

Literature on Recent Advances in Applied Micro Methods*

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November 25, 2020

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*The references listed here are mainly from the applied econometrics courses taught by Michal Kolesár (ECO 539B, Fall 2019, Princeton University) and Arindrajit Dube (ECON 797B, Fall 2020, UMass Amherst). I also added papers that have circulated on #EconTwitter and those that have been suggested to me after I shared the first version of this draft. In particular, I thank Kirill Borusyak, Otavio Canozzi Conceição, Kevin Grier, Sean Higgins, Pedro Picchetti, Esteban Quiñones, and Jorge Rodríguez for their suggestions. Additional suggestions are welcome (“more is better” after all!).

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1 OLS

- **Acharya, Blackwell, and Sen (2016)**, “Explaining Causal Findings Without Bias: Detecting and Assessing Direct Effects,” APSR

“Researchers seeking to establish causal relationships frequently control for variables on the purported causal pathway, checking whether the original treatment effect then disappears. Unfortunately, this common approach may lead to biased estimates. In this article, we show that the bias can be avoided by focusing on a quantity of interest called the controlled direct effect. Under certain conditions, the controlled direct effect enables researchers to rule out competing explanations—an important objective for political scientists. To estimate the controlled direct effect without bias, we describe an easy-to-implement estimation strategy from the biostatistics literature. We extend this approach by deriving a consistent variance estimator and demonstrating how to conduct a sensitivity analysis. Two examples—one on ethnic fractionalization’s effect on civil war and one on the impact of historical plough use on contemporary female political participation—illustrate the framework and methodology.”

- **Ibragimov and Müller (2016)**, “Inference with Few Heterogeneous Clusters,” RE-Stat

“Suppose estimating a model on each of a small number of potentially heterogeneous clusters yields approximately independent, unbiased, and Gaussian parameter estimators. We make two contributions in this setup. First, we show how to compare a scalar parameter of interest between treatment and control units using a two-sample t -statistic, extending previous results for the one-sample t -statistic. Second, we develop a test for the appropriate level of clustering; it tests the null hypothesis that clustered standard errors from a much finer partition are correct. We illustrate the approach by revisiting empirical studies involving clustered, time series, and spatially correlated data.”

- **Imbens and Kolesár (2016)**, “Robust Standard Errors in Small Samples: Some Practical Advice,” REStat

“We study the properties of heteroskedasticity-robust confidence intervals for regression parameters. We show that confidence intervals based on a degrees-of-freedom correction suggested by Bell and McCaffrey (2002) are a natural extension of a principled approach to the Behrens-Fisher problem. We suggest a further improvement for the case with clustering. We show that these standard errors can lead to substantial improvements in coverage rates even for samples with fifty or more clusters. We recommend that researchers routinely calculate the Bell-McCaffrey degrees-of-freedom adjustment

to assess potential problems with conventional robust standard errors.”

- **Abadie, Athey, Imbens, and Wooldridge (2017)**, “When Should You Adjust Standard Errors for Clustering?,” NBER WP

“In empirical work in economics it is common to report standard errors that account for clustering of units. Typically, the motivation given for the clustering adjustments is that unobserved components in outcomes for units within clusters are correlated. However, because correlation may occur across more than one dimension, this motivation makes it difficult to justify why researchers use clustering in some dimensions, such as geographic, but not others, such as age cohorts or gender. It also makes it difficult to explain why one should not cluster with data from a randomized experiment. In this paper, we argue that clustering is in essence a design problem, either a sampling design or an experimental design issue. It is a sampling design issue if sampling follows a two stage process where in the first stage, a subset of clusters were sampled randomly from a population of clusters, while in the second stage, units were sampled randomly from the sampled clusters. In this case the clustering adjustment is justified by the fact that there are clusters in the population that we do not see in the sample. Clustering is an experimental design issue if the assignment is correlated within the clusters. We take the view that this second perspective best fits the typical setting in economics where clustering adjustments are used. This perspective allows us to shed new light on three questions: (i) when should one adjust the standard errors for clustering, (ii) when is the conventional adjustment for clustering appropriate, and (iii) when does the conventional adjustment of the standard errors matter.”

- **Canay, Santos, and Shaikh (2018)**, “The Wild Bootstrap with a “Small” Number of “Large” Clusters,” REStat

“This paper studies the wild bootstrap-based test proposed in Cameron et al. (2008). Existing analyses of its properties require that number of clusters is “large.” In an asymptotic framework in which the number of clusters is “small,” we provide conditions under which an unstudentized version of the test is valid. These conditions include homogeneity-like restrictions on the distribution of covariates. We further establish that a studentized version of the test may only over-reject the null hypothesis by a “small” amount that decreases exponentially with the number of clusters. We obtain qualitatively similar result for “score” bootstrap-based tests, which permit testing in nonlinear models.”

- **Cattaneo, Jansson, and Newey (2018)**, “Inference in Linear Regression Models with Many Covariates and Heteroscedasticity,” JASA

“The linear regression model is widely used in empirical work in economics, statistics, and many other disciplines. Researchers often include many covariates in their linear model specification in an attempt to control for confounders. We give inference methods that allow for many covariates and heteroscedasticity. Our results are obtained using high-dimensional approximations, where the number of included covariates is allowed to grow as fast as the sample size. We find that all of the usual versions of Eicker–White heteroscedasticity consistent standard error estimators for linear models are inconsistent under this asymptotics. We then propose a new heteroscedasticity consistent standard error formula that is fully automatic and robust to both (conditional) heteroscedasticity of unknown form and the inclusion of possibly many covariates. We apply our findings to three settings: parametric linear models with many covariates, linear panel models with many fixed effects, and semiparametric semi-linear models with many technical regressors. Simulation evidence consistent with our theoretical results is provided, and the proposed methods are also illustrated with an empirical application. Supplementary materials for this article are available online.”

- **Abadie, Athey, Imbens, and Wooldridge (2020), “Sampling-Based Versus Design-Based Uncertainty in Regression Analysis,” ECMA**

“Consider a researcher estimating the parameters of a regression function based on data for all 50 states in the United States or on data for all visits to a website. What is the interpretation of the estimated parameters and the standard errors? In practice, researchers typically assume that the sample is randomly drawn from a large population of interest and report standard errors that are designed to capture sampling variation. This is common even in applications where it is difficult to articulate what that population of interest is, and how it differs from the sample. In this article, we explore an alternative approach to inference, which is partly design-based. In a design-based setting, the values of some of the regressors can be manipulated, perhaps through a policy intervention. Design-based uncertainty emanates from lack of knowledge about the values that the regression outcome would have taken under alternative interventions. We derive standard errors that account for design-based uncertainty instead of, or in addition to, sampling-based uncertainty. We show that our standard errors in general are smaller than the usual infinite-population sampling-based standard errors and provide conditions under which they coincide.”

- **Colella, Lalive, Sakalli, and Thoenig (2020), “Inference with Arbitrary Clustering,” WP**

“Analyses of spatial or network data are now very common. Nevertheless, statistical

inference is challenging since unobserved heterogeneity can be correlated across neighboring observational units. We develop an estimator for the variance-covariance matrix (VCV) of OLS and 2SLS that allows for arbitrary dependence of the errors across observations in space or network structure and across time periods. As a proof of concept, we conduct Monte Carlo simulations in a geospatial setting based on U.S. metropolitan areas. Tests based on our estimator of the VCV asymptotically correctly reject the null hypothesis, whereas conventional inference methods, e.g., those without clusters or with clusters based on administrative units, reject the null hypothesis too often. We also provide simulations in a network setting based on the IDEAS structure of coauthorship and real-life data on scientific performance. The Monte Carlo results again show that our estimator yields inference at the correct significance level even in moderately sized samples and that it dominates other commonly used approaches to inference in networks. We provide guidance to the applied researcher with respect to (i) whether or not to include potentially correlated regressors and (ii) the choice of cluster bandwidth. Finally, we provide a companion statistical package (`acreg`) enabling users to adjust the OLS and 2SLS coefficient's standard errors to account for arbitrary dependence."

- **Śłoczyński (2020)**, "Interpreting OLS Estimands When Treatment Effects Are Heterogeneous: Smaller Groups Get Larger Weights," *REStat*
 "Applied work often studies the effect of a binary variable ("treatment") using linear models with additive effects. I study the interpretation of the OLS estimands in such models when treatment effects are heterogeneous. I show that the treatment coefficient is a convex combination of two parameters, which under certain conditions can be interpreted as the average treatment effects on the treated and untreated. The weights on these parameters are inversely related to the proportion of observations in each group. Reliance on these implicit weights can have serious consequences for applied work, as I illustrate with two well-known applications. I develop simple diagnostic tools that empirical researchers can use to avoid potential biases. Software for implementing these methods is available in R and Stata. In an important special case, my diagnostics only require the knowledge of the proportion of treated units."

2 RCT

- **Muralidharan, Romero, and Wüthrich (2019)**, "Factorial Designs, Model Selection, and (Incorrect) Inference in Randomized Experiments," *NBER WP*
 "Cross-cutting or factorial designs are widely used in field experiments. Standard t-tests

using the fully-saturated “long” model provide valid inference on the main treatment effects and all interactions. However, t-tests using a “short” model (without interactions) yield greater power for inference on the main treatment effects if the interactions are zero. We show that the assumption of zero interactions is problematic and leads to a significant increase in incorrect inference regarding the main treatment effects relative to a “business as usual” counterfactual. Further, we show that pre-testing the interactions and ignoring them if they are not significant also leads to incorrect inference (due to the implied model selection). We examine econometric approaches to improve power relative to the long model while controlling size for all values of the interaction. Modest “local” power improvements are possible, but come at the cost of lower power for most values of the interaction. For the design of new experiments, an alternative is to leave the interaction cells empty. This design-based approach yields global power improvements while controlling size and we recommend it for policy experiments where a “business as usual” counterfactual is especially important.”

- **Young (2019)**, “Channeling Fisher: Randomization Tests and the Statistical In-significance of Seemingly Significant Experimental Results,” QJE

“I follow R. A. Fisher’s, *The Design of Experiments* (1935), using randomization statistical inference to test the null hypothesis of no treatment effects in a comprehensive sample of 53 experimental papers drawn from the journals of the American Economic Association. In the average paper, randomization tests of the significance of individual treatment effects find 13% to 22% fewer significant results than are found using authors’ methods. In joint tests of multiple treatment effects appearing together in tables, randomization tests yield 33% to 49% fewer statistically significant results than conventional tests. Bootstrap and jackknife methods support and confirm the randomization results.”

3 Diff-in-Diff & Event Studies¹

- **Brewer, Crossley, and Joyce (2017)**, “Inference with Difference-in-Differences Re-visited,” JEM

“A growing literature on inference in difference-in-differences (DiD) designs has been pessimistic about obtaining hypothesis tests of the correct size, particularly with few groups. We provide Monte Carlo evidence for four points: (i) it is possible to obtain tests of the correct size even with few groups, and in many settings very straightfor-

¹See also Andrew Baker’s blog posts on [diff-in-diff methods](#) and [event-study analysis](#).

ward methods will achieve this; (ii) the main problem in DiD designs with grouped errors is instead low power to detect real effects; (iii) feasible GLS estimation combined with robust inference can increase power considerably whilst maintaining correct test size – again, even with few groups, and (iv) using OLS with robust inference can lead to a perverse relationship between power and panel length.”

- **Athey and Imbens (2018)**, “Design-Based Analysis in Difference-In-Differences Settings with Staggered Adoption,” NBER WP

“In this paper we study estimation of and inference for average treatment effects in a setting with panel data. We focus on the setting where units, e.g., individuals, firms, or states, adopt the policy or treatment of interest at a particular point in time, and then remain exposed to this treatment at all times afterwards. We take a design perspective where we investigate the properties of estimators and procedures given assumptions on the assignment process. We show that under random assignment of the adoption date the standard Difference-In-Differences estimator is an unbiased estimator of a particular weighted average causal effect. We characterize the properties of this estimand, and show that the standard variance estimator is conservative.”

- **Borusyak and Jaravel (2018)**, “Revisiting Event Study Designs, with an Application to the Estimation of the Marginal Propensity to Consume,” WP

“A broad empirical literature uses “event study” research designs for treatment effect estimation, a setting in which all units in the panel receive treatment but at random times. We make four novel points about identification and estimation of causal effects in this setting and show their practical relevance. First, we show that in the presence of unit and time fixed effects, it is impossible to identify the linear component of the path of pre-trends and dynamic treatment effects. Second, we propose graphical and statistical tests for pre-trends. Third, we consider commonly-used “static” regressions, with a treatment dummy instead of a full set of leads and lags around the treatment event, and we show that OLS does not recover a reasonable weighted average of the treatment effects: long-run effects are weighted negatively, and we introduce different estimators robust to this issue. Fourth, we show that equivalent problems of under-identification and negative weighting arise in difference-in-differences settings when the control group is allowed to be on a different time trend or in the presence of unit-specific time trends. We show the practical relevance of these issues in a series of examples from the existing literature. We focus on the estimation of the marginal propensity to consume out of tax rebates: according to our preferred specification, the marginal propensity to consume is much lower than (about half of) the main estimates in the

literature. The main message for practitioners is that because of identification issues and negative weighting in event study designs, results from common specifications are likely to seem non-robust. These problems can be alleviated in a principled way by using parametric and semi-parametric estimators and tests.”

- **de Chaisemartin and d’Haultfoeuille (2018)**, “Fuzzy Differences-in-Differences,” **REStud**

“Difference-in-differences (DID) is a method to evaluate the effect of a treatment. In its basic version, a “control group” is untreated at two dates, whereas a “treatment group” becomes fully treated at the second date. However, in many applications of the DID method, the treatment rate only increases more in the treatment group. In such fuzzy designs, a popular estimator of the treatment effect is the DID of the outcome divided by the DID of the treatment. We show that this ratio identifies a local average treatment effect only if the effect of the treatment is stable over time, and if the effect of the treatment is the same in the treatment and in the control group. We then propose two alternative estimands that do not rely on any assumption on treatment effects, and that can be used when the treatment rate does not change over time in the control group. We prove that the corresponding estimators are asymptotically normal. Finally, we use our results to reassess the returns to schooling in Indonesia.”

- **Arkhangelsky and Imbens (2019)**, “Double-Robust Identification for Causal Panel Data Models,” **WP**

“We study identification and estimation of causal effects of a binary treatment in settings with panel data. We highlight that there are two paths to identification in the presence of unobserved confounders. First, the conventional path based on making assumptions on the relation between the potential outcomes and the unobserved confounders. Second, a design-based path where assumptions are made about the relation between the treatment assignment and the confounders. We introduce different sets of assumptions that follow the two paths, and develop double robust approaches to identification where we exploit both approaches, similar in spirit to the double robust approaches to estimation in the program evaluation literature.”

- **Cengiz, Dube, Lindner, and Zipperer (2019)**, “The Effect of Minimum Wages on Low-Wage Jobs,”² **QJE**

“We estimate the effect of minimum wages on low-wage jobs using 138 prominent state-

²Even though its title makes it sound like it is irrelevant, this paper has been added because it describes another method to deal with heterogeneous treatment effects in event-study designs, by using stacked diff-in-diff by event – see Online Appendix G of that paper for more detail.

level minimum wage changes between 1979 and 2016 in the United States using a difference-in-differences approach. We first estimate the effect of the minimum wage increase on employment changes by wage bins throughout the hourly wage distribution. We then focus on the bottom part of the wage distribution and compare the number of excess jobs paying at or slightly above the new minimum wage to the missing jobs paying below it to infer the employment effect. We find that the overall number of low-wage jobs remained essentially unchanged over the five years following the increase. At the same time, the direct effect of the minimum wage on average earnings was amplified by modest wage spillovers at the bottom of the wage distribution. Our estimates by detailed demographic groups show that the lack of job loss is not explained by labor-labor substitution at the bottom of the wage distribution. We also find no evidence of disemployment when we consider higher levels of minimum wages. However, we do find some evidence of reduced employment in tradeable sectors. We also show how decomposing the overall employment effect by wage bins allows a transparent way of assessing the plausibility of estimates.”

- **Ferman and Pinto (2019)**, “Inference in Differences-in-Differences with Few Treated Groups and Heteroskedasticity,” *REStat*

“We derive an inference method that works in differences-in-differences settings with few treated and many control groups in the presence of heteroskedasticity. As a leading example, we provide theoretical justification and empirical evidence that heteroskedasticity generated by variation in group sizes can invalidate existing inference methods, even in data sets with a large number of observations per group. In contrast, our inference method remains valid in this case. Our test can also be combined with feasible generalized least squares, providing a safeguard against misspecification of the serial correlation.”

- **Abraham and Sun (2020)**, “Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects,” *JE*

“To estimate the dynamic effects of an absorbing treatment, researchers often use two-way fixed effects regressions that include leads and lags of the treatment. We show that in settings with variation in treatment timing across units, the coefficient on a given lead or lag can be contaminated by effects from other periods, and apparent pretrends can arise solely from treatment effects heterogeneity. We propose an alternative estimator that is free of contamination, and illustrate the relative shortcomings of two-way fixed effects regressions with leads and lags through an empirical application.”

- **Callaway and Sant’Anna (2020)**, “Difference-in-Differences with Multiple Time Pe-

riods,” WP

“In this article, we consider identification, estimation, and inference procedures for treatment effect parameters using Difference-in-Differences (DID) with (i) multiple time periods, (ii) variation in treatment timing, and (iii) when the “parallel trends assumption” holds potentially only after conditioning on observed covariates. We show that a family of causal effect parameters are identified in staggered DID setups, even if differences in observed characteristics create non-parallel outcome dynamics between groups. Our identification results allow one to use outcome regression, inverse probability weighting, or doubly-robust estimands. We also propose different aggregation schemes that can be used to highlight treatment effect heterogeneity across different dimensions as well as to summarize the overall effect of participating in the treatment. We establish the asymptotic properties of the proposed estimators and prove the validity of a computationally convenient bootstrap procedure to conduct asymptotically valid simultaneous (instead of pointwise) inference. Finally, we illustrate the relevance of our proposed tools by analyzing the effect of the minimum wage on teen employment from 2001–2007. Open-source software is available for implementing the proposed methods.”

- **de Chaisemartin and d’Haultfoeuille (2020)**, “Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects,” AER

“Linear regressions with period and group fixed effects are widely used to estimate treatment effects. We show that they estimate weighted sums of the average treatment effects (ATE) in each group and period, with weights that may be negative. Due to the negative weights, the linear regression coefficient may for instance be negative while all the ATEs are positive. We propose another estimator that solves this issue. In the two applications we revisit, it is significantly different from the linear regression estimator.”

- **Goodman-Bacon (2020)**, “Difference-in-Differences with Variation in Treatment Timing,” WP

“The canonical difference-in-differences (DD) estimator contains two time periods, “pre” and “post”, and two groups, “treatment” and “control”. Most DD applications, however, exploit variation across groups of units that receive treatment at different times. This paper shows that the general estimator equals a weighted average of all possible two-group/two-period DD estimators in the data. This defines the DD estimand and identifying assumption, a generalization of common trends. I discuss how to interpret DD estimates and propose a new balance test. I show how to decompose the difference between two specifications, and provide a new analysis of models that include

time-varying controls.”

- **Rambachan and Roth (2020)**, “An Honest Approach to Parallel Trends,” WP

“This paper proposes robust inference methods for difference-in-differences and event-study designs that do not require that the parallel trends assumption holds exactly. Instead, the researcher must only impose restrictions on the possible differences in trends between the treated and control groups. Several common intuitions expressed in applied work can be captured by such restrictions, including the notion that pre-treatment differences in trends are informative about counterfactual post-treatment differences in trends. Our methodology then guarantees uniformly valid (“honest”) inference when the imposed restrictions are satisfied. We first show that fixed length confidence intervals have near-optimal expected length for a practically-relevant class of restrictions. We next introduce a novel inference procedure that accommodates a wider range of restrictions, which is based on the observation that inference in our setting is equivalent to testing a system of moment inequalities with a large number of linear nuisance parameters. The resulting confidence sets are consistent, and have optimal local asymptotic power for many parameter configurations. We recommend researchers conduct sensitivity analyses to show what conclusions can be drawn under various restrictions on the possible differences in trends”

- **Sant’Anna and Zhao (2020)**, “Doubly Robust Difference-in-Differences Estimators,” JE

“This article proposes doubly robust estimators for the average treatment effect on the treated (ATT) in difference-in-differences (DID) research designs. In contrast to alternative DID estimators, the proposed estimators are consistent if either (but not necessarily both) a propensity score or outcome regression working models are correctly specified. We also derive the semiparametric efficiency bound for the ATT in DID designs when either panel or repeated cross-section data are available, and show that our proposed estimators attain the semiparametric efficiency bound when the working models are correctly specified. Furthermore, we quantify the potential efficiency gains of having access to panel data instead of repeated cross-section data. Finally, by paying particular attention to the estimation method used to estimate the nuisance parameters, we show that one can sometimes construct doubly robust DID estimators for the ATT that are also doubly robust for inference. Simulation studies and an empirical application illustrate the desirable finite-sample performance of the proposed estimators. Open-source software for implementing the proposed policy evaluation tools is available.”

4 Standard IV

- **Andrews and Armstrong (2017)**, “Unbiased Instrumental Variables Estimation under Known First-Stage Sign,” QE

“We derive mean-unbiased estimators for the structural parameter in instrumental variables models with a single endogenous regressor where the sign of one or more first-stage coefficients is known. In the case with a single instrument, there is a unique non-randomized unbiased estimator based on the reduced-form and first-stage regression estimates. For cases with multiple instruments we propose a class of unbiased estimators and show that an estimator within this class is efficient when the instruments are strong. We show numerically that unbiasedness does not come at a cost of increased dispersion in models with a single instrument: in this case the unbiased estimator is less dispersed than the two-stage least squares estimator. Our finite-sample results apply to normal models with known variance for the reduced-form errors, and imply analogous results under weak-instrument asymptotics with an unknown error distribution.”

- **Mogstad and Torgovitsky (2018)**, “Identification and Extrapolation of Causal Effects with Instrumental Variables,” ARE

“Instrumental variables (IV) are widely used in economics to address selection on unobservables. Standard IV methods produce estimates of causal effects that are specific to individuals whose behavior can be manipulated by the instrument at hand. In many cases, these individuals are not the same as those who would be induced to treatment by an intervention or policy of interest to the researcher. The average causal effect for the two groups can differ significantly if the effect of the treatment varies systematically with unobserved factors that are correlated with treatment choice. We review the implications of this type of unobserved heterogeneity for the interpretation of standard IV methods and for their relevance to policy evaluation. We argue that making inferences about policy-relevant parameters typically requires extrapolating from the individuals affected by the instrument to the individuals who would be induced to treatment by the policy under consideration. We discuss a variety of alternatives to standard IV methods that can be used to rigorously perform this extrapolation. We show that many of these approaches can be nested as special cases of a general framework that embraces the possibility of partial identification.”

- **Andrews, Stock, and Sun (2019)**, “Weak Instruments in Instrumental Variables Regression: Theory and Practice,” ARE

“When instruments are weakly correlated with endogenous regressors, conventional

methods for instrumental variables (IV) estimation and inference become unreliable. A large literature in econometrics has developed procedures for detecting weak instruments and constructing robust confidence sets, but many of the results in this literature are limited to settings with independent and homoskedastic data, while data encountered in practice frequently violate these assumptions. We review the literature on weak instruments in linear IV regression with an emphasis on results for nonhomoskedastic (heteroskedastic, serially correlated, or clustered) data. To assess the practical importance of weak instruments, we also report tabulations and simulations based on a survey of papers published in the *American Economic Review* from 2014 to 2018 that use IV. These results suggest that weak instruments remain an important issue for empirical practice, and that there are simple steps that researchers can take to better handle weak instruments in applications.”

- **Evdokimov and Kolesár (2019)**, “Inference in Instrumental Variable Regression Analysis with Heterogeneous Treatment Effects,” WP

“We study inference in an instrumental variables model with heterogeneous treatment effects and possibly many instruments and/or covariates. In this case two-step estimators such as the two-stage least squares (TSLS) or versions of the jackknife instrumental variables (JIV) estimator estimate a particular weighted average of the local average treatment effects. The weights in these estimands depend on the first-stage coefficients, and either the sample or population variability of the covariates and instruments, depending on whether they are treated as fixed (conditioned upon) or random. We give new asymptotic variance formulas for the TSLS and JIV estimators, and propose consistent estimators of these variances. The heterogeneity of the treatment effects generally increases the asymptotic variance. Moreover, when the treatment effects are heterogeneous, the conditional asymptotic variance is smaller than the unconditional one. Our results are also useful when the treatment effects are constant, because they provide the asymptotic distribution and valid standard errors for the estimators that are robust to the presence of many covariates.”

- **Lee, McCrary, Moreira, and Porter (2020)**, “Valid t-ratio Inference for IV,” WP

“In the single IV model, current practice relies on the first-stage F exceeding some threshold (e.g., 10) as a criterion for trusting t-ratio inferences, even though this yields an anti-conservative test. We show that a true 5 percent test instead requires an F greater than 104.7. Maintaining 10 as a threshold requires replacing the critical value 1.96 with 3.43. We re-examine 57 AER papers and find that corrected inference causes half of the initially presumed statistically significant results to be insignificant. We in-

troduce a more powerful test, the tF procedure, which provides F-dependent adjusted t-ratio critical values.”

- **Mogstad, Torgovitsky, and Walters (2020a), “Policy Evaluation with Multiple Instrumental Variables,” WP**

“Marginal treatment effect methods are widely used for causal inference and policy evaluation with instrumental variables. However, they fundamentally rely on the well-known monotonicity (threshold-crossing) condition on treatment choice behavior. Recent research has shown that this condition cannot hold with multiple instruments unless treatment choice is effectively homogeneous. Based on these findings, we develop a new marginal treatment effect framework under a weaker, partial monotonicity condition. The partial monotonicity condition is implied by standard choice theory and allows for rich heterogeneity even in the presence of multiple instruments. The new framework can be viewed as having multiple different choice models for the same observed treatment variable, all of which must be consistent with the data and with each other. Using this framework, we develop a methodology for partial identification of clearly stated, policy-relevant target parameters while allowing for a wide variety of nonparametric shape restrictions and parametric functional form assumptions. We show how the methodology can be used to combine multiple instruments together to yield more informative empirical conclusions than one would obtain by using each instrument separately. The methodology provides a blueprint for extracting and aggregating information about treatment effects from multiple controlled or natural experiments while still allowing for rich heterogeneity in both treatment effects and choice behavior.”

- **Mogstad, Torgovitsky, and Walters (2020b), “The Causal Interpretation of Two-Stage Least Squares with Multiple Instrumental Variables,” NBER WP**

“Empirical researchers often combine multiple instrumental variables (IVs) for a single treatment using two-stage least squares (2SLS). When treatment effects are heterogeneous, a common justification for including multiple IVs is that the 2SLS estimand can be given a causal interpretation as a positively-weighted average of local average treatment effects (LATEs). This justification requires the well-known monotonicity condition. However, we show that with more than one instrument, this condition can only be satisfied if choice behavior is effectively homogeneous. Based on this finding, we consider the use of multiple IVs under a weaker, partial monotonicity condition. We characterize empirically verifiable sufficient and necessary conditions for the 2SLS estimand to be a positively-weighted average of LATEs under partial monotonicity. We apply these results to an empirical analysis of the returns to college with multiple instruments. We

show that the standard monotonicity condition is at odds with the data. Nevertheless, our empirical checks show that the 2SLS estimate retains a causal interpretation as a positively-weighted average of the effects of college attendance among complier groups.”

- **Young (2020)**, “Consistency Without Inference: Instrumental Variables in Practical Application,” WP

“I use Monte Carlo simulations, the jackknife and multiple forms of the bootstrap to study a comprehensive sample of 1359 instrumental variables regressions in 31 papers published in the journals of the American Economic Association. Monte Carlo simulations based upon published regressions show that non-iid error processes in highly leveraged regressions, both prominent features of published work, adversely affect the size and power of IV estimates, while increasing the bias of IV relative to OLS. Weak instrument pre-tests based upon F-statistics are found to be largely uninformative of both size and bias. In published papers, statistically significant IV results generally depend upon only one or two observations or clusters, IV has little power as, despite producing substantively different estimates, it rarely rejects the OLS point estimate or the null that OLS is unbiased, while the statistical significance of excluded instruments is substantially exaggerated.”

5 Shift-Share IV³

- **Adão, Kolesár, and Morales (2019)**, “Shift-Share Designs: Theory and Inference,” QJE

“We study inference in shift-share regression designs, such as when a regional outcome is regressed on a weighted average of sectoral shocks, using regional sector shares as weights. We conduct a placebo exercise in which we estimate the effect of a shift-share regressor constructed with randomly generated sectoral shocks on actual labor market outcomes across U.S. commuting zones. Tests based on commonly used standard errors with 5% nominal significance level reject the null of no effect in up to 55% of the placebo samples. We use a stylized economic model to show that this overrejection problem arises because regression residuals are correlated across regions with similar sectoral shares, independent of their geographic location. We derive novel inference methods that are valid under arbitrary cross-regional correlation in the regression residuals. We

³The references in this section are taken from a guest lecture that Peter Hull gave in Arindrajit Dube’s ECON 797B Fall 2020 course at UMass Amherst – see lecture slides [here](#).

show using popular applications of shift-share designs that our methods may lead to substantially wider confidence intervals in practice.”

- **Borusyak, Hull, and Jaravel (2020)**, “Quasi-Experimental Shift-Share Research Designs,” WP

“Many studies use shift-share (or “Bartik”) instruments, which average a set of shocks with exposure share weights. We provide a new econometric framework for shift-share instrumental variable (SSIV) regressions in which identification follows from the quasi-random assignment of shocks, while exposure shares are allowed to be endogenous. The framework is motivated by an equivalence result: the orthogonality between a shift-share instrument and an unobserved residual can be represented as the orthogonality between the underlying shocks and a shock-level unobservable. SSIV regression coefficients can similarly be obtained from an equivalent shock-level regression, motivating shock-level conditions for their consistency. We discuss and illustrate several practical insights delivered by this framework in the setting of Autor et al. (2013).”

- **Borusyak and Hull (2020)**, “Non-Random Exposure to Exogenous Shocks: Theory and Applications,” NBER WP

“We develop new tools for causal inference in settings where exogenous shocks affect the treatment status of multiple observations jointly, to different extents. In these settings researchers may construct treatments or instruments that combine the shocks with predetermined measures of shock exposure. Examples include measures of spillovers in social and transportation networks, simulated eligibility instruments, and shift-share instruments. We show that leveraging the exogeneity of shocks for identification generally requires a simple but non-standard recentering, derived from the specification of counterfactual shocks that might as well have been realized. We further show how specification of counterfactual shocks can be used for finite-sample inference and specification tests, and we characterize the recentered instruments that are asymptotically efficient. We use this framework to estimate the employment effects of Chinese market access growth due to high-speed rail construction and the insurance coverage effects of expanded Medicaid eligibility.”

- **Goldsmith-Pinkham, Sorkin, and Swift (2020)**, “Bartik Instruments: What, When, Why, and How,” AER

“The Bartik instrument is formed by interacting local industry shares and national industry growth rates. We show that the typical use of a Bartik instrument assumes a pooled exposure research design, where the shares measure differential exposure to common shocks, and identification is based on exogeneity of the shares. Next, we show

how the Bartik instrument weights each of the exposure designs. Finally, we discuss how to assess the plausibility of the research design. We illustrate our results through two applications: estimating the elasticity of labor supply, and estimating the elasticity of substitution between immigrants and natives.”

6 RDD

- **Calonico, Cattaneo, and Titiunik (2014)**, “Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs,” ECMA

“In the regression-discontinuity (RD) design, units are assigned to treatment based on whether their value of an observed covariate exceeds a known cutoff. In this design, local polynomial estimators are now routinely employed to construct confidence intervals for treatment effects. The performance of these confidence intervals in applications, however, may be seriously hampered by their sensitivity to the specific bandwidth employed. Available bandwidth selectors typically yield a “large” bandwidth, leading to data-driven confidence intervals that may be biased, with empirical coverage well below their nominal target. We propose new theory-based, more robust confidence interval estimators for average treatment effects at the cutoff in sharp RD, sharp kink RD, fuzzy RD, and fuzzy kink RD designs. Our proposed confidence intervals are constructed using a bias-corrected RD estimator together with a novel standard error estimator. For practical implementation, we discuss mean squared error optimal bandwidths, which are by construction not valid for conventional confidence intervals but are valid with our robust approach, and consistent standard error estimators based on our new variance formulas. In a special case of practical interest, our procedure amounts to running a quadratic instead of a linear local regression. More generally, our results give a formal justification to simple inference procedures based on increasing the order of the local polynomial estimator employed. We find in a simulation study that our confidence intervals exhibit close-to-correct empirical coverage and good empirical interval length on average, remarkably improving upon the alternatives available in the literature. All results are readily available in R and STATA using our companion software packages described in Calonico, Cattaneo, and Titiunik (2014d, 2014b).”

- **Grembi, Nannicini, and Troiano (2016)**, “Do Fiscal Rules Matter?,”⁴ AEJ Applied
“Fiscal rules are laws aimed at reducing the incentive to accumulate debt, and many

⁴Even though its title makes it sound like it is irrelevant, this paper has been added because it thoroughly covers the identifying assumptions of the “difference-in-discontinuities estimator,” which intuitively combines a diff-in-diff strategy with an RD design.

countries adopt them to discipline local governments. Yet, their effectiveness is disputed because of commitment and enforcement problems. We study their impact applying a quasi-experimental design in Italy. In 1999, the central government imposed fiscal rules on municipal governments, and in 2001 relaxed them below 5,000 inhabitants. We exploit the before/after and discontinuous policy variation, and show that relaxing fiscal rules increases deficits and lowers taxes. The effect is larger if the mayor can be reelected, the number of parties is higher, and voters are older.”

- **Armstrong and Kolesár (2018)**, “Optimal Inference in a Class of Regression Models,” ECMA

“We consider the problem of constructing confidence intervals (CIs) for a linear functional of a regression function, such as its value at a point, the regression discontinuity parameter, or a regression coefficient in a linear or partly linear regression. Our main assumption is that the regression function is known to lie in a convex function class, which covers most smoothness and/or shape assumptions used in econometrics. We derive finite-sample optimal CIs and sharp efficiency bounds under normal errors with known variance. We show that these results translate to uniform (over the function class) asymptotic results when the error distribution is not known. When the function class is centrosymmetric, these efficiency bounds imply that minimax CIs are close to efficient at smooth regression functions. This implies, in particular, that it is impossible to form CIs that are substantively tighter using data-dependent tuning parameters, and maintain coverage over the whole function class. We specialize our results to inference on the regression discontinuity parameter, and illustrate them in simulations and an empirical application.”

- **Canay and Kamat (2018)**, “Approximate Permutation Tests and Induced Order Statistics in the Regression Discontinuity Design,” REStud

“In the regression discontinuity design (RDD), it is common practice to assess the credibility of the design by testing whether the means of baseline covariates do not change at the cut-off (or threshold) of the running variable. This practice is partly motivated by the stronger implication derived by Lee (2008), who showed that under certain conditions the distribution of baseline covariates in the RDD must be continuous at the cut-off. We propose a permutation test based on the so-called induced ordered statistics for the null hypothesis of continuity of the distribution of baseline covariates at the cut-off; and introduce a novel asymptotic framework to analyse its properties. The asymptotic framework is intended to approximate a small sample phenomenon: even though the total number n of observations may be large, the number of effective obser-

vations local to the cut-off is often small. Thus, while traditional asymptotics in RDD require a growing number of observations local to the cut-off as $n \rightarrow \infty$, our framework keeps the number q of observations local to the cut-off fixed as $n \rightarrow \infty$. The new test is easy to implement, asymptotically valid under weak conditions, exhibits finite sample validity under stronger conditions than those needed for its asymptotic validity, and has favourable power properties relative to tests based on means. In a simulation study, we find that the new test controls size remarkably well across designs. We then use our test to evaluate the plausibility of the design in Lee (2008), a well-known application of the RDD to study incumbency advantage.”

- **Ganong and Jäger (2018)**, “A Permutation Test for the Regression Kink Design,” JASA

“The regression kink (RK) design is an increasingly popular empirical method for estimating causal effects of policies, such as the effect of unemployment benefits on unemployment duration. Using simulation studies based on data from existing RK designs, we empirically document that the statistical significance of RK estimators based on conventional standard errors can be spurious. In the simulations, false positives arise as a consequence of nonlinearities in the underlying relationship between the outcome and the assignment variable, confirming concerns about the misspecification bias of discontinuity estimators pointed out by Calonico, Cattaneo, and Titiunik. As a complement to standard RK inference, we propose that researchers construct a distribution of placebo estimates in regions with and without a policy kink and use this distribution to gauge statistical significance. Under the assumption that the location of the kink point is random, this permutation test has exact size in finite samples for testing a sharp null hypothesis of no effect of the policy on the outcome. We implement simulation studies based on existing RK applications that estimate the effect of unemployment benefits on unemployment duration and show that our permutation test as well as inference procedures proposed by Calonico, Cattaneo, and Titiunik improve upon the size of standard approaches, while having sufficient power to detect an effect of unemployment benefits on unemployment duration. Supplementary materials for this article are available online.”

- **Kolesár and Rothe (2018)**, “Inference in Regression Discontinuity Designs with a Discrete Running Variable,” AER

“We consider inference in regression discontinuity designs when the running variable only takes a moderate number of distinct values. In particular, we study the common practice of using confidence intervals (CIs) based on standard errors that are clustered

by the running variable as a means to make inference robust to model misspecification (Lee and Card 2008). We derive theoretical results and present simulation and empirical evidence showing that these CIs do not guard against model misspecification, and that they have poor coverage properties. We therefore recommend against using these CIs in practice. We instead propose two alternative CIs with guaranteed coverage properties under easily interpretable restrictions on the conditional expectation function.”

- **Gelman and Imbens (2019)**, “Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs,” JBES

“It is common in regression discontinuity analysis to control for third, fourth, or higher-degree polynomials of the forcing variable. There appears to be a perception that such methods are theoretically justified, even though they can lead to evidently nonsensical results. We argue that controlling for global high-order polynomials in regression discontinuity analysis is a flawed approach with three major problems: it leads to noisy estimates, sensitivity to the degree of the polynomial, and poor coverage of confidence intervals. We recommend researchers instead use estimators based on local linear or quadratic polynomials or other smooth functions.”

- **Armstrong and Kolesár (2020)**, “Simple and Honest Confidence Intervals in Nonparametric Regression,” QE

“We consider the problem of constructing honest confidence intervals (CIs) for a scalar parameter of interest, such as the regression discontinuity parameter, in nonparametric regression based on kernel or local polynomial estimators. To ensure that our CIs are honest, we use critical values that take into account the possible bias of the estimator upon which the CIs are based. We show that this approach leads to CIs that are more efficient than conventional CIs that achieve coverage by undersmoothing or subtracting an estimate of the bias. We give sharp efficiency bounds of using different kernels, and derive the optimal bandwidth for constructing honest CIs. We show that using the bandwidth that minimizes the maximum mean-squared error results in CIs that are nearly efficient and that in this case, the critical value depends only on the rate of convergence. For the common case in which the rate of convergence is $n^{-2/5}$, the appropriate critical value for 95% CIs is 2.18, rather than the usual 1.96 critical value. We illustrate our results in a Monte Carlo analysis and an empirical application.”

- **Bugni and Canay (2020)**, “Testing Continuity of a Density via g -order statistics in the Regression Discontinuity Design,” JE

“In the regression discontinuity design (RDD), it is common practice to assess the credibility of the design by testing the continuity of the density of the running variable at

the cut-off, e.g., McCrary (2008). In this paper we propose an approximate sign test for continuity of a density at a point based on the so-called g -order statistics, and study its properties under two complementary asymptotic frameworks. In the first asymptotic framework, the number q of observations local to the cut-off is fixed as the sample size n diverges to infinity, while in the second framework q diverges to infinity slowly as n diverges to infinity. Under both of these frameworks, we show that the test we propose is asymptotically valid in the sense that it has limiting rejection probability under the null hypothesis not exceeding the nominal level. More importantly, the test is easy to implement, asymptotically valid under weaker conditions than those used by competing methods, and exhibits finite sample validity under stronger conditions than those needed for its asymptotic validity. In a simulation study, we find that the approximate sign test provides good control of the rejection probability under the null hypothesis while remaining competitive under the alternative hypothesis. We finally apply our test to the design in Lee (2008), a well-known application of the RDD to study incumbency advantage.”

- **Cattaneo, Jansson, and Ma (2020)**, “Simple Local Polynomial Density Estimators,” JASA

“This article introduces an intuitive and easy-to-implement nonparametric density estimator based on local polynomial techniques. The estimator is fully boundary adaptive and automatic, but does not require prebinning or any other transformation of the data. We study the main asymptotic properties of the estimator, and use these results to provide principled estimation, inference, and bandwidth selection methods. As a substantive application of our results, we develop a novel discontinuity in density testing procedure, an important problem in regression discontinuity designs and other program evaluation settings. An illustrative empirical application is given. Two companion Stata and R software packages are provided.”

7 Synthetic Control

- **Abadie (2020)**, “Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects,” JEL
- **Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2020)**, “Synthetic Difference in Differences,” WP

“We present a new estimator for causal effects with panel data that builds on insights

behind the widely used difference in differences and synthetic control methods. Relative to these methods, we find, both theoretically and empirically, that the proposed “synthetic difference in differences” estimator has desirable robustness properties, and that it performs well in settings where the conventional estimators are commonly used in practice. We study the asymptotic behavior of the estimator when the systematic part of the outcome model includes latent unit factors interacted with latent time factors, and we present conditions for consistency and asymptotic normality.”

- **Athey, Bayati, Doudchenko, Imbens, and Khosravi (2020), “Matrix Completion Methods for Causal Panel Data Models,” WP**

“In this paper we study methods for estimating causal effects in settings with panel data, where some units are exposed to a treatment during some periods and the goal is estimating counterfactual (untreated) outcomes for the treated unit/period combinations. We develop a class of matrix completion estimators that uses the observed elements of the matrix of control outcomes corresponding to untreated unit/periods to impute the “missing” elements of the control outcome matrix, corresponding to treated units/periods. The approach estimates a matrix that well-approximates the original (incomplete) matrix, but has lower complexity according to the nuclear norm for matrices. We generalize results from the matrix completion literature by allowing the patterns of missing data to have a time series dependency structure. We present novel insights concerning the connections between the matrix completion literature, the literature on interactive fixed effects models and the literatures on program evaluation under unconfoundedness and synthetic control methods. We show that all these estimators can be viewed as focusing on the same objective function. They differ in the way they deal with lack of identification, in some cases solely through regularization (our proposed nuclear norm matrix completion estimator) and in other cases primarily through imposing hard restrictions (the unconfoundedness and synthetic control approaches). proposed method outperforms unconfoundedness-based or synthetic control estimators.”

8 Matching

- **Otsu and Rai (2017), “Bootstrap Inference of Matching Estimators for Average Treatment Effects,” JASA**

“It is known that the naive bootstrap is not asymptotically valid for a matching estimator of the average treatment effect with a fixed number of matches. In this article, we propose asymptotically valid inference methods for matching estimators based on

the weighted bootstrap. The key is to construct bootstrap counterparts by resampling based on certain linear forms of the estimators. Our weighted bootstrap is applicable for the matching estimators of both the average treatment effect and its counterpart for the treated population. Also, by incorporating a bias correction method in Abadie and Imbens (2011), our method can be asymptotically valid even for matching based on a vector of covariates. A simulation study indicates that the weighted bootstrap method is favorably comparable with the asymptotic normal approximation. As an empirical illustration, we apply the proposed method to the National Supported Work data. Supplementary materials for this article are available online.”

- **Adusumilli (2018), “Bootstrap Inference for Propensity Score Matching,” WP**

“Propensity score matching, where the propensity scores are estimated in a first step, is widely used for estimating treatment effects. In this context, the naive bootstrap is invalid (Abadie and Imbens, 2008). This paper proposes a novel bootstrap procedure for the propensity score matching estimator, and demonstrates its consistency. The proposed bootstrap is built around the notion of ‘potential errors’, introduced in this paper. Precisely, each observation is associated with two potential error terms, corresponding to each of the potential states - treated or control - only one of which is realized. Thus, the variability of the estimator stems not only from the randomness of the potential errors themselves, but also from the probabilistic nature of treatment assignment, which randomly realizes one of the potential error terms. The proposed bootstrap takes both sources of randomness into account by resampling the potential errors as a pair as well as re-assigning new values for the treatments. Simulations and real data examples demonstrate the superior performance of the proposed method relative to using the asymptotic distribution for inference, especially when the degree of overlap in propensity scores is poor. General versions of the procedure can also be applied to other causal effect estimators such as inverse probability weighting and propensity score sub-classification, potentially leading to higher order refinements for inference in such contexts.”

9 Bunching

- **Kleven (2016), “Bunching,” ARE**

“Recent years have seen a surge of applied work using bunching approaches, a development that is closely linked to the increased availability of administrative data. These approaches exploit the incentives for bunching created by discontinuities in the slope

of choice sets (kinks) or in the level of choice sets (notches) to study the behavior of individuals and firms. Although the bunching approach was originally developed in the context of taxation, it is beginning to find applications in many other areas, such as social security, social insurance, welfare programs, education, regulation, private sector prices, and reference-dependent preferences. This review provides a guide to bunching estimation, discusses its strengths and weaknesses, surveys a range of applications across fields, and considers reasons for the ubiquity of kinks and notches.”

10 Decomposition

- **Fortin, Lemieux, and Firpo (2011)**, “Decomposition Methods in Economics,” HLE
 “This chapter provides a comprehensive overview of decomposition methods that have been developed since the seminal work of Oaxaca and Blinder in the early 1970s. These methods are used to decompose the difference in a distributional statistic between two groups, or its change over time, into various explanatory factors. While the original work of Oaxaca and Blinder considered the case of the mean, our main focus is on other distributional statistics besides the mean, such as quantiles, the Gini coefficient or the variance. We discuss the assumptions required for identifying the different elements of the decomposition, as well as various estimation methods proposed in the literature. We also illustrate how these methods work in practice by discussing existing applications and working through a set of empirical examples throughout the paper.”
- **Chernozhukov, Fernández-Val, and Melly (2013)**, “Inference on Counterfactual Distributions,” ECMA
 “Counterfactual distributions are important ingredients for policy analysis and decomposition analysis in empirical economics. In this article, we develop modeling and inference tools for counterfactual distributions based on regression methods. The counterfactual scenarios that we consider consist of *ceteris paribus* changes in either the distribution of covariates related to the outcome of interest or the conditional distribution of the outcome given covariates. For either of these scenarios, we derive joint functional central limit theorems and bootstrap validity results for regression-based estimators of the status quo and counterfactual outcome distributions. These results allow us to construct simultaneous confidence sets for function-valued effects of the counterfactual changes, including the effects on the entire distribution and quantile functions of the outcome as well as on related functionals. These confidence sets can be used to test functional hypotheses such as no-effect, positive effect, or stochastic dominance.

Our theory applies to general counterfactual changes and covers the main regression methods including classical, quantile, duration, and distribution regressions. We illustrate the results with an empirical application to wage decompositions using data for the United States.”

11 General

- **Abadie and Cattaneo (2018)**, “Econometric Methods for Program Evaluation,” ARE “Program evaluation methods are widely applied in economics to assess the effects of policy interventions and other treatments of interest. In this article, we describe the main methodological frameworks of the econometrics of program evaluation. In the process, we delineate some of the directions along which this literature is expanding, discuss recent developments, and highlight specific areas where new research may be particularly fruitful.”

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