

Inference for Regression with Variables Generated by AI or Machine Learning

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Outline

1. Introduction
2. Setup and Examples
3. Two-Step Inference is Biased
4. How to Do Valid Inference
5. Application: Remote Work and Wage Inequality
6. Application: Central Bank Communication
7. Conclusion

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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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 is 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 $(Y_i, \theta_i, \hat{\theta}_i)$ 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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Our paper provides methods for valid inference without validation data.

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Setup

Want: perform inference on γ and/or α in the model

$$Y_i = \gamma^T \theta_i + \alpha^T \mathbf{q}_i + \varepsilon_i, \quad \mathbb{E}[\varepsilon_i | \theta_i, \mathbf{q}_i] = 0,$$

- θ_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 θ_i

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Two-Step Strategy:

1. Estimate $\hat{\theta}_i$ of θ_i obtained from unstructured data \mathbf{x}_i
2. Regress Y_i on $\hat{\theta}_i$ and \mathbf{q}_i . Perform inference treating $\hat{\theta}_i$ 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** (β) and **sampling error** (C_i).

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

Configuration	Bias			RMdSE			Coverage		
	1	2	3	1	2	3	1	2	3
<i>n</i> = 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
<i>n</i> = 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
<i>n</i> = 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

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Asymptotics: General Case

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

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

(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

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

- 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

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

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

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

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 $\hat{\theta}_i$ as if they are the true latent θ_i
- Take-away: if κ is large, consider using resources to improve precision of $\hat{\theta}_i$

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- $\kappa = 0$: two-step inference is **valid**: treat $\hat{\theta}_i$ as if they are the true latent θ_i
- Take-away: if κ is large, consider **using resources to improve precision of $\hat{\theta}_i$**
- 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**

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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

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

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

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

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

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

Validity of Bias-Corrected Inference

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

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

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

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

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

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

Joint Estimation: Computation

- Joint likelihood: $f(Y_i, \mathbf{x}_i, \boldsymbol{\theta}_i | \mathbf{q}_i; \gamma, \alpha, \dots)$
- Integrated likelihood in terms of observables only:

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

- 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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- 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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- \mathbf{q}_i are controls (including shadow short rate)
- 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 [0.012, 0.066]	0.114 [0.027, 0.198]
Policy Rate (q_i)	-0.004 [-0.011, 0.003]	-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

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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