Structural Models in Accounting

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Philosophy

I thought this summer school was about learning math, why do we have to talk about philosophy?

Statistics in Social Sciences

Suppose we estimate a reduced-form statistical model with observables (y_i, x_i) such that:

$$y_i = \alpha + \beta x_i + \epsilon_i, \tag{1}$$

subject to $\mathbb{E}(x_i \epsilon_i) = 0$.

Things we can do with this model:

1. We can recover some descriptive facts about conditional means $\mathbb{E}(y_i | x_i)$.
2. We can falsify a theory that, say, predicts $\beta > 0$.
3. If x_i is a firm policy variable we control, we can measure the effect of changing x_i on y_i.

Statistics in Social Sciences (2)

Suppose we estimate a reduced-form statistical model with observables (y_i, x_i) such that:

$$y_i = \alpha + \beta x_i + \epsilon_i, \tag{2}$$

subject to $\mathbb{E}(x_i \epsilon_i) = 0$.

Things we *cannot do* with this model:

1. We can't measure welfare.
2. We can't predict the effect of any policy except changing x_i for an infinitesimal subset of the population. We have to wait for a policy to be implemented to advise policy-makers about the benefits of the policy.
3. We can't draw implications for other variables z_i that are not in equation (2).
4. We can't select non-linear functional forms unless the dataset is enormous.
5. We can't measure most elements of a theory.
6. We can't draw quantitative implications from a theory.
7. (philosophy) All theories will be rejected - even general relativity is rejected in the small - what does it mean to falsify a theory we already know we can reject?
8. (philosophy) Even if we knew (2) was true, we wouldn't know the real world completely because (y_i, x_i, u_i) are the result of unobserved primitives.

What are ecomomic primitives?

From Terry (2015), The Macro Impact of Short-Termism

Table IV: GMM Parameter Estimates

Parameter	Explanation	Estimate (SE)
ρ_a	Prof. persistence	0.903 (0.0325)
σ_a	Prof. volatility	0.070 (0.0029)
σ_ε	Transitory shock vol.	0.099 (0.0071)
A	R&D level	0.256 (0.1168)
ξ	Earnings miss disruption	0.001 (0.0006)
γ_m	Manipulation cost	0.290 (0.3679)

Marinovic (Rand, 2013): Internal control system, earnings quality, and the dynamics of financial reporting. What are firm's propensities to report earnings truthfully?

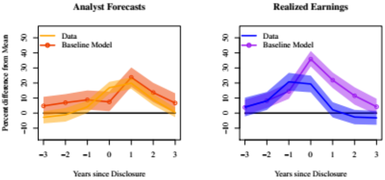
Percentiles	$\hat{\gamma}$
p1	0.236
p5	0.914
p10	0.959
p25	0.961
p50	0.997
p75	1.000

What are Targeted and Untargeted Moments?

From Choi (2018), Accrual Accounting and Resource Allocation: A General Equilibrium Analysis

Moment	US Empirical	Simulated
$corr(a^c_{it}, a^c_{it-1})$	0.9660	0.9616
$corr(a^e_{it}, a^e_{it-1})$	0.9833	0.9778
$cov(\Delta a^c_{it}, \Delta a^e_{it})$	0.0238	0.0238
$var(\Delta a^c_{it})$	0.0551	0.0552
$var(\Delta a^e_{it})$	0.0313	0.0312
$corr(\Delta i_{it+1}, \Delta a^c_{it})$	0.2120	0.2136
$corr(\Delta i_{it+1}, \Delta a^e_{it})$	0.2889	0.2880
J statistic	0.0433	
	(0.9786)	

From Bertomeu, Marinovic, Terry, Varas (2020), The Dynamics of Concealment



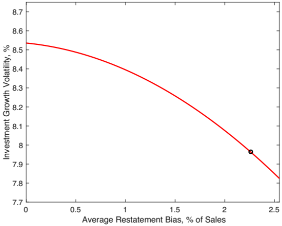
What are Counterfactuals?

Ideal counterfactuals: concrete policy experiment we could quantify.
Cheynel and Zhou (2018), The Consequences of Mandating Auditor Rotation: Evidence from a Dynamic Structural Model

Mandatory rotation if tenure exceeds 5 years

Year	Rotation	No rotation
2016	35%	23%
2017	29%	24%
2018	30%	23%
2019	32%	24%
2020	34%	24%
2021	31%	23%
2022	33%	23%
2023	32%	23%
2024	32%	24%
2025	32%	24%
Long run	32%	23%

From Terry, Whited, Zakolyukina (2018), Information vs. Investment



What are subsamples breakdowns?

Ideal subsamples: Vary as expected from theory or from intuition.

Beyer, Guttman and Marinovic (TAR, 2013), Earnings Management and Earnings Quality: Theory and Evidence

Table 12: Ratio of of the variance of the noise added by earnings manipulation, σ_η^2, to the variance of the earnings innovation, σ_v^2, for quarterly data.

	σ_v^2	σ_η^2	*Estimate*	*Std. Dev.*	*z-Statistic*	*p-Value*	*95% Conf.*	*Interval*
Industry 1: Consumer non-Durables	.003	.001	.543	.083	6.533	.000	.380	.705
Industry 2: Consumer Durables	.004	.001	.402	.087	4.618	.000	.231	.572
Industry 3: Manufacturing	.003	.001	.548	.064	8.602	.000	.423	.673
Industry 4: Energy	.009	.006	.716	.210	3.407	.001	.304	1.129
Industry 5: Chemicals	.001	.001	.781	.294	2.659	.008	.205	1.357
Industry 6: Business Equipment	.004	.002	.540	.050	1.877	.000	.443	.638
Industry 7: Telecom	.001	.005	9.585	31.312	.306	.760	-51.785	7.955
Industry 8: Utilities	.001	.001	.714	.188	3.797	.000	.345	1.082
Industry 9: Wholesale and Retail	.004	.002	.537	.065	8.258	.000	.410	.665
Industry 10: Healthcare	.002	.002	1.044	.179	5.822	.000	.692	1.395
Industry 11: Finance	.003	.002	.652	.064	1.187	.000	.527	.777
Industry 12: Other	.005	.003	.639	.077	8.277	.000	.488	.791
Mean			1.392					
Median			.646					

Bertomeu, Cheynel, Li and Liang (2019), How uncertain is the market about managers' reporting objectives? Evidence from structural estimation

Table 12: Estimation by Growth Opportunity

Portfolio	Mean $_x$ μ_x	Std.Dev.$_x$ σ_x	Intensity d
Aggregate	**-4.40E-05**	**0.0052**	**23.9540**
	(0.0003)	*(0.0005)*	*(1.9010)*
Low	-0.0005	0.0040	30.4650
	(0.0003)	*(0.0004)*	*(2.4734)*
Medium	6.69E-05	0.0009	37.0557
	(0.0005)	*(0.0014)*	*(4.8196)*
High	-8.83E-05	0.0072	18.7564
	(0.0006)	*(0.0013)*	*(2.1568)*

What are outside calibrations?

Calibrations: for parameters that cannot be well-identified from dataset, either by matching other moments or from industry knowledge.
Bertomeu, Marinovic, Terry, Varas (2020), The Dynamics of Concealment

Table 3. Outside Calibration of Some Earnings and Forecast Parameters

Parameter, Role	Value	Targeted Moment	Data	Model
ρ, Earnings Persistence	0.85	Corr(e_t, e_{t-1})	0.85	0.85
σ_u, Earnings Volatility	0.45	St Dev(IHS($e_t - \mathbb{E}e_t$))	0.72	0.72
σ_n, Analyst Precision	0.68	St Dev(IHS($c_t - e_t$))	0.59	0.59

From Liang et Al. (2017), The Real Effects of Accounting: A Quantitative Assessment

Table 1: Calibrated values

Parameter	Description	Value
α	Managerial myopia	0.56
β	Discount factor	0.995
γ	Capital share	0.69
δ_k	Capital depreciation rate	0.02
ρ	Persistence of firm-level productivity shock	0.91
σ_θ	Std.Dev of firm-level productivity shock	0.12
κ	Constant drift in AR(1) for productivity shock	0.11
c	Personal cost of investment	1.50
b	Accounting quality	0.66

$\rightarrow$ Justification from prior studies, outside estimation, sensitivity.

What are outside validations?

From Gerakos and Syverson (JAR 2015), Competition in the Audit Market: Policy Implications

Panel A: Conditional logit estimated on Arthur Andersen clients

		Highest Predicted Probability					
		E&Y	Deloitte	KPMG	PwC	Non–Big 4	Total
Actual choice	E&Y	133	20	53	7	6	219
		60.7%	*9.1%*	*24.2%*	*3.2%*	*2.7%*	
	Deloitte	40	69	40	7	2	158
		25.3%	*43.7%*	*25.3%*	*4.4%*	*1.3%*	
	KPMG	51	18	129	8	4	210
		24.3%	*8.6%*	*61.4%*	*3.8%*	*1.9%*	
	PwC	31	18	38	32	2	121
		25.6%	*14.9%*	*31.4%*	*26.4%*	*1.7%*	
	Non–Big 4	14	4	14	1	16	49
		28.6%	*8.2%*	*28.6%*	*2.0%*	*32.7%*	
	Total	269	129	274	55	30	

What is a restricted Model?

From Bertomeu, Ma, Marinovic (TAR, 2020), How often do managers withhold information?. Re-estimate simpler models.

	ξ
Perfect information	0.1201
	(.0101)
No disclosure benefit	0.2598
	(.0126)
No price motive	0.1634
	(.0279)
No preference shocks	0.0672
	(0.0156)
Only price motive	0.1308
	(0.0084)

Marinovic, Liang, Varas (TAR, 2018), The credibility of financial reporting: A reputation-based approach

Table 1: *Model Estimation*

The estimation is conducted using the Particle swarm optimization (PSO) algorithm. PSO starts with a group of particles (solutions) randomly drawn from the region. In each iteration, each particle will update its velocity and position after comparing the best solution (fitness value) it has achieved and the global best obtained by any particle in the population. We estimate four models using Actual EPS. In the first model, the manager is naively assumed to honest with probability 1, *i.e.* $\gamma = 1$. The second model assumes that the true earnings follow a iid process. The third model is the baseline model, where the true earnings follow an AR(1) process and the the manager's payoff is $E_T[x_T]$. The last model, also assumes the true earnings follow an AR(1) process and the manager's incentive is $E_T[x_T + \lambda e_T]$. Standard errors are presented in parentheses.

Models	γ	μ	σ	φ	λ	Log lik
Model Naive		1.183	1.242	0.506		
with $\gamma = 1$	-	(0.053)	(0.032)	(0.019)	-	-1261.37
Model *iid*, ($\varphi = 0$)	0.993	2.406	1.444			
with $V = x_T$	(0.009)	(0.053)	(0.038)	-	-	-1310.47
Model Baseline, *AR(1)*	0.932	1.201	1.231	0.480		
with $V = x_T$	(0.040)	(0.087)	(0.031)	(0.032)	-	-1257.01
Model General, *AR(1)*	0.932	1.200	1.231	0.480	0.001	
with $V = x_T + \lambda e_T$	(0.040)	(0.087)	(0.031)	(0.032)	(0.022)	-1257.01

What is Identification?

Ideally: show that each moments implies a single set of parameters; in practice, not easy because these are non-linear equations.

- Provide intuition as to what empirical facts identify moments.
- Plot whether moments are sensitive to comparative statics in a single parameter.
- Check for multiple optima, check for the objective function not being constant around estimates.

Zakolyukina (JAR 2015): How Common Are Intentional GAAP Violations? Estimates from a Dynamic Model estimates a dynamic model where managers can choose to engage in a slippery road of manipulations.

The first moment condition is the fraction of restating firms. This moment is sensitive to, and thus better identifies, the probability of detection, g, and the constant penalty parameter, κ_1. The second moment condition is the average manager's wealth, $w^{(1)} = c^{(1)} + n^{(1)}p^{(1)}$, in the year the manager manipulates for the first time. This moment identifies the probability of detection, g, and penalty parameters, κ_1 and κ_2. To show this, Observation A.1 in the appendix derives the following restriction on this wealth:

$$w^{(1)} < \frac{(1-g)}{g\phi\sqrt{2\kappa_1\kappa_2}}, \qquad (5)$$

which shows the wealth decreasing in the probability of detection, g, and penalty parameters, κ_1 and κ_2.

What is Set Identification?

Gayle and Miller (RES, 2015): Identifying and testing models of managerial compensation show observing pay and performance is not sufficient to identify the cost of agency. Li (MS 2020): Are Top Management Teams Compensated as Teams? A Structural Modeling Approach shows that we can use set identification to test team-based model vs. individual based model

Table 4: The Risk Aversion Parameter's 95% Confidence Regions

A: *Individual Model*—different likelihood ratios + different Lagrange multipliers of incentive compatibility constraint

Sector	[A, D/E]	Risk Aversion	Certainty Equivalent	Homogeneous within Size	Homogeneous within Sector	Homogeneous across Sectors
Primary	[S, S]	(33.62, 54.60)	(0.67, 0.79)			
	[S, L]	(4.83, 54.60)	(0.14, 0.79)	(33.62, 54.60)		
	[L, S]	(16.25, 54.60)	(0.43, 0.79)			
	[L, L]	(1.83, 2.34)	(0.05, 0.07)	(,)	(,)	
Consumer Goods	[S, S]	(1.83, 3.79)	(0.05, 0.11)			
	[S, L]	(4.83, 33.62)	(0.14, 0.67)	(,)		
	[L, S]	(0.70, 1.13)	(0.02, 0.03)			
	[L, L]	(1.83, 2.34)	(0.05, 0.07)	(,)	(,)	
Service	[S, S]	(16.25, 54.60)	(0.43, 0.79)			
	[S, L]	(1.83, 54.60)	(0.05, 0.79)	(16.25, 54.60)		
	[L, S]	(3.79, 7.85)	(0.11, 0.23)			
	[L, L]	(4.83, 54.60)	(0.14, 0.79)	(4.83, 7.85)	(,)	(,)

B: *Team Model*—same likelihood ratio + different Lagrange multipliers of incentive compatibility constraint

Sector	[A, D/E]	Risk Aversion	Certainty Equivalent	Homogeneous within Size	Homogeneous within Sector	Homogeneous across Sectors
Primary	[S, S]	(1.62E-07, 54.60)	(0.00, 0.79)			
	[S, L]	(2.63E-07, 54.60)	(0.00, 0.79)	(2.63E-07, 54.60)		
	[L, S]	(7.82E-08, 20.70)	(0.00, 0.51)			
	[L, L]	(1.43E-08, 10.00)	(0.00, 0.28)	(7.82E-08, 10.00)	(2.63E-07, 10.00)	
Consumer Goods	[S, S]	(7.82E-08, 20.70)	(0.00, 0.51)			
	[S, L]	(2.97E-08, 33.62)	(0.00, 0.67)	(7.82E-08, 20.70)		
	[L, S]	(8.83E-09, 1.13)	(0.00, 0.03)			
	[L, L]	(1.83E-08, 2.34)	(0.00, 0.07)	(1.83E-08, 1.13)	(7.82E-08, 1.13)	
Service	[S, S]	(2.63E-07, 54.60)	(0.00, 0.79)			
	[S, L]	(1.62E-07, 54.60)	(0.00, 0.79)	(2.63E-07, 54.60)		
	[L, S]	(3.78E-08, 12.75)	(0.00, 0.35)			
	[L, L]	(5.44E-09, 54.60)	(0.00, 0.79)	(3.78E-08, 12.75)	(2.63E-07, 12.75)	(2.63E-07, 1.13)

See also Levi-Gayle, Li and Miller (2018) How Well Does Agency Theory Explain Executive Compensation?

What is reduced-form (in structural)?

Check if regression of the simulated data match empirical facts, Breuer and Windisch (JAR 2019): Investment Dynamics and Earnings-Return Properties: A Structural Approach

TABLE 3

Asymmetric Earnings Persistence

Specification:	(1) Levels	(2) Changes	(3) Price-Scaled Changes (Basu [1997])	(4) Capital-Scaled Changes (Ball and Shivakumar [2005])
Dependent Variable (Y_t):	Earnings (t)	ΔEarnings (t)	ΔEarnings (t)/ Price ($t-1$)	ΔEarnings (t)/ Capital (t)
Y_{t-1}	0.733***	−0.117***	0.028***	0.059***
	(0.003)	(0.009)	(0.006)	(0.007)
$D(Y_{t-1} < 0)$	0.404***	−0.283**	−0.004***	−0.007***
	(0.152)	(0.122)	(0.001)	(0.001)
$Y_{t-1} \times D(Y_{t-1} < 0)$	−0.286***	0.019	−0.415***	−0.435***
	(0.020)	(0.012)	(0.012)	(0.012)
Firm-fixed effects	Yes	Yes	Yes	Yes
Observations	96,000	96,000	96,000	96,000
Number of clusters	4,000	4,000	4,000	4,000
Adjusted-R^2	0.513	0.009	0.033	0.029

The table presents estimates of conditional autoregressive models of earnings (levels and (scaled) changes). The estimates are based on 100,000 observations simulated using our dynamic investment model calibrated with the parameter values as provided in table 1. A firm is defined as 25 consecutive (nonoverlapping) simulated observations. The regressions are estimated with firm-fixed effects. Standard errors in parentheses are clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

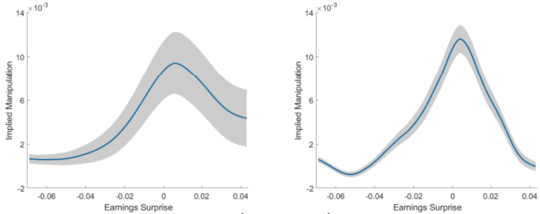
What is Policy Analysis?

Use a structural model to recover bias pre vs. post a policy change, Bertomeu, Cheynel, Li and Liang (MS, 2020)

Figure 4: Implied Earnings Management

Panel A: Pre-SOX Period

Panel B: Post-SOX Period



Implied earnings management is obtained by $\hat{R}(x) - x = \frac{\theta}{2}\hat{\gamma}'(\hat{R}(x))$, where θ is estimated using maximum likelihood estimation. Panel A presents the implied earnings management in the pre period (1990-2001) and Panel B presents the implied earnings management in the post period (2003 - 2014). The shaded areas are confidence intervals for one standard deviation. Both Earnings surprise and implied earnings management are scaled by the beginning-of-the-year book value of equity.

What are proxies?

Structural models can deliver proxies that have an intuitive interpretation, often in dollar terms. Cheynel and Liu-Watts (RASt, 2020) A simple structural estimator of disclosure costs. From distribution of disclosures, one can write down a firm-level estimator for disclosure costs $\hat{c}_i$.

$$\hat{c}_i = \tau_i + \frac{q_i}{1-q_i} m_i$$

where τ_i is the lowest disclosure, q_i is the frequency of disclosure and m_i is the average disclosure (of firm i).

	N	Mean	Median	St.Dev.	Min	Max
$\hat{c}_{NP}$ (361 with positive costs)	1,081	0.08%	0.00%	0.16%	0.00%	0.54%
$\hat{c}_{NP}$ for Terciles						
Group 1	720	0.00	0.00	0.00	0.00	0.00
Group 2	172	0.05%	0.04%	0.04%	0.00%	0.14%
Group 3	189	0.40%	0.44%	0.15%	0.14%	0.54%
$\hat{c}_{NP}$ (in $millions)	1,081	$1.3	$0.0	$8.2	$0.0	$166.6

Table 8 Cost measure, insider trading, and information asymmetry proxies

	(1)	(2)	(3)	(4)
	Dependent variable:			
	TRADES (AbsInsiderTrades /NumberofShares)		Bid-Ask Spread (SPREAD)	
$\hat{c}_{NP}$	31.777***		81.004***	
	[2.73]		[4.37]	
$\hat{c}_{NP}$ Terciles		0.043**		0.084***
		[2.04]		[2.78]

What is robustness?

Zakolyukina (JAR 2015): How Common Are Intentional GAAP Violations? Estimates from a Dynamic Model estimates a dynamic model where managers can choose to engage in a slippery road of manipulations.

Table 7. Structural Parameter Estimates: Sensitivity to Time Discount Factor and Wealth Multiplier

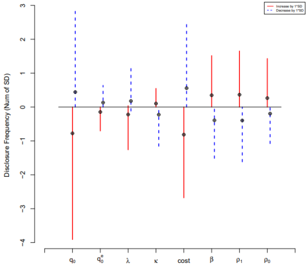
$g \times 100$	$\kappa_1 \times 100$	κ_2	f_1	f_2	γ	*J*-Test *p*-Value
Revenue recognition errors, $\delta = 0.9$ and $\eta = 0.5$						
2.686***	0.043	5.550***	−1.819***	−0.495***	1.004***	14.797
(1.040)	(1.154)	(0.179)	(0.123)	(0.112)	(0.004)	0.022
Revenue recognition errors, $\delta = 0.9$ and $\eta = 1.5$						
2.530**	1.533**	5.217***	−1.784***	−0.519***	0.876***	13.851
(1.181)	(0.674)	(0.519)	(0.134)	(0.120)	(0.149)	0.031
Revenue recognition errors, $\delta = 0.85$ and $\eta = 1$						
2.984*	1.881**	5.025***	−1.809***	−0.497***	0.946***	13.735
(1.642)	(0.948)	(0.130)	(0.178)	(0.156)	(0.207)	0.033
Revenue recognition errors, $\delta = 0.95$ and $\eta = 1$						
2.960***	1.868***	5.121***	−1.790***	−0.515***	0.931***	13.709
(0.879)	(0.566)	(0.834)	(0.155)	(0.113)	(0.064)	0.033

This table reports the estimated structural parameters, with standard errors in parentheses: g is the probability of detection; κ_1 and κ_2 are parameters of the penalty function; f_1 and f_2 are parameters of the probability of leaving for reasons not related to manipulation; and γ is the coefficient of relative risk aversion. I estimate the model for the restatements correcting revenue recognition errors only based on the sample of 1,136 CEOs for different values of time discount factor, δ, and wealth multiplier, η. The *J*-test is the test of overidentifying restrictions with the corresponding *p*-value underneath. *, **, and *** significance at the 10%, 5%, and 1% level, respectively.

What are marginal effects?

Zhou (MS forth.): Disclosure Dynamics and Investor Learning, dynamic disclosure model with bayesian learning about fundamentals. Can use simulations to estimate marginal effects of structural parameters.

Figure 6: Marginal effects of structural parameters



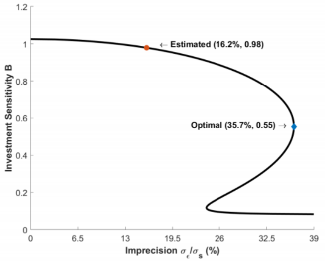
This figure plots the marginal effects of model parameters (see section 2.2.4 for the definition of the parameters). I simulate 2,000 firms and 12 periods each firm with parameter values drawn from their cross-sectional distributions. I vary each parameter by one standard deviation of its cross-sectional distribution and compute the average change in disclosure frequency over the following 12 years. The red solid (blue dashed) line corresponds to the 5th percentile and 95th percentile of *the change in disclosure frequency* when I increase (decrease) the parameter at the horizontal axis by one standard deviation of its cross-sectional distribution. I also vary investors' prior beliefs by one standard deviation of earnings shock with the results denoted by q_0^ϵ. Disclosure frequency is expressed in terms of the number of standard deviations of the empirical disclosure frequency, which is about 22%. The black dots represent the mean.

What is welfare?

If structural model involves productive decisions affected by information, one can measure the social value of information, see Liang (2020) How Much Does Imprecision in Accounting Measurement Enhance Value?

Figure 7: Imprecision and Investment Sensitivity – R&D Sample

This figure plots the relation between accounting measurement noise σ_ϵ and R&D investment sensitivity B. It is calculated using Equation (18): $B^2\sigma_\theta^2\left(\sqrt{\frac{2\gamma}{Bc-1}}-1\right)-\sigma_\epsilon^2=0$, where the parameters σ_θ, γ and c are substituted with estimates from the R&D sample. The round dot is the estimated relation, with σ_ϵ of 0.05 and B of 0.98. The diamond dot corresponds to the accounting measurement noise $\sigma_\epsilon = 0.11$ and the sensitivity of the optimal investment function, $B^{FB} = 0.55$.



Challenges and Criticisms of Structural

- Social interactions are too complex to be modelled; theories in social sciences are too simple to fit the real world
- We can't abstract away from anything to understand something about the real world
- All structural models are rejected (if one tries hard enough), we shouldn't use a model that's rejected.
- Estimates from structural models change across industries and periods.
- It's too complicated
- Theory is sufficient to explain the real world, structural takes itself too seriously
- One needs to be both a theorist and an econometrician to do structural
- We can't be sure what model is the right one and can't evaluate them all
- It's too hard to publish
- Whatever structural can do can be done with reduced-form
- and my favorite: I don't believe in structural, if I see a structural paper, I won't read it, I'll just reject it.

General philosophy of science relevant for structural

1. Understanding Friedman's instrumentalism. What does it mean and not mean?
2. Empirical useful for policy-making and the Lucas critique.
3. Kuhn's contemporary views of science as research programs, vs. falsification of individual ideas.
4. Returning back to Hume and objective experience in science: statistical testing $\neq$ empiricism $\neq$ falsification $\neq$ science.

This Talk: a summary

Structural opens the door to many questions that are unavailable under other methods (examples). Not a single method, nor a single set of steps to conduct that works for any question.

$\rightarrow$ still obeys principles of scientific discourse: some models fit better than others, some models are more elegant, some models have more persuasive assumptions, some models are more ambitious.

$\rightarrow$ Obvious trade-offs: bigger question may imply less fit, more fit may require more clunky fixes.

Don't apply a mechanical plan of to-do's, let your model speak to what's interesting.

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