Inference for Regression with Variables Generated by AI or Machine Learning

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Outline

Motivation

Economists now routinely generate variables by AI/ML methods

- quantify unstructured data (text, images, ...)
- measure subtle concepts (uncertainty, sentiment, ...)
- generate variables previously too costly, labor-intensive, or infeasible to collect

The generated variables are inputs to downstream econometric models

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The generated variables are inputs to downstream econometric models

Almost all papers use a two-step strategy:

1. Generate estimate $\hat{\theta}_i$ of true variable θ_i using AI/ML algorithm
2. Plug estimates $(\hat{\theta}_i)$ into an econometric model, treating $\hat{\theta}_i$ as regular numeric data

This Paper

1. Two-step strategy leads to invalid inference: CIs have right width but wrong centering (bias)

   Bias depends on relative importance of

   (a) measurement error in $\hat{\theta}_i$

   (b) sampling error in downstream model

   Valid two-step inference requires (a) $\ll$ (b)

   This is not the case in most leading applications

2. Two solutions: bias correction + one-step strategy
   NB: Measurement error in AI/ML-generated variables in non-classical.

3. Shows empirical relevance in several empirical applications

Valid Inference Without Validation Data

Recent work (mainly stats/poli sci) has pointed out potential for generated variables to cause problems

- General ML-generated variables: Fong and Tyler (2021), Allon et al. (2023), Angelopoulos et al. (2023a, 2023b), Zhang et al. (2023), Zrnic and Candès (2024), and Miao and Lu (2024)
- LLM-generated variables: Egami et al. (2023, 2024), Ludwig et al. (2025), Carlson and Dell (2025).

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This strand proposes bias corrections assuming a validation subsample in which $(Y_i, \boldsymbol{\theta}_i, \hat{\boldsymbol{\theta}}_i)$ are observed

- Inference valid when size of labeled/unlabeled data approximately equal.
- Typically requires human labelers to construct validation set

  But use of ML/AI typically motivated by large cost of labeling.
- In economic data, unclear a true label is observed (sentiment, uncertainty).

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- In economic data, unclear a true label is observed (sentiment, uncertainty).

Our paper provides methods for valid inference without validation data.

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Setup

Want: perform inference on γ and/or $\boldsymbol{\alpha}$ in the model

$$Y_i = \gamma^T \boldsymbol{\theta}_i + \boldsymbol{\alpha}^T \mathbf{q}_i + \varepsilon_i, \qquad \mathbb{E}\left[\varepsilon_i \middle| \boldsymbol{\theta}_i, \mathbf{q}_i\right] = 0,$$

- $\boldsymbol{\theta}_i$ is a latent variable of economic interest
- $\mathbf{q}_i$ are observed numeric covariates
- Unstructured/high-dim dataset $\mathbf{x}_i$ available for estimating $\boldsymbol{\theta}_i$

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Two-Step Strategy:

1. Estimate $\hat{\boldsymbol{\theta}}_i$ of $\boldsymbol{\theta}_i$ obtained from unstructured data $\mathbf{x}_i$
2. Regress Y_i on $\hat{\boldsymbol{\theta}}_i$ and $\mathbf{q}_i$. Perform inference treating $\hat{\boldsymbol{\theta}}_i$ as regular numeric data.

Example 1: AI/ML-Generated Labels

- Leading use case: missing θ_i is binary (e.g., race indicator): Goldsmith-Pinkham and Shue (2023), Adams-Prassl et. al. (2023), Argyle et al. (2025), and Wu and Yang (2024)
- Generate estimate $\hat{\theta}_i$ of θ_i using unstructured data $\mathbf{x}_i$ (e.g., voter registration data)
- Regress Y_i on $\hat{\theta}_i$ and controls $\mathbf{q}_i$

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- Regress Y_i on $\hat{\theta}_i$ and controls $\mathbf{q}_i$
- Measurement error due to misclassification error:

$$\Pr(\theta_i = 1 | \mathbf{x}_i, \mathbf{q}_i) \neq \Pr(\hat{\theta}_i = 1 | \mathbf{x}_i, \mathbf{q}_i)$$

Example 2: Indices

- Several influential works generate indices by classifying documents + aggregating: Baker Bloom Davis (2016), Caldara and Iacoviello (2022), Gorodnichenko Pham Talavera (2023).
- Each month observe C_i documents (e.g., set of newspapers)
- Of these, X_i are classified as pertaining to concept (e.g., policy uncertainty)
- Latent true uncertainty $\theta_i \in [0, 1]$
- Naive estimator: $\hat{\theta}_i = X_i / C_i$ (cf. BBD's EPU measure)

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- Naive estimator: $\hat{\theta}_i = X_i / C_i$ (cf. BBD's EPU measure)
- Natural model is $X_i | C_i, \theta_i \sim \text{Binomial}(C_i, \theta_i \beta_1 + (1 - \theta_i)\beta_0)$ where β_x is the probability that a document with true label x is classified a one.
- Measurement error in $\hat{\theta}_i$ arises from misclassification error ($\boldsymbol{\beta}$) and sampling error (C_i).

Example 2: Indices — Simulation Calibrated to Gorodnichenko et al. (2023)

	Bias			RMdSE			Coverage		
Configuration	1	2	3	1	2	3	1	2	3
				$n = 200$					
2-Step	-0.433	-0.218	-0.037	0.048	0.025	0.018	0.378	0.824	0.931
Joint	-0.003	0.007	0.004	0.024	0.020	0.018	0.945	0.948	0.938
				$n = 800$					
2-Step	-0.215	-0.041	0.084	0.024	0.010	0.012	0.507	0.942	0.894
Joint	0.004	-0.006	-0.006	0.011	0.010	0.010	0.956	0.950	0.950
				$n = 3200$					
2-Step	-0.042	0.085	0.158	0.006	0.009	0.017	0.887	0.739	0.353
Joint	-0.005	-0.002	-0.003	0.005	0.005	0.005	0.942	0.941	0.943

Outline

Asymptotics: General Case

- Consider a sequence of DGPs for $(Y_i, \boldsymbol{\theta}_i, \hat{\boldsymbol{\theta}}_i, \mathbf{q}_i, \mathbf{x}_i)_{i=1}^n$ indexed by sample size n, in which

$$\frac{1}{\sqrt{n}} \sum_{i=1}^{n} \hat{\boldsymbol{\theta}}_i (\hat{\boldsymbol{\theta}}_i - \boldsymbol{\theta}_i)^T \to_p \kappa \, \boldsymbol{\Omega},$$

  (expressions are DGP-specific)

- Scalar $\kappa \geq 0$ measures the importance of measurement error relative to sampling error

- Positive κ allows both sampling error and measurement error to play a role

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- Scalar $\kappa \geq 0$ measures the importance of measurement error relative to sampling error
- Positive κ allows both sampling error and measurement error to play a role
- Example 1 expression is

$$\sqrt{n} \times \underbrace{\mathbb{E}\left[\hat{\theta}_i (1 - \theta_i)\right]}_{\text{false-positive rate}} \to \kappa, \qquad \boldsymbol{\Omega} = 1$$

- Reflects prevailing trend: increasingly large data sets + increasingly accurate algorithms

Theorem on Two-Step Inference

Theorem: Two-Step Inference is Invalid Unless $\kappa = 0$

1. OLS estimator $\hat{\psi} = (\hat{\gamma}, \hat{\alpha})$ of $\psi = (\gamma, \alpha)$ from regressing Y_i on $\hat{\xi}_i = (\hat{\theta}_i, \mathbf{q}_i)$ has asy dist

$$\sqrt{n}\left(\hat{\psi} - \psi\right) \to_d N\left(-\kappa \mathbb{E}[\xi_i \xi_i^T]^{-1} \begin{pmatrix} \mathbf{\Omega} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \psi \,,\, \underbrace{\mathbb{E}[\xi_i \xi_i^T]^{-1} \mathbb{E}[\varepsilon_i^2 \xi_i \xi_i^T] \mathbb{E}[\xi_i \xi_i^T]^{-1}}_{=:\mathbf{V}}\right)$$

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   where $\boldsymbol{\xi}_i = (\boldsymbol{\theta}_i, \mathbf{q}_i)$ are the "true" covariates

2. Eicker–Huber–White standard errors are consistent for all $\kappa \geq 0$:

$$\hat{\mathbf{V}} := \left(\frac{1}{n}\sum_{i=1}^{n} \hat{\boldsymbol{\xi}}_i \hat{\boldsymbol{\xi}}_i^T\right)^{-1} \left(\frac{1}{n}\sum_{i=1}^{n} \hat{\varepsilon}_i^2 \hat{\boldsymbol{\xi}}_i \hat{\boldsymbol{\xi}}_i^T\right) \left(\frac{1}{n}\sum_{i=1}^{n} \hat{\boldsymbol{\xi}}_i \hat{\boldsymbol{\xi}}_i^T\right)^{-1} \to_p \mathbf{V}$$

Implications

- $\kappa \in (0, \infty)$: two-step inference is **biased**
  - degree of bias is increasing in κ (relative importance of measurement vs sampling error)
  - no variance distortion, unlike generated regressors
- $\kappa = 0$: two-step inference is **valid**: treat $\hat{\boldsymbol{\theta}}_i$ as if they are the true latent $\boldsymbol{\theta}_i$
- Take-away: if κ is large, consider using resources to improve precision of $\hat{\boldsymbol{\theta}}_i$

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- Take-away: if κ is large, consider using resources to improve precision of $\hat{\boldsymbol{\theta}}_i$
- To the extent empirical papers flag concerns about 2-step inference, usually about std errors
- Common intuition is wrong: problem is measurement error not standard errors

Outline

How to Do Valid Inference

1. **Explicit Bias Correction**: use analytical expressions in Theorem to adjust two-step estimates/CIs

   Advantage: Simple and scalable

   Disadvantage: Not feasible in complex models; poor approximation with large κ

2. **Joint Estimation**: MLE using joint likelihood for upstream IR model + regression model

   Advantage: General purpose and flexible

   Disadvantage: More computationally demanding

Bias Correction

- First-order asymptotic bias of OLS estimator $\hat{\psi}$ is

$$-\kappa\,\mathbb{E}\left[\boldsymbol{\xi}_i\boldsymbol{\xi}_i^T\right]^{-1}\begin{pmatrix}\boldsymbol{\Omega} & \mathbf{0}\\ \mathbf{0} & \mathbf{0}\end{pmatrix}\psi$$

- Given estimators $\hat{\kappa}$ and $\hat{\boldsymbol{\Omega}}$ of κ and $\boldsymbol{\Omega}$, can construct bias-corrected estimators:

Additive $$\hat{\psi}^{bca} = \left(\mathbf{I} + \frac{\hat{\kappa}}{\sqrt{n}}\left(\frac{1}{n}\sum_{i=1}^{n}\hat{\boldsymbol{\xi}}_i\hat{\boldsymbol{\xi}}_i^T\right)^{-1}\begin{bmatrix}\hat{\boldsymbol{\Omega}} & \mathbf{0}\\ \mathbf{0} & \mathbf{0}\end{bmatrix}\right)\hat{\psi}$$

Multiplicative $$\hat{\psi}^{bcm} = \left(\mathbf{I} - \frac{\hat{\kappa}}{\sqrt{n}}\left(\frac{1}{n}\sum_{i=1}^{n}\hat{\boldsymbol{\xi}}_i\hat{\boldsymbol{\xi}}_i^T\right)^{-1}\begin{bmatrix}\hat{\boldsymbol{\Omega}} & \mathbf{0}\\ \mathbf{0} & \mathbf{0}\end{bmatrix}\right)^{-1}\hat{\psi}$$

- Bias-corrected CIs: center at $\hat{\psi}^{bca}$ or $\hat{\psi}^{bcm}$ and use 2-step std errors

Theory for Bias-Correction

Validity of Bias-Corrected Inference

If $\hat{\kappa} \rightarrow_p \kappa$ and $\hat{\boldsymbol{\Omega}} \rightarrow_p \boldsymbol{\Omega}$, the under conditions of previous theorem, have

1. Bias-corrected estimators are asymptotically equivalent and correctly centered

$$\sqrt{n}\left(\hat{\boldsymbol{\psi}}^{bcm} - \boldsymbol{\psi}\right) = \sqrt{n}\left(\hat{\boldsymbol{\psi}}^{bca} - \boldsymbol{\psi}\right) + o_p(1) \rightarrow_d N\left(\mathbf{0}\,, \mathbf{V}\right)$$

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2. Bias-corrected CIs have correct coverage:

$$\lim_{n\rightarrow\infty} \Pr\left(\psi_i \in \hat{\psi}_i^{bc} \pm 1.96\sqrt{\frac{\hat{\mathbf{V}}_{ii}}{n}}\right) = 0.95.$$

Bias Correction: Labels Example

- Here need to estimate $\kappa = \sqrt{n} \lim_{n \to \infty} \mathbb{E}\left[\hat{\theta}_i(1-\theta_i)\right]$
- Just need an estimate of FPR from an external sample (as in Bursztyn Chaney Hassan Rao (2024))

$$\hat{\kappa} = \sqrt{n}\widehat{FPR}, \qquad \widehat{FPR} = \frac{1}{m}\sum_{i=1}^{m} \hat{\theta}_i(1-\theta_i)$$

- We show $\hat{\kappa} \to_p \kappa$ provided $n/m^2 \to 0$ (small subsample)
- We also provide finite-sample correction to standard errors (complex expression).

Joint Estimation: Computation

- Joint likelihood: $f(Y_i, \mathbf{x}_i, \boldsymbol{\theta}_i | \mathbf{q}_i; \gamma, \boldsymbol{\alpha}, ...)$

- Integrated likelihood in terms of observables only:

$$f(Y_i, \mathbf{x}_i | \mathbf{q}_i; \gamma, \boldsymbol{\alpha}, ...) = \underbrace{\int f(Y_i, \mathbf{x}_i, \boldsymbol{\theta}_i | \mathbf{q}_i; \gamma, \boldsymbol{\alpha}, ...) \, d\boldsymbol{\theta}_i}_{\text{intractable}}$$

- Use Bayesian computation:
  - Integrates out $\boldsymbol{\theta}_i$ as part of the sampling algorithm
  - Resulting credible sets are valid frequentist confidence intervals for large n by BvM theorem

- Sampling: Hamiltonian MC implemented in probabilistic programming language `NumPyro` $\Rightarrow$ allows for estimation of models on large scale

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- Note: in examples, we are **not** attempting to specify a likelihood for the AI/ML algorithm

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Hansen Lambert Bloom Davis Sadun Taska (WP, 2023)

- Consider $n = 16,315$ SD food+accom sector (NAICS code 72) job postings from January 2022
- Regress log wages Y_i on ML-generated remote work indicator $\hat{\theta}_i$
- Fixed effects for SOC code (job type) and full/part time

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- Regress log wages Y_i on ML-generated remote work indicator $\hat{\theta}_i$
- Fixed effects for SOC code (job type) and full/part time
- For bias correction, use estimate $\widehat{FPR} \approx 0.009$.
- For joint estimation, use three-component Gaussian mixture for errors $\varepsilon_i | \theta_i$

Bias Correction with Minimal Human Effort

Advantage 1: Smaller Auxiliary Dataset

Existing papers: bias correction when m and n are comparable.

We estimate FPR with $m = 1000$. $n/m = 16$, $n/m^2 = 0.016$.

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Advantage 2: Only Need Partial Labeling

Existing papers: build full validation dataset by inspecting each posting.

This paper: only examine labeled "ones", 26 in this dataset.

Two-Step Estimates Smaller

	No Fixed Effects			With Fixed Effects		
	Est.	Std Err	95% CI	Est.	Std Err	95% CI
OLS	0.648	0.024	[0.599, 0.697]	0.363	0.021	[0.321, 0.406]
BC	1.052	0.140	[0.777, 1.326]	0.641	0.099	[0.446, 0.836]
1-Step	0.563	0.016	[0.532, 0.595]	0.448	0.017	[0.415, 0.480]

Corrected CIs to the right of Two-Step CIs

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Central Bank Communication

- Does written central bank communication drive long rates? Estimate

$$Y_i = \gamma\theta_i + \boldsymbol{\alpha}'\mathbf{q}_i + u_i$$

  - Y_i is the path factor from Gürkaynak, Sack, and Swanson (2005) (mkt perceptions of future rates)
  - θ_i is a hawkish/dovish index (cf. Gorodnichenko, Pham, Talavera (2023))
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- Hawkish/dovish index:
  - classify FOMC sentences as hawkish/dovish/neutral using fine-tuned BERT + aggregate
  - sentiment estimate

$$\hat{\theta}_i = \frac{N_i^H - N_i^D}{N_i^H + N_i^D}$$

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- Compare two-step and joint estimation over 02/1995-06/2023

Central Bank Communication: Joint Estimation Effect Size 3x Larger

	Estimation Strategy	
	Two-Step	Joint
Sentiment (θ_i)	0.039	0.114
	[0.012, 0.066]	[0.027, 0.198]
Policy Rate (q_i)	-0.004	-0.003
	[-0.011, 0.003]	[-0.011, 0.004]
β_0		0.009
		[0.001, 0.026]
β_1		0.676
		[0.585, 0.768]
Observations	200	200
R^2	0.0425	0.1429

Central Bank Communication: Material Misclassification Error

	Estimation Strategy	
	Two-Step	Joint
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Conclusion

- Empirical work routinely uses AI/ML algorithms to generate new variables
- Common empirical practice leads to invalid inference
- We propose two solutions: bias correction + joint estimation. Neither requires validation data.
- Illustrate important differences in simulations + applications
- Packages: `ValidMLInference` (Python) and `MLBC` (R)
- Works in progress: specific methods tailored to important use cases, e.g. VARs and impulse response analysis w/ Hansen and Shin