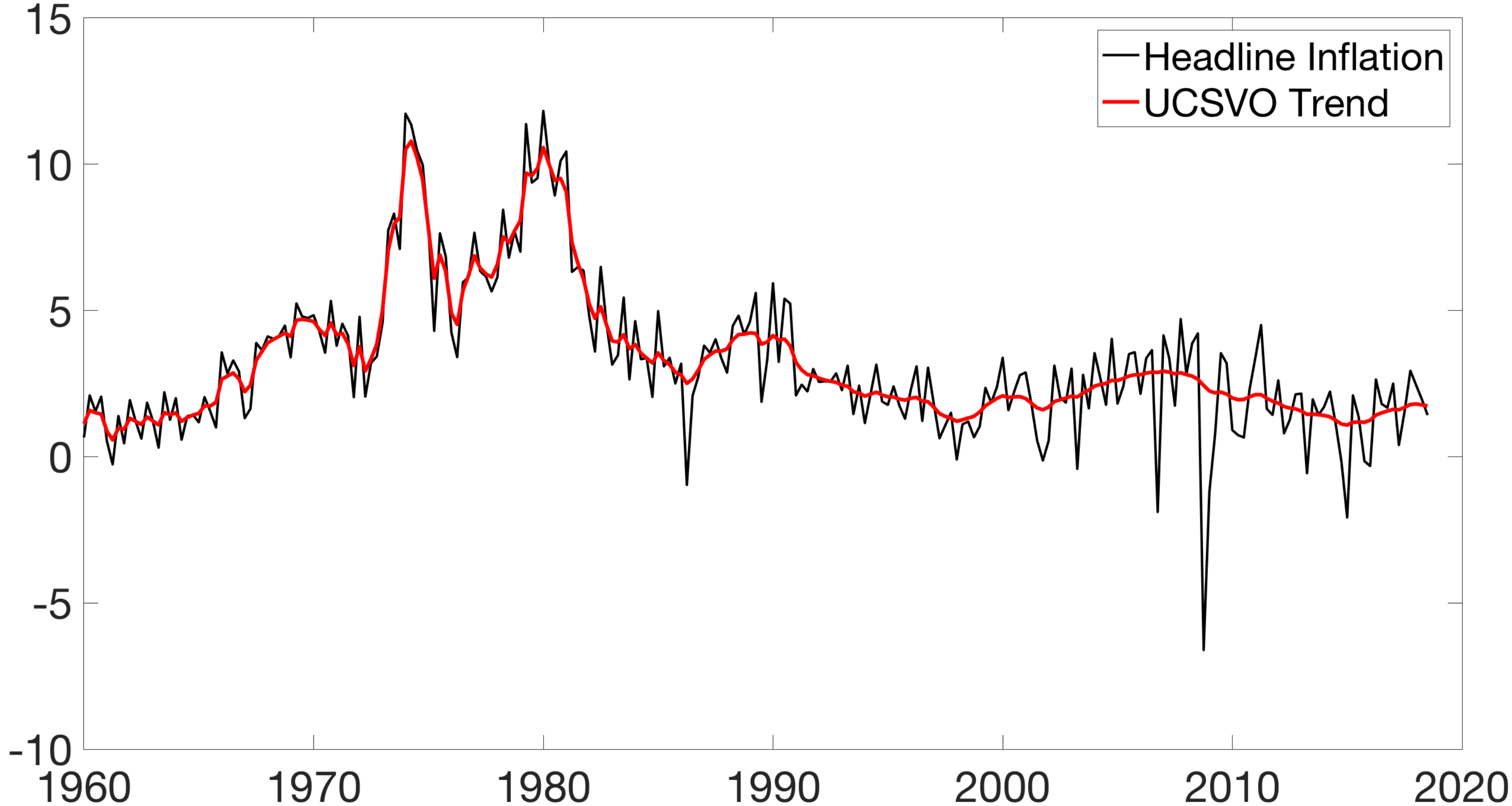
$\ln(\sigma_t^2) = \ln(\sigma_{t-1}^2) + \gamma \nu_t$

which is a linear state-space model with non-Gaussian measurement error.

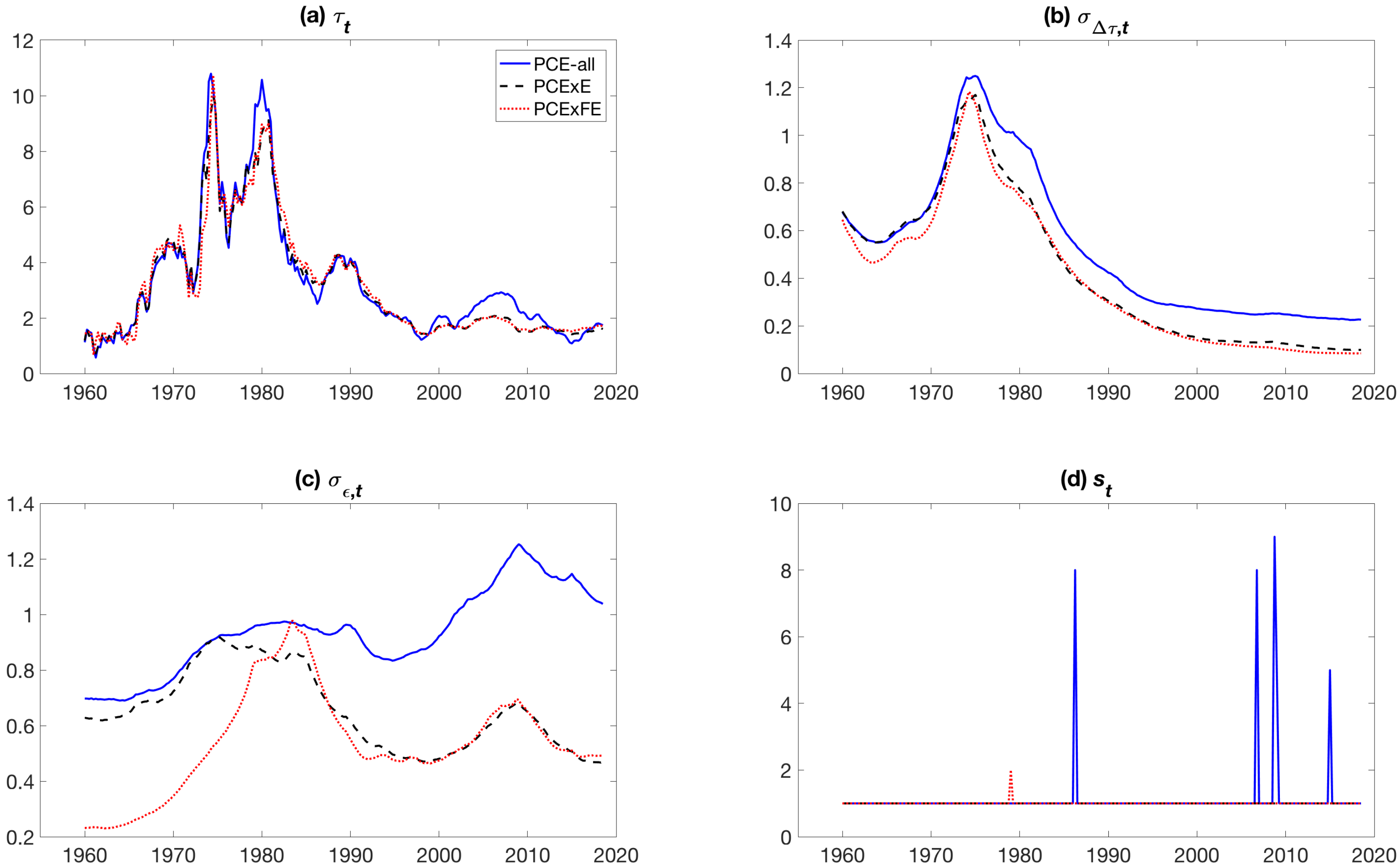
- KSC approximate $\ln(\chi_1^2)$ using a mixture of normals: $\ln(\eta_t^2) \sim \sum_{i=1}^{n} w_{it} a_{it}$,

where w_{it} are iid (0-1) variables with $w_{it} = 1$ for only value of i at each t, and with $p(w_{it} = 1) = p_i$. The a_{it} variables are $a_{it} \sim N(\mu_i, \sigma_i^2)$, and $n = 7$.

○ Omori, Chib, Shephard, and Nakajima (2007) propose a more accurate 10-component Gaussian mixture approximation.



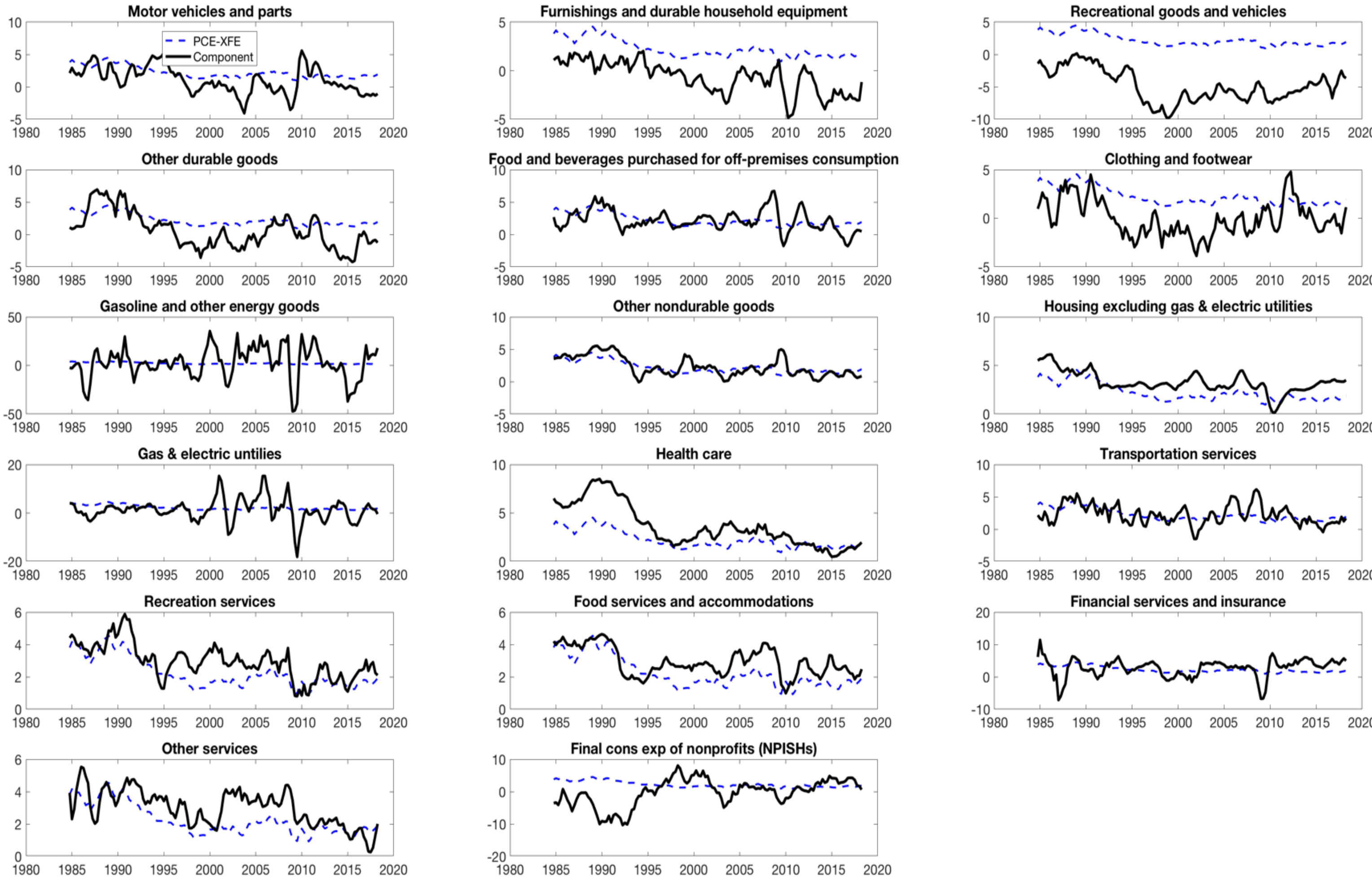
Headline Inflation
UCSVO Trend
15
10
5
0
-5
-10
1960
1970
1980
1990
2000
2010
2020



(a) τ_t
PCE-all
PCExE
PCExFE
(b) $\sigma_{\Delta\tau,t}$
(c) $\sigma_{\epsilon,t}$
(d) s_t

17 PCE Sectors

Sector	**Share**
Motor vehicles and parts	0.042
Furnishings and durable household equip.	0.027
Recreational goods and vehicles	0.031
Other durable goods	0.016
Food and bev.s purch. for off-premises cons.*	0.077
Clothing and footwear	0.033
Gasoline and other energy goods*	0.030
Other nondurable goods	0.081
Housing & utilities	0.182
Housing excluding gas & electric utilities	0.162
Gas & electric utilities*	0.020
Health care	0.158
Transportation services	0.033
Recreation services	0.039
Food services and accommodations	0.063
Financial services and insurance	0.076
Other services	0.085
Final cons exp of nonprof. insti. serving h.h.	0.028


Motor vehicles and parts
PCE-XFE
Component
Furnishings and durable household equipment
Recreational goods and vehicles
Other durable goods
Food and beverages purchased for off-premises consumption
Clothing and footwear
Gasoline and other energy goods
Other nondurable goods
Housing excluding gas & electric utilities
Gas & electric untilies
Health care
Transportation services
Recreation services
Food services and accommodations
Financial services and insurance
Other services
Final cons exp of nonprofits (NPISHs)

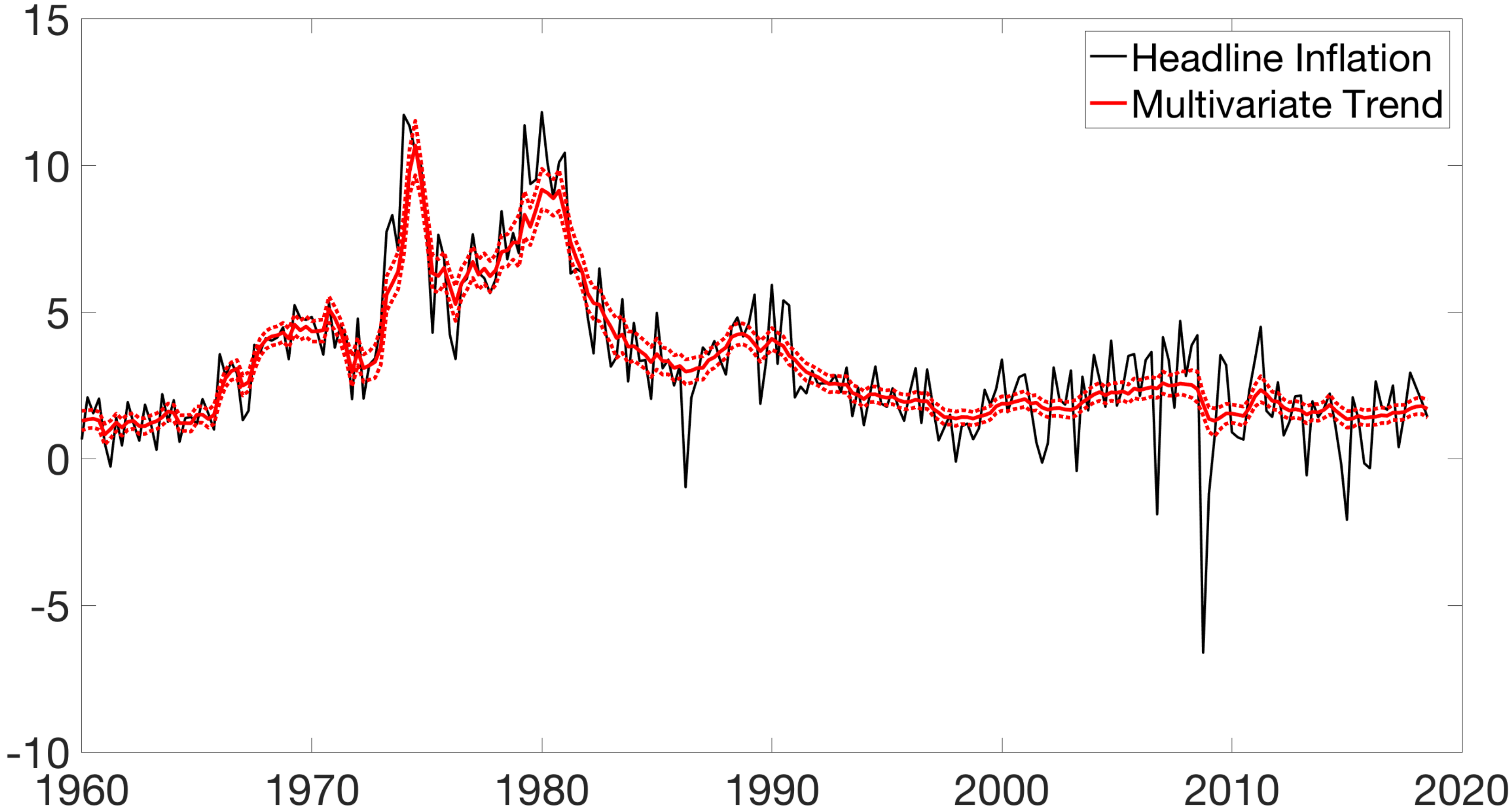
Multivariate model

$$\begin{bmatrix} \pi_{1t} \\ \pi_{2t} \\ \vdots \\ \pi_{nt} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix}_t \tau_t^C + \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix} \varepsilon_t^C + \begin{bmatrix} \tau_{1t}^u \\ \tau_{2t}^u \\ \vdots \\ \tau_{2t}^u \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t}^u \\ \varepsilon_{2t}^u \\ \vdots \\ \varepsilon_{2t}^u \end{bmatrix}$$

Aggregate (average) inflation and trend

$$\begin{aligned} \bar{\pi}_t &= \left[\bar{\alpha}\tau_t^c + \bar{\tau}_t^u \right] + \left[\bar{\beta}\varepsilon_t^c + \bar{\varepsilon}_t^u \right] \\ &= \qquad \tau_t \qquad + \qquad \varepsilon_t \end{aligned}$$

where the averages are computed using consumption share weights.



Headline Inflation
Multivariate Trend
15
10
5
0
-5
-10
1960
1970
1980
1990
2000
2010
2020

Recent Values of Inflation in the United States
(Quarterly inflation in percentage points at an annual rate)

	Inflation measures			Estimates from 17 component model	
Date	Headline	XFE		Trend	67% Band
2016:Q3	1.81	2.11		1.49	1.29 – 1.70
2016:Q4	1.67	1.21		1.48	1.29 – 1.68
2017:Q1	2.50	2.05		1.60	1.40 – 1.80
2017:Q2	0.40	0.94		1.49	1.28 – 1.70
2017:Q3	1.56	1.38		1.52	1.32 – 1.73
2017:Q4	2.94	2.00		1.62	1.41 – 1.83
2018:Q1	2.45	2.25		1.70	1.48 – 1.92
2018:Q2	1.96	2.21		1.82	1.57 – 2.06
2018:Q3	1.42	1.30		1.69	1.42 – 1.96

A 207-Variable Macro Dataset for the U.S.

Table 1 Quarterly time series in the full dataset

	Category	Number of series	Number of series used for factor estimation
(1)	NIPA	20	12
(2)	Industrial production	11	7
(3)	Employment and unemployment	45	30
(4)	Orders, inventories, and sales	10	9
(5)	Housing starts and permits	8	6
(6)	Prices	37	24
(7)	Productivity and labor earnings	10	5
(8)	Interest rates	18	10
(9)	Money and credit	12	6
(10)	International	9	9
(11)	Asset prices, wealth, and household balance sheets	15	10
(12)	Other	2	2
(13)	Oil market variables	10	9
	Total	207	139

Notes: The real activity dataset consists of the variables in the categories 1–4.

Table A.1: Data Series

	Name	Description	Sample Period	T	O	F
	(1) NIPA					
1	GDP	Real Gross Domestic Product 3 Decimal	1959:Q1-2014:Q4	5	0	0
2	Consumption	Real Personal Consumption Expenditures	1959:Q1-2014:Q4	5	0	0
3	Cons:Dur	Real Personal Consumption Expenditures: Durable Goods Quantity Index	1959:Q1-2014:Q4	5	0	1
4	Cons:Svc	Real Personal Consumption Expenditures: Services Quantity Index	1959:Q1-2014:Q4	5	0	1
5	Cons:NonDur	Real Personal Consumption Expenditures: Nondurable Goods Quantity Index	1959:Q1-2014:Q4	5	0	1
6	Investment	Real Gross Private Domestic Investment 3 Decimal	1959:Q1-2014:Q4	5	0	0
7	FixedInv	Real Private Fixed Investment Quantity Index	1959:Q1-2014:Q4	5	0	0
8	Inv:Equip	Real Nonresidential Investment: Equipment Quantity Idenx	1959:Q1-2014:Q4	5	0	1
9	FixInv:NonRes	Real Private Nonresidential Fixed Investment Quantity Index	1959:Q1-2014:Q4	5	0	1
10	FixedInv:Res	Real Private Residential Fixed Investment Quantity Index	1959:Q1-2014:Q4	5	0	1
11	Ch. Inv/GDP	Change in Inventories /GDP	1959:Q1-2014:Q4	1	0	1
12	Gov.Spending	Real Government Consumption Expenditures & Gross Investment 3 Decimal	1959:Q1-2014:Q4	5	0	0
13	Gov:Fed	Real Federal Consumption Expenditures Quantity Index	1959:Q1-2014:Q4	5	0	1
14	Real_Gov Receipts	Government Current Receipts (Nominal) Defl by GDP Deflator	1959:Q1-2014:Q3	5	0	1
15	Gov:State&Local	Real State & Local Consumption Expenditures Quantity Index	1959:Q1-2014:Q4	5	0	1
16	Exports	Real Exports of Goods & Services 3 Decimal	1959:Q1-2014:Q4	5	0	1
17	Imports	Real Imports of Goods & Services 3 Decimal	1959:Q1-2014:Q4	5	0	1
18	Disp-Income	Real Disposable Personal Income	1959:Q1-2014:Q4	5	0	0
19	Ouput:NFB	Nonfarm Business Sector: Output	1959:Q1-2014:Q4	5	0	0
20	Output:Bus	Business Sector: Output	1959:Q1-2014:Q4	5	0	0
	(2) Industrial Production					
21	IP: Total index	IP: Total index	1959:Q1-2014:Q4	5	0	0
22	IP: Final products	Industrial Production: Final Products (Market Group)	1959:Q1-2014:Q4	5	0	0
23	IP: Consumer goods	IP: Consumer goods	1959:Q1-2014:Q4	5	0	0
24	IP: Materials	Industrial Production: Materials	1959:Q1-2014:Q4	5	0	0
25	IP: Dur gds materials	Industrial Production: Durable Materials	1959:Q1-2014:Q4	5	0	1
26	IP: Nondur gds materials	Industrial Production: nondurable Materials	1959:Q1-2014:Q4	5	0	1
27	IP: Dur Cons. Goods	Industrial Production: Durable Consumer Goods	1959:Q1-2014:Q4	5	0	1
28	IP: Auto	IP: Automotive products	1959:Q1-2014:Q4	5	0	1
29	IP:NonDur Cons God	Industrial Production: Nondurable Consumer Goods	1959:Q1-2014:Q4	5	0	1
30	IP: Bus Equip	Industrial Production: Business Equipment	1959:Q1-2014:Q4	5	0	1
31	Capu Tot	Capacity Utilization: Total Industry	1967:Q1-2014:Q4	1	0	1
	(3) Employment and Unemployment					
32	Emp:Nonfarm	Total Nonfarm Payrolls: All Employees	1959:Q1-2014:Q4	5	0	0
33	Emp: Private	All Employees: Total Private Industries	1959:Q1-2014:Q4	5	0	0

34	Emp: mfg	All Employees: Manufacturing	1959:Q1-2014:Q4	5	0	0
35	Emp:Services	All Employees: Service-Providing Industries	1959:Q1-2014:Q4	5	0	0
36	Emp:Goods	All Employees: Goods-Producing Industries	1959:Q1-2014:Q4	5	0	0
37	Emp: DurGoods	All Employees: Durable Goods Manufacturing	1959:Q1-2014:Q4	5	0	1
38	Emp: Nondur Goods	All Employees: Nondurable Goods Manufacturing	1959:Q1-2014:Q4	5	0	0
39	Emp: Const	All Employees: Construction	1959:Q1-2014:Q4	5	0	1
40	Emp: Edu&Health	All Employees: Education & Health Services	1959:Q1-2014:Q4	5	0	1
41	Emp: Finance	All Employees: Financial Activities	1959:Q1-2014:Q4	5	0	1
42	Emp: Infor	All Employees: Information Services	1959:Q1-2014:Q4	5	1	1
43	Emp: Bus Serv	All Employees: Professional & Business Services	1959:Q1-2014:Q4	5	0	1
44	Emp:Leisure	All Employees: Leisure & Hospitality	1959:Q1-2014:Q4	5	0	1
45	Emp:OtherSvcs	All Employees: Other Services	1959:Q1-2014:Q4	5	0	1
46	Emp: Mining/NatRes	All Employees: Natural Resources & Mining	1959:Q1-2014:Q4	5	1	1
47	Emp:Trade&Trans	All Employees: Trade Transportation & Utilities	1959:Q1-2014:Q4	5	0	1
48	Emp: Gov	All Employees: Government	1959:Q1-2014:Q4	5	0	0
49	Emp:Retail	All Employees: Retail Trade	1959:Q1-2014:Q4	5	0	1
50	Emp:Wholesal	All Employees: Wholesale Trade	1959:Q1-2014:Q4	5	0	1
51	Emp: Gov(Fed)	Employment Federal Government	1959:Q1-2014:Q4	5	2	1
52	Emp: Gov (State)	Employment State government	1959:Q1-2014:Q4	5	0	1
53	Emp: Gov (Local)	Employment Local government	1959:Q1-2014:Q4	5	0	1
54	Emp: Total (HHSurve)	Emp Total (Household Survey)	1959:Q1-2014:Q4	5	0	0
55	LF Part Rate	LaborForce Participation Rate (16 Over) SA	1959:Q1-2014:Q4	2	0	0
56	Unemp Rate	Urate	1959:Q1-2014:Q4	2	0	0
57	Urate_ST	Urate Short Term (< 27 weeks)	1959:Q1-2014:Q4	2	0	0
58	Urate_LT	Urate Long Term (>= 27 weeks)	1959:Q1-2014:Q4	2	0	0
59	Urate: Age16-19	Unemployment Rate - 16-19 yrs	1959:Q1-2014:Q4	2	0	1
60	Urate:Age>20 Men	Unemployment Rate - 20 yrs. & over Men	1959:Q1-2014:Q4	2	0	1
61	Urate: Age>20 Women	Unemployment Rate - 20 yrs. & over Women	1959:Q1-2014:Q4	2	0	1
62	U: Dur<5wks	Number Unemployed for Less than 5 Weeks	1959:Q1-2014:Q4	5	0	1
63	U:Dur5-14wks	Number Unemployed for 5-14 Weeks	1959:Q1-2014:Q4	5	0	1
64	U:dur>15-26wks	Civilians Unemployed for 15-26 Weeks	1959:Q1-2014:Q4	5	0	1
65	U: Dur>27wks	Number Unemployed for 27 Weeks & over	1959:Q1-2014:Q4	5	0	1
66	U: Job losers	Unemployment Level - Job Losers	1967:Q1-2014:Q4	5	0	1
67	U: LF Reenty	Unemployment Level - Reentrants to Labor Force	1967:Q1-2014:Q4	5	1	1
68	U: Job Leavers	Unemployment Level - Job Leavers	1967:Q1-2014:Q4	5	0	1
69	U: New Entrants	Unemployment Level - New Entrants	1967:Q1-2014:Q4	5	1	1
70	Emp:SlackWk	Employment Level - Part-Time for Economic Reasons All Industries	1959:Q1-2014:Q4	5	1	1
71	EmpHrs:Bus Sec	Business Sector: Hours of All Persons	1959:Q1-2014:Q4	5	0	0
72	EmpHrs:nfb	Nonfarm Business Sector: Hours of All Persons	1959:Q1-2014:Q4	5	0	0
73	AWH Man	Average Weekly Hours: Manufacturing	1959:Q1-2014:Q4	1	0	1
74	AWH Privat	Average Weekly Hours: Total Private Industry	1964:Q1-2014:Q4	2	0	1
75	AWH Overtime	Average Weekly Hours: Overtime: Manufacturing	1959:Q1-2014:Q4	2	0	1
76	HelpWnted	Index of Help-Wanted Advertising in Newspapers (Data truncated in 2000)	1959:Q1-1999:Q4	1	0	0

	(4) Orders, Inventories, and Sales					
77	MT Sales	Manufacturing and trade sales (mil. Chain 2005 $)	1959:Q1-2014:Q3	5	0	0
78	Ret. Sale	Sales of retail stores (mil. Chain 2000 $)	1959:Q1-2014:Q3	5	0	1
79	Orders (DurMfg)	Mfrs' new orders durable goods industries (bil. chain 2000 $)	1959:Q1-2014:Q4	5	0	1
80	Orders (Cons. Gds & Mat.)	Mfrs' new orders consumer goods and materials (mil. 1982 $)	1959:Q1-2014:Q4	5	0	1
81	UnfOrders(DurGds)	Mfrs' unfilled orders durable goods indus. (bil. chain 2000 $)	1959:Q1-2014:Q4	5	0	1
82	Orders(NonDefCap)	Mfrs' new orders nondefense capital goods (mil. 1982 $)	1959:Q1-2014:Q4	5	0	1
83	VendPerf	ISM Manufacturing: Supplier Deliveries Index©	1959:Q1-2014:Q4	1	0	1
84	NAPM:INV	ISM Manufacturing: Inventories Index©	1959:Q1-2014:Q4	1	0	1
85	NAPM:ORD	ISM Manufacturing: New Orders Index©; Index;	1959:Q1-2014:Q4	1	0	1
86	MT Invent	Manufacturing and trade inventories (bil. Chain 2005 $)	1959:Q1-2014:Q3	5	0	1
	(5) Housing Starts and Permits					
87	Hstarts	Housing Starts: Total: New Privately Owned Housing Units Started	1959:Q1-2014:Q3	5	0	0
88	Hstarts >5units	Privately Owned Housing Starts: 5-Unit Structures or More	1959:Q1-2014:Q3	5	0	0
89	Hpermits	New Private Housing Units Authorized by Building Permit	1960:Q1-2014:Q4	5	0	1
90	Hstarts:MW	Housing Starts in Midwest Census Region	1959:Q1-2014:Q3	5	0	1
91	Hstarts:NE	Housing Starts in Northeast Census Region	1959:Q1-2014:Q3	5	0	1
92	Hstarts:S	Housing Starts in South Census Region	1959:Q1-2014:Q3	5	0	1
93	Hstarts:W	Housing Starts in West Census Region	1959:Q1-2014:Q3	5	0	1
94	Constr. Contracts	Construction contracts (mil. sq. ft.) (Copyright McGraw-Hill)	1963:Q1-2014:Q4	4	0	1
	(6) Prices					
95	PCED	Personal Consumption Expenditures: Chain-type Price Index	1959:Q1-2014:Q4	6	0	0
96	PCED_LFE	Personal Consumption Expenditures: Chain-type Price Index Less Food and Energy	1959:Q1-2014:Q4	6	0	0
97	GDP Defl	Gross Domestic Product: Chain-type Price Index	1959:Q1-2014:Q4	6	0	0
98	GPDI Defl	Gross Private Domestic Investment: Chain-type Price Index	1959:Q1-2014:Q4	6	0	1
99	BusSec Defl	Business Sector: Implicit Price Deflator	1959:Q1-2014:Q4	6	0	1
100	PCED_Goods	Goods	1959:Q1-2014:Q4	6	0	0
101	PCED_DurGoods	Durable goods	1959:Q1-2014:Q4	6	0	0
102	PCED_NDurGoods	Nondurable goods	1959:Q1-2014:Q4	6	0	0
103	PCED_Serv	Services	1959:Q1-2014:Q4	6	0	0
104	PCED_HouseholdServices	Household consumption expenditures (for services)	1959:Q1-2014:Q4	6	0	0
105	PCED_MotorVec	Motor vehicles and parts	1959:Q1-2014:Q4	6	0	1
106	PCED_DurHousehold	Furnishings and durable household equipment	1959:Q1-2014:Q4	6	0	1
107	PCED_Recreation	Recreational goods and vehicles	1959:Q1-2014:Q4	6	0	1
108	PCED_OthDurGds	Other durable goods	1959:Q1-2014:Q4	6	0	1
109	PCED_Food_Bev	Food and beverages purchased for off-premises consumption	1959:Q1-2014:Q4	6	0	1
110	PCED_Clothing	Clothing and footwear	1959:Q1-2014:Q4	6	0	1
111	PCED_Gas_Enrgy	Gasoline and other energy goods	1959:Q1-2014:Q4	6	0	1
112	PCED_OthNDurGds	Other nondurable goods	1959:Q1-2014:Q4	6	0	1

113	PCED_Housing-Utilities	Housing and utilities	1959:Q1-2014:Q4	6	0	1
114	PCED_HealthCare	Health care	1959:Q1-2014:Q4	6	0	1
115	PCED_TransSvg	Transportation services	1959:Q1-2014:Q4	6	0	1
116	PCED_RecServices	Recreation services	1959:Q1-2014:Q4	6	0	1
117	PCED_FoodServ_Acc.	Food services and accommodations	1959:Q1-2014:Q4	6	0	1
118	PCED_FIRE	Financial services and insurance	1959:Q1-2014:Q4	6	0	1
119	PCED_OtherServices	Other services	1959:Q1-2014:Q4	6	0	1
120	CPI	Consumer Price Index For All Urban Consumers: All Items	1959:Q1-2014:Q4	6	0	0
121	CPI_LFE	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy	1959:Q1-2014:Q4	6	0	0
122	PPI:FinGds	Producer Price Index: Finished Goods	1959:Q1-2014:Q4	6	0	0
123	PPI	Producer Price Index: All Commodities	1959:Q1-2014:Q3	6	0	0
124	PPI:FinConsGds	Producer Price Index: Finished Consumer Goods	1959:Q1-2014:Q4	6	0	1
125	PPI:FinConsGds (Food)	Producer Price Index: Finished Consumer Foods	1959:Q1-2014:Q4	6	0	1
126	PPI:IndCom	Producer Price Index: Industrial Commodities	1959:Q1-2014:Q4	6	0	1
127	PPI:IntMat	Producer Price Index: Intermediate Materials: Supplies & Components	1959:Q1-2014:Q4	6	0	1
128	Real_P:SensMat	Index of Sensitive Matrerials Prices (Discontinued) Defl by PCE(LFE) Def	1959:Q1-2004:Q1	5	0	1
129	Real_Commod: spot price	Spot market price index:BLS & CRB: all commodities(1967=100) Defl by PCE(LFE)	1959:Q1-2009:Q1	5	0	0
130	NAPM com price	ISM Manufacturing: Prices Paid Index©	1959:Q1-2014:Q4	1	0	1
131	Real_Price:NatGas	PPI: Natural Gas Defl by PCE(LFE)	1967:Q1-2014:Q4	5	0	1
	(7) Productivity and Earnings					
132	Real_AHE:PrivInd	Average Hourly Earnings: Total Private Industries Defl by PCE(LFE)	1964:Q1-2014:Q4	5	0	0
133	Real_AHE:Const	Average Hourly Earnings: Construction Defl by PCE(LFE)	1959:Q1-2014:Q4	5	0	0
134	Real_AHE:MFG	Average Hourly Earnings: Manufacturing Defl by PCE(LFE)	1959:Q1-2014:Q4	5	0	0
135	CPH:NFB	Nonfarm Business Sector: Real Compensation Per Hour	1959:Q1-2014:Q4	5	0	1
136	CPH:Bus	Business Sector: Real Compensation Per Hour	1959:Q1-2014:Q4	5	0	1
137	OPH:nfb	Nonfarm Business Sector: Output Per Hour of All Persons	1959:Q1-2014:Q4	5	0	1
138	OPH:Bus	Business Sector: Output Per Hour of All Persons	1959:Q1-2014:Q4	5	0	0
139	ULC:Bus	Business Sector: Unit Labor Cost	1959:Q1-2014:Q4	5	0	0
140	ULC:NFB	Nonfarm Business Sector: Unit Labor Cost	1959:Q1-2014:Q4	5	0	1
141	UNLPay:nfb	Nonfarm Business Sector: Unit Nonlabor Payments	1959:Q1-2014:Q4	5	0	1
	(8) Interest Rates					
142	FedFunds	Effective Federal Funds Rate	1959:Q1-2014:Q4	2	0	1
143	TB-3Mth	3-Month Treasury Bill: Secondary Market Rate	1959:Q1-2014:Q4	2	0	1
144	TM-6MTH	6-Month Treasury Bill: Secondary Market Rate	1959:Q1-2014:Q4	2	0	0
145	EuroDol3M	3-Month Eurodollar Deposit Rate (London)	1971:Q1-2014:Q4	2	0	0
146	TB-1YR	1-Year Treasury Constant Maturity Rate	1959:Q1-2014:Q4	2	0	0
147	TB-10YR	10-Year Treasury Constant Maturity Rate	1959:Q1-2014:Q4	2	0	0
148	Mort-30Yr	30-Year Conventional Mortgage Rate	1971:Q2-2014:Q4	2	0	0
149	AAA Bond	Moody's Seasoned Aaa Corporate Bond Yield	1959:Q1-2014:Q4	2	0	0
150	BAA Bond	Moody's Seasoned Baa Corporate Bond Yield	1959:Q1-2014:Q4	2	0	0

151	BAA_GS10	BAA-GS10 Spread	1959:Q1-2014:Q4	1	0	1
152	MRTG_GS10	Mortg-GS10 Spread	1971:Q2-2014:Q4	1	0	1
153	tb6m_tb3m	tb6m-tb3m	1959:Q1-2014:Q4	1	0	1
154	GS1_tb3m	GS1_Tb3m	1959:Q1-2014:Q4	1	0	1
155	GS10_tb3m	GS10_Tb3m	1959:Q1-2014:Q4	1	0	1
156	CP_Tbill Spread	CP3FM-TB3MS	1959:Q1-2014:Q4	1	0	1
157	Ted_spr	MED3-TB3MS (Version of TED Spread)	1971:Q1-2014:Q4	1	0	1
158	gz_spread	Gilchrist-Zakrajsek Spread (Unadjusted)	1973:Q1-2012:Q4	1	0	0
159	gz_ebp	Gilchrist-Zakrajsek Excess Bond Premium	1973:Q1-2012:Q4	1	0	1
	(9) Money and Credit					
160	Real_mbase	St. Louis Adjusted Monetary Base; Bil. of $; M; SA; Defl by PCE(LFE)	1959:Q1-2014:Q4	5	0	0
161	Real_InsMMF	Institutional Money Funds Defl by PCE(LFE)	1980:Q1-2014:Q4	5	0	0
162	Real_m1	M1 Money Stock Defl by PCE(LFE)	1959:Q1-2014:Q4	5	0	0
163	Real_m2	M2SL Defl by PCE(LFE)	1959:Q1-2014:Q4	5	0	0
164	Real_mzm	MZM Money Stock Defl by PCE(LFE)	1959:Q1-2014:Q4	5	0	0
165	Real_C&Lloand	Commercial and Industrial Loans at All Commercial Banks Defl by PCE(LFE)	1959:Q1-2014:Q4	5	0	1
166	Real_ConsLoans	Consumer (Individual) Loans at All Commercial Banks/ Outlier Code because of change in data in April 2010. See FRB H8 Release Defl by PCE(LFE)	1959:Q1-2014:Q4	5	1	1
167	Real_NonRevCredit	Total Nonrevolving Credit Outstanding Defl by PCE(LFE)	1959:Q1-2014:Q4	5	0	1
168	Real_LoansRealEst	Real Estate Loans at All Commercial Banks Defl by PCE(LFE)	1959:Q1-2014:Q4	5	0	1
169	Real_RevolvCredit	Total Revolving Credit Outstanding Defl by PCE(LFE)	1968:Q1-2014:Q4	5	1	1
170	Real_ConsuCred	Total Consumer Credit Outstanding Defl by PCE(LFE)	1959:Q1-2014:Q4	5	0	0
171	FRBSLO_Consumers	FRB Senior Loans Officer Opions. Net Percentage of Domestic Respondents Reporting Increased Willingness to Make Consumer Installment Loans (Fred from 1982:Q2 on Earlier is DB series)	1970:Q1-2014:Q4	1	0	1
	(10) International Variables					
172	Ex rate: major	FRB Nominal Major Currencies Dollar Index (Linked to EXRUS in 1973:1)	1959:Q1-2014:Q4	5	0	1
173	Ex rate: Euro	U.S. / Euro Foreign Exchange Rate	1999:Q1-2014:Q4	5	0	1
174	Ex rate: Switz	Foreign exchange rate: Switzerland (Swiss franc per U.S.$) Fred 1971. EXRSW previous	1971:Q1-2014:Q4	5	0	1
175	Ex rate: Japan	Foreign exchange rate: Japan (yen per U.S.$) Fred 1971- EXRJAN previous	1971:Q1-2014:Q4	5	0	1
176	Ex rate: UK	Foreign exchange rate: United Kingdom (cents per pound) Fred 1971-> EXRUK Previous	1971:Q1-2014:Q4	5	0	1
177	EX rate: Canada	Foreign exchange rate: Canada (Canadian $ per U.S.$) Fred 1971 -> EXRCAN previous	1971:Q1-2014:Q4	5	0	1
178	OECD GDP	OECD: Gross Domestic Product by Expenditure in Constant Prices: Total Gross; Growth Rate (Quartely); Fred Series NAEXKP01O1Q657S	1961:Q2-2013:Q4	1	0	1
179	IP Europe	OECD: Total Ind. Prod (excl Construction) Europe Growth Rate (Quarterly); Fred Series PRINTO01OEQ657S	1960:Q2-2013:Q4	1	0	1
180	Global Ec Activity	Kilian's estimate of glaobal economic activity in industrial commodity markets (Kilian website)	1968:Q1-2014:Q4	1	0	1
	(11) **Asset Prices, Wealth, and Household Balance Sheets**					
181	S&P 500	S&P's Common Stock Price Index: Composite (1941-43=10)	1959:Q1-2014:Q4	5	0	1
182	Real_HHW:TA	Households and nonprofit organizations; total assets (FoF) Seasonally Adjusted (RATS X11) Defl by PCE(LFE)	1959:Q1-2014:Q3	5	0	0

183	Real_HHW:TL	Households and nonprofit organizations; total liabilities Seasonally Adjusted (RATS X11) Defl by PCE(LFE)	1959:Q1-2014:Q3	5	0	1
184	liab_PDI	Liabilities Relative to Person Disp Income	1959:Q1-2014:Q3	5	0	0
185	Real_HHW:W	Households and nonprofit organizations; net worth (FoF) Seasonally Adjusted (RATS X11) Defl by PCE(LFE)	1959:Q1-2014:Q3	5	0	1
186	W_PDI	Networth Relative to Personal Disp Income	1959:Q1-2014:Q3	1	0	0
187	Real_HHW:TFA	Households and nonprofit organizations; total financial assets Seasonally Adjusted (RATS X11) Defl by PCE(LFE)	1959:Q1-2014:Q3	5	0	0
188	Real_HHW:TA_RE	TotalAssets minus Real Estate Assets Defl by PCE(LFE)	1959:Q1-2014:Q3	5	0	1
189	Real_HHW:TNFA	Households and nonprofit organizations; total nonfinancial assets (FoF) Seasonally Adjusted (RATS X11) Defl by PCE(LFE)	1959:Q1-2014:Q3	5	0	0
190	Real_HHW:RE	Households and nonprofit organizations; real estate at market value Seasonally Adjusted (RATS X11) Defl by PCE(LFE)	1959:Q1-2014:Q3	5	0	1
191	DJIA	Common Stock Prices: Dow Jones Industrial Average	1959:Q1-2014:Q4	5	0	1
192	VXO	VXO (Linked by N. Bloom) .. Average daily VIX from 2009 ->	1962:Q3-2014:Q4	1	0	1
193	Real_Hprice:OFHEO	House Price Index for the United States Defl by PCE(LFE)	1975:Q1-2014:Q4	5	0	1
194	Real_CS_10	Case-Shiller 10 City Average Defl by PCE(LFE)	1987:Q1-2014:Q4	5	0	1
195	Real_CS_20	Case-Shiller 20 City Average Defl by PCE(LFE)	2000:Q1-2014:Q4	5	0	1
	(12) Other					
196	Cons. Expectations	Consumer expectations NSA (Copyright University of Michigan)	1959:Q1-2014:Q4	1	0	1
197	PoilcyUncertainty	Baker Bloom Davis Policy Uncertainty Index	1985:Q1-2014:Q4	2	0	1
	(13) Oil Market Variables					
198	World Oil Production	World Oil Production.1994:Q1 on from EIA (Crude Oil including Lease Condensate); Data prior to 1994 from From Baumeister and Peerlman (2013)	1959:Q1-2014:Q3	5	0	0
199	World Oil Production	World Oil Production.1994:Q1 on from EIA (Crude Oil including Lease Condensate); Data prior to 1994 from From Baumeister and Peerlman (2013); Seasonally adjusted using RATS X11 (note seasonality before 1970)	1959:Q1-2014:Q3	5	0	1
200	IP: Energy Prds	IP: Consumer Energy Products	1959:Q1-2014:Q4	5	0	1
201	Petroleum Stocks	U.S. Ending Stocks excluding SPR of Crude Oil and Petroleum Products (Thousand Barrels); SA using X11 in RATS	1959:Q1-2014:Q4	5	0	1
202	Real_Price:Oil	PPI: Crude Petroleum Defl by PCE(LFE)	1959:Q1-2014:Q4	5	0	1
203	Real_Crudeoil Price	Crude Oil: West Texas Intermediate (WTI) - Cushing Oklahoma Defl by PCE(LFE)	1986:Q1-2014:Q4	5	0	1
204	Real_CrudeOil	Crude Oil Prices: Brent - Europe Defl by PCE(LFE) Def	1987:Q3-2014:Q4	5	0	1
205	Real_Price Gasoline	Conventional Gasoline Prices: New York Harbor Regular Defl by PCE(LFE)	1986:Q3-2014:Q4	5	0	1
206	Real_Refiners Acq. Cost (Imports)	U.S. Crude Oil Imported Acquisition Cost by Refiners (Dollars per Barrel) Defl by PCE(LFE)	1974:Q1-2014:Q4	5	0	1
207	Real_CPI Gasoline	CPI Gasoline (NSA) BLS: CUUR0000SETB01 Defl by PCE(LFE)	1959:Q1-2014:Q4	5	0	1

Dealing with large datasets

(1) Outliers

(2) Non-stationarities and 'trends'

Usual transformations (logs, differences, spreads, etc.)

Low-frequency 'demeaning'

(3) Aggregates (139 vs. 207)

(4) Estimate factors using standarized data ('weights' in weighted least squares). [$\min_{\{F_t\},\{\lambda_i\}} \sum_{i,t} (X_{it} - \lambda_i' F_t)^2$]

Low-frequency 'demeaning' weights and sprectral gain

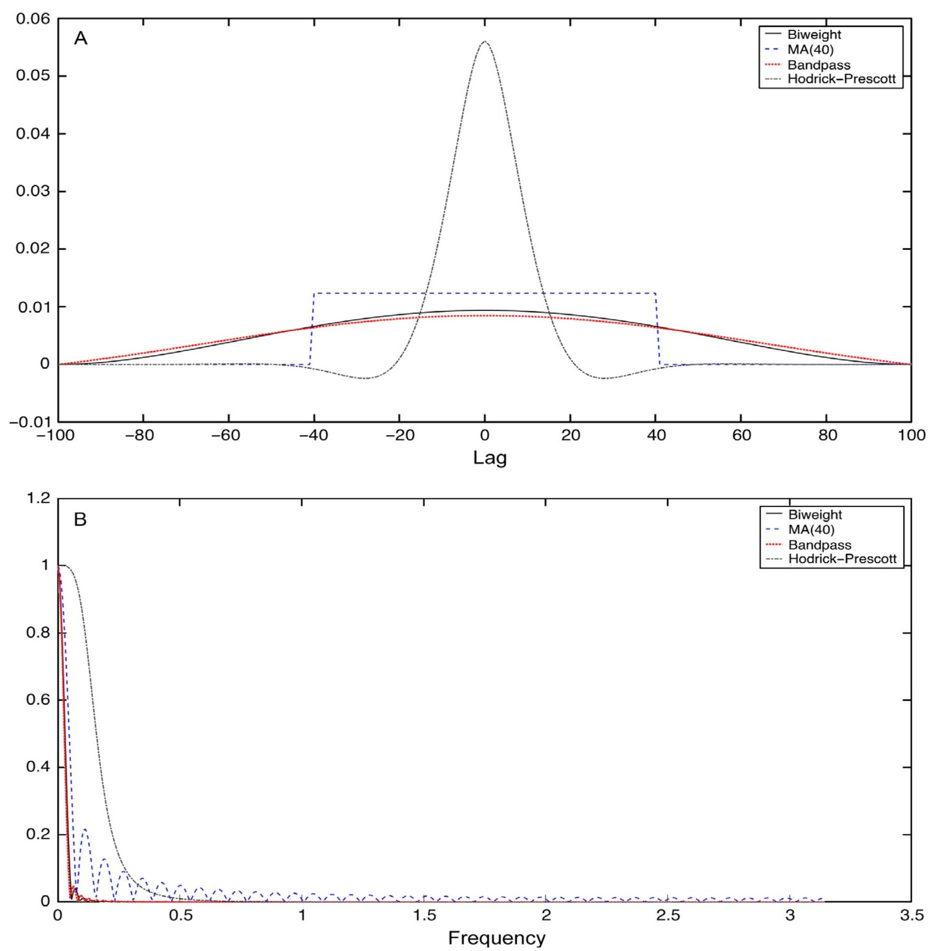


Fig. 2 Lag weights and spectral gain of trend filters. *Notes:* The biweight filter uses a bandwidth (truncation parameter) of 100 quarters. The bandpass filter is a 200-quarter low-pass filter truncated after 100 leads and lags (Baxter and King, 1999). The moving average is equal-weighted with 40 leads and lags. The Hodrick and Prescott (1997) filter uses 1600 as its tuning parameter.

How Many Factors?

(1) Scree plot

(2) Information criteria

(3) Others

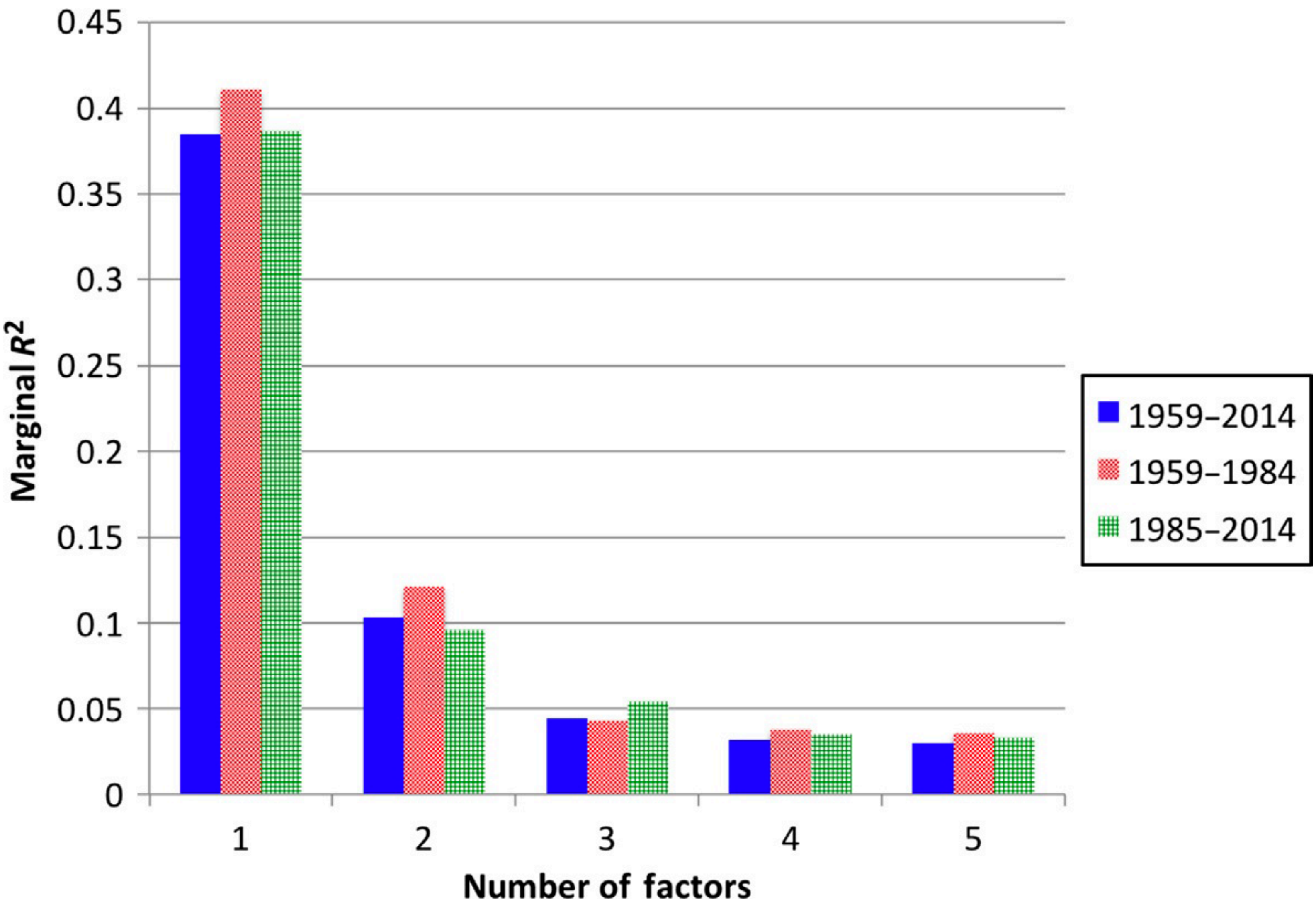
Least squares objective function for r factors:

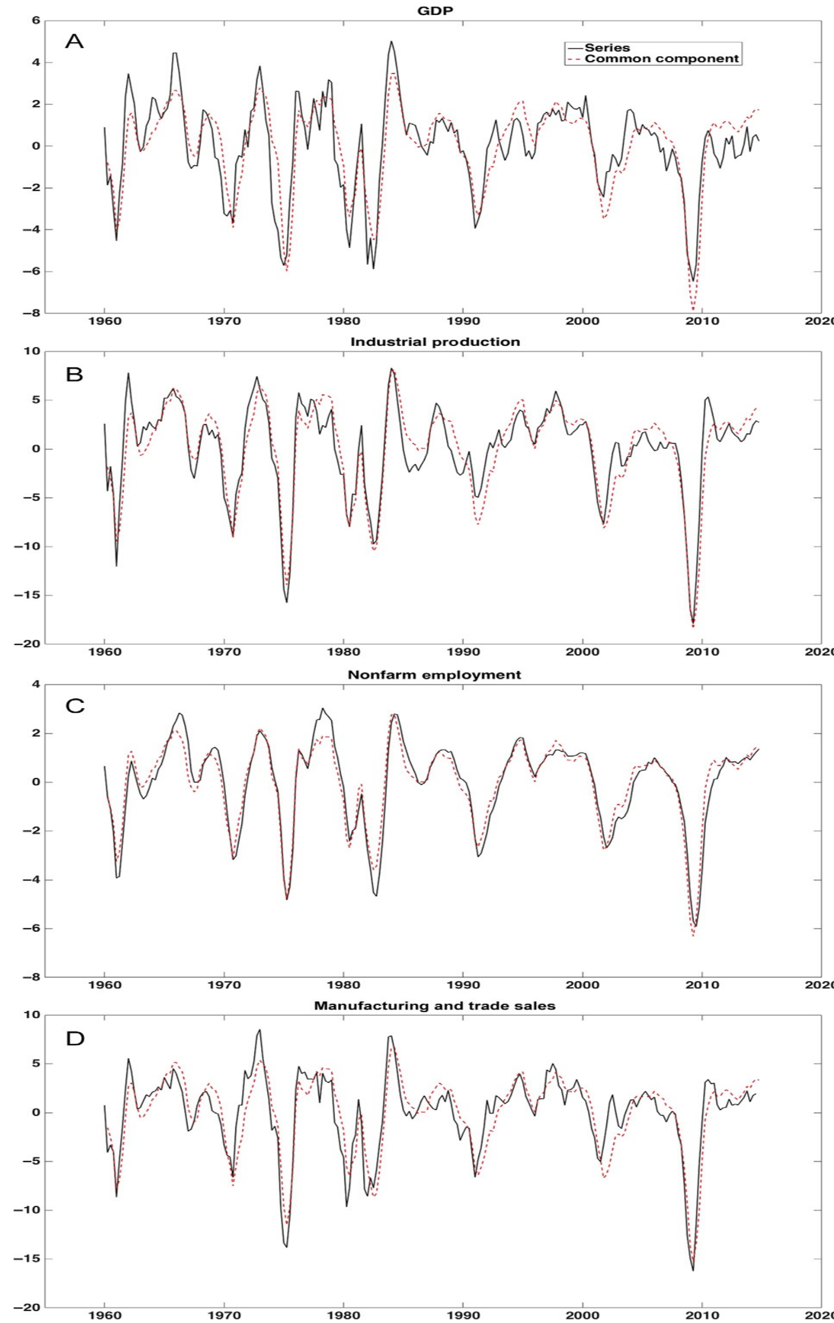
$$SSR(r) = \min_{\{F_t\},\{\lambda_i\}} \sum_{i,t} (X_{it} - \lambda_i' F_t)^2$$

where F_t and λ_i are $r \times 1$ vectors.

Scree plot: Marginal (trace) R^2 for factor k:

Scree plot for 58 real variables





etrended four-quarter growth rates of US GDP, industrial production, nonfarm

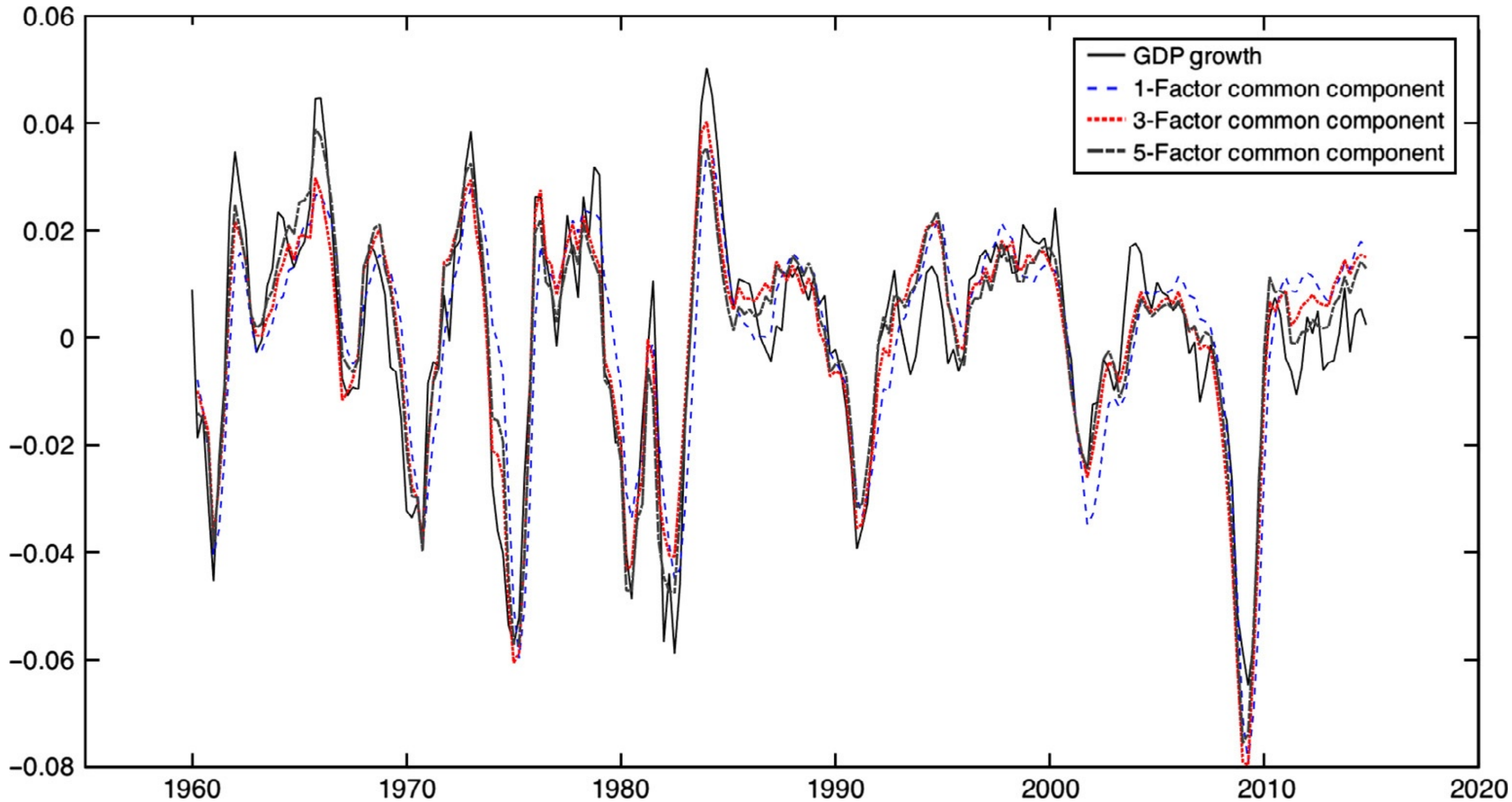
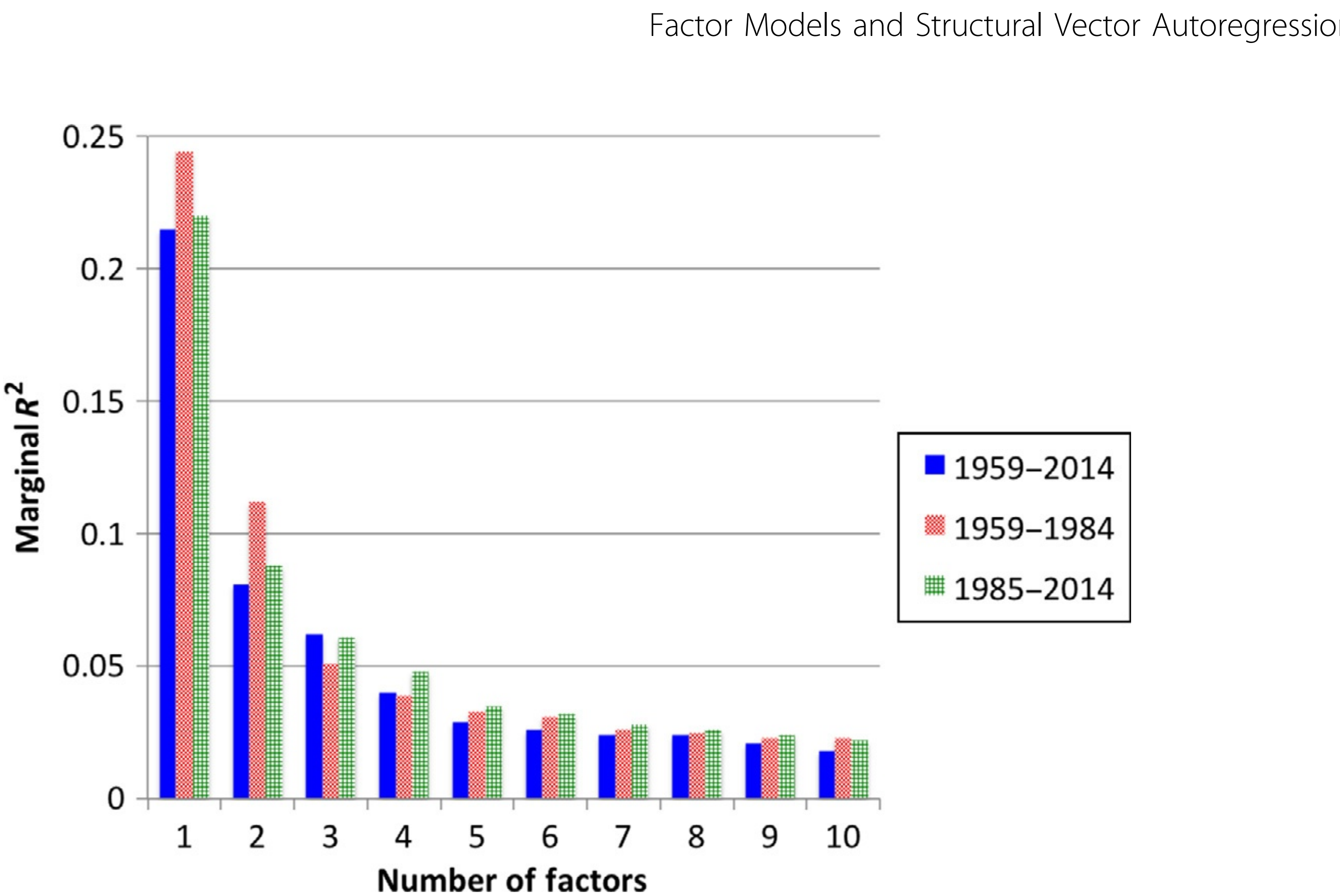


Fig. 4 Four-quarter GDP growth (*black*) and its common component based on 1, 3, and 5 static factors: real activity dataset.

Scree plot – Full data set (139 variables)



Information criteria: Bai and Ng

$\text{IC}(r) = \ln(\text{SSR}(r)) + rg(\text{sample size})$

Sample size: n and T

$$\text{BNIC}(r) = \ln\left(\text{SSR}(r)\right) + r\left(\frac{n+T}{nT}\right)\ln\left(\min(n,T)\right)$$

Note: when $n = T$ this is $\text{BNIC}(r) = \ln(\text{SSR}(r)) + 2r\times\ln(T)/T$.

Table 2 Statistics for estimating the number of static factors

(A) Real activity dataset ($N = 58$ disaggregates used for estimating factors)

Number of static factors	Trace R^2	Marginal trace R^2	BN-IC_{p2}	AH-ER
1	0.385	0.385	−0.398	**3.739**
2	0.489	0.103	−0.493	2.338
3	0.533	0.044	**−0.494**	1.384
4	0.565	0.032	−0.475	1.059
5	0.595	0.030	−0.458	1.082

(B) Full dataset ($N = 139$ disaggregates used for estimating factors)

Number of static factors	Trace R^2	Marginal trace R^2	BN-IC_{p2}	AH-ER
1	0.215	0.215	−0.183	**2.662**
2	0.296	0.081	−0.233	1.313
3	0.358	0.062	−0.266	1.540
4	0.398	0.040	**−0.271**	1.368
5	0.427	0.029	−0.262	1.127
6	0.453	0.026	−0.249	1.064
7	0.478	0.024	−0.235	1.035
8	0.501	0.024	−0.223	1.151
9	0.522	0.021	−0.205	1.123
10	0.540	0.018	−0.185	1.057

'Static' and 'Dynamic' factors (again)

$$X_t = \lambda(L)f_t + e_t \text{ and } \phi(L)f_t = \eta_t$$

$$X_t = \begin{pmatrix} \lambda_0 & \lambda_1 & \cdots & \lambda_k \end{pmatrix} \begin{pmatrix} f_t \\ f_{t-1} \\ \vdots \\ f_{t-k} \end{pmatrix} + e_t$$

$$\begin{pmatrix} f_t \\ f_{t-1} \\ \vdots \\ f_{t-k} \end{pmatrix} = \begin{bmatrix} \phi_1 & \phi_2 & \cdots & \phi_{k+1} \\ 1 & 0 & \cdots & 0 \\ & \ddots & \ddots & \\ & & 1 & 0 \end{bmatrix} \begin{pmatrix} f_{t-1} \\ f_{t-2} \\ \vdots \\ f_{t-k-1} \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \eta_t$$

or

$$X_t = \Lambda F_t + e_t$$
$$F_t = \Phi F_{t-1} + \mathrm{G}\eta_t$$

Number of static factors (r) = number of elements in F

Number of dynamic factors (q) = number of elements in f = number of elements in η = number of common shocks.

Determining q: Several ways. Here is one:

$$X_t = \Lambda F_t + e_t = \Lambda \eta_t + \beta F_{t-1} + e_t \quad \text{(with } \beta = \Lambda\Phi\text{).}$$

$$\Rightarrow$$

Use BNIC on the residuals from the regression of X_t onto $\hat{F}_{t-1}$.

(C) Amenguel-Watson estimate of number of dynamic factors: BN-IC_{pi} values, full dataset ($N = 139$)

No. of dynamic factors	Number of static factors									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	−0.098	−0.071	−0.072	−0.068	−0.069	−0.065	−0.064	−0.064	−0.064	−0.060
2		**−0.085**	−0.089	−0.087	−0.089	−0.084	−0.084	−0.084	−0.085	−0.080
3			**−0.090**	**−0.088**	**−0.091**	**−0.088**	**−0.088**	**−0.086**	**−0.086**	**−0.084**
4				−0.077	−0.080	−0.075	−0.075	−0.073	−0.072	−0.069
5					−0.064	−0.060	−0.062	−0.057	−0.055	−0.052
6						−0.045	−0.043	−0.040	−0.037	−0.036
7							−0.024	−0.022	−0.020	−0.018
8								−0.002	0.000	0.003
9									0.021	0.023
10										0.044

Notes: BN-IC_{p2} denotes the Bai and Ng (2002) IC_{p2} information criterion. AH-ER denotes the Ahn and Horenstein (2013) ratio of $(i+1)$th to ith eigenvalues. The minimal BN-IC_{p2} entry in each column, and the maximal Ahn–Horenstein ratio entry in each column, is the respective estimate of the number of factors and is shown in bold. In panel C, the BN-IC_{p2} values are computed using the covariance matrix of the residuals from the regression of the variables onto lagged values of the column number of static factors, estimated by principal components.

Table 3 Importance of factors for selected series for various numbers of static and dynamic factors: full dataset DFM

Series	A. R^2 of common component			B. Fraction of four quarters ahead forecast error variance due to common component		
	Number of static factors r			Number of dynamic factors q with $r=8$ static factors		
	1	4	8	1	4	8
Real GDP	0.54	0.65	0.81	0.39	0.77	0.83
Employment	0.84	0.92	0.93	0.79	0.86	0.90
Housing starts	0.00	0.52	0.67	0.49	0.51	0.75
Inflation (PCE)	0.05	0.51	0.64	0.34	0.66	0.67
Inflation (core PCE)	0.02	0.13	0.17	0.24	0.34	0.41
Labor productivity (NFB)	0.02	0.30	0.59	0.12	0.46	0.54
Real hourly labor compensation (NFB)	0.00	0.25	0.70	0.19	0.67	0.71
Federal funds rate	0.25	0.41	0.54	0.52	0.54	0.62
Ted-spread	0.26	0.59	0.61	0.18	0.33	0.59
Term spread (10 year–3 month)	0.00	0.36	0.72	0.32	0.38	0.63
Exchange rates	0.01	0.22	0.70	0.05	0.60	0.68
Stock prices (SP500)	0.06	0.49	0.73	0.14	0.29	0.79
Real money supply (MZ)	0.00	0.25	0.34	0.15	0.24	0.29
Business loans	0.11	0.49	0.51	0.13	0.16	0.23
Real oil prices	0.04	0.68	0.70	0.40	0.66	0.71
Oil production	0.09	0.10	0.12	0.01	0.04	0.12

(Use VAR(4) and AR(4) for e's to compute forecast error variances)

What about many more factors?
(Full 138-variable dataset)

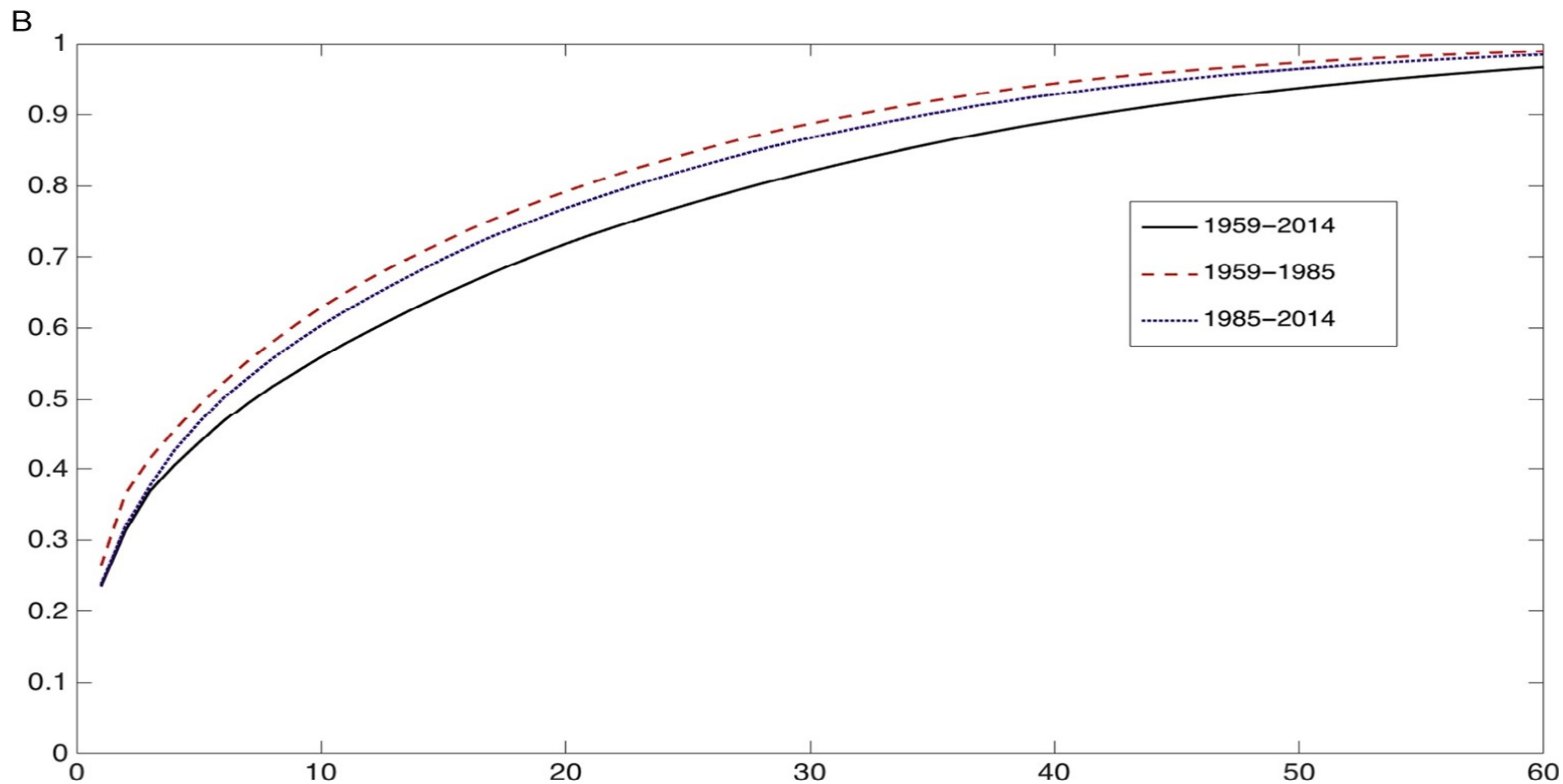


Fig. 6 (A) Scree plot for full dataset: full sample, pre-1984, and post-1984. (B) Cumulative R^2 as a

Is there useful information in additional factors? (For forecasting, maybe)

Instability in Factor Models (references in paper)

Two key results:

(1) Common discrete changes increase the number of factors

(2) Idiosynchratic (or weakly correlated) changes have little effect on estimated factors.

Return to single factor model: $X_{it} = \lambda_{i,t} f_t + e_t$

Result 1:

Suppose $\lambda_{i,t} = \begin{cases} \lambda_{i1} \text{ for } t \le T_1 \\ \lambda_{i2} \text{ for } t > T_1 \end{cases}$ and break is pervasive:

Write

$$X_{it} = (\lambda_{i1} \ \lambda_{i2}) \begin{pmatrix} f_{1t} \\ f_{2t} \end{pmatrix} + e_{it} \text{ where}$$

$f_{1t} = \begin{cases} f_t \text{ for } t \le T_1 \\ 0 \text{ for } t > T_1 \end{cases}$ and f_{2t} is defined analogously

$$X_{it} = \lambda_{i,t} f_t + e_t$$

$$\Rightarrow$$

$$\frac{1}{n}\sum_{i=1}^{n} X_{it} = \left(\frac{1}{n}\sum_{i=1}^{n}\lambda_{i,t}\right) f_t + \frac{1}{n}\sum_{i=1}^{n} e_{it}$$

Results 2 follows from this.

Odds and ends:

(1) Testing for breaks in λs. (Chow-tests, sup-Wald (QLR) tests etc.)

(2) Testing for instability of second moments of common components, var(ΛF_t).

(3) What's changing, λ_i or second moments of F_t? (the composite, $\lambda_i F_t$ affects X_{it}). (What changed during Great Recession … Stock-Watson BPEA 2012)

Stability in the 207-variable macro dataset (some results shown already previous figures)

Table 4 Stability tests for the four- and eight-factor full dataset DFMs
(A) Fraction of rejections of stability null hypothesis

Level of test	Chow test (1984q4 break)	QLR test
(i) Four factors		
1%	0.39	0.62
5%	0.54	0.77
10%	0.63	0.83
(ii) Eight factors		
1%	0.55	0.94
5%	0.65	0.98
10%	0.72	0.98

(B) Distribution of correlations between full- and split-sample common components					
	Percentile of distribution				
	5%	**25%**	**50%**	**75%**	**5%**
(i) Four factors					
1959–84	0.65	0.89	0.96	0.99	1.00
1985–2014	0.45	0.83	0.95	0.97	0.99
(ii) Eight factors					
1959–84	0.57	0.83	0.92	0.97	0.99
1985–2014	0.43	0.80	0.94	0.97	0.99

(C) Results by category (four factors)

Category	Number of series	Fraction of Chow test rejections for 5% test	Median correlation between full- and split-sample common components	
			1959–84	1985–2014
NIPA	20	0.50	0.98	0.96
Industrial production	10	0.50	0.98	0.97
Employment and unemployment	40	0.40	0.99	0.99
Orders, inventories, and sales	10	0.80	0.98	0.96
Housing starts and permits	8	0.75	0.96	0.91
Prices	35	0.49	0.88	0.90
Productivity and labor earnings	10	0.80	0.92	0.67
Interest rates	12	0.33	0.98	0.94
Money and credit	9	0.89	0.93	0.89
International	3	0.00	0.97	0.97
Asset prices, wealth, and household balance sheets	12	0.58	0.95	0.92
Other	1	1.00	0.95	0.91
Oil market variables	6	0.83	0.79	0.79

Notes: These results are based on the 176 series with data available for at least 80 quarters in both the pre- and post-84 samples. The Chow tests in (A) and (C) test for a break in 1984q4.

Dynamic Factor Models,
Factor Augmented VARs,
and SVARs in Macroeconomics

-- Part 2: SVARs and SDFMs --

Mark Watson
Princeton University

Central Bank of Chile
October 22-24, 2018

Reference: Stock, James H. and Mark W. Watson (2016)
Handbook of Macroeconomics, Vol 2. chapter

DFM:

$$X_t = \Lambda F_t + u_t$$

$$\Phi(\mathrm{L})F_t = \mathrm{G}\eta_t$$

Question: Identify "structural" shocks in η_t and their effects on $\{X_t\}$

And how is this related to the analogous question in VARs

Start with discussion of VAR and then return to DFM

SVAR

Y_t is an $n\times 1$ vector of observables (*n* typically 'small')

VAR dynamics: $E(Y_t \mid \text{lags of } Y_t) = A_1Y_{t-1} + \ldots + A_pY_{t-p}$.

so that $Y_t = A_1Y_{t-1} + \ldots + A_pY_{t-p} + \eta_t$ or $A(\mathrm{L})Y_t = \eta_t$.

η_t = 1-period ahead forecast error. (Note change of notation from DFM.)

No constant term for notational convenience.

VMA representation:

$$Y_t = \mathrm{C(L)}^{-1}\eta_t \text{ where } \mathrm{C(L)} = \mathrm{A(L)}^{-1}$$

Note: $\mathrm{C(L)} = \mathrm{C}_0 + \mathrm{C}_1\mathrm{L} + \mathrm{C}_2\mathrm{L}^2 + \ldots$ and $\mathrm{C}_0 = \mathrm{I}$

SVAR (Sims (1980)): Why do we make forecast errors?

$\eta_t = \mathrm{H}\varepsilon_t$ where ε_t are 'structural' shocks. (Shocks interpretable in the context of particular theoretical economic models).

$Y_t = \mathrm{C(L)}\eta_t = \mathrm{C(L)H}\varepsilon_t = \mathrm{D(L)}\varepsilon_t$ is structural MA

and with $\mathrm{B(L)} = \mathrm{H}^{-1}\mathrm{A(L)}$

$\mathrm{B(L)}Y_t = \varepsilon_t$ is SVAR

From SMA: $Y_t = \mathrm{D}_0\varepsilon_t + \mathrm{D}_1\varepsilon_{t-1} + \ldots$ with $\mathrm{D}_k = \mathrm{C}_k\mathrm{H}$

Note: $\dfrac{\partial Y_{i,t+k}}{\partial \varepsilon_{jt}} = \mathrm{D}_{k,ij}$. (These are "impulse responses" or "dynamic causal effects" or 'dynamic multipliers' …)

Issues:

1. $E(Y_t \mid \text{lags if } Y_t) = A_1Y_{t-1} + \ldots + A_pY_{t-p}$. Reasonable?

2. $C(L) = A(L)^{-1}$; when is this a well-defined one-sided inverse?

3. Estimation of A(L) and C(L). When do usual large-sample linear properties obtain?

4. $\eta_t = H\varepsilon_t$ with H non-singular. Reasonable?

5. Identification of H.

6. Properties of $\hat{C}_k\hat{H}$.

Issues:

1. $E(Y_t \mid \text{lags if } Y_t) = A_1 Y_{t-1} + \ldots + A_p Y_{t-p}$. Reasonable?

2. $C(L) = A(L)^{-1}$; when is this a well-defined one-sided inverse?

3. Estimation of A(L) and C(L). When do usual large-sample linear properties obtain.

"Hayashi": Roots of A(L) outside unit circle (difference equation is stable). η_t are MDS with appropriate moments.

Issue: $\eta_t = \mathrm{H}\varepsilon_t$ with H non-singular. Reasonable?

In some cases NO:

Non-invertibility: Static problem H is $n_Y \times n_\varepsilon$. What if $n_\varepsilon > n_Y$?

Dynamics:

Invertibility (required here): Can I determine ε_t from current and lagged *Y*.

'Recoverability' (Chahrour and Jurado (2017), Plagbor-Moller and Wolf (2018)): Can I determine ε_t from current, lagged and *future Y*.

Simplist example:

$$Y_t = \varepsilon_t - \theta\varepsilon_{t-1}$$

$$\varepsilon_t = \sum_{j=0}^{t-1} \theta^j Y_{t-j} + \theta^t \varepsilon_0 \text{ (so invertible when } |\theta| < 1).$$

Also

$$\varepsilon_t = -\theta^{-1} \sum_{j=1}^{T-1} \theta^{-j} Y_{t+j} + \theta^{-T} \varepsilon_T$$

(so recoverable as long as $|\theta| \neq 1$)

More complicated example:

(Fernandez-Villaverde, Rubio-Ramirez, Sargent and Watson (2007))

$$y_{t+1} = \mathrm{C}x_t + \mathrm{D}w_{t+1}$$

$$x_{t+1} = \mathrm{A}x_t + \mathrm{B}w_{t+1}$$

Invertibilty: eigenvalues of $(\mathrm{A} - \mathrm{BD}^{-1}\mathrm{C})$ are less than 1 in modulus.

(Recoverability): When is $\mathrm{var}\left(w_t \mid \left\{ y_{t+j} \right\}_{j=-\infty}^{\infty} \right) = 0$? (Exercise)

Issue 5: Identification of H

$$\eta = \mathrm{H}\varepsilon \;\Rightarrow\; \Sigma_{\eta\eta} = \mathrm{H}\Sigma_{\varepsilon\varepsilon}\mathrm{H}'$$

$\Sigma_{\eta\eta}$ estimable from data, so question is whether their a unique solution for H and $\Sigma_{\varepsilon\varepsilon}$ from $\Sigma_{\eta\eta} = \mathrm{H}\Sigma_{\varepsilon\varepsilon}\mathrm{H}'$.

'Order condition' .. count equations and unknowns.

- $n(n+1)/2$ elements in $\Sigma_{\eta\eta}$ (number of equations)

- $n^2 + n(n+1)/2$ in H and $\Sigma_{\varepsilon\varepsilon}$ (number of unknowns) .. n^2 too many parameters

    - Uncorrelated Structural Shocks: Restrict $\Sigma_{\varepsilon\varepsilon}$ to be diagonal: $n^2 + n$ unknowns .. $n(n+1)/2$ too many parameters.

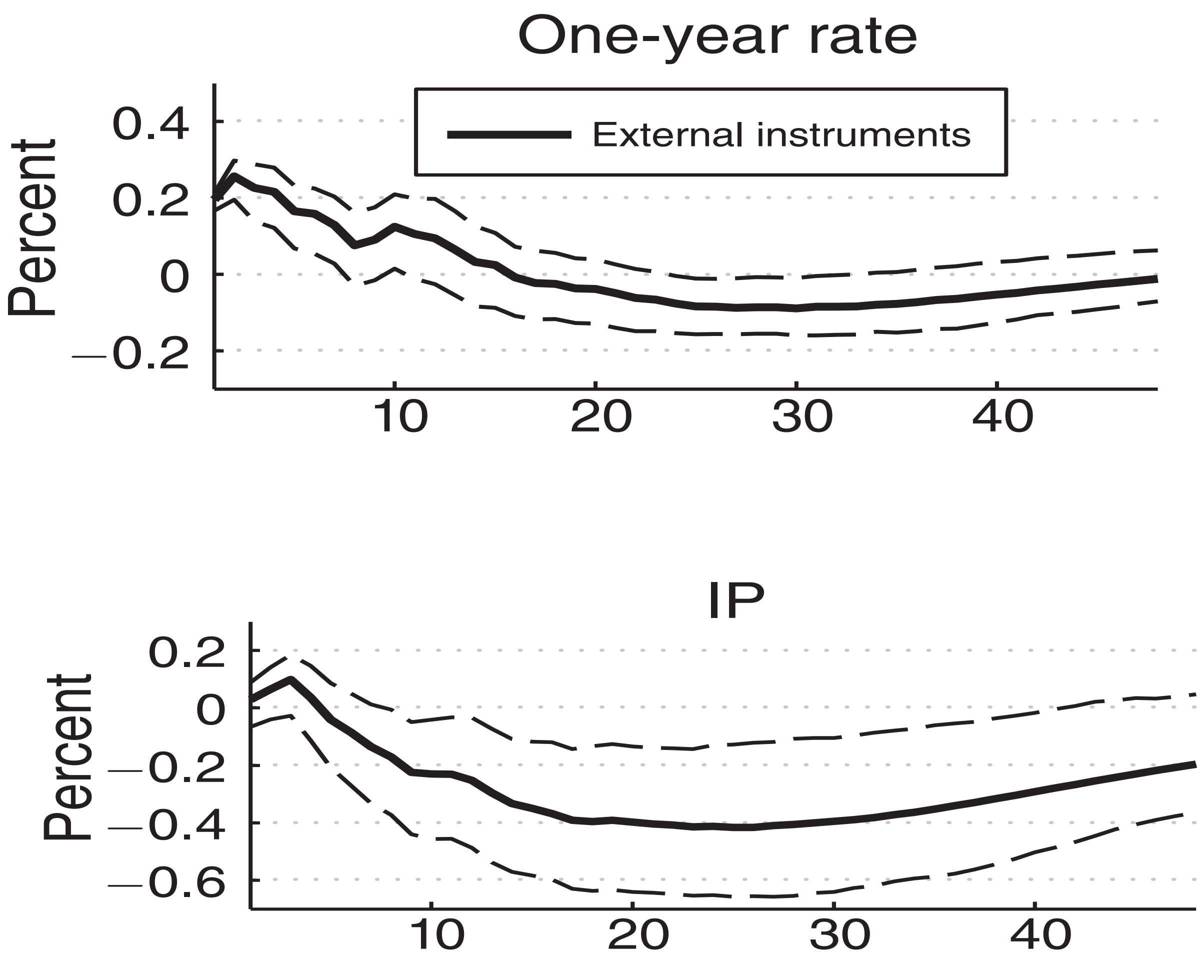
o Scale normalization

scalar model: $\eta_t = \mathrm{H}\varepsilon_t$ ('units' of ε_t are not identified)

2 normalizations: (1) $\sigma_\varepsilon = 1$

(2) $\mathrm{H} = 1$ (or $\mathrm{H}^{-1} = 1$)

Standard deviation normalization: Gertler Karadi (2015) – IRF or Monetary Policy Shock



Scale normalization does not matter in population.

It will matter for inference.

Moving from one normalization to another involves dividing by $\hat{H}$ or $\hat{\sigma}_{\varepsilon}$.

We will use normalization on elements of H.

- e.g., Diagonal elements of H are unity

- Alternatives:
  - $\Sigma_{\varepsilon\varepsilon} = I$
  - Diagonal elements of $H^{-1} = I$. (Scale normalization used in classical simultaneous equations literature.)

Back to counting: with scale normalization the model needs only $n(n-1)/2$ additional restrictions.

Example: VAR(1) with $n = 3$

$$Y_t = \mathrm{A}Y_{t-1} + \begin{bmatrix} 1 & H_{12} & H_{13} \\ H_{21} & 1 & H_{23} \\ H_{31} & H_{32} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}$$

$$Y_t = \mathrm{A}Y_{t-1} + \begin{bmatrix} 1 & H_{12} & H_{13} \\ H_{21} & 1 & H_{23} \\ H_{31} & H_{32} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}$$

Timing restriction example: $Y_t = \mathrm{A}Y_{t-1} + \begin{bmatrix} 1 & 0 & 0 \\ H_{21} & 1 & 0 \\ H_{31} & H_{32} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}$

Long-run restriction example:

Arithmetic: Let D = $A(L)^{-1}H$ and let $Z_t = (1-L)^{-1} Y_t$ then

$$\lim_{k\to\infty} \frac{\partial Z_{i,t+k}}{\partial \varepsilon_{j,t}} = D_{ij}.$$

Restrict H so that D_{ij} has $n(n\text{-}1)/2$ zeros.

And so forth.

Identification of one shock, say ε_{1t} and its effect on Y_{t+k}

Recall: $Y_t = \mathrm{C(L)}\,\eta_t = \mathrm{C(L)H}\varepsilon_t$ with $\mathrm{C(L)} = \mathrm{A(L)}^{-1}$

Thus

$$Y_t = \mathrm{C(L)}\begin{bmatrix} H_1 & H_\bullet \end{bmatrix}\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{\bullet,t} \end{bmatrix} = \mathrm{C(L)H}_1\varepsilon_{1t} + \text{distributed lag of } \varepsilon_{\bullet t}$$

where $\bullet$ denotes elements 2 through n

To identify the effect of ε_1 on Y_{t+k} we need only identify the first column of H.

And, if H_1 is known ('identified') and H is invertible, then it turns out ε_{1t} can be 're-constructed' from η_t (up to scale) – Algebra in paper.

Identification of H_1

$$Y_t = AY_{t-1} + \begin{bmatrix} 1 & H_{12} & H_{13} \\ H_{21} & 1 & H_{23} \\ H_{31} & H_{32} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}$$

Timing restriction example: $Y_t = AY_{t-1} + \begin{bmatrix} 1 & 0 & 0 \\ H_{21} & 1 & H_{23} \\ H_{31} & H_{32} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}$

$\varepsilon_1 = \eta_1$, and H_1 is identified by regressing η_t onto $\eta_{1,t}$.

Similar for other timing restrictions, long-run restrictions, etc.

Other populator identification schemes

(1) Heteroskedasticity

(2) Sign Restrictions

(3) External Instruments ('Proxy variables')

Identification by Heteroskedasticity (Rigobon (2003), Rigobon and Sack (2003,2004))

Idea: $\Sigma^1_{\varepsilon\varepsilon}$ and $\Sigma^2_{\varepsilon\varepsilon} \Rightarrow \Sigma^1_{\eta\eta} = H\Sigma^1_{\varepsilon\varepsilon}H'$ and $\Sigma^2_{\eta\eta} = H\Sigma^2_{\varepsilon\varepsilon}H'$

Order condition (counting):

Number of equations (unique elements in $\Sigma^1_{\eta\eta}$ and $\Sigma^2_{\eta\eta}$): $n(n+1) = n^2 + n$

Number of unknowns: (H, $\Sigma^1_{\varepsilon\varepsilon}$ and $\Sigma^2_{\varepsilon\varepsilon}$): $(n^2-n) + 2n = n^2 + n$.

Note: 'rank condition' .. relative variances of ε_t must change to get independent information on elements of H.

Potentially powerful tool.

Generalizes to time-varying conditional heteroskedasticity.

Example:

$$\begin{pmatrix} \Sigma^j_{\eta_1\eta_1} & \Sigma^j_{\eta_1\eta_2} \\ \Sigma^j_{\eta_2\eta_1} & \Sigma^j_{\eta_2\eta_2} \end{pmatrix} = \begin{pmatrix} 1 & H_{12} \\ H_{21} & 1 \end{pmatrix} \begin{pmatrix} \sigma^2_{\varepsilon_1,j} & 0 \\ 0 & \sigma^2_{\varepsilon_2} \end{pmatrix} \begin{pmatrix} 1 & H_{21} \\ H_{12} & 1 \end{pmatrix}, \quad j = 1, 2.$$

Algebra $\Rightarrow$

$$H_{21} = \frac{\Sigma^2_{\eta_1\eta_2} - \Sigma^1_{\eta_1\eta_2}}{\Sigma^2_{\eta_1\eta_1} - \Sigma^1_{\eta_1\eta_1}}$$

Estimator:

$$\hat{H}_{21} = \frac{\hat{\Sigma}^2_{\eta_1\eta_2} - \hat{\Sigma}^1_{\eta_1\eta_2}}{\hat{\Sigma}^2_{\eta_1\eta_1} - \hat{\Sigma}^1_{\eta_1\eta_1}}$$

$$\hat{H}_{21} = \frac{\hat{\Sigma}^2_{\eta_1\eta_2} - \hat{\Sigma}^1_{\eta_1\eta_2}}{\hat{\Sigma}^2_{\eta_1\eta_1} - \hat{\Sigma}^1_{\eta_1\eta_1}}$$

Denominator: $\hat{\Sigma}^2_{\eta_1\eta_1} - \hat{\Sigma}^1_{\eta_1\eta_1} = \left(\Sigma^2_{\eta_1\eta_1} - \Sigma^1_{\eta_1\eta_1}\right) + \text{Sampling Error}\left(\hat{\Sigma}^2_{\eta_1\eta_1} - \hat{\Sigma}^1_{\eta_1\eta_1}\right)$

Estimator will have poor sampling properties when denominator is noisy:

$\text{Sampling Error}\left(\hat{\Sigma}^2_{\eta_1\eta_1} - \hat{\Sigma}^1_{\eta_1\eta_1}\right)$ is big relative to $\left(\Sigma^2_{\eta_1\eta_1} - \Sigma^1_{\eta_1\eta_1}\right)$.

Or, (1) when change in variance is small or one or both of the samples is small.

Inequality (Sign) Restrictions (Faust (1998), Uhlig (2005))

Typical identifying restrictions: $R\mathrm{H} = r$ where R and r are pre-specified are can be computed from the data. (Or $R\mathrm{H}_1 = r$, when focused on a single shock.)

Inequality Restrictions: $R\mathrm{H} \geq r$.

This 'set identified' the impulse responses.

Determining the identified set. A computational method using $\Sigma_{\varepsilon\varepsilon} = \mathrm{I}$ normalization.

$\Sigma_{\eta\eta} = \mathrm{H}\Sigma_{\varepsilon\varepsilon}\mathrm{H}' = \mathrm{HH}'$, so H is a matrix square root of $\Sigma_{\eta\eta}$ $\Rightarrow$

$\mathrm{H} = \Sigma_{\eta\eta}^{1/2}C$ where $\Sigma_{\eta\eta}^{1/2}$ is any particular matrix square root (e.g., the Cholesky factor) and C is an orthonormal matrix (so $\mathrm{CC}' = \mathrm{I}$).

(1) Compute $\Sigma_{\eta\eta}^{1/2}$

(2) For a particular value of C, compute H = $\Sigma_{\eta\eta}^{1/2} C$.

(3) Check to see if RH $\geq r$. If so, keep H. If not discard H.

(4) Repeat step 2 for ***all*** possible values of C.

(5) The resulting values of H from (3) are the set of values of H that are identified by the inequality restriction.

Inference in a "set identified" model

Easy example: Suppose θ is a parameter of interest. You know that θ is restricted to lie between μ_L and μ_U. That is $\mu_L \leq \theta \leq \mu_U$.

You have an i.i.d. sample of data on (X_i, Y_i) where:

$$\begin{pmatrix} X_i \\ Y_i \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_L \\ \mu_U \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \right)$$

and you want to conduct inference about θ. What should you do?

Frequentist: Data give you information about μ_L and μ_U. Estimate these bounds. That's it.

Bayes: Priors on μ_L, μ_U and θ. Form posterior. Data tells you about μ_L, μ_U, but nothing more about θ. Likelihood is flat for all values of θ between μ_L and μ_U. In large samples posterior for θ is the prior, but truncated at μ_L and μ_U.

Bayes and frequentist inference couldn't be more different here. For example, a 95% Bayes posterior credible set for θ has a frequentist coverage of 0% or 100%. (The Bayes 95% set is a 0% or 100% confidence set.)

What should you do:

(1) Estimate the identified set. (Estimate μ_L and μ_U in the example. Sampling uncertainty is over the boundary of this set.)

(2) Do Bayes analysis. Prior is critical. In large samples the prior *is* the posterior. Think carefully about prior.

What you shouldn't do.

(3) Do Bayes analysis without careful thought about prior.

Back to Sign-restricted VARs: Baumeister and Hamilton (2015, 2017).

SVAR (one lag for notationaly convenience):

$Y_t = \mathrm{A}Y_{t-1} + \eta_t = AY_{t\text{-}1} + \mathrm{H}\varepsilon_t$ or

$$\mathrm{B}_0 Y_t = \mathrm{B}_1 Y_{t-1} + \varepsilon_t$$

with $\mathrm{B}_0 = \mathrm{H}^{-1}$ and $\mathrm{B}_1 = \mathrm{H}^{-1}\mathrm{A}$.

Baumeister-Hamilton, use normalization with 1's on diagonal of B_0 ($= \mathrm{H}^{-1}$). They advocate using informative priors about off-diagonal elements of B_0, loose priors on B_1 and variances of ε_t + sign restrictions.

Alternative (originally used on Uhlig(2005) and many others)

(1) Compute $\Sigma_{\eta\eta}^{1/2}$

(2) For a particular value of C, compute H = $\Sigma_{\eta\eta}^{1/2}C$.

(3) Check to see if RH $\geq r$. If so, keep H. If not discard H.

(4) Repeat step 2 for all possible values of C.

(5) ~~The resulting values of H from (3) are the set of values of H that are identified by the inequality restriction.~~ Use the values from (3) as the posterior.

This amounts to having a flat prior on C ('Harr' prior on columns of orthonormal matrix).

What is a flat prior on C?

2-dimensional problem: $C = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$ with $\theta \sim U(0,2\pi)$

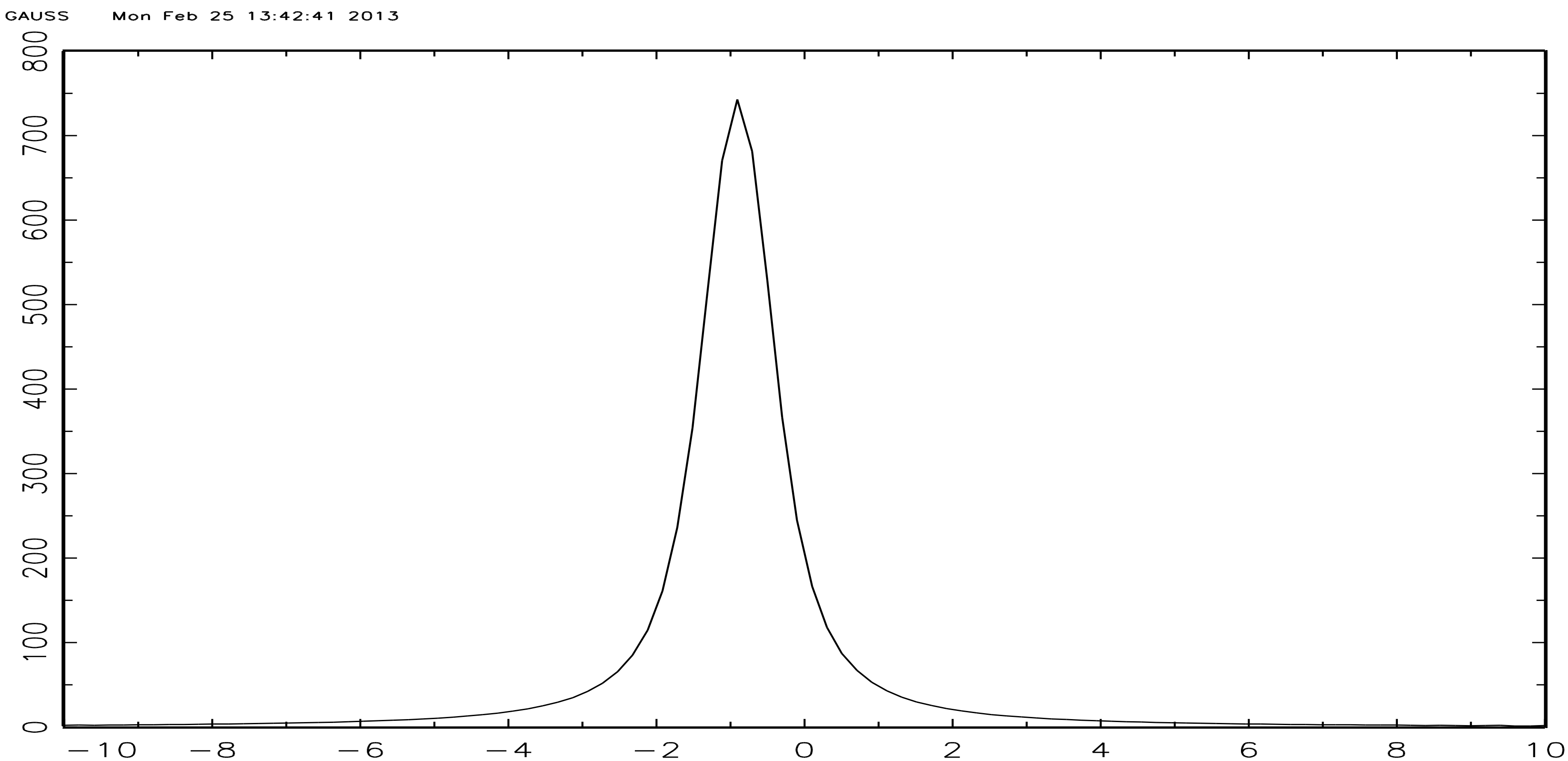
H = $\Sigma_{\eta\eta}^{1/2} C$, so $B_0 = H^{-1} = C^{-1}\Sigma_{\eta\eta}^{-1/2}$. Write $B_0 = \begin{pmatrix} 1 & b_{12} \\ b_{21} & 1 \end{pmatrix}$, so that

$$Y_{1t} = -b_{12}Y_{2t} + \text{lags} + \varepsilon_{1t}$$

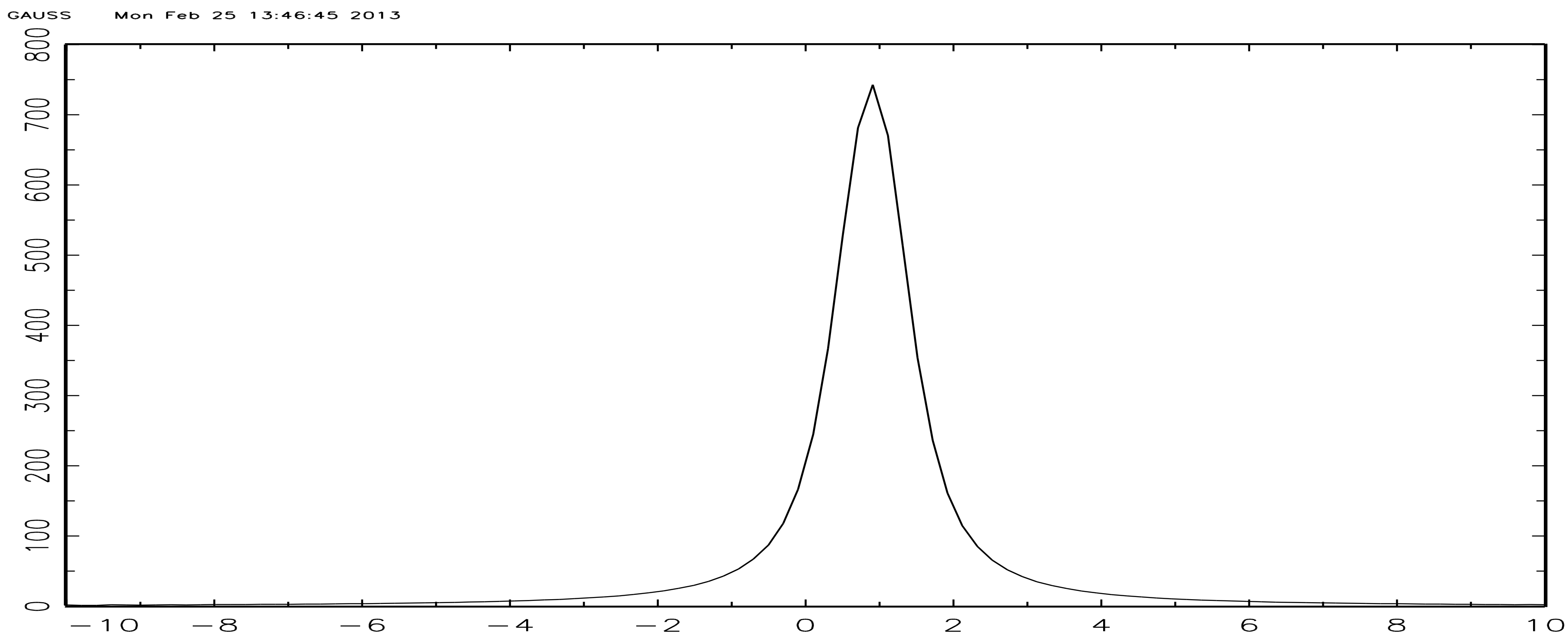
$$Y_{2t} = -b_{21}Y_{1t} + \text{lags} + \varepsilon_{2t}$$

Prior on C is 'flat'. What is implied prior on b_{12} ?

Implied prior for b_{12} … $\Sigma_{\eta\eta} = \begin{bmatrix} 1 & 0.9 \\ 0.9 & 1 \end{bmatrix}$



Implied prior for b_{12} … $\Sigma_{\eta\eta} = \begin{bmatrix} 1 & -0.9 \\ -0.9 & 1 \end{bmatrix}$



Prior on C is flat and does not depend on $\Sigma_{\eta\eta}$.

Implied Prior on b_{12} is not flat, not symmetric, and depends on $\Sigma_{\eta\eta}$.

Bottom line: With sign-restricted SVARs, data cannot completely pin down the effects of ε_t on Y_{t+k}.

Frequentist: Determine what the data can say about this.

Bayesian: Add judgement (prior) + data to make probabilistic statements about the effects. Prior matters.

Identification of H: (3) External Instruments ('Proxy variables')

(Discussion follows Stock-Watson (2018) *Economic Journal* paper)

Step back for a moment and consider general problem of estimating Dynamic causal effects and IRFs

$$Y_t = \underbrace{D_0}_{n_Y}\, \varepsilon_t + D_1\, \underbrace{\varepsilon_{t-1}}_{n_\varepsilon} + \ldots = D(L)\varepsilon_t$$

(Note: D_0 = H in our discussion above.)

<u>DO NOT ASSUME INVERTIBILITY (yet)</u>

Estimating dynamic causal effects in macroeconomics

Standard Approach:

- Estimate VAR for Y
- Assume "invertibility" to relate ε_t to VAR forecast errors.
- Impose some restrictions on H for identification

Alternative Approach:

- Find an "external" instrument Z that captures some exogenous variation in one of the structural shocks.
- Use instrument (with or without VAR step) to estimate dynamic causal effects.

Some references on external instruments

VARs: Stock (2008), Stock and Watson (2012), Mertens and Ravn (2013, 2014), Gertler and Karadi (2015), Caldera and Kamps (2017), Montiel Olea, Stock and Watson (2012), Lumsford (2015), Jentsch and Lunsford (2016), Drautzburg(2017), Carriero, Momtaz, Theodoridis and Theophilopoulou (2015), …

Local-projections: Jordà, Schularick, and Taylor (2015), Ramey and Zubairy (2017), Ramey (2016), Mertens (2015), Fieldhouse, Mertens, Ravn (2017) …

A Running Empirical Example: Gertler-Karadi (2015)

- Y_t = [R_t, $100\times\Delta\ln(IP)$, $100\times\Delta\ln(CPI)$, EBP]

- Monetary policy shock = $\varepsilon_{1,t}$

- Causal Effects: $E(Y_{i,t+h} \mid \varepsilon_{1,t} = 1) - E(Y_{i,t+h} \mid \varepsilon_{1,t} = 0) = \Theta_{h,i}$

- Kuttner (2001)-like instrument, Z_t = change in Federal Funds rate futures in short window around FOMC announcements.
  - Z_t correlated with $\varepsilon_{1,t}$ but uncorrelated with $\varepsilon_{2:n_\varepsilon,t} = (\varepsilon_{2,t}, \varepsilon_{3,t}, \ldots, \varepsilon_{n_\varepsilon,t})$.

Direct estimation of $\mathrm{D}_{h,i1}$

$$Y_t = \mathrm{D}_0\,\varepsilon_t + \mathrm{D}_1\,\varepsilon_{t-1} + \ldots = \mathrm{D(L)}\varepsilon_t$$

$$Y_{i,t+h} = \mathrm{D}_{h,i1}\,\varepsilon_{1,t} + u_t \qquad \text{(LP)}$$

$$u_t = \{\varepsilon_{t+h}, \ldots, \varepsilon_{t+1}, \varepsilon_{2:n_\varepsilon,t}, \varepsilon_{t-1}, \ldots\}$$

$\{x\}$: linear combinations of elements of x

$$\mathrm{E}(\varepsilon_{1,t}\,u_t) = 0$$

But $\varepsilon_{1,t}$ is not observed

IV estimation of $\mathbf{D}_{h,i1}$

$$Y_{i,t+h} = \mathrm{D}_{h,i1}\varepsilon_{1,t} + \{\varepsilon_{t+h}, \ldots, \varepsilon_{t+1}, \varepsilon_{2:n_\varepsilon,t}, \varepsilon_{t-1}, \ldots\}$$

$$Y_{1,t} = \mathbf{D}_{0,11}\varepsilon_{1,t} + \{\varepsilon_{2:n_\varepsilon,t}, \varepsilon_{t-1}, \ldots\} = \varepsilon_{1,t} + \{\varepsilon_{2:n_\varepsilon,t}, \varepsilon_{t-1}, \ldots\}$$

(unit-effect normalization $\mathbf{D}_{0,11} = 1$)

$$Y_{i,t+h} = \mathbf{D}_{h,i1}\boldsymbol{Y}_{1,t} + \{\varepsilon_{t+h}, \ldots, \varepsilon_{t+1}, \varepsilon_{2:n_\varepsilon,t}, \varepsilon_{t-1}, \ldots\}$$

Condition LP-IV:

(i) $\mathrm{E}(\varepsilon_{1,t}Z_t) = \alpha \neq 0$

(ii) $\mathrm{E}(\varepsilon_{2:n_\varepsilon,t}Z_t') = 0$

(iii) $\mathrm{E}(\varepsilon_{t+j}Z_t') = 0$ for $j \neq 0$

Odds and ends

- HAR SEs
- Dyn. Causal Effects for levels vs. differences
- Weak-instrument robust inference
- "News" Shocks
  - replace $D_{0,11} = 1$ normalization with $D_{k,11} = 1$ normalization
- Smoothness constraints (Barnichon &Brownlees, Plagborg-Møller, …)
- ε_{1t} (or its variance) is not identified. (see Plagborg-Møller-Wolf for bounds).

Results for [R and $100\times\ln(IP)$]
(1990m1 -2012:m6)

	lag (*h*)	**(a)**
R	0	**1.00 (0.00)**
	6	-0.07 (1.34)
	12	-1.05 (2.51)
	24	-2.09 (5.66)
IP	0	-0.59 (0.71)
	6	-2.15 (3.42)
	12	-3.60 (6.23)
	24	-2.99 (10.21)
Controls		none
First-stage *F*		1.7

Results for [R and $100 \times \ln(IP)$] (1990m1 -2012:m6)

	lag (*h*)	**(a)**
R	0	1.00 (0.00)
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Controls		none
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	24	-2.09 (5.66)
IP	0	-0.59 (0.71)
	6	-2.15 (3.42)
	12	-3.60 (6.23)
	24	-2.99 (10.21)
Controls		none
First-stage *F*		1.7

IV Estimation of $\mathrm{D}_{h,i2}$ with additional controls -1

$$Y_{i,t+h} = \mathrm{D}_{h,i1} Y_{1,t} + \{\varepsilon_{t+h}, \ldots, \varepsilon_{t+1}, \varepsilon_{2:n_\varepsilon,t}, \varepsilon_{t-1}, \ldots\}$$

2 Motivations for adding controls:

(1) eliminate part of error term

- controls should be uncorrelated with $\varepsilon_{1,t}$.
  - Examples: lags of Z, Y, other macro variables, 'factors,' etc., leads of Z.

(2) Z_t may be correlated with error, but uncorrelated after adding controls

(a) *Example:* GK-Z = $\{\Delta FFF_t, \Delta FFF_{t-1}\}$. *Add lags of FFF_t.*

IV Estimation of $\mathrm{D}_{h,i1}$ with additional controls - 2

$$Y_{i,t+h} = \mathrm{D}_{h,i1} Y_{1,t} + \gamma' W_t + u_t$$

$$x_t^{\perp} = x_t - \mathrm{Proj}(x_t \mid W_t)$$

Condition LP-IV$^{\perp}$

(i) $E\left(\varepsilon_{1,t}^{\perp} Z_t^{\perp\prime}\right) = \alpha' \neq 0$

(ii) $E\left(\varepsilon_{2:n_\varepsilon,t}^{\perp} Z_t^{\perp\prime}\right) = 0$

(iii) $E\left(\varepsilon_{t+j}^{\perp} Z_t^{\perp\prime}\right) = 0$ for $j \neq 0$.

Results for [R and 100 ×ln(IP)]

$$Y_{i,t+h} = \mathrm{D}_{h,i1} Y_{1,t} + \gamma' W_t + \{\varepsilon_{t+h}, \ldots, \varepsilon_{t+1}, \varepsilon_{2:n_\varepsilon,t}, \varepsilon_{t-1}, \ldots\}$$

	lag (h)	(a)	(b)	(c)
R	0	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)
	6	-0.07 (1.34)	1.12 (0.52)	0.67 (0.57)
	12	-1.05 (2.51)	0.78 (1.02)	-0.12 (1.07)
	24	-2.09 (5.66)	-0.80 (1.53)	-1.57 (1.48)
IP	0	-0.59 (0.71)	0.21 (0.40)	0.03 (0.55)
	6	-2.15 (3.42)	-3.80 (3.14)	-4.05 (3.65)
	12	-3.60 (6.23)	-6.70 (4.70)	-6.86 (5.49)
	24	-2.99 (10.21)	-9.51 (7.70)	-8.13 (7.62)
Controls		none	4 lags of (*z*,*y*)	4 lags of (*z*,*y*,*factors*)
First-stage *F*		1.7	23.7	18.6

Results for [R and 100 ×ln(IP)]

$$Y_{i,t+h} = \mathrm{D}_{h,i1} Y_{1,t} + \gamma' W_t + \{\varepsilon_{t+h}, \ldots, \varepsilon_{t+1}, \varepsilon_{2:n_\varepsilon,t}, \varepsilon_{t-1}, \ldots\}$$

	lag (h)	(a)	(b)	(c)
R	0	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)
	6	-0.07 (1.34)	1.12 (0.52)	0.67 (0.57)
	12	-1.05 (2.51)	0.78 (1.02)	-0.12 (1.07)
	24	-2.09 (5.66)	-0.80 (1.53)	-1.57 (1.48)
IP	0	-0.59 (0.71)	0.21 (0.40)	0.03 (0.55)
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	12	-3.60 (6.23)	-6.70 (4.70)	-6.86 (5.49)
	24	-2.99 (10.21)	-9.51 (7.70)	-8.13 (7.62)
Controls		none	4 lags of (z,y)	4 lags of (z,y,*factors*)
First-stage *F*		1.7	23.7	18.6

Results for [R and 100 ×ln(IP)]

$$Y_{i,t+h} = \mathrm{D}_{h,i1} Y_{1,t} + \gamma' W_t + \{\varepsilon_{t+h}, \ldots, \varepsilon_{t+1}, \varepsilon_{2:n_\varepsilon,t}, \varepsilon_{t-1}, \ldots\}$$

	lag (h)	(a)	(b)	(c)
R	0	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)
	6	-0.07 (1.34)	1.12 (0.52)	0.67 (0.57)
	12	-1.05 (2.51)	0.78 (1.02)	-0.12 (1.07)
	24	-2.09 (5.66)	-0.80 (1.53)	-1.57 (1.48)
IP	0	-0.59 (0.71)	0.21 (0.40)	0.03 (0.55)
	6	-2.15 (3.42)	-3.80 (3.14)	-4.05 (3.65)
	12	-3.60 (6.23)	-6.70 (4.70)	-6.86 (5.49)
	24	-2.99 (10.21)	-9.51 (7.70)	-8.13 (7.62)
Controls		none	4 lags of (*z,y*)	4 lags of (*z,y,factors*)
First-stage *F*		1.7	23.7	18.6

SVARs with External Instruments - 1

VAR: $Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + \eta_t$

Structural MA: $Y_t = H\varepsilon_t + D_1\, \varepsilon_{t-1} + \ldots = D(L)\varepsilon_t$

($D_0 = H$ in notation above)

Invertibility: $\varepsilon_t = \text{Proj}(\varepsilon_t | Y_t, Y_{t-1}, \ldots)$

$\Rightarrow$

$\eta_t = H\varepsilon_t$ with H nonsingular (so $n_y = n_\varepsilon$)

SVARs with External Instruments - 2

$$A(L)Y_t = \nu_t = D_0\varepsilon_t$$

$$\Rightarrow \; Y_t = C(L)H\varepsilon_t \text{ with } C(L)=A(L)^{-1}$$

$$\text{thus } D_{h,i1} = C_h H_{i1}$$

Unit-effect normalization yields: $\eta_{i,t} = H_{i1}\,\eta_{1,t} + \{\varepsilon_{2:n_\varepsilon,t}\}$

Condition SVAR-IV

(i) $E(\varepsilon_{1,t}Z_t) = \alpha \neq 0$

(ii) $E(\varepsilon_{2:n_\varepsilon,t}Z_t') = 0$

SVAR with external instruments – estimation

1. Regress $Y_{i,t}$ onto $Y_{1,t}$ using instruments Z_t and p lags of Y_t as controls. This yields $\hat{H}_{i1}$.

2. Estimate a VAR(p) and invert the VAR to obtain $\hat{C}(\mathrm{L}) = \hat{A}(\mathrm{L})^{-1}$.

3. Estimate the dynamic causal effects of shock 1 on the vector of variables as

$$\hat{D}_{h,1} = \hat{\mathrm{C}}_h \hat{H}_1$$

(odds and ends: (1) News shocks; (2) Dif. sample periods in (1) and (2))

SVAR with external instruments – inference

- Strong instruments:

$$\sqrt{T}\begin{pmatrix} \hat{A} - A \\ \hat{H}_1 - H_1 \end{pmatrix} \xrightarrow{d} \text{Normal} + \delta\text{-method}$$

- Weak instruments:
  - $\sqrt{T}(\hat{A} - A) \xrightarrow{d}$ Normal.
  - $\hat{H}_1 - H_1 \xrightarrow{d}$ NonNormal.
  - Use weak-instrument robust methods. (Montiel Olea, Stock and Watson (2018)).

Results for [R and $100 \times \ln(IP)$]

	lag (h)	LP-IV *1990m1-2012m6*	SVAR-IV *IV: 1990m1-2012m6* *VAR:1980m7-2012m6*
R	0	1.00 (0.00)	1.00 (0.00)
	6	1.12 (0.52)	0.89 (0.31)
	12	0.78 (1.02)	0.78 (0.46)
	24	-0.80 (1.53)	0.40 (0.49)
IP	0	0.21 (0.40)	0.16 (0.59)
	6	-3.80 (3.14)	-0.81 (1.19)
	12	-6.70 (4.70)	-1.87 (1.54)
	24	-9.51 (7.70)	-2.16 (1.65)
Controls		4 lags of (Z, Y)	12 lags of Y 4 lags of Z
First-stage F		23.7	20.5

Results for [R and $100 \times \ln(IP)$]

	lag (h)	**LP-IV** *1990m1-2012m6*	**SVAR-IV** *IV: 1990m1-2012m6* *VAR:1980m7-2012m6*
R	0	1.00 (0.00)	1.00 (0.00)
	6	1.12 (0.52)	0.89 (0.31)
	12	0.78 (1.02)	0.78 (0.46)
	24	-0.80 (1.53)	0.40 (0.49)
IP	0	0.21 (0.40)	0.16 (0.59)
	6	-3.80 (3.14)	-0.81 (1.19)
	12	-6.70 (4.70)	-1.87 (1.54)
	24	-9.51 (7.70)	-2.16 (1.65)
Controls		4 lags of (Z, Y)	12 lags of Y 4 lags of Z
First-stage F		23.7	20.5

SDFM
SVAR analysis, but now using DFM

SVAR problems that the DFM might solve:

(a) Many variable, thus invertibility is more plausible.

(b) Errors-in-variables, several indicators for same theoretical concept ('aggregate prices','oil prices', etc.)

(c) Framework for computing IRFs from structural shocks to many variables.

Can't I just do a VAR? .. No

Table 5 Approximating the eight-factor DFM by a eight-variable VAR

	Canonical correlation							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
(A) Innovations								
VAR-A	0.76	0.64	0.6	0.49				
VAR-B	0.83	0.67	0.59	0.56	0.37	0.33	0.18	0.01
VAR-C	0.86	0.81	0.78	0.76	0.73	0.58	0.43	0.35
VAR-O	0.83	0.80	0.69	0.56	0.50	0.26	0.16	0.02
(B) Variables and factors								
VAR-A	0.97	0.85	0.79	0.57				
VAR-B	0.97	0.95	0.89	0.83	0.61	0.43	0.26	0.10
VAR-C	0.98	0.93	0.90	0.87	0.79	0.78	0.57	0.41
VAR-O	0.98	0.96	0.88	0.84	0.72	0.39	0.18	0.02

Notes: All VARs contain four lags of all variables. The canonical correlations in panel A are between the VAR residuals and the residuals of a VAR estimated for the eight static factors.

VAR-A was chosen to be typical of four-variable VARs seen in empirical applications. Variables: GDP, total employment, PCE inflation, and Fed funds rate.

VAR-B was chosen to be typical of eight-variable VARs seen in empirical applications. Variables: GDP, total employment, PCE inflation, Fed funds, ISM manufacturing index, real oil prices (PPI-oil), corporate paper-90-day treasury spread, and 10 year–3 month treasury spread.

VAR-C variables were chosen by stepwise maximization of the canonical correlations between the VAR innovations and the static factor innovations. Variables: industrial commodities PPI, stock returns (SP500), unit labor cost (NFB), exchange rates, industrial production, Fed funds, labor compensation per hour (business), and total employment (private).

VAR-O variables: real oil prices (PPI-oil), global oil production, global commodity shipment index, GDP, total employment (private), PCE inflation, Fed funds rate, and trade-weighted US exchange rate index.

Entries are canonical correlations between (A) factor innovations and VAR residuals and (B) factors and observable variables.

The SDFM:

$$\underset{t}{\overset{n\times 1}{X}} = \overset{n\times r}{\Lambda}\, \underset{t}{\overset{r\times 1}{F}} + \underset{t}{\overset{n\times 1}{e}}$$

$$\overset{r\times r}{\Phi(L)}\, \underset{t}{\overset{r\times 1}{F}} = \overset{r\times q}{G}\, \underset{t}{\overset{q\times 1}{\eta}}$$

where $\Phi(L) = I - \Phi_1 L - \ldots - \Phi_p L^p$,

$$\underset{t}{\overset{q\times 1}{\eta}} = \overset{q\times q}{H}\, \underset{t}{\overset{q\times 1}{\varepsilon}}$$

$X_t = \Lambda\Phi(L)^{-1}GH\varepsilon_t + e_t$

IRFs: $\Lambda\Phi(L)^{-1}GH$

IRF from ε_{1t}: $\Lambda\Phi(L)^{-1}GH_1$

Three Normalizations

1. $\Lambda F_t = \Lambda PP^{-1} F_t$ for any matrix P. Set P rows of Λ equal to rows of identity matrix. Rearranging the order of the Xs this yields

$$\begin{pmatrix} X_{1:r} \\ X_{r+1:n} \end{pmatrix}_t = \begin{pmatrix} I_r \\ \Lambda_{r+1:n} \end{pmatrix} F_t + e_t$$

This 'names' the first factor as the X_1 factor, the second factor as the X_2 factor and so forth. Example: $X_{1,t}$ is the logarithm of oil prices, then $F_{1,t}$ is called the oil price factor.

2. G = I (if $q = r$) or $G_{1:q} = I_q$ if $q < r$. Recall

$$X_t = \lambda(L)f_t + e_t \text{ and } \phi(L)f_t = \eta_t$$

$$X_t = \begin{pmatrix} \lambda_0 & \lambda_1 & \cdots & \lambda_k \end{pmatrix} \begin{pmatrix} f_t \\ f_{t-1} \\ \vdots \\ f_{t-k} \end{pmatrix} + e_t$$

$$\begin{pmatrix} f_t \\ f_{t-1} \\ \vdots \\ f_{t-k} \end{pmatrix} = \begin{bmatrix} \phi_1 & \phi_2 & \cdots & \phi_{k+1} \\ 1 & 0 & \cdots & 0 \\ & \ddots & \ddots & \\ & & 1 & 0 \end{bmatrix} \begin{pmatrix} f_{t-1} \\ f_{t-2} \\ \vdots \\ f_{t-k-1} \end{pmatrix} + \begin{pmatrix} I \\ 0 \\ \vdots \\ 0 \end{pmatrix} \eta_t$$

where f_t and η_t are $q \times 1$.

3. The diagonal elements of H are unity. That is, ε_{1t} has a unit effect of $F_{1,t}$ and so forth. Same as in SVAR.

Putting these together:

$X_{1:q,t} = H\varepsilon_t$ + lags of $\varepsilon_t + e_t$

(Same normalization used in SVAR, but only applied to the first q elements of X_t).

$F_{1:q,t} = H\varepsilon_t$ + lags of ε_t

etc.

This means that everything in SVARs carry over here.

Additional flexibility in SDFM

(1) Measurement error allowed: With normalization, F follows SVAR, and $X = \Lambda F + e$.

(2) Multiple measurements: Example Oil prices

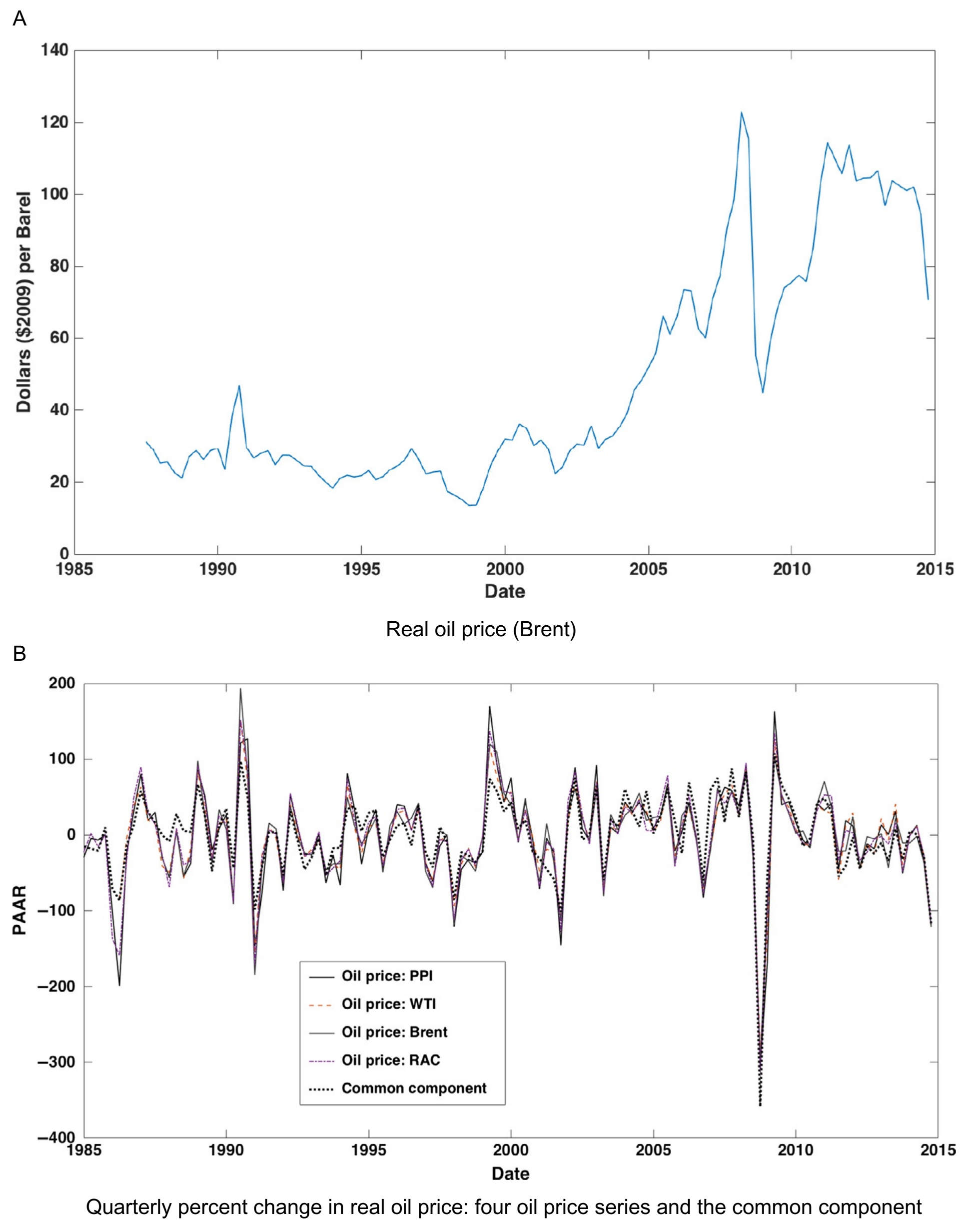


Fig. 7 Real oil price (2009 dollars) and its quarterly percent change.

$$\begin{bmatrix} p_t^{PPI-Oil} \\ p_t^{Brent} \\ p_t^{WTI} \\ p_t^{RAC} \\ X_{5:n,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ & \Lambda_{5:n} & & \end{bmatrix} \begin{bmatrix} F_t^{oil} \\ F_{2:r,t} \end{bmatrix} + e_t$$

(3) "Factor Augmented" VAR) (FAVAR) (Bernanke, Boivin, Eliasz (2005))

Easily implemented in this framework:

$$\begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \begin{pmatrix} 1 & 0_{1\times r} \\ \multicolumn{2}{c}{\Lambda} \end{pmatrix} \begin{pmatrix} \tilde{F}_t \\ F_t \end{pmatrix} + \begin{pmatrix} 0 \\ e_t \end{pmatrix}$$

$$F_t^+ = \Phi(L) F_{t-1}^+ + G\eta_t$$

where

$$F_t^+ = \begin{pmatrix} \tilde{F}_t \\ F_t \end{pmatrix},$$

$$\eta_t = H\varepsilon_t.$$

Example: Macroeconomic Effects of Oil Supply Shocks

2 Identifications:

(1) Oil Price exogenous

$$\eta_t = \begin{pmatrix} 1 & 0 \\ H_{\bullet 1} & H_{\bullet\bullet} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{oil} \\ \tilde{\eta}_{\bullet t} \end{pmatrix}$$

$$\begin{bmatrix} p_t^{PPI-Oil} \\ p_t^{Brent} \\ p_t^{WTI} \\ p_t^{RAC} \\ X_{5:n,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ \lambda_{21} & \lambda_{22} & \lambda_{23} & \cdots & \lambda_{28} \\ \lambda_{31} & & & \cdots & \lambda_{38} \\ \lambda_{41} & & & \cdots & \lambda_{48} \\ \Lambda_{5:n} & & & & \end{bmatrix} \begin{bmatrix} F_t^{oilprice} \\ F_{2,t} \\ F_{3,t} \\ \vdots \\ F_{8,t} \end{bmatrix} + \begin{bmatrix} e_t^{PPI-oil} \\ e_t^{Brent} \\ e_t^{WTI} \\ e_t^{RAC} \\ e_t^{X} \end{bmatrix}$$

SVAR, FAVAR and SDFM versions

(2) Killian (2009) Identification

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ H_{12} & 1 & 0 & 0 \\ H_{13} & H_{23} & 1 & 0 \\ H_{1\bullet} & H_{2\bullet} & H_{3\bullet} & H_{\bullet\bullet} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{OS} \\ \varepsilon_t^{GD} \\ \varepsilon_t^{OD} \\ \tilde{\eta}_{\bullet t} \end{pmatrix}$$

$$\begin{bmatrix} GlobalActivity_t \\ p_t^{PPI-Oil} \\ p_t^{Brent} \\ p_t^{WTI} \\ p_t^{RAC} \\ X_{7:n,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & 0 & \cdots & 0 \\ \Lambda_{8:n} & & & & & \end{bmatrix} \begin{bmatrix} F_t^{Globalactivity} \\ F_t^{oilprice} \\ F_{4:r,t} \end{bmatrix} + e_t$$

Some Results

Table 6 Fraction of the variance explained by the eight factors at horizons $h = 1$ and $h = 6$ for selected variables: 1985:Q1–2014:Q4

Variable	$h = 1$	$h = 6$
GDP	0.60	0.80
Consumption	0.37	0.76
Fixed investment	0.38	0.76
Employment (non-ag)	0.56	0.94
Unemployment rate	0.44	0.90
PCE inflation	0.70	0.63
PCE inflation—core	0.10	0.34
Fed funds rate	0.48	0.71
Real oil price	0.74	0.78
Oil production	0.06	0.27
Global commodity shipment index	0.39	0.51
Real gasoline price	0.72	0.80

Oil Price Exogenous

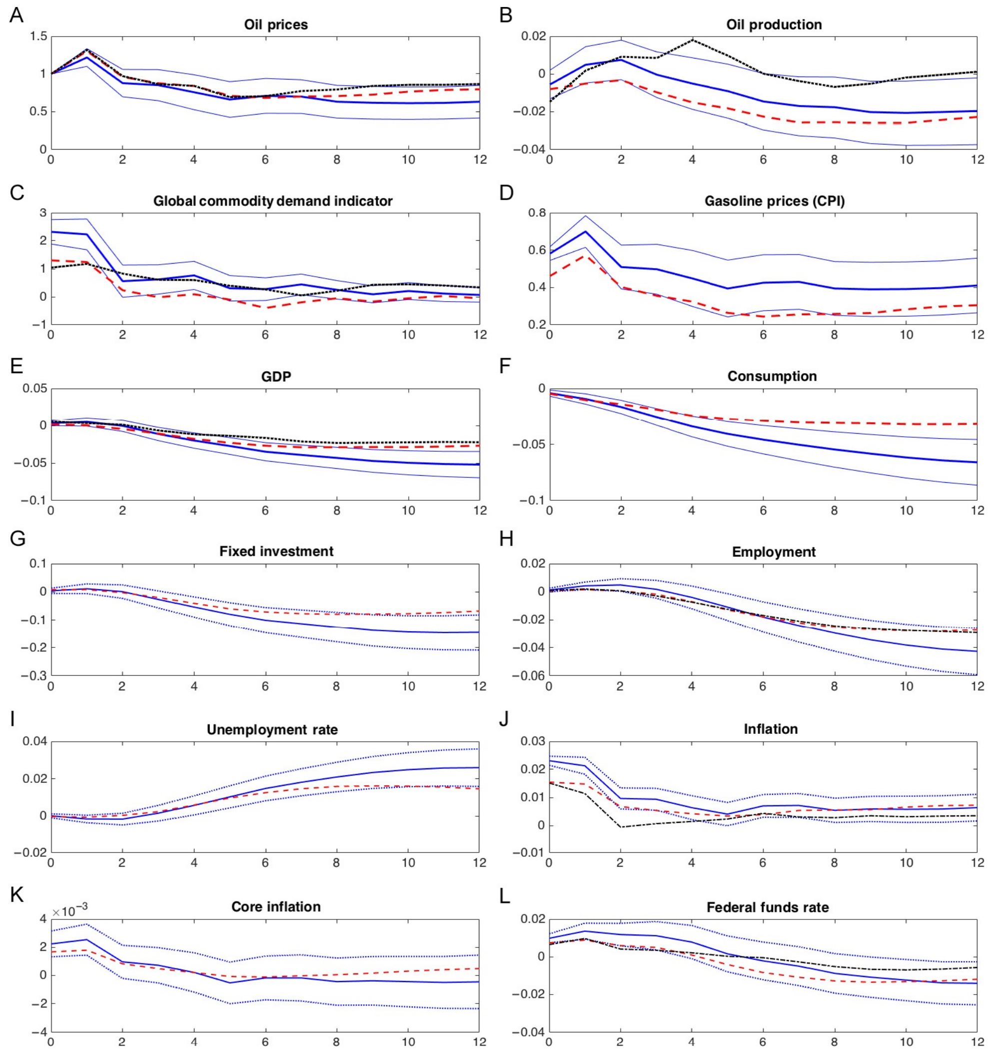


Fig. 8 Structural IRFs from the SDFM (*blue* (*dark gray* in the print version) *solid* with ±1 standard error bands), FAVAR (*red* (*gray* in the print version) *dashed*), and SVAR (*black dots*) for selected variables with respect to an oil price shock: "oil prices exogenous" identification. Units: standard deviations for Global Commodity Demand and percentage points for all other variables.

Killian identification IRFs (see paper)

Variance Explained:

Table 7 Forecast error variance decompositions for six periods ahead forecasts of selected variables: FAVARs and SDFMs

	A. Oil price exogenous		B. Kilian (2009) identification					
			Oil supply		Global demand		Oil spec. demand	
Variable	**F**	**D**	**F**	**D(O)**	**F**	**D(U)**	**F**	**D(U)**
GDP	0.07	0.07	0.04	0.01	0.02	0.04	0.09	0.04
Consumption	0.19	0.22	0.09	0.08	0.02	0.22	0.11	0.01
Fixed investment	0.04	0.04	0.05	0.04	0.03	0.04	0.03	0.01
Employment (non-ag)	0.03	0.02	0.04	0.01	0.02	0.01	0.03	0.01
Unemployment rate	0.04	0.03	0.04	0.03	0.02	0.03	0.04	0.01
PCE inflation	0.28	0.40	0.02	0.04	0.09	0.16	0.17	0.29
PCE inflation—core	0.05	0.04	0.01	0.02	0.03	0.05	0.02	0.02
Fed funds rate	0.02	0.04	0.00	0.01	0.05	0.11	0.03	0.02
Real oil price	0.81	0.53	0.14	0.10	0.22	0.44	0.42	0.09
Oil production	0.03	0.01	0.75	0.78	0.07	0.02	0.03	0.01
Global commodity shipment index	0.11	0.23	0.05	0.07	0.79	0.33	0.03	0.02
Real gasoline price	0.61	0.48	0.05	0.06	0.25	0.43	0.34	0.08

Notes: Entries are the fractions of the six periods ahead forecast error of the row variable explained by the column shock, for the "oil price exogenous" identification results (columns A) and the Kilian identification scheme (columns B). For each shock, "F" refers to the FAVAR treatment in which the factor is treated as observed and "D" refers to the SDFM treatment. In the hybrid SDFM using the Kilian (2009) identification scheme, the oil supply factor is treated as observed (the oil production variable) (D(O)) while the global demand and oil-specific demand factors are treated as unobserved (D(U)).

International Long-run Growth Dynamics

(work in progress)

Ulrich Müller, Jim Stock, Mark Watson

Central Bank of Chile, October 2018

Original motivation for work

Long-horizon predictive distributions for global GDP/Population as an input into determining the "Social Cost of Carbon" (SCC) from CO_2 emissions.

(SCC is used by regulators and others)

Reference: *NAS* (2017)

Damages are long-lived $\Rightarrow$ Predictive distributions over 100, 200, or more years.

Damages depend on location $\Rightarrow$ Joint predictive distributions for many countries.

Develop a statistical model for joint long-run dynamics for many countries

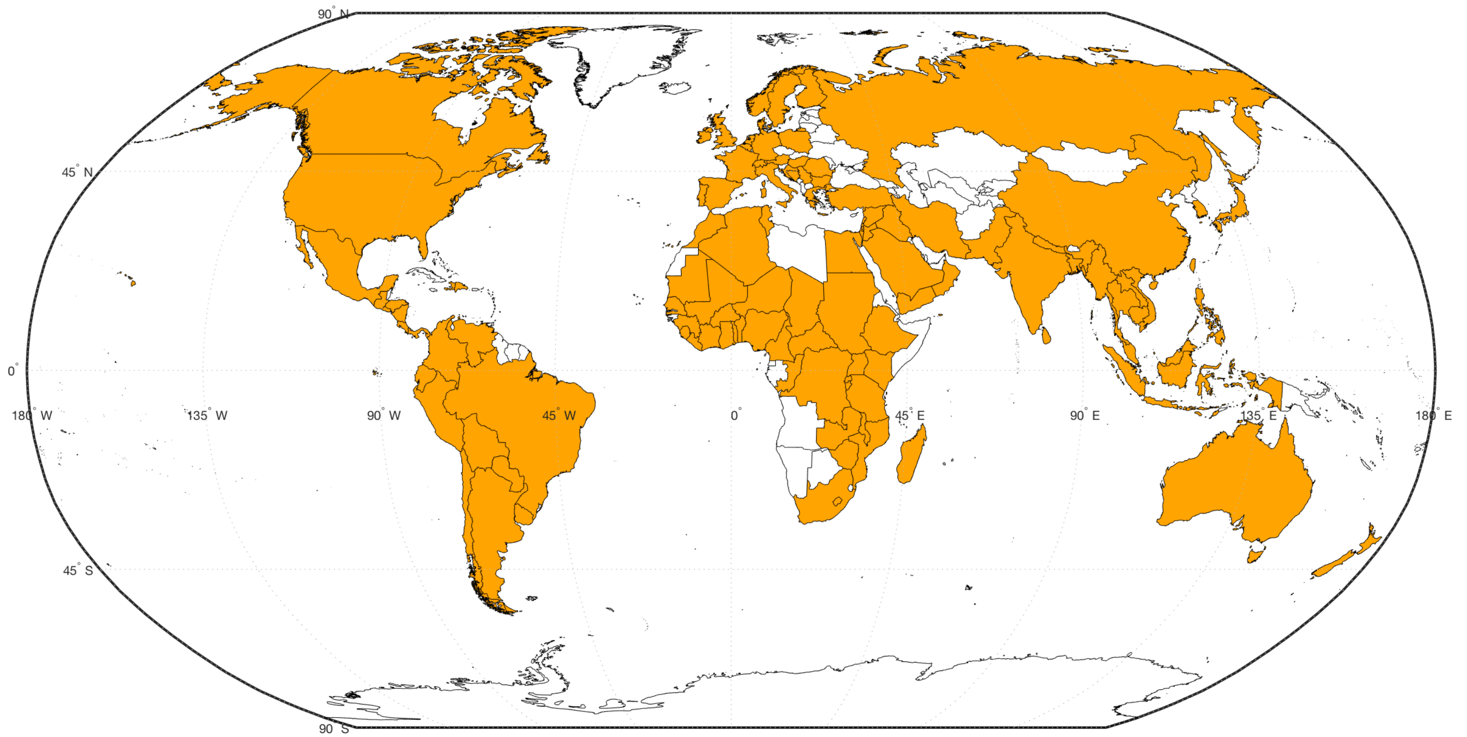
Useful for:

(1) Reduced form description of cross-country long-run growth dynamics (convergence, persistence of development gaps, etc.)

(2) Long-run international probabilistic forecasts (original motivation)

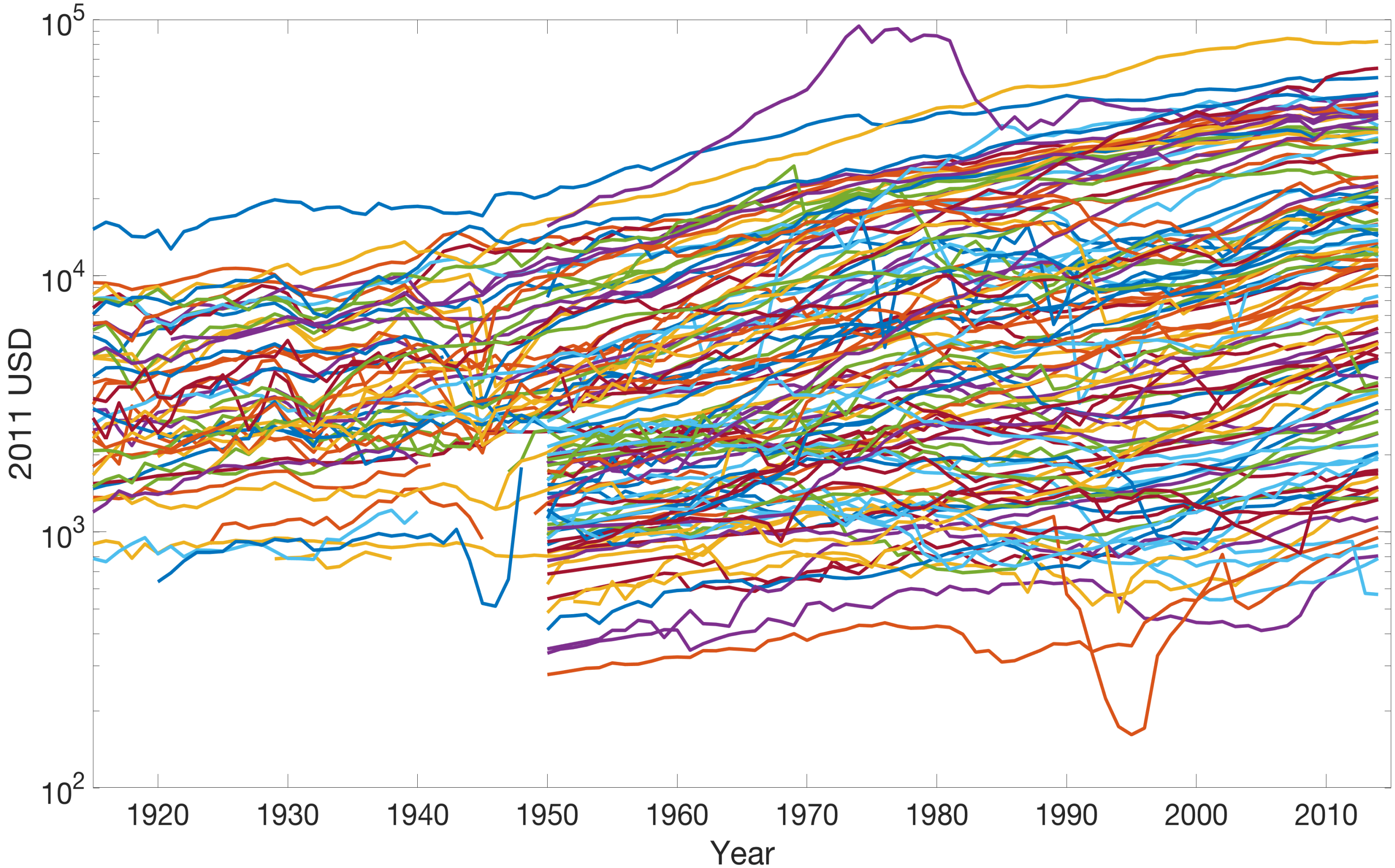
Data: Annual 1915-2014 for 112 countries

(Merged: PWT 1950-2014 and Maddison 1915-1949
countries with at least 50 years of post-1949 data and population > 3 million)

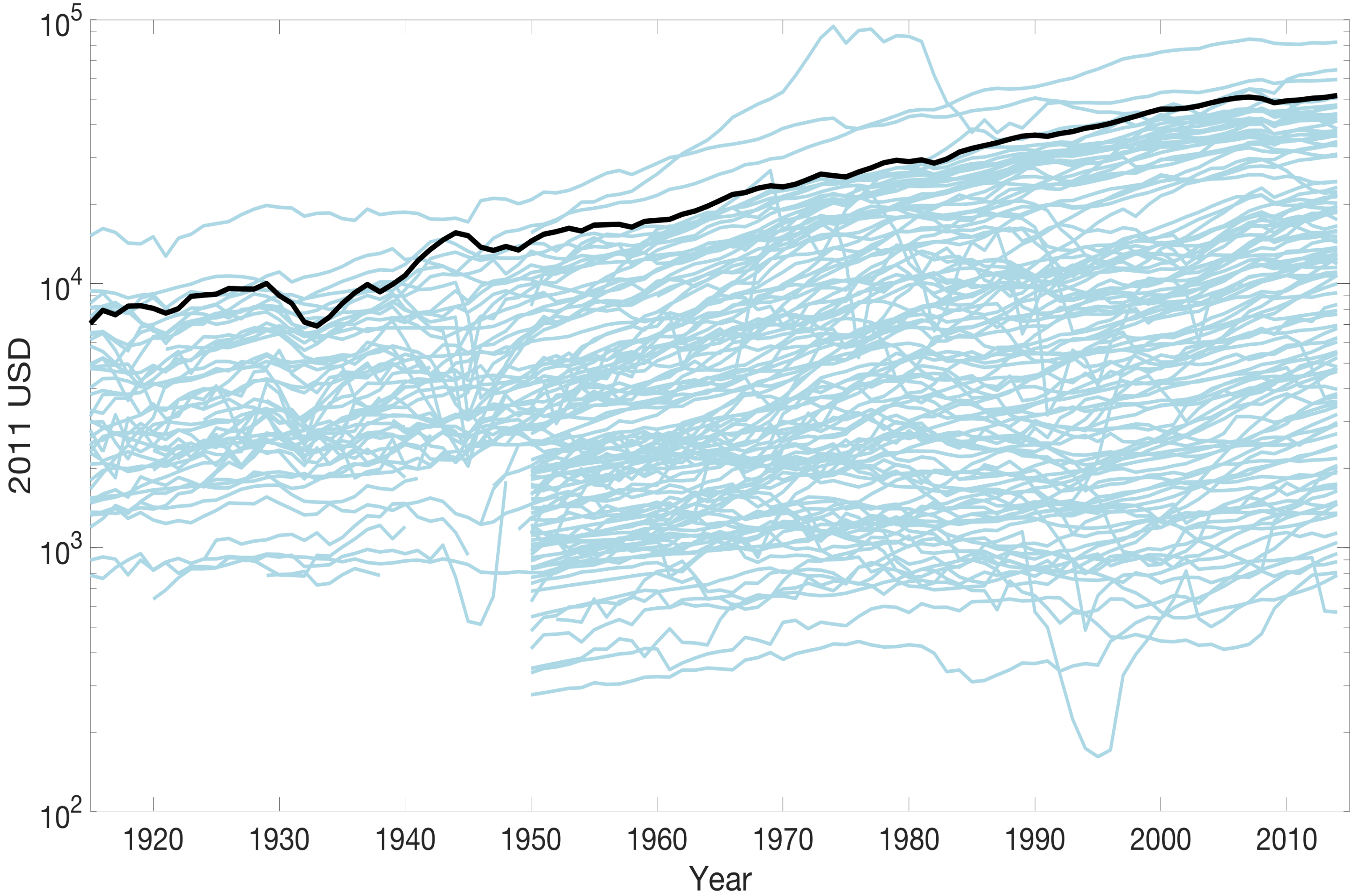


- 97% of World GDP in 2014 and 96% of World Population
- Unbalanced Panel (39-52 countries before 1950, 107 in 1950, 110 in 1952 and 112 in 1960)

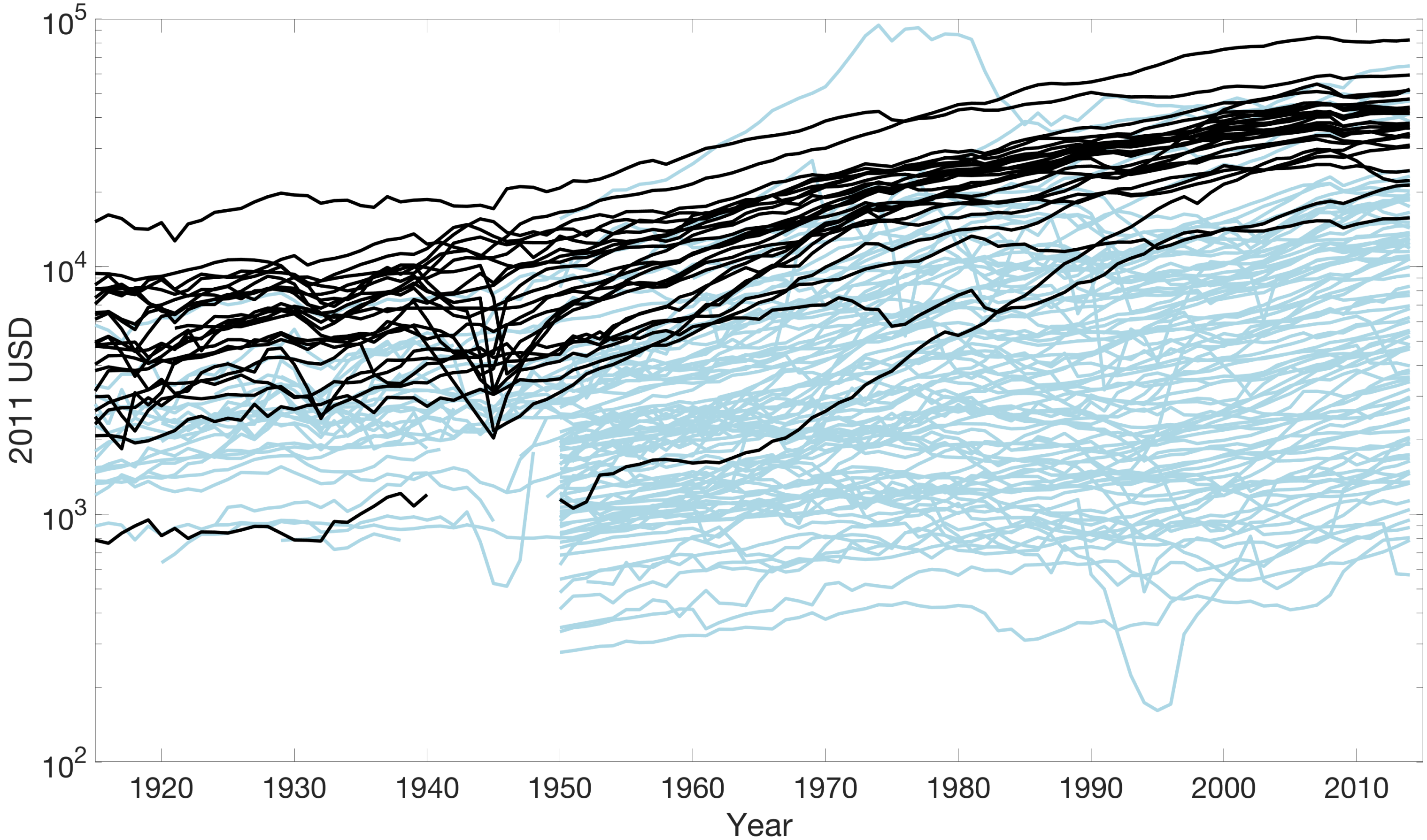
Data: GDP/Population for 112 countries



United States

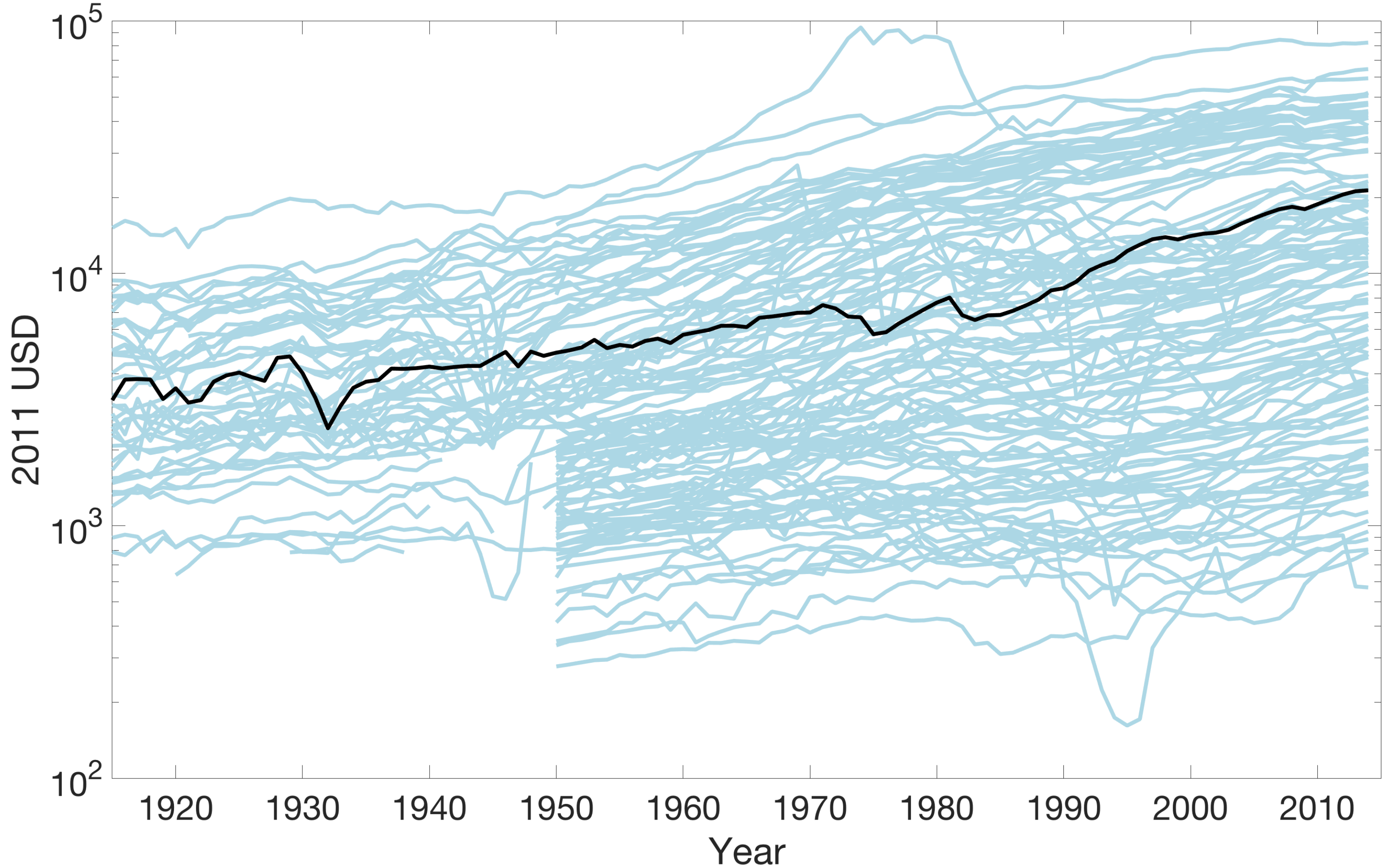


OECD



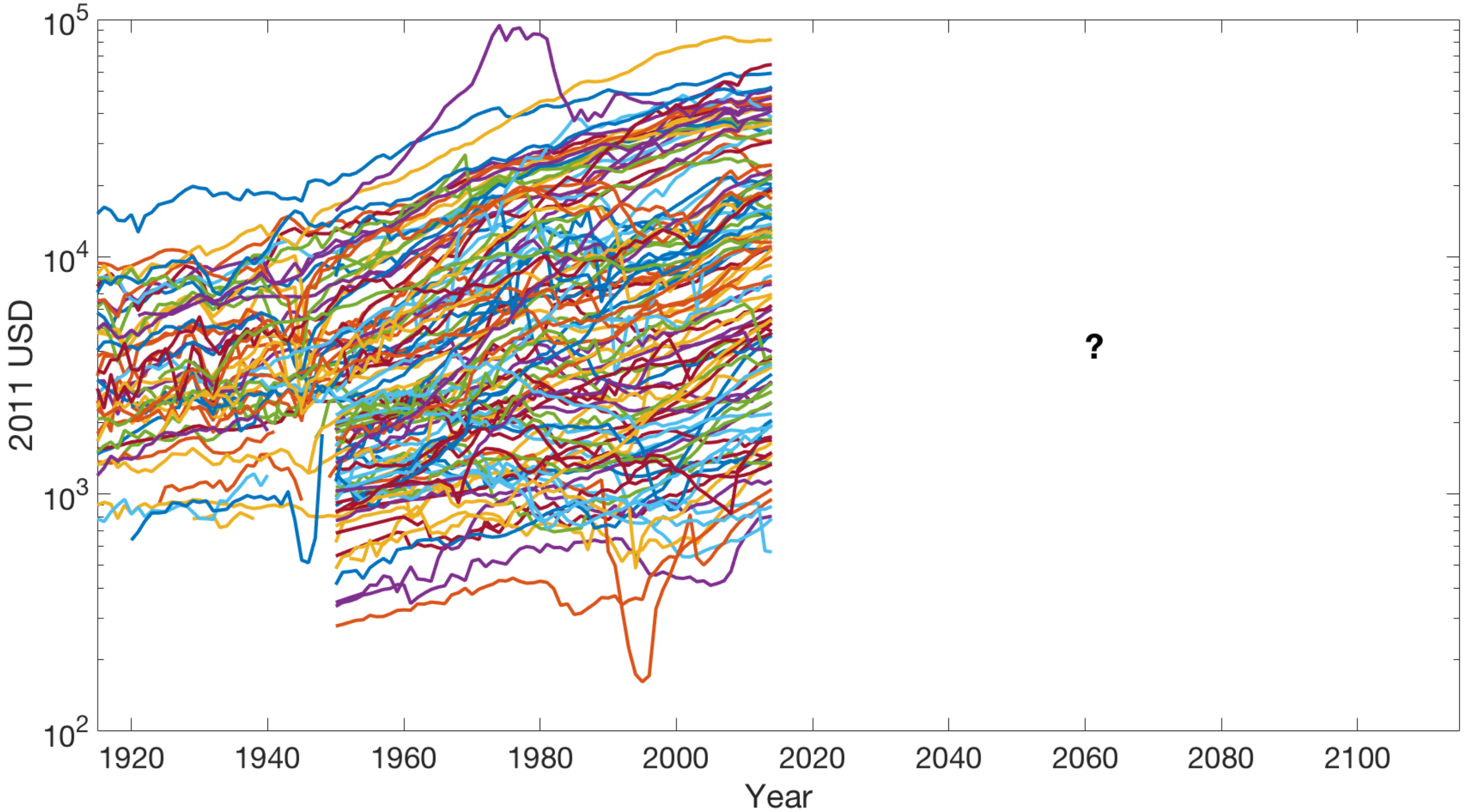
10^5
10^4
10^3
10^2
2011 USD
1920
1930
1940
1950
1960
1970
1980
1990
2000
2010
Year

Chile

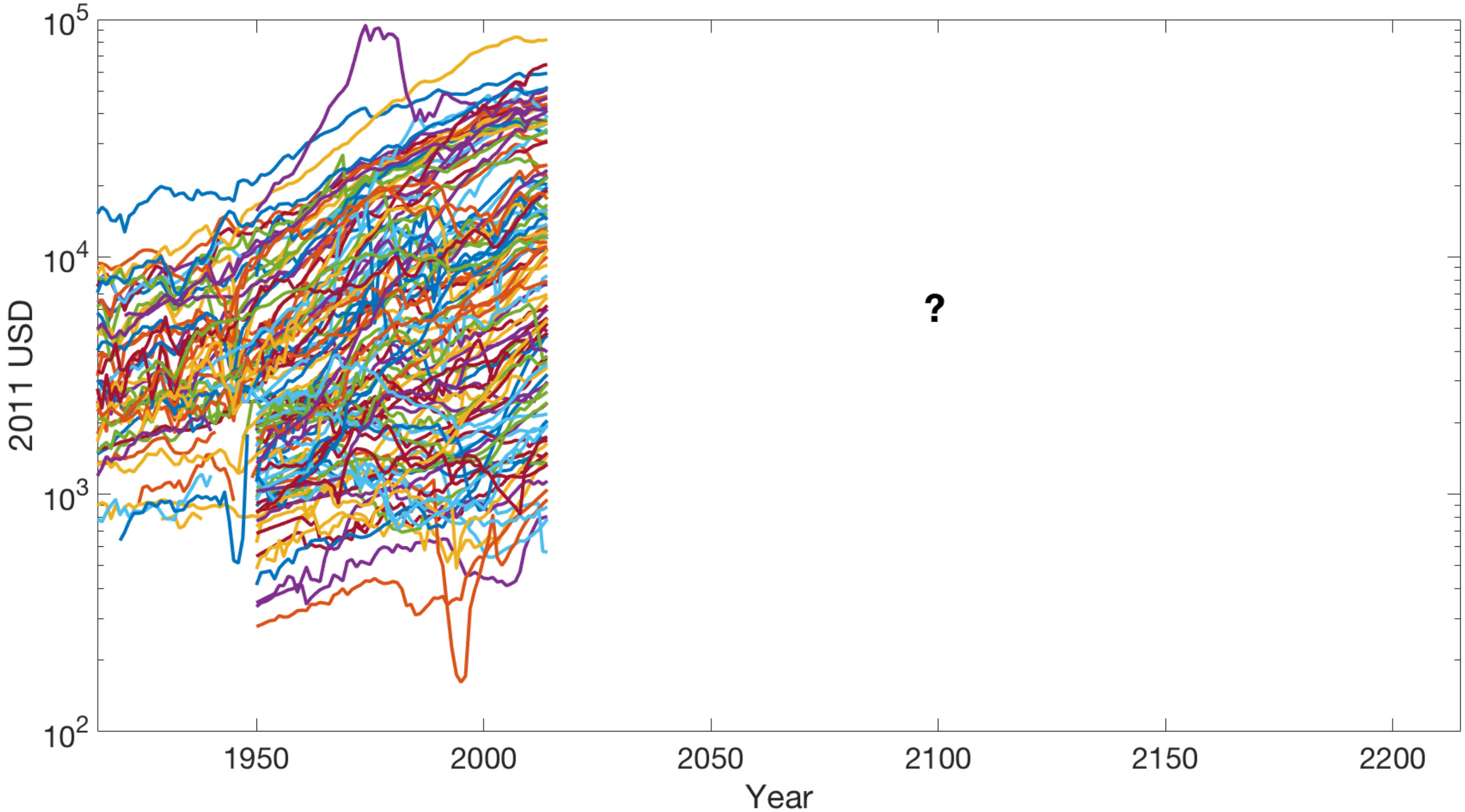


10^5
10^4
10^3
10^2
2011 USD
1920
1930
1940
1950
1960
1970
1980
1990
2000
2010
Year

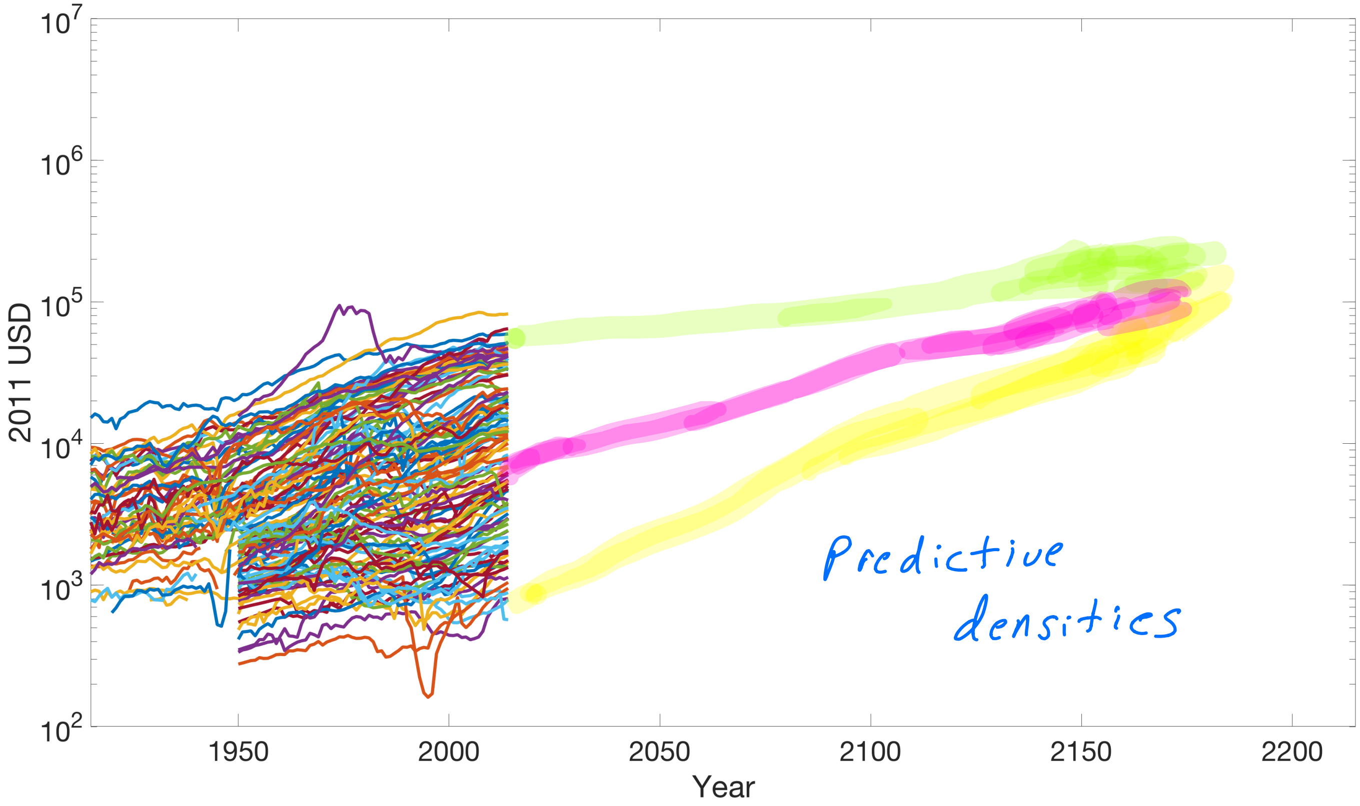
Long-Run Forecasting Problem

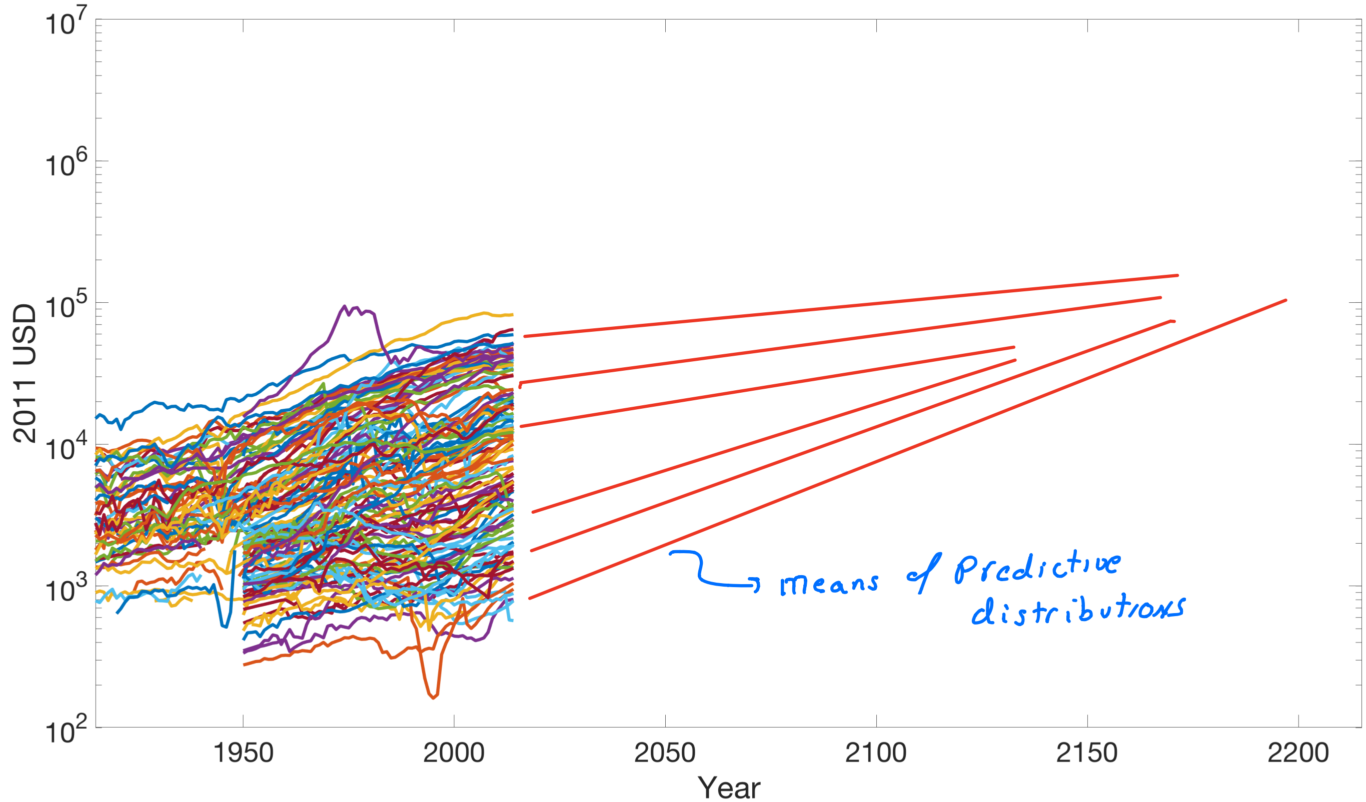


or

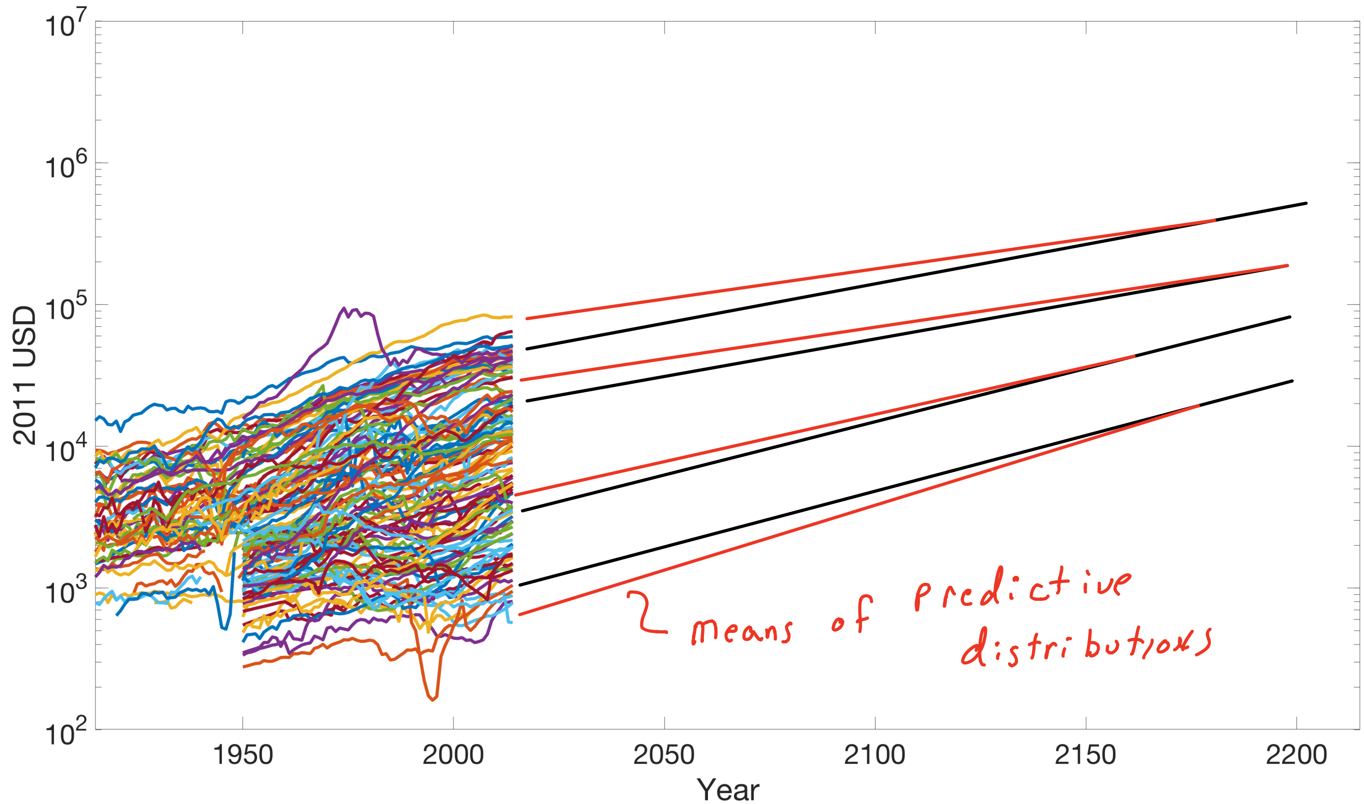


Convergence, persistence and comovement

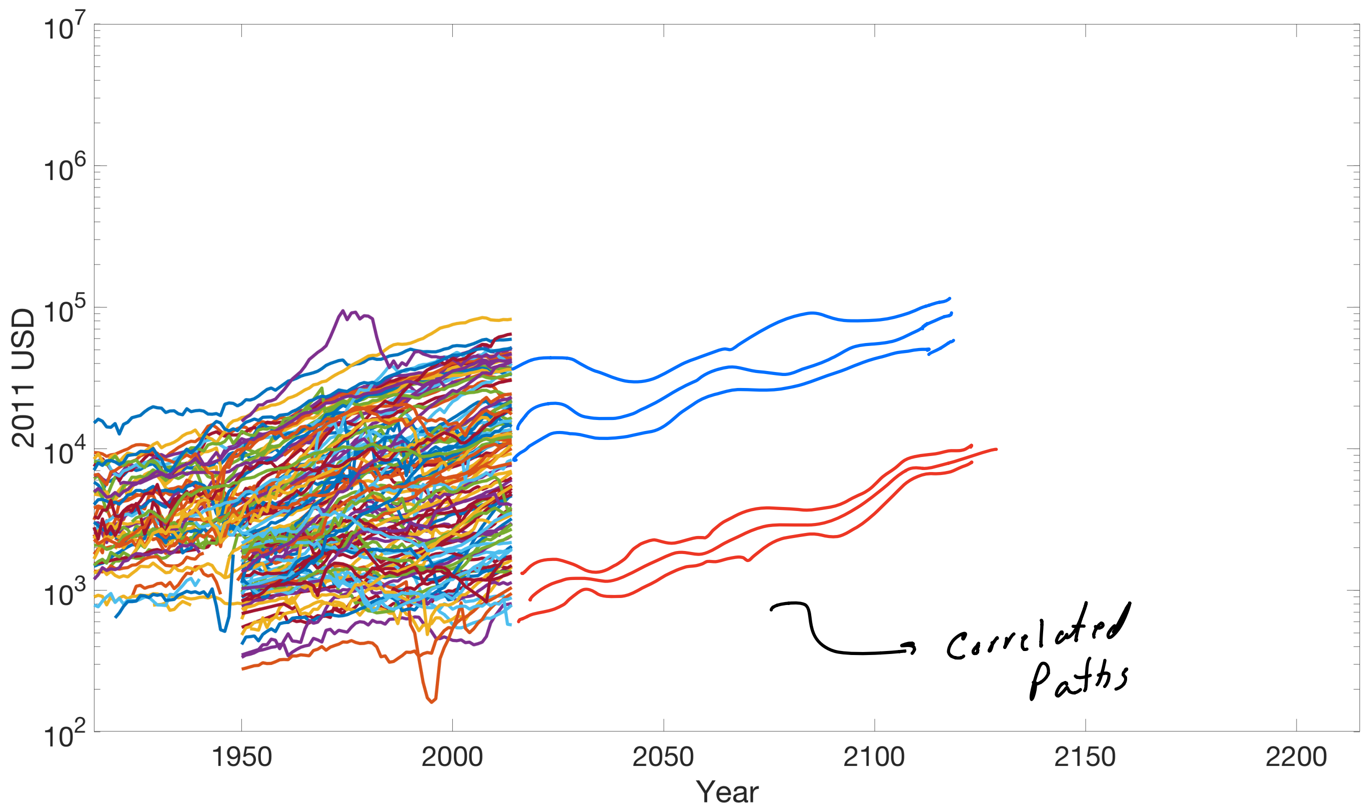




10^7
10^6
10^5
10^4
10^3
10^2
2011 USD
1950
2000
2050
2100
2150
2200
Year
means of Predictive distributions



10^7
10^6
10^5
10^4
10^3
10^2
2011 USD
1950
2000
2050
2100
2150
2200
Year
2 means of predictive distributions



10^7
10^6
10^5
10^4
10^3
10^2
2011 USD
1950
2000
2050
2100
2150
2200
Year
Correlated Paths

Outline:

1. Look at the data to determine sensible features of a model.

2. Simplification: focus on 'long-run' variation/covariation.

3. Detailed description of model.

4. Estimation mechanics

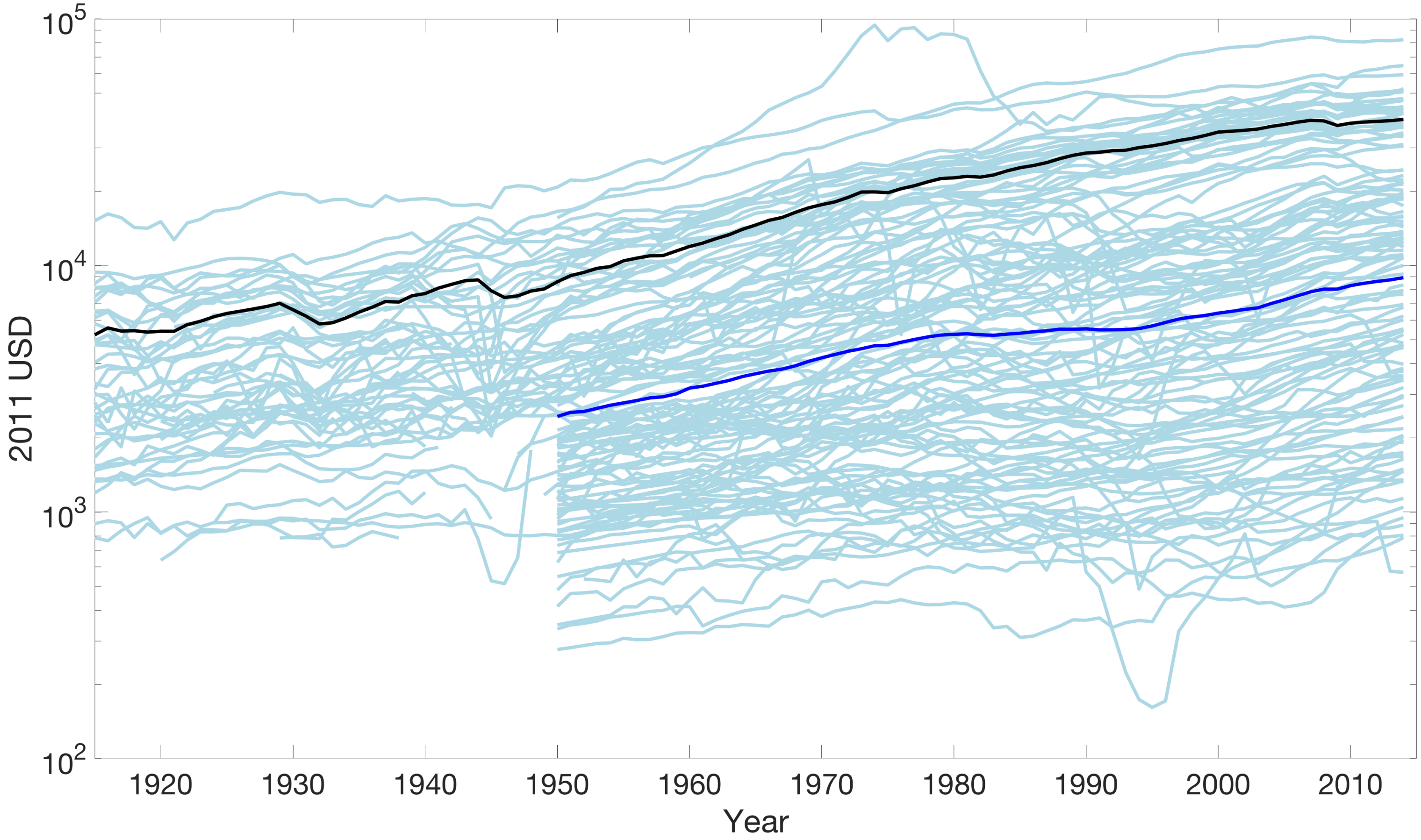
5. Results
    a. Convergence
    b. Long-run predictions

6. Different modelling choices

Notation: $\boldsymbol{Y_{it}}$ *= per-capita GDP for country i in year t.*

4 Features of the data and implications for modelling

Feature 1: "Common" Growth Factor



OECD and Average all countries

Model: $y_{it} = \ln(Y_{it})$

$$y_{it} = f_t + c_{it}$$

common global growth factor

country i factor

Feature 2: No reduction in cross-sectional dispersion

Medians, IQR and 90-10 range for histograms of y_{it}

Average value over	median	75th-25th	90th-10th
1950 - 1954	7.8	1.5	2.6
1960 - 1964	7.9	1.6	2.7
1985 - 1989	8.6	2.2	3.3
2010 - 2014	9.3	2.1	3.4

Model:

$$y_{it} = f_t + c_{it}$$

(long-run) variance of c_{it} is constant

(examined in more detail in *Different modeling choices* below)

Feature 3: Substantial persistence in cross section

Averages of y_{it} over 25+ year periods: Probability of moving from quartile i (1960-1987) to quartile j (1988-2014)

		Quartile in 1988-2014			
		1	2	3	4
Quartile in 1960-1987	1	0.786	0.214	0	0
	2	0.214	0.643	0.107	0.036
	3	0	0.143	0.714	0.143
	4	0	0	0.179	0.821

- Country in Q1; years until Prob(Q3 + Q4) > 0.25 $\approx$ 220 years
- Country in Q4: years until Prob(Q1 + Q2) > 0.25 $\approx$ 80 years

- Kremer, Onatski, Stock (2001) using 5 year transitions of relative income levels: Half-life = 285 years (Related: Quah (1993), Jones (1997, 2016))

Model:

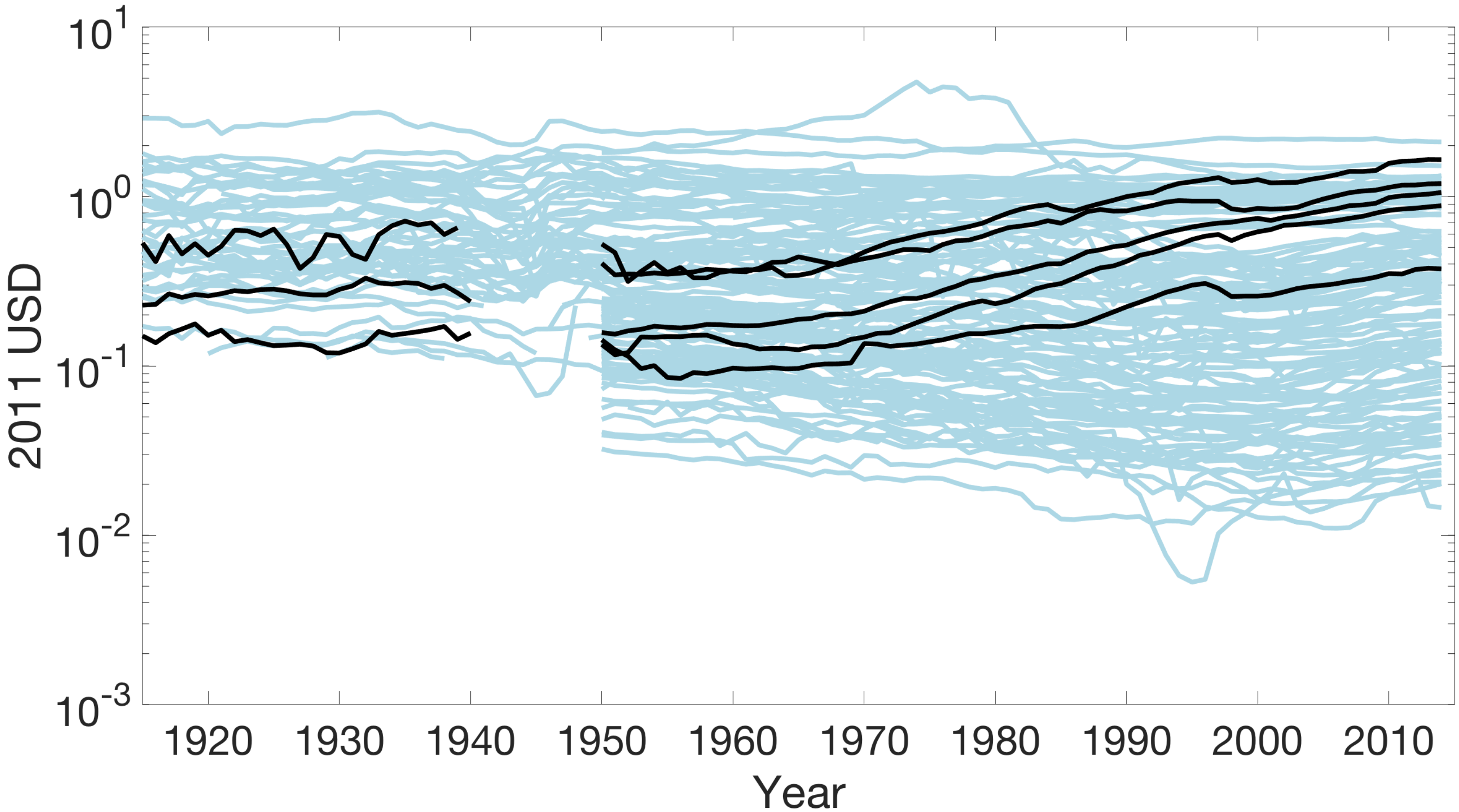
$$y_{it} = f_t + c_{it}$$

(long-run) variance of c_{it} is constant

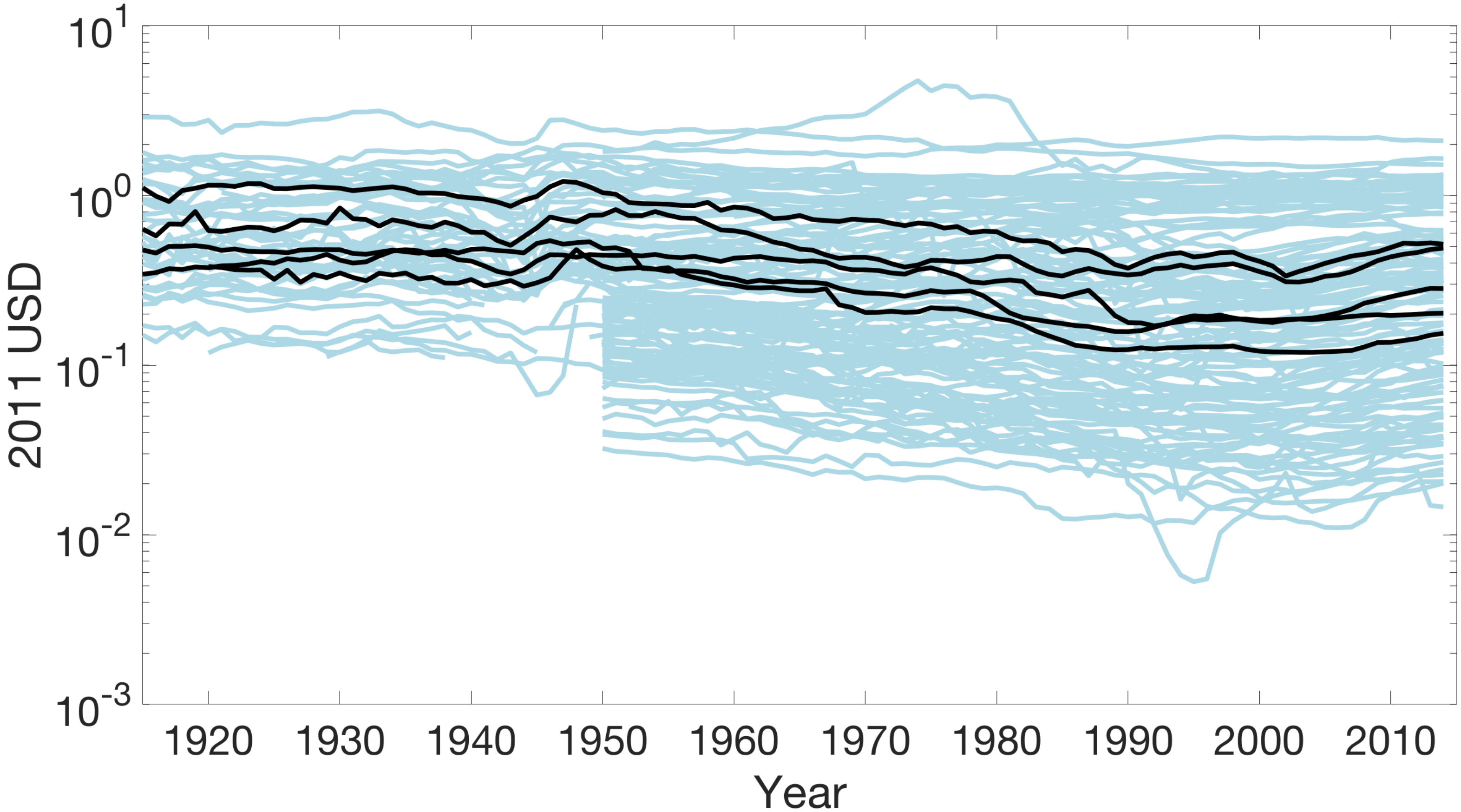
c_{it} is very persistent (but stationary)

Feature 4: Comovement of y_{it} within cross section

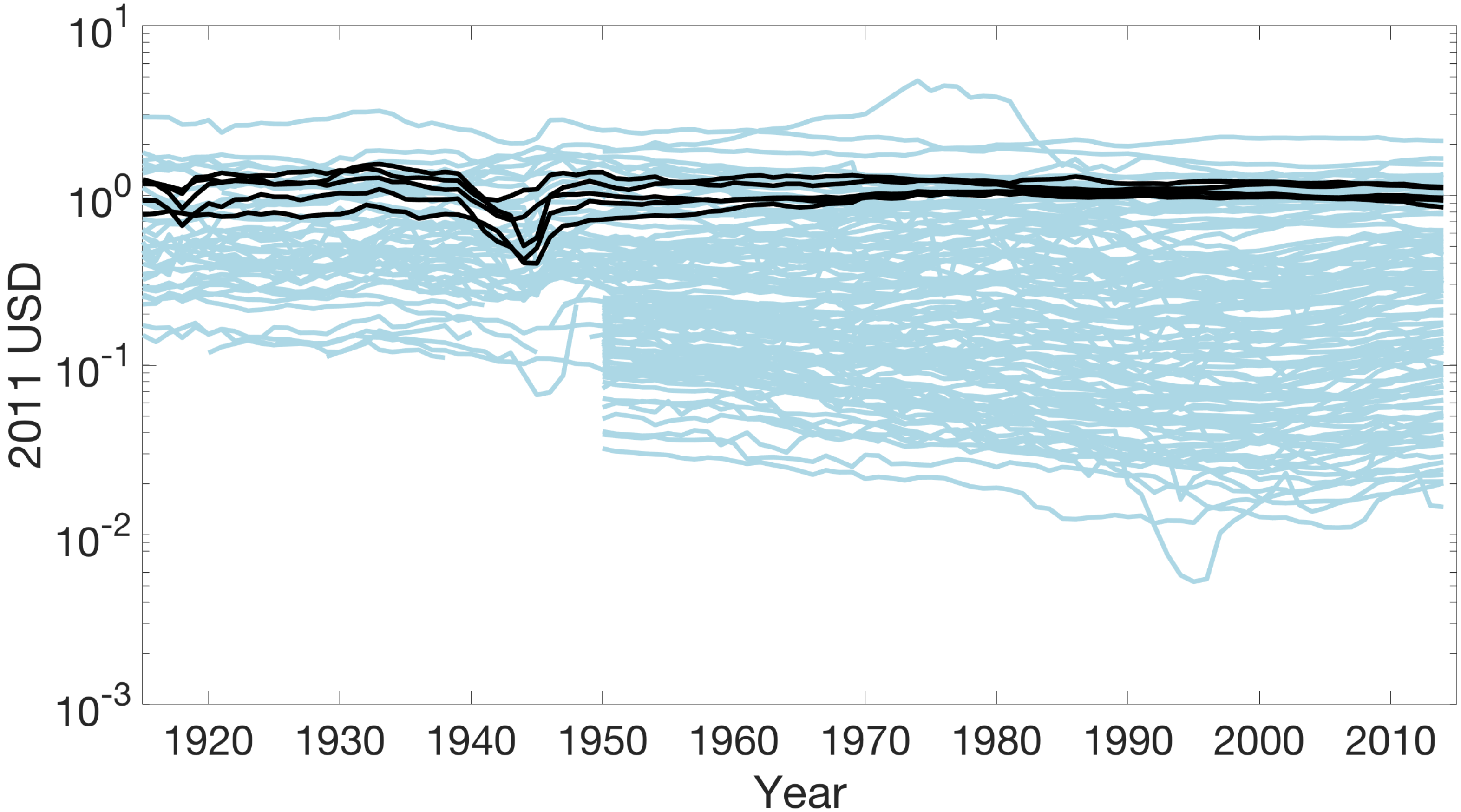
Examples:
(a) Hong Kong, South Korea, Singapore, Taiwan, Thailand



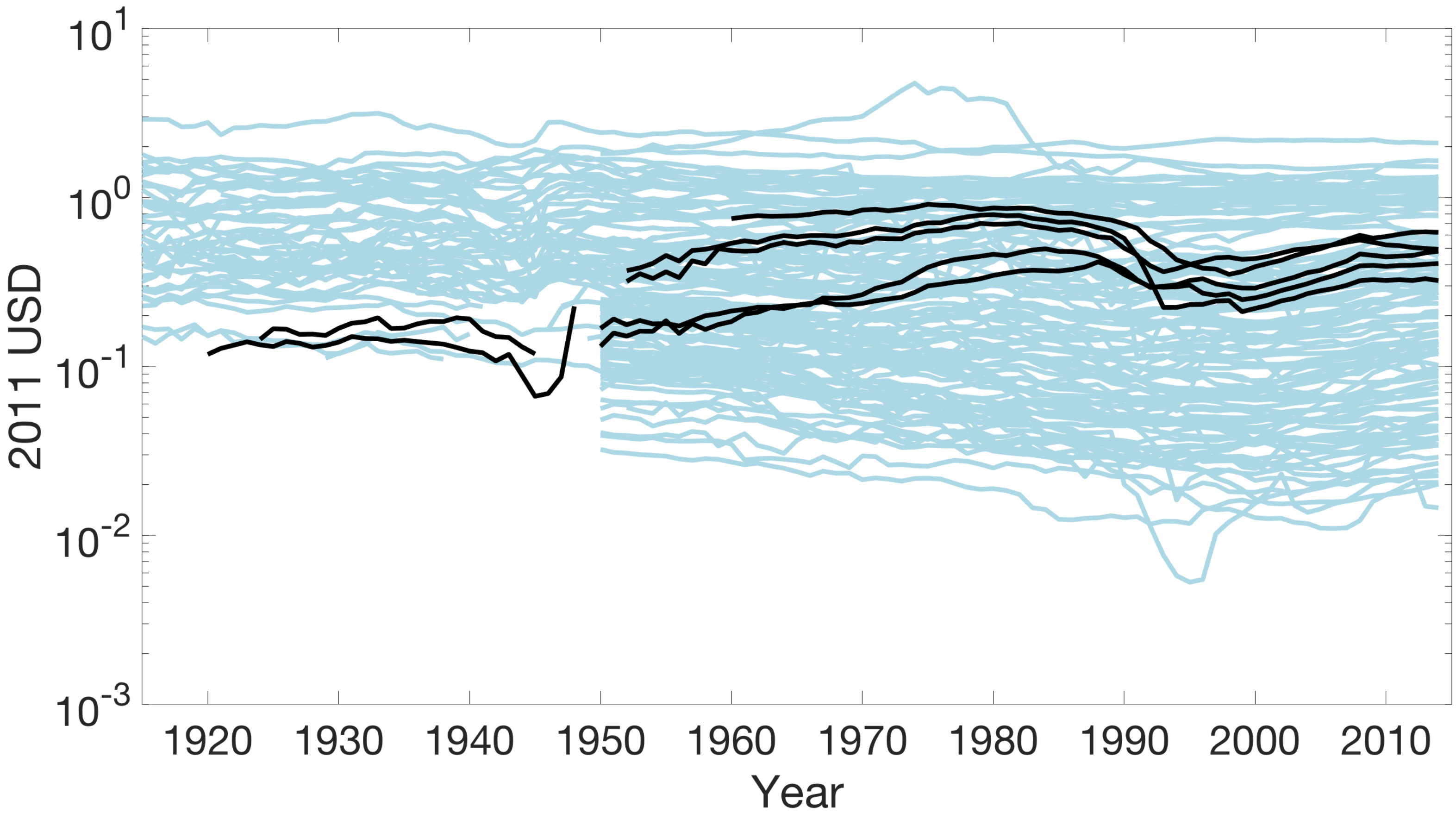
(b) Argentina, Bolivia, El Salvador, Uruguay, Peru



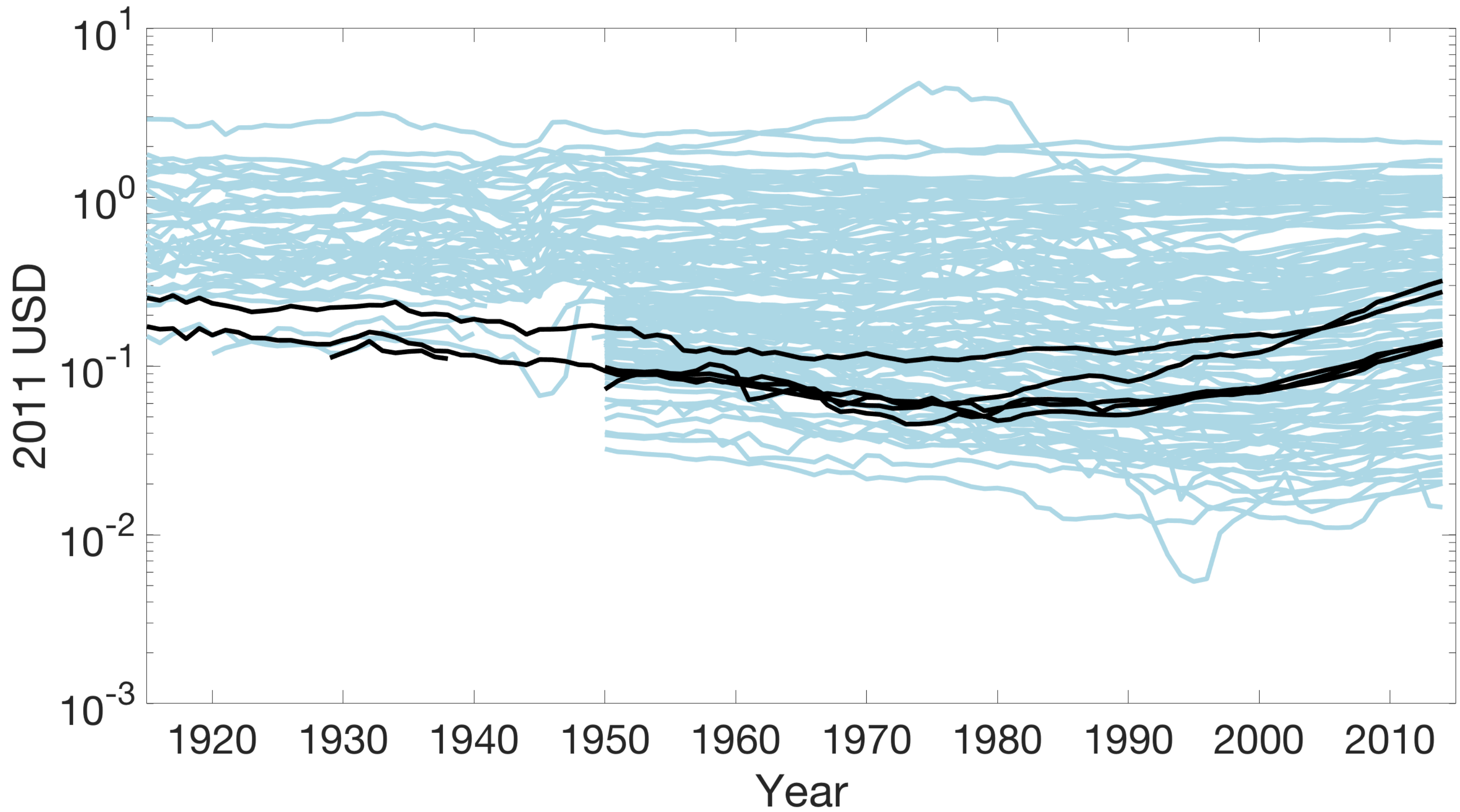
(c) Belgium, France, Italy, Netherlands, Denmark



(d) Bulgaria, Croatia, Russia, Serbia, Romania



(e) China, India, Laos, Sri Lanka, Vietnam



Model:

$$y_{it} = f_t + c_{it}$$

(long-run) variance of c_{it} is constant

c_{it} is very persistent (but stationary)

c_{it} is correlated within "groups"

Outline:

1. ~~Look at the data to determine some sensible features of a model.~~

2. **Simplify problem: focus on 'long-run' variation/covariation.**

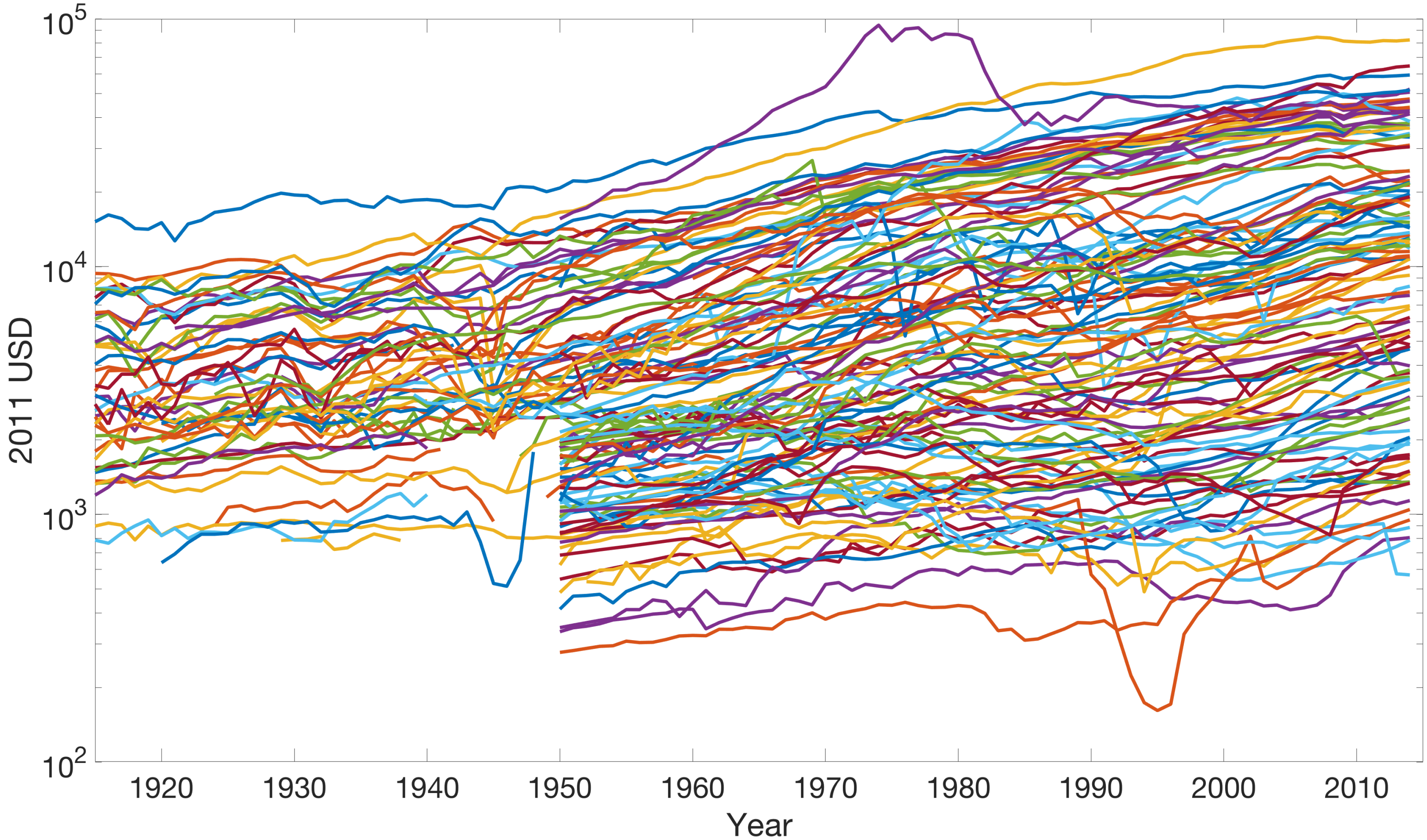
3. Detailed description of model.

4. Estimation mechanics

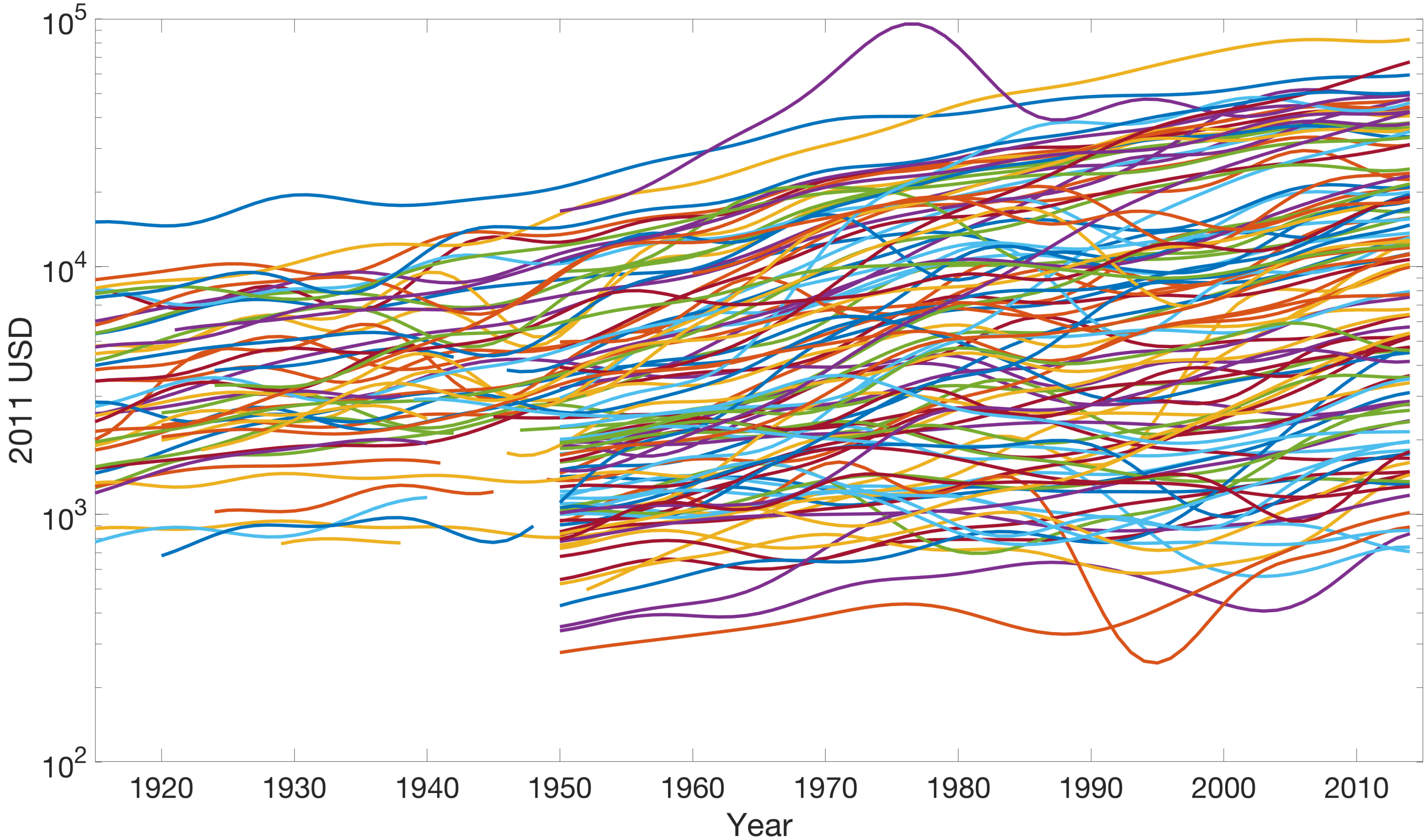
5. Results
    a. Convergence
    b. Long-run predictions

6. Different modelling choices

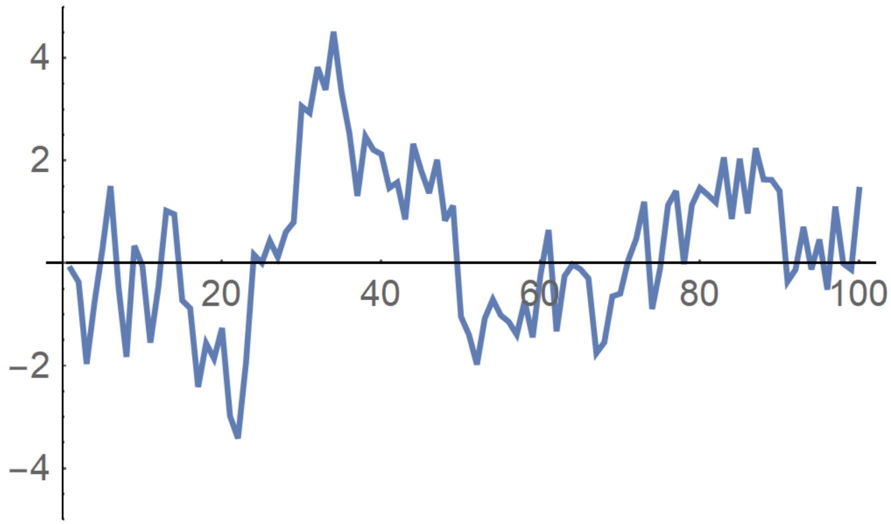
Original Data

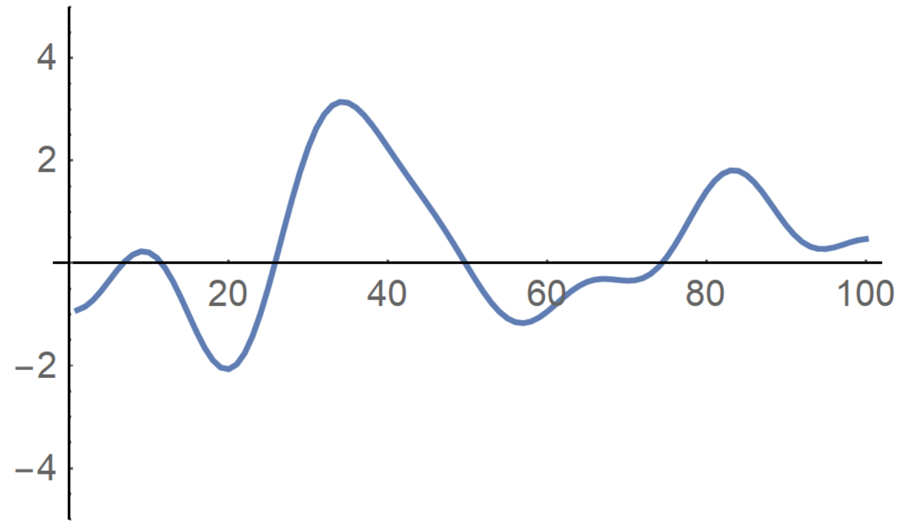


Low-Frequency Transformed Data

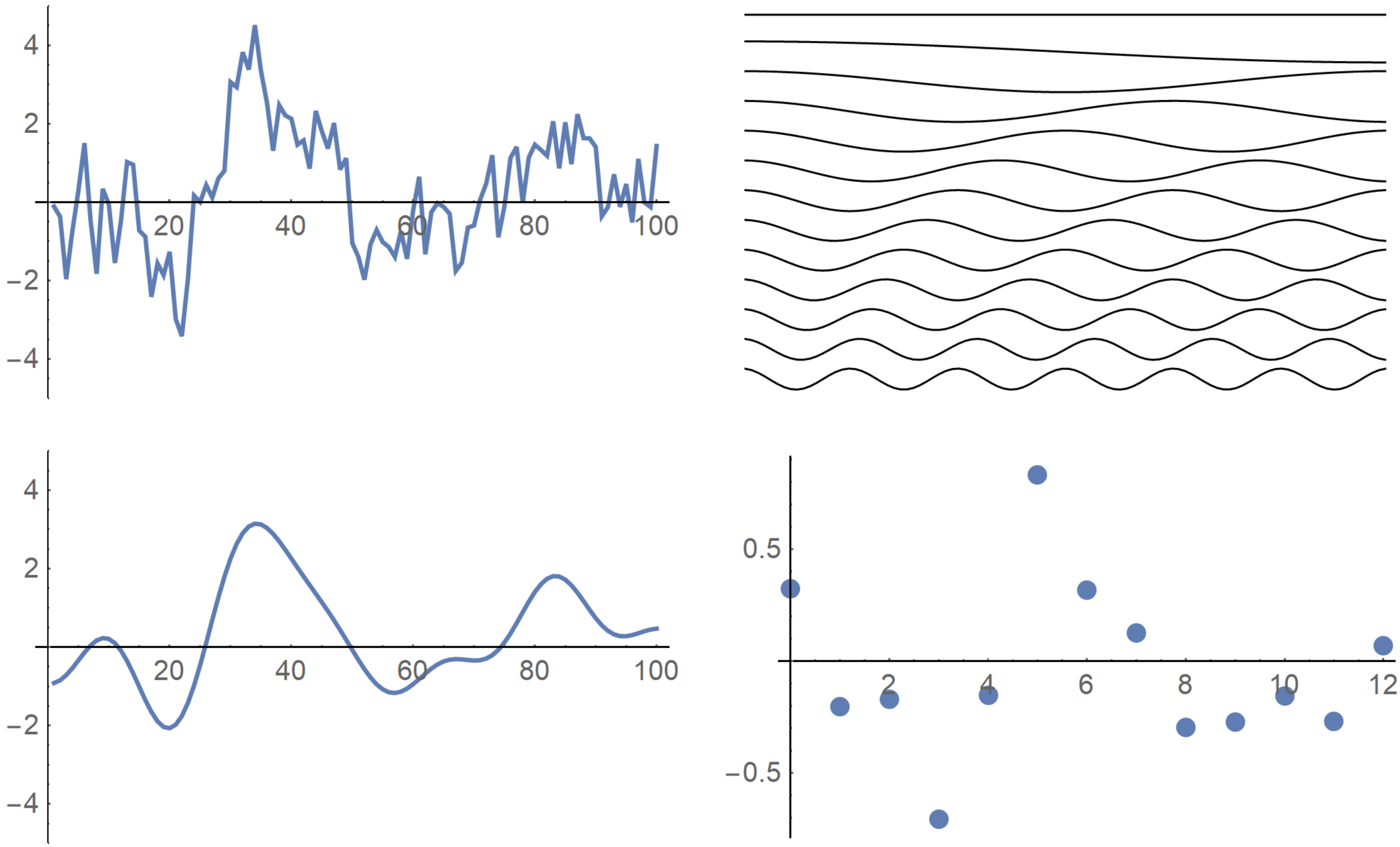


A Simplification: Focus on low-frequency variability in data

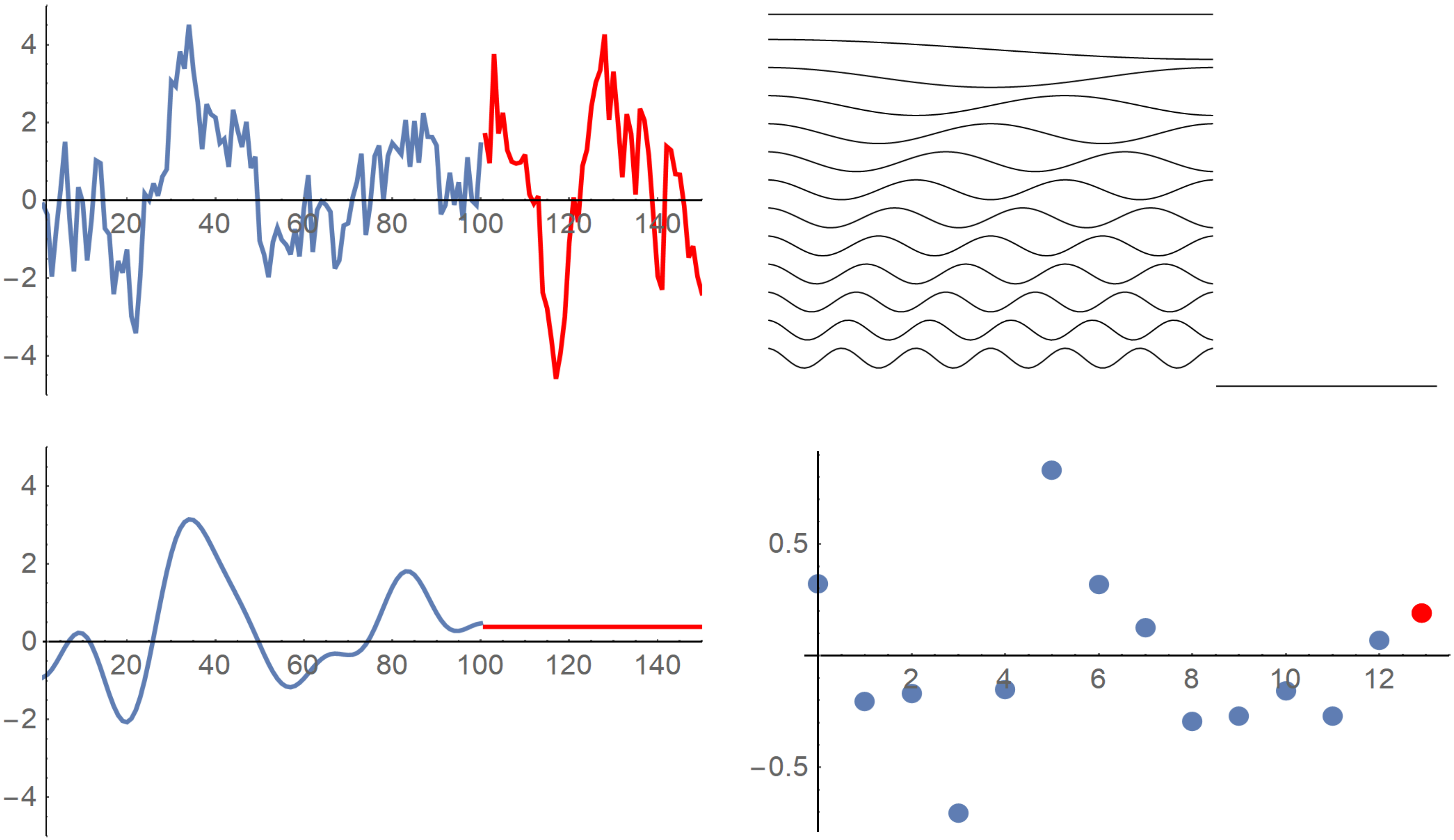




Low-frequency data compression



Implications for long-run forecasting:



Simplification: Focus on low-frequency variability in data

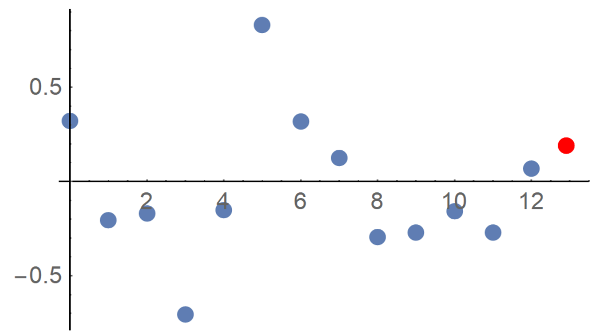
Selected Literature

- I(0): classic time series work on periodogram analysis, band-spectrum regression (Engle (1974)), etc.

- More recent:

    - Müller (2004): HAR/HAC inference ('Student-*t* inference', etc.)

    - Müller and Watson (2008), (2013), (2016), (2018)



Why is this a simplification ?

- Number of observations: (fewer dots than time series observations)

- Dots are "averages" of data $\Rightarrow$ *Normally distributed*
  - Rationalizes Gaussian likelihood
  - Prediction of future (red dot) from past (blue dots)

- Modelling: only low-frequency features of model matter

- Inference: $Y \sim \mathrm{N}(0,\Sigma(\theta))$ … inference about parameters of covariance matrix of normal

Outline:

1. ~~Look at the data to determine some sensible features of a model.~~

2. ~~Simplify problem: focus on 'long-run' variation/covariation.~~

3. **Detailed description of model**

4. Estimation mechanics

5. Results
   a. Convergence
   b. Long-run predictions

6. Different modelling choices

Details of model: Cross-country covariation:

$$y_{it} = f_t + c_{it}$$

$$c_{i,t} = \mu + \lambda_{c,i}\, g_{J(i),t} + u_{c,i,t}$$

$$g_{j,t} = \lambda_{g,j}\, h_{K(j),t} + u_{g,j,t}$$

"Clustered" factor model for c_{it} (Frühwirth-Schnatter and Kaufmann (2008), Hamilton and Owyang (2012), etc.) with added hierarchical structure.

Details of model: **Cross-country covariation**

$$y_{it} = f_t + c_{it}$$

$$c_{it} = \mu + \lambda_{c,i}\, \boldsymbol{g}_{\boldsymbol{J(i),t}} + u_{c,i,t}$$

- $\boldsymbol{g}_{\boldsymbol{J(i),t}}$ is a "group factor"
- Each country is a member of 1 group

$$g_{j,t} = \lambda_{g,j}\, h_{K(j),t} + u_{g,j,t}$$

Details of model: **Cross-country covariation**

$$y_{it} = f_t + c_{it}$$

$$c_{it} = \mu + \lambda_{c,i}\, \boldsymbol{g_{J(i),t}} + u_{c,i,t}$$

- $\boldsymbol{g_{J(i),t}}$ is a "group factor"
- Each country is a member of 1 group

$$\boldsymbol{g_{j,t}} = \lambda_{g,j}\, \boldsymbol{h_{K(j),t}} + u_{g,j,t}$$

- Correlation across groups
- $\boldsymbol{h_{K(j),t}}$ is a "group-of-group factor"
- Each group is a member of 1 group-of-group

Details of model: **Temporal Covariation**

(Note: Only low-frequency characteristics of model matter.)

$$y_{it} = f_t + c_{it}$$

$$f_t = f_0 + \underbrace{m_t}_{\text{local growth rate}} \times t + \underbrace{a_t}_{\text{deviation from local trend}}$$

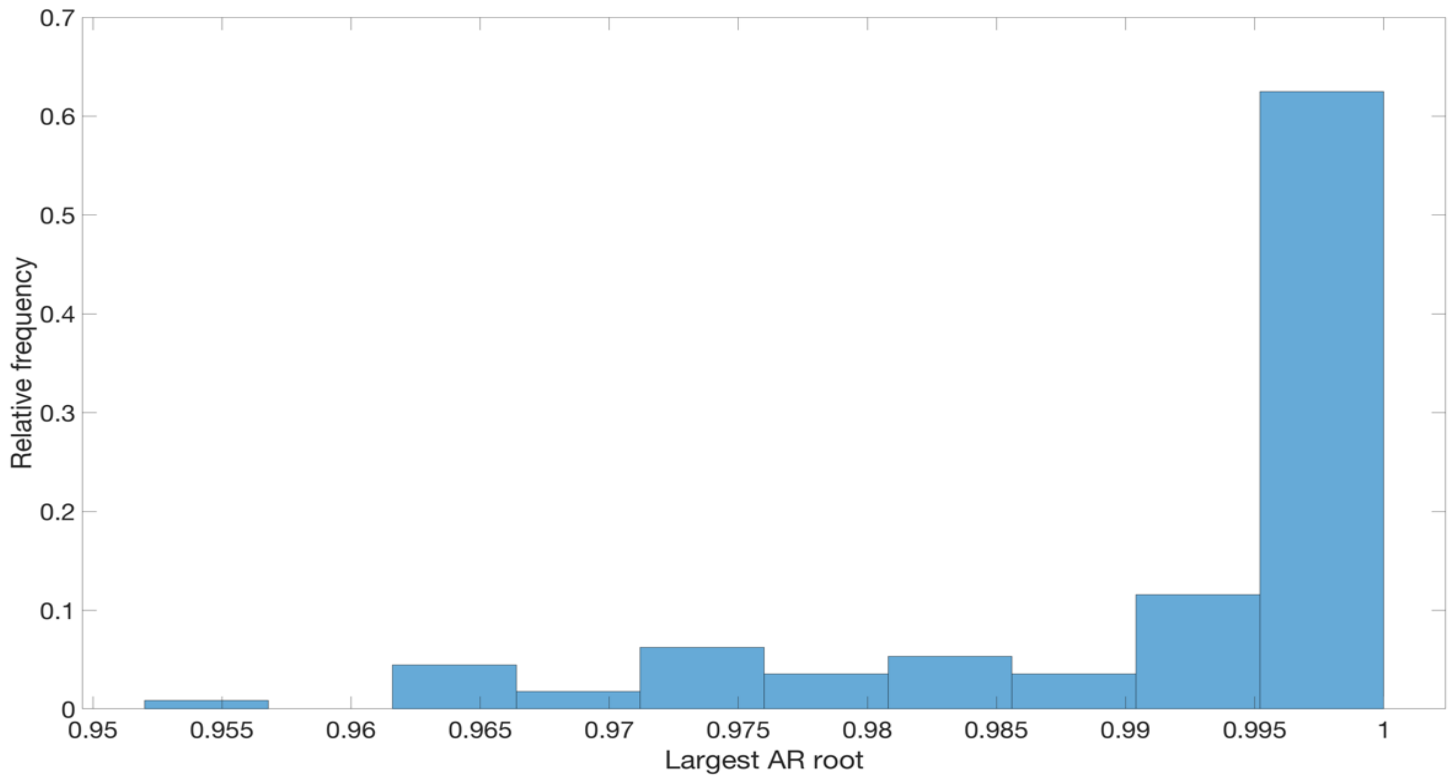
m_t, a_t are independent Gaussian random walks: $\Delta m_t = \varepsilon_{m,t}$, $\Delta a_t = \varepsilon_{a,t}$

With $\text{var}(\varepsilon_{m,t}) \ll \text{var}(\varepsilon_{a,t})$, f_t evolves like a random walk with drift, but with a slowly varying drift term (m_t). ("local-level" model for f_t).

$$y_{it} = f_t + c_{it}$$

- c_{it} is "very" persistent
- $c_{it} - \bar{c}_{i,1:T}$ is persistent
  - ADF$^{\mu}$ statistics
    - Fraction of ADF_tstats < –2.57 (10% CV) = 0.17
    - Fraction of ADF_tstats < –2.86 (5% CV) = 0.10

Histogram of 112 median unbiased estimate of largest AR root from ADF$^{\mu}$ statistics (Stock (19xx)).



Deviation from country-specific means have half – life of 140 years:

$(0.995)^{140} \approx 0.5$

AR component process: $\mathrm{AR}^{\mathrm{Comp}}(\rho_1, \rho_2)$

$$x_t = x_{1,t} + x_{2,t}$$

$$x_{1,t} = \rho_1 x_{1,t-1} + e_{1,t}$$

$$x_{2,t} = \rho_2 x_{2,t-1} + e_{2,t}$$

$$\rho_2 < \rho_1 < 1$$

An alternative model: $(1-\rho L)^d x_t = e_t$

Parameterization: separating persistence and variability

$$y_{it} = f_t + c_{it}$$

$$c_{it} = \mu + \lambda_{c,i}\, g_{J(i),t} + u_{c,i,t}$$

$$g_{j,t} = \lambda_{g,j}\, h_{K(j)} + u_{g,j,t}$$

$$u_{c,i,t} = s_{c,i} w_{c,i,t}$$

$$u_{g,j,t} = s_{g,j} w_{g,j,t}$$

$$h_{k,t} = s_{h,k} w_{h,k,t}$$

where $w_{\cdot,\cdot,t}$ are independent $\mathrm{AR}^{\mathrm{C}}(\rho_{\cdot 1}, \rho_{\cdot 2})$ processes with unit variance and $s_{\cdot}$ are scale factors.

Outline:

1. ~~Look at the data to determine some sensible features of a model.~~

2. ~~Simplify problem: focus on 'long-run' variation/covariation.~~

3. ~~Detailed description of model~~

4. **Estimation mechanics**

5. Results
   a. Convergence
   b. Long-run predictions

6. Different modelling choices

Estimation:

$$y_{it} = f_t + c_{it}$$

$$c_{i,t} = \mu + \lambda_{c,i}\, g_{J(i),t} + u_{c,i,t}$$

$$g_{j,t} = \lambda_{g,j}\, h_{K(j)} + u_{g,j,t}$$

Many parameters:

- f: $(m_0, f_0,\ \sigma_{\Delta m},\ \sigma_{\Delta a})$
- group factors: 25 g-factors, 10 h-factors, (112 - $\lambda_{c,i}$, 25 - $\lambda_{g,j}$)
- persistence: 112 + 25 + 10 values of $(\rho_1, \rho_2, \sigma_1/\sigma_2)$
- variability: 112 + 25 + 10 values of s.

Observations: (number of dots) = $N_{Countries} \times N_{dots/country} \approx 112 \times 10.5$

Estimation by Bayes methods: Some priors will matter

Parameters with priors that don't matter much:

(1) f_t:

- Shrinkage toward OECD: $\overline{y}_t^{OECD} = f_t + \overline{c}_t^{OECD}$ with $\overline{c}_t^{OECD} \sim N(0,\text{small})$

- f_0, m_0, and overall scale (uninformative priors)

(2) c_{it}:

- mean μ, 'average' value of scales s. (Uninformative priors)

- exchangeable hierarchical priors on relative scales and factor loadings (λ_i) (shrunk toward uniform with sensible support).

Parameters with prior that matter:

(1) m_t is local average annual growth rate of f_t:

$\sigma(m_{t+h} - m_t) = \boldsymbol{\sigma_{\Delta m}} \times h^{1/2}$

- $h = 50$
  - Very large value of $\sigma_{\Delta m} \Rightarrow \sigma(m_{t+h} - m_t) = 2\%$
  - Very small value $\sigma_{\Delta m} \Rightarrow \sigma(m_{t+h} - m_t) = 0\%$
  - Prior with linearly decreasing weights between these two values. Mean yields $\sigma_{\Delta m}\sqrt{h} =$ (2/3)% for $h = 50$.

(2) $(\rho_{i,1}, \rho_{i,2}, \sigma_{i,1}/\sigma_{i,2})$: for each of the 112+25+10 components. These are exchangeable with hierarchical prior that is shrunk toward a prior with 'half-life' distributions given below:

half-life : h such that $\mathrm{cor}(x_t, x_{t+h}) = ½$

Percentile	0.10	0.25	0.50	0.75	0.90
h	45	83	193	371	539

Estimation: Practical details

(1) Gaussian Likelihood ... *dots* $\sim N(0,\Sigma(\theta))$,

$$\Sigma(\theta) = \Sigma_1(\theta_1) + \Sigma_2(\theta_2) + \Sigma_3(\theta_3) \ldots + \Sigma_N(\theta_N)$$

(2) Handful of parameters with standard diffuse priors, analytic posterior

(3) Other parameters specified on grid. ($\Sigma_i(\theta_i)$ can be precomputed)

(4) Exchangeable (over countries, factors, etc.) Dirichlet (multinomial) prior on grid of values.

(5) UM computes a zillion draws in 3 minutes.

Outline:

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2. ~~Simplify problem: focus on 'long-run' variation/covariation.~~

3. ~~Detailed description of model~~

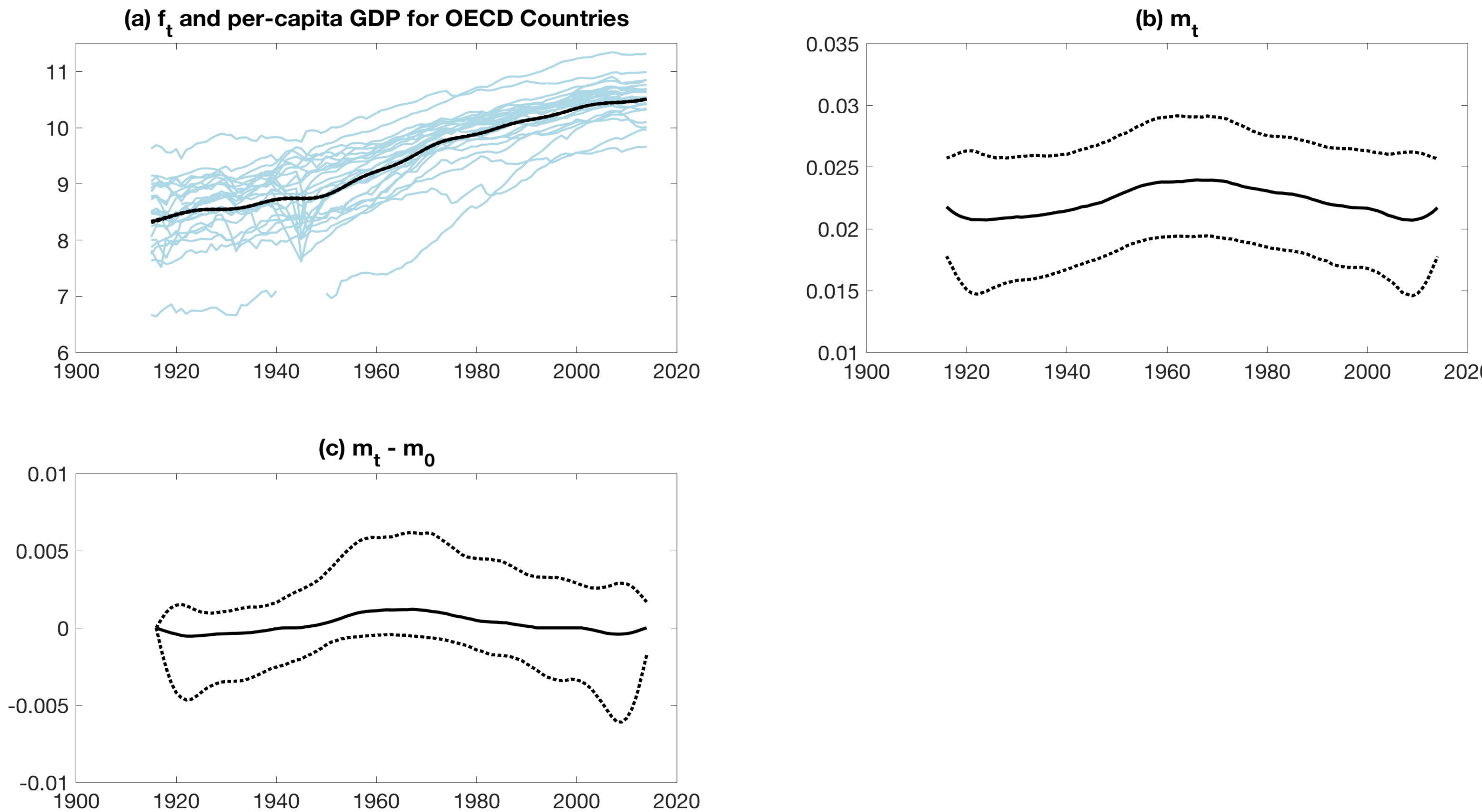
4. ~~Estimation mechanics~~

5. **Results**
   a. Convergence
   b. Long-run predictions

6. Different modelling choices

Selected Results: f-factor

$$y_t = f_t + c_{i,t} \qquad f_t = f_0 + m_t \times t + a_t$$

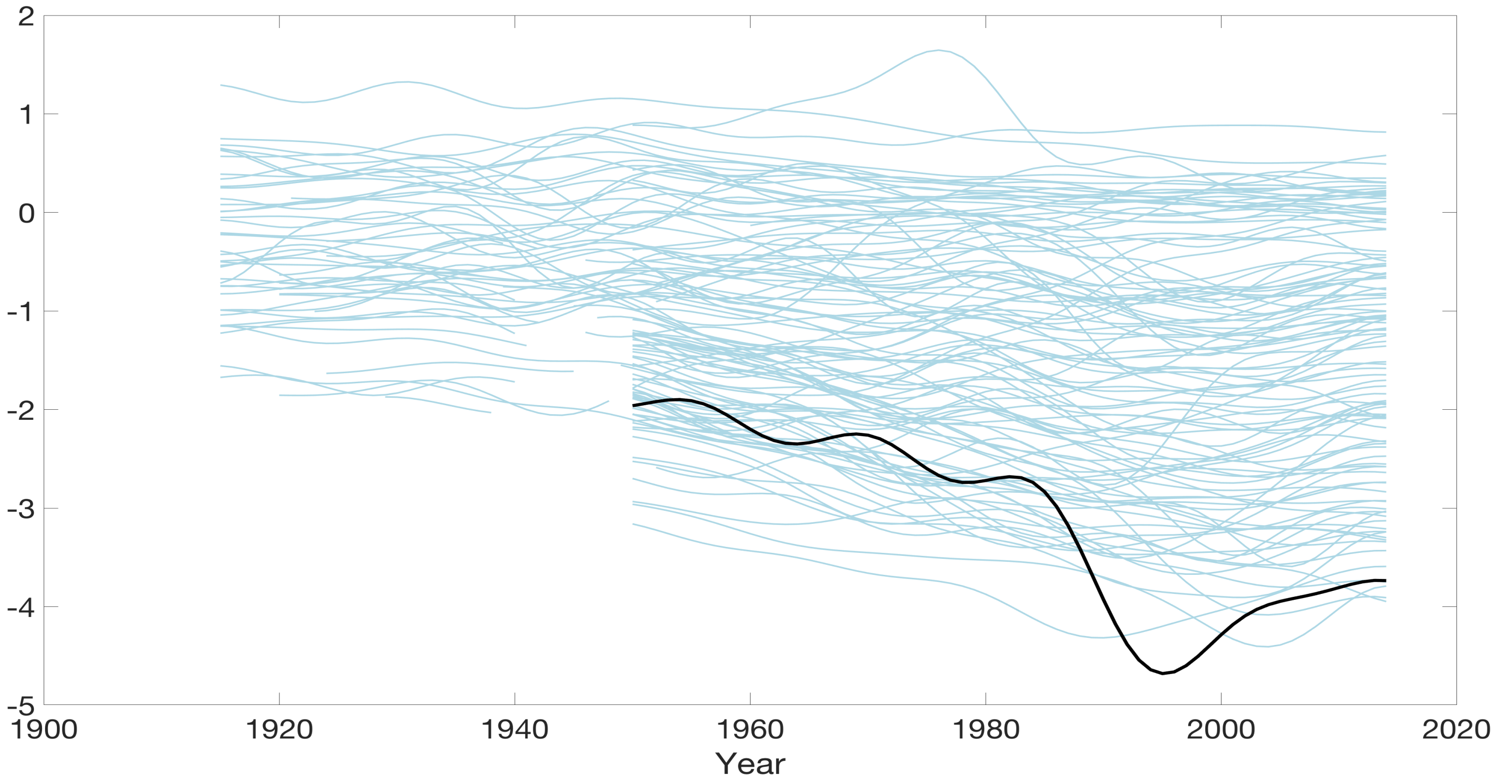


Median and 68% pointwise credible set

(WIP . narrowing of bands in (c) at end of sample)

Selected Results: Persistence and variance of c_{it}

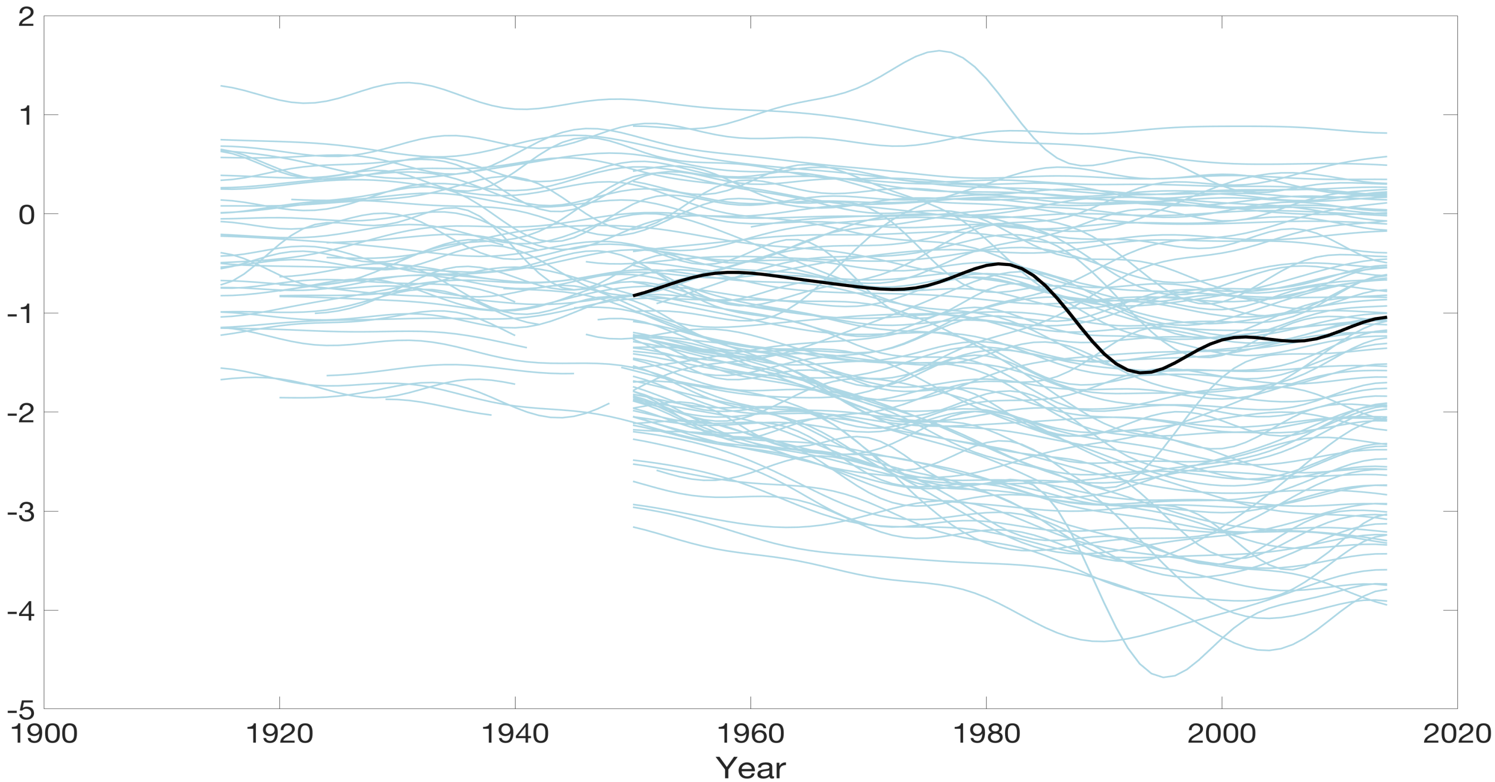
Posterior means of c_{it}: Liberia



Percentiles of posterior

	0.05	0.16	0.50	0.84	0.95
half-life	37	44	63	98	136
σ_c	1.3	1.4	1.5	1.6	1.7
$\sigma_{\Delta_{50} c_{it}}$	1.1	1.2	1.4	1.6	1.7

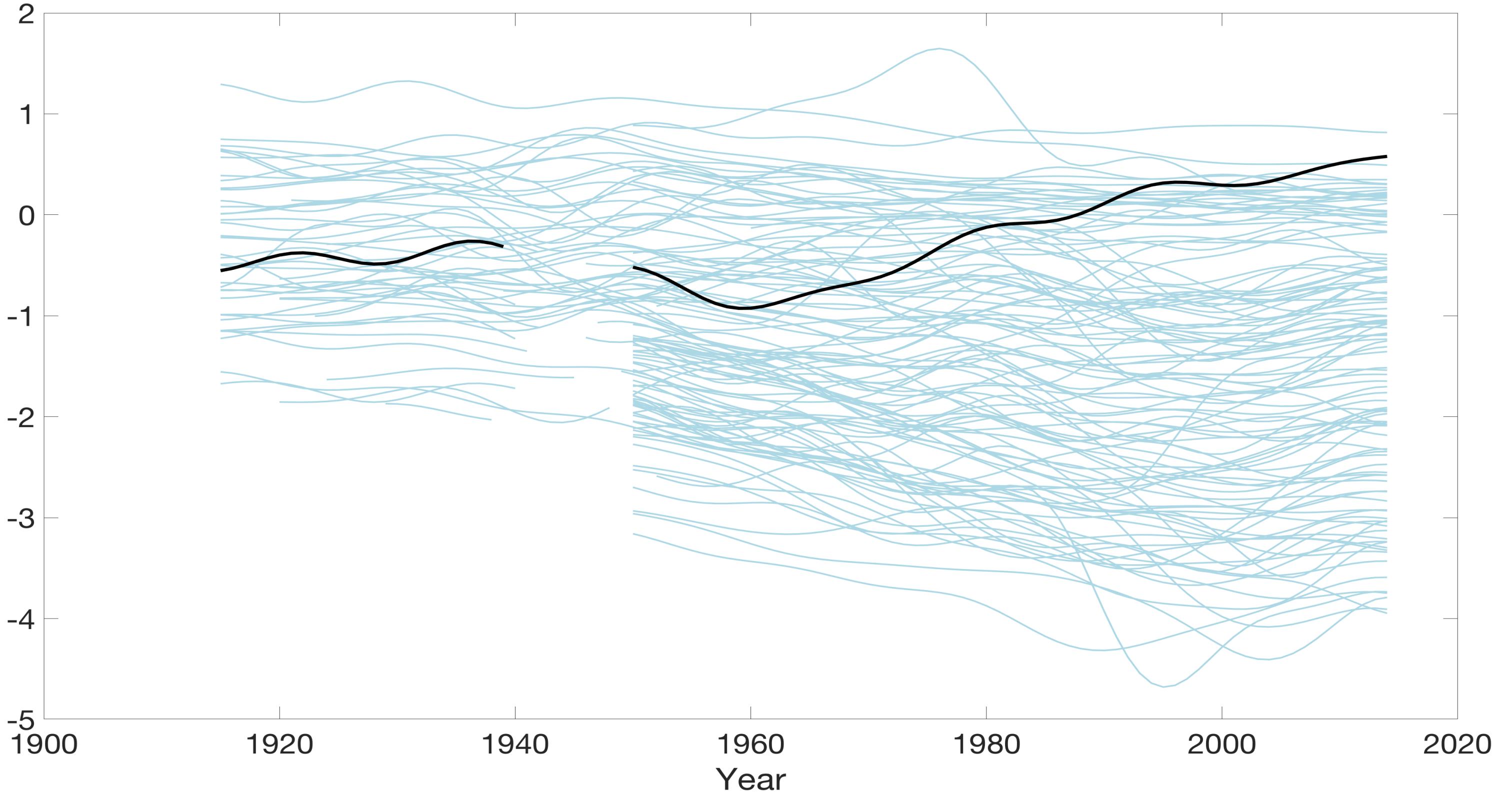
Posterior means of c_{it}: Iraq



Percentiles of posterior

	0.05	0.16	0.50	0.84	0.95
half-life	38	50	85	158	229
σ_c	0.8	0.9	1.2	1.5	1.6
$\sigma_{\Delta_{50} c_{it}}$	0.7	0.8	1.0	1.2	1.3

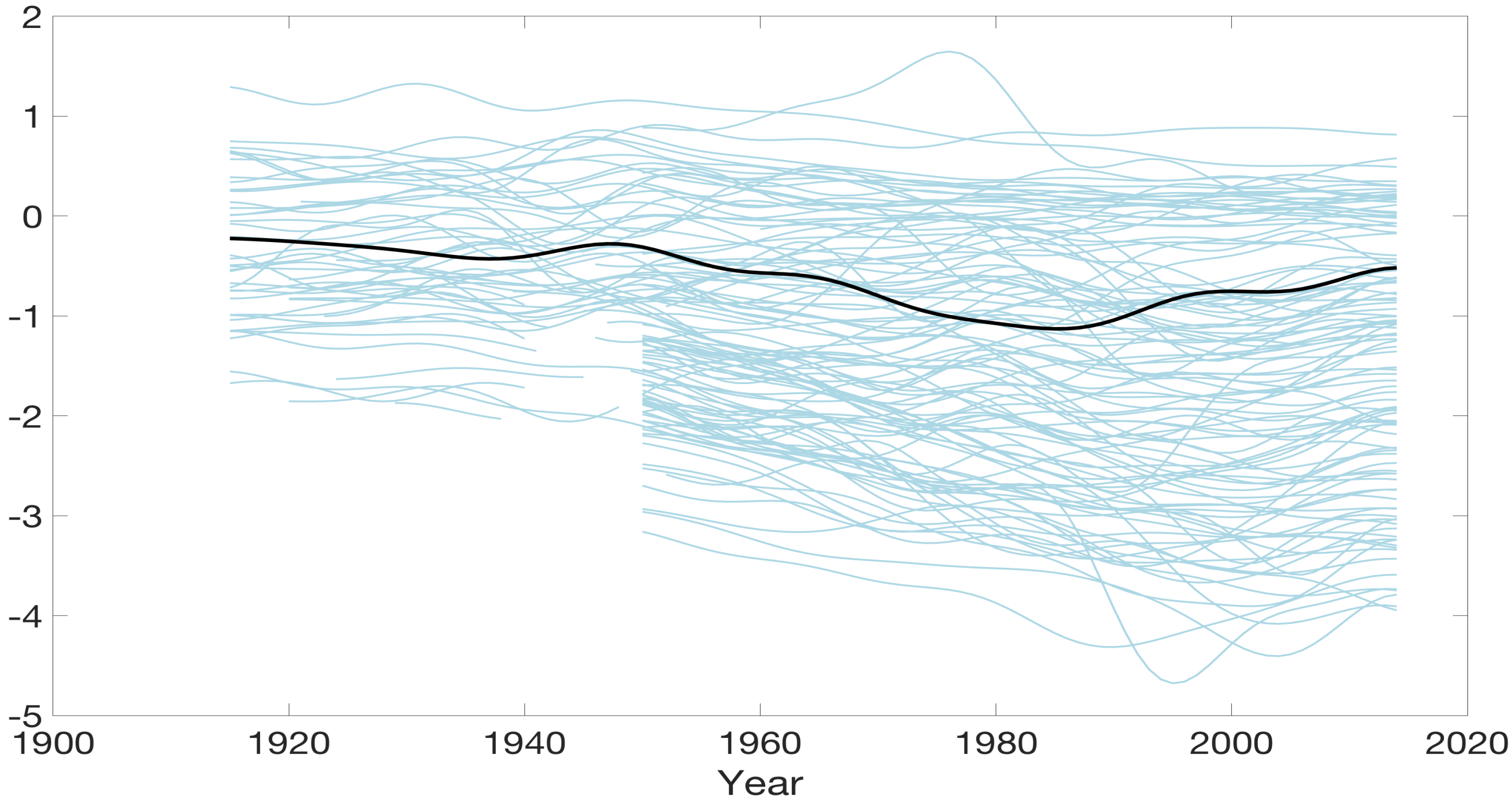
Posterior means of c_{it}: Singapore



Percentiles of posterior

	0.05	0.16	0.50	0.84	0.95
half-life	62	90	163	277	370
σ_c	0.8	0.9	1.1	1.4	1.5
$\sigma_{\Delta_{50} c_{it}}$	0.6	0.6	0.8	1.0	1.1

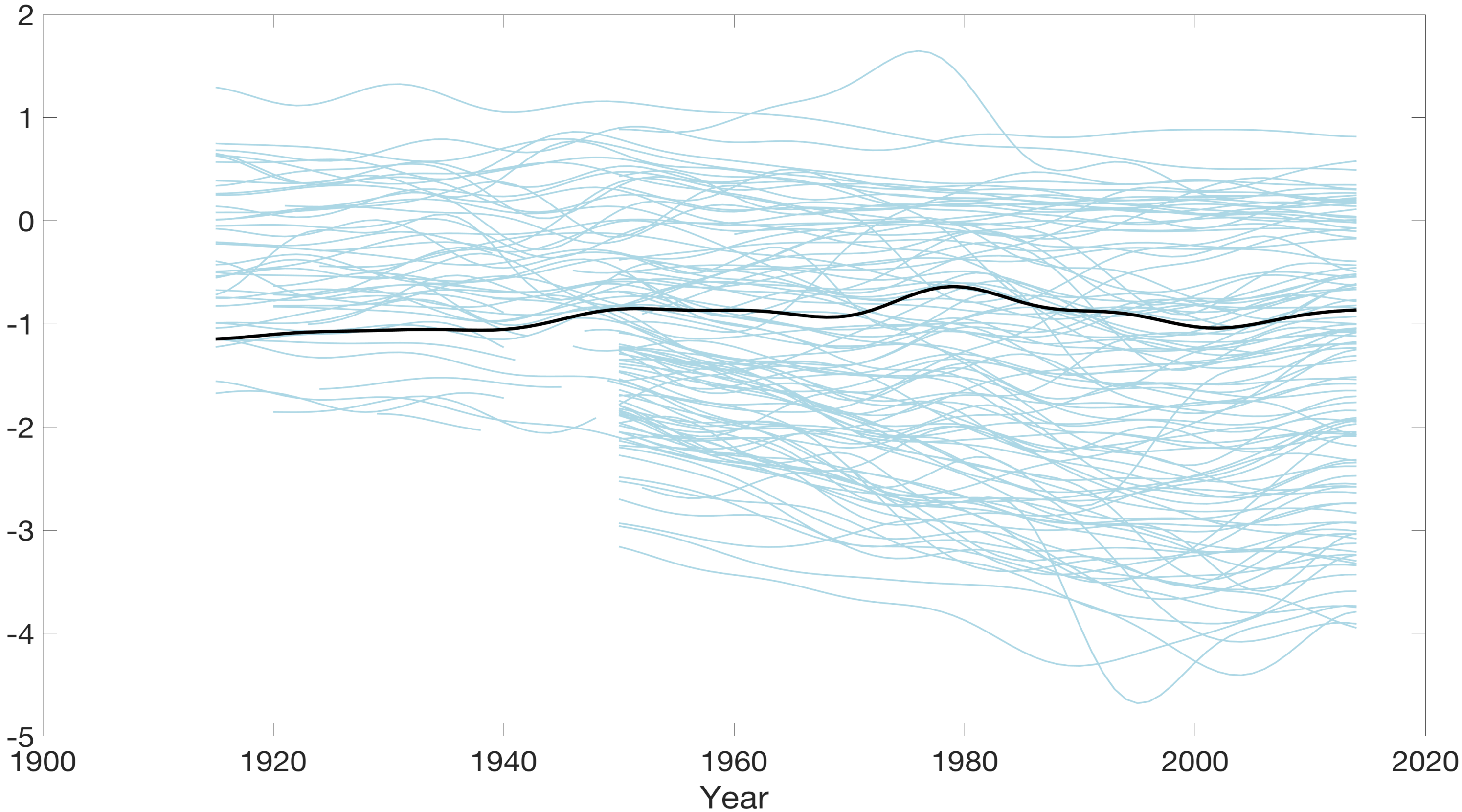
Posterior means of c_{it}: Chile



Percentiles of posterior

	0.05	0.16	0.50	0.84	0.95
half-life	117	168	270	416	387
σ_c	0.9	1.0	1.2	1.4	1.5
$\sigma_{\Delta_{50}c_{it}}$	0.5	0.6	0.7	0.8	0.9

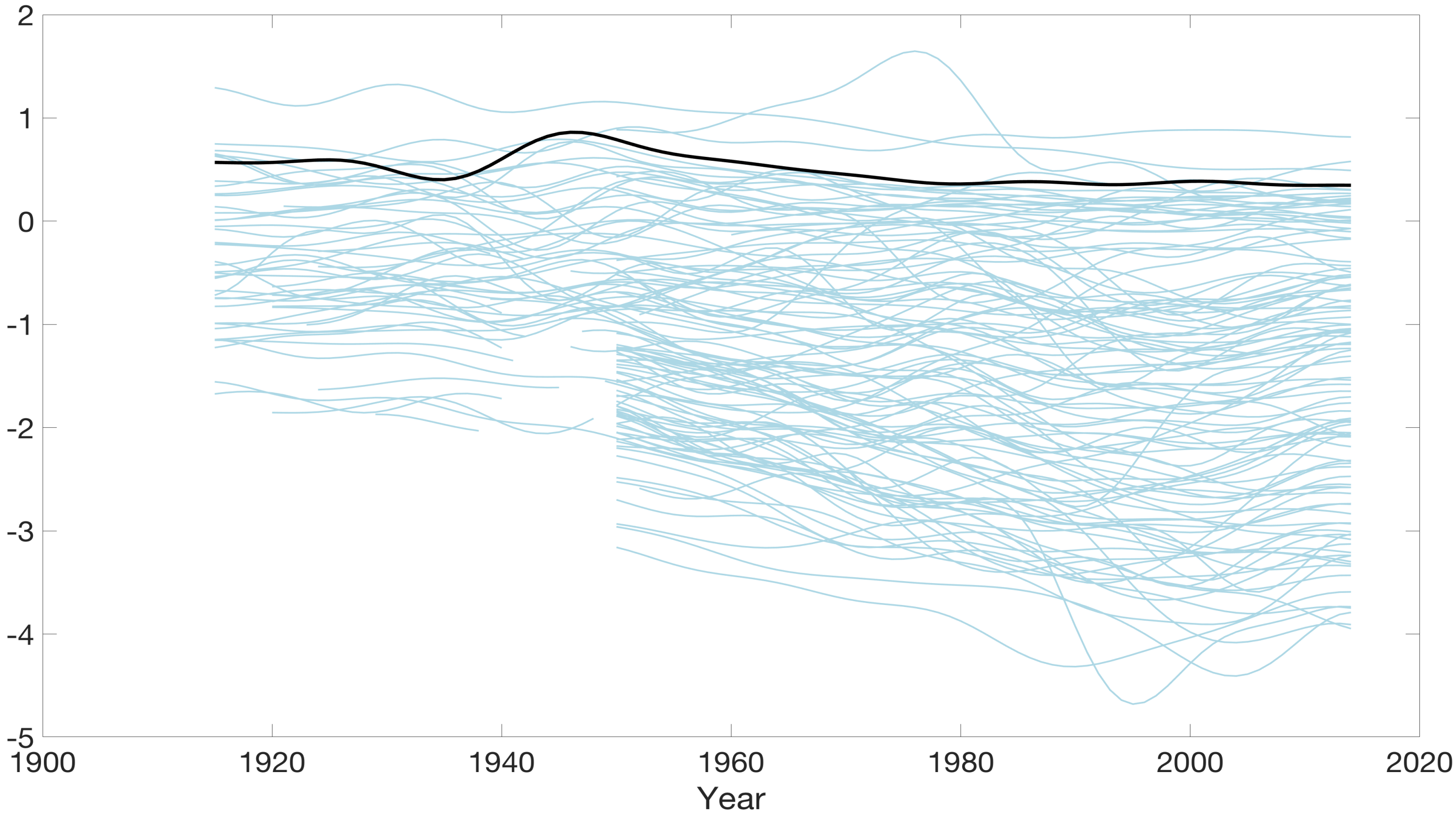
Posterior means of c_{it}: Brazil



Percentiles of posterior

	0.05	0.16	0.50	0.84	0.95
half-life	155	206	313	441	523
σ_c	0.7	0.7	0.9	1.1	1.2
$\sigma_{\Delta_{50}c_{it}}$	0.6	0.7	0.8	0.9	1.0

Posterior means of c_{it}: United States



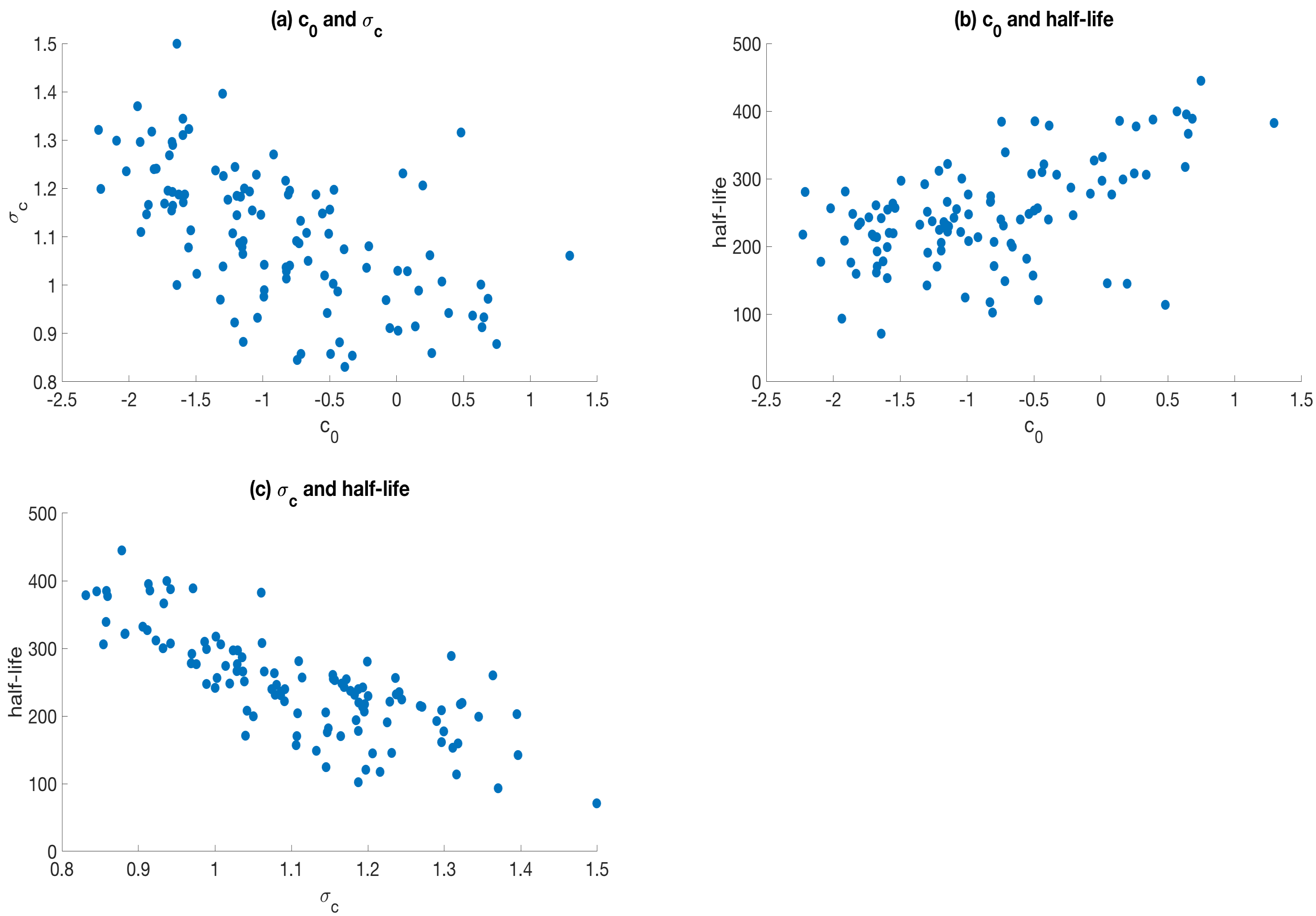
Percentiles of posterior

	0.05	0.16	0.50	0.84	0.95
half-life	218	277	396	527	599
σ_c	0.7	0.8	0.9	1.1	1.3
$\sigma_{\Delta_{50} c_{it}}$	0.3	0.4	0.4	0.5	0.5

Distribution of Posterior Means Across 112 Countries

	Percentile				
	0.05	0.16	0.50	0.84	0.95
Half-life	120	171	242	321	386
σ_c	0.86	0.94	1.11	1.27	1.35
$\sigma_{\Delta_{50} c_{it}}$	0.40	0.48	0.66	0.84	0.97

Selected Results: Initial Conditions, σ_c and half-life



Selected Results: **Covariability**

Posterior Means of pairwise correlations

	$\Delta_{50}\, y_{i,t}$		$\Delta_{50}\, c_{i,t}$
average	0.37		0.08
largest	0.95 (France, Netherlands)		0.92 (France, Netherlands)
smallest	0.12 (Liberia, Saudi Arabia)		0.00 (Fraction $< 0.01 = 0.39$)

Average Pairwise Correlations of $\Delta_{50} c_{it}$ (Posterior means) in Selected 5-country groups

Countries					Correlation
China	India	Laos	Sri Lanka	Vietnam	0.71
Hong Kong	Korea	Singapore	Taiwan	Thailand	0.67
Cent. African Rep.	Guinea	Haiti	Senegal	Madagascar	0.63
Belgium	Denmark	France	Italy	Netherlands	0.59
Benin	Bangladesh	Kenya	Nepal	Tanzania	0.53
Bulgaria	HRV	ROU	Russia	Serbia	0.51
Australia	Canada	Great Britain	New Zealand	United States	0.47
Burkino FAso	Ghana	Mozambique	Chad	Uganda	0.45
Brazil	Costa Rica	Dominincan Rep.	Ecuador	Poland	0.41
Cote d'Ivoire	Mauritania	Niger	Togo	Zambia	0.41
Argentina	Bolivia	Peru	El Salvador	Uruguay	0.40
Switzerland	Finland	Norway	Portugal	Sweden	0.36

Selected Results: Long-run Forecasts

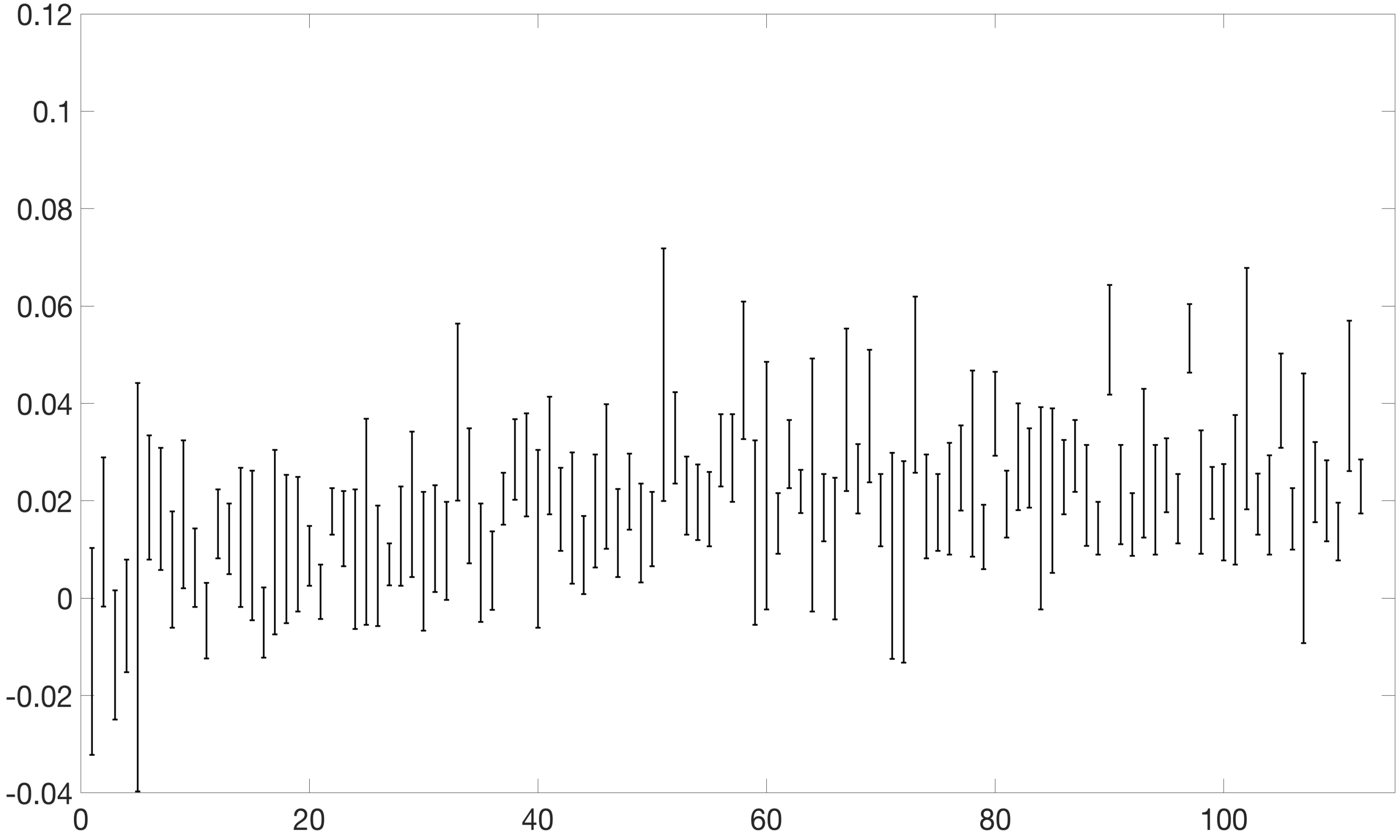
Average growth over next h years: $\left(y_{i,T+h} - y_{i,T}\right)/h$ for $h = 50, 100$

Univariate Benchmarks (location, scale, equivariant prediction intervals):

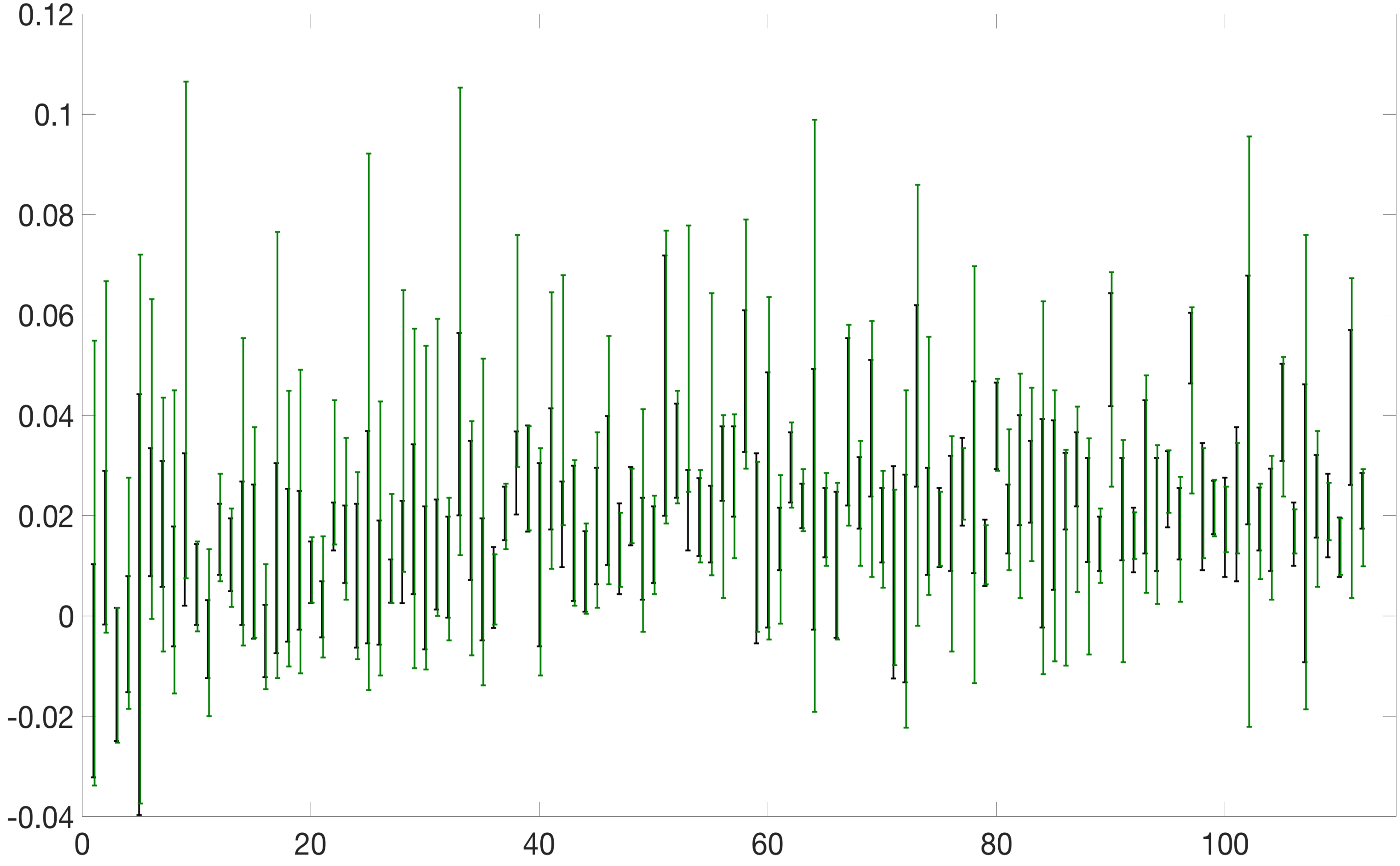
- $(1-L)y_{it} = \mu + u_{it}$
- $(1-L)^{1+\boldsymbol{d}} y_{it} = \mu + u_{it}$ $\quad$ ($d \sim U(-0.4, 1.0)$)

Univariate benchmarks: $(1\text{-}L)y_{it} = \mu + u_{it}$

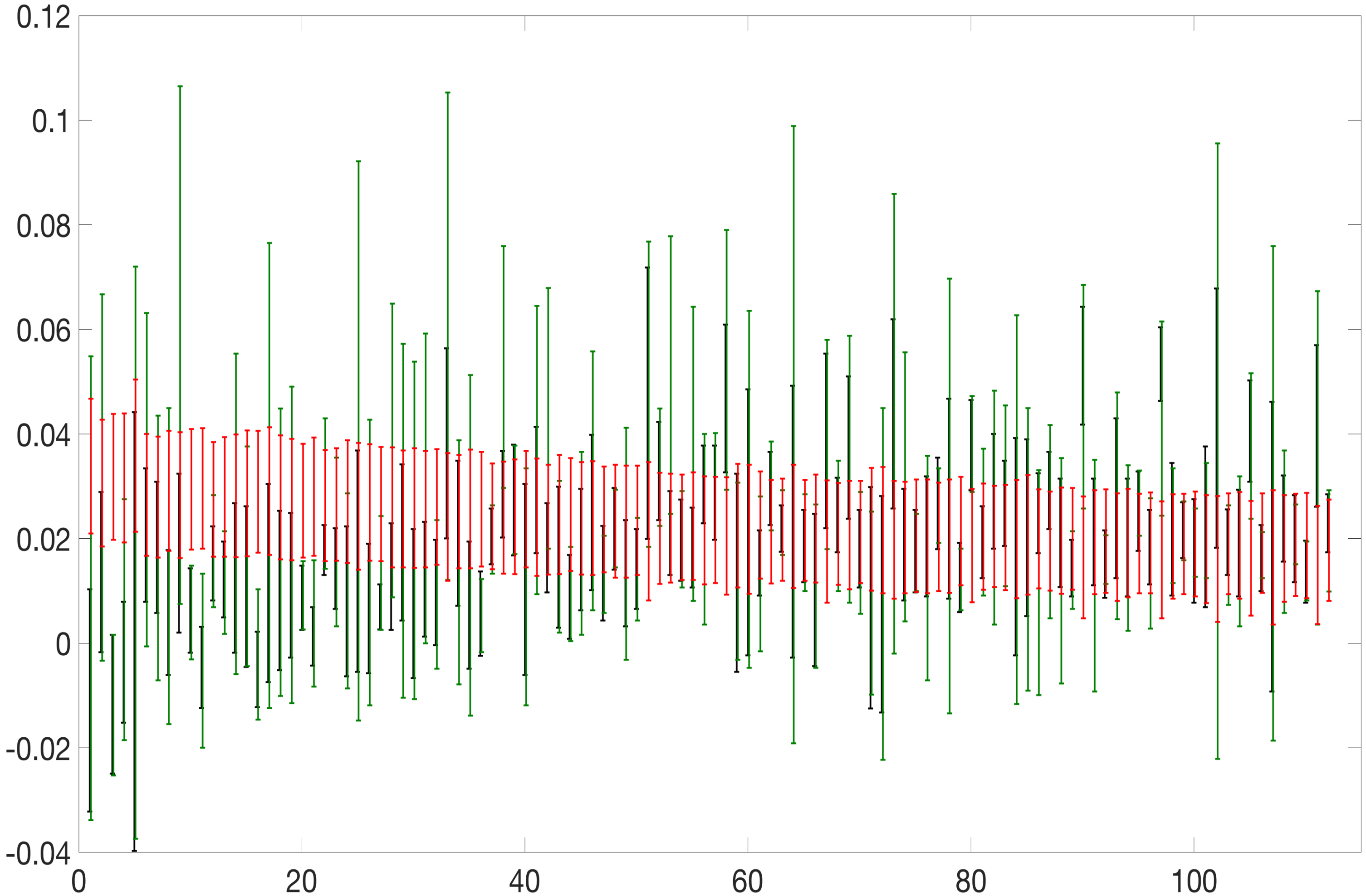
67% prediction intervals for average growth over next 100 years. Countries ordered from poorest to richest (2010-2014)



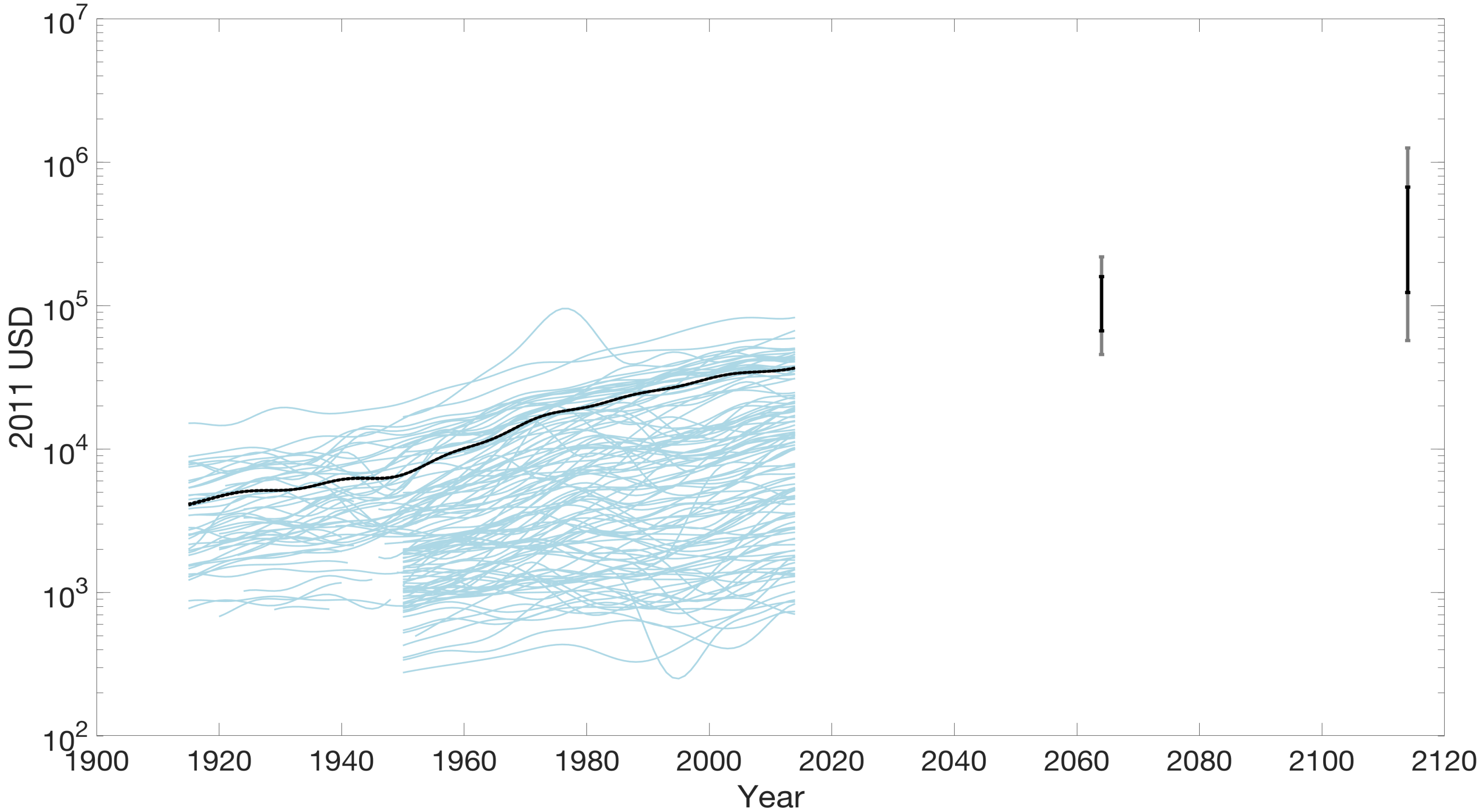
Univariate benchmarks: (1-L)$y_{it} = \mu + u_{it}$ and (1-L)$^{1+d}y_{it} = \mu + u_{it}$



Univariate and Multivariate



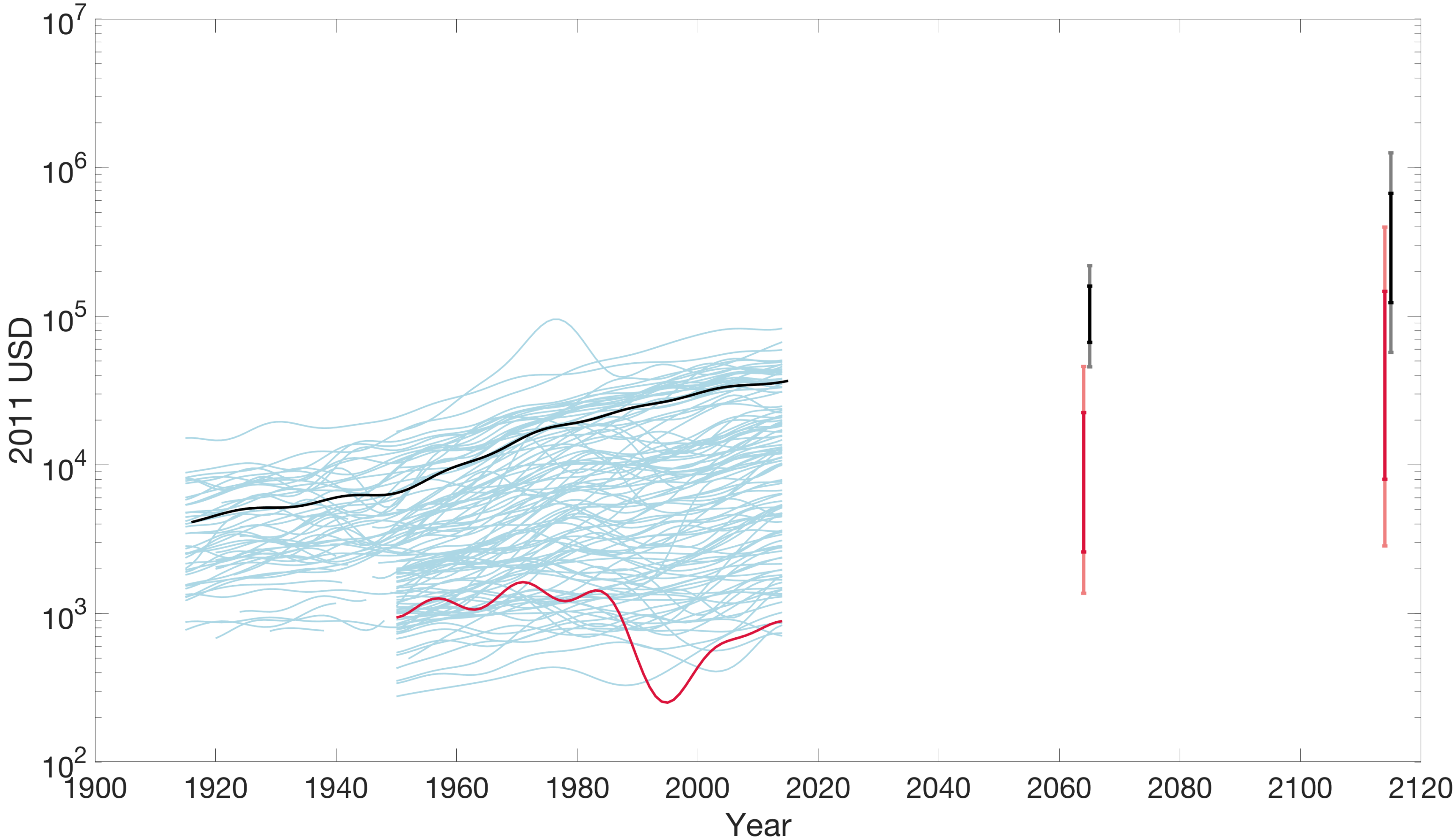
50 and 100 year forecasts: *f*-factor



Percentiles of Predictive Distribution: 100-year average growth rate (PAAR)

	5%	16%	50%	84%	95%
f-factor	0.4	1.2	2.1	2.9	3.5

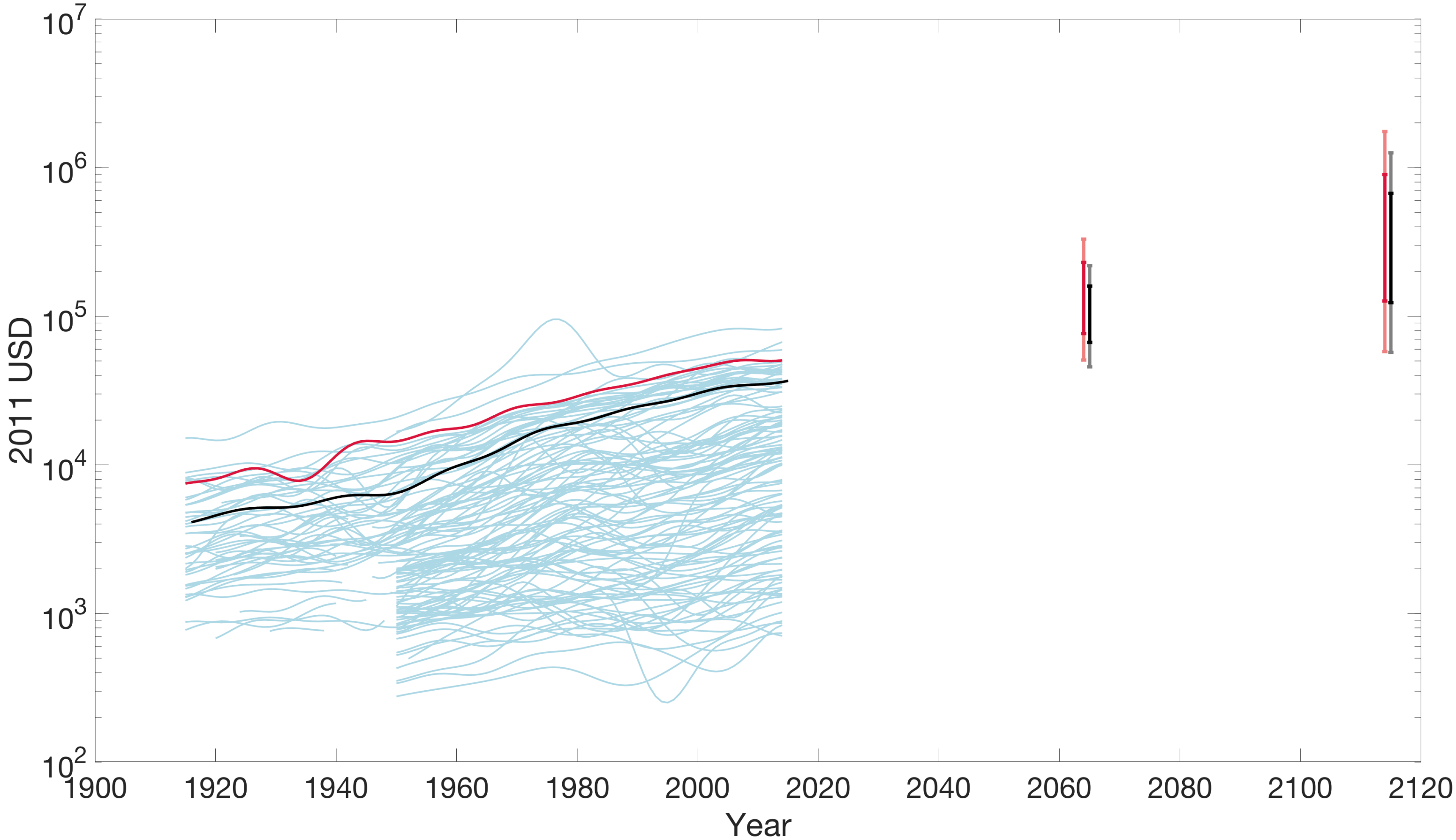
50 and 100 year forecasts: Liberia



Percentiles of Predictive Distribution: 100-year average growth rate (PAAR)

	5%	16%	50%	84%	95%
f-factor	0.4	1.2	2.1	2.9	3.5
Liberia	1.1	2.2	3.6	5.0	6.0

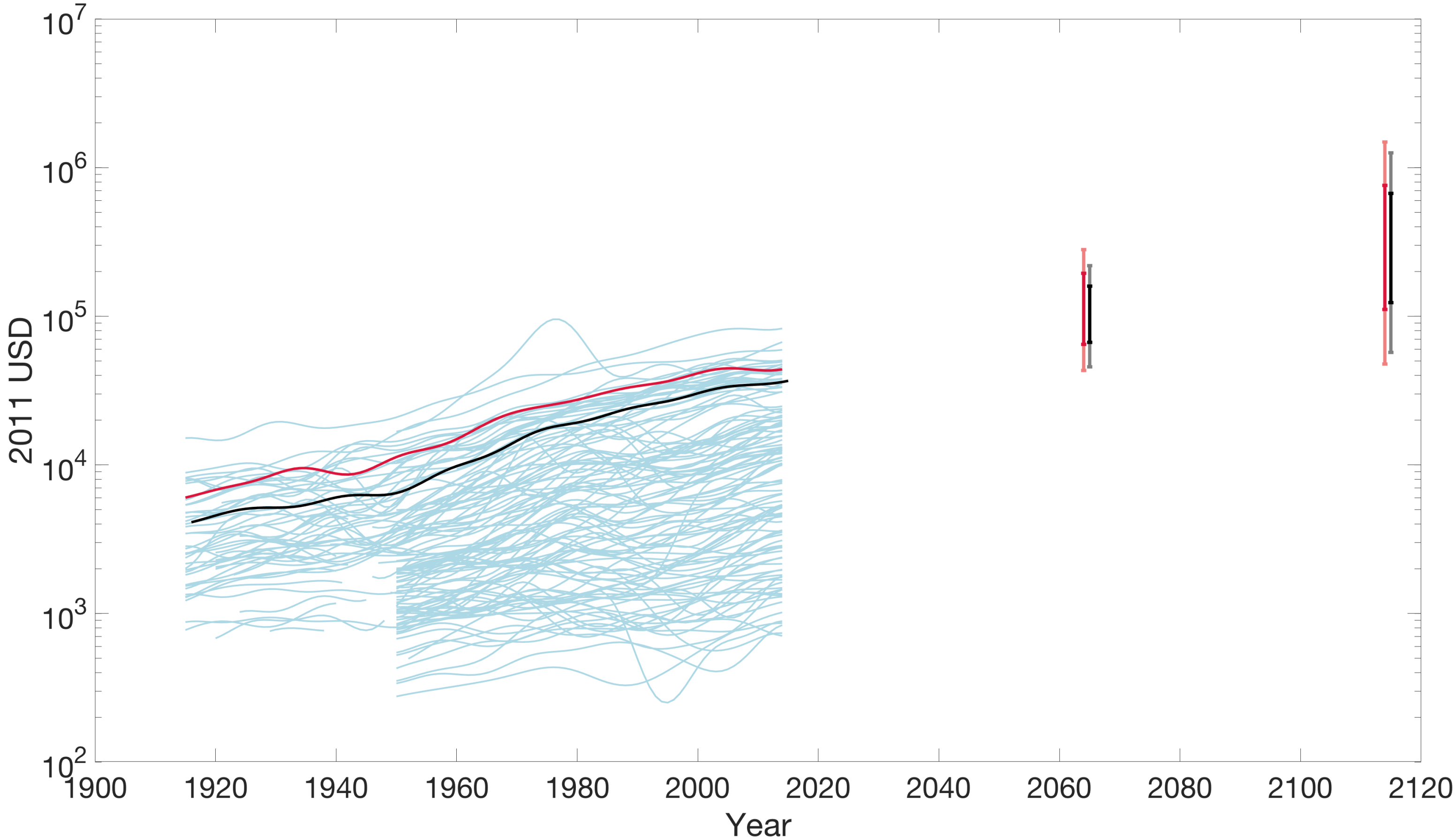
50 and 100 year forecasts: USA



Percentiles of Predictive Distribution: 100-year average growth rate (PAAR)

	5%	16%	50%	84%	95%
f-factor	0.4	1.2	2.1	2.9	3.5
USA	0.1	0.9	1.9	2.9	3.5

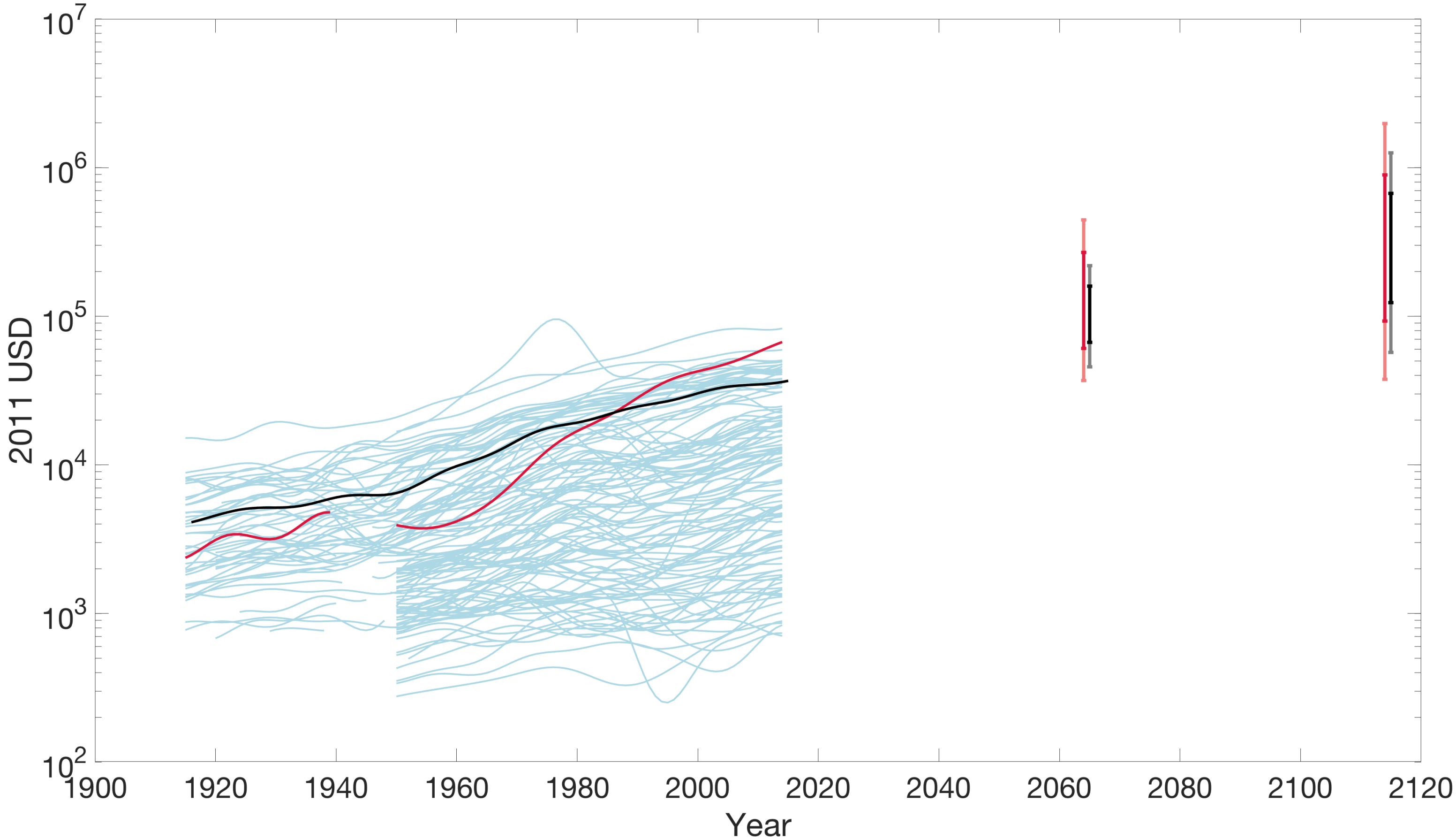
50 and 100 year forecasts: Denmark



Percentiles of Predictive Distribution: 100-year average growth rate (PAAR)

	5%	16%	50%	84%	95%
f-factor	0.4	1.2	2.1	2.9	3.5
Denmark	0.1	0.9	1.9	2.9	3.5

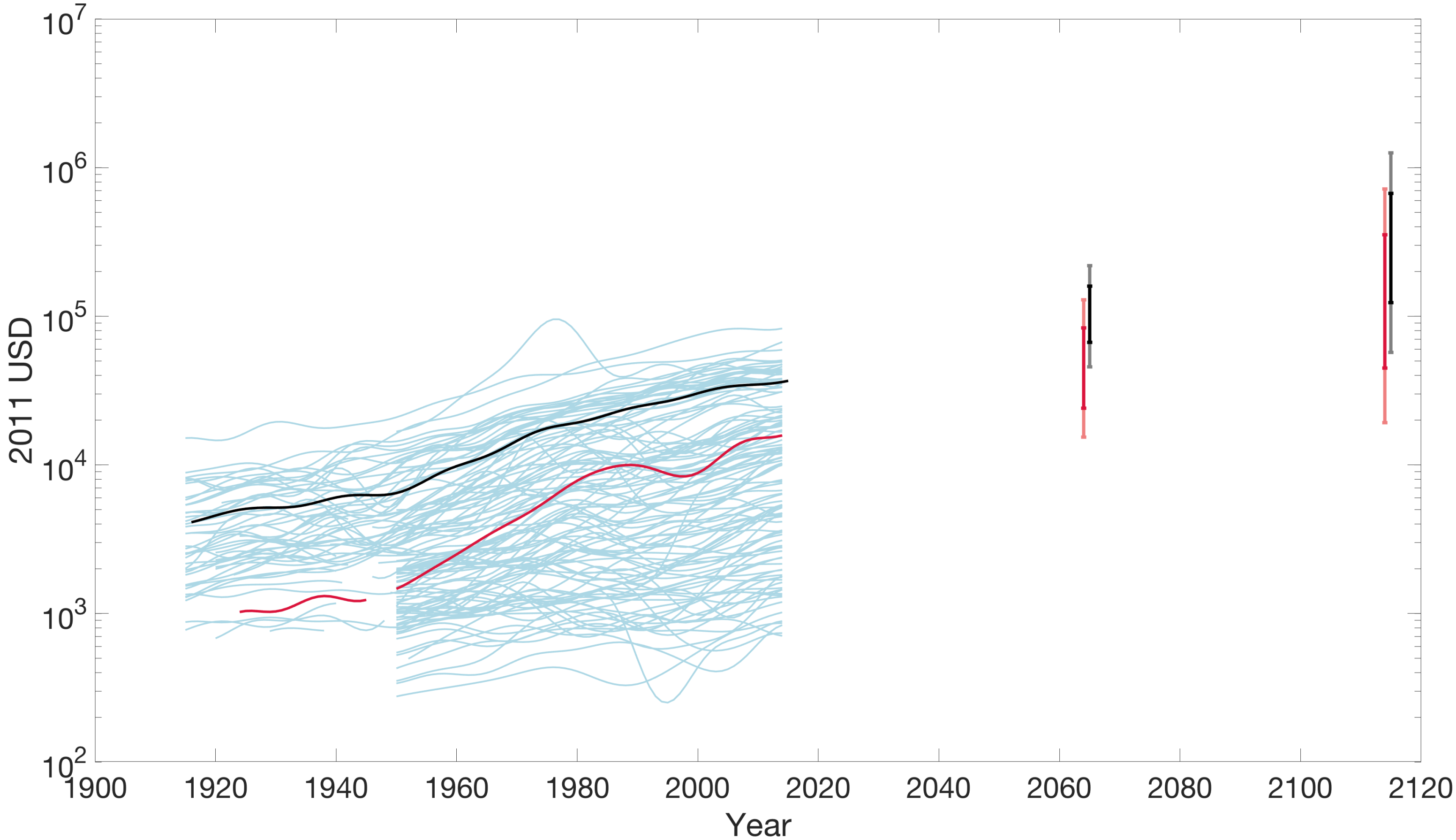
50 and 100 year forecasts: Singapore



Percentiles of Predictive Distribution: 100-year average growth rate (PAAR)

	5%	16%	50%	84%	95%
f-factor	0.4	1.2	2.1	2.9	3.5
Singapore	–0.5	0.4	1.5	2.6	3.4

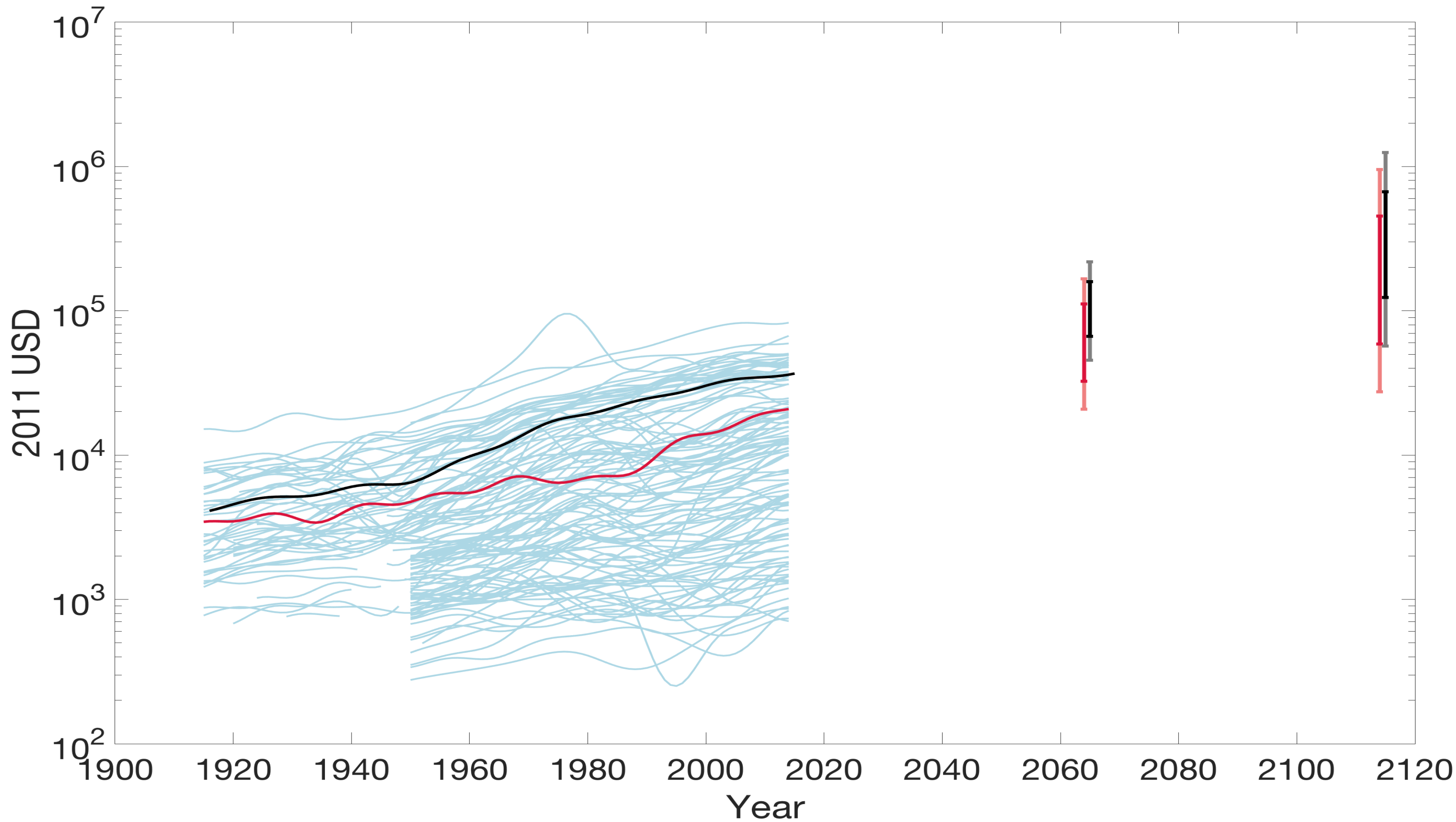
50 and 100 year forecasts: Bulgaria



Percentiles of Predictive Distribution: 100-year average growth rate (PAAR)

	5%	16%	50%	84%	95%
f-factor	0.4	1.2	2.1	2.9	3.5
Bulgaria	0.2	1.0	2.1	3.1	3.8

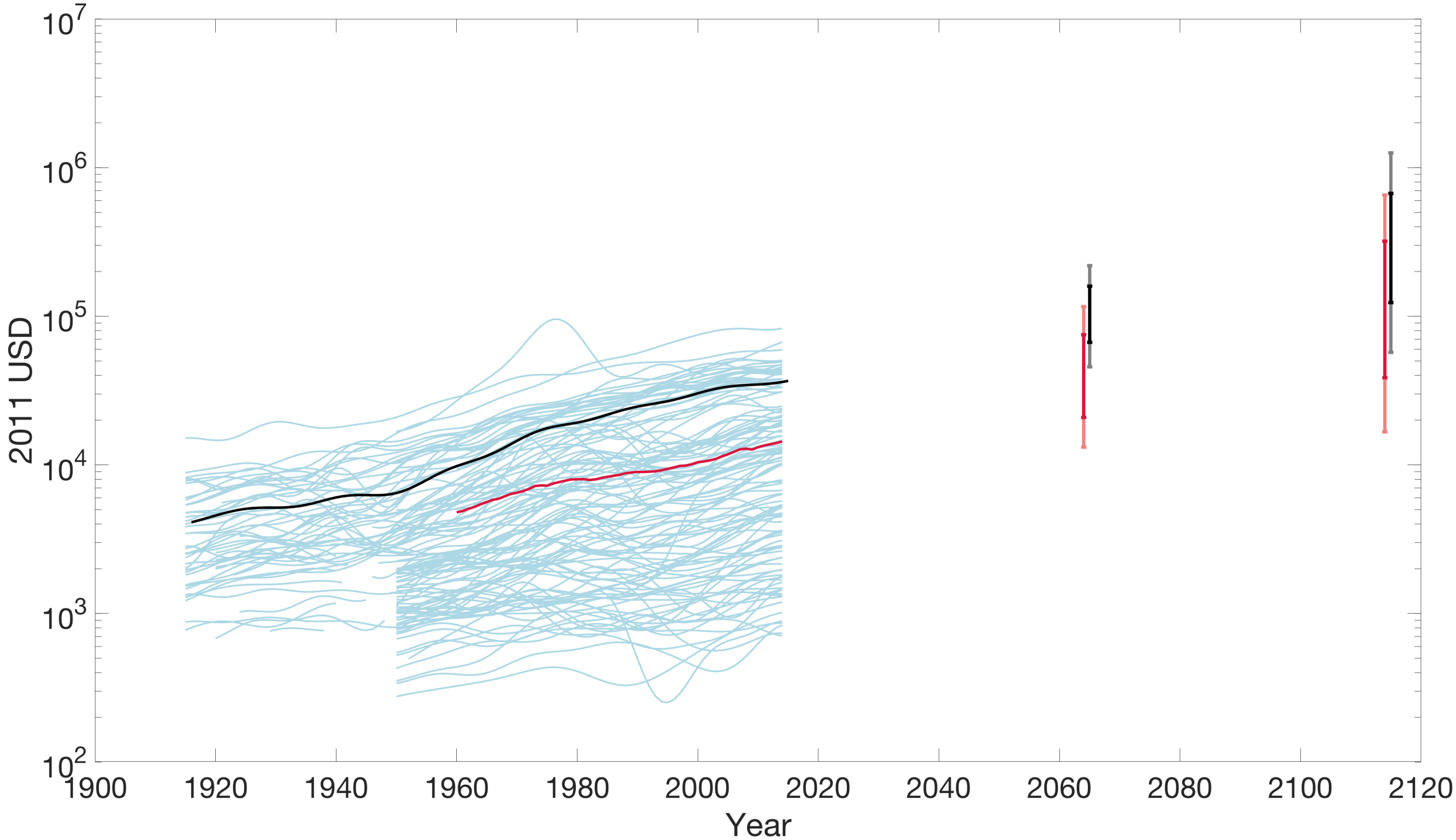
50 and 100 year forecasts: Chile



Percentiles of Predictive Distribution: 100-year average growth rate (PAAR)

	5%	16%	50%	84%	95%
f-factor	0.4	1.2	2.1	2.9	3.5
Chile	0.3	1.0	2.1	3.1	3.8

50 and 100 year forecasts: global average (2014 population weights)

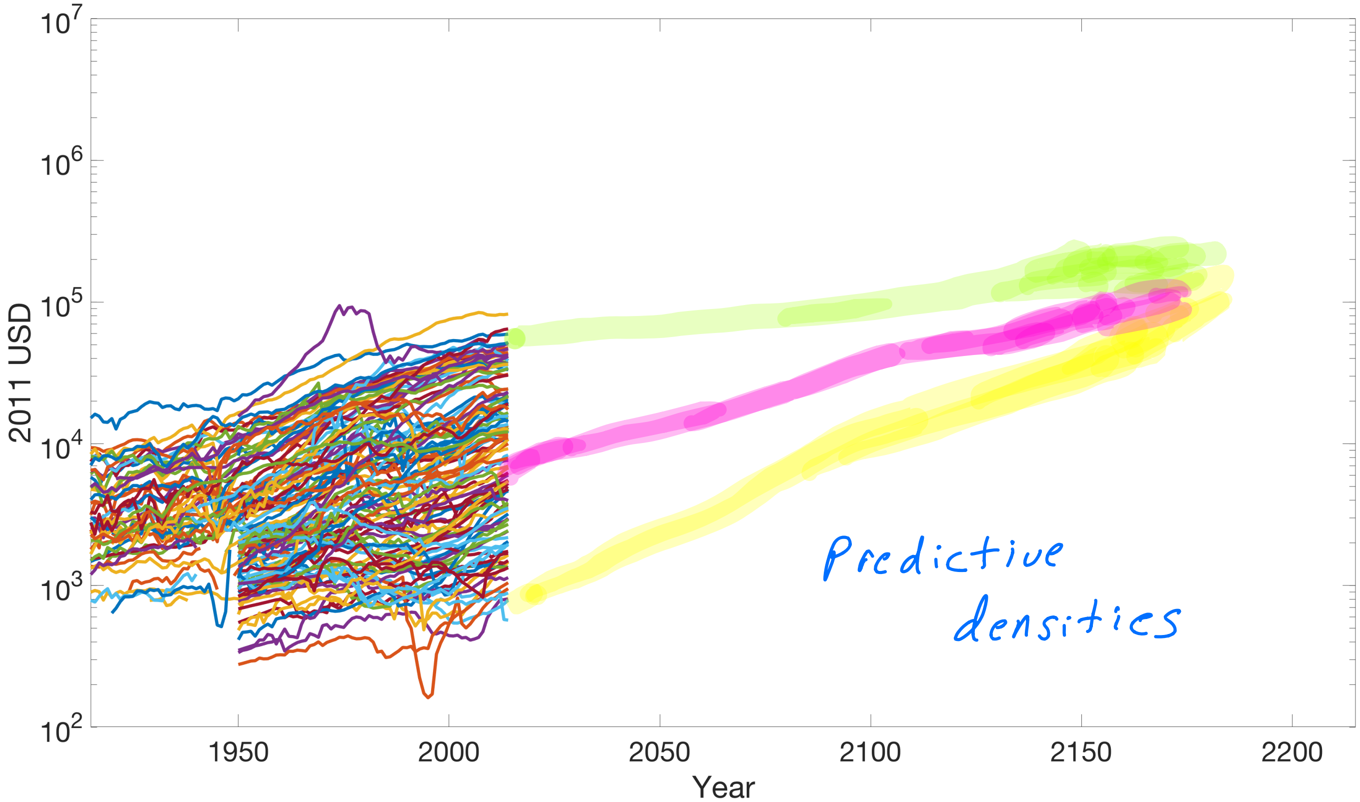


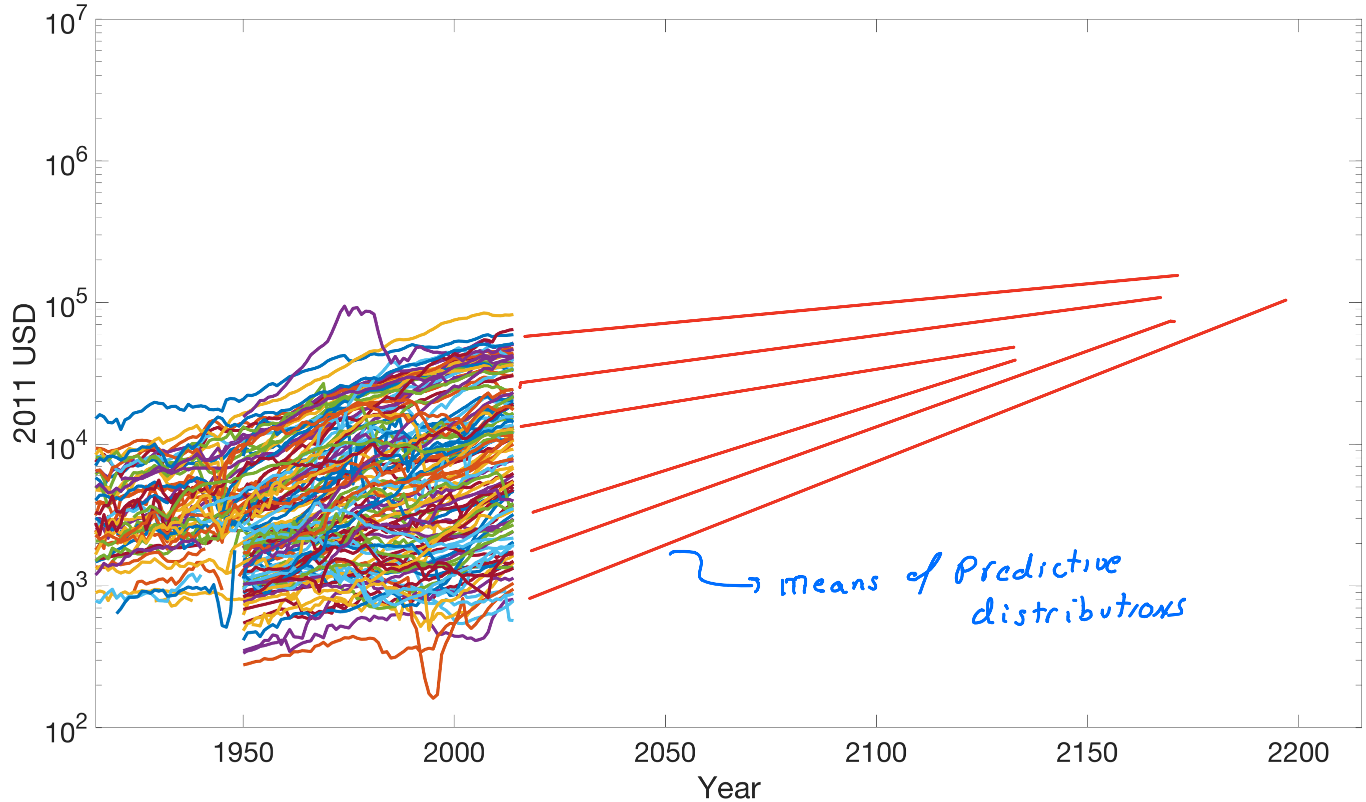
Percentiles of Predictive Distribution: 100-year average growth rate (PAAR)

	5%	16%	50%	84%	95%
f-factor	0.4	1.2	2.1	2.9	3.5
Global avg.	0.5	1.3	2.3	3.2	3.8

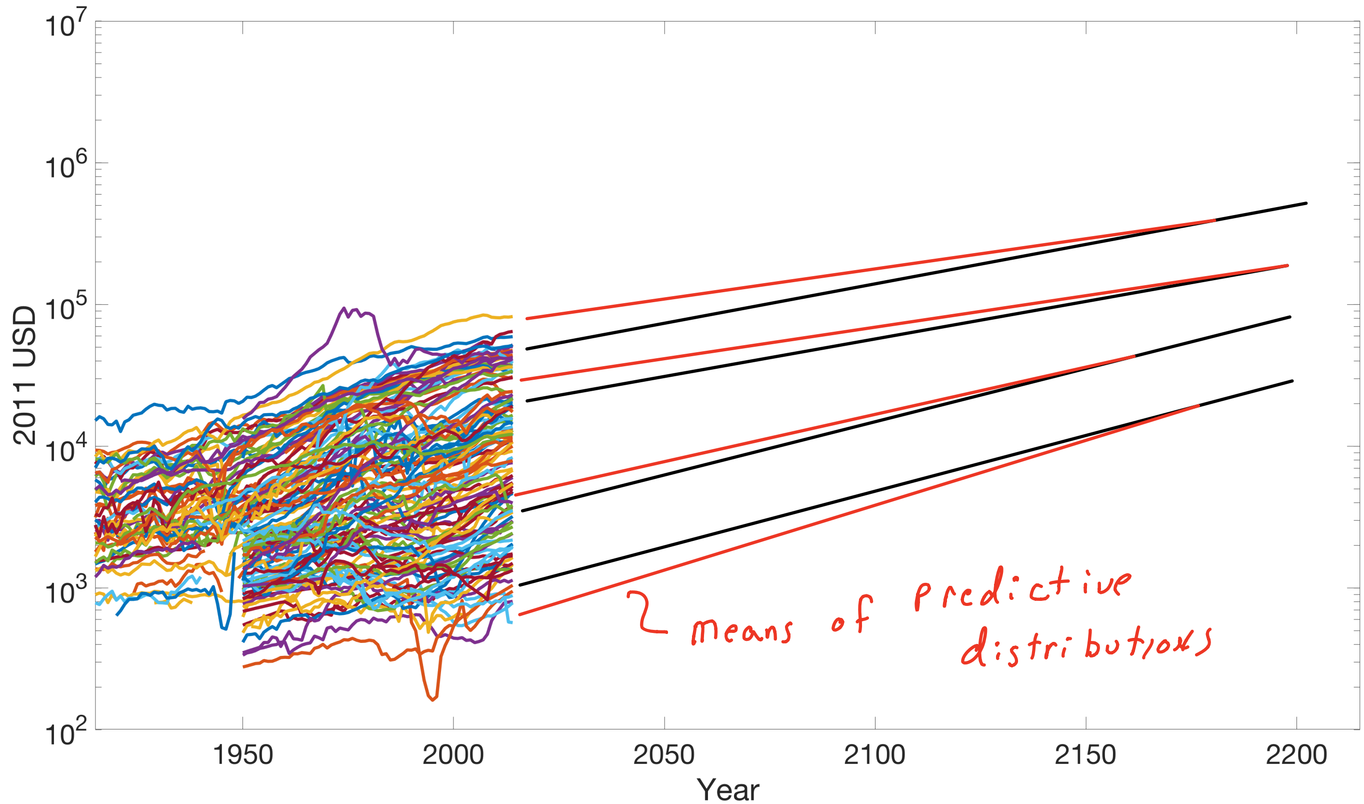
Summary

Convergence, persistence and comovement

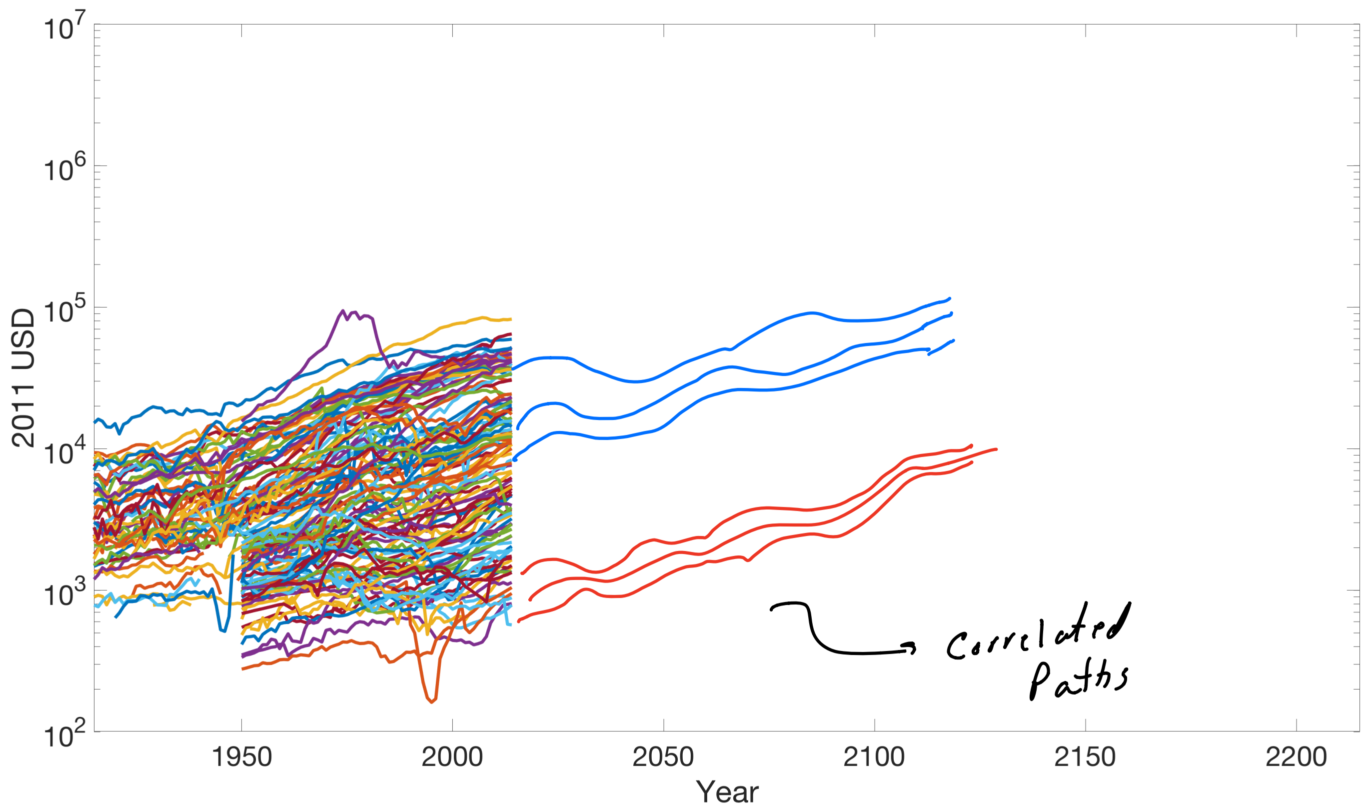




10^7
10^6
10^5
10^4
10^3
10^2
2011 USD
1950
2000
2050
2100
2150
2200
Year
means of predictive distributions



10^7
10^6
10^5
10^4
10^3
10^2
2011 USD
1950
2000
2050
2100
2150
2200
Year
2 means of predictive distributions



10^7
10^6
10^5
10^4
10^3
10^2
2011 USD
1950
2000
2050
2100
2150
2200
Year
Correlated Paths

That's it so far …

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CURRENT POSITIONS/AFFILIATIONS:

Professor of Economics and Public Affairs, Princeton University, 1995-2005, Howard Harrison and Gabrielle Snyder Beck Professor of Economics and Public Affairs, 2006-present.
Research Associate, National Bureau of Economic Research, 1988-present.
Consultant, Federal Reserve Bank of Richmond, 1996-2009, 2013-present.

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Professor of Economics, Northwestern University, 1989-1995.
Consultant, Federal Reserve Bank of Chicago, 1990-1995.
Visiting Associate Professor of Economics, University of Chicago, 1989-1990.
Associate Professor of Economics, Northwestern University, 1986-1989.
Associate Professor of Economics, Harvard University, 1984-1986.
Assistant Professor of Economics, Harvard University, 1980-1984.
Associate Editor, *American Economic Association Journal, Macroeconomics*, 2007-2008.
Associate Editor, *Journal of Economic Literature*, 2004-2008.
Advisory Board Member, *Journal of Monetary Economics*, 1995-2008.
Advisory Editor, *Macroeconomic Dynamics*, 2002-present.
Co-Editor, *The Review of Economics and Statistics,* 2008-2010; Chair, 2011-2014.
Editorial Board Member, *Advanced Texts in Econometrics*, Oxford University Press, 2002-2010.
Co-Editor, *Journal of Business and Economic Statistics,* 1995-1997.
Co-Editor of the *Journal of Applied Econometrics*, 1988-1995.
Associate Editor of *Econometrica*, 1989-1995.
Associate Editor of the *Journal of Monetary Economics*, 1989-1995.
Associate Editor of *Journal of Business and Economic Statistics*, 1991-1995.
Associate Editor of the *Journal of Applied Econometrics*, 1987-1988, 1995-1998.
Associate Editor of the *Journal of the American Statistical Association*, 1986-1988.
Faculty Research Fellow, National Bureau of Economic Research, 1986-1988.

FELLOWSHIPS, GRANTS AND HONORS

Regents Fellowship, UC San Diego, 1976, 1979-1980.
Harvard Graduate Society Research Grant 1981-1983.
Clark Fund Research Grant 1982-1986.
National Science Foundation Research Grants 1982-2009.
Honorable Mention, Galbraith Award for Graduate Teaching 1983, 1985.

Galbraith Award for Graduate Teaching 1986.
National Bureau of Economic Research Grant (Leading Indicators), 1987-2004.
Fellow of the Econometric Society, 1993-present.
Fellow of the American Academy of Arts and Sciences, 2005-present.
Honorary Doctorate (Honoris Causa), University of Bern, 2005.
Graduate Mentoring Award, Princeton University, 2008.
Isaac Kerstenstzky Scholarly Achievement Award (CIRET/FGV), 2010.
Fellow of the International Institute of Forecasters, 2017.

ADMINISTRATIVE POSITIONS (PRINCETON UNIVERSITY):
Acting Chair, Department of Economics, 2000-01, 2011-12
Associate Chair, Department of Economics, 2002-04, 2012-13
Acting Associate Dean, Woodrow Wilson School, 2008
Interim Dean, Woodrow Wilson School, 2009

PUBLICATIONS

BOOKS:

1. *Business Cycles, Indicators, and Forecasting*, edited by James H. Stock and Mark W. Watson, University of Chicago Press for the NBER, 1993.

2. *The Collected Works of C.W.J. Granger,* edited by Eric Ghysels, Norman Swanson and Mark W. Watson, Cambridge University Press, 2001.

3. *Introduction to Econometrics*, with James Stock, Addison-Wesley, 2003. Second Edition, 2007. Third Edition, 2010. Third Updated Edition, 2014. *Brief* Edition, 2008.

4. *Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle*, edited by Tim Bollerslev, Jeffrey R. Russell, and Mark W. Watson, Oxford University Press, 2010.

JOURNAL ARTICLES:

1. A One-Factor Multivariate Time Series Model of Metropolitan Wage Rates (with R.F. Engle), *Journal of the American Statistical Association*, Vol. 76, No. 376, 1981, pp. 774-781.

2. Alternative Algorithms for Estimation of Dynamic MIMIC, Factor, and Time Varying Coefficient Regression Models (with R.F. Engle), *Journal of Econometrics*, Vol. 23, pp. 385-400.

3. Testing the Interpretation of Indices in a Macroeconomic Index Model (with D. F. Kraft), *Journal of Monetary Economics*, Vol. 13, No. 2, 1984, pp. 165-182.

4. A DYMIMIC Model of Housing Price Determination (with R.F. Engle and D.M. Lilien), *Journal of Econometrics*, Vol. 28, pp. 307-326.

5. Testing for Regression Coefficient Stability with a Stationary AR(1) Alternative (with R.F. Engle), *Review of Economics and Statistics*, Vol. LXVII, 1985, 341-345.

6. Bank Rate Policy Under the Interwar Gold Standard: A Dynamic Probit Model (with B.J. Eichengreen and R. Grossman), *The Economic Journal*, Vol. 95 (September 1985), pp. 725-745.

7. Errors-in-Variables and Seasonal Adjustment Procedures (with J.A. Hausman), *Journal of the American Statistical Association*, September 1985, Vol. 80, pp. 531-540.

8. Uncertainty in Model Based Seasonal Adjustment Procedures and Construction of Minimax Filters, *Journal of the American Statistical Association*, Vol. 82, Number 398, pp. 395-408.

9. Forecasting Commercial Electricity Sales (with L.M. Pastuszek and E. Cody), *Journal of Forecasting*, Vol. 6, Number 2, April-June 1987 pp. 117-136.

10. Recursive Solution Methods for Dynamic Linear Rational Expectations Models, *Journal of Econometrics*, May 1989, Vol. 41, pp. 65-91.

11. Univariate Detrending with Stochastic Trends, *Journal of Monetary Economics*, June 1986, Vol. 18, pp. 49-75.

12. Testing For Common Trends (with J.H. Stock), *Journal of the American Statistical Association, December* 1988, 83, pp. 1097-1107. (Reprinted in *Long-Run Economic Relationships*, Readings in Cointegration, edited by R.F. Engle and C.W.J. Granger, Oxford University Press.)

13. Inference in Linear Time Series Models with Some Unit Roots (with C.A. Sims and J.H. Stock), *Econometrica*, Vol. 58, No. 1. (Reprinted in *Time Series*, edited by Andrew Harvey, Edgar Elgar Publishing.

14. Interpreting the Evidence on Money-Income Causation (with J.H. Stock), *Journal of Econometrics*, Vol. 40, Number 1, pp. 161-182.

15. Stochastic Trends and Economic Fluctuations (with Robert King, Charles Plosser, and James Stock), *American Economic Review*, Vol. 81, No. 4, (September 1991), pp. 819-40.

16. Variable Trends and Economic Fluctuations (with J.H. Stock), *Journal of Economic Perspectives*, Summer 1988, pp. 147-174. (Reprinted in Long-Run Economic Relationships, Readings in Cointegration, edited by R.F. Engle and C.W.J. Granger, Oxford University Press.)

17. The Convergence of Multivariate "Unit Root" Distributions to their Asymptotic Limits: The Case of Money-Income Causality (with L.Ljungqvist, M. Park, J.H. Stock), *Journal of Economic Dynamics and Control*, 12, pp. 489-502.

18. A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems (with James H. Stock), Econometrica, Vol. 61, No. 4 (July 1993), pp. 783-820.

19. Measures of Fit for Calibrated Models, *Journal of Political Economy*, Vol. 101, No. 6, 1993, pp. 1011-1041.

20. Business Cycle Durations and Postwar Stabilization of the U.S. Economy, *American Economic Review*, March 1994.

21. Testing for Cointegration When Some of the Cointegrating Vectors are Prespecified, (with M.T.K. Horvath), *Econometric Theory*, Vol. 11, No. 5 (December 1995), pp. 952-984.

22. Money, Prices, Interest Rates and the Business Cycle (with Robert King), *Review of Economics and Statistics*, Vol. LXXVIII, Number 1, (February 1996), pp. 35-53. (Expanded version available as Federal Reserve Bank of Chicago, Working Paper WP-95-10, July 1995.)

23. Estimating Deterministic Trends in the Presence of Serially Correlated Errors, (with Eugene Canjels), *Review of Economics and Statistics*, 1997, pp. 184-200.

24. Evidence on Structural Instability in Macroeconomic Time Series Relations, (with James H. Stock), *Journal of Business and Economic Statistics*. Vol. 14, No. 1, (January 1996) pp. 11-30.

25. The NAIRU, Unemployment, and Monetary Policy, (with Douglas Staiger and James Stock), *Journal of Economic Perspectives*, Winter 1997.

26. Asymptotically Median Unbiased Estimation of Coefficient Variance in a Time Varying Parameter Model, (with James Stock), *Journal of the American Statistical Association*, Vol. 93, No. 441, March 1998, pp. 349-358.

27. The Solution of Singular Linear Difference Systems Under Rational Expectations, (with Robert King), *International Economic Review*, 39(4), November 1998, 1015-26.

28. A Dynamic Factor Model Framework for Forecast Combination (with Y.L. Chan and J.S. Stock), *Spanish Economic Review*, 1, 1999, pp. 91-121

29. Forecasting Inflation (with James H. Stock), *Journal of Monetary Economics*, 1999, Vol. 44, no. 2.

30. Vector Autoregressions (with James H. Stock), *Journal of Economic Perspectives,* Fall 2001, Vol. 15, No. 4, 101-116.

31. Macroeconomic Forecasting Using Diffusion Indexes (with James H. Stock), *Journal of Business and Economic Statistics*, April 2002, Vol. 20 No. 2, 147-162.

32. Macroeconomic Forecasting in the Euro Area: Country Specific versus Area-Wide Information (with Massimiliano Marcellino and James H. Stock), *European Economic Review,* Volume 47, Issue 1, February 2003, pages 1-18.

33. System Reduction and Solution Algorithms for Singular Linear Difference Systems under Rational Expectations (with Robert G. King), *Computational Economics*, (October 2002), 20, pp. 57-86.

34. Forecasting Using Principal Components from a Large Number of Predictors (with J.H. Stock), *Journal of the American Statistical Association,* 2002.

35. Forecasting Output and Inflation: The Role of Asset Prices, (with James H. Stock), *Journal of Economic Literature*, 2003.

36. Combination Forecasts Of Output Growth In A Seven-Country Data Set, (with James Stock), *Journal of Forecasting,* 2004, 23(6), pp 405-430.

37. Understanding Changes in International Business Cycle Dynamics, (with James Stock), *Journal of the European Economic Association,* September 2005.

38. A Comparison of Direct and Iterated Multistep AR Methods for Forecasting Macroeconomic Time Series (with Massimiliano Marcellino and James Stock), *Journal of Econometrics* , 2006, vol. 135, pp. 499-526.

39. Consistent Estimation of the Number of Dynamic Factors in a Large N And T Panel (with Dante Amengual), *Journal of Business and Economic Statistics*, 2007 (January).

40. Why Has Inflation Become Harder to Forecast? (with James Stock), *Journal of Money, Credit and Banking,* 2007, Vol. 39, Number 1, pp. 3-34; Erratum, *Journal of Money, Credit and Banking,* 2007, Vol. 39, Number 7, pp. 1849.

41. A, B, C's and (D)'s For Understanding VARS (with Jesus Fernandez-Villaverde, Juan F. Rubio-Ramirez, and Thomas J. Sargent), *American Economic Review,* 2007 (June), Vol. 97, Number 3, pp. 1021-1026.

42. Heteroskedasticity-Robust Standard Errors for Fixed Effect Panel Data Regression (with James H. Stock), *Econometrica*, Vol. 76, No. 1 (January, 2008), pp. 155-174.

43. Testing Models of Low-Frequency Variability (with Ulrich Müller), *Econometrica*, Vol. 76, No. 5 (September, 2008), 979–1016.

44. Indicators for Dating Business Cycles: Cross-History Selection and Comparisons (with James H. Stock), *American Economic Review*, Vol. 100, No. 2, May 2010, pp 16-19.

45. Relative Goods' Prices and Pure Inflation (with Ricardo Reis), *American Economic Journal Macroeconomics*, 2 (3), (July 2010.), 128-157.

46. Sectoral vs. Aggregregate Shocks: A Structural Factor Analysis of Industrial Production (with Andrew Foerster and Pierre-Danieal Sarte), *Journal of Political Economy*, 2011 (January), pp 1-38.

47. Generalized Shrinkage Methods for Forecasting Using Many Predictors (with James H. Stock), *Journal of Business and Economic Statistics,* 2012 (October), Vol. 30, No. 4, 481-493.

48. Inflation and Unit Labor Cost (with Robert G. King), *Journal of Money, Banking, and Credit*, Vol. 44, No. 2, 2012 (December), pp. 111-149.

49. Low-Frequency Robust Cointegration Testing (with Ulrich Müller), *Journal of Econometrics*, 177 (2013), pp 66-81.

50. Consistent Factor Estimation in Dynamic Factor Models with Structural Instability (with Brandon J. Bates, Mikkel Plagborg-Møller, and James H. Stock), *Journal of Econometrics*, (2013), 177, pp 289-304.

51. Estimating Turning Points Using Large Data Sets (with James H. Stock), *Journal of Econometrics*, (2014), 178, pp 368-381.

52. Inflation Persistence, the NAIRU, and the Great Recession, *American Economic Review*, Vol. 104, No. 5, May 2014, pp 31-36.

53. Nearly Optimal Tests When a Nuisance Parameter is Present Under the Null Hypothesis (with Graham Elliott and Ulrich Müller), *Econometrica*, Vol. 83, Issue 2, March 2015, pp. 771-811.

54. Presidents and the Economy: A Econometric Investigation (with Alan Blinder), *American Economic Review*, Vol. 106, No. 4, April 2016: pp. 1015-1045.

55. Core and Trend Inflation (with James H. Stock), *Review of Economics and Statistics*, 98(4), October 2016: pp. 770-784.

56. Measuring Uncertainty about Long-Run Predictions (with Ulrich Müller), *Review of Economic Studies,* 83 (4), October 2016, pp. 1711-1740.

57. Twenty Years of Time Series Econometrics in Ten Pictures (with James Stock), *Journal of Economic Perspectives*, Vol. 31, No. 2 (Spring 2017), pp. 59-86.

ARTICLES IN BOOKS AND OTHER PERIODICALS:

1. Formulation Generale et Estimation de Models Multidimensionnels Temporels a Facteurs Explicatifs Non-observables (with R.F. Engle), *Cahiers du Seminaire D'Econometric*, No. 22, 1980, pp. 109 - 125.

2. Bubbles, Rational Expectations, and Financial Markets (with O.J. Blanchard) in *Crisis in the Economic and Financial Structure: Bubbles, Bursts, and Shocks*, Paul Wachtel (editor), Lexington Books, 1982, translated as "Bulles, anticipations rationnelles et marches financiers," *Annales De L'insee*, no. 54, 1984, pp. 79-100.

3. Time Series and Spectral Methods in Econometrics (with C.W.J. Granger), *Handbook of Econometrics*, Vol. 2, Z. Griliches and M. Intriligator (editors), North Holland, 1984, pp. 979-1022.

4. Are Business Cycles All Alike (with O.J. Blanchard), Robert J. Gordon (editor), *The American Business Cycle*, NBER and Chicago Press, 1986.

5. The Kalman Filter: Applications to Forecasting and Rational Expectations Models (with R.F. Engle), in *Advances in Econometrics*, Fifth World Congress, edited by T. Bewley, Cambridge University Press.

6. Sources of Business Cycle Fluctuations (with Matthew D. Shapiro), *NBER Macroeconomics Annual*, Vol. 3, 1988, M.I.T. Press, pp. 111-156.

7. A Probability Model of the Coincident Economic Indicators (with James H. Stock), in *Leading Economic Indicators: New Approaches and Forecasting Records*, edited by K. Lahiri and G. Moore, Cambridge University Press, 1991.

8. New Indexes of Coincident and Leading Economic Indicators (with James H. Stock), *NBER Macroeconomics Annual*, Vol. 4, 1989, M.I.T. Press.

9. The Budgetary Process: Characteristics and Cautions (with Dana Naimark), Chapter 4 in *State and Local Finance for the 1990's: A Case Study of Arizona*, edited by T. McGuire and D. Naimark, Arizona State University Press.

10. General Fund Projections and History, Chapter 20 in *State and Local Finance for the 1990's: A Case Study of Arizona,* edited by T. McGuire and D. Naimark, Arizona State University Press.

11. Seasonal Adjustment of Preliminary Data (with Jerry A. Hausman), *Papers and Proceeding of the American Statistical Association, Business and Economics Section*, 1990.

12. A Procedure for Predicting Recessions with Leading Indicators: Econometric Issues and Recent Experience (with James Stock), in *New Research on Business Cycles, Indicators and Forecasting*, James Stock and Mark Watson (editors), University of Chicago Press, 1993.

13. Using Econometric Models to Predict Recessions, *Economic Perspectives*, (Research Periodical of the Chicago Federal Reserve Bank), September/October, 1991.

14. Forecasting with Leading Indicators: Lessons for the 1990 Recession in the United States (with James Stock), *Konjunktur-Prognoser & Konjunkturpolitik, Ekonomiska Radets Arsbok* 1992, pp. 77-102.

15. Vector Autoregressions and Cointegration, *Handbook of Econometrics*, Vol. 4, Robert F. Engle and Dan McFadden (editors), North Holland.

16. The Post-War U.S. Phillips Curve: A Revisionist Econometric History, (with Robert King), *Carnegie-Rochester Conference on Public Policy*, 1994, Vol. 41, pp. 157-219.

17. Stability of the Unemployment-Inflation Relation, (with Robert King and James Stock), *Economic Perspectives*, (Research Periodical of the Chicago Federal Reserve Bank), 1995.

18. How Precise are Estimates of the Natural Rate of Unemployment, (with Douglas Staiger and James Stock), in C. Romer and D. Romer (eds.), *Reducing Inflation: Motivation and Strategy*, University of Chicago Press.

19. Systematic Monetary Policy and the Effects of Oil Price Shocks, (with Ben S. Bernanke and Mark Gertler), *Brookings Papers on Economic Behavior*, 1997:I.

20. Testing Long Run Neutrality (with Robert King), Federal Reserve Bank of Richmond *Economic Quarterly*, 1997

21. Business Cycle Fluctuations in U.S. Macroeconomic Time Series, (with James Stock), in John Taylor and Michael Woodford (Eds.) *Handbook of Econometrics*, North Holland, 1999.

22. Explaining the Increased Variability in Long Term Interest Rates, Federal Reserve Bank of Richmond *Economic Quarterly*, Winter 2000.

23. A Comparison of Linear and Nonlinear Univariate Models for Forecasting Macroeconomic Time Series, (with James Stock), *Festschrift in Honor of C.W.J. Granger*, R.F.Engle and H. White (eds.), Oxford University Press, 1999.

24. Time Series: Cycles, *International Encyclopedia of the Social and Behavioral Sciences, Statistics Volume,* Stephen E. Fienberg and Joseph B. Kadane, Editors, 2001, Elsevier Science.

25. Macroeconomic Forecasting Using Many Predictors, in M. Dewatripont, L. Hansen and S. Turnovsky (eds.), *Advances in Economics and Econometrics*, Theory and Applications, Eighth World Congress of the Econometric Society, Vol. III, pp. 87-115.

26. Prices, Wages and the U.S. NAIRU in the 1990s (with Douglas Staiger and James H. Stock), *Sustainable Employment*, edited by Alan Krueger and Robert Solow, Russell Sage Foundation, 2002.

27. Has the Business Cycle Changed and Why? (with James H. Stock), *NBER Macroeconomics Annual 2002*, Mark Gertler and Ken Rogoff (eds.), MIT Press.

28. How Did Leading Indicator Forecasts Perform During the 2001 Recession? (with James H. Stock), Federal Reserve Bank of Richmond *Economic Quarterly*, Summer 2003.

29. Has the Business Cycle Changed? Evidence and Explanations, (with James Stock), *Monetary Policy and Uncertainty: Adapting to a Changing* Economy, FRB Kansas City symposium, Jackson Hole, Wyoming, August 28-30, 2003, pp 9-57.

30. Macroeconomic Forecasting Using Many Predictors (with James H. Stock), *Handbook of Economic Forecasting*, Graham Elliott, Clive Granger, Allan Timmerman (eds.), North Holland, 2006.

31. How Accurate are Real-Time Estimates of Output Trends and Gaps?, Federal Reserve Bank of Richmond *Economic Quarterly*, Spring 2007.

32. Cointegration, entry for *The New Palgrave Dictionary*, 2nd edition, edited by Lawrence Blume and Steven Durlauf.

33. Macroeconomic Forecasting, entry for *The New Palgrave Dictionary*, 2nd edition, edited by Lawrence Blume and Steven Durlauf.

34. *Understanding the Evolving the Evolving Inflation Process.* (with Stephen G. Cecchetti, Peter Hooper, Bruce C. Kasman, and Kermit L. Schoenholtz). U.S. Monetary Policy Forum Report No. 1, Rosenberg Institute for Global Finance, Brandeis International Business School and Initiative on Global Financial Markets, University of Chicago Graduate School of Business, 2007.

35. Forecasting in Dynamic Factor Models Subject to Structural Instability (with James H. Stock), in *The Methodology and Practice of Econometrics, A Festschrift in Honour of Professor David F. Hendry*, Jennifer Castle and Neil Shephard (eds), 2008, Oxford: Oxford University Press.

36. Phillips Curve Inflation Forecasts (with James H. Stock), in *Understanding Inflation and the Implications for Monetary Policy, a Phillips Curve Retrospective*, Federal Reserve Bank of Boston, 2009.

37. The Evolution of National and Regional Factors in U.S. Housing Construction (with James H. Stock), forthcoming in *Volatility and Time Series Econometrics: Essays in Honour of Robert F. Engle*, Tim Bollerslev, Jeffrey Russell and Mark Watson (eds), 2009, Oxford: Oxford University Press.

38. Financial Conditions Indexes: A Fresh Look after the Financial Crisis (with Jan Hatzius, Peter Hooper, Frederic Mishkin, and Kermit Schoenholtz), U.S. Monetary Policy Forum Report No. 4, Initiative on Global Financial Markets, University of Chicago Graduate School of Business, 2010.

39. Modeling Inflation After the Crisis (with James H. Stock), *Macroeconomic Policy: Post-Crisis and Risks Ahead*, FRB Kansas City symposium, Jackson Hole, Wyoming, August 26-28, 2010.

40. Dynamic Factor Models (with James H. Stock), *Oxford Handbook of Forecasting*, Michael P. Clements and David F. Hendry (eds), 2011, Oxford University Press.

41. Disentangling the Channels of the 2007-2009 Recession (with James Stock), *Brookings Papers on Economic Activity*, Spring 2012, 81-135.

42. Low-Frequency Econometrics (with Ulrich Müller), *Advances in Economics and Econometrics* (World Congress of the Econometric Society 2015), forthcoming.

43. Factor Models and Structural Vector Autoregressions in Macroeconomics (with James Stock), *Handbook of Macroeconomics*, vol. 2A, John B. Taylor and Harald Uhlig (eds), 2016, Chapter 8, pp 415-526.

44. The Disappointing Recovery of Output after 2009 (with John. G. Fernald, Robert E. Hall, and James H. Stock), *Brookings Papers on Economic Activity,* Spring 2017.

NOTES, COMMENTS AND REVIEWS:

1. Imperfect Information and Wage Inertia in the Business Cycle: A Comment, *Journal of Political Economy*, Vol. 91, No. 5, 1983, pp. 876-879.

2. Comment on "Irregular Data Revisions," by A.C. Harvery, C.R. McKenzie, D.P.C. Blake, and M.J. Desai, in Applied Time Series Analysis of Economic Data, edited by Arnold Zellner, U.S. Department of the Census, Economic Research Report ER-5

3. Does GNP Have a Unit Root ? (with J.H. Stock), *Economics Letters*, 22, pp. 147-151.

4. Comment on "Vector Autoregressions and Reality," by David Runkle, *Journal of Business and Economic Statistics,* 1987.

5. Comment on "A Reexamination of Friedman's Consumption Puzzle" by James H. Stock, *Journal of Business and Economic Statistics*, 1988.

6. Comment on "Sensitivity Analysis of Seasonal Adjustments: Empirical Case Studies" by J.B. Carlin and A.P. Dempster, Journal of the American Statistical Association, March 1989.

7. Review of Time Series Analysis by John Cryer, *Journal of the American Statistical Association,* December 1987, Volume 82, Number 400, 1195.

8. Software Review *Journal of Applied Econometrics*, 4, pp. 205-206.

9. Review of The Collected Works of John W. Tukey, Vols. I, II, and V, edited by D. Brillinger and W.P. Cleveland, *Journal of the American Statistical Association*, 1988.

10. Comment on "Inflation Indicators and Inflation Policy" by Stephen G. Cecchetti, NBER *Macroeconomics Annual*, 1995.

11. Comment on "Is Seasonal Adjustment a Linear or Nonlinear Data Filtering Process," *Journal of Business and Economic Statistics*, Vol. 14, No. 3, July 1996

12. Comment on "On the Fit of a Neoclassical Monetary Model in High Inflation: Israel 1972-1990" by Eckstein and Bental, *Journal of Money, Banking and Credit*, November 1997.

13. Comment on "Assessing Changes in the Monetary Transmission Mechanism: A VAR Approach," by Jean Boivin and Marc Giannone, *Federal Reserve Bank of New York Policy Review,* 8(1), 2002.

14. Comment on "Market Anticipations of Monetary Policy Actions" by William Poole, Robert H. Rasche and Daniel L. Thornton, Federal Reserve Bank of St. Louis *Review*, Jul/Aug 2002, 84(4).

15. Comment on "Monetary Policy in Real Time," by Domenico Giannone, Lucrezia Reichlin, and Luca Sala, *NBER Macroeconomics Annual*, 2004.

16. Comment on "What's Real About the Business Cycle" by James Hamilton, forthcoming Federal Reserve Bank of St. Louis *Review*, 2005.

17. Comment on "Assessing Structural VARs" by L. Christiano, M. Eichenbaum, and R. Vigfusson, *NBER Macroeconomics Annual*, 2006.

18. Comment on "Shocks and Crashes" by M. Lettau and S. Ludvigson, *NBER Macroeconomics Annual*, 2013.

19. Comment on "Trends and Cycles in China's Macroeconomy," by C. Chang, K. Chen, D.F. Waggoner, and T. Zha, *NBER Macroeconomics Annual*, 2015.

20. Comment on "Macroeconomic Effects of Disruptions in Global Food Commodity Markets: Evidence for the United States," by Jasmien De Winne and Gert Peersman, *Brookings Papers on Economic Activity*, Fall 2016.

UNPUBLISHED PAPERS:

1. Confidence Sets in Regressions with Highly Serially Correlated Regressors, (with James Stock), November 1996.

2. Empirical Bayes Forecasts of One Time Series Using Many Predictors (with Thomas Knox and James H. Stock), September 2000, revised March 2002.

3. Optimal Tests for Reduced Rank Time Variation in Regression Coefficients and Level Variation in the Multivariate Local Level Model (with Piotr Eliasz and James Stock).

4. Implications of Dynamic Factor Models for VAR Analysis (with James Stock), revised June 2005.

5. Measuring Changes in the Value of the Numeraire (with Ricardo Reis), May 2007.

6. Long-Run Covariability (with Ulrich Müller), August 2016.

PROFESSIONAL SERVICE AND MISC:

Program Committee, North American Winter Meetings of the Econometric Society, 1987.
Program Committee, North American Summer Meetings of the Econometric Society, 1988.
Co-Organizer, NBER/NSF Time Series Conference, Chicago Il, 1988.
Program Committee, World Congress of the Econometric Society, 1990.
National Science Foundation, Economics Advisory Panel, 1990-1992.
Chair, Program Committee, North American Winter Meetings of the Econometric Soc., 1995.
Fellows Nominating Committee, Econometric Society, 1997.
Business Cycle Indicators Advisory Committee, The Conference Board, 1996-present, (Chair 2010-present)
Program Committee, World Congress of the Econometric Society, 2000.
Co-Organizer NBER/NSF Co-Organizer, NBER/NSF Conference on Forecasting & Empirical Methods in Macroeconomics & Finance, 2001-2012.
Cornell Department of Economics Review Panel, 2001.
Program Committee, Winter Meetings of the Econometric Society, 2002.
Nominating Committee, American Economic Association, 2002.
Sloan Foundation Fellowship Selection Committee in Economics, 2004-2010.
Selection Committee, Robert F. Engle Prize in Financial Econometrics (*Journ. of Fin. Econometrics*), 2005.
Co-Editor (with Kenneth West), June 2005 special issue of the *Journal of Money Credit and Banking*.
Program Committee, Summer Meetings of the Econometric Society, 2006.
U.S. Monetary Policy Forum Panelist, 2007-2011
University of Pennsylvania, Department of Economics Review Panel, 2009.
NBER Business Cycle Dating Committee, 2009-Present.
UC Irvine Department of Economics Review Panel, 2010.
UC Riverside Department of Economics Review Panel, 2011.
Program Co-chair, International Association of Applied Econometrics, 2016.
University of Washington, Department of Economics Review Panel, 2016.