Longitudinal Data Analysis

methods@manchester summer school

Day 5

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30/06—04/07

Today

- Common issues with longitudinal data
    - Attrition bias
    - Measurement equivalence
    - Temporal gaps
- Growth curve models
    - Some examples of papers
    - What else can we do?
- Cross-lagged panel models
    - Some examples of papers
    - What else can we do?
- Difference-in-differences
    - Some examples of papers
    - What else can we do?

Common issues with longitudinal data

Common issues with longitudinal data

Attrition bias

- Loss of participants over time can introduce systematic bias.
- *Solutions*: model the probability of dropping out to investigate systematic attrition; use inverse probability weighting; apply multiple imputation or full information maximum likelihood (FIML)

Measurement equivalence

- Are variables measuring the same construct over time?
- *Solutions*: test for configural, metric, and scalar invariance; adjust models if necessary

Temporal spacing of observations

- Are the time intervals between waves appropriate for the research question?
- *Solutions*: correctly specify time in the model; use time as a continuous variable where possible; theory matters!

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Growth curve models: real-life examples and where next?

Latent growth curve models

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DOI: 10.1111/1745-9125.12230

CRIMINOLOGY

ARTICLE

Evaluating the shared and unique predictors of legal cynicism and police legitimacy from adolescence into early adulthood*

Amy Nivette[1] | Manuel Eisner[2,3] | Denis Ribeaud[3]

[1]Department of Sociology, Utrecht University, The Netherlands

[2]Institute of Criminology, University of Cambridge, United Kingdom

[3]Jacobs Centre for Productive Youth Development, University of Zurich, Switzerland

(Nivette et al., 2019)

Nivette et al's paper using LGCM

Latent growth curve models (LGCMs) were used to model patterns of change in legal cynicism between ages 13 and 20, as well as police legitimacy between ages 15 and 20. Specifically, we used a structural equation modeling framework to estimate the latent intercept and slope based on observed repeated measures of legal cynicism and police legitimacy (Curran, Obeidat, & Losardo, 2010). LGCMs are beneficial in that they can be employed to estimate a unique intercept and slope for each individual, as well as can allow for the inclusion of covariates to examine their potential influence on legal attitudinal trajectories (Bollen & Curran, 2006).

(Nivette et al., 2019, p. 81)

Nivette et al's paper using LGCM

TABLE 4 Comparative parameter estimates and fit statistics for unconditional growth models of legal cynicism (ages 13–20)

Variable	Model 1: Intercept Only	Model 2: Linear Slope		Model 3: Nonlinear Slope		
	Intercept	Intercept	Slope	Intercept	Slope	Quad. Slope
Mean	2.17***	2.21***	−.13***	2.17***	.37***	−.07***
	[2.14, 2.19]	[2.18, 2.24]	[−.18, −.07]	[2.13, 2.20]	[.19, .56]	[−.09, −.05]
Variance	.13	.16	.30	.18	2.40	.02
	[.12, .15]	[.14, .19]	[.23, .40]	[.15, .21]	[1.62, 3.56]	[.01, .04]
Covariance (Int, Slope)			−.09***		−.22***	
Covariance (Int, Quad. Slope)					.01	
Covariance (Slope, Quad. Slope)					−.24***	
Model Fit Statistics						
X^2	182.63***		100.57**		19.99***	
RMSEA	.12		.11		.06	
CFI	.82		.90		.98	
CD	.74		.85		.90	
Log likelihood	−3116.92		−3075.89		−3035.61	

Notes: N = 1,034. CD = coefficient of determination; CFI = comparative fit index; Quad. = quadratic; RMSEA = root mean square error of approximation. 95% confidence intervals reported in brackets; variances across waves are held to be equal. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Nivette et al's paper using LGCM

TABLE 6 Conditional latent growth curve results for time-varying covariates (unconstrained) on legal cynicism during adolescence (ages 13–20)

	Model 1		Model 2	
Time-Varying Predictors	***b***	**95% CI**	***b***	**95% CI**
Legal Attitudes				
Police legitimacy			$-.11^{***}$	[−.15, −.08]
Socialization Domains				
Parental involvement	−.02	[−.06, .01]	−.02	[−.06, .01]
Parental supervision	$-.05^{*}$	[−.08, −.01]	$-.04^{*}$	[−.08, −.01]
School commitment	$-.05^{*}$	[−.08, −.01]	$-.04^{*}$	[−.08, −.01]
Teacher–child bond	.00	[−.03, .04]	.01	[−.02, .05]
Peer disapproval of deviance	$-.09^{***}$	[−.13, −.06]	$-.08^{***}$	[−.12, −.05]
Police contact (1 = yes)	.07	[−.04, .17]	.03	[−.07, .14]
Individual Propensities				
Low self-control	$.30^{***}$	[.26, .33]	$.29^{***}$	[.26, .33]
Morality	$-.21^{***}$	[−.25, −.18]	$-.20^{***}$	[−.24, −.17]
Deviant behavior	$.15^{***}$	[.12, .18]	$.14^{***}$	[.11, .17]

Notes: $N = 1{,}034$. All continuous variables are z-standardized; the model was estimated using robust standard errors; all estimates are independent of TICs and growth factors. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Nivette et al's paper using LGCM

TABLE 7 Conditional latent growth curve results for time-invariant covariates (unconstrained) on legal cynicism during adolescence (ages 13–20)

	Model 1: Without Police Legitimacy			Model 2: With Police Legitimacy		
Time-Invariant Predictors	**Intercept**	**Linear Slope**	**Quad. Slope**	**Intercept**	**Linear Slope**	**Quad. Slope**
Gender (1 = male)	−.11*	−.11	.04	−.10	−.28	.06
	[−.21, −.01]	[−.69, .46]	[−.03, .12]	[−.20, .00]	[−.85, .30]	[−.01, .14]
Migrant background (1 = both parents born abroad)	.11*	.06	−.02	.12*	.02	−.01
	[.01, .21]	[−.52, .64]	[−.09, .06]	[.02, .22]	[−.55, .60]	[−.09, .06]

Notes: $N = 1{,}034$. All continuous variables are z-standardized; the model was estimated using robust standard errors; all estimates are independent of TVCs and growth factors. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Growth curve models

J Quant Criminol (2018) 34:367–396
https://doi.org/10.1007/s10940-017-9338-9

ORIGINAL PAPER

Using Longitudinal Self-Report Data to Study the Age–Crime Relationship

Jaeok Kim[1] · Shawn D. Bushway[1]

(Kim and Bushway, 2018)

Kim and Bushway's paper using GCM

Analytical Strategy

We follow the basic analytic strategy of previous studies and use a growth curve model which estimates the change in criminal involvements as a function of age. It is also called hierarchical linear modeling or mixed level modeling because it models within-individual change at level 1, and allows the mean level of an outcome variable as well as the rate of change to vary across individual at level 2 (Raudenbush and Chan 1992, 1993). As the first step of analysis, we estimate a growth curve model for each birth cohort, which makes it possible to compare age–crime curves of different birth cohorts graphically. We have five different cohorts which are defined based on the birth year of a respondent: cohort 80, 81, 82, 83, and 84. The following is an equation for a growth curve model for a given birth cohort:

Level-1 model

$$Y_{it} = \pi_{0i} + \pi_{1i}(\mathrm{AGE})_{it} + \pi_{2i}\left(\mathrm{AGE}^2\right)_{it} + \pi_{3i}\left(\mathrm{AGE}^3\right)_{it} + e_{it} \quad (1)$$

Level-2 model

$$\pi_{0i} = \beta_{00} + u_{0i}$$

$$\pi_{1i} = \beta_{10} + u_{1i}$$

where Y_{it} is the crime score for person i at wave t (t = 1, 2, …, 7). Age is centered at 18 so that π_{0i} refers to the crime score of person i at age 18. To find the best model fit for each cohort, we start from a linear age model, and add quadratic and cubic terms allowing for non-linearity of the age effect. π_{1i} is the linear change in the crime score for person i while π_{2i} is the quadratic effect of age and π_{3i} is the cubic effect of age for person i. e_{it} refers to the within-individual random error for person i at wave t, and these errors are assumed mutually independent and have normal distribution with mean of zero and variance of σ^2. At level-2, we add a random intercept and a random coefficient that allow variation in crime score across individuals.[5] β_{00} refers to the grand mean crime score at age 18, and u_{0i} is the random effect of person i on crime score at age 18. β_{10} is the grand mean rate of change in crime score, and u_{1i} is the random effect of person i on the rate of change in crime score. Random effects (u_{0i} and u_{1i}) are assumed bivariate normal distribution with mean of zero, variances γ_{00} and γ_{10}, respectively. The equation for the combined model is written as follows:

(Kim and Bushway, 2018, pp. 374-375)

Kim and Bushway's paper using GCM

Table 1 Cohort-specific growth curve model for general crime scale

Predictor	Cohort 80 (N = 7639)		Cohort 81 (N = 8608)		Cohort 82 (N = 8697)		Cohort 83 (N = 8983)		Cohort 84 (N = 8775)	
	Coef. (S.E.)	z	Coef. (S.E.)	z	Coef. (S.E.)	z	Coef. (S.E.)	z	Coef. (S.E.)	z
Fixed effects										
For base rate										
Intercept	0.499*** (0.025)	23.86	0.424*** (0.019)	22.41	0.398*** (0.016)	24.99	0.341*** (0.016)	21.64	0.329*** (0.017)	19.18
For linear change										
Intercept	−0.120*** (0.007)	−16.74	−0.096*** (0.005)	−18.70	−0.083*** (0.005)	−17.47	−0.059*** (0.004)	−13.13	−0.090*** (0.009)	−10.20
For quadratic change										
Intercept	0.010*** (0.002)	6.25	0.007*** (0.002)	4.30					−0.012*** (0.002)	−6.97

Parameter	Cohort 80 (N = 7639)		Cohort 81 (N = 8608)		Cohort 82 (N = 8697)		Cohort 83 (N = 8983)		Cohort 84 (N = 8775)	
	Estimate	z	Estimate	z	Estimate	z	Estimate	z	Estimate	z
Variance components										
Variance (base rate)	0.418***	−16.86	0.347***	−22.34	0.268***	−26.15	0.245***	−26.20	0.229***	−22.09
Variance (linear change)	0.015***	−53.20	0.016***	−54.95	0.015***	−50.69	0.012***	−47.87	0.006***	−31.91
Covariance	−0.071***	−18.59	−0.066***	−14.05	0.048***	−12.09	−0.015***	−5.16	−0.003	−0.93
Variance (residual)	0.408***	−46.25	0.437***	−44.96	0.481***	−40.11	0.478***	−41.28	0.516***	−36.72
ICC	0.52		0.45		0.37		0.35		0.31	

* $p < .05$; ** $p < .01$; *** $p < .001$

Kim and Bushway's paper using GCM

378 J Quant Criminol (2018) 34:367–396

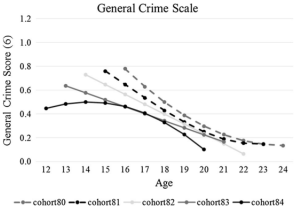

Fig. 1 Age–crime curve for general crime score by cohort

J Quant Criminol (2018) 34:367–396 381

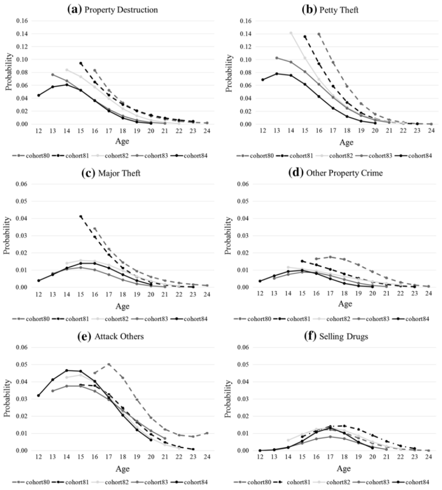

Fig. 3 Age–crime curve for general crime scale items by cohort

Where next?

Extensions from growth curve models

Grouped trajectories?

⇝ Group-Based Trajectory Models (GBTM)

- See Nagin (2010) for an overview and Neil et al. (2021) for an application

⇝ Growth Mixture Models (GMM)

- See Jung and Wickrama (2008) and Kreuter and Muthén (2008) for an overview and Na et al. (2015) for an application

Non-linear latent trajectories?

⇝ Latent Change Score Models (LCSM)

- See Ghisletta and McArdle (2014) and McArdle and Grimm (2010) for an overview and Howardson et al. (2017) for an application

⇝ Latent Variable-Autoregressive Latent Trajectory Model (LV-ALT)

- See Bianconcini and Bollen (2018) and Bauldry and Bollen (2018)

Cross-lagged panel models: real-life examples and where next?

Random Intercepts Cross-Lagged Panel Model

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American Psychology-Law Society
Law and Human Behavior

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2020, Vol. 44, No. 5, 377–393
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Reassessing the Relationship Between Procedural Justice and Police Legitimacy

Jose Pina-Sánchez
University of Leeds

Ian Brunton-Smith
University of Surrey

(Pina-Sánchez and Brunton-Smith, 2020)

Pina-Sánchez & Brunton-Smith's paper using RI-CLPM

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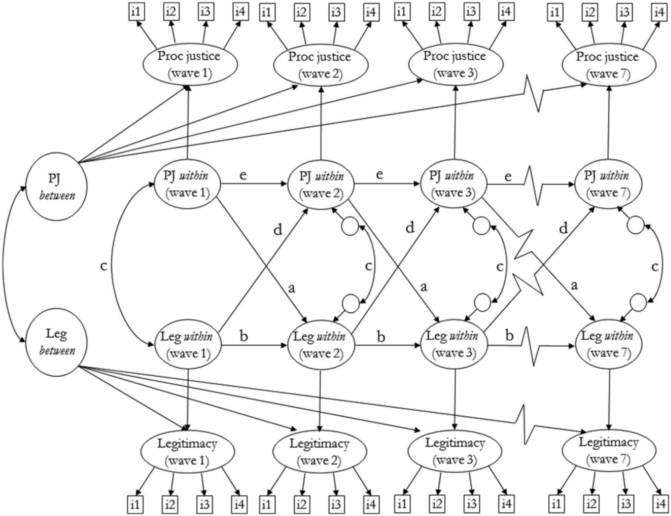

Figure 1. Graphical representation of the random intercepts cross-lagged panel model.

Pina-Sánchez & Brunton-Smith's paper using RI-CLPM

Table 4
Results From the Random Intercepts Cross-Lagged Panel Models

Coefficient's label	Mode 1: Treatment Coef.	95% CI	*SE*	*p* value	Model 2: Voice Coef.	95% CI	*SE*	*p* value
Procedural justice (w2)								
Procedural justice (w1)	0.08	[−0.04, 0.20]	0.06	.18	−0.006	[−0.08, 0.06]	0.04	.87
Legitimacy (w1)	0.02	[−0.05, 0.09]	0.04	.60	0.00	[−0.15, 0.15]	0.08	.99
Procedural justice (w3)								
Procedural justice (w2)	0.07	[−0.08, 0.21]	0.07	.38	0.03	[−0.05, 0.11]	0.04	.44
Legitimacy (w2)	0.06	[−0.03, 0.15]	0.05	.19	0.06	[−0.11, 0.23]	0.09	.47
Procedural justice (w4)								
Procedural justice (w3)	0.17	[0.05, 0.30]	0.06	.005	0.15	[0.06, 0.23]	0.05	.001
Legitimacy (w3)	−0.03	[−0.12, 0.07]	0.05	.60	0.14	[−0.05, 0.33]	0.09	.14
Procedural justice (w5)								
Procedural justice (w4)	0.17	[0.06, 0.28]	0.06	.003	0.09	[−0.005, 0.19]	0.05	.06
Legitimacy (w4)	0.06	[−0.04, 0.15]	0.05	.26	−0.11	[−0.31, 0.09]	0.10	.27
Procedural justice (w6)								
Procedural justice (w5)	0.22	[0.13, 0.31]	0.05	<.001	0.08	[−0.02, 0.17]	0.05	.12
Legitimacy (w5)	−0.04	[−0.13, 0.31]	0.04	.32	0.18	[0.01, 0.35]	0.09	.04
Procedural justice (w7)								
Procedural justice (w6)	0.37	[0.29, 0.45]	0.04	<.001	0.14	[0.03, 0.26]	0.06	.02
Legitimacy (w6)	0.02	[−0.06, 0.09]	0.04	.64	0.14	[−0.04, 0.31]	0.09	.12
Legitimacy (w2)								
Procedural justice (w1)	0.03	[−0.10, 0.16]	0.07	.65	0.02	[−0.02, 0.05]	0.02	.42
Legitimacy (w1)	0.20	[0.11, 0.29]	0.05	<.001	0.21	[0.12, 0.29]	0.05	<.001
Legitimacy (w3)								
Procedural justice (w2)	−0.19	[−0.35, −0.04]	0.08	.02	−0.03	[−0.07, 0.02]	0.02	.28
Legitimacy (w2)	0.29	[0.18, 0.39]	0.05	<.001	0.26	[0.16, 0.37]	0.05	<.001
Legitimacy (w4)								
Procedural justice (w3)	0.03	[−0.11, 0.16]	0.07	.68	−0.004	[−0.06, 0.05]	0.03	.87
Legitimacy (w3)	0.29	[0.17, 0.41]	0.06	<.001	0.29	[0.18, 0.40]	0.06	<.001
Legitimacy (w5)								
Procedural justice (w4)	−0.001	[−0.12, 0.12]	0.06	.99	0.06	[0.003, 0.11]	0.03	.04
Legitimacy (w4)	0.27	[0.16, 0.39]	0.06	<.001	0.26	[0.15, 0.38]	0.06	<.001
Legitimacy (w6)								
Procedural justice (w5)	−0.008	[−0.11, 0.09]	0.05	.87	0.02	[−0.04, 0.08]	0.03	.48
Legitimacy (w5)	0.40	[0.30, 0.50]	0.05	<.001	0.40	[0.30, 0.50]	0.05	<.001
Legitimacy (w7)								
Procedural justice (w6)	0.009	[−0.08, 0.10]	0.05	.86	0.10	[0.04, 0.16]	0.03	.002
Legitimacy (w6)	0.43	[0.34, 0.52]	0.05	<.001	0.41	[0.32, 0.50]	0.05	<.001
Contemporaneous effects								
Procedural justice (w1) – Legitimacy (w1)	0.04	[0.02, 0.06]	0.01	.001	0.09	[0.04, 0.13]	0.02	<.001
Procedural justice (w2) – Legitimacy (w2)	0.04	[0.02, 0.06]	0.01	<.001	0.04	[−0.002, 0.08]	0.02	.06
Procedural justice (w3) – Legitimacy (w3)	0.04	[0.03, 0.06]	0.01	<.001	0.05	[0.02, 0.09]	0.02	.006
Procedural justice (w4) – Legitimacy (w4)	0.04	[0.02, 0.06]	0.01	<.001	0.05	[0.008, 0.08]	0.02	.02
Procedural justice (w5) – Legitimacy (w5)	0.03	[0.005, 0.05]	0.01	.01	0.06	[0.02, 0.10]	0.02	.005
Procedural justice (w6) – Legitimacy (w6)	0.04	[0.02, 0.06]	0.01	<.001	0.06	[0.02, 0.10]	0.02	.003
Procedural justice (w7) – Legitimacy (w7)	0.04	[0.02, 0.06]	0.009	<.001	0.07	[0.03, 0.11]	0.02	.001
Random effects								
Variance random intercepts procedural justice	0.15	[0.13, 0.17]	0.01	<.001	0.21	[0.18, 0.25]	0.02	<.001
Variance random intercepts legitimacy	0.32	[0.28, 0.36]	0.02	<.001	0.31	[0.28, 0.35]	0.02	<.001
Covariance procedural justice – legitimacy	0.09	[0.07, 0.11]	0.009	<.001	0.11	[0.09, 0.14]	0.01	<.001
Goodness of fit								

Dynamic Panel Model with Fixed Effects

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DOI: 10.1111/1745-9125.12383

CRIMINOLOGY

ORIGINAL ARTICLE

The promise and perils of the sharing economy: The impact of Airbnb lettings on crime

Charles C. Lanfear[1] | David S. Kirk[2]

(Lanfear and Kirk, 2024)

Lanfear & Kirk's paper using DPM

4.2 | Estimation strategy

Three features of the theoretical model in the last section present challenges for estimation: (1) both contemporaneous and lagged effects of Airbnb properties on crime—which likely vary across different types of crime; (2) effects of past crime on the future volume of active Airbnb lettings; and (3) unobserved, time-stable features that impact the volume of active Airbnb lettings and crime. We address these challenges by estimating the effects of short-term rentals on counts of six types of crime using Allison et al.'s (2017) maximum likelihood structural equation (ML-SEM) fixed-effects dynamic panel method.[15] The ML-SEM method is closely related to the Arellano-Bond (AB) method commonly used in economics (Arellano & Bond, 1991; Arellano & Bover, 1995) but is more efficient, more flexible (e.g., relaxes time invariance of error terms), and does not suffer from challenges regarding instrument selection or proliferation of weak instruments in long panels (see Roodman, 2009).

(Lanfear and Kirk, 2024, p. 783)

Lanfear & Kirk's paper using DPM

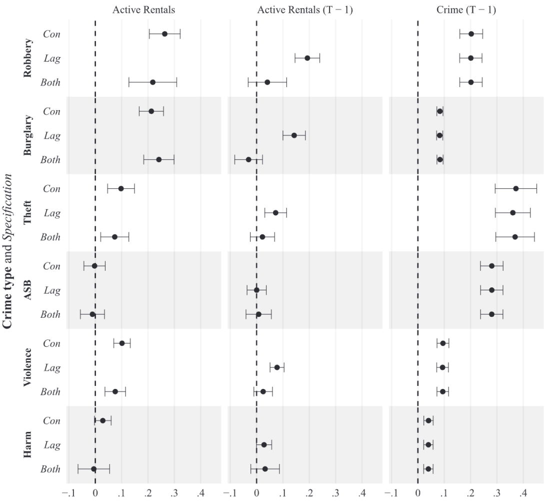

FIGURE 4 ML-SEM estimated quarterly effects on crime from active short-term lettings and past crime.

Note. Fully standardized, 95% confidence intervals.

Extensions of the RI-CLPM and the DPM

- Three extensions of the random intercept cross-lagged panel model
  - See Mulder and Hamaker (2021)
- A critique of the random intercept cross-lagged panel model
  - See Lüdtke and Robitzsch (2021)
- What you—and can't—do with three-wave panel data
  - See Vaisey and Miles (2017)
- How to deal with reverse causality using panel data?
  - See Leszczensky and Wolbring (2019)

Difference-in-differences: real-life examples and where next?

Multi-period difference-in-differences

Journal of Quantitative Criminology
https://doi.org/10.1007/s10940-025-09620-y

ORIGINAL PAPER

Check for updates

When 'Eyes on the Street' Are Not Enough: Insights from Itinerant Street Markets

Carlos Díaz[1] · Sebastian Fossati[2] · Nicolas Trajtenberg[3]

Accepted: 20 June 2025
© The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2025

(Díaz et al., 2025)

Díaz et al.'s paper using TWFE

Journal of Quantitative Criminology

In this study, we employ a difference-in-differences framework using the two-stage estimation method for two-way fixed effects (TWFE) regressions proposed by Gardner et al. (2025). In our case, for each of the five 100-meter buffers, we estimate the regression

$$y_{jt} = \mu_j + \eta_t + \sum_k \tau^k D_{jt}^k + \varepsilon_{jt}, \qquad (2)$$

with $-2 \leq k \leq 2$ and $k \neq -1$, and where y_{jt} is the number of crime reports per square kilometer in a given buffer of street market j on date t during the usual market hours (i.e., from 7 a.m. to 3 p.m.); μ_j is a vector of time-invariant market fixed effects (*unit fixed effects*); η_t is a vector of shocks in a given time period that equally affect all units (*time fixed effects*); and D_{jt}^k are the leads ($k < 0$) and lags ($k \geq 0$) of the treatment caused by street market j.

Díaz et al.'s paper using TWFE

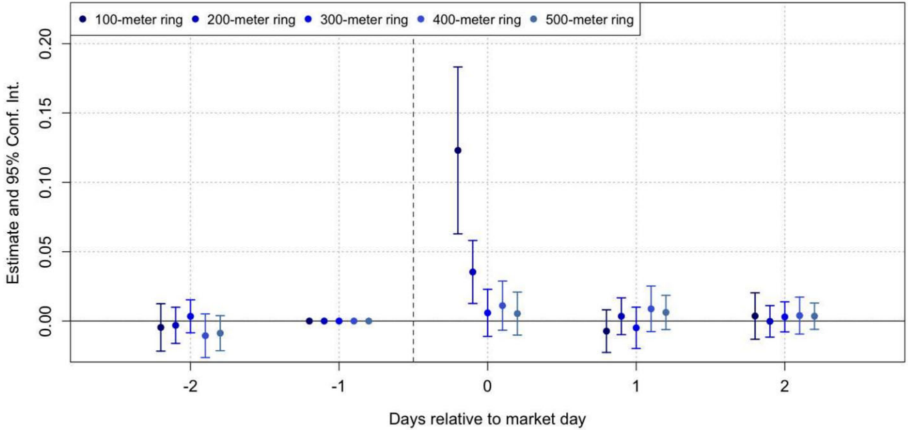

Fig. 4 Event study for thefts (police reports per km^2 during market hours)

Difference-in-differences setup

Article

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Did the Murder of George Floyd Damage Public Perceptions of Police and Law in the United States?

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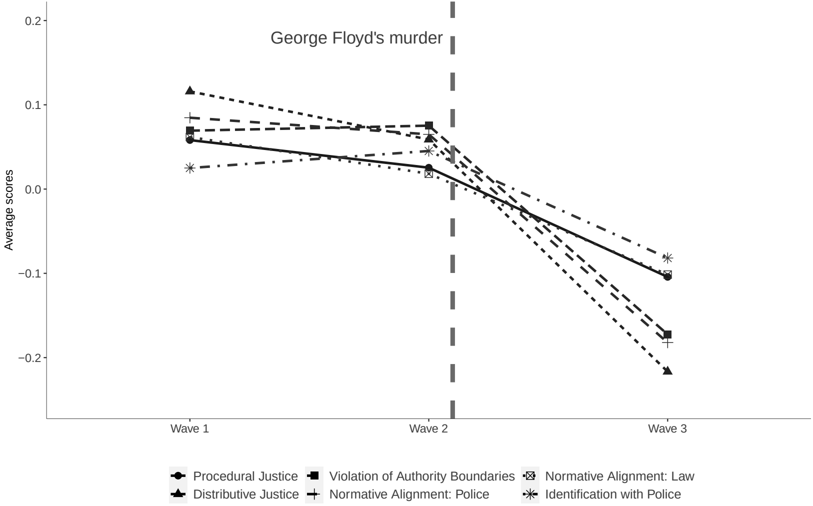
(Fine et al., 2025)

Fine et al.'s paper using DiD



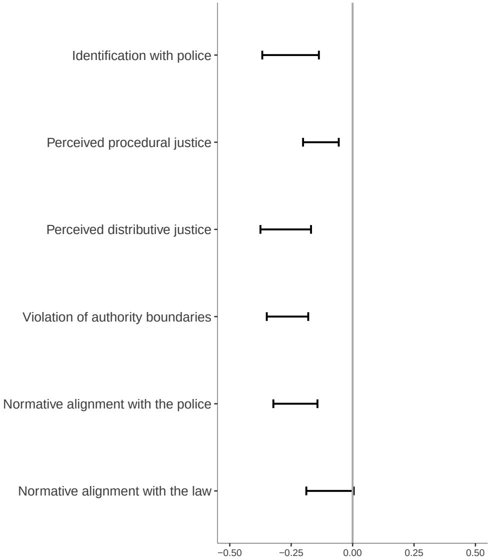
Fine et al.'s paper using DiD

We explain our modeling strategy in greater detail in the Appendix. But in summary: we calculate change scores of outcome variables between Waves 1 and 2 and then between Waves 2 and 3; and because the murder of George Floyd and sudden surge in protests against police killings of unarmed Black men happened between Waves 2 and 3, we consider the latter to represent outcome scores of the treatment group and the former, because no similar scale meaningful event happened between Waves 1 and 2, to indicate outcome scores of the control group. Since every respondent belongs to the control group at first and then moves to the treatment group, we use each respondent's change scores between Waves 1 and 2 as the baseline to estimate the counterfactual change scores among those same respondents, between Waves 2 and 3, in the counterfactual scenario where they were not exposed to Floyd's murder.

We then organize the data set in such a way that our unit of analysis consists of respondent-change observations: each respondent has two rows in the data set, one indicating change scores from Waves 1 to 2, and one indicating change scores from Waves 2 to 3, as well as a new variable indicating treatment (i.e., changes from Waves 2 to 3) or control status (i.e., changes from Waves 1 to 2). We then regress change scores of each outcome variable on this treatment variable. Formally, we regress:

$$\Delta y_{i,t'} = \alpha_i + \gamma \cdot T_{i,t'} + \epsilon_{i,t'}$$

Fine et al.'s paper using DiD



Advancements in causal inference with panel data

Synthetic control methods

- See Abadie et al. (2015) for an overview and Piza and Connealy (2022) for an application

Limitations of the TWFE estimator

- See Imai and Kim (2020), Callaway and Sant'Anna (2020), and Goodman-Bacon (2018)

Staggered difference-in-differences

- See Callaway and Sant'Anna (2020) and Sun and Abraham (2021)

Matching with difference-in-differences

- See Imai et al. (2023) for an overview and Oliveira (2024) for an application

Summary

Different longitudinal modelling strategies

Research situation	GCM/LGCM	CLPM	DiD
Interest in change over time	✓	✓	✓
Focus on within-individual change	✓	✓	✓
Time-varying predictors/outcomes	✓	✓	✓
Estimate developmental trajectories	✓	–	–
Interest in life-course processes	✓	–	–
Dynamic reciprocal effects	–	✓	–
Control for reverse causality	–	✓	–
Causal impact of an event/policy	–	–	✓
External shocks and natural experiments	–	–	✓
Analysing differences between and within units	✓	–	–

Thank you!

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