

A new approach for policymakers to testing models and policies

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- d) Estimate by FIML (= Bayesian with flat priors)? **Bad small sample bias**/flat likelihood surfaces — poor statistical accuracy.
- a)-d) all widely used today. For policymakers not useful: in practice they use 'suite of models' and rely on own beliefs.

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- Matlab Programme INDIRECT now available for download, plus supporting manual, papers etc. — www.patrickminford.net/Indirect

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- Direct and Indirect Inf. both tests of DSGEM's 'specification': compare properties below.

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- Variation of these α_S give their var-covar matrix, $\Omega(\alpha[\hat{\theta}])$.

Joint distribution implied by DSGEM illustrated for 2 VAR coefficients only (constructed distribution, not SW):

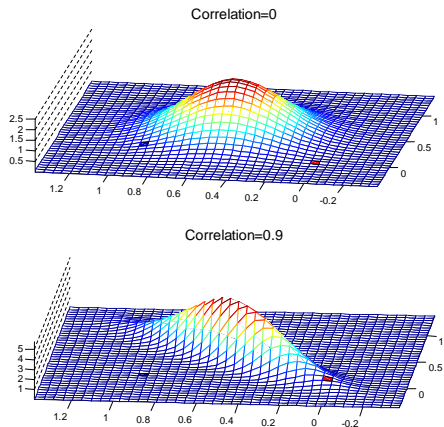


Figure: Bivariate Normal Distributions (0.1, 0.9 shaded blue and 0, 0 shaded red) with correlation of 0 and 0.9.

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- PDF of k simulated VAR coeffs, α_S , given by joint normal

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 Has approx Chi-squared distribution (k).
- Test: reject if Wald with data-estimated α_T :
$$[a_T - \alpha_S(\hat{\theta})]' \{\Omega(\alpha[\hat{\theta}])\}^{-1} [a_T - \alpha_S(\hat{\theta})]$$
 exceeds W_C (critical value from IIW distribution).

Wald statistic for joint distribution of $k=30$ coefficients (Smets Wouters DSGEM)

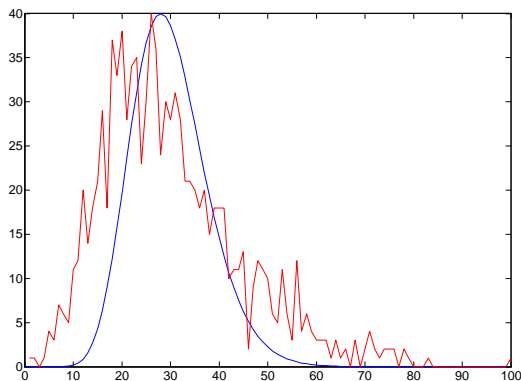


Figure: Histogram of Wald statistic for SW model, with asymptotic Chi-squared distribution for $k=30$

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- Various ways to get estimator: we use search algorithms (typically Simulated Annealing), find estimator halves FIML small sample bias.

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- Power of test: percent of 1000 MC samples which reject null on upper 5% tail.

Monte Carlo results — stationary data

Model Null	IIW	LR
True	5.0	5.0
False by- 1(%)	19.8	6.3
3	52.1	8.8
5	87.3	13.1
7	99.4	21.6
10	100.0	53.4
15	100.0	99.3
20	100.0	99.7

Table: Rejection Rates for Wald and Likelihood Ratio for 3 Variable VAR(1) on STATIONARY DATA

Monte Carlo results — non-stationary data

Model Null	IIW	LR
True	5.0	5.0
False by- 1(%)	7.9	5.2
3	49.2	5.8
5	97.8	6.2
7	100	7.4
10	100	9.6
15	100	15.6
20	100	26.5

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- **But** IIW uses *model-restricted* variance matrix, $\Omega(\alpha[\hat{\theta}])$: this *changes* with changing Falseness, $\Omega(\alpha_T)$ does not.

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Model Null		IIW	LR	LR-like-f-l	Wald UNR
	True	5.0	5.0	5.0	5.0
False by-	3(%)	52.1	8.8	21.8	7.5
	5	87.3	13.1	37.5	30.7
	7	99.4	21.6	58.9	75.0
	10	100.0	53.4	84.0	97.0
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Understanding power differences visually

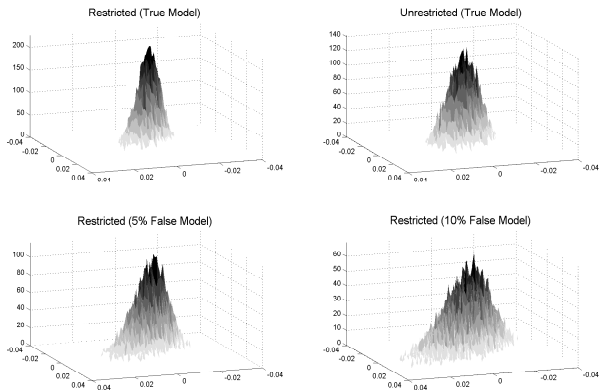


Figure: Restricted VAR and Unrestricted VAR Coefficient Distributions

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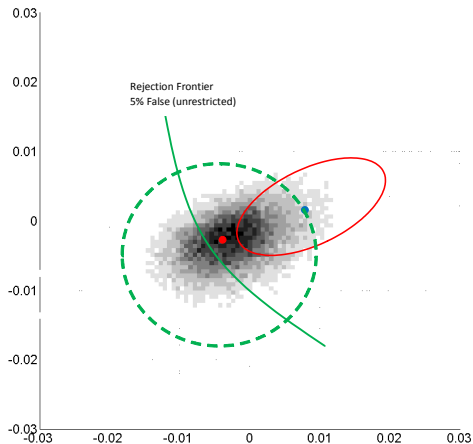
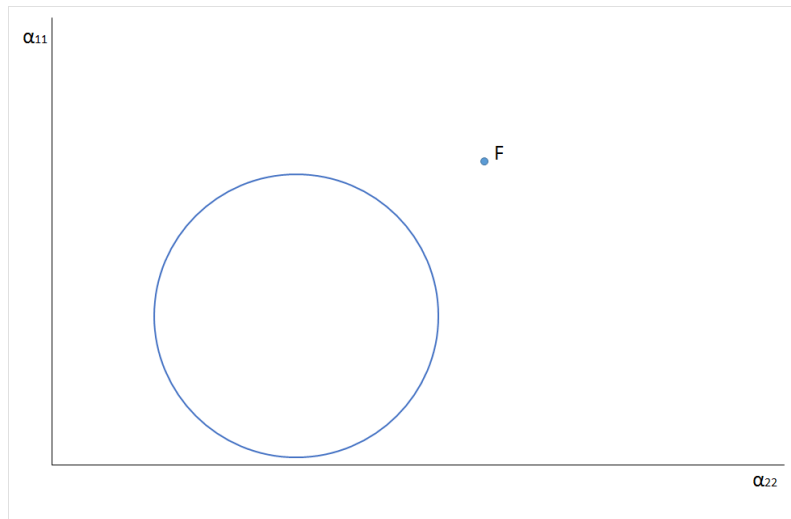
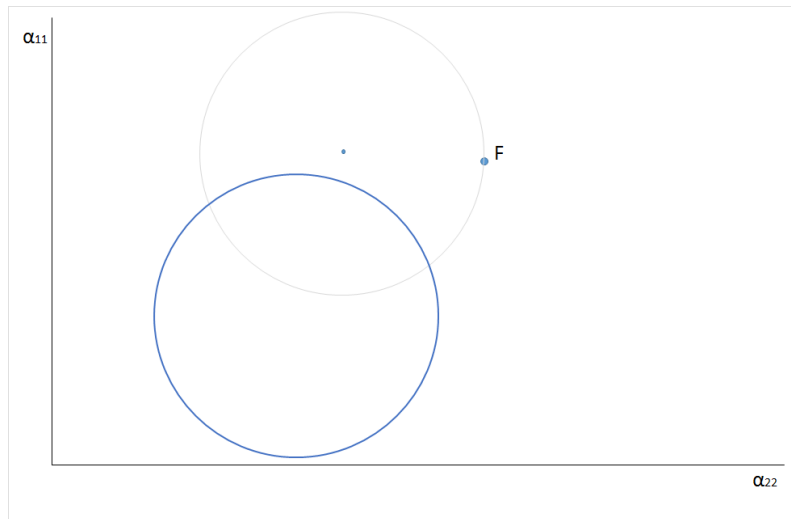


Figure: Two 95% contours for tests of 5% False Model — Green=Unrestricted; Red=Restricted.

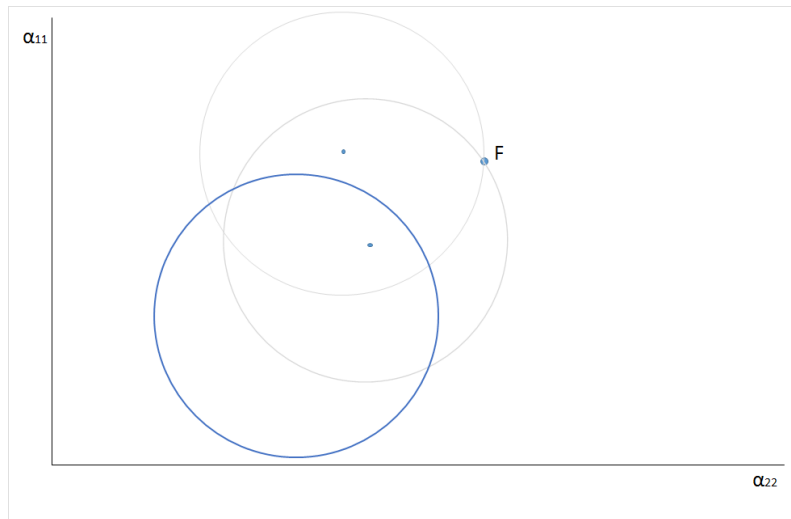
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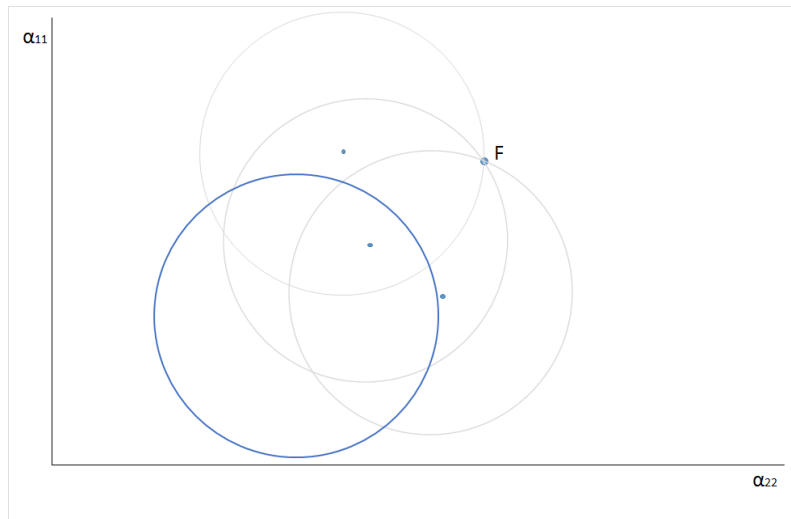
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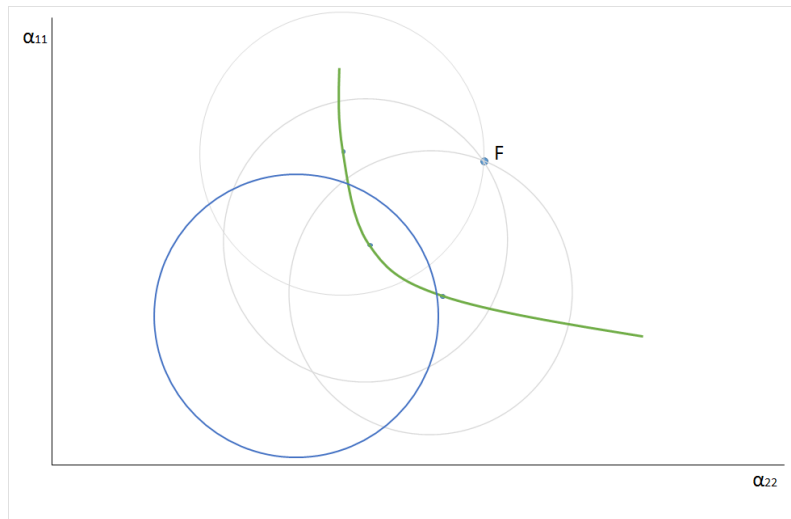
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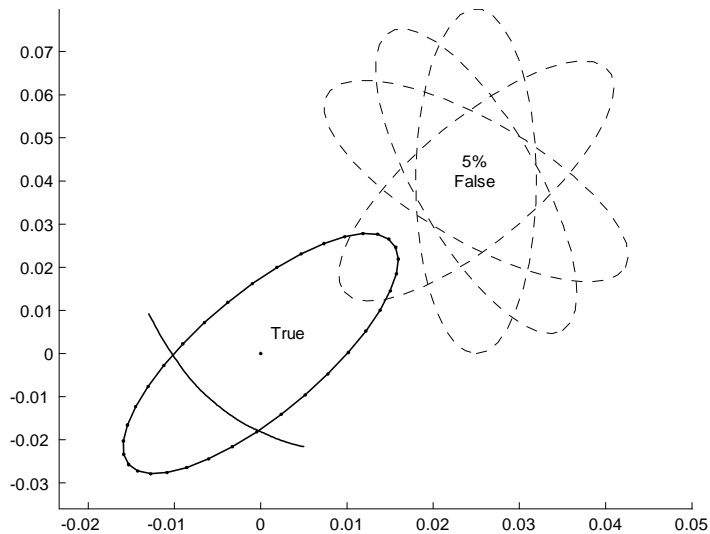
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- Wald UNR and IIW asymptotically equivalent when model is true (stationary, no exog variables) but not when model is false (hence power difference).
- IIW requires $\Omega(\alpha[\hat{\theta}])$ which only calculable numerically as in INDIRECT.

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- Gives rise to trade-off between power and tractability.

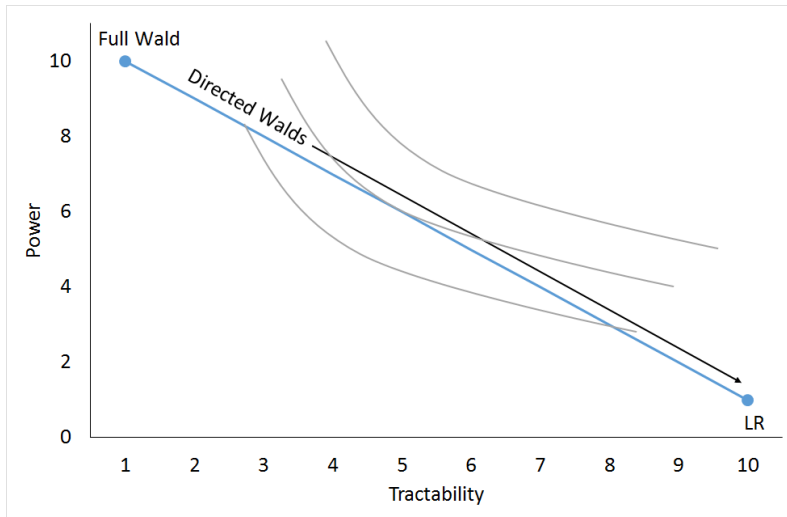


Figure: Maximising Friedman utility

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- **Use tests to establish worst case scenarios for policy reforms. If reforms still viable, policymakers happy!**

Application to DSGEM about monetary reform

Crises per 1000 yrs	Base case	Monetary Reform	PLT	NGDPT	PLT+ M. Refm	NGDPT+ M. Refm
MODEL						
True	20.8	6.62	2.15	1.83	1.41	1.31
IIW: 7% False	57.4	18.6	10.3	8.7	11.8	10.3
LR: 50% F	70.4	<i>Explosive</i>	33.3	33.4	34.4	34.2

Notes:

Base Case: monetary policies as estimated over the sample period;

Monetary Reform: Monetary Base rule (responds to credit premium) + Taylor Rule;

PLT: substituting Price Level Target for Inflation Target in Taylor Rule;

NGDPT: substituting Nominal GDP target for inflation and output targets in Taylor Rule.

Table: Policy analysis when model have varying falseness

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- **Illustration only!** Policymakers should redo Monte Carlo analysis for particular model/data set. Power functions could alter.
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- Procedure here for getting realistic idea of risks for policy reforms so can adapt as necessary.

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- Programmes available for download to implement in user-friendly way. Happy to help early users and get feedback!