Maastricht University

Tobias Schnabel

School of Business and Economics

# Matrix Completion Estimation in Differential Timing Settings

**Supervisor: Prof. Martin Schumann**

## Motivation

- Difference-in-Differences (DiD) is the workhorse model used to estimate **treatment effects** in modern Research in Applied Economics, Policy Evaluation, Accounting, and Finance
- Canonical DiD performs well when the treatment effects are homogeneous across units and **constant over time**
- In most applications, **neither is a realistic assumption**
- Many new estimators developed in the past 5 years to address these shortcomings, I discuss 5 prominent ones
- Athey et al. (2021) introduce Matrix Completion Estimation (**MC-NNM**) method from Machine Learning field to Econometrics
- Not as intuitive as DiD, but only requires **2 assumptions** to work, not ≥6 like DiD
- MC-NNM is also **universally applicable** to any panel data set, if there exists a never-treated group

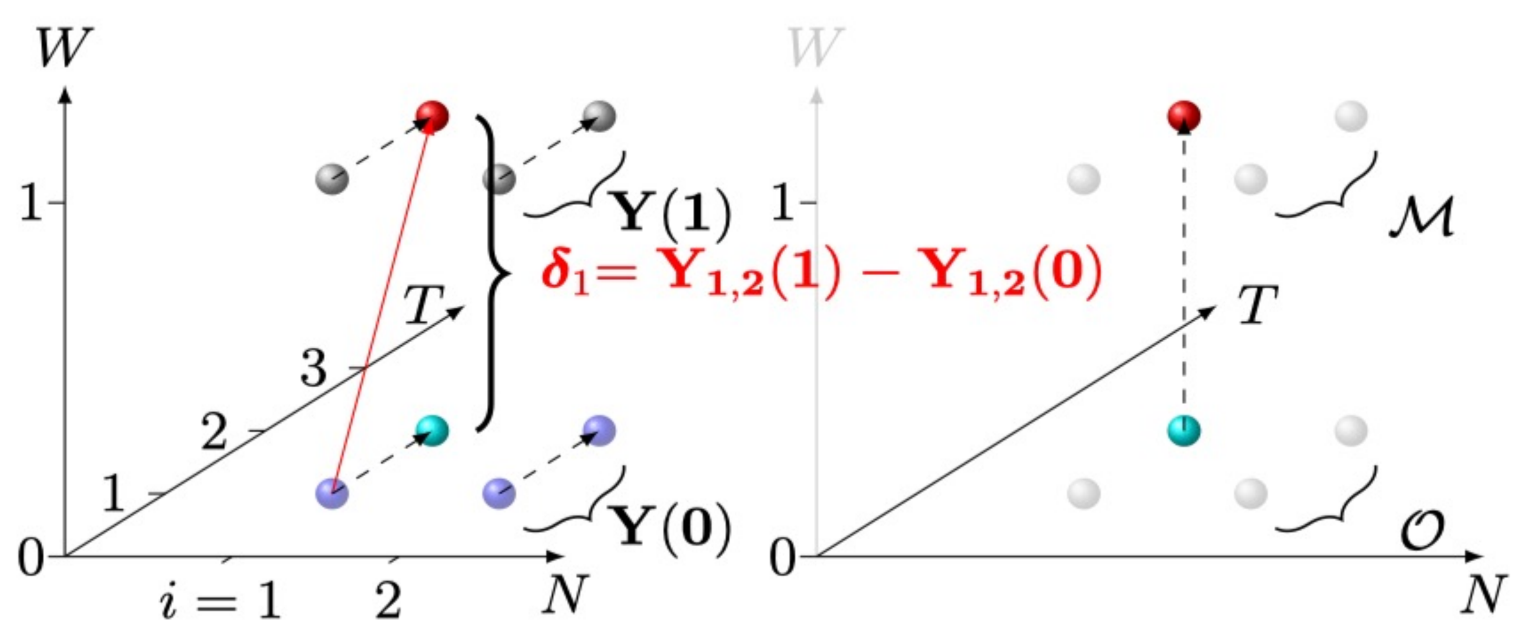
$$\mathbf{Y} = \begin{array}{c} \left(\begin{array}{ccccc} \checkmark & \checkmark & \checkmark & \dots & \checkmark \\ \checkmark & ? & ? & \dots & ? \\ \checkmark & \checkmark & ? & \dots & ? \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \checkmark & \checkmark & \checkmark & \dots & ? \end{array}\right) \end{array} \begin{array}{l} \text{(control unit)} \\ \text{(unit in early group)} \\ \text{(unit in mid group)} \\ \\ \text{(unit in late group)} \end{array} \qquad \mathbf{W}_{N\times T} = \begin{pmatrix} 0 & 0 & 1 & \dots & 0 \\ 1 & 1 & 0 & \dots & 1 \\ 0 & 1 & 0 & \dots & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & 0 & \dots & 1 \end{pmatrix}$$

### Research Question

Does the Matrix Completion Estimator outperform DiD estimators in settings with staggered adoption?

## Methodology

1. I use the Rubin Causal Model of Potential outcomes to explain **what we want to estimate**
2. I then synthesize the literature on why canonical DiD tends to be **problematic** in settings with differential timing of treatment
3. I introduce MCE, connect it to DiD and explain **how and why it works**




4. I execute **8 different Monte Carlo Simulations** to contrast how well MCE does compared to DiD and 4 new estimators: Callaway & Sant'Anna (2021); Sun & Abraham (2021); Borusyak, Jaravel, & Spiess (2023); de Chaisemartin & D'Haultfœuille (2020)

## Results

My eight simulations are based on 8 Data-Generating Processes and are increasing in how challenging the data is to handle for the six estimators:

1. In the simplest case, DiD works perfectly fine, MCE does equally well
2. In a setting with a **treatment effect that increases over time**, MC-NNM performs better than DiD and second-best overall

The next 6 simulations all feature a differential timing of treatment (staggered) setting

3. With homogeneous and time-invariant treatment effects, MC-NNM performs better than DiD and (co-)best overall
4. With **heterogeneous** but time-invariant treatment effects, MC-NNM performs second-best after DiD
5. With homogeneous but **time-varying** treatment effects, MC-NNM performs best
6. With heterogeneous **and** time-varying treatment effects, MC-NNM performs better than DiD and third-best overall
7. With heterogeneous **and** time-varying treatment effects and a covariate, where **common trends assumption holds only conditionally**, MC-NNM outperforms all other estimators
8. With heterogeneous **and** time-varying treatment effects and a covariate, where **common trends assumption does not hold**, MC-NNM performs better than DiD but only third-best overall (two estimators who should not work well here surprisingly do)

Full interactive results available here: https://tobias-schnabel.github.io/matrix-completion/Results.html

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## Conclusions

- My results show encouraging signs of MC-NNM's performance in a variety of data configurations, exactly as claimed by Athey et al. (2021)
- As my results show, MC-NNM performs reasonably well in all simulations, especially compared to DiD, but it is outperformed by application-specific estimators in some simulations
- My conclusion from these results is that MC-NNM is preferable to DiD as a *go-to*, *off-the-shelf* model and should become a standard benchmark to include
- But it is not a silver bullet to solve all problems, and more research on why it does or does not perform well in certain cases is needed

## Primary References


- 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, no. 536 (October): 1716–1730. https://doi.org/10.1080/01621459.2021.1891924
- Roth, Jonathan, and Pedro H. C. Sant'Anna. 2023. Efficient Estimation for Staggered Rollout Designs. https://arxiv.org/abs/2102.01291


**Correspondence to:**
Tobias Schnabel,
t.schnabel@student.maastrichtuniversity.nl

Maastricht University
P.O. Box 616
6200 MD Maastricht, The Netherlands