Measurement Issues in India's GDP

A Synthetic Control Approach

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However, no income-side data available for India.

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- Synthetic Control Method (**SCM**) (Abadie and Gardeazabal, 2003; Abadie, Diamond, and Hainmueller, 2010)
- Generalized Synthetic Control Method (GSCM) (Xu, 2017).

Methodology

Let data be observed J+1 countries, where i=1 is India (treated unit). The rest of the countries are unaffected by the treatment and are referred to as the *donor* pool.

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$${\hat{Y}}_{1t}^N = \sum_{j=2}^{J+1} w_j^* Y_{jt} \, .$$

where $\mathbf{W^*}=(w_2^*,\dots,w_{J+1}^*)$ is a vector of *optimal* weights. The weights are chosen such that synthetic India best represents the *predictors* of India's GDP before the treatment. Hence, the optimal weights minimize

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$$||\mathbf{X}_1 - \mathbf{X}_0 \mathbf{W}|| = \sqrt{(\mathbf{X}_1 - \mathbf{X}_0 \mathbf{W})' \mathbf{V} (\mathbf{X}_1 - \mathbf{X}_0 \mathbf{W})}$$

where X_1 consists of the pre-intervention predictors of India's GDP and X_0 consists of pre-intervention predictors of the donor countries' GDP.

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$${\hat Y}_{1t}^N = x_{1t}' \hat eta + \hat \lambda_1' \hat f_t$$

where x_{1t} is a vector of covariates, $\hat{\beta}$ consists of estimated parameters for covariates, $\hat{\lambda}_1$ are estimated common factors, and \hat{f}_t are estimated factor loadings. The optimal number of factors are chosen via cross-validation.

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Using both methods, we are interested in estimating the average treatment effect for India, given by

$$\hat{lpha}_{1t}=Y_{1t}^{I}-\hat{Y}_{1t}^{N}$$

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Specifications

- SCM using predictors (covariates) of GDP
- GSCM without covariates (matching only on GDP)
- GSCM with economic covariates only
- GSCM with economic and education covariates

Data

Dependent variable: log real GDP in 2011 Local Currency Units

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Covariates

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The standard SC model is estimated using the tidysynth package and the GSC model is estimated using the gsynth package.

Results

SCM

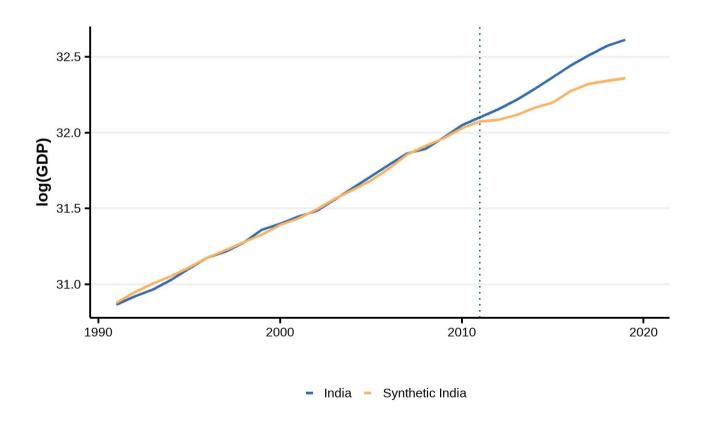


Figure - 1: Log GDP trend for actual and synthetic India (1991 - 2019).

GSCM (Baseline Model)

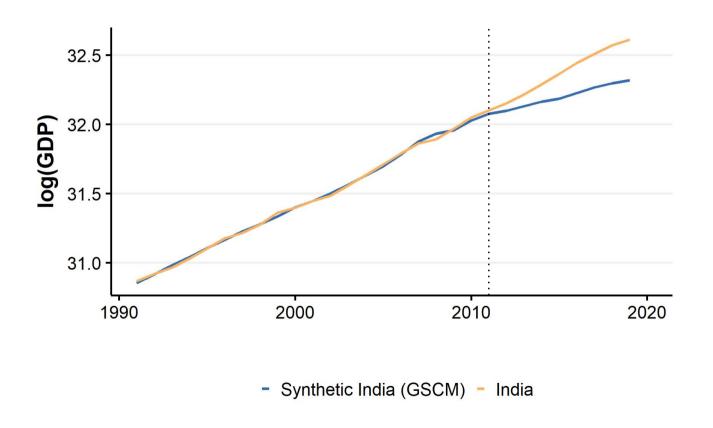


Figure - 2: Log GDP trend for actual and synthetic India (1991 - 2019).

GSCM (with economic covariates)

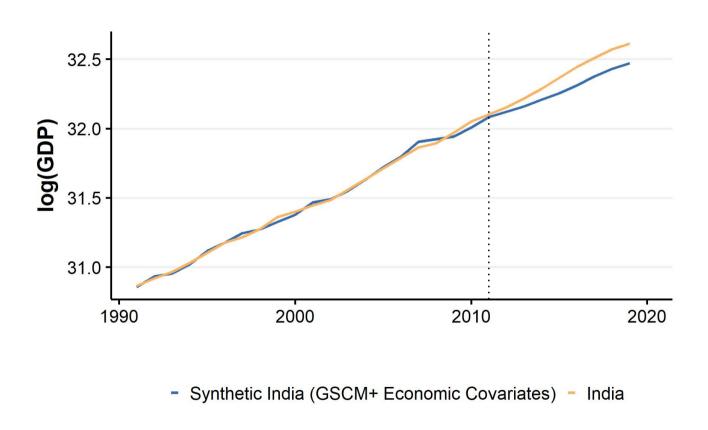


Figure - 3: Log GDP trend for actual and synthetic India (1991 - 2019).

GSCM (with all covariates)

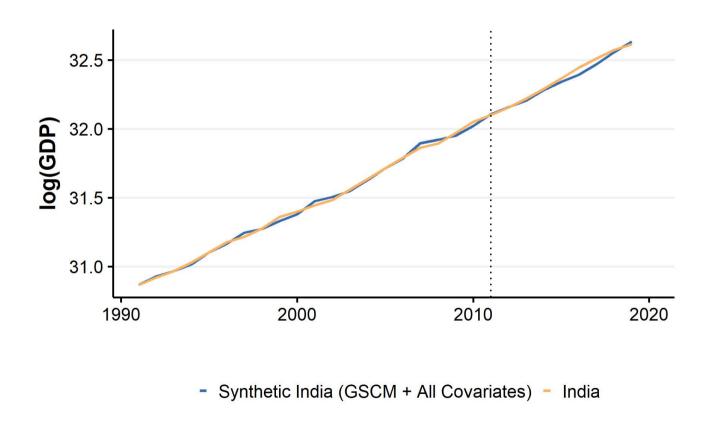


Figure - 4: Log GDP trend for actual and synthetic India (1991 - 2019).

Difference in growth rates

Year	SCM	GSCM	GSCM+EC	GSCM+AC
2012	4.45	3.06	1.38	-0.03
2013	3.00	3.00	[2.47	1.58
2014	2.33	3.83	2.35	-0.31
2015	4.34	5.38	2.96	1.54
2016	0.27	3.79	2.26	2.90
2017	1.73	2.51	0.18	-1.23
2018	4.29	3.45	0.89	-2.32
2019	2.35	1.93	-0.25	-3.72
Avg	2.6	3.0	1.1	-0.5

Table - 1: Difference between actual and synthetic GDP growth rates for various methods (in percentage).

Note: EC stands for "Economic Covariates", while AC stands for "All Covariates".

Inference

SCM: MSPE ratios

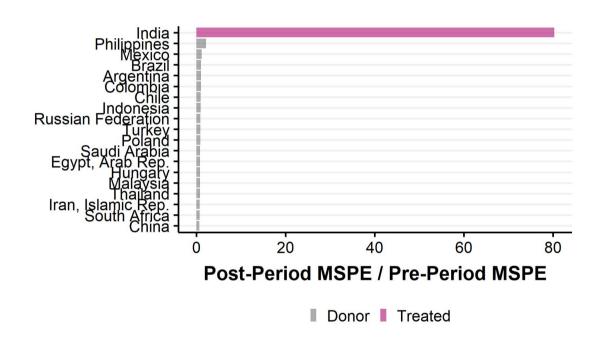


Figure - 5: Ratios of Post to Pre Intervention MSPE for India and donor countries.

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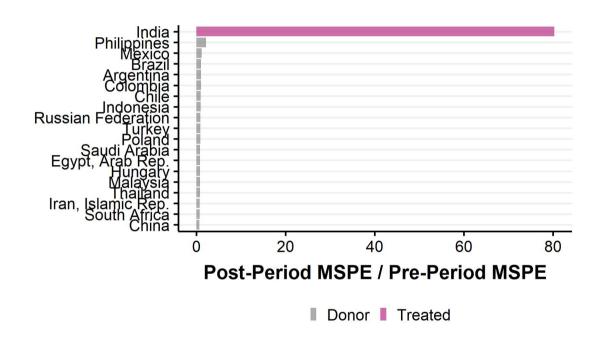


Figure - 5: Ratios of Post to Pre Intervention MSPE for India and donor countries.

Interpretation: The ratio of MSPE's is a measure of how close the two trends are before and after the intervention. If the intervention affects the unit of interest, then the ratio is the largest for that unit, as seen here.

SCM: Fisher's exact p-values

Country	Туре	Fisher's exact p-value
India	Treated	0.053
Philippines	Donor	0.105
Mexico	Donor	0.158
Brazil	Donor	0.211
Argentina	Donor	0.263
Colombia	Donor	0.316
Chile	Donor	0.368
Indonesia	Donor	0.421
Russian Federation	Donor	0.474
Turkey	Donor	0.526

Table - 2: p-values for India and donor countries.

Model	Average ATT	Std. Err	p-value
Baseline GSCM	0.166	0.256	0.516
GSCM with Economic covariates	0.094	0.139	0.499
GSCM with all covariates	0.013	0.154	0.928

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- Sparse control data: Large number of missing values for co variates lead to significantly reduced sample size.

Robustness Checks

Backdating (SCM)

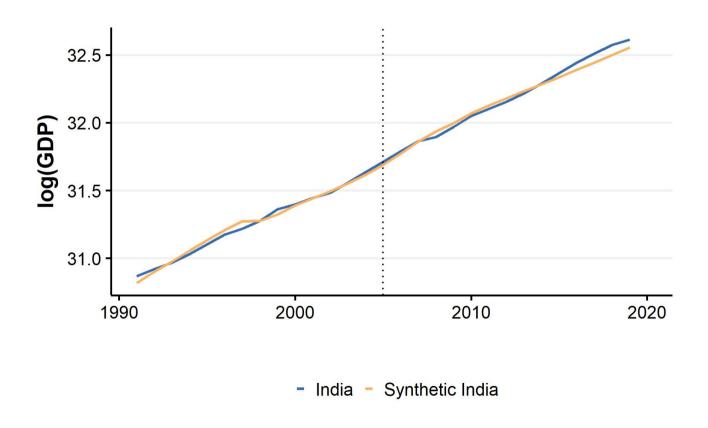


Figure - 6: Log GDP trend for actual and synthetic India with backdated treatment (1991 - 2019).

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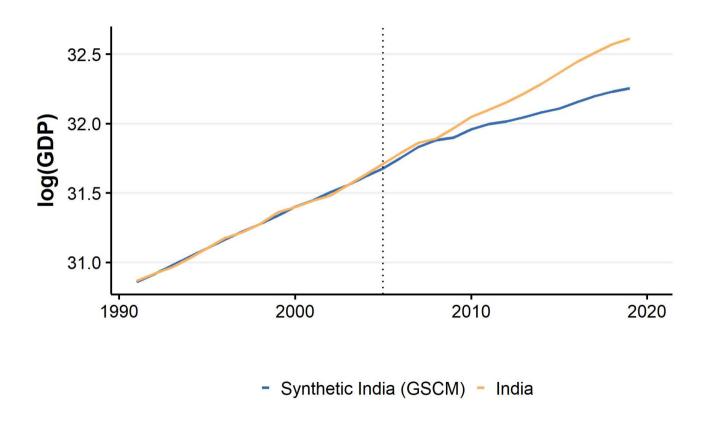


Figure - 7: Log GDP trend for actual and synthetic India with backdated treatment (1991 - 2019).

GSCM with quarterly data

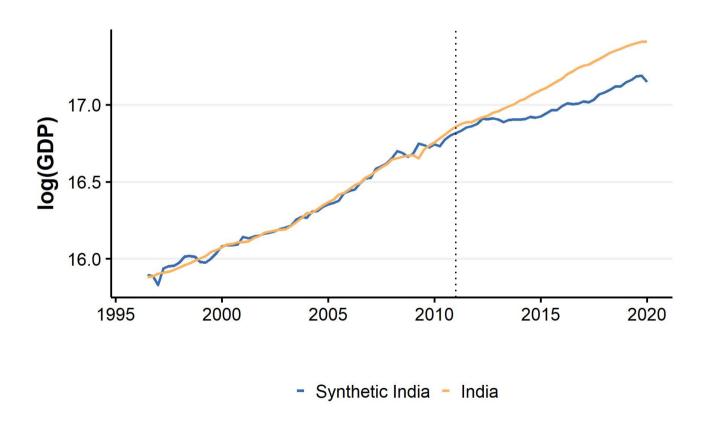


Figure - 8: Log GDP trend for actual and synthetic India with quarterly data (1996 - 2019).

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- **Future Avenues**: Using advances in causal panel data modelling, like matrix completion (Athey, Bayati, Doudchenko, et al., 2021) to deal with problem of sparse covariate data, and other estimators like synthetic difference-in-differences (Arkhangelsky, Athey, Hirshberg, et al., 2021).