DAVIDE VIVIANO

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CONTACT INFORMATION

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EDUCATION

Ph.D. in Economics, *University of California, San Diego*, U.S.A.	*2017 - 2022 (expected)*
MSc. in Data Science, *Barcelona Graduate School of Economics*, Spain joint program Universitat Pompeu Fabra and Autonoma Barcelona	*2016 - 2017*
BSc. in Economics, *Luiss Guido Carli*, Rome, Italy	*2013 - 2016*
Exchange Program at the *University of British Columbia*, Vancouver, CA	*2015*

REFERENCES

Graham Elliott (Committee Chair)	Prof. of Economics, UC San Diego	grelliott@ucsd.edu
James Fowler	Prof. of Political Science, UC San Diego	jhfowler@ucsd.edu
Yixiao Sun	Prof. of Economics, UC San Diego	yisun@ucsd.edu
Kaspar Wüthrich	Assistant Prof. of Economics, UC San Diego	kwuthrich@ucsd.edu
Paul Niehaus	Associate Prof. of Economics, UC San Diego	pniehaus@ucsd.edu

FIELDS OF INTEREST

Theoretical and Applied Econometrics (Primary); Development Economics (Secondary)

RELEVANT POSITIONS HELD

Research Intern, *Facebook Inc.* Manager: Brian Karrer; Team: Core Data Science; Topic: Network Experiments	*Summer 2020*
Research Assistant, *Universitat Pompeu Fabra* Mentors: O. Papaspiliopoulos and D. Rossell	*Summer 2017*
Research Assistant, *Luiss Guido Carli* Mentor: Giuseppe Ragusa.	*Summer 2016*

SCHOLARSHIPS AND AWARDS

Walter Heller Memorial Prize (Best 3rd Year Paper), *UC San Diego*	*Fall 2020*
Clive Granger Research Scholarship, *UC San Diego*	*Fall 2020*
Summer Research Fellowship/RAship, *UC San Diego* Mentors: G. Elliott, Y. Sun, K. Wüthrich	*Summers 2018, 2019, 2021*
HPC at UC Award, *San Diego Super Computer Center*	*2020 - 2021*
Advancement to Candidacy Fellowship, *UC San Diego*	*a.y. 2020-2021*
Graduate Tuition Scholarship and TAship, *UC San Diego*	*August 2017 - Present*
Graduate Fellowship, *UC San Diego*	*a.y. 2017-2018*
Graduate Tuition Fellowship (75%), *Barcelona GSE*	*a.y. 2016-2017*
Exchange Program Fellowship, *Luiss University*	*Fall 2015*

WORKING PAPERS

Policy design in experiments with unknown interference, link (Job Market Paper)
Davide Viviano

This paper proposes an experimental design for estimation and inference on welfare-maximizing policies in the presence of spillover effects. I consider a setting where units are organized into a *finite* number of large clusters and interact in unobserved ways within each cluster. As a first contribution, I introduce a single-wave experiment to estimate the marginal effect of a change in the treatment probabilities taking spillovers into account. The design randomizes treatments independently within clusters and induces local perturbations to treatment probabilities within pairs of clusters. Using the estimated marginal effect, I construct a practical test for whether a given treatment allocation rule maximizes welfare. The idea is that researchers should report estimates of the marginal effect and test for welfare-maximizing policies: the marginal effect indicates the direction for a welfare improvement, and the test provides evidence on whether it is worth conducting additional experiments to estimate a welfare-improving treatment allocation. As a second contribution, I design a multiple-wave experiment to estimate treatment assignment rules and maximize welfare. I derive small-sample guarantees on the difference between the maximum attainable welfare and the welfare evaluated at the estimated policy (regret). A corollary of such guarantees is that the regret converges to zero linearly in the number of iterations and clusters. Simulations calibrated to existing experiments on information diffusion and cash-transfer programs illustrate that the method can lead to large welfare improvements.

Policy Targeting under Network Interference, link (reject and resubmit request at *Review of Economic Studies*)
Davide Viviano

This paper studies the problem of optimally allocating treatments in the presence of spillover effects, using information from a quasi-experiment, such as an existing experiment or observational study. I introduce a method that maximizes the sample analog of average social welfare when spillovers occur. The proposed method presents several attractive features for applications: (i) it does not necessitate network information of the target population; (ii) it exploits heterogeneity in treatment effects for targeting individuals; (iii) it does not rely on the correct specification of a particular structural model; (iv) it accommodates arbitrary constraints on the policy function. I construct semi-parametric welfare estimators with known and unknown propensity scores and cast the optimization problem into a mixed-integer linear program, which can be solved using off-the-shelf algorithms. I derive the first set of guarantees on the regret of treatment rules in the presence of spillovers; here, the regret defines the difference between the maximum attainable welfare and the welfare evaluated at the estimated policy. An application for targeting information on social networks illustrates the advantages of the method.

Fair Policy Targeting, link (Revision request at *Journal of the American Statistical Association*, 2^{nd} round)
Davide Viviano and Jelena Bradic

One of the major concerns of targeting interventions on individuals in social welfare programs is discrimination: individualized treatments may induce disparities on sensitive attributes such as age, gender, or race. This paper addresses the question of the design of fair and efficient treatment allocation rules. We adopt the non-maleficence perspective of "first do no harm": we select the fairest allocation *within* the Pareto frontier. We cast the optimization into a mixed-integer linear program formulation, which can be solved using off-the-shelf algorithms. We derive regret bounds on the unfairness of the estimated policy function and small sample guarantees on the Pareto frontier under general notions of fairness. Finally, we illustrate our method using an application from education economics.

Synthetic Learner: Model Free Inference over Time, link (R&R at *Journal of Econometrics*)

Davide Viviano and Jelena Bradic

In this paper, we develop a non-parametric algorithm for detecting the effects of treatment over time in the context of Synthetic Controls. The method builds on counterfactual predictions from many algorithms without necessarily assuming that the algorithms correctly capture the model. We introduce an inferential procedure for detecting treatment effects and show that the testing procedure is asymptotically valid for stationary, beta mixing processes without imposing any restriction on the set of base algorithms under consideration. The class of algorithms may include Random Forest, Lasso, or any other machine-learning estimator. We discuss consistency guarantees for average treatment effect estimates and derive regret bounds for the proposed methodology. Numerical studies and an application illustrate the advantages of the method.

(When) Should you adjust inference for multiple hypothesis testing?, link
Davide Viviano, Kaspar Wüthrich and Paul Niehaus (alphabetical first author ordering)

The use of multiple hypothesis testing adjustments varies widely in applied economic research, without consensus on when and how it should be done. We provide a game-theoretic foundation for this practice. Adjustments are often - but not always - appropriate in our framework when research influences multiple policy decisions. These adjustments depend on the nature of scale economies in the research production function and on economic interactions between policy decisions, with control of classical notions of compound error rates emerging in some but not all cases. When research examines multiple outcomes, on the other hand, this motivates either very conservative testing procedures or aggregating outcomes into sufficient statistics for policy-making.

Dynamic covariate balancing: estimating treatment effects over time, link
Davide Viviano and Jelena Bradic

This paper studies the problem of estimation and inference on the effects of dynamic (time-varying) treatments. We consider a setting where individuals select treatment dynamically based on past information. The researcher aims to conduct inference on the effect of a treatment history controlling for high-dimensional covariates. A key challenge is that the propensity score is unknown to researchers. This paper derives novel balancing equations for estimating dynamic treatment effects without necessitating the propensity score and combines such equations with penalized projection methods. The projection method and balancing equations are estimated sequentially using information from the estimators obtained in previous steps. We study the asymptotic properties for estimation and inference and derive the parametric $n^{-1/2}$ convergence rate of the proposed procedure in high dimensions. Simulations and an empirical application illustrate the advantage of the method over state-of-the-art competitors.

Experimental Design under Network Interference, link
Davide Viviano

This paper studies the design of experiments in the presence of spillovers for precise inference on treatment effects. It considers a fully connected network, local dependence among individuals, and a general class of estimands, which encompasses average treatment and average spillover effects. I study the design where the experimenter optimizes over participants and treatment assignments to minimize the variance of the estimators of interest, using a first-wave (pilot) experiment to estimate the variance. I provide the first statistical framework for the design of two-wave network experiments and illustrate the existence of a trade-off in the choice of the pilot study. A larger pilot guarantees a more precise estimator of the variance, but it imposes stricter restrictions on the design of the main experiment. I exploit this trade-off to formally characterize the pilots size relative to the main experiment. I derive guarantees for asymptotic inference on causal effects and finite-sample upper bounds on the regret of the proposed design mechanism. Simulations illustrate the advantage of the method.

PROFESSIONAL ACTIVITIES

Presentations

2021 (online) Young Economists Symposium (Princeton), EEA-ESEM congress (section on causal inference and high-dimensional, and section on treatment effects) Center for Causal Inference Symposium (Pardee Rand), Econometric Society North American Summer Meeting, NYU Quantitative Methods Workshop (invited talk), 6th Annual Conference of Networks and Economics, ASSA 2021 (section on spillover effects), EGSR Conference (University of Washington in St. Louis)

2020 EGSR Conference (University of Washington in St. Louis), Young Economists Symposium (UPenn, online), Econometric Society World Congress (online)

2019 Causal Learning with Interactions (Cemmap), EGSR Conference (University of Washington in St. Louis)

Referee Service

Annals of Applied Statistics
Biometrika
Journal of Econometrics
Review of Economics and Statistics
The American Statistician

TEACHING EXPERIENCE

As a Teaching Assistant at UC San Diego

Environmental Economics (ECON131)	*Falls 2018, 2019, 2021*
Economic and Business Forecasting (ECON178)	*Winters 2019, 2020, 2021*
Econometrics B (ECON220B)	*Springs 2019, 2021*
Demographic Analysis and Forecasting (ECON125)	*Spring 2020*
Econometrics A (ECON220A)	*Fall 2020*

SOFTWARE

DynBalancing: an R-package for inference on treatment effects over time and high-dimensions, link

OTHER ACTIVITIES

Co-Founder: Ermes I.T., Rome, Tecnopolo Lazio Innova, *2017-2018*
Sponsored by European Space Agency (ESA)

Executive member of CODISU, Luiss Guido Carli, *2015-2016.*
Board for students' financial support. Elected as student representative.

OTHER INFORMATION

Computing: Unix, R, Python, MATLAB, Julia, HTML, LaTeX, SQL.
Languages: Italian (Mother Tongue), English (Fluent), Spanish (Fluent), French (Basic).
Citizenship: Italian

November 11, 2021