Bail Reform & Recidivism Series

Supplemental Document: *Controlled-Interrupted Time Series Methods and Robustness Check Results*

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STRENGTH IN NUMBERS

JOHN JAY COLLEGE OF CRIMINAL JUSTICE

Controlled-Interrupted Time Series Methods

We used interrupted time series analysis (ITSA) to estimate the impact of bail reform on recidivism in New York City. With a single-group ITSA design, the impact of an intervention is estimated using a simple before-and-after comparison. However, an important limitation of this approach is that it cannot rule out possible time-varying confounders. To address this limitation, we added a control series made up of cases subject to similar confounders (e.g., changes related to the Covid-19 pandemic), but unaffected by the reform of interest (changes to bail eligibility). By estimating changes pre- and post-reform and between the treatment (bail ineligible) and control (bail eligible) groups, this approach allowed us to isolate the causal effect of the reform.

The controlled-interrupted time series models were estimated using an ordinary-least squares segmented regression approach. Each model includes a time variable (indicating time from the start of the study), a dummy variable for the start of the reform (November 2019 for the main analysis and September 2019 for the supplemental analysis), a dummy variable for cohort assignment (bail ineligible vs. bail eligible), and interactions among these terms. Stata's user-written ITSA command was used to estimate the controlled-interrupted time series models, and the LINCOM command was used to estimate the differences in post-intervention slopes.[1]

Steps to Address Risk of Model Misspecification

Controlled-interrupted time series models are at risk of model misspecification from autocorrelation and seasonality.[2] To address these methodological concerns, we took the following steps. First, preliminary modeling suggested first-order autocorrelation in our outcome measures. To deal with autocorrelation, we used the Prais-Winsten estimator, a recursive process using the generalized least-square method to estimate the coefficients and error autocorrelation of a model until the AR(1) coefficient converges. Second, we tested for seasonality by estimating each model along with a set of monthly dummy variables.[3] None of the dummy variables was statistically significant, indicating an absence of seasonality.

One additional assumption in multiple-group ITSA is that the pre-intervention trends in the treatment and control groups run parallel to each other (i.e., the parallel trend assumption). This is to ensure that the trajectories of the groups had not already begun to diverge prior to the intervention for unrelated reasons. In addition to visually checking for parallel trends, we statistically tested the assumption by regressing the differences in the pre-intervention period between the treatment and control groups on time.[4] Null findings from these analyses suggest that this assumption was not violated. In other words, prior to the implementation of bail reform, re-arrest rate trends were similar between cases that respectively became bail-eligible and remained bail-ineligible.

Robustness Checks

Comparability of the Public and Non-Public Datasets

The re-arrest measures used in this study come from two separate sources: the two-year re-arrest measures were constructed using non-public data provided by the Office of Court Administration,[5] and pre-constructed six-month pretrial re-arrest measures were pulled from the open-source Department of Criminal Justice Services/Office of Court Administration dataset. To assess consistency, we constructed additional re-arrest measures with the non-public data with the same tracking period as the open-source data (6 months pretrial or until final disposition, whichever came first), and then compared re-arrest rates across the two. The two analyses yielded broadly consistent findings despite the small methodological differences between the databases (e.g., the non-public re-arrest measures are restricted to prosecuted re-arrests, whereas the open-source data also includes non-prosecuted re-arrests).

Intervention Timing

To account for anticipatory changes in bail-setting practices, we repeated our analyses but moved up the interruption date from November 2019 to September 2019. The results were generally consistent across the models. The two-year recidivism analyses with the September interruption showed statistically significant differences in post-intervention trends only for violent felony re-arrest in the "high risk" subgroup ($t = 2.15$, $p = .04$; see Tables S1-S2 below), while the finding was only marginally significant with a November interruption date.

The pretrial re-arrest analyses yielded the same results regardless of the interruption date. Like the main analysis with the November interruption, using the September interruption showed differences in post-intervention trends in the subgroup analysis only for violent felony re-arrest ($t = 2.24$, $p = .03$; see Tables S3-S4 below).

Table S1

Controlled-Interrupted Time Series Models: Two-Year Recidvism with September Interruption

	Coef.	*p*-value	95% Confidence Interval	
Any Re-Arrest				
Treatment	.57	**.01**	.19	.96
Control	.84	**.00**	.65	1.03
Difference	-.27	.22	-.70	.17
Felony Re-Arrest				
Treatment	.54	**.02**	-.11	.97
Control	.82	**.00**	.48	1.17
Difference	-.29	.30	-.84	.27
VFO Re-Arrest				
Treatment	.41	**.00**	.16	.66
Control	.48	**.00**	.35	.62
Difference	-.07	.60	-.36	.21

Note: *p*-values shown in bold indicate statistical significance.

Table S2

Controlled-Interrupted Time Series Models:
Two-Year Recidvism Among Subgroup with September Interruption

	Coef.	*p*-value	95% Confidence Interval	
Any Re-Arrest				
Treatment	.85	**.01**	.22	1.47
Control	1.54	**.00**	1.00	2.09
Difference	-.70	.10	-1.53	.13
Felony Re-Arrest				
Treatment	1.41	**.00**	.81	2.01
Control	1.60	**.00**	1.16	2.05
Difference	-.19	.60	-.94	.55
VFO Re-Arrest				
Treatment	1.30	**.00**	.81	1.79
Control	.71	**.00**	.44	.99
Difference	.59	.04	.03	1.15

Note: *p*-values shown in bold indicate statistical significance.

Table S3

Controlled-Interrupted Time Series Models:
Pretrial Recidivism (Capped at 6 Months) with September Interruption

	Coef.	*p*-value	95% Confidence Interval	
Any Re-Arrest				
Treatment	.96	**.02**	.16	1.76
Control	.57	**.01**	.18	.97
Difference	.39	.38	-.50	1.28
Felony Re-Arrest				
Treatment	1.08	**.00**	.44	1.72
Control	.69	**.00**	.27	1.12
Difference	.38	.32	-.39	1.16
VFO Re-Arrest				
Treatment	.61	**.00**	.36	.85
Control	.38	**.00**	.16	.59
Difference	.23	.16	-.10	.56

Note: *p*-values shown in bold indicate statistical significance.

Table S4

Controlled-Interrupted Time Series Models:
Pretrial Recidivism (Capped at 6 Months) Among Subgroup with September Interruption

	Coef.	*p*-value	95% Confidence Interval	
Any Re-Arrest				
Treatment	1.57	**.01**	.37	2.77
Control	.89	**.03**	.10	1.68
Difference	.68	.34	-.75	2.12
Felony Re-Arrest				
Treatment	2.07	**.00**	1.21	2.93
Control	1.25	**.00**	.60	1.89
Difference	.82	.13	-.25	1.89
VFO Re-Arrest				
Treatment	1.22	**.00**	.88	1.56
Control	.66	**.00**	.28	1.05
Difference	.56	**.03**	.05	1.07

Note: *p*-values shown in bold indicate statistical significance.

Endnotes

1 Linden, A. (2017). A comprehensive set of postestimation measures to enrich interrupted time-series analysis. The Stata Journal, 17(1), 73-88; Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time series analysis: forecasting and control. John Wiley & Sons.

2 McDowall, D., McCleary, R., Meidinger, E. E., & Hay, R. A. (1980). Interrupted time series analysis. SAGE Publications, Inc..; Bottomley, C., Scott, J. A. G., & Isham, V. (2019). Analysing interrupted time series with a control. Epidemiologic Methods, 8(1), 20180010

3 Wooldridge, J. M. (2015). Introductory econometrics: A modern approach. Cengage learning.

4 Bottomley, Scott, & Isham (2019), Op Cit.

5 OCA data provided herein does not constitute an official record of the New York State Unified Court System, which does not represent or warrant the accuracy thereof. The opinions, findings, and conclusions expressed in this publication are those of the authors and not those of the New York State Unified Court System, which assumes no liability for its contents or use thereof.

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