

SAME ROOT DIFFERENT LEAVES: TIME SERIES AND CROSS-SECTIONAL METHODS IN PANEL DATA

DENNIS SHEN

Department of Data Sciences & Operations, University of Southern California

PENG DING

Department of Statistics, University of California, Berkeley

JASJEET SEKHON

Departments of Statistics & Data Science and Political Science, Yale University

BIN YU

Departments of Statistics and EECS, University of California, Berkeley

One dominant approach to evaluate the causal effect of a treatment is through panel data analysis, whereby the behaviors of multiple units are observed over time. The information across time and units motivates two general approaches: (i) horizontal regression (i.e., unconfoundedness), which exploits time series patterns, and (ii) vertical regression (e.g., synthetic controls), which exploits cross-sectional patterns. Conventional wisdom often considers the two approaches to be different. We establish this position to be partly false for estimation but generally true for inference. In the absence of any assumptions, we show that both approaches yield algebraically equivalent point estimates for several standard estimators. However, the source of randomness assumed by each approach leads to a distinct estimand and quantification of uncertainty even for the same point estimate. This emphasizes that researchers should carefully consider where the randomness stems from in their data, as it has direct implications for the accuracy of inference.

KEYWORDS: Horizontal regression, vertical regression, unconfoundedness, synthetic controls, causal inference, minimum norm estimators.

1. INTRODUCTION

IN A SEMINAL PAPER, [Abadie and Gardeazabal \(2003\)](#) set out to investigate the economic impact of terrorism in Basque Country. To estimate this effect, [Abadie and Gardeazabal \(2003\)](#) introduced the synthetic controls framework. At its core, synthetic controls constructs a synthetic Basque Country from a weighted composition of control regions that are unaffected by the instability to estimate Basque Country's economic evolution in the absence of terrorism. This novel concept has inspired an entire subliteration within econometrics that is “arguably the most important innovation in the policy evaluation literature in the last 15 years” ([Athey and Imbens \(2017\)](#)).

Researchers have historically tackled problems of this flavor using repeated observations of units across time, that is, panel data, where a subset of units are exposed to a

Dennis Shen: dennis.shen@marshall.usc.edu

Peng Ding: pengdingpku@berkeley.edu

Jasjeet Sekhon: jasjeet.sekhon@yale.edu

Bin Yu: binyu@berkeley.edu

We sincerely thank Alberto Abadie, Avi Feller, Devavrat Shah, and three anonymous referees for their thoughtful comments and insightful feedback. We gratefully acknowledge support from NSF Grants 1945136, 1953191, 2022448, 2023505 on Collaborative Research: Foundations of Data Science Institute (FODSI), and ONR Grant N00014-17-1-2176.

© 2023 The Authors. *Econometrica* published by John Wiley & Sons Ltd on behalf of The Econometric Society. Dennis Shen is the corresponding author on this paper. This is an open access article under the terms of the [Creative Commons Attribution-NonCommercial-NoDerivs](#) License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

treatment during some time periods while the other units are unaffected. In the study above, the per capita gross domestic product (GDP) of 17 Spanish regions are measured from 1955 to 1998. Basque Country is the sole treated unit and the remaining regions are the control units; the pre- and post-treatment periods are defined as the time horizons before and after the first wave of terrorist activity in 1970, respectively.

Synthetic controls has become a cornerstone for panel studies in recent years and across numerous fields. Beforehand, the unconfoundedness approach (Rosenbaum and Rubin (1983), Imbens and Wooldridge (2009)) served as a common workhorse. Whereas synthetic controls posits a relation between treated and control units that is stable across time, unconfoundedness posits a relation between treated and pretreatment periods that is stable across units. Accordingly, synthetic controls exploits cross-sectional correlation patterns while unconfoundedness exploits time series correlation patterns. Following the terminology introduced in Athey, Bayati, Doudchenko, Imbens, and Khosravi (2021), we refer to unconfoundedness and synthetic controls based methods as horizontal (HZ) and vertical (VT) regressions, respectively. Given their conceptual and computational distinctions, the two approaches are often considered to be different from one another (Athey et al. (2021)).

Yet, contrary to conventional wisdom, it turns out that HZ and VT regressions can yield identical point estimates. As Figure 1(a) shows, when the regression models are learned via ordinary least squares (OLS) with the minimum ℓ_2 -norm solution, then the two approaches produce the same economic evolution for Basque Country in the absence of terrorism. Figure 1(b), by contrast, shows that when the regression models are enforced to lie within the simplex—as proposed by Abadie and Gardeazabal (2003) for VT regression—then the two approaches output contrasting economic trajectories. To make matters more intriguing, Figure 2 indicates that even when the two regressions arrive at the same point estimate, the corresponding confidence intervals can be markedly different under different sources of randomness. The juxtaposition of these figures begs two questions:

Q1: “When are HZ and VT point estimates identical?”

Q2: “How does the source of randomness impact inference?”

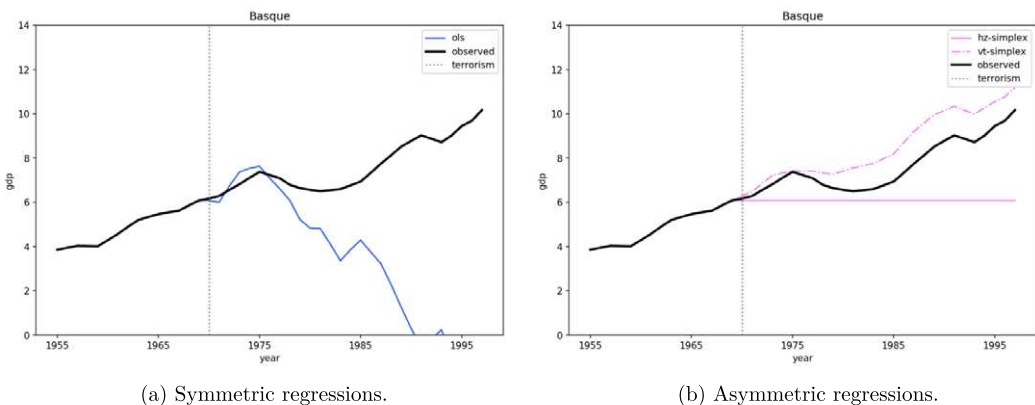


FIGURE 1.—1(a): Estimates of OLS with minimum ℓ_2 -norm; see Section 3.1.1. 1(b): Estimates of simplex regression. HZ and VT estimates correspond to colored solid and dashed-dotted lines, respectively. The outset of terrorism is the vertical line and Basque Country’s observed GDP is in solid black.

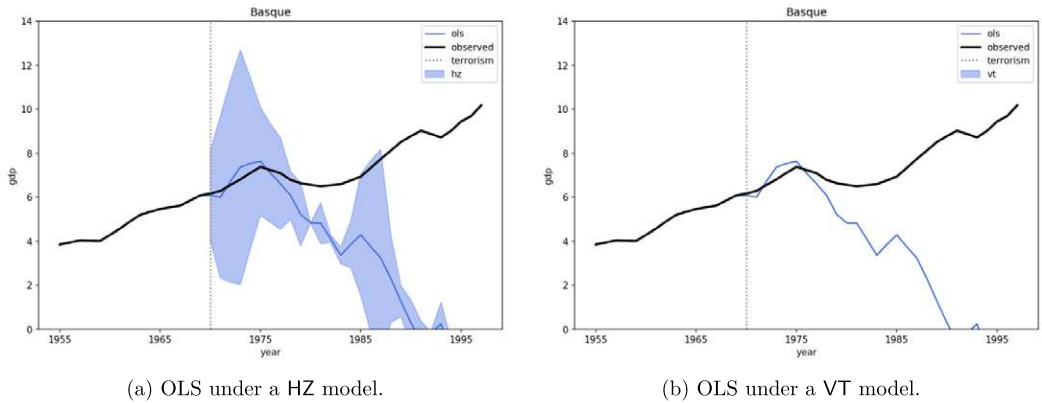


FIGURE 2.—Confidence intervals for OLS with minimum ℓ_2 -norm constructed from HZ-based (left) and VT-based (right) generative models; see Section 4.1.1. The VT-based confidence intervals are degenerate.

Contribution. This article provides a technical contribution to Q1 and a conceptual contribution to Q2. For Q1, we classify various widely studied regression formulations into (i) a symmetric class that yields algebraically identical point estimates and (ii) an asymmetric class that yields algebraically contrasting point estimates. These results hold without any assumptions on the data generating process or data configuration.

With this result in place, we proceed to tackle Q2 by staying within the symmetric class and studying properties of the estimator with randomness stemming from (i) time series patterns, (ii) cross-sectional patterns, and (iii) both patterns simultaneously. We conduct our analysis from a *model-based* perspective, which attributes randomness to the potential outcomes, and a *design-based* perspective, which attributes randomness to the mechanism assignment of treatment. Even under the most stylized assumptions within each framework, we demonstrate that each source of randomness leads to a distinct estimand and variance for the same point estimate.

While the specific estimands and variances may vary with the underlying assumptions, the general message remains invariant. In this spirit, we construct distinct confidence intervals for each source of randomness based on our model-based assumptions and asymptotic analysis. Though these intervals are unlikely to be practical for real-world settings, they are a useful device to conduct data-inspired simulations and empirical applications in illustrating our key concept. Indeed, our findings highlight that the confidence interval developed for one estimand often has incorrect coverage for another. Altogether, our results emphasize that the source of randomness that researchers assume has direct implications for the accuracy of inference that can be conducted. This further motivates the need for a principled framework to check researchers' assumptions, which is left as important future work.

Organization. Section 2 overviews the panel data framework. Section 3 provides a technical answer to Q1 and Section 4 provides a conceptual answer to Q2. Section 5 illustrates key concepts developed in this article. Section 6 summarizes our findings. We relegate mathematical proofs to Appendices A and B.

Notation. Let $\mathbf{I}$ be the identity matrix. Let $\mathbf{1}$ and $\mathbf{0}$ be the vectors of ones and zeros, respectively. All vectors are stated as column vectors. The curled inequality $\succeq$ denotes the

generalized inequality, that is, componentwise inequality between vectors and matrix inequality between symmetric matrices. Let $\circ$ denote the elementwise product. For vectors $\mathbf{a}$ and $\mathbf{b}$, let $\langle \mathbf{a}, \mathbf{b} \rangle = \mathbf{a}'\mathbf{b}$ denote the inner product. Let $\text{tr}(\mathbf{A})$ denote the trace of $\mathbf{A}$. We define $0/0 = 0$ when applicable.

2. THE PANEL DATA FRAMEWORK

Panel data contain observations of N units over T time periods. The Basque study, for instance, consists of per capita GDP across $N = 17$ Spanish regions over $T = 43$ years. In each time period t , each unit i is characterized by two potential outcomes, $Y_{it}(0)$ and $Y_{it}(1)$, which correspond to its outcome in the absence and presence of a binary treatment, respectively. The potential outcomes framework posits that each region possesses two possible levels of economic activity each year, one that is immune to terrorism and one that is affected by terrorism. This implicitly assumes that there are no spillover effects between regions, otherwise known as the stable unit value treatment assumption (Imbens and Rubin (2015)).

Let $A_i \in \{0, 1\}$ and $B_t \in \{0, 1\}$ be the indicator variables for whether the i th unit and t th period are treated. We write the observed outcome as

$$Y_{it} = A_i B_t \cdot Y_{it}(1) + (1 - A_i B_t) \cdot Y_{it}(0). \quad (1)$$

Often, we observe all N units without treatment (control) for T_0 time periods, that is., $A_i = B_t = 0$ for all $i \leq N$ and $t \leq T_0$. For the remaining $T_1 = T - T_0$ time periods, N_1 units receive treatment while the remaining $N_0 = N - N_1$ units remain under control; that is, if we label the first N_0 units as the control group, then $A_i = B_t = 0$ for all $i \leq N_0$ and $t > T_0$, and $A_i = B_t = 1$ for all $i > N_0$ and $t > T_0$. In the study of Abadie and Gardeazabal (2003), Basque Country is the single treated unit; thus, $N_1 = 1$ and $N_0 = 16$. The first wave of terrorist activity partitions the time horizon into pre- and post-treatment periods of lengths $T_0 = 15$ and $T_1 = 28$ years, respectively.

For ease of exposition, this article considers a *single* treated unit and *single* treated period indexed by the N th unit and T th time period, respectively, that is, $A_N = B_T = 1$ and $A_i = B_t = 0$ for all other $i \leq N_0$ and $t \leq T$. However, our results hold for any (i, t) pair where $i > N_0$ is a treated unit and $t > T_0$ is a treated period. We organize our observed control data into an $N \times T$ matrix, $\mathbf{Y} = [Y_{it}]$, as shown in Figure 3. In our example, $\mathbf{y}_N = [Y_{Nt} : t \leq T_0] \in \mathbb{R}^{T_0}$ represents Basque Country's economic evolution prior to the outset of terrorism; $\mathbf{Y}_0 = [Y_{it} : i \leq N_0, t \leq T_0] \in \mathbb{R}^{N_0 \times T_0}$ represents the control regions' economic evolution prior to the outset of terrorism; and $\mathbf{y}_T = [Y_{iT} : i \leq N_0] \in \mathbb{R}^{N_0}$ represents the control regions' economic evolution after the outset of terrorism. Our object of interest is Basque Country's counterfactual GDP in the absence of terrorism, $Y_{NT}(0)$.

$$\mathbf{Y} = \begin{pmatrix} Y_{11} & \cdots & Y_{1T_0} & Y_{1T} \\ \vdots & \ddots & \vdots & \vdots \\ Y_{N_0 1} & \cdots & Y_{N_0 T_0} & Y_{N_0 T} \\ Y_{N1} & \cdots & Y_{NT_0} & ? \end{pmatrix} = \begin{pmatrix} \mathbf{Y}_0 & \mathbf{y}_T \\ \mathbf{y}'_N & ? \end{pmatrix} \begin{matrix} \text{control units} \\ \text{treated unit} \end{matrix}$$

pretreatment period treated period
pretreatment period treated period

FIGURE 3.—Panel data format with rows and columns indexed by units and time, respectively.

2.1. Time Series versus Cross-Sectional Based Regressions

The information across time and units motivates two natural ways to estimate the missing (N, T) th entry. These perspectives are explored in two large and mostly separate bodies of work (Athey et al. (2021)).

2.1.1. Horizontal Regression and Unconfoundedness

The unconfoundedness literature operates on the concept that “history is a guide to the future.” As such, unconfoundedness methods express outcomes in the treated period as a weighted composition of outcomes in the pretreatment periods. Among the myriad of approaches, one special case is carried out by regressing the control units’ treated period outcomes y_T on its lagged outcomes Y_0 and applying the learned regression coefficients to the treated unit’s lagged outcomes y_N to predict the missing (N, T) th outcome. Following Athey et al. (2021), we refer to such methods as horizontal (HZ) regression.

2.1.2. Vertical Regression and Synthetic Controls

The synthetic controls literature is built on the concept that “similar units behave similarly.” Therefore, synthetic controls methods express the treated unit’s outcomes as a weighted composition of control units’ outcomes. This is carried out by regressing the treated unit’s lagged outcomes y_N on the control units’ lagged outcomes Y_0 and applying the learned regression coefficients to the control units’ treated period outcomes y_T to predict the missing (N, T) th outcome. Following Athey et al. (2021), we refer to such methods as vertical (VT) regression.

2.1.3. Conventional Wisdom

The dimensions of the data often guide the choice of estimator. In fact, the unregularized forms of HZ and VT regressions are cautioned against when $T > N$ and $N > T$, respectively, due to overfitting (Abadie, Diamond, and Hainmueller (2015), Doudchenko and Imbens (2016), Li and Bell (2017), Athey et al. (2021)). With regularization, however, Athey et al. (2021) argued the two approaches can be applied to the same setting. This allows HZ and VT regressions to be systematically compared through methods such as cross-validation.

3. POINT ESTIMATION

We tackle Q1 by studying algebraic properties of the HZ and VT point estimates.

Additional Notation. We denote the singular value decomposition (SVD) of Y_0 as $Y_0 = \sum_{\ell=1}^R s_\ell \mathbf{u}_\ell \mathbf{v}_\ell' = \mathbf{U} \mathbf{S} \mathbf{V}'$, where $\mathbf{u}_\ell \in \mathbb{R}^{N_0}$ and $\mathbf{v}_\ell \in \mathbb{R}^{T_0}$ are the left and right singular vectors, respectively, $s_\ell \in \mathbb{R}$ are the ordered singular values, and $R = \text{rank}(Y_0) \leq \min\{N_0, T_0\}$. Let $\mathbf{U} \in \mathbb{R}^{N_0 \times R}$ and $\mathbf{V} \in \mathbb{R}^{T_0 \times R}$ be the matrices formed by the left and right singular vectors, respectively, and $\mathbf{S} \in \mathbb{R}^{R \times R}$ be the diagonal matrix of singular values. The pseudoinverse is given by $Y_0^\dagger = \sum_{\ell=1}^R (1/s_\ell) \mathbf{v}_\ell \mathbf{u}_\ell' = \mathbf{V} \mathbf{S}^{-1} \mathbf{U}'$.

3.1. Classifying Notable Least Squares Formulations

We present several of the most widely studied regression formulations in the HZ and VT literatures. This list is far from exhaustive given the vastness of these literatures.

3.1.1. Description of Least Squares Formulations

Penalized Least Squares. A large class of formulations are expressed as follows:

(a) HZ regression: for $\lambda_1, \lambda_2 \geq 0$,

$$\hat{\alpha} = \underset{\alpha}{\operatorname{argmin}} \|\mathbf{y}_T - \mathbf{Y}_0 \alpha\|_2^2 + \lambda_1 \|\alpha\|_1 + \lambda_2 \|\alpha\|_2^2, \quad \text{with } \hat{Y}_{NT}^{\text{hz}}(0) = \langle \mathbf{y}_N, \hat{\alpha} \rangle. \quad (2)$$

(b) VT regression: for $\lambda_1, \lambda_2 \geq 0$,

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \|\mathbf{y}_N - \mathbf{Y}_0' \beta\|_2^2 + \lambda_1 \|\beta\|_1 + \lambda_2 \|\beta\|_2^2, \quad \text{with } \hat{Y}_{NT}^{\text{vt}}(0) = \langle \mathbf{y}_T, \hat{\beta} \rangle. \quad (3)$$

We overview common choices for (λ_1, λ_2) and describe the corresponding strategy.

I: Ordinary least squares (OLS). Arguably, the mother of all regressions is OLS, where $\lambda_1 = \lambda_2 = 0$. OLS is an unconstrained problem with possibly infinitely many solutions. In such settings, one particular solution is the vector with minimum ℓ_2 -norm; this minimizer is unique and described through the pseudoinverse. OLS has been analyzed in numerous panel study works, including [Hsiao, Ching, and Wan \(2012\)](#), [Li and Bell \(2017\)](#), and [Li \(2020\)](#). Recent works have also shown OLS to be a benign overfitter in the high-dimensional regime ([Bartlett, Long, Lugosi, and Tsigler \(2020\)](#), [Spiess, Imbens, and Venugopal \(2023\)](#)), that is, OLS can predict well despite interpolating the in-sample data (zero in-sample residuals).

II: Principal component regression (PCR). To formalize PCR, let $\mathbf{Y}_0^{(k)} = \sum_{\ell=1}^k s_\ell \mathbf{u}_\ell \mathbf{v}_\ell'$ denote the rank $k < R$ approximation of $\mathbf{Y}_0$ that retains the top k principal components. HZ and VT PCR corresponds to replacing $\mathbf{Y}_0$ with $\mathbf{Y}_0^{(k)}$ within (2) and (3), respectively, with $\lambda_1 = \lambda_2 = 0$. In words, PCR first finds a k -dimensional representation of the covariate matrix via principal component analysis; then, PCR performs OLS with the compressed k -dimensional covariates. Within the synthetic controls literature, [Amjad, Shah, and Shen \(2018\)](#), [Amjad, Misra, Shah, and Shen \(2019\)](#) and [Agarwal, Shah, and Shen \(2021\)](#) utilized PCR.

III: Ridge regression. Ridge considers $\lambda_1 = 0$ and $\lambda_2 > 0$. When $\mathbf{Y}_0$ is rank deficient, the gram matrix, that is, $\mathbf{Y}_0' \mathbf{Y}_0$ for HZ regression and $\mathbf{Y}_0 \mathbf{Y}_0'$ for VT regression, is ill-conditioned. This can discourage the usage of OLS. Ridge provides a remedy by adding a *ridge* on the diagonal of the gram matrix, which increases all eigenvalues by λ_2 , thus removing the singularity problem. [Ben-Michael, Feller, and Rothstein \(2021\)](#) explored properties of a doubly robust estimator that utilizes HZ ridge regression.

IV: Lasso regression. Lasso considers $\lambda_1 > 0$ and $\lambda_2 = 0$. Lasso is a popular tool for estimating sparse linear coefficients in high-dimensional regimes. Because the criterion is not strictly convex, there are possibly infinitely many solutions. Thus, for our analysis of lasso only, we make the mild assumption that the entries of $\mathbf{Y}_0$ are drawn from a continuous distribution. This guarantees the lasso solution to be unique ([Tibshirani \(2013\)](#)). Several notable works in the synthetic controls literature, for example, [Li and Bell \(2017\)](#), [Carvalho, Masini, and Medeiros \(2018\)](#), and [Chernozhukov, Wüthrich, and Zhu \(2021\)](#), analyze the lasso.

V: Elastic net regression. Elastic net considers $\lambda_1, \lambda_2 > 0$. At a high level, elastic net selects variables similarly to the lasso, but deals with correlated variables more gracefully as with ridge. When $\lambda_2 > 0$, the criterion is strictly convex so the solution is unique. [Doudchenko and Imbens \(2016\)](#) proposed an elastic net synthetic controls variant.

Constrained Least Squares. VI: *Simplex regression.* The next formulation constrains the regression weights to lie within the simplex, that is, the weights are nonnegative and sum to one:

(a) HZ regression: for $\lambda \geq 0$,

$$\hat{\alpha} = \underset{\alpha: \alpha' \mathbf{1} = 1, \alpha \geq 0}{\operatorname{argmin}} \|\mathbf{y}_T - \mathbf{Y}_0 \alpha\|_2^2 + \lambda \|\alpha\|_2^2, \quad \text{with } \hat{Y}_{NT}^{\text{hz}}(0) = \langle \mathbf{y}_N, \hat{\alpha} \rangle. \quad (4)$$

(b) VT regression: for $\lambda \geq 0$,

$$\hat{\beta} = \underset{\beta: \beta' \mathbf{1} = 1, \beta \geq 0}{\operatorname{argmin}} \|\mathbf{y}_N - \mathbf{Y}_0' \beta\|_2^2 + \lambda \|\beta\|_2^2, \quad \text{with } \hat{Y}_{NT}^{\text{vt}}(0) = \langle \mathbf{y}_T, \hat{\beta} \rangle. \quad (5)$$

We consider a vanishing ℓ_2 penalty since $\lambda = 0$ (standard formulation) can induce multiple minima (Abadie and LHour (2021)). When $\lambda > 0$, the criterion becomes strictly convex and the solution is unique. Simplex regression is the original formulation set forth in the pioneering works of Abadie and Gardeazabal (2003), Abadie, Diamond, and Hainmueller (2010), and Abadie, Diamond, and Hainmueller (2015), and its properties continue to be actively studied today. Beyond avoiding extrapolation, other attractive aspects of VT simplex regression include interpretability, sparsity, and transparency (Abadie (2021)). However, while VT simplex regression is heavily studied and utilized in practice, HZ simplex regression is considerably less commonplace.

3.1.2. Classification Results

To answer Q1, we classify the regression formulations into (i) a *symmetric* class and (ii) an *asymmetric* class. We use the shorthand $\text{HZ} = \text{VT}$ if the two approaches produce algebraically identical point estimates and $\text{HZ} \neq \text{VT}$ otherwise.

I: Symmetric class. We first state the symmetric formulations.

THEOREM 1: $\text{HZ} = \text{VT}$ for (i) OLS with $(\hat{\alpha}, \hat{\beta})$ as the minimum ℓ_2 -norm solutions:

$$\hat{Y}_{NT}^{\text{hz}}(0) = \hat{Y}_{NT}^{\text{vt}}(0) = \langle \mathbf{y}_N, \mathbf{Y}_0^\dagger \mathbf{y}_T \rangle = \sum_{\ell=1}^R (1/s_\ell) \langle \mathbf{y}_N, \mathbf{v}_\ell \rangle \langle \mathbf{u}_\ell, \mathbf{y}_T \rangle;$$

(ii) PCR with the same choice of $k < R$:

$$\hat{Y}_{NT}^{\text{hz}}(0) = \hat{Y}_{NT}^{\text{vt}}(0) = \langle \mathbf{y}_N, (\mathbf{Y}_0^{(k)})^\dagger \mathbf{y}_T \rangle = \sum_{\ell=1}^k (1/s_\ell) \langle \mathbf{y}_N, \mathbf{v}_\ell \rangle \langle \mathbf{u}_\ell, \mathbf{y}_T \rangle;$$

(iii) ridge regression with the same choice of $\lambda_2 > 0$:

$$\hat{Y}_{NT}^{\text{hz}}(0) = \hat{Y}_{NT}^{\text{vt}}(0) = \langle \mathbf{y}_N, (\mathbf{Y}_0' \mathbf{Y}_0 + \lambda_2 \mathbf{I})^{-1} \mathbf{Y}_0' \mathbf{y}_T \rangle = \sum_{\ell=1}^R \frac{s_\ell}{s_\ell^2 + \lambda_2} \langle \mathbf{y}_N, \mathbf{v}_\ell \rangle \langle \mathbf{u}_\ell, \mathbf{y}_T \rangle.$$

Theorem 1 might seem familiar at first glance. As observed in Abadie, Diamond, and Hainmueller (2015) and Ben-Michael, Feller, and Rothstein (2021, Lemma 2), the point estimates associated with HZ OLS and HZ ridge can be written as linear combinations of the elements in $\mathbf{y}_T$, which take the same *linear forms* as the corresponding VT point

estimates. However, their results stop short of establishing algebraic equivalence as in Theorem 1. In this view, Theorem 1 is perhaps surprising. It demonstrates that the HZ and VT perspectives—while appearing to be different—are, in fact, two equivalent ways of approaching the same problem when the regression model belongs to the symmetric class. Notably, this equivalence holds without any assumptions on the data generating process.

Additionally, Theorem 1 holds for any data configuration. Thus, it clarifies that HZ and VT OLS are *not* invalid when $T > N$ and $N > T$, respectively. In fact, the OLS estimate can even be written as $\langle \hat{\alpha}, Y_0' \hat{\beta} \rangle$, which incorporates both regression models. Prior misconceptions likely arose from the fact that infinitely many solutions can exist depending on the dimensions of the data and chosen approach. Among these solutions, however, is the one with minimum ℓ_2 -norm, which is the arrived-upon solution when the objective is optimized via gradient descent. This phenomenon is known as “implicit regularization,” where the optimization algorithm is biased towards a particular solution even though the bias is not explicit in the objective function (Neyshabur, Tomioka, and Srebro (2015), Gunasekar, Woodworth, Bhojanapalli, Neyshabur, and Srebro (2017)).

Through its connection to the ℓ_2 -penalty, the minimum ℓ_2 -norm also offers a high-level intuition for the root of symmetry. More specifically, observe that the ridge model converges to the OLS model with minimum ℓ_2 -norm as $\lambda_2 \rightarrow 0$. Since the PCR model is precisely the OLS minimum ℓ_2 -norm model that is restricted to the space spanned by the top k principal components, we conjecture that the geometry of the ℓ_2 -ball is the likely source of symmetry for HZ and VT point estimation.

II: Asymmetric class. Next, we state the class of asymmetric formulations.

THEOREM 2: HZ $\neq$ VT for (i) *lasso*, (ii) *elastic net*, and (iii) *simplex regression*.

A common thread of the objective functions in the asymmetric class is a penalty or constraint that promotes sparse models. Such regularizers are noticeably absent in the symmetric formulations. This suggests that geometries of the ℓ_1 -ball and simplex that encourage sparsity are likely sources of asymmetry for HZ and VT point estimation.

3.2. Doubly Robust Regression

These recent years have seen a surge of interest in doubly robust (DR) estimators. Within panel data, we discuss two prominent works that are rising in popularity.

3.2.1. Synthetic Difference-in-Differences

An important approach that continues to dominate empirical work in panel data is the difference-in-differences (DID) estimator (Ashenfelter (1978)). In essence, DID posits an additive outcome model with unit- and time-specific fixed effects, known colloquially as the “parallel trends” assumption. Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021) anchored on the DID principle and leveraged concepts from unconfoundedness and synthetic controls to derive a DR estimator called synthetic difference-in-differences (SDID). In our setting, the SDID prediction for the missing (N, T) th potential outcome is

$$\begin{aligned} \hat{Y}_{NT}^{\text{sdid}}(0) &= \sum_{i \leq N_0} \hat{\beta}_i Y_{iT} + \sum_{t \leq T_0} \hat{\alpha}_t Y_{Nt} - \sum_{i \leq N_0} \sum_{t \leq T_0} \hat{\beta}_i \hat{\alpha}_t Y_{it} \\ &= \langle y_T, \hat{\beta} \rangle + \langle y_N, \hat{\alpha} \rangle - \langle \hat{\beta}, Y_0 \hat{\alpha} \rangle, \end{aligned} \tag{6}$$

where $\hat{\alpha}$ and $\hat{\beta}$ represent general HZ and VT models, respectively. Observe that $\hat{\alpha} = (1/T_0)\mathbf{1}$ and $\hat{\beta} = (1/N_0)\mathbf{1}$ recovers DID. Moving beyond simple DID to performing a weighted two-way bias removal, Arkhangelsky et al. (2021) proposed to learn $\hat{\alpha}$ via simplex regression and $\hat{\beta}$ via simplex regression with an ℓ_2 -penalty.

3.2.2. Augmented Synthetic Controls

Ben-Michael, Feller, and Rothstein (2021) introduced the augmented synthetic control (ASC) estimator, which uses an outcome model to correct the bias induced by the classical synthetic controls estimator.¹ Concretely, the ASC estimator predicts the missing (N, T) th potential outcome as

$$\hat{Y}_{NT}^{\text{asc}}(0) = \hat{M}_{NT}(0) + \sum_{i \leq N_0} \hat{\beta}_i (Y_{iT} - \hat{M}_{iT}(0)), \quad (7)$$

where $\hat{M}_{iT}(0)$ is the estimator for the (i, T) th entry. Ben-Michael, Feller, and Rothstein (2021) instantiated $\hat{M}_{iT}(0) = \sum_{t \leq T_0} \hat{\alpha}_t Y_{it}$. Plugging this HZ outcome model into (7) then gives

$$\hat{Y}_{NT}^{\text{asc}}(0) = \langle \mathbf{y}_N, \hat{\alpha} \rangle + \langle \mathbf{y}_T, \hat{\beta} \rangle - \langle \hat{\beta}, \mathbf{Y}_0 \hat{\alpha} \rangle. \quad (8)$$

We consider this particular variant of ASC since it takes the same form as SDID, as seen in (6). In contrast to Arkhangelsky et al. (2021), Ben-Michael, Feller, and Rothstein (2021) learned $\hat{\alpha}$ via ridge regression and $\hat{\beta}$ via simplex regression.

3.2.3. Connecting DR Regression to HZ and VT Regressions

We refer to SDID (6) and ASC (8) as DR regression. To complement the existing results on DR regression for panel data, we leverage Theorem 1 to study properties of DR regression when $(\hat{\alpha}, \hat{\beta})$ come from the symmetric class.

COROLLARY 1: DR = HZ = VT for (i) $(\hat{\alpha}, \hat{\beta})$ as the OLS minimum ℓ_2 -norm solutions and (ii) $(\hat{\alpha}, \hat{\beta})$ as the PCR solutions with the same choice of $k < R$.

Corollary 1 affirms that when HZ and VT regressions are algebraically equivalent—namely, when $(\hat{\alpha}, \hat{\beta})$ are implicitly regularized or learned via PCR—then they are each a DR estimator. Hence, even though the formulas for HZ and VT regressions suggest that they only use one pattern, their numerical equivalence to DR regression suggests that they implicitly exploit *both* patterns in the data. This result is similar in spirit to the OLS case discussed in Robins, Sued, Lei-Gomez, and Rotnitzky (2007) with a linear propensity score model. Of course, one may not consider this setting to be a useful case of DR regression, just as in the OLS and linear propensity score case, but this equivalence between the three regressions remains an interesting observation.

3.3. Intercepts

Intercepts can be included in the HZ regression model by modifying the ℓ_2 -errors in (2) and (4) as $\|\mathbf{y}_T - \mathbf{Y}_0 \alpha - \alpha_0 \mathbf{1}\|_2^2$; similarly, they can be included in the VT regression model by modifying ℓ_2 -errors in (3) and (5) as $\|\mathbf{y}_N - \mathbf{Y}'_0 \beta - \beta_0 \mathbf{1}\|_2^2$. We discuss the role of intercepts for point estimation below.

¹See Abadie and L'Hour (2021) for a bias correction of synthetic controls through regression.

COROLLARY 2: HZ $\neq$ VT for (i) OLS, (ii) PCR, and (iii) ridge with intercepts.

We develop an intuition for Proposition 2 by interpreting intercepts in panel studies. A nonzero time intercept, α_0 , allows for a permanent constant difference between the treated and pretreatment periods; a nonzero unit intercept, β_0 , allows for a permanent constant difference between the treated and control units. These systematic structures then create an asymmetry between the two regressions. Below, we propose a methodology based on centering the data that allows for intercepts yet retains symmetry.

3.3.1. Including Intercepts and Retaining Symmetry Through Data Centering

Let $\ddot{Y}_0$ denote the twice centered version of Y_0 , that is, the rows and columns of $\ddot{Y}_0$ are mean zero. This can be satisfied by multiplying $I - (1/N_0)\mathbf{1}\mathbf{1}'$ and $I - (1/T_0)\mathbf{1}\mathbf{1}'$ to the left and right, respectively, of Y_0 . Consider the following modified formulations:

(a) HZ regression: for $\lambda \geq 0$,

$$(\hat{\alpha}_0, \hat{\alpha}_1, \hat{\alpha}) = \underset{(\alpha_0, \alpha_1, \alpha)}{\operatorname{argmin}} \|\mathbf{y}_T - \ddot{Y}_0 \alpha - \alpha_0 \mathbf{1}\|_2^2 + \|\mathbf{y}_N - \alpha_1 \mathbf{1}\|_2^2 + \lambda \|\alpha\|_2^2, \quad (9)$$

$$\hat{Y}_{NT}^{\text{hz}}(0) = \langle \mathbf{y}_N, \hat{\alpha} \rangle + \hat{\alpha}_0 + \hat{\alpha}_1. \quad (10)$$

(b) VT regression: for $\lambda \geq 0$,

$$(\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}) = \underset{(\beta_0, \beta_1, \beta)}{\operatorname{argmin}} \|\mathbf{y}_N - \ddot{Y}'_0 \beta - \beta_0 \mathbf{1}\|_2^2 + \|\mathbf{y}_T - \beta_1 \mathbf{1}\|_2^2 + \lambda \|\beta\|_2^2, \quad (11)$$

$$\hat{Y}_{NT}^{\text{vt}}(0) = \langle \mathbf{y}_T, \hat{\beta} \rangle + \hat{\beta}_0 + \hat{\beta}_1. \quad (12)$$

Similarly to before, OLS corresponds to $\lambda = 0$, PCR corresponds to OLS with $\ddot{Y}_0^{(k)}$ for $k < R$ in place of $\ddot{Y}_0$, and ridge regression corresponds to any $\lambda > 0$.

COROLLARY 3: HZ = VT for the symmetric estimators in Theorem 1 under the formulations set in (9) and (11) with $\ddot{Y}_0$ being twice centered.

We inspect (10) and (12) to understand the implications of Corollary 3. First, we recall Theorem 1, which establishes that the HZ and VT estimates share the same “base” estimate, that is, $\langle \mathbf{y}_N, \hat{\alpha} \rangle = \langle \mathbf{y}_T, \hat{\beta} \rangle$. Next, we note that $\hat{\alpha}_0 = \hat{\beta}_1 = (1/N_0)\mathbf{1}'\mathbf{y}_T$ and $\hat{\beta}_0 = \hat{\alpha}_1 = (1/T_0)\mathbf{1}'\mathbf{y}_N$, which correspond to the time and unit fixed effects, respectively. Intuitively, the modified point estimates in (10) and (12) include both fixed effect models to compensate for $\ddot{Y}_0$ being twice centered. Putting everything together, the modified HZ and VT point estimates are algebraically identical.

4. INFERENCE

To answer Q2, we study the inferential properties of the counterfactual prediction. Formal discussions for classical inference require an explicit postulation on the source of randomness. This article takes both a *model-based* approach, which makes assumptions about the distribution of the potential outcomes, and a *design-based* approach, which makes assumptions about the assignment mechanism of treatment. Within each setting, we consider a natural notion of randomness stemming from (i) time series patterns, (ii) cross-sectional patterns, and (iii) both patterns simultaneously.

Before we formalize these notions, we emphasize that the goal of this section is *not* to accurately model reality and propose novel confidence intervals for practice. The goal is to provide a simple example that illustrates the role of randomness in conducting inference; namely, that each source of randomness leads to a unique uncertainty quantification even for the same point estimate.

Setting. To isolate the role of randomness, we focus on OLS and its minimum ℓ_2 -norm solutions: $\hat{\alpha} = Y_0^\dagger y_T$ and $\hat{\beta} = (Y_0')^\dagger y_N$. Recall that Theorem 1 and Corollary 1 establish that the HZ, VT, and DR approaches yield algebraically equivalent point estimates for this setting. As such, we denote the point estimate as $\hat{Y}_{NT}(0)$ without any superscripts.

4.1. Model-Based Inference

Recall (1). The model-based perspective views the potential outcomes, $\{Y_{it}(0), Y_{it}(1)\}$, as stochastic and treatment assignments, $\{A_i, B_i\}$, as fixed. Within this framework, we consider a classical regression model.

4.1.1. Three Generative Models

I: **HZ model.** The HZ model considers time series patterns as the source of randomness.

ASSUMPTION 1: We have

$$Y_{iT} = \sum_{t \leq T_0} \alpha_t^* Y_{it} + \varepsilon_{iT}, \quad i = 1, \dots, N_0. \quad (13)$$

Here, α^* is a vector of unknown coefficients and $\{\varepsilon_{iT}\}_{i=1}^{N_0}$ are zero mean idiosyncratic errors that are independent over $i = 1, \dots, N_0$, conditional on (y_N, Y_0) .

Assumption 1 implies that the regressors, that is, lagged outcomes, are uncorrelated with the errors; this is also known as strict exogeneity. This motivates the HZ approach, whereby the statistical uncertainty of $\hat{Y}_{NT}(0)$ is governed by the construction of $\hat{\alpha}$ from (y_T, Y_0) , that is, the in-sample uncertainty.

II: **VT model.** The VT model considers cross-sectional patterns as the source of randomness.

ASSUMPTION 2: We have

$$Y_{Nt} = \sum_{i \leq N_0} \beta_i^* Y_{it} + \varepsilon_{Nt}, \quad t = 1, \dots, T_0. \quad (14)$$

Here, β^* is a vector of unknown coefficients and $\{\varepsilon_{Nt}\}_{t=1}^{T_0}$ are zero mean idiosyncratic errors that are independent over $t = 1, \dots, T_0$, conditional on (y_T, Y_0) .

Assumption 2 is analogous to Assumption 1. Hence, the statistical uncertainty of $\hat{Y}_{NT}(0)$ under the VT model is governed by the construction of $\hat{\beta}$ from (y_N, Y_0) .

III: **DR model.** We introduce a new model, the DR model, that considers aspects of the previous HZ and VT models. At a high level, the DR model considers time series and cross-sectional patterns as two distinct sources of randomness.

ASSUMPTION 3: We have (13) and (14). Here, $\{\varepsilon_{iT}\}_{i=1}^{N_0}$ and $\{\varepsilon_{Nt}\}_{t=1}^{T_0}$ have zero mean and are independent over $i = 1, \dots, N_0$ and $t = 1, \dots, T_0$, conditional on Y_0 .

Assumption 3 posits that Y_0 contains all measured confounders and the errors are independent across both time and units. As a result, the statistical uncertainty of $\widehat{Y}_{NT}(0)$ under the DR model is governed by the constructions of both $\widehat{\alpha}$ and $\widehat{\beta}$.

4.1.2. Model-Based Asymptotic Results on Inference

Equipped with our three models, we offer a model-based response to Q2.

Notation. Let $\Sigma_T^{\text{hz}} = \text{Cov}(\varepsilon_T | y_N, Y_0)$, $\Sigma_N^{\text{vt}} = \text{Cov}(\varepsilon_N | y_T, Y_0)$, $\Sigma_T^{\text{dr}} = \text{Cov}(\varepsilon_T | Y_0)$, and $\Sigma_N^{\text{dr}} = \text{Cov}(\varepsilon_N | Y_0)$, where $\varepsilon_T = [\varepsilon_{iT} : i \leq N_0]$ and $\varepsilon_N = [\varepsilon_{Nt} : t \leq T_0]$. Let $(\sigma_{iT}^{\text{hz}})^2 = \text{Var}(\varepsilon_{iT} | y_N, Y_0)$ for $i = 1 \leq N_0$. We define $\{(\sigma_{Nt}^{\text{vt}})^2, (\sigma_{iT}^{\text{dr}})^2, (\sigma_{Nt}^{\text{dr}})^2\}$ for $i = 1 \leq N_0$ and $t = 1 \leq T_0$ with respect to $(\Sigma_N^{\text{vt}}, \Sigma_T^{\text{dr}}, \Sigma_N^{\text{dr}})$ analogously.

Recalling the SVD of Y_0 from Section 3, we denote $H^u = UU'$ and $H^v = VV'$ as the projections onto the columnspace and rowspace of Y_0 , respectively.

THEOREM 3:

(i) [HZ model] Suppose Assumption 1 holds and

$$\left(\sum_{i \leq N_0} \mathbb{E}[\widehat{\beta}_i \varepsilon_{iT} |^3 | y_N, Y_0] \right)^2 = o \left(\left(\sum_{i \leq N_0} \widehat{\beta}_i^2 (\sigma_{iT}^{\text{hz}})^2 \right)^3 \right). \quad (15)$$

Then as $N_0 \rightarrow \infty$, we have

$$(v_0^{\text{hz}})^{-1/2} \cdot (\widehat{Y}_{NT}(0) - \mu_0^{\text{hz}}) \xrightarrow{d} \mathcal{N}(0, 1),$$

where $\mu_0^{\text{hz}} = \langle y_N, H^v \alpha^* \rangle$ and $v_0^{\text{hz}} = \widehat{\beta}' \Sigma_T^{\text{hz}} \widehat{\beta}$.

(ii) [VT model] Suppose Assumption 2 holds and

$$\left(\sum_{t \leq T_0} \mathbb{E}[\widehat{\alpha}_t \varepsilon_{Nt} |^3 | y_T, Y_0] \right)^2 = o \left(\left(\sum_{t \leq T_0} \widehat{\alpha}_t^2 (\sigma_{Nt}^{\text{vt}})^2 \right)^3 \right). \quad (16)$$

Then as $T_0 \rightarrow \infty$, we have

$$(v_0^{\text{vt}})^{-1/2} \cdot (\widehat{Y}_{NT}(0) - \mu_0^{\text{vt}}) \xrightarrow{d} \mathcal{N}(0, 1),$$

where $\mu_0^{\text{vt}} = \langle y_T, H^u \beta^* \rangle$ and $v_0^{\text{vt}} = \widehat{\alpha}' \Sigma_N^{\text{vt}} \widehat{\alpha}$.

(iii) [DR model] Suppose Assumption 3 holds and

$$\begin{aligned} & \left(\sum_{i \leq N_0} \sum_{t \leq T_0} \mathbb{E}[|(Y_0^\dagger)_{it} \{ \mathbb{E}[Y_{iT} | Y_0] \varepsilon_{Nt} + \mathbb{E}[Y_{Nt} | Y_0] \varepsilon_{iT} + \varepsilon_{iT} \varepsilon_{Nt} \}|^3 | Y_0] \right)^2 \\ &= o \left(\left(\sum_{i \leq N_0} \sum_{t \leq T_0} (Y_0^\dagger)_{it}^2 \{ \mathbb{E}[Y_{iT} | Y_0]^2 (\sigma_{Nt}^{\text{dr}})^2 + \mathbb{E}[Y_{Nt} | Y_0]^2 (\sigma_{iT}^{\text{dr}})^2 \right. \right. \\ & \quad \left. \left. + (\sigma_{iT}^{\text{dr}})^2 (\sigma_{Nt}^{\text{dr}})^2 \} \right)^3 \right). \end{aligned} \quad (17)$$

Then as $N_0, T_0 \rightarrow \infty$, we have

$$(v_0^{\text{dr}})^{-1/2} \cdot (\widehat{Y}_{NT}(0) - \mu_0^{\text{dr}}) \xrightarrow{d} \mathcal{N}(0, 1),$$

where $\mu_0^{\text{dr}} = \langle \alpha^*, Y_0' \beta^* \rangle$ and

$$v_0^{\text{dr}} = (H^u \beta^*)' \Sigma_T^{\text{dr}} (H^u \beta^*) + (H^v \alpha^*)' \Sigma_N^{\text{dr}} (H^v \alpha^*) + \text{tr}(Y_0^\dagger \Sigma_T^{\text{dr}} (Y_0')^\dagger \Sigma_N^{\text{dr}}).$$

Technical Interpretation. If $\{\varepsilon_{iT}, (\sigma_{iT}^{\text{hz}})^2\}$ are bounded, then (15) translates to $\sum_{i \leq N_0} |\widehat{\beta}_i|^3 = o(\|\widehat{\beta}\|_2^3)$, which rules out outlier coefficients; an analogous interpretation is derived for (16). Similarly, if $(\varepsilon_{iT}, \varepsilon_{Nt})$ and $(\sigma_{iT}^2, \sigma_{Nt}^2)$ are bounded for all (i, t) , then (17) loosely translates to

$$\sum_{i \leq N_0} |\widehat{\beta}_i|^3 + \sum_{t \leq T_0} |\widehat{\alpha}_t|^3 + \sum_{i \leq N_0} \sum_{t \leq T_0} |(Y_0^\dagger)_{it}|^3 = o(\|\widehat{\beta}\|_2^3 + \|\widehat{\alpha}\|_2^3 + \|Y_0^\dagger\|_F^3),$$

where $\|\cdot\|_F$ denotes the Frobenius norm. In effect, this bounds the magnitudes of the HZ and VT OLS coefficients and pseudoinverse matrix entries.

Conceptual Interpretation. Theorem 3 shows that the estimand and variance are controlled by time series patterns under the HZ model, cross-sectional patterns under the VT model, and both patterns under the DR model. Therefore, the emphasis is this: *each model measures uncertainty with respect to a distinct estimand*. This clarifies that the assumed source of randomness has substantive implications for conducting inference.

4.1.3. Model-Based Confidence Intervals Under Homoskedastic Errors

In Section 5, we study the trade-offs of conducting inference under different sources of randomness through data-inspired simulations and empirical applications. To this end, we construct separate HZ, VT, and DR confidence intervals based on the results in Theorem 3. Since the focus of Theorem 3 is conceptual, we consider homoskedastic errors to simplify our exposition.

Formally, let Σ_T^{hz} have identical diagonal elements, that is, $\Sigma_T^{\text{hz}} = (\sigma_T^{\text{hz}})^2 \cdot \mathbf{I}$; we define $(\Sigma_N^{\text{vt}}, \Sigma_T^{\text{dr}}, \Sigma_N^{\text{dr}})$ analogously with respect to $(\sigma_N^{\text{vt}}, \sigma_T^{\text{dr}}, \sigma_N^{\text{dr}})$. Motivated by Theorem 3, we construct the three confidence intervals as follows: for $\theta \in (0, 1)$, we have

$$\begin{aligned} \mathcal{CI}^{\text{hz}}(\theta) &:= \left[\widehat{Y}_{NT}(0) \pm z_{\frac{\theta}{2}} \sqrt{\widehat{v}_0^{\text{hz}}} \right], \\ \mathcal{CI}^{\text{vt}}(\theta) &:= \left[\widehat{Y}_{NT}(0) \pm z_{\frac{\theta}{2}} \sqrt{\widehat{v}_0^{\text{vt}}} \right], \\ \mathcal{CI}^{\text{dr}}(\theta) &:= \left[\widehat{Y}_{NT}(0) \pm z_{\frac{\theta}{2}} \sqrt{\widehat{v}_0^{\text{dr}}} \right], \end{aligned} \quad (18)$$

where $z_{\frac{\theta}{2}}$ is the upper $\theta/2$ quantile of $\mathcal{N}(0, 1)$ and $(\widehat{v}_0^{\text{hz}}, \widehat{v}_0^{\text{vt}}, \widehat{v}_0^{\text{dr}})$ are the estimators of $(v_0^{\text{hz}}, v_0^{\text{vt}}, v_0^{\text{dr}})$. We define

$$\widehat{v}_0^{\text{hz}} = \widehat{\beta}' \widehat{\Sigma}_T \widehat{\beta}, \quad \widehat{v}_0^{\text{vt}} = \widehat{\alpha}' \widehat{\Sigma}_N \widehat{\alpha}, \quad \widehat{v}_0^{\text{dr}} = \widehat{v}_0^{\text{hz}} + \widehat{v}_0^{\text{vt}} - \text{tr}(Y_0^\dagger \widehat{\Sigma}_T (Y_0')^\dagger \widehat{\Sigma}_N), \quad (19)$$

where $\widehat{\Sigma}_T$ and $\widehat{\Sigma}_N$ are standard estimators of $(\Sigma_T^{\text{hz}}, \Sigma_T^{\text{dr}})$ and $(\Sigma_N^{\text{vt}}, \Sigma_N^{\text{dr}})$, respectively:

$$\widehat{\Sigma}_T = \frac{1}{N_0 - R} \|(I - H^u)y_T\|_2^2 \cdot I,$$

$$\widehat{\Sigma}_N = \frac{1}{T_0 - R} \|(I - H^v)y_N\|_2^2 \cdot I;$$

recall that $R = \text{rank}(Y_0) = \text{tr}(H^u) = \text{tr}(H^v)$.

It is clear from (19) that $(\widehat{v}_0^{\text{hz}}, \widehat{v}_0^{\text{vt}})$ are plug-in estimators for $(v_0^{\text{hz}}, v_0^{\text{vt}})$. For this reason, we discuss $\widehat{v}_0^{\text{dr}}$ with respect to v_0^{dr} . Recall $\widehat{\alpha} = H^v \alpha$ and $\widehat{\beta} = H^u \beta$ by construction. To justify the negative trace in $\widehat{v}_0^{\text{dr}}$, note that $\widehat{v}_0^{\text{hz}}$ is a quadratic involving (y_N, y_T) . Since both quantities are random, the expectation of $\widehat{v}_0^{\text{hz}}$ induces an additional term that precisely corresponds to the trace term in v_0^{dr} . The same property holds for $\widehat{v}_0^{\text{vt}}$. Thus, $\widehat{v}_0^{\text{dr}}$ corrects for this bias via the negative trace.

LEMMA 1:

(i) [HZ model] Suppose Assumption 1 holds. Then we have

$$\mathbb{E}[\widehat{\Sigma}_T | y_N, Y_0] = \Sigma_T^{\text{hz}} \quad \text{and} \quad \mathbb{E}[\widehat{v}_0^{\text{hz}} | y_N, Y_0] = v_0^{\text{hz}}.$$

(ii) [VT model] Suppose Assumption 2 holds. Then we have

$$\mathbb{E}[\widehat{\Sigma}_N | y_T, Y_0] = \Sigma_N^{\text{vt}} \quad \text{and} \quad \mathbb{E}[\widehat{v}_0^{\text{vt}} | y_T, Y_0] = v_0^{\text{vt}}.$$

(iii) [DR model] Suppose Assumption 3 holds. Then we have

$$\mathbb{E}[\widehat{\Sigma}_T | Y_0] = \Sigma_T^{\text{dr}}, \quad \mathbb{E}[\widehat{\Sigma}_N | Y_0] = \Sigma_N^{\text{dr}}, \quad \text{and} \quad \mathbb{E}[\widehat{v}_0^{\text{dr}} | Y_0] = v_0^{\text{dr}}.$$

Lemma 1 states that the HZ, VT, and DR variance estimators are unbiased. This is a well-known result within the OLS literature, albeit it is typically formalized under the stricter full column rank assumption.

REMARK 1: We discuss heteroskedastic variance estimators in the Supplemental Material (Shen, Ding, Sekhon, and Yu (2023)).

4.2. Design-Based Inference

The design-based perspective views the potential outcomes, $\{Y_{it}(0), Y_{it}(1)\}$, as fixed and treatment assignments, $\{A_i, B_i\}$, as stochastic. Within this framework, we consider the assignment mechanisms introduced in Bottmer, Imbens, Spiess, and Warnick (2021). As Bottmer et al. (2021) noted, these assumptions are not always plausible, but they underlie the placebo tests that are commonly used in synthetic controls analyses.

4.2.1. Three Designs

Let $A \in \{0, 1\}^N$ with $\mathbf{1}'A = 1$ and $B \in \{0, 1\}^T$ with $\mathbf{1}'B = 1$ be the indicator vectors for the treated unit and treated time period, respectively.

I: HZ design. The HZ design considers the treated period to be randomly selected.

ASSUMPTION 4: We have

$$\mathbb{P}(\mathbf{B} = \mathbf{b}) = \begin{cases} 1/T, & \text{if } b_t \in \{0, 1\} \forall t \text{ and } \mathbf{1}'\mathbf{b} = 1, \\ 0, & \text{otherwise.} \end{cases} \quad (20)$$

II: **VT design.** The VT design considers the treated unit to be randomly selected.

ASSUMPTION 5: We have

$$\mathbb{P}(\mathbf{A} = \mathbf{a}) = \begin{cases} 1/N, & \text{if } a_i \in \{0, 1\} \forall i \text{ and } \mathbf{1}'\mathbf{a} = 1, \\ 0, & \text{otherwise.} \end{cases} \quad (21)$$

III: **DR design.** The DR design considers both the treated period and treated unit to be randomly selected.

ASSUMPTION 6: We have (20) and (21), where $\mathbf{A}$ and $\mathbf{B}$ are independent.

4.2.2. Design-Based Estimator

To conduct design-based analysis, we consider all possible treatment assignments, not only the realized assignment. Let $Y_{it}^*(0)$ be the OLS fit of $Y_{it}(0)$ using outcomes up to and including time t , but not thereafter, that is, $Y_{it}^*(0) = \langle \mathbf{x}, \mathbf{W}^\dagger \mathbf{z} \rangle$, where $\mathbf{W} = [Y_{j\tau} : j \neq i, \tau < t]$, $\mathbf{x} = [Y_{i\tau} : \tau < t]$, and $\mathbf{z} = [Y_{jt} : j \neq i]$. The design-based estimator is

$$\hat{Y}(0) = \sum_{i \leq N} \sum_{t \leq T} A_i B_t \cdot Y_{it}^*(0).$$

Again, the stochasticity of $\hat{Y}(0)$ stems from the assignments since $Y_{it}^*(0)$ is fixed. Hence, the model-based and design-based estimators share the same point estimate for the realized assignment, but differ in their formulations and attributions of randomness.

4.2.3. Connecting Model-Based and Design-Based Perspectives

In Table I, we summarize the estimands associated with the model-based and design-based estimators for the three sources of randomness in consideration. We examine the realized (N, T) th assignment for concreteness.

Since the model-based and design-based frameworks attribute randomness differently, their expectations are taken over different probability measures. Nevertheless, the two

TABLE I
MODEL-BASED AND DESIGN-BASED ESTIMANDS UNDER DIFFERENT SOURCES OF RANDOMNESS.

Source of Randomness	Model-Based Estimand	Design-Based Estimand
Time	$\mathbb{E}[\hat{Y}_{NT}(0) \mathbf{y}_N, \mathbf{Y}_0] = \sum_{t \leq T_0} \tilde{\alpha}_t^* Y_{Nt}$	$\mathbb{E}[\hat{Y}(0) \mathbf{A}] = \frac{1}{T} \sum_{t \leq T} Y_{Nt}^*(0)$
Unit	$\mathbb{E}[\hat{Y}_{NT}(0) \mathbf{y}_T, \mathbf{Y}_0] = \sum_{i \leq N_0} \tilde{\beta}_i^* Y_{iT}$	$\mathbb{E}[\hat{Y}(0) \mathbf{B}] = \frac{1}{N} \sum_{i \leq N} Y_{iT}^*(0)$
Time and Unit	$\mathbb{E}[\hat{Y}_{NT}(0) \mathbf{Y}_0] = \sum_{i \leq N_0} \sum_{t \leq T_0} \alpha_t^* \beta_i^* Y_{it}$	$\mathbb{E}[\hat{Y}(0)] = \frac{1}{NT} \sum_{i \leq N} \sum_{t \leq T} Y_{it}^*(0)$

Note: We use the shorthand $\tilde{\alpha}^* = \mathbf{H}^v \alpha^*$ and $\tilde{\beta}^* = \mathbf{H}^u \beta^*$ and consider the realized (N, T) th assignment.

estimators recover similar estimands for each source of randomness. With time sourced randomness, both estimands are weighted compositions of outcomes across time, which Bottmer et al. (2021) called the “HZ” effect. With unit sourced randomness, both estimands are weighted compositions of outcomes across units, also called the “VT” effect. Finally, with time and unit sourced randomness, both estimands are weighted compositions of outcomes across time and units, which we coin the “DR” effect.

4.3. From Insights to Practice

Theorem 3 and Table I illustrate that different sources of randomness lead to different estimands and different quantifications of uncertainty even for the same point estimate. The connection between assumptions of randomness and resulting estimands has also been highlighted in related contexts, for example, Abadie, Athey, Imbens, and Wooldridge (2020), Bottmer et al. (2021), and Sekhon and Shem-Tov (2021). Translated to practice, these results stress that researchers’ assumptions on the source of randomness matter for inference, as they usually do in observational research. As we demonstrate in the next section, these choices are substantively important in the three applications we consider.

5. ILLUSTRATIONS

This section illustrates key concepts developed in this article using three canonical studies from the synthetic controls literature: (i) terrorism in Basque Country, (ii) California’s Proposition 99 (Abadie, Diamond, and Hainmueller (2010)), and (iii) reunification of West Germany (Abadie, Diamond, and Hainmueller (2015)).

5.1. Background on Case Studies

- (i) *Basque study*. See Sections 1–2 for details.
- (ii) *California study*. This study examines the effect of California’s Proposition 99, an anti-tobacco legislation, on its tobacco consumption. The panel data contain per capita cigarette sales of $N = 39$ U.S. states over $T = 31$ years. There are $T_0 = 18$ pretreatment observations and $N_0 = 38$ control units. The aim is to estimate California’s cigarette sales in the absence of Proposition 99.
- (iii) *West Germany study*. This study examines the economic impact of the 1990 reunification in West Germany. The panel data contain per capita GDP of $N = 17$ countries over $T = 44$ years. There are $T_0 = 30$ pretreatment observations and $N_0 = 16$ control units. The aim is to estimate West Germany’s GDP in the absence of reunification.

5.2. Data-Inspired Simulation Studies

In an attempt to document our analysis in a realistic environment, we calibrate our simulations to our three studies. As previewed in Section 4.1.3, we conduct a model-based analysis using the confidence intervals derived from Theorem 3. We reiterate that these intervals may not be practical for many real-world settings as they are rooted in our stylized assumptions and asymptotic analysis. Hence, the purpose of this section is not to advocate for their usage. Instead, these intervals are simply a device to better understand the trade-offs in conducting inference under different sources of randomness.

5.2.1. Data Generating Process

We consider the single treated unit and time period setting. Specifically, we consider the actual treated unit, for example, Basque Country, and focus on the first post-treatment period, for example, one year after the outset of terrorism; hence, $T = T_0 + 1$. Using the actual data, we generate the underlying regression models as

$$\boldsymbol{\alpha}^* = \underset{\boldsymbol{\alpha}}{\operatorname{argmin}} \|\mathbf{y}_T^* - \mathbf{Y}_0^* \boldsymbol{\alpha}\|_2^2 \quad \text{and} \quad \boldsymbol{\beta}^* = \underset{\boldsymbol{\beta}}{\operatorname{argmin}} \|\mathbf{y}_N^* - (\mathbf{Y}_0^*)' \boldsymbol{\beta}\|_2^2,$$

where $\mathbf{y}_N^* = [Y_{Nt} : t \leq T_0]$, $\mathbf{y}_T^* = [Y_{iT} : i \leq N_0]$, and $\mathbf{Y}_0^* = [Y_{it} : i \leq N_0, t \leq T_0]$.

Observationally, we have access to $(\mathbf{y}_N, \mathbf{y}_T, \mathbf{Y}_0)$, which are defined as follows: Let $\mathbf{Y}_0$ be the rank- r approximation of $\mathbf{Y}_0^*$, where r is chosen as the minimum number of singular values needed to capture at least 99.9% of $\mathbf{Y}_0^*$'s spectral energy. We sample $\mathbf{y}_T \sim \mathcal{N}(\mathbf{Y}_0 \boldsymbol{\alpha}^*, (N_0 - r)^{-1} \|\mathbf{y}_T^* - \mathbf{Y}_0^* \boldsymbol{\alpha}^*\|_2^2 \mathbf{I})$ and $\mathbf{y}_N \sim \mathcal{N}(\mathbf{Y}_0' \boldsymbol{\beta}^*, (T_0 - r)^{-1} \|\mathbf{y}_N^* - (\mathbf{Y}_0^*)' \boldsymbol{\beta}^*\|_2^2 \mathbf{I})$. We then define three (latent) estimands: (i) $\mu_0^{\text{hz}} = \langle \mathbf{y}_N, \mathbf{H}^v \boldsymbol{\alpha}^* \rangle$, (ii) $\mu_0^{\text{vt}} = \langle \mathbf{y}_T, \mathbf{H}^u \boldsymbol{\beta}^* \rangle$, and (iii) $\mu_0^{\text{dr}} = \langle \boldsymbol{\alpha}^*, \mathbf{Y}_0' \boldsymbol{\beta}^* \rangle$, where $(\mathbf{H}^u, \mathbf{H}^v)$ are computed from $\mathbf{Y}_0$. These estimands correspond to Theorem 3 and Table I.

5.2.2. Simulation Results

For the purposes of stability, we conduct 5000 replications of the above DGP for each study. In the ℓ th simulation repeat, we learn the regression coefficients as

$$\hat{\boldsymbol{\alpha}}^{(\ell)} = \underset{\boldsymbol{\alpha}}{\operatorname{argmin}} \|\mathbf{y}_T^{(\ell)} - \mathbf{Y}_0 \boldsymbol{\alpha}\|_2^2 \quad \text{and} \quad \hat{\boldsymbol{\beta}}^{(\ell)} = \underset{\boldsymbol{\beta}}{\operatorname{argmin}} \|\mathbf{y}_N^{(\ell)} - \mathbf{Y}_0' \boldsymbol{\beta}\|_2^2.$$

The point estimate is $\hat{Y}_{NT}^{(\ell)}(0) = \langle \mathbf{y}_N^{(\ell)}, \hat{\boldsymbol{\alpha}}^{(\ell)} \rangle = \langle \mathbf{y}_T^{(\ell)}, \hat{\boldsymbol{\beta}}^{(\ell)} \rangle$. We construct separate HZ, VT, and DR (homoskedastic) confidence intervals, denoted as $(\hat{v}_0^{\text{hz}(\ell)}, \hat{v}_0^{\text{vt}(\ell)}, \hat{v}_0^{\text{dr}(\ell)})$, centered around the point estimate. The estimands do not change in our replications.

In Tables II and III, we report the coverage probabilities (CP) and average lengths (AL), respectively, for each confidence interval with respect to each estimand at the 95% nominal mark across all simulation repeats; see Figure 4 for an illustration of one repeat. Across all three studies and with respect to μ_0^{hz} , the coverage of the HZ interval is closer to the nominal coverage than that of the VT and DR intervals as the latter two can substantially under- or overcover. This storyline is consistent for the VT interval with respect to μ_0^{vt} and the DR interval with respect to μ_0^{dr} .

Collectively, our formal results and simulations demonstrate that (i) the choice of estimand directly affects the accuracy of inference; and (ii) the variance formulas devel-

TABLE II
COVERAGE PROBABILITY FOR NOMINAL 95% CONFIDENCE INTERVALS ACROSS 5000 REPLICATIONS.

Case study	$\hat{v}_0^{\text{hz}}$			$\hat{v}_0^{\text{vt}}$			$\hat{v}_0^{\text{dr}}$		
	μ_0^{hz}	μ_0^{vt}	μ_0^{dr}	μ_0^{hz}	μ_0^{vt}	μ_0^{dr}	μ_0^{hz}	μ_0^{vt}	μ_0^{dr}
Basque	0.93	0.75	0.67	0.99	0.93	0.88	1.00	0.97	0.94
California	0.94	1.00	0.91	0.66	0.94	0.61	0.97	1.00	0.95
W. Germany	0.94	1.00	0.91	0.49	0.94	0.47	0.95	1.00	0.94

TABLE III

AVERAGE COVERAGE LENGTH FOR NOMINAL 95% CONFIDENCE INTERVALS ACROSS 5000 REPLICATIONS.

Case study	$\widehat{v}_0^{\text{hz}}$	$\widehat{v}_0^{\text{vt}}$	$\widehat{v}_0^{\text{dr}}$
Basque	0.02	0.03	0.04
California	0.07	0.03	0.08
W. Germany	0.03	0.01	0.03

Note: The length is normalized by the magnitude of the corresponding point estimate.

oped for one estimand may not have the correct coverage for another. Therefore, researchers should carefully consider the source of randomness in their data as it can have a significant influence over their ability to conduct valid inference. These conclusions are in line with those drawn in Sekhon and Shem-Tov (2021), which analyzes the classical difference-in-means estimator for standard estimands in randomized experiments.

5.3. Empirical Applications

Next, we analyze our three case studies of interest. All estimators are trained on pre-treatment data only, and the point and variance estimation formulas are separately applied for the treated unit at each post-treatment period $t > T_0$. We continue to use the confidence intervals in (18) from Section 4.1.3.

5.3.1. Implementation Details

For ridge, lasso, and elastic net regressions, we use the default `scikit-learn` hyperparameters (λ_1, λ_2) . For PCR, we choose the number of principal components k via the approach described in Section 5.2. This yields $k = 2$ for the Basque study, $k = 3$ for the California study, and $k = 4$ for the West Germany study. We implement simplex regression using the code made available at <https://matheusfacure.github.io/python-causality-handbook/15-Synthetic-Control.html>.

5.3.2. Point Estimation

Figure 5 visualizes the counterfactual trajectories generated by the estimators in Section 3.1. Our findings reinforce Theorems 1 and 2. On a separate note, we observe that within the Basque study, the OLS estimates are wildly different from the others—likely due to overfitting—and HZ simplex regression reduces to the last observation carried forward (LOCF) estimator. In the California and West Germany studies, the estimates are

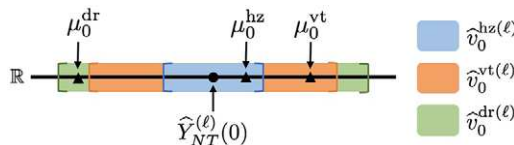


FIGURE 4.—Example illustration of Section 5.2.2 for one simulation repeat. Here, the HZ interval (blue) covers the HZ estimand but undercovers the VT and DR estimands. The VT interval (orange) covers the HZ and VT estimands but undercovers the DR estimand; however, relative to the HZ interval, the VT interval overcovers the HZ estimand. The DR interval (green) covers all estimands but overcovers the HZ and VT estimands relative to their respective intervals.

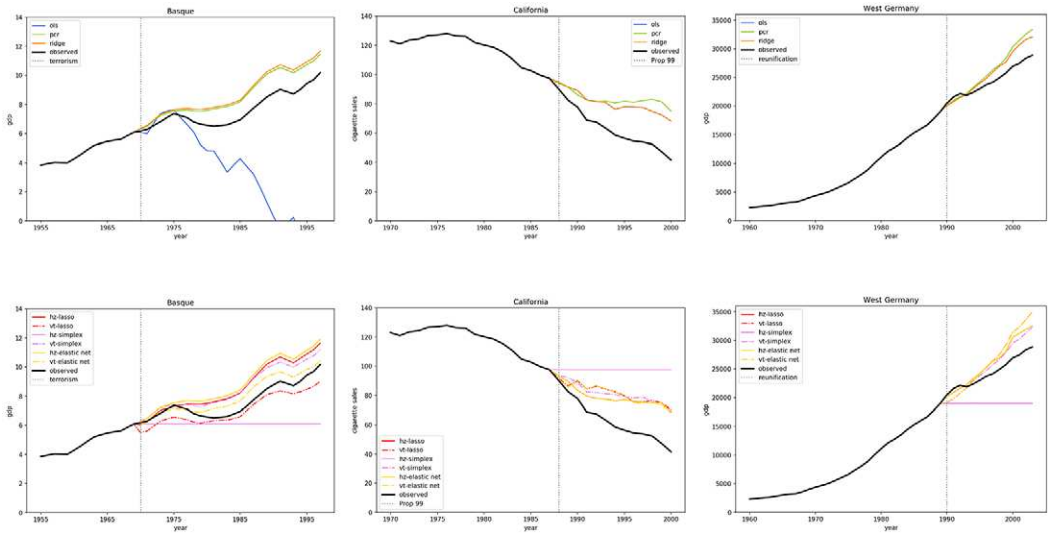


FIGURE 5.—Top and bottom figures correspond to symmetric and asymmetric estimators, respectively. From left to right, the figures are indexed by the Basque, California, and West Germany studies. Across all figures, the treated year is the dotted vertical line; the observed trajectory is in solid black; and the HZ and VT counterfactual trajectories are colored solid and dashed-dotted lines, respectively.

all qualitatively similar with the exception of the HZ simplex regression, which again reduces to LOCF. In fact, the OLS and ridge estimates appear to overlap, as well as the lasso and elastic net estimates.

5.3.3. Inference

We present the OLS-based confidence intervals in Figure 6.² As a final reminder, the emphasis of Figure 6 is that the intervals associated with each model can vary in width; we do not put any stock in the specific magnitudes of these widths. With this in mind, consider the Basque study. The top row of plots shows that μ_0^{vt} is more accurately estimated than both μ_0^{hz} and μ_0^{dr} . Put differently, there is less uncertainty about conducting inference on μ_0^{vt} relative to the other estimands. At the same time, these plots indicate that if μ_0^{hz} or μ_0^{dr} are the estimands of interest, then the VT confidence interval will undercover in both settings. Analogous statements apply to the remaining subfigures. As with our simulations, the large potential differences in coverage reinforce the importance of properly reasoning through the source of randomness in the data.

6. CONCLUSION

This article contributes to panel data analysis in two primary ways: (i) we prove that HZ, VT, and DR approaches—while seemingly very different—all yield algebraically identical point estimates for several standard estimators, that is, these approaches can be equiva-

²As Figure 6 shows, OLS-based confidence intervals can be degenerate due to zero in-sample residuals (interpolation). One rectification is to substitute OLS with PCR. In the Supplemental Material, we discuss advantages of PCR over OLS and present inferential results for PCR.

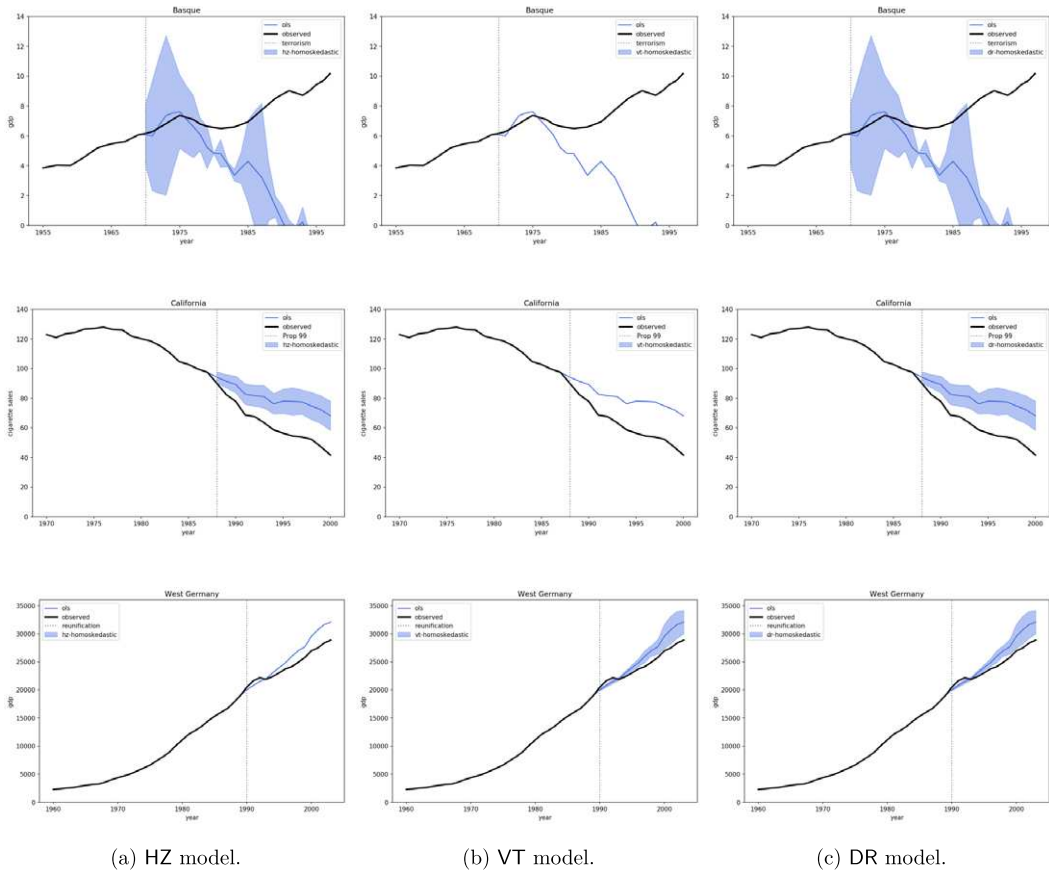


FIGURE 6.—OLS estimates with confidence intervals from Section 4.1.3. From top to bottom, the rows are indexed by the Basque, California, and West Germany studies. From left to right, the columns are indexed by the HZ, VT, and DR models. The VT intervals for Basque and California, and HZ interval for West Germany, are degenerate due to zero in-sample residuals from interpolation.

lent ways of looking at the same problem in the absence of any additional considerations; (ii) further, we demonstrate that even though these approaches may share the same point estimate, the source of randomness assumed by each approach leads to different estimates and different quantifications of uncertainty.

Our results show that assumptions made by researchers that may appear arbitrary about the source of randomness result in different inferences. This is expected in observational work because no randomization was actually implemented. Nevertheless, it is important to check the sensitivity of reported results to these randomness source assumptions. A potentially fruitful path forward is to build upon the principles of predictability, computability, and stability (PCS) (Yu and Kumbier (2020)) to create measures that incorporate our uncertainty over randomness source assumptions. We leave it to future work to formalize a treatment of this problem.

APPENDIX A: PROOFS FOR SECTION 3

This section provides the proofs for the formal results in Section 3.

A.1. Proof of Theorem 1

PROOF: (i) [OLS] Consider HZ regression. The optimality conditions state

$$\nabla_{\alpha} \|y_T - Y_0 \alpha\|_2^2 = 0.$$

Solving for α , we derive $Y_0' Y_0 \alpha = Y_0' y_T$. Using the pseudoinverse, we obtain $\hat{\alpha} = (Y_0' Y_0)^{\dagger} Y_0' y_T = Y_0^{\dagger} y_T$. Thus, the HZ prediction is given by $\hat{Y}_{NT}^{\text{hz}}(0) = \langle y_N, Y_0^{\dagger} y_T \rangle$.

Following the arguments above for VT regression, we obtain $\hat{\beta} = (Y_0')^{\dagger} y_N$ and $\hat{Y}_{NT}^{\text{vt}}(0) = \langle y_T, (Y_0')^{\dagger} y_N \rangle$. Given that $(Y_0')^{\dagger} = (Y_0^{\dagger})'$, the proof for OLS is complete.

(ii) [PCR] The proof follows that of OLS with $Y_0^{(k)}$ in place of Y_0 .

(iii) [Ridge] Following the proof for OLS, we obtain $\hat{Y}_{NT}^{\text{hz}}(0) = \langle y_N, (Y_0' Y_0 + \lambda_2 I)^{-1} Y_0' y_T \rangle$ and $\hat{Y}_{NT}^{\text{vt}}(0) = \langle y_T, (Y_0 Y_0' + \lambda_2 I)^{-1} Y_0 y_N \rangle$. Observing $(Y_0' Y_0 + \lambda I)^{-1} Y_0' = Y_0' (Y_0 Y_0' + \lambda I)^{-1}$ completes the proof. Q.E.D.

A.2. Proof of Theorem 2

To prove Theorem 2, we first establish our results for lasso and elastic net in Appendix A.2.1 and simplex regression in Appendix A.2.2, and then assemble them together in Appendix A.2.3.

A.2.1. Lasso and Elastic Net Regressions

We first establish a general result in Lemma 2 for ℓ_p -penalties, where $p = 2/K$ and K is an integer ≥ 1 , based on the contributions of Hoff (2017). More formally, consider the following:

(a) HZ regression: for $K \geq 1$ and $\lambda > 0$,

$$\hat{\alpha} = \underset{\alpha}{\operatorname{argmin}} \|y_T - Y_0 \alpha\|_2^2 + \lambda \|\alpha\|_p^p, \quad \text{with } \hat{Y}_{NT}^{\text{hz}}(0) = \langle y_N, \hat{\alpha} \rangle. \quad (22)$$

(b) VT regression: for $K \geq 1$ and $\lambda > 0$,

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \|y_N - Y_0' \beta\|_2^2 + \lambda \|\beta\|_p^p, \quad \text{with } \hat{Y}_{NT}^{\text{vt}}(0) = \langle y_T, \hat{\beta} \rangle. \quad (23)$$

Note that $K = 2$ yields lasso regression while $K > 2$ yields non-convex penalties. As such, we will use Lemma 2 to establish our results for lasso and elastic net regressions. We relegate the proof of Lemma 2 to Appendix A.2.4.

LEMMA 2: For any $K \geq 1$ and $\lambda > 0$, a HZ and VT regression solution is

$$\hat{Y}_{NT}^{\text{hz}}(0) = \langle y_N, \hat{\alpha}_1 \circ \cdots \circ \hat{\alpha}_K \rangle, \quad \text{and} \quad \hat{Y}_{NT}^{\text{vt}}(0) = \langle y_T, \hat{\beta}_1 \circ \cdots \circ \hat{\beta}_K \rangle,$$

where for every $k \leq K$,

$$\hat{\alpha}_k = \left(D(\hat{\alpha}_{\sim k}) Y_0' Y_0 D(\hat{\alpha}_{\sim k}) + \frac{\lambda}{K} I \right)^{-1} D(\hat{\alpha}_{\sim k}) Y_0' y_T,$$

$$\widehat{\beta}_k = \left(D(\widehat{\beta}_{\sim k}) Y_0 Y_0' D(\widehat{\beta}_{\sim k}) + \frac{\lambda}{K} I \right)^{-1} D(\widehat{\beta}_{\sim k}) Y_0 y_N,$$

$\widehat{\alpha}_{\sim k} = \widehat{\alpha}_1 \circ \cdots \circ \widehat{\alpha}_{k-1} \circ \widehat{\alpha}_{k+1} \circ \cdots \circ \widehat{\alpha}_K$, $\widehat{\beta}_{\sim k} = \widehat{\beta}_1 \circ \cdots \circ \widehat{\beta}_{k-1} \circ \widehat{\beta}_{k+1} \circ \cdots \circ \widehat{\beta}_K$, and $D(\widehat{\alpha}_{\sim k})$ and $D(\widehat{\beta}_{\sim k})$ are diagonal matrices formed from $\widehat{\alpha}_{\sim k}$ and $\widehat{\beta}_{\sim k}$, respectively.

LEMMA 3—Lasso and Elastic Net Regressions: $\text{HZ} \neq \text{VT}$ for (i) lasso and (ii) elastic net.

PROOF: (i) [Lasso] By Lemma 2 for $K = 2$ and $\lambda = \lambda_1 > 0$, a HZ regression solution is

$$\widehat{Y}_{NT}^{\text{hz}}(0) = \langle y_N, \widehat{\alpha}_1 \circ \widehat{\alpha}_2 \rangle, \quad (24)$$

where $\widehat{\alpha}_{1+k} = (D(\widehat{\alpha}_{2-k}) Y_0' Y_0 D(\widehat{\alpha}_{2-k}) + (\lambda_1/2) I)^{-1} D(\widehat{\alpha}_{2-k}) Y_0' y_T$ for $k \in \{0, 1\}$.

Similarly, a VT regression solution is given by

$$\widehat{Y}_{NT}^{\text{vt}}(0) = \langle y_T, \widehat{\beta}_1 \circ \widehat{\beta}_2 \rangle, \quad (25)$$

where $\widehat{\beta}_{1+k} = (D(\widehat{\beta}_{2-k}) Y_0 Y_0' D(\widehat{\beta}_{2-k}) + (\lambda_1/2) I)^{-1} D(\widehat{\beta}_{2-k}) Y_0 y_N$ for $k \in \{0, 1\}$.

From (24), we see that the HZ regression solution can be linear in y_N and at least quadratic in y_T . On the other hand, (25) reveals that the VT regression solution can be linear in y_T and at least quadratic in y_N . Since the lasso solution is unique under the assumption the entries of Y_0 are drawn from a continuous distribution, this implies that HZ and VT regressions do not yield matching estimates in general.

(ii) [Elastic net] Consider HZ regression. We rewrite (2) in a lasso formulation:

$$\widehat{\alpha}^* = \underset{\alpha^*}{\operatorname{argmin}} \|y_T^* - Y_0^* \alpha^*\|_2^2 + \lambda^* \|\alpha^*\|_1, \quad (26)$$

where $q^* = (y_T', \mathbf{0})'$, $Y_0^* = (1 + \lambda_2)^{-1/2} (Y_0', \sqrt{\lambda_2} I)'$, $\lambda^* = (1 + \lambda_2)^{-1/2} \lambda_1$, and $\alpha^* = (1 + \lambda_2)^{1/2} \alpha$. We apply Lemma 2 to (26) with $K = 2$ and $\lambda = \lambda^* > 0$ to obtain

$$\widehat{Y}_{NT}^{\text{hz}}(0) = \frac{\langle y_N, \widehat{\alpha}_1^* \circ \widehat{\alpha}_2^* \rangle}{\sqrt{1 + \lambda_2}}, \quad (27)$$

where $\widehat{\alpha}_{1+k}^* = ((1 + \lambda_2)^{-1/2} D(\widehat{\alpha}_{2-k}^*) (Y_0' Y_0 + \lambda_2 I) D(\widehat{\alpha}_{2-k}^*) + \frac{\lambda_1}{2} I)^{-1} D(\widehat{\alpha}_{2-k}^*) Y_0' y_T$ for $k \in \{0, 1\}$.

Similarly, for VT regression, we proceed as above to obtain

$$\widehat{Y}_{NT}^{\text{vt}}(0) = \frac{\langle y_T, \widehat{\beta}_1^* \circ \widehat{\beta}_2^* \rangle}{\sqrt{1 + \lambda_2}}, \quad (28)$$

where $\widehat{\beta}_{1+k}^* = ((1 + \lambda_2)^{-1/2} D(\widehat{\beta}_{2-k}^*) (Y_0 Y_0' + \lambda_2 I) D(\widehat{\beta}_{2-k}^*) + \frac{\lambda_1}{2} I)^{-1} D(\widehat{\beta}_{2-k}^*) Y_0 y_N$ for $k \in \{0, 1\}$.

From (27), we see that the HZ solution can be linear in y_N and at least quadratic in y_T . On the other hand, (28) reveals that the VT solution can be linear in y_T and at least quadratic in y_N . Since the elastic net regression solution is unique, this implies that HZ and VT regressions do not yield matching estimates in general. Q.E.D.

A.2.2. Simplex Regression

LEMMA 4—Simplex regression: $\text{HZ} \neq \text{VT}$ for simplex regression.

PROOF: Consider HZ regression. We write the Lagrangian of (4) as

$$\hat{\alpha} = \underset{\alpha}{\operatorname{argmin}} \|y_T - Y_0\alpha\|_2^2 + \lambda\|\alpha\|_2^2 - (\theta^{\text{hz}})' \alpha + \nu^{\text{hz}}(\mathbf{1}'\alpha - 1),$$

where $\theta^{\text{hz}} \in \mathbb{R}^{T_0}$ and $\nu^{\text{hz}} \in \mathbb{R}$. By the Karush-Kuhn-Tucker (KKT) conditions, optimality is achieved if the following are satisfied: (i) $\hat{\alpha} \geq \mathbf{0}$ and $\mathbf{1}'\hat{\alpha} = 1$; (ii) $\hat{\theta}^{\text{hz}} \geq \mathbf{0}$; (iii) $\hat{\theta}_i^{\text{hz}}\hat{\alpha}_i = 0$ for $i = 1, \dots, T_0$; (iv) $\hat{\alpha} = (Y_0'Y_0 + \lambda I)^{-1}(Y_0'y_T + (1/2)\hat{\theta}^{\text{hz}} - (\hat{\nu}^{\text{hz}}/2)\mathbf{1})$. Thus, given primal and dual feasible variables $(\hat{\alpha}, \hat{\theta}^{\text{hz}}, \hat{\nu}^{\text{hz}})$, we can write the final HZ prediction as

$$\hat{Y}_{NT}^{\text{hz}}(0) = \hat{Y}_{NT}^{\text{hz,ols}}(0) + (1/2)y_N'(Y_0'Y_0 + \lambda I)^{-1}(\hat{\theta}^{\text{hz}} - \hat{\nu}^{\text{hz}}\mathbf{1}),$$

where $\hat{Y}_{NT}^{\text{hz,ols}}(0) = y_N'(Y_0'Y_0 + \lambda I)^{-1}Y_0'y_T$ converges to the prediction corresponding to the OLS solution with minimum ℓ_2 -norm as $\lambda \rightarrow 0^+$. Similarly, for VT regression, the KKT conditions are (i) $\hat{\beta} \geq \mathbf{0}$ and $\mathbf{1}'\hat{\beta} = 1$; (ii) $\hat{\theta}^{\text{vt}} \geq \mathbf{0}$; (iii) $\hat{\theta}_i^{\text{vt}}\hat{\beta}_i = 0$ for $i = 1, \dots, N_0$; (iv) $\hat{\beta} = (Y_0Y_0' + \lambda I)^{-1}(Y_0y_N + (1/2)\hat{\theta}^{\text{vt}} - (\hat{\nu}^{\text{vt}}/2)\mathbf{1})$. For primal and dual feasible variables $(\hat{\beta}, \hat{\theta}^{\text{vt}}, \hat{\nu}^{\text{vt}})$, this yields

$$\hat{Y}_{NT}^{\text{vt}}(0) = \hat{Y}_{NT}^{\text{vt,ols}}(0) + (1/2)y_T'(Y_0Y_0' + \lambda I)^{-1}(\hat{\theta}^{\text{vt}} - \hat{\nu}^{\text{vt}}\mathbf{1}),$$

where $\hat{Y}_{NT}^{\text{vt,ols}}(0) = y_T'(Y_0Y_0' + \lambda I)^{-1}Y_0y_N$ converges to the prediction corresponding to the OLS solution with minimum ℓ_2 -norm as $\lambda \rightarrow 0^+$. Notably, as per Theorem 1, $\hat{Y}_{NT}^{\text{hz,ols}}(0) = \hat{Y}_{NT}^{\text{vt,ols}}(0) = \hat{Y}_{NT}^{\text{ols}}(0)$ for any $\lambda \geq 0$. As a result,

$$\hat{Y}_{NT}^{\text{hz}}(0) = \hat{Y}_{NT}^{\text{ols}}(0) + (1/2)y_N'(Y_0'Y_0 + \lambda I)^{-1}(\hat{\theta}^{\text{hz}} - \hat{\nu}^{\text{hz}}\mathbf{1}), \quad (29)$$

$$\hat{Y}_{NT}^{\text{vt}}(0) = \hat{Y}_{NT}^{\text{ols}}(0) + (1/2)y_T'(Y_0Y_0' + \lambda I)^{-1}(\hat{\theta}^{\text{vt}} - \hat{\nu}^{\text{vt}}\mathbf{1}). \quad (30)$$

As seen from (29) and (30), the leading terms in the HZ and VT simplex regression predictions are identical. The remaining terms, however, can differ from one another. As an example, consider $N = T$ with $Y_0 = I$, $y_N = \mathbf{0}$, $y_T = (1 + \lambda)(\hat{\theta}^{\text{vt}} - \hat{\nu}^{\text{vt}}\mathbf{1})$. By construction, observe that $\hat{\beta} = (2(1 + \lambda))^{-1}(\hat{\theta}^{\text{vt}} - \hat{\nu}^{\text{vt}}\mathbf{1})$. Recall from the KKT conditions for VT regression that $\hat{\beta} \geq \mathbf{0}$ and $\mathbf{1}'\hat{\beta} = 1$. Therefore, at least one entry of $(\hat{\theta}^{\text{vt}} - \hat{\nu}^{\text{vt}}\mathbf{1})$ must be strictly positive. This yields

$$(1 + \lambda)^{-1}y_T'(\hat{\theta}^{\text{vt}} - \hat{\nu}^{\text{vt}}\mathbf{1}) = (\hat{\theta}^{\text{vt}} - \hat{\nu}^{\text{vt}}\mathbf{1})'(\hat{\theta}^{\text{vt}} - \hat{\nu}^{\text{vt}}\mathbf{1}) > 0.$$

Combining the above, we obtain $\hat{Y}_{NT}^{\text{hz}}(0) = 0$ and $\hat{Y}_{NT}^{\text{vt}}(0) > 0$.

Q.E.D.

A.2.3. Putting Everything Together—Proof of Theorem 2

PROOF: The proof is immediate from Lemmas 3 and 4.

Q.E.D.

A.2.4. Proof of Lemma 2: ℓ_p -Penalties

PROOF: We recall the Hadamard product parameterization (HPP): for any vector $\mathbf{z}$ and integer $K \geq 1$, $\|\mathbf{z}\|_p^p = \min_{\mathbf{z}_1 \circ \dots \circ \mathbf{z}_K = \mathbf{z}} (1/K) \sum_{k=1}^K \|\mathbf{z}_k\|_2^2$, where $\circ$ denotes the Hadamard (componentwise) product. We rewrite our subclass of ℓ_p -penalties, that is, (22) and (23), as sums of ℓ_2 -penalties via the HPP technique:

$$(\hat{\boldsymbol{\alpha}}_1, \dots, \hat{\boldsymbol{\alpha}}_K) = \underset{\boldsymbol{\alpha}_1, \dots, \boldsymbol{\alpha}_K}{\operatorname{argmin}} \left\| \mathbf{y}_T - \mathbf{Y}_0(\boldsymbol{\alpha}_1 \circ \dots \circ \boldsymbol{\alpha}_K) \right\|_2^2 + \frac{\lambda}{K} \sum_{k=1}^K \|\boldsymbol{\alpha}_k\|_2^2, \quad (31)$$

$$(\hat{\boldsymbol{\beta}}_1, \dots, \hat{\boldsymbol{\beta}}_K) = \underset{\boldsymbol{\beta}_1, \dots, \boldsymbol{\beta}_K}{\operatorname{argmin}} \left\| \mathbf{y}_N - \mathbf{Y}'_0(\boldsymbol{\beta}_1 \circ \dots \circ \boldsymbol{\beta}_K) \right\|_2^2 + \frac{\lambda}{K} \sum_{k=1}^K \|\boldsymbol{\beta}_k\|_2^2, \quad (32)$$

where $\hat{\boldsymbol{\alpha}} = \hat{\boldsymbol{\alpha}}_1 \circ \dots \circ \hat{\boldsymbol{\alpha}}_K$ and $\hat{\boldsymbol{\beta}} = \hat{\boldsymbol{\beta}}_1 \circ \dots \circ \hat{\boldsymbol{\beta}}_K$. Below, we leverage the results of Hoff (2017), which provides an alternating ridge regression algorithm to solve for (31)–(32).

Consider HZ regression. Let us solve for $\boldsymbol{\alpha}_k$ by fixing $\boldsymbol{\alpha}_{k'}$ for $k' \neq k$. To begin, observe that $(\boldsymbol{\alpha}_1 \circ \dots \circ \boldsymbol{\alpha}_K)' \mathbf{Y}'_0 \mathbf{Y}_0 (\boldsymbol{\alpha}_1 \circ \dots \circ \boldsymbol{\alpha}_K) = \boldsymbol{\alpha}'_k (\mathbf{Y}'_0 \mathbf{Y}_0 \circ \boldsymbol{\alpha}_{\sim k} \boldsymbol{\alpha}'_{\sim k}) \boldsymbol{\alpha}_k$ and $(\boldsymbol{\alpha}_1 \circ \dots \circ \boldsymbol{\alpha}_K)' \mathbf{Y}'_0 \mathbf{y}_T = \boldsymbol{\alpha}'_k (\boldsymbol{\alpha}_{\sim k} \circ \mathbf{Y}'_0 \mathbf{y}_T)$, where $\boldsymbol{\alpha}_{\sim k} = \boldsymbol{\alpha}_1 \circ \dots \circ \boldsymbol{\alpha}_{k-1} \circ \boldsymbol{\alpha}_{k+1} \circ \dots \circ \boldsymbol{\alpha}_K$. This allows us to write the optimality conditions as

$$\nabla_{\boldsymbol{\alpha}_k} \left\{ \boldsymbol{\alpha}'_k (\mathbf{Y}'_0 \mathbf{Y}_0 \circ \boldsymbol{\alpha}_{\sim k} \boldsymbol{\alpha}'_{\sim k}) + (\lambda/K) \mathbf{I} \right\} \boldsymbol{\alpha}_k - 2 \boldsymbol{\alpha}'_k (\boldsymbol{\alpha}_{\sim k} \circ \mathbf{Y}'_0 \mathbf{y}_T) = 0.$$

This is quadratic in $\boldsymbol{\alpha}_k$ for fixed $\boldsymbol{\alpha}_{\sim k}$. Thus, the unique minimizer at convergence is

$$\hat{\boldsymbol{\alpha}}_k = (\mathbf{Y}'_0 \mathbf{Y}_0 \circ \hat{\boldsymbol{\alpha}}_{\sim k} \hat{\boldsymbol{\alpha}}'_{\sim k} + (\lambda/K) \mathbf{I})^{-1} (\hat{\boldsymbol{\alpha}}_{\sim k} \circ \mathbf{Y}'_0 \mathbf{y}_T),$$

where $\hat{\boldsymbol{\alpha}}_{\sim k} = \hat{\boldsymbol{\alpha}}_1 \circ \dots \circ \hat{\boldsymbol{\alpha}}_{k-1} \circ \hat{\boldsymbol{\alpha}}_{k+1} \circ \dots \circ \hat{\boldsymbol{\alpha}}_K$. Leveraging properties of the Hadamard product in Styan (1973), we rewrite $\mathbf{Y}'_0 \mathbf{Y}_0 \circ \hat{\boldsymbol{\alpha}}_{\sim k} \hat{\boldsymbol{\alpha}}'_{\sim k} = \mathbf{D}(\hat{\boldsymbol{\alpha}}_{\sim k}) \mathbf{Y}'_0 \mathbf{Y}_0 \mathbf{D}(\hat{\boldsymbol{\alpha}}_{\sim k})$ and $\mathbf{Y}'_0 \mathbf{y}_T \circ \hat{\boldsymbol{\alpha}}_{\sim k} = \mathbf{D}(\hat{\boldsymbol{\alpha}}_{\sim k}) \mathbf{Y}'_0 \mathbf{y}_T$, where $\mathbf{D}(\hat{\boldsymbol{\alpha}}_{\sim k})$ is the diagonal matrix formed from $\hat{\boldsymbol{\alpha}}_{\sim k}$. Thus, $\hat{\boldsymbol{\alpha}}_k = (\mathbf{D}(\hat{\boldsymbol{\alpha}}_{\sim k}) \mathbf{Y}'_0 \mathbf{Y}_0 \mathbf{D}(\hat{\boldsymbol{\alpha}}_{\sim k}) + (\lambda/K) \mathbf{I})^{-1} \mathbf{D}(\hat{\boldsymbol{\alpha}}_{\sim k}) \mathbf{Y}'_0 \mathbf{y}_T$. Turning to VT regression, we have $\hat{\boldsymbol{\beta}}_k = (\mathbf{D}(\hat{\boldsymbol{\beta}}_{\sim k}) \mathbf{Y}_0 \mathbf{Y}'_0 \mathbf{D}(\hat{\boldsymbol{\beta}}_{\sim k}) + (\lambda/K) \mathbf{I})^{-1} \mathbf{D}(\hat{\boldsymbol{\beta}}_{\sim k}) \mathbf{Y}_0 \mathbf{y}_N$, where $\hat{\boldsymbol{\beta}}_{\sim k} = \hat{\boldsymbol{\beta}}_1 \circ \dots \circ \hat{\boldsymbol{\beta}}_{k-1} \circ \hat{\boldsymbol{\beta}}_{k+1} \circ \dots \circ \hat{\boldsymbol{\beta}}_K$ and $\mathbf{D}(\hat{\boldsymbol{\beta}}_{\sim k})$ is the diagonal matrix formed from $\hat{\boldsymbol{\beta}}_{\sim k}$. This completes the proof. *Q.E.D.*

A.3. Proof of Corollary 1

PROOF: Consider OLS. Recall that $\hat{\mathbf{Y}}_{NT}^{\text{hz}}(0) = \langle \mathbf{y}_N, \hat{\boldsymbol{\alpha}} \rangle$ with $\hat{\boldsymbol{\alpha}} = \mathbf{Y}'_0 \mathbf{y}_T$ and $\hat{\mathbf{Y}}_{NT}^{\text{vt}}(0) = \langle \mathbf{y}_T, \hat{\boldsymbol{\beta}} \rangle$ with $\hat{\boldsymbol{\beta}} = (\mathbf{Y}'_0)^\dagger \mathbf{y}_N$. By Theorem 1, $\hat{\mathbf{Y}}_{NT}^{\text{hz}}(0) = \hat{\mathbf{Y}}_{NT}^{\text{vt}}(0)$. Thus,

$$\hat{\mathbf{Y}}_{NT}^{\text{dr}}(0) = \langle \mathbf{y}_T, \hat{\boldsymbol{\beta}} \rangle + \langle \mathbf{y}_N, \hat{\boldsymbol{\alpha}} \rangle - \langle \hat{\boldsymbol{\alpha}}, \mathbf{Y}'_0 \hat{\boldsymbol{\beta}} \rangle = 2 \langle \mathbf{y}_T, \hat{\boldsymbol{\beta}} \rangle - \langle \hat{\boldsymbol{\alpha}}, \mathbf{Y}'_0 \hat{\boldsymbol{\beta}} \rangle. \quad (33)$$

Since $(\mathbf{Y}'_0)^\dagger = (\mathbf{Y}'_0)'$, we have

$$\langle \hat{\boldsymbol{\alpha}}, \mathbf{Y}'_0 \hat{\boldsymbol{\beta}} \rangle = \mathbf{y}'_T (\mathbf{Y}'_0)^\dagger \mathbf{Y}'_0 (\mathbf{Y}'_0)^\dagger \mathbf{y}_N = \mathbf{y}'_T (\mathbf{Y}'_0)^\dagger \mathbf{y}_N = \mathbf{y}'_T \hat{\boldsymbol{\beta}}. \quad (34)$$

Plugging (34) into (33), we conclude $\hat{\mathbf{Y}}_{NT}^{\text{dr}}(0) = 2 \langle \mathbf{y}_T, \hat{\boldsymbol{\beta}} \rangle - \langle \mathbf{y}_T, \hat{\boldsymbol{\beta}} \rangle = \hat{\mathbf{Y}}_{NT}^{\text{vt}}(0) = \hat{\mathbf{Y}}_{NT}^{\text{hz}}(0)$. Now, observe that the same arguments above hold when $\mathbf{Y}_0^{(k)}$ takes the place of $\mathbf{Y}_0$ for any $k < R$. Therefore, the same reduction can be derived for PCR. *Q.E.D.*

A.4. Proof of Corollary 2

PROOF: Let $\mathbf{Y}_0^{\text{hz}} = [\mathbf{1}, \mathbf{Y}_0]$ and $\mathbf{Y}_0^{\text{vt}} = [\mathbf{1}, \mathbf{Y}_0']$. The proof is immediate from Theorem 1 by noting that $(\mathbf{Y}_0^{\text{hz}})' \neq \mathbf{Y}_0^{\text{vt}}$. Q.E.D.

A.5. Proof of Corollary 3

PROOF: Consider HZ ridge regression. The optimality conditions give

$$\nabla_{(\alpha_0, \alpha_1, \alpha)} \{ \|\mathbf{y}_T - \mathbf{Y}_0 \alpha - \alpha_0 \mathbf{1}\|_2^2 + \|\mathbf{y}_N - \alpha_1 \mathbf{1}\|_2^2 + \lambda \|\alpha\|_2^2 \} = 0.$$

Solving for α_0 , we have $\hat{\alpha}_0 = (1/N_0) \langle \mathbf{y}_T, \mathbf{1} \rangle$, which uses $\mathbf{Y}_0' \mathbf{1} = \mathbf{0}$. Solving for α_1 , we have $\hat{\alpha}_1 = (1/T_0) \langle \mathbf{y}_N, \mathbf{1} \rangle$. Finally, solving for α , we have $\hat{\alpha} = (\mathbf{Y}_0' \mathbf{Y}_0 + \lambda \mathbf{I})^{-1} \mathbf{Y}_0' \mathbf{y}_T$.

Identical arguments for VT regression yield $\hat{\beta}_0 = (1/T_0) \langle \mathbf{y}_N, \mathbf{1} \rangle$, $\hat{\beta}_1 = (1/N_0) \langle \mathbf{y}_T, \mathbf{1} \rangle$, and $\hat{\beta} = (\mathbf{Y}_0 \mathbf{Y}_0' + \lambda \mathbf{I}) \mathbf{Y}_0 \mathbf{y}_N$.

Further, Theorem 1 gives $\langle \mathbf{y}_N, \hat{\alpha} \rangle = \langle \mathbf{y}_T, \hat{\beta} \rangle$. Observing that $\hat{\alpha}_0 = \hat{\beta}_1$ and $\hat{\beta}_0 = \hat{\alpha}_1$ proves our ridge result. Setting $\lambda = 0$ and using the pseudoinverse, we have our OLS result. The result for PCR is established from OLS by substituting $\mathbf{Y}_0^{(k)}$ for $\mathbf{Y}_0$. This completes the proof. Q.E.D.

APPENDIX B: PROOFS FOR SECTION 4

This section provides the proofs for the formal results in Section 4.

B.1. Proof of Theorem 3

To establish Theorem 3, we first state a few useful results.

LEMMA 5—Theorem 2.7.1 of [Lehmann \(2000\)](#): Let X_i for $i = 1, \dots, n$ be independently distributed with means $\mathbb{E}[X_i] = \zeta_i$ and variances σ_i^2 , and with finite third moments. Let $\bar{X} = (1/n) \sum_{i=1}^n X_i$. Then $\text{Var}(\bar{X})^{-1/2} \cdot (\bar{X} - \mathbb{E}[\bar{X}]) \xrightarrow{d} \mathcal{N}(0, 1)$, provided

$$\left(\sum_{i=1}^n \mathbb{E}[|X_i - \zeta_i|^3] \right)^2 = o \left(\left(\sum_{i=1}^n \sigma_i^2 \right)^3 \right).$$

LEMMA 6: Consider a random vector $\mathbf{x}$ and random matrix $\mathbf{A}$. Let $\mathbb{E}[\mathbf{x}|\mathbf{A}] = \mathbf{0}$ and $\text{Cov}(\mathbf{x}|\mathbf{A}) = \Sigma$. Then $\mathbb{E}[\mathbf{x}' \mathbf{A} \mathbf{x} | \mathbf{A}] = \text{tr}(\mathbf{A} \Sigma)$.

FINISHING PROOF OF THEOREM 3: (i) [HZ model] Let Assumption 1 hold. By (15), Lemma 5 yields

$$\text{Var}(\hat{Y}_{NT}(0) | \mathbf{y}_N, \mathbf{Y}_0)^{-1/2} \cdot (\hat{Y}_{NT}(0) - \mathbb{E}[\hat{Y}_{NT}(0) | \mathbf{y}_N, \mathbf{Y}_0]) \xrightarrow{d} \mathcal{N}(0, 1).$$

To evaluate $\mathbb{E}[\hat{Y}_{NT}(0) | \mathbf{y}_N, \mathbf{Y}_0]$, we first observe that

$$\mathbb{E}[\hat{Y}_{NT}(0) | \mathbf{y}_N, \mathbf{Y}_0] = \mathbb{E}[\langle \mathbf{y}_N, \mathbf{Y}_0^\dagger \mathbf{y}_T \rangle | \mathbf{y}_N, \mathbf{Y}_0] = \mathbf{y}_N' \mathbf{Y}_0^\dagger \mathbf{Y}_0 \alpha^* = \mathbf{y}_N' \mathbf{H}^v \alpha^*. \quad (35)$$

Moving to the variance term, we note that

$$\text{Var}(\hat{Y}_{NT}(0) | \mathbf{y}_N, \mathbf{Y}_0) = \mathbf{y}_N' \text{Cov}(\hat{\alpha} | \mathbf{y}_N, \mathbf{Y}_0) \mathbf{y}_N. \quad (36)$$

Towards evaluating the above, we note that

$$\text{Cov}(\widehat{\boldsymbol{\alpha}}|y_N, Y_0) = \mathbf{Y}_0^\dagger \text{Cov}(\boldsymbol{\varepsilon}_T|y_N, Y_0)(\mathbf{Y}_0')^\dagger = \mathbf{Y}_0^\dagger \boldsymbol{\Sigma}_T^{\text{hz}}(\mathbf{Y}_0')^\dagger. \quad (37)$$

Plugging (37) into (36), we obtain

$$\text{Var}(\widehat{Y}_{NT}(0)|y_N, Y_0) = y_N' \mathbf{Y}_0^\dagger \boldsymbol{\Sigma}_T^{\text{hz}}(\mathbf{Y}_0')^\dagger y_N = \widehat{\boldsymbol{\beta}}' \boldsymbol{\Sigma}_T^{\text{hz}} \widehat{\boldsymbol{\beta}}, \quad (38)$$

where we recall that $\widehat{\boldsymbol{\beta}} = (\mathbf{Y}_0')^\dagger y_N$. Putting it all together, we conclude

$$(\widehat{\boldsymbol{\beta}}' \boldsymbol{\Sigma}_T^{\text{hz}} \widehat{\boldsymbol{\beta}})^{-1/2} \cdot (\widehat{Y}_{NT}(0) - \langle y_N, \mathbf{H}^v \boldsymbol{\alpha}^* \rangle) \xrightarrow{d} \mathcal{N}(0, 1).$$

(ii) [VT model] Let Assumption 2 hold. Following the arguments above, we have

$$(\widehat{\boldsymbol{\alpha}}' \boldsymbol{\Sigma}_N^{\text{vt}} \widehat{\boldsymbol{\alpha}})^{-1/2} \cdot (\widehat{Y}_{NT}(0) - \langle y_T, \mathbf{H}^u \boldsymbol{\beta}^* \rangle) \xrightarrow{d} \mathcal{N}(0, 1).$$

(iii) [DR model] Let Assumption 3 hold. We write

$$\widehat{Y}_{NT}(0) = y_N' \mathbf{Y}_0^\dagger y_T = \sum_{i \leq N_0} \sum_{t \leq T_0} (\mathbf{Y}_0^\dagger)_{it} Y_{iT} Y_{Nt}. \quad (39)$$

Observe that (39) is a sum of independent random variables with $\mathbb{E}[Y_{iT} Y_{Nt}|Y_0] = \mathbb{E}[Y_{iT}|Y_0] \mathbb{E}[Y_{Nt}|Y_0]$ and $\text{Var}(Y_{iT} Y_{Nt}|Y_0) = \mathbb{E}[Y_{iT}|Y_0]^2 \sigma_{Nt}^2 + \mathbb{E}[Y_{Nt}|Y_0]^2 \sigma_{iT}^2 + \sigma_{iT}^2 \sigma_{Nt}^2$. Lemma 5 then establishes that

$$\text{Var}(\widehat{Y}_{NT}(0)|Y_0)^{-1/2} \cdot (\widehat{Y}_{NT}(0) - \mathbb{E}[\widehat{Y}_{NT}(0)|Y_0]) \xrightarrow{d} \mathcal{N}(0, 1).$$

Our aim is to evaluate $\mathbb{E}[\widehat{Y}_{NT}(0)|Y_0]$ and $\text{Var}(\widehat{Y}_{NT}(0)|Y_0)$. Towards the former, we use Assumption 3 with the law of total expectation to obtain

$$\begin{aligned} \mathbb{E}[\widehat{Y}_{NT}(0)|Y_0] &= \mathbb{E}[\mathbb{E}[y_N' \mathbf{Y}_0^\dagger (\mathbf{Y}_0 \boldsymbol{\alpha}^* + \boldsymbol{\varepsilon}_T)|\boldsymbol{\varepsilon}_N, Y_0]|Y_0] \\ &= \mathbb{E}[(\mathbf{Y}_0' \boldsymbol{\beta}^* + \boldsymbol{\varepsilon}_N)' \mathbf{Y}_0^\dagger \mathbf{Y}_0 \boldsymbol{\alpha}^*|Y_0] = \langle \boldsymbol{\beta}^*, \mathbf{Y}_0 \boldsymbol{\alpha}^* \rangle. \end{aligned}$$

Note that we have used the fact that y_N is deterministic given $(\boldsymbol{\varepsilon}_N, Y_0)$. Similarly, by the law of total variance,

$$\text{Var}(\widehat{Y}_{NT}(0)|Y_0) = \mathbb{E}[\text{Var}(\widehat{Y}_{NT}(0)|\boldsymbol{\varepsilon}_N, Y_0)|Y_0] + \text{Var}(\mathbb{E}[\widehat{Y}_{NT}(0)|\boldsymbol{\varepsilon}_N, Y_0]|Y_0). \quad (40)$$

Following the derivation of (38), we have

$$\begin{aligned} \mathbb{E}[\text{Var}(\widehat{Y}_{NT}(0)|\boldsymbol{\varepsilon}_N, Y_0)|Y_0] &= (\mathbf{Y}_0' \boldsymbol{\beta}^*)' \mathbf{A} (\mathbf{Y}_0' \boldsymbol{\beta}^*) + \mathbb{E}[\boldsymbol{\varepsilon}_N' \mathbf{A} \boldsymbol{\varepsilon}_N|Y_0] \\ &\quad + 2\mathbb{E}[\boldsymbol{\varepsilon}_N' \mathbf{Y}_0' \boldsymbol{\beta}^*|Y_0], \end{aligned} \quad (41)$$

where $\mathbf{A} = \mathbf{Y}_0^\dagger \boldsymbol{\Sigma}_T^{\text{dr}} (\mathbf{Y}_0')^\dagger$. Notice that Assumption 3 gives $\mathbb{E}[\boldsymbol{\varepsilon}_N' \mathbf{Y}_0' \boldsymbol{\beta}^*|Y_0] = 0$. Since $\mathbf{A}$ is deterministic given Y_0 , Lemma 6 yields

$$\mathbb{E}[\boldsymbol{\varepsilon}_N' \mathbf{A} \boldsymbol{\varepsilon}_N|Y_0] = \text{tr}(\mathbf{A} \boldsymbol{\Sigma}_N^{\text{dr}}). \quad (42)$$

Following the arguments that led to the derivation of (35), we have

$$\text{Var}(\mathbb{E}[\widehat{Y}_{NT}(0)|\varepsilon_N, Y_0]|Y_0) = \text{Var}(\mathbf{y}'_N \mathbf{H}^v \boldsymbol{\alpha}^* | Y_0) = (\mathbf{H}^v \boldsymbol{\alpha}^*)' \boldsymbol{\Sigma}_N^{\text{dr}} (\mathbf{H}^v \boldsymbol{\alpha}^*). \quad (43)$$

Plugging (41), (42), and (43) into (40), we arrive at our desired result. Q.E.D.

B.2. Proof of Lemma 1

We first state a useful lemma to prove Lemma 1.

LEMMA 7—DR model: *Let Assumption 3 hold. Then,*

$$\begin{aligned} \mathbb{E}[\widehat{v}_0^{\text{dr}}|Y_0] &= (\mathbf{H}^u \boldsymbol{\beta}^*)' \mathbb{E}[\widehat{\boldsymbol{\Sigma}}_T|Y_0] (\mathbf{H}^u \boldsymbol{\beta}^*) + \text{tr}(Y_0^\dagger \mathbb{E}[\widehat{\boldsymbol{\Sigma}}_T|Y_0] (Y_0')^\dagger \boldsymbol{\Sigma}_N^{\text{dr}}) \\ &\quad + (\mathbf{H}^v \boldsymbol{\alpha}^*)' \mathbb{E}[\widehat{\boldsymbol{\Sigma}}_N|Y_0] (\mathbf{H}^v \boldsymbol{\alpha}^*) + \text{tr}(Y_0^\dagger \boldsymbol{\Sigma}_T^{\text{dr}} (Y_0')^\dagger \mathbb{E}[\widehat{\boldsymbol{\Sigma}}_N|Y_0]) \\ &\quad - \text{tr}(Y_0^\dagger \mathbb{E}[\widehat{\boldsymbol{\Sigma}}_T|Y_0] (Y_0')^\dagger \mathbb{E}[\widehat{\boldsymbol{\Sigma}}_N|Y_0]). \end{aligned}$$

FINISHING PROOF OF LEMMA 1: Let $\mathbf{H}_\perp^u = \mathbf{I} - \mathbf{H}^u$ and $\mathbf{H}_\perp^v = \mathbf{I} - \mathbf{H}^v$.

(i) [HZ model] Let Assumption 1 hold. Taking note that $\mathbf{H}_\perp^u Y_0 = \mathbf{0}$,

$$\begin{aligned} \|\mathbf{H}_\perp^u \mathbf{y}_T\|_2^2 &= \mathbf{y}_T' \mathbf{H}_\perp^u \mathbf{y}_T \\ &= (\mathbf{Y}_0 \boldsymbol{\alpha} + \boldsymbol{\varepsilon}_T)' \mathbf{H}_\perp^u (\mathbf{Y}_0 \boldsymbol{\alpha} + \boldsymbol{\varepsilon}_T) \\ &= \boldsymbol{\varepsilon}_T' \mathbf{H}_\perp^u \boldsymbol{\varepsilon}_T. \end{aligned}$$

Applying Lemma 6 then gives

$$\mathbb{E}[\boldsymbol{\varepsilon}_T' \mathbf{H}_\perp^u \boldsymbol{\varepsilon}_T | \mathbf{y}_N, Y_0] = \text{tr}(\mathbf{H}_\perp^u) (\sigma_T^{\text{hz}})^2 = (N_0 - R) (\sigma_T^{\text{hz}})^2, \quad (44)$$

where the final equality follows because the trace of a projection matrix equals its rank. Taken altogether, we have $\mathbb{E}[\widehat{\boldsymbol{\Sigma}}_T | \mathbf{y}_N, Y_0] = \boldsymbol{\Sigma}_T^{\text{hz}}$. Therefore,

$$\mathbb{E}[\widehat{v}_0^{\text{hz}} | \mathbf{y}_N, Y_0] = \widehat{\boldsymbol{\beta}}' \mathbb{E}[\widehat{\boldsymbol{\Sigma}}_T | \mathbf{y}_N, Y_0] \widehat{\boldsymbol{\beta}} = v_0^{\text{hz}}.$$

(ii) [VT model] Let Assumption 2 hold. Following the arguments above, we conclude that $\mathbb{E}[\widehat{\boldsymbol{\Sigma}}_N | \mathbf{y}_T, Y_0] = \boldsymbol{\Sigma}_N^{\text{vt}}$ and $\mathbb{E}[\widehat{v}_0^{\text{vt}} | \mathbf{y}_T, Y_0] = v_0^{\text{vt}}$.

(iii) [DR model] Let Assumption 3 hold. Following the arguments that led to (44), we obtain $\mathbb{E}[\widehat{\boldsymbol{\Sigma}}_T | Y_0] = \boldsymbol{\Sigma}_T^{\text{dr}}$ and $\mathbb{E}[\widehat{\boldsymbol{\Sigma}}_N | Y_0] = \boldsymbol{\Sigma}_N^{\text{dr}}$. Applying Lemma 7 then gives $\mathbb{E}[\widehat{v}_0^{\text{dr}} | Y_0] = v_0^{\text{dr}}$. The proof is complete. Q.E.D.

B.2.1. Proof of Lemma 7

PROOF: By linearity of expectations,

$$\mathbb{E}[\widehat{v}_0^{\text{dr}} | Y_0] = \mathbb{E}[\widehat{v}_0^{\text{hz}} | Y_0] + \mathbb{E}[\widehat{v}_0^{\text{vt}} | Y_0] - \mathbb{E}[\text{tr}(Y_0^\dagger \widehat{\boldsymbol{\Sigma}}_T (Y_0')^\dagger \widehat{\boldsymbol{\Sigma}}_N) | Y_0]. \quad (45)$$

We evaluate each term in (45).

Beginning with the first term, note that the randomness in $\widehat{\Sigma}_T$ stems from ϵ_T and $\widehat{\beta}$ is deterministic given (ϵ_N, Y_0) . As such, Assumption 3 with Lemma 6 gives

$$\begin{aligned}\mathbb{E}[\widehat{v}_0^{\text{hz}}|Y_0] &= \mathbb{E}[\widehat{\beta}'\widehat{\Sigma}_T\widehat{\beta}|Y_0] \\ &= \mathbb{E}[\mathbb{E}[\widehat{\beta}'\widehat{\Sigma}_T\widehat{\beta}|\epsilon_N, Y_0]|Y_0] \\ &= \mathbb{E}[y_N' Y_0^\dagger \mathbb{E}[\widehat{\Sigma}_T|Y_0] (Y_0')^\dagger y_N | Y_0] \\ &= \mathbb{E}[(Y_0' \beta^* + \epsilon_N) Y_0^\dagger \mathbb{E}[\widehat{\Sigma}_T|Y_0] (Y_0')^\dagger (Y_0' \beta^* + \epsilon_N) | Y_0] \\ &= (H^u \beta^*)' \mathbb{E}[\widehat{\Sigma}_T|Y_0] (H^u \beta^*) + \text{tr}(Y_0^\dagger \mathbb{E}[\widehat{\Sigma}_T|Y_0] (Y_0')^\dagger \Sigma_N^{\text{dr}}).\end{aligned}$$

By an analogous argument, we derive

$$\mathbb{E}[\widehat{v}_0^{\text{vt}}|Y_0] = (H^v \alpha^*)' \mathbb{E}[\widehat{\Sigma}_N|Y_0] (H^v \alpha^*) + \text{tr}(Y_0^\dagger \Sigma_T^{\text{dr}} (Y_0')^\dagger \mathbb{E}[\widehat{\Sigma}_N|Y_0]).$$

Finally, we use the linearity of the trace operator with Assumption 3 to obtain

$$\begin{aligned}\mathbb{E}[\text{tr}(Y_0^\dagger \widehat{\Sigma}_T (Y_0')^\dagger \widehat{\Sigma}_N) | Y_0] &= \mathbb{E}[\mathbb{E}[\text{tr}(Y_0^\dagger \widehat{\Sigma}_T (Y_0')^\dagger \widehat{\Sigma}_N) | \epsilon_N, Y_0] | Y_0] \\ &= \mathbb{E}[\text{tr}(Y_0^\dagger \mathbb{E}[\widehat{\Sigma}_T|Y_0] (Y_0')^\dagger \widehat{\Sigma}_N) | Y_0] \\ &= \text{tr}(Y_0^\dagger \mathbb{E}[\widehat{\Sigma}_T|Y_0] (Y_0')^\dagger \mathbb{E}[\widehat{\Sigma}_N|Y_0]).\end{aligned}$$

Putting everything together completes the proof.

Q.E.D.

REFERENCES

- ABADIE, ALBERTO, AND JAVIER GARDEAZABAL (2003): “The Economic Costs of Conflict: A Case Study of the Basque Country,” *American Economic Review*, 93 (1), 113–132. [2125,2126,2128,2131]
- ABADIE, ALBERTO (2021): “Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects,” *Journal of Economic Literature*, 59 (2), 391–425. [2131]
- ABADIE, ALBERTO, AND JÉRÉMY L’HOUR (2021): “A Penalized Synthetic Control Estimator for Disaggregated Data,” *Journal of the American Statistical Association*, 116 (536), 1817–1834. [2131,2133]
- ABADIE, ALBERTO, SUSAN ATHEY, GUIDO W. IMBENS, AND JEFFREY M. WOOLDRIDGE (2020): “Sampling-Based versus Design-Based Uncertainty in Regression Analysis,” *Econometrica*, 88 (1), 265–296. [2140]
- ABADIE, ALBERTO, ALEXIS DIAMOND, AND JENS HAINMUELLER (2010): “Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California’s Tobacco Control Program,” *Journal of the American Statistical Association*, 105 (490), 493–505. [2131,2140]
- (2015): “Comparative Politics and the Synthetic Control Method,” *American Journal of Political Science*, 59 (2), 495–510. [2129,2131,2140]
- AGARWAL, ANISH, DEVAVRAT SHAH, AND DENNIS SHEN (2021): “Synthetic Interventions,”. arXiv preprint arXiv:2006.07691. [2130]
- AMJAD, MUHAMMAD, VISHAL MISRA, DEVAVRAT SHAH, AND DENNIS SHEN (2019): “MRSC: Multi-Dimensional Robust Synthetic Control,” *Proc. ACM Meas. Anal. Comput. Syst.*, 3 (2), 37. [2130]
- AMJAD, MUHAMMAD, DEVAVRAT SHAH, AND DENNIS SHEN (2018): “Robust Synthetic Control,” *Journal of Machine Learning Research*, 19 (22), 1–51. [2130]
- ARKHANGELSKY, DMITRY, SUSAN ATHEY, DAVID A. HIRSHBERG, GUIDO W. IMBENS, AND STEFAN WAGER (2021): “Synthetic Difference-in-Differences,” *American Economic Review*, 111 (12), 4088–4118. [2132,2133]
- ASHENFELTER, ORLEY (1978): “Estimating the Effect of Training Programs on Earnings,” *The Review of Economics and Statistics*, 60 (1), 47–57. [2132]
- ATHEY, SUSAN, AND GUIDO W. IMBENS (2017): “The State of Applied Econometrics: Causality and Policy Evaluation,” *Journal of Economic Perspectives*, 31 (2), 3–32. [2125]

- ATHEY, SUSAN, MOHSEN BAYATI, NIKOLAY DOUDCHENKO, GUIDO IMBENS, AND KHASHAYAR KHOSRAVI (2021): "Matrix Completion Methods for Causal Panel Data Models," *Journal of the American Statistical Association*, 116 (536), 1716–1730. [2126,2129]
- BARTLETT, PETER L., PHILIP M. LONG, GÁBOR LUGOSI, AND ALEXANDER TSIGLER (2020): "Benign Overfitting in Linear Regression," *Proceedings of the National Academy of Sciences*, 117 (48), 30063–30070. [2130]
- BEN-MICHAEL, ELI, AVI FELLER, AND JESSE ROTHSTEIN (2021): "The Augmented Synthetic Control Method," *Journal of the American Statistical Association*, 116 (536), 1789–1803. [2130,2131,2133]
- BOTTMER, LEA, GUIDO IMBENS, JANN SPIESS, AND MERRILL WARNICK (2023): "A Design-Based Perspective on Synthetic Control Methods," *Journal of Business & Economic Statistics*, 0 (0), 1–12. [2138,2140]
- CARVALHO, CARLOS, RICARDO MASINI, AND MARCELO C. MEDEIROS (2018): "ArCo: An Artificial Counterfactual Approach for High-Dimensional Panel Time-Series Data," *Journal of Econometrics*, 207 (2), 352–380. [2130]
- CHERNOZHUKOV, VICTOR, KASPAR WÜTHRICH, AND YINCHU ZHU (2021): "An Exact and Robust Conformal Inference Method for Counterfactual and Synthetic Controls," *Journal of the American Statistical Association*, 116 (536), 1849–1864. [2130]
- DOUDCHENKO, NIKOLAY, AND GUIDO W. IMBENS (2016): "Balancing, Regression, Difference-in-Differences and Synthetic Control Methods: A Synthesis," Working Paper 22791, National Bureau of Economic Research. [2129,2130]
- GUNASEKAR, SURIYA, BLAKE WOODWORTH, SRINADH BHOJANAPALLI, BEHNAM NEYSHABUR, AND NATHAN SREBRO (2017): "Implicit Regularization in Matrix Factorization," *Advances in Neural Information Processing Systems*. [2132]
- HOFF, PETER D. (2017): "Lasso, Fractional Norm and Structured Sparse Estimation Using a Hadamard Product Parametrization," *Computational Statistics & Data Analysis*, 115 (C), 186–198. [2145,2148]
- HSIAO, CHENG, H. STEVE CHING, AND SHUI KI WAN (2012): "A Panel Data Approach for Program Evaluation: Measuring the Benefits of Political and Economic Integration of Hong Kong With Mainland China," *Journal of Applied Econometrics*, 27 (5), 705–740. [2130]
- IMBENS, GUIDO W., AND DONALD B. RUBIN (2015): *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction*. USA: Cambridge University Press. [2128]
- IMBENS, GUIDO W., AND JEFFREY M. WOOLDRIDGE (2009): "Recent Developments in the Econometrics of Program Evaluation," *Journal of Economic Literature*, 47 (1), 5–86. [2126]
- LEHMANN, ERICH L. (2000): *Elements of Large-Sample Theory*. New York: Springer. [2149]
- LI, KATHLEEN T. (2020): "Statistical Inference for Average Treatment Effects Estimated by Synthetic Control Methods," *Journal of the American Statistical Association*, 115 (532), 2068–2083. [2130]
- LI, KATHLEEN T., AND DAVID R. BELL (2017): "Estimation of Average Treatment Effects With Panel Data: Asymptotic Theory and Implementation," *Journal of Econometrics*, 197 (1), 65–75. [2129,2130]
- NEYSHABUR, BEHNAM, RYOTA TOMIOKA, AND NATHAN SREBRO (2015): "In Search of the Real Inductive Bias: on the Role of Implicit Regularization in Deep Learning," in *International Conference on Learning Representations*. [2132]
- ROBINS, JAMES, MARIELA SUED, QUANHONG LEI-GOMEZ, AND ANDREA ROTNITZKY (2007): "Comment: Performance of Double-Robust Estimators When "Inverse Probability" Weights Are Highly Variable," *Statistical Science*, 22 (4), 544–559. [2133]
- ROSENBAUM, PAUL, AND DONALD RUBIN (1983): "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika*, 70, 41–55. [2126]
- SEKHON, JASJEET S., AND YOTAM SHEM-TOV (2021): "Inference on a New Class of Sample Average Treatment Effects," *Journal of the American Statistical Association*, 116 (534), 798–804. [2140,2142]
- SHEN, DENNIS, PENG DING, JASJEET SEKHON, AND BIN YU (2023): "Supplement to 'Same Root Different Leaves: Time Series and Cross-Sectional Methods in Panel Data'," *Econometrica Supplemental Material*, 91, <https://doi.org/10.3982/ECTA21248>. [2138]
- SPIESS, JANN, GUIDO IMBENS, AND AMAR VENUGOPAL (2023): *Double and Single Descent in Causal Inference With an Application to High-Dimensional Synthetic Control*. [2130]
- STYAN, GEORGE P. H. (1973): "Hadamard Products and Multivariate Statistical Analysis," *Linear Algebra and its Applications*, 6, 217–240. [2148]
- TIBSHIRANI, RYAN J. (2013): "The Lasso Problem and Uniqueness," *Electronic Journal of Statistics*, 7, 1456–1490. [2130]

YU, BIN, AND KARL KUMBIER (2020): “Veridical Data Science,” *Proceedings of the National Academy of Sciences*, 117 (8), 3920–3929. [2144]

Co-editor Guido W. Imbens handled this manuscript.

Manuscript received 10 October, 2022; final version accepted 12 October, 2023; available online 12 October, 2023.

The replication package for this paper is available at <https://doi.org/10.5281/zenodo.8423395>. The Journal checked the data and codes included in the package for their ability to reproduce the results in the paper and approved online appendices.

SUPPLEMENT TO “SAME ROOT DIFFERENT LEAVES: TIME SERIES AND
CROSS-SECTIONAL METHODS IN PANEL DATA”
(*Econometrica*, Vol. 91, No. 6, November 2023, 2125–2154)

DENNIS SHEN

Department of Data Sciences & Operations, University of Southern California

PENG DING

Department of Statistics, University of California, Berkeley

JASJEET SEKHON

Departments of Statistics & Data Science and Political Science, Yale University

BIN YU

Departments of Statistics and EECS, University of California, Berkeley

THIS SUPPLEMENT IS STRUCTURED as follows. Appendix C complements Section 4.1.3 of the main body by presenting confidence intervals under heteroskedastic errors. Appendix D provides an extended discussion on principal component regression (PCR).

APPENDIX C: CONFIDENCE INTERVALS FOR HETEROSKEDASTIC NOISE

In Section 4.1.3, we presented confidence intervals under homoskedastic noise. Here, we present confidence intervals that are also motivated by Theorem 3 but for the heteroskedastic noise setting, that is, $(\Sigma_T^{\text{hz}}, \Sigma_N^{\text{vt}}, \Sigma_T^{\text{dr}}, \Sigma_N^{\text{dr}})$ are diagonal matrices whose nonzero entries are not necessarily identical. We construct our confidence intervals as in (18) and (19) of Section 4.1.3 using two popular strategies to estimate the covariance matrix.

Additional Notation. Recall $H^u = UU'$ and $H^v = VV'$. We define $H_\perp^u = I - H^u$ and $H_\perp^v = I - H^v$. With this notation, the HZ and VT in-sample errors can be written as $H_\perp^u y_T = y_T - Y_0 \hat{\alpha}$ and $H_\perp^v y_N = y_N - Y_0' \hat{\beta}$, respectively.

C.1. Jackknife Variance Estimation

The first estimator is based on the jackknife. Traditionally, the jackknife estimates the covariance of the regression coefficients $(\hat{\alpha}, \hat{\beta})$. By analyzing said estimates, we derive the following:

$$\hat{\Sigma}_T^{\text{jack}} = \text{diag}([H_\perp^u \circ H_\perp^u \circ I]^\dagger [H_\perp^u y_T \circ H_\perp^u y_T]), \quad (46)$$

$$\hat{\Sigma}_N^{\text{jack}} = \text{diag}([H_\perp^v \circ H_\perp^v \circ I]^\dagger [H_\perp^v y_N \circ H_\perp^v y_N]). \quad (47)$$

Dennis Shen: dennis.shen@marshall.usc.edu

Peng Ding: pengdingpku@berkeley.edu

Jasjeet Sekhon: jasjeet.sekhon@yale.edu

Bin Yu: binyu@berkeley.edu

LEMMA 8:

- (i) [HZ model] Suppose Assumption 1 holds. If $(\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u \circ \mathbf{I})$ is nonsingular, then we have

$$\mathbb{E}[\widehat{\boldsymbol{\Sigma}}_T^{\text{jack}} | \mathbf{y}_N, \mathbf{Y}_0] = \boldsymbol{\Sigma}_T^{\text{hz}} + \boldsymbol{\Delta}^{\text{hz}} \quad \text{and} \quad \mathbb{E}[\widehat{v}_0^{\text{hz, jack}} | \mathbf{y}_N, \mathbf{Y}_0] = v_0^{\text{hz}} + \widehat{\boldsymbol{\alpha}}' \boldsymbol{\Delta}^{\text{hz}} \widehat{\boldsymbol{\alpha}},$$

where $\Delta_{\ell\ell}^{\text{hz}} = \sum_{j \neq \ell} (\sigma_{jT}^{\text{hz}})^2 (H_{\ell j}^u)^2 (1 - H_{\ell\ell}^u)^{-2}$ for $\ell = 1, \dots, N_0$.

- (ii) [VT model] Suppose Assumption 2 holds. If $(\mathbf{H}_\perp^v \circ \mathbf{H}_\perp^v \circ \mathbf{I})$ is nonsingular, then we have

$$\mathbb{E}[\widehat{\boldsymbol{\Sigma}}_N^{\text{jack}} | \mathbf{y}_T, \mathbf{Y}_0] = \boldsymbol{\Sigma}_N^{\text{vt}} + \boldsymbol{\Gamma}^{\text{vt}} \quad \text{and} \quad \mathbb{E}[\widehat{v}_0^{\text{vt, jack}} | \mathbf{y}_T, \mathbf{Y}_0] = v_0^{\text{vt}} + \widehat{\boldsymbol{\beta}}' \boldsymbol{\Gamma}^{\text{vt}} \widehat{\boldsymbol{\beta}},$$

where $\Gamma_{\ell\ell}^{\text{vt}} = \sum_{j \neq \ell} (\sigma_{Nj}^{\text{vt}})^2 (H_{\ell j}^v)^2 (1 - H_{\ell\ell}^v)^{-2}$ for $\ell = 1, \dots, T_0$.

- (iii) [DR model] Suppose Assumption 3 holds. If $(\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u \circ \mathbf{I})$ and $(\mathbf{H}_\perp^v \circ \mathbf{H}_\perp^v \circ \mathbf{I})$ are nonsingular, then we have

$$\begin{aligned} \mathbb{E}[\widehat{\boldsymbol{\Sigma}}_T^{\text{jack}} | \mathbf{Y}_0] &= \boldsymbol{\Sigma}_T^{\text{dr}} + \boldsymbol{\Delta}^{\text{dr}}, \\ \mathbb{E}[\widehat{\boldsymbol{\Sigma}}_N^{\text{jack}} | \mathbf{Y}_0] &= \boldsymbol{\Sigma}_N^{\text{dr}} + \boldsymbol{\Gamma}^{\text{dr}}, \\ \mathbb{E}[\widehat{v}^{\text{dr, jack}}(\mathbf{Y}_0) | \mathbf{Y}_0] &= v_0^{\text{dr}} + (\mathbf{H}^u \boldsymbol{\beta}^*)' \boldsymbol{\Delta}^{\text{dr}} (\mathbf{H}^u \boldsymbol{\beta}^*) + (\mathbf{H}^v \boldsymbol{\alpha}^*)' \boldsymbol{\Gamma}^{\text{dr}} (\mathbf{H}^v \boldsymbol{\alpha}^*) \\ &\quad + \text{tr}(\mathbf{Y}_0' \boldsymbol{\Delta}^{\text{dr}} (\mathbf{Y}_0')^\dagger \boldsymbol{\Gamma}^{\text{dr}}), \end{aligned}$$

where $\Delta_{\ell\ell}^{\text{dr}}$ and $\Gamma_{\ell\ell}^{\text{dr}}$ are defined analogously to $\Delta_{\ell\ell}^{\text{hz}}$ and $\Gamma_{\ell\ell}^{\text{vt}}$, respectively, with $(\sigma_{jT}^{\text{dr}})^2$ and $(\sigma_{Nj}^{\text{dr}})^2$ in place of $(\sigma_{jT}^{\text{hz}})^2$ and $(\sigma_{Nj}^{\text{vt}})^2$, respectively.

Lemma 8 establishes that the jackknife is conservative, provided $(\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u \circ \mathbf{I})$ and $(\mathbf{H}_\perp^v \circ \mathbf{H}_\perp^v \circ \mathbf{I})$ are nonsingular. Strictly speaking, the jackknife is well defined if these quantities are singular, as seen through the pseudoinverse in (46) and (47). Lemma 8 considers the nonsingular case for simplicity. We remark that $\max_\ell H_{\ell\ell}^u < 1$ and $\max_\ell H_{\ell\ell}^v < 1$ are sufficient conditions for invertibility.

C.2. Hartley–Rao–Kiefer (HRK) Variance Estimation

Next, we consider the covariance estimator proposed by Hartley, Rao, and Kiefer (1969). We index this estimator by the authors, Hartley–Rao–Kiefer (HRK):

$$\begin{aligned} \widehat{\boldsymbol{\Sigma}}_T^{\text{HRK}} &= \text{diag}([\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u]^{-1} [\mathbf{H}_\perp^u \mathbf{y}_T \circ \mathbf{H}_\perp^u \mathbf{y}_T]), \\ \widehat{\boldsymbol{\Sigma}}_N^{\text{HRK}} &= \text{diag}([\mathbf{H}_\perp^v \circ \mathbf{H}_\perp^v]^{-1} [\mathbf{H}_\perp^v \mathbf{y}_N \circ \mathbf{H}_\perp^v \mathbf{y}_N]). \end{aligned}$$

LEMMA 9:

- (i) [HZ model] Suppose Assumption 1 holds. If $(\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u)$ is nonsingular, then we have

$$\mathbb{E}[\widehat{\boldsymbol{\Sigma}}_T^{\text{HRK}} | \mathbf{y}_N, \mathbf{Y}_0] = \boldsymbol{\Sigma}_T^{\text{hz}} \quad \text{and} \quad \mathbb{E}[\widehat{v}_0^{\text{hz, HRK}} | \mathbf{y}_N, \mathbf{Y}_0] = v_0^{\text{hz}}.$$

(ii) [VT model] Suppose Assumption 2 holds. If $(\mathbf{H}_\perp^v \circ \mathbf{H}_\perp^v)$ is nonsingular, then we have

$$\mathbb{E}[\widehat{\boldsymbol{\Sigma}}_N^{\text{HRK}} | \mathbf{y}_T, \mathbf{Y}_0] = \boldsymbol{\Sigma}_N^{\text{vt}} \quad \text{and} \quad \mathbb{E}[\widehat{v}_0^{\text{vt,HRK}} | \mathbf{y}_T, \mathbf{Y}_0] = v_0^{\text{vt}}.$$

(iii) [DR model] Suppose Assumption 3 holds. If $(\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u)$ and $(\mathbf{H}_\perp^v \circ \mathbf{H}_\perp^v)$ are nonsingular, then we have

$$\mathbb{E}[\widehat{\boldsymbol{\Sigma}}_T^{\text{HRK}} | \mathbf{Y}_0] = \boldsymbol{\Sigma}_T^{\text{dr}}, \quad \mathbb{E}[\widehat{\boldsymbol{\Sigma}}_N^{\text{HRK}} | \mathbf{Y}_0] = \boldsymbol{\Sigma}_N^{\text{dr}}, \quad \text{and} \quad \mathbb{E}[\widehat{v}_0^{\text{dr,HRK}} | \mathbf{Y}_0] = v_0^{\text{dr}}.$$

Lemma 9 establishes that the HRK estimator is unbiased, provided $(\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u)$ and $(\mathbf{H}_\perp^v \circ \mathbf{H}_\perp^v)$ are invertible. To discuss sufficient conditions for invertibility, consider $(\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u)$. A sufficient condition is strict diagonal dominance (Varga, 1962): $(1 - H_{\ell\ell}^u)^2 > \sum_{j \neq \ell} (H_{\ell j}^u)^2$. Notice that $\mathbf{H}^u$ is an orthogonal projector and is thus idempotent, that is, $(\mathbf{H}^u)^2 = \mathbf{H}^u$, and symmetric. Therefore,

$$H_{\ell\ell}^u = (H_{\ell\ell}^u)^2 + \sum_{j \neq \ell} (H_{\ell j}^u)^2 \implies \sum_{j \neq \ell} (H_{\ell j}^u)^2 = H_{\ell\ell}^u (1 - H_{\ell\ell}^u),$$

which allows us to simplify the condition as $(1 - H_{\ell\ell}^u)^2 > H_{\ell\ell}^u - (H_{\ell\ell}^u)^2$. Thus, $\max_\ell H_{\ell\ell}^u < 1/2$ is a sufficient condition for invertibility. Since $\text{tr}(\mathbf{H}^u) = R$, this restricts $R < N_0/2$. The same arguments apply for $(\mathbf{H}^v \circ \mathbf{H}^v)$.

C.3. Discussion

We highlight that Lemmas 1 (from Section 4.1.3), 8, and 9 only hold in expectation. For any particular realization, $\widehat{v}_0^{\text{dr}}$ may exhibit unexpected properties. For instance, if $\text{tr}(\mathbf{Y}_0^\dagger \widehat{\boldsymbol{\Sigma}}_T (\mathbf{Y}_0')^\dagger \widehat{\boldsymbol{\Sigma}}_N) > \max\{\widehat{v}_0^{\text{hz}}, \widehat{v}_0^{\text{vt}}\}$, then $\widehat{v}_0^{\text{dr}} < \min\{\widehat{v}_0^{\text{hz}}, \widehat{v}_0^{\text{vt}}\}$; thus, the mixed coverage will be smaller than both HZ and VT coverages. In fact, $\widehat{v}_0^{\text{dr}}$ can be negative if $\text{tr}(\mathbf{Y}_0^\dagger \widehat{\boldsymbol{\Sigma}}_T (\mathbf{Y}_0')^\dagger \widehat{\boldsymbol{\Sigma}}_N) > \widehat{v}_0^{\text{hz}} + \widehat{v}_0^{\text{vt}}$, which may occur if both HZ and VT in-sample errors are “too large.” For these scenarios, one naïve solution is to modify $\widehat{v}_0^{\text{dr}}$ as $\widehat{v}_0^{\text{dr}} = \widehat{v}_0^{\text{hz}} + \widehat{v}_0^{\text{vt}}$, which is conservative by Lemmas 1, 8, and 9. However, this case is arguably better resolved with a different point estimator altogether.

C.4. Empirical Applications—Extended

We extend our analysis in Section 5.3.3 to include results with the heteroskedastic confidence intervals. Figure C.1 presents the jackknife-based confidence intervals for our three case studies. We underscore that the conclusions drawn in Section 5.3.3 hold here as well. We remark that the conditions necessary for the HRK-based confidence intervals do not hold for OLS.

C.5. Deferred Proofs From This Section

We present the proofs for this section.

C.5.1. Proof of Lemma 8

PROOF: Before we establish the biases of $(\widehat{\boldsymbol{\Sigma}}_T^{\text{jack}}, \widehat{\boldsymbol{\Sigma}}_N^{\text{jack}})$, we first justify their forms. Jackknife is a popular approach to estimate the covariances of $(\widehat{\boldsymbol{\alpha}}, \widehat{\boldsymbol{\beta}})$. Below, we follow the

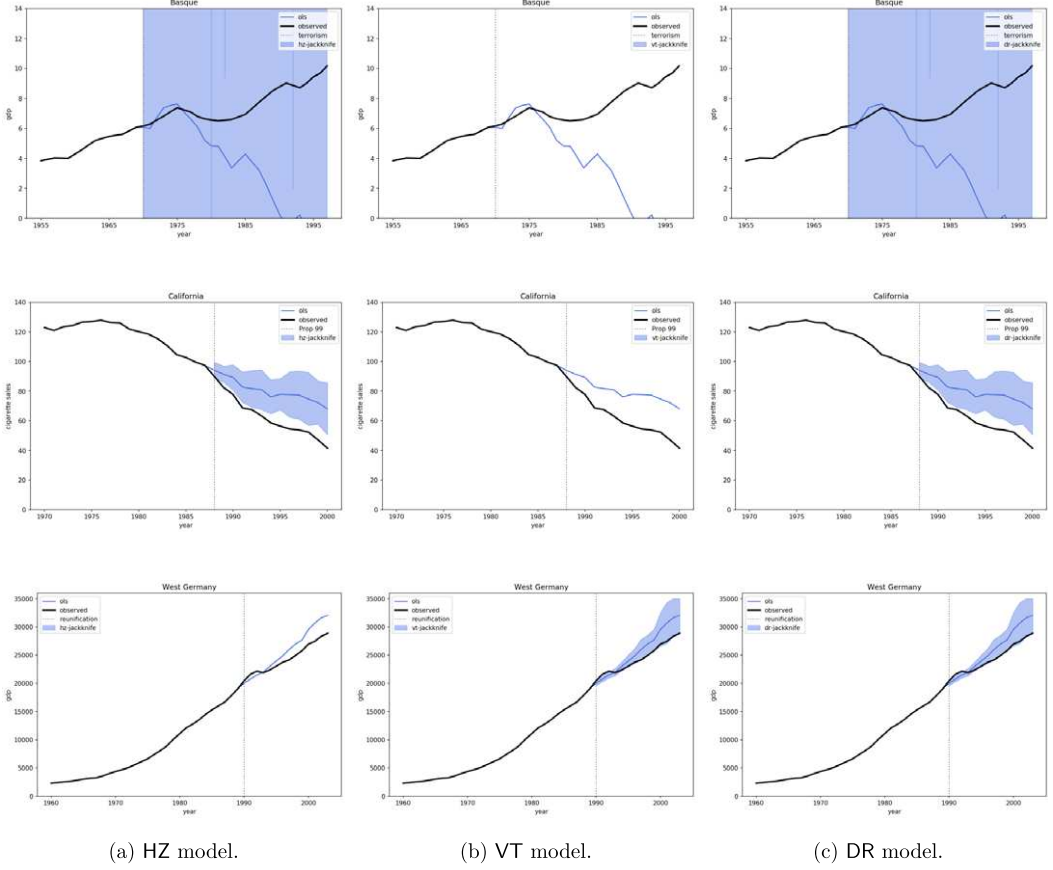


FIGURE C.1.—OLS estimates with jackknife confidence intervals. From top to bottom, the rows are indexed by the Basque, California, and West Germany studies. From left to right, the columns are indexed by the HZ, VT, and DR models.

standard techniques to derive the jackknife estimate of these objects, which will then be used to derive $(\hat{\Sigma}_T^{\text{jack}}, \hat{\Sigma}_N^{\text{jack}})$. Without loss of generality, we begin with $\hat{\alpha}$. Notably, while standard derivations consider Y_0 with full column rank, we consider a general matrix Y_0 that may be rank deficient. This difference is subtle so the following proof is by no means novel. We provide it simply for completeness.

To describe the jackknife, we define $\hat{\alpha}_{\sim i}$ as the minimum ℓ_2 -norm solution to (2), where $\lambda_1 = \lambda_2 = 0$, without the i th observation, that is,

$$\hat{\alpha}_{\sim i} = (Y'_{0,\sim i} Y_{0,\sim i})^\dagger Y'_{0,\sim i} y_{T,\sim i}, \quad (48)$$

where $Y_{0,\sim i}$ and $y_{T,\sim i}$ correspond to Y_0 and y_T without the i th observation. We define the pseudo-estimator as $\tilde{\alpha}_i = T_0 \hat{\alpha} - (T_0 - 1) \hat{\alpha}_{\sim i}$. With these quantities defined, we write the jackknife variance estimator as

$$\hat{V}^{\text{jack}} = \frac{1}{(T_0 - 1)^2} \sum_{i \leq N_0} (\tilde{\alpha}_i - \hat{\alpha})(\tilde{\alpha}_i - \hat{\alpha})'. \quad (49)$$

To evaluate this quantity, we will rewrite $\widehat{\alpha}_{\sim i}$ in a more convenient form. In particular,

$$\begin{aligned} Y'_{0,\sim i} Y_{0,\sim i} &= Y'_0 Y'_0 - y_i y'_i, \\ Y'_{0,\sim i} y_{T,\sim i} &= Y'_0 y_T - y_i y_{iT}, \end{aligned}$$

where $y_i = [Y_{it} : t \leq T_0]$ is the i th row of Y_0 . We do not assume that $Y'_0 Y_0$ is nonsingular. As such, we use a generalized form of the Sherman–Morrison formula (Cline, 1965, Meyer, 1973) to obtain

$$(Y'_{0,\sim i} Y_{0,\sim i})^\dagger = (Y'_0 Y_0)^\dagger + (1 - H_{ii}^u)^{-1} (Y'_0 Y_0)^\dagger y_i y'_i (Y'_0 Y_0)^\dagger. \quad (50)$$

Recall $\widehat{\alpha} = (Y'_0 Y_0)^\dagger Y'_0 y_T$ and note $Y_{iT} - y'_i \widehat{\alpha}$ is the i th element of $\widehat{\varepsilon}_T = H_\perp^u y_T$. Using these facts, we plug (50) into (48) to yield

$$\begin{aligned} \widehat{\alpha}_{\sim i} &= [(Y'_0 Y_0)^\dagger + (1 - H_{ii}^u)^{-1} (Y'_0 Y_0)^\dagger y_i y'_i (Y'_0 Y_0)^\dagger] (Y'_0 y_T - y_i y_{iT}) \\ &= \widehat{\alpha} - (Y'_0 Y_0)^\dagger y_i y_{iT} + (1 - H_{ii}^u)^{-1} (Y'_0 Y_0)^\dagger y_i y'_i \widehat{\alpha} \\ &\quad - H_{ii}^u (1 - H_{ii}^u)^{-1} (Y'_0 Y_0)^\dagger y_i y_{iT} \\ &= \widehat{\alpha} - (1 - H_{ii}^u)^{-1} (Y'_0 Y_0)^\dagger y_i \widehat{\varepsilon}_{iT}. \end{aligned} \quad (51)$$

Inserting (51) into our pseudo-estimate, we have

$$\begin{aligned} \tilde{\alpha}_i &= T_0 \widehat{\alpha} - (T_0 - 1) (\widehat{\alpha} - (1 - H_{ii}^u)^{-1} (Y'_0 Y_0)^\dagger y_i \widehat{\varepsilon}_{iT}) \\ &= \widehat{\alpha} + (T_0 - 1) (1 - H_{ii}^u)^{-1} (Y'_0 Y_0)^\dagger y_i \widehat{\varepsilon}_{iT}. \end{aligned} \quad (52)$$

Inserting (52) into (49), we have

$$\begin{aligned} \widehat{\mathcal{V}}^{\text{jack}} &= (Y'_0 Y_0)^\dagger \left(\sum_{i \leq N_0} \frac{\widehat{\varepsilon}_{iT}^2}{(1 - H_{ii}^u)^2} y_i y'_i \right) (Y'_0 Y_0)^\dagger \\ &= (Y'_0 Y_0)^\dagger Y'_0 \Omega Y_0 (Y'_0 Y_0)^\dagger, \end{aligned}$$

where Ω is a diagonal matrix with $\Omega_{ii} = \widehat{\varepsilon}_{iT}^2 (1 - H_{ii}^u)^{-2}$. Equivalently, $\Omega = \text{diag}([H_\perp^u \circ H_\perp^u \circ I]^\dagger [\widehat{\varepsilon}_T \circ \widehat{\varepsilon}_T])$. It then follows that

$$y'_N \widehat{\mathcal{V}}^{\text{jack}} y_N = \widehat{\beta}' \Omega \widehat{\beta}.$$

To arrive at (46), we define $\widehat{\Sigma}_T^{\text{jack}} = \Omega$. This corresponds to the EHW estimator with the jackknife correction. We derive (47) for $\widehat{\beta}$ by applying the same arguments above. Now, we will evaluate the biases of $(\widehat{\Sigma}_T^{\text{jack}}, \widehat{\Sigma}_N^{\text{jack}})$.

(i) [HZ model] Let Assumption 1 hold. We define $(\sigma_{iT}^{\text{hz}})^2 = \text{Var}(\varepsilon_{iT} | y_N, Y_0)$ for $i = 1, \dots, N_0$. Observe that

$$\mathbb{E}[(H_\perp^u \circ H_\perp^u \circ I)^\dagger (\widehat{\varepsilon}_T \circ \widehat{\varepsilon}_T) | y_N, Y_0] = (H_\perp^u \circ H_\perp^u \circ I)^\dagger \mathbb{E}[\widehat{\varepsilon}_T \circ \widehat{\varepsilon}_T | y_N, Y_0]. \quad (53)$$

To evaluate (53), we follow the derivations of (35) and (37) to obtain

$$\mathbb{E}[\widehat{\boldsymbol{\epsilon}}_T | \mathbf{y}_N, \mathbf{Y}_0] = \mathbf{H}_\perp^u \mathbf{Y}_0 \boldsymbol{\alpha}^* = \mathbf{0}, \quad (54)$$

$$\text{Cov}(\widehat{\boldsymbol{\epsilon}}_T | \mathbf{y}_N, \mathbf{Y}_0) = \mathbf{H}_\perp^u \boldsymbol{\Sigma}_T^{\text{hz}} \mathbf{H}_\perp^u. \quad (55)$$

Recall that $\mathbb{E}[X^2] = \text{Var}(X) + \mathbb{E}[X]^2$ for any random variable X . Thus, combining (54) with (55) gives

$$\mathbb{E}[\widehat{\boldsymbol{\epsilon}}_T \circ \widehat{\boldsymbol{\epsilon}}_T | \mathbf{y}_N, \mathbf{Y}_0] = (\mathbf{H}_\perp^u \boldsymbol{\Sigma}_T^{\text{hz}} \mathbf{H}_\perp^u \circ \mathbf{I}) \mathbf{1}. \quad (56)$$

Let $\widehat{\boldsymbol{\gamma}} = \mathbb{E}[\widehat{\boldsymbol{\epsilon}}_T \circ \widehat{\boldsymbol{\epsilon}}_T | \mathbf{y}_N, \mathbf{Y}_0]$. By (56), the ℓ th entry of $\widehat{\boldsymbol{\gamma}}$ can be written as

$$\widehat{\gamma}_\ell = \sum_{j \neq \ell} (H_{j\ell}^u)^2 (\sigma_{jT}^{\text{hz}})^2 + (1 - H_{\ell\ell}^u)^2 (\sigma_{\ell T}^{\text{hz}})^2,$$

where $H_{j\ell}^u$ is the (j, ℓ) th entry of $\mathbf{H}^u$. In turn, this allows us to rewrite (56) as

$$\widehat{\boldsymbol{\gamma}} = (\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u) \boldsymbol{\Sigma}_T^{\text{hz}} \mathbf{1}. \quad (57)$$

Next, let $\widehat{\boldsymbol{\zeta}} = (\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u \circ \mathbf{I})^{-1} \widehat{\boldsymbol{\gamma}}$. Notice that the ℓ th entry of $\widehat{\boldsymbol{\zeta}}$ is given by

$$\widehat{\zeta}_\ell = (\sigma_{\ell T}^{\text{hz}})^2 + \sum_{j \neq \ell} \frac{(H_{\ell j}^u)^2}{(1 - H_{\ell\ell}^u)^2} (\sigma_{jT}^{\text{hz}})^2.$$

Therefore, $\text{diag}(\widehat{\boldsymbol{\zeta}}) = \boldsymbol{\Sigma}_T^{\text{hz}} + \boldsymbol{\Delta}^{\text{hz}}$, where $\Delta_{\ell\ell}^{\text{hz}} = \sum_{j \neq \ell} (\sigma_{jT}^{\text{hz}})^2 (H_{\ell j}^u)^2 (1 - H_{\ell\ell}^u)^{-2}$ for $\ell = 1, \dots, N_0$. Notice if $\max_\ell H_{\ell\ell}^u < 1$, then $(\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u \circ \mathbf{I})$ is nonsingular, that is, the pseudo-inverse is precisely the inverse. In this situation, plugging the above into (53) gives

$$\begin{aligned} \mathbb{E}[\widehat{\boldsymbol{\Sigma}}_T^{\text{jack}} | \mathbf{y}_N, \mathbf{Y}_0] &= \text{diag}((\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u \circ \mathbf{I})^{-1} \mathbb{E}[\widehat{\boldsymbol{\epsilon}}_T \circ \widehat{\boldsymbol{\epsilon}}_T | \mathbf{y}_N, \mathbf{Y}_0]) \\ &= \text{diag}((\mathbf{H}_\perp^u \circ \mathbf{H}_\perp^u \circ \mathbf{I})^{-1} \widehat{\boldsymbol{\gamma}}) \\ &= \text{diag}(\widehat{\boldsymbol{\zeta}}) \\ &= \boldsymbol{\Sigma}_T^{\text{hz}} + \boldsymbol{\Delta}^{\text{hz}}. \end{aligned} \quad (58)$$

From this, we conclude that

$$\begin{aligned} \mathbb{E}[\widehat{\mathbf{v}}_0^{\text{hz,jack}} | \mathbf{y}_N, \mathbf{Y}_0] &= \widehat{\boldsymbol{\beta}}' \mathbb{E}[\widehat{\boldsymbol{\Sigma}}_T^{\text{jack}} | \mathbf{y}_N, \mathbf{Y}_0] \widehat{\boldsymbol{\beta}} \\ &= \widehat{\boldsymbol{\beta}}' (\boldsymbol{\Sigma}_T^{\text{hz}} + \boldsymbol{\Delta}^{\text{hz}}) \widehat{\boldsymbol{\beta}} \\ &= \mathbf{v}_0^{\text{hz}} + \widehat{\boldsymbol{\beta}}' \boldsymbol{\Delta}^{\text{hz}} \widehat{\boldsymbol{\beta}}, \end{aligned}$$

where we note that $\widehat{\boldsymbol{\beta}}' \boldsymbol{\Delta}^{\text{hz}} \widehat{\boldsymbol{\beta}} \geq 0$.

(ii) [VT model] Let Assumption 2 hold. Following the arguments above, we conclude $\mathbb{E}[\widehat{\boldsymbol{\Sigma}}_N^{\text{jack}} | \mathbf{y}_T, \mathbf{Y}_0] = \boldsymbol{\Sigma}_N^{\text{vt}} + \boldsymbol{\Gamma}^{\text{vt}}$, where $\Gamma_{\ell\ell}^{\text{vt}} = \sum_{j \neq \ell} (\sigma_{Nj}^{\text{vt}})^2 (H_{\ell j}^v)^2 (1 - H_{\ell\ell}^v)^{-2}$ for $\ell = 1, \dots, T_0$. Thus, $\mathbb{E}[\widehat{\mathbf{v}}_0^{\text{vt,jack}} | \mathbf{y}_T, \mathbf{Y}_0] = \mathbf{v}_0^{\text{vt}} + \widehat{\boldsymbol{\alpha}}' \boldsymbol{\Gamma}^{\text{vt}} \widehat{\boldsymbol{\alpha}} \geq 0$.

(iii) [DR model] Let Assumption 3 hold. We define $(\sigma_{iT}^{\text{dr}})^2 = \text{Var}(\varepsilon_{iT}|Y_0)$ for $i = 1, \dots, N_0$ and $(\sigma_{Nt}^{\text{dr}})^2 = \text{Var}(\varepsilon_{Nt}|Y_0)$ for $t = 1, \dots, T_0$. Following the arguments that led to (58), we obtain $\mathbb{E}[\widehat{\Sigma}_T^{\text{jack}}|Y_0] = \Sigma_T^{\text{dr}} + \Delta^{\text{dr}}$, where $\Delta_{\ell\ell}^{\text{dr}} = \sum_{j \neq \ell} (\sigma_{jT}^{\text{dr}})^2 (H_{\ell j}^u)^2 (1 - H_{\ell\ell}^u)^{-2}$ for $\ell = 1, \dots, N_0$. Similarly, we obtain $\mathbb{E}[\widehat{\Sigma}_N^{\text{jack}}|Y_0] = \Sigma_N^{\text{dr}} + \Gamma^{\text{dr}}$, where $\Gamma_{\ell\ell}^{\text{dr}} = \sum_{j \neq \ell} (\sigma_{Nj}^{\text{dr}})^2 (H_{\ell j}^v)^2 (1 - H_{\ell\ell}^v)^{-2}$ for $\ell = 1, \dots, T_0$. Applying Lemma 7 then gives

$$\mathbb{E}[\widehat{v}_0^{\text{dr, jack}}|Y_0] = v_0^{\text{dr}} + (H^u \beta^*)' \Delta^{\text{dr}} (H^u \beta^*) + (H^v \alpha^*)' \Gamma^{\text{dr}} (H^v \alpha^*) + \text{tr}(Y_0^\dagger \Delta^{\text{dr}} (Y_0')^\dagger \Gamma^{\text{dr}}).$$

The proof is complete. Q.E.D.

C.5.2. Proof of Lemma 9

PROOF: We adopt the strategy of Hartley, Rao, and Kiefer (1969) to prove our desired result.

(i) [HZ model] Let Assumption 1 hold. As in the proof of Lemma 8, we define $\widehat{\varepsilon}_T = H_\perp^u y_T$. Observe

$$\mathbb{E}[(H_\perp^u \circ H_\perp^u)^{-1} (\widehat{\varepsilon}_T \circ \widehat{\varepsilon}_T) | y_N, Y_0] = (H_\perp^u \circ H_\perp^u)^{-1} \mathbb{E}[\widehat{\varepsilon}_T \circ \widehat{\varepsilon}_T | y_N, Y_0]. \quad (59)$$

To evaluate (59), we plug in (57) to obtain

$$\mathbb{E}[(H_\perp^u \circ H_\perp^u)^{-1} (\widehat{\varepsilon}_T \circ \widehat{\varepsilon}_T) | y_N, Y_0] = (H_\perp^u \circ H_\perp^u)^{-1} (H_\perp^u \circ H_\perp^u) \Sigma_T^{\text{hz}} \mathbf{1} = \Sigma_T^{\text{hz}} \mathbf{1}. \quad (60)$$

Plugging (60) into (59) yields

$$\mathbb{E}[\widehat{\Sigma}_T^{\text{HRK}} | y_N, Y_0] = \text{diag}((H_\perp^u \circ H_\perp^u)^{-1} \mathbb{E}[\widehat{\varepsilon}_T \circ \widehat{\varepsilon}_T | y_N, Y_0]) = \Sigma_T^{\text{hz}}. \quad (61)$$

It then follows that $\mathbb{E}[\widehat{v}_0^{\text{hz, HRK}} | y_N, Y_0] = v_0^{\text{hz}}$.

(ii) [VT model] Let Assumption 2 hold. Following the same arguments as above, we conclude $\mathbb{E}[\widehat{\Sigma}_N^{\text{HRK}} | y_T, Y_0] = \Sigma_N^{\text{vt}}$ and $\mathbb{E}[\widehat{v}_0^{\text{vt, HRK}} | y_T, Y_0] = v_0^{\text{vt}}$.

(iii) [DR model] Let Assumption 3 hold. Following the arguments that led to (61), we obtain $\mathbb{E}[\widehat{\Sigma}_T^{\text{HRK}} | Y_0] = \Sigma_T^{\text{dr}}$ and $\mathbb{E}[\widehat{\Sigma}_N^{\text{HRK}} | Y_0] = \Sigma_N^{\text{dr}}$. Applying Lemma 7 then gives $\mathbb{E}[\widehat{v}_0^{\text{dr, HRK}} | Y_0] = v_0^{\text{dr}}$. The proof is complete. Q.E.D.

APPENDIX D: PRINCIPAL COMPONENT REGRESSION

The results in Section 4, which are stated for OLS, immediately extend to PCR by replacing Y_0 with $Y_0^{(k)}$ for any $k < R$. See Section 3 for details of the PCR method.

D.1. Comparing PCR to OLS

Intuitively, PCR-based models postulate that the data are inherently low-dimensional. We comment on several benefits of PCR over OLS. To begin, the HZ and VT OLS variance estimators constructed in Section 4.1.3 can suffer from degeneracy when N and T are of different sizes. That is, if $N < T$, then the HZ in-sample error is zero (assuming full column rank), which causes the HZ coverage to collapse on the point estimate; analogous statements hold for the VT coverage when $N > T$. The PCR-based variance estimators, on the other hand, can avoid degeneracy through the number of chosen principal components k (regularization). On a related note, the nonsingularity conditions required for the

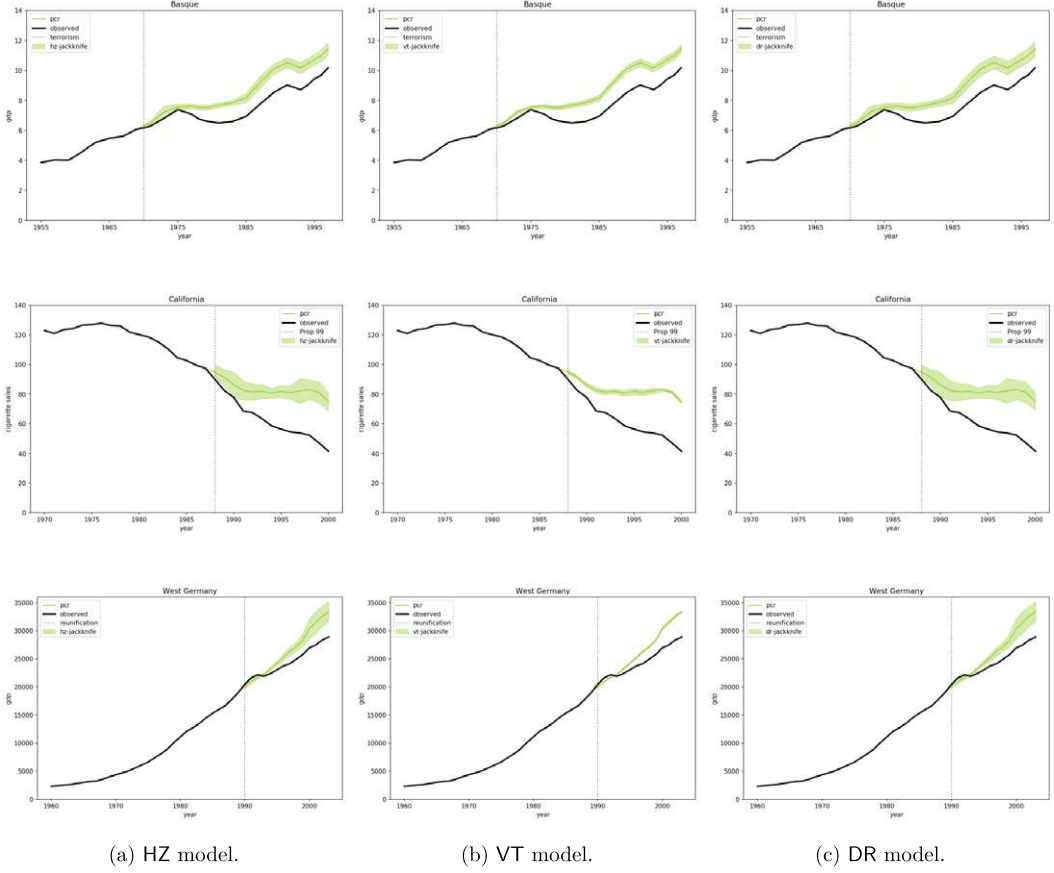


FIGURE D.1.—PCR estimates with jackknife confidence intervals. From top to bottom, the rows are indexed by the Basque, California, and West Germany studies. From left to right, the columns are indexed by the HZ, VT, and DR models.

jackknife and HRK variance estimators can also be controlled by k . See Agarwal, Shah, and Shen (2021) for various methods on choosing k .

D.2. Empirical Applications—Extended

Here, we extend our analysis in Section 5.3.3 to include results for PCR. We present the PCR-based confidence intervals for our three case studies in Figure D.1. For visualization ease, we only plot the jackknife intervals. Notably, the same conclusions drawn for OLS hold for PCR as well.

REFERENCES

- AGARWAL, ANISH, DEVAVRAT SHAH, AND DENNIS SHEN (2021): “Synthetic Interventions,”. arXiv preprint arXiv:2006.07691. [8]
- CLINE, RANDALL E. (1965): “Representations for the Generalized Inverse of Sums of Matrices,” *Journal of the Society for Industrial and Applied Mathematics: Series B, Numerical Analysis*, 2 (1), 99–114. [5]
- HARTLEY, HERMAN O., J. N. K. RAO, AND GRACE KIEFER (1969): “Variance Estimation With One Unit per Stratum,” *Journal of the American Statistical Association*, 64 (327), 841–851. [2,7]

- MEYER, CARL D. (1973): “Generalized Inversion of Modified Matrices,” *SIAM Journal on Applied Mathematics*, 24 (3), 315–323. [5]
- VARGA, RICHARD S. (1962): *Matrix Iterative Analysis*. Prentice-Hall Series in Automatic Computation. Englewood Cliffs: Prentice-Hall. [3]

Co-editor Guido W. Imbens handled this manuscript.

Manuscript received 10 October, 2022; final version accepted 12 October, 2023; available online 12 October, 2023.