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published in
Multivariate Behavioral Research
2023

DOI (link to publisher)
10.1080/00273171.2022.2160954

citation for published version (APA)
Singh, M., Dolan, C. V., & Neale, M. C. (2023). Integrating Cross-Lagged Panel Models with Instrumental Variables to Extend the Temporal Generalizability of Causal Inference. *Multivariate Behavioral Research*, *58*(1), 148-149. https://doi.org/10.1080/00273171.2022.2160954

Routledge
Taylor & Francis Group

Multivariate Behavioral Research

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/hmbr20

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To cite this article: Madhurbain Singh, Conor V. Dolan & Michael C. Neale (2023) Integrating Cross-Lagged Panel Models with Instrumental Variables to Extend the Temporal Generalizability of Causal Inference, Multivariate Behavioral Research, 58:1, 148-149, DOI: 10.1080/00273171.2022.2160954

To link to this article: https://doi.org/10.1080/00273171.2022.2160954

Published online: 09 Jan 2023.

MULTIVARIATE BEHAVIORAL RESEARCH
2023, VOL. 58, NO. 1, 148–149
https://doi.org/10.1080/00273171.2022.2160954

Integrating Cross-Lagged Panel Models with Instrumental Variables to Extend the Temporal Generalizability of Causal Inference

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The lagged effects in cross-lagged panel models (CLPM) depend on the time interval between repeated measures (Kuiper & Ryan, 2018), usually becoming undetectable at longer intervals. If a study fails to detect a lagged effect, one cannot distinguish whether it is due to the absence of causal effects or too long of a time interval. Therefore, a lack of evidence for causal influences in CLPM cannot be generalized to the overall causal relationship between two variables.

To address this limitation, we present a model integrating instrumental variables (IVs) in CLPM (henceforth, IV-CLPM). Instrumental variables regression (IVR) utilizes exogenous predictors (i.e., the IVs) of a hypothesized exposure variable to estimate its effect on the outcome, without needing any temporal ordering of the two variables (Maydeu-Olivares et al., 2019). Therefore, IV-CLPM (Figure 1) allows for IVR-based estimation of cross-sectional (i.e., "proximal") effects between X and Y at each wave, in addition to the lagged (i.e., "distal") effects traditionally estimated in CLPM. The IVR-estimated proximal effects at T_1 (b_{XY1} and b_{YX1}) reflect the causal process that unfolded *before* the first assessment. The distal effects (b_{XY12} and b_{YX12}) represent the influence of X_1 on Y_2 and of Y_1 on X_2, given the time interval between T_1 and T_2. Lastly, the proximal effects at T_2 (b_{XY2} and b_{YX2}) reflect the causal influences that accumulated *during* the study period but were not captured by the

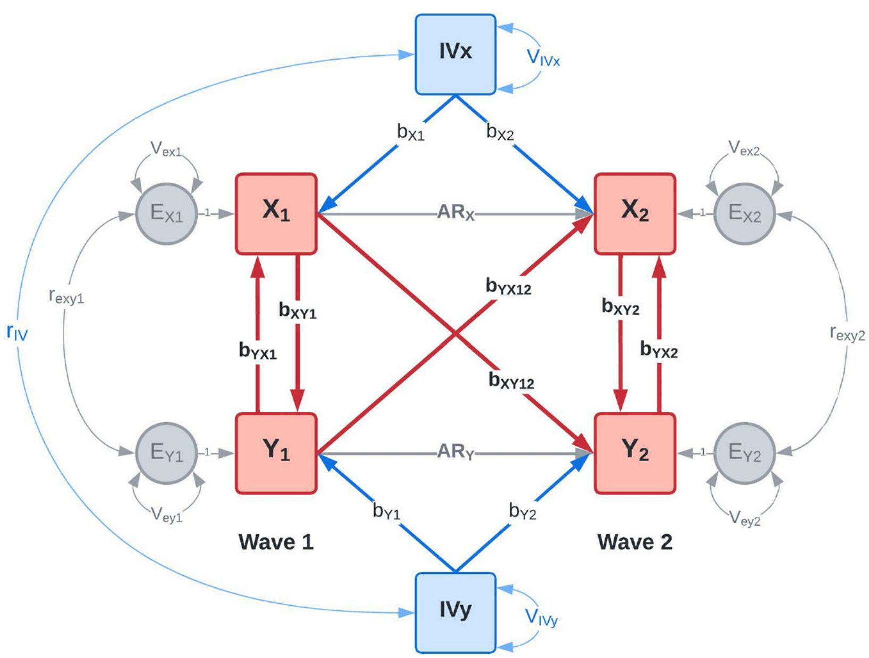

Figure 1. The proposed IV-CLPM model integrates the instrumental variables for X and Y (*IVx* and *IVy*) in a cross-lagged panel model (CLPM), allowing for bidirectional IV regression (IVR)-based estimation of cross-sectional effects at each wave. The model is locally identified.

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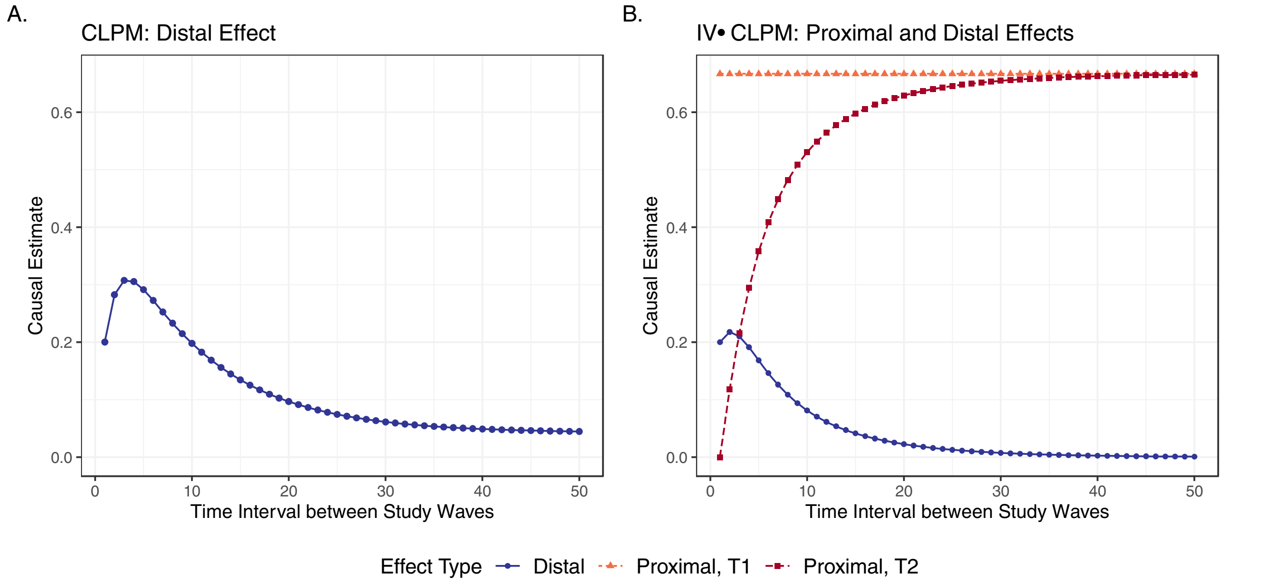

Figure 2. Impact of the time interval between two study waves on (A.) the distal effect in CLPM and (B.) the distal and proximal effects in IV-CLPM. The plots illustrate the estimates for the effect of X on Y obtained from models fitted to a stationary time-series with bidirectional first-order causal effects, with the effect of X_i on $Y_{i+1} = 0.2$, the effect of Y_i on $X_{i+1} = 0.2$, first-order autoregression (AR1) of $X = 0.7$, AR1 of $Y = 0.7$, and the cross-sectional correlation between the residuals of X and $Y = 0.3$. Both models were fitted with wave 1 fixed at an arbitrary time point, T_i, and wave 2 at $T_j = T_i + \Delta T$, where ΔT (the time interval) was increased sequentially from 1 to 50.

distal effects. The terms "proximal" and "distal" underscore the temporal relationship between the exposure and the outcome, indicating whether the outcome (e.g., Y_2) was assessed contemporaneously (b_{XY2}) or subsequently (b_{XY12}).

To demonstrate the impact of the time interval between study waves on the causal inference in CLPM and IV-CLPM, we simulated stationary time-series data, to which we fitted both models with sequentially increasing time intervals (Figure 2). Given stationarity, the estimated parameters depend on the time interval, $\Delta T = T_j - T_i$ $(i < j)$, but not on the time points, T_i and T_j. We demonstrate that, as the distal effects become undetectable at prolonged time intervals, the causal relationship between X and Y remains detectable in the proximal effects in IV-CLPM. Therefore, IV-CLPM can help detect causation even when the traditional CLPM's causal estimates decay at longer intervals, thus addressing the ambiguity of non-significant causal estimates in the latter. Significant proximal effects, with negligible distal effects, would imply that the time interval is too long for studying lagged effects between a pair of variables. Furthermore, the relative effect sizes of the proximal and distal effects could shed light on the relative translational importance of past and concurrent assessments of the exposure.

Article information

Funding: The authors are grateful for support from NIH grant R01DA049867.

Acknowledgments: The first author would like to express their appreciation to their graduate advisor and SMEP sponsor, Michael C. Neale.

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References

Kuiper, R. M., & Ryan, O. (2018). Drawing conclusions from cross-lagged relationships: Re-considering the role of the time-interval. *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(5), 809–823. https://doi.org/10.1080/10705511.2018.1431046

Maydeu-Olivares, A., Shi, D., & Rosseel, Y. (2019). Instrumental variables two-stage least squares (2SLS) vs. maximum likelihood structural equation modeling of causal effects in linear regression models. *Structural Equation Modeling: A Multidisciplinary Journal*, *26*(6), 876–892. https://doi.org/10.1080/10705511.2019.1607740