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Recent Methodological Advances in Panel Data Collection, Analysis, and Application

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Panel studies have become an indispensable part of today's research world especially when addressing causal questions and tracking changes over time. Three conditions are essential for effective panel data analysis: 1) having a sufficiently long time series with a substantial number of observations, 2) ensuring measurement consistency over time, and 3) using a meaningful model for selecting elements from the target population. To meet these conditions, survey research provides appropriate tools (e.g., effective motivational strategies to encourage panel participation or statistical techniques to assess selection and measurement bias). However, it is crucial for researchers and data analysts to not only use these resources, but also remain vigilant regarding potential pitfalls. In addition, new data collection methods are emerging that require researchers to assess their capabilities. This special issue addresses these demands by presenting research on incentive systems and their effects, measurement problems in panel studies, and new applications of panel data.

Keywords: panel; data collection, panel analysis

The list of panel studies has grown considerably in recent times, and this expansion is warranted for several reasons. Due to the widely acknowledged challenges associated with cross-sectional analyses when addressing causal questions and the constraints of randomized experiments, scholars increasingly rely on panel data for causal inference. Additionally, panel data represents the sole practical resource for exploring changes within individual entities over time, ensuring temporal order of cause and effects and offering a valuable solution to the issue of ecological fallacy in the study of social dynamics.

The selection of entities to observe in panel data analysis is contingent upon the specific research inquiry. In the realm of social sciences, these entities typically encompass individuals, households, or businesses. Nowadays, worldwide panel studies encompass an extensive array of diverse subjects. For example, there are large-scale and long-running general population household panels like the Panel Study of Income Dynamics (PSID) in the U.S., Understanding Society in the U.K., and the Socio-Economic Panel (SOEP) in Germany. But there exists also a great variety of topic-specific panel studies such as the German National Education Panel Study (NEPS), the Japanese Life Course Panel Survey of the Youth (JLPS-Y), the African Cape Area Panel Study (CAPS) on health issues, and the Australian Election Study (AES), to mention just very few.

For panel studies to yield valuable and high-quality findings, three essential conditions must be satisfied. Firstly, a sufficiently long time series of a substantial number of observations is necessary to map changes both within and between entities. Secondly, it is imperative that the measurements remain consistent over time, ensuring that the same variables are assessed consistently for the observed entities across different time points. Thirdly, to create broad statements about the population, the underlying sample must originate from a quantifiable and well-controlled data generation process.

To attain the first condition, effective procedures for recruiting and maintaining the observational units within the panel are necessary, but also getting reliable and valid responses is mandatory. In essence, this entails the implementation of motivation strategies and the maintenance of a seamless survey process. Common methods of motivation are providing information and incentives and maintaining contact. That is, respondents receive information about the study and its objectives commonly through letters, brochures (sent via postal mail or electronically), and web pages. Incentives foster high survey participation, especially when providing unconditional monetary incentives shortly before the survey (Pforr et al., 2015). Also staying in touch with respondents between survey waves is advantageous in this respect, as it helps to uphold their commitment to the study

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and ensures that contact information remains up to date.

A seamless survey process requires questionnaires that are understandable, i.e., not too complex concerning cognition and visualization, and, at best, entertaining as well as survey environments without disturbance and inconvenience. That way, respondents can answer truthy and without feeling uncomfortable, thus minimizing the risk of misreporting, satisficing, item-nonresponse and break offs. Instruments to reach this include preloads (e.g., answers from previous waves are given as a starting point), short questionnaires, and targeted survey modes (e.g., self-administered surveys for sensitive questions and interviewer-based modes for complex questions such as inquiries on household income).

It is crucial to acknowledge potential mode and interviewer effects may introduce bias in target statistics when dealing with panel data, especially when combining modes for cost-efficiency. For instance, in a scenario where both Computer-Assisted Personal Interviews (CAPI) and Computer-Assisted Web Interviews (CAWI) are used simultaneously, there is a significant likelihood that each mode will yield varying attitude estimates (see Groves et al., 2011, for reference). This is because selection and measurement may function differently across modes (e.g., Campanelli et al., 2015; Martin & Lynn, 2011; Vannieuwenhuyze et al., 2010). This circumstance also makes it difficult to satisfy the second condition: invariance of measurements over time.

Meeting this requirement is essential when analysing panel data as it guarantees the consistency of constructs. Correcting measurement errors is possible when they are identified or can be modelled (see, for example, Nakamura, 1990). However, addressing this issue necessitates awareness and the use of suitable methodologies, such as measurement models. In general, measurement invariance serves as a quality benchmark and is one of the minimum criteria when designing new questions and item sets (e.g., Leitgöb et al., 2023; Vandenberg & Lance, 2000). Nonetheless, many studies do not automatically adhere to this standard (see, for instance, Rutkowski & Svetina, 2014). There is also limited effort dedicated to regularly evaluating existing measurement instruments for their suitability and limited awareness in applied panel research for this important precondition. Additionally, issues of comparability can arise when translating questions into different languages. A direct translation does not guarantee that respondents will interpret the questions in the same way. Question comprehension and response patterns can be influenced by culture (e.g., Dong & Dumas, 2020; Emerson et al., 2017). Therefore, translations should also provide evidence of measurement invariance, which is often overlooked (ibid.). The likely reason is the contemporary need for swift data collection and analysis, sometimes at the expense of data quality and result reliability. Survey methodology research has a role in highlighting this shortfall (Meitinger et al., 2020).

The third essential requirement for effective panel data analysis is having a meaningful model for the selection of elements from the target population. The statistical theory of sampling makes this a mandatory condition (Kish, 1995). A straightforward method to meet this requirement is to use a random sample drawn according to a well-defined sampling design. Such a design enables the calculation of inclusion probabilities, which are used to determine design weights for extrapolation purposes.

In the course of a panel study, it is common to experience attrition with participants dropping out over time. Typically, this attrition is quantifiable based on the initial gross amount of survey entities, as specified in the sample design. Data from the panel itself (pre-wave information), as well as contextual details about both respondents and non-respondents. The latter is available, for example, through interviewer observations or external data sources such as small-scale regional data.

However, when the data-generating process is unknown (e.g., in non-probability samples), it becomes very difficult to carry out this correction effectively. There are adjustment procedures such as reweighting claiming to make non-probability samples useful for generalization to the population level (e.g., Liu et al., 2022). However, they rely on assumptions that are frequently quite demanding (Kohler, 2019; Kohler et al., 2019) or require an extensive amount of benchmark information sourced from random samples, population registries, or census data. Ideally, these benchmark data would be available on a longitudinal basis, which is seldom the case for population registries and census data. As a result, well-constructed and well-maintained panel surveys often remain the only viable data source for tracking societal changes on a micro, meso and macro level with acceptable data quality.

Hence, survey research needs to consistently introduce and enhance effective techniques for choosing panel samples across diverse settings (such as households, individuals, and businesses) and in various domains (including general population surveys, health assessments, and studies of migrant communities). Moreover, there is an ongoing and pressing requirement for methods to sustain panel stability over multiple survey waves and concepts for regularly refreshing (probability) panel samples.

In this context, this special issue explores scientific inquiries related to panel data within the dynamic interaction between methodological rigor and practical data needs. The following eight papers published in this special issue advance knowledge on the collection and analysis of panel data in important ways:

A first set of studies addresses the issue of suitable incentive schemes in panel studies and highlights the effectiveness of prepaid incentives. Becker (2023) delves into this topic theoretically, emphasizing the concept of reciprocity in unconditional prepaid incentives, and provides empirical evidence for important heterogeneity in panelists' preference for strong reciprocity.

Beste et al. (2023), on the other hand, experiment with various machine learning methods to assess their utility in predicting fieldwork outcomes based on prior wave data, leading to the development of an adaptive incentive scheme that they test through experimentation.

Another group of papers in the special issue deals with response behaviour and measurement issues. Kraemer et al. (2023) investigate satisficing behaviour across different panel waves, utilizing a six-wave experimental approach. They detect satisficing behaviour within individual waves but not consistently across waves.

Rettig and Struminskaya (2023) also address the problem of memory effects in panel studies. They do find such effects, but only on a small scale. Consequently, they conclude that the potential for measurement errors due to memory effects across panel waves is minimal (especially after four months or longer).

Cornesse et al. (2023) explore the impact of significantly increasing survey frequency in an ongoing panel. They present an experimental study conducted during the initial pandemic period where respondents were queried weekly. They identify conditioning effects solely on questions related to COVID-19.

Paccagnella and Guidolin (2023) study the application of anchoring vignettes to address measurement invariance between groups. They investigate both priming effects and panel conditioning effects finding evidence of such effects in questions measuring customer satisfaction with a service.

Finally, two papers in this special issue contribute to the use of panel data in specific substantive research areas. Kopycka et al. (2023) describe an innovative use of cross-national panel data to create a new index for assessing employment precarity. They validate this index by measuring adverse labour market experiences in both Germany and the U.S. using data from established panel studies.

Lastly, Barth and Blasius (2023) present a panel study focused on metropolitan dwellings and their role in understanding neighbourhood development. The primary emphasis of their study lies in analysing rent development and its measurement.

References

Barth, A., & Blasius, J. (2023). Assessing rental price dynamics in two gentrified neighbourhoods in cologne by means of a dwelling panel. *Survey Research Methods*, *17*(3), 395–410. https://doi.org/10.18148/srm/2023.v17i3.7987

Becker, R. (2023). The researcher, the incentive, the panelists and their response: The role of strong reciprocity for the panelists' survey participation. *Survey Research Methods*, *17*(3), 223–242. https://doi.org/10.18148/srm/2023.v17i3.7975

Beste, J., Frodermann, C., Trappmann, M., & Unger, S. (2023). Case prioritization in a panel survey based on predicting hard to survey households by machine learning algorithms. *Survey Research Methods*, *17*(3), 243–268. https://doi.org/10.18148/srm/2023.v17i3.7988

Campanelli, P., Blake, M., Mackie, M., & Hope, S. (2015). *Mixed modes and measurement error: Using cognitive interviewing to explore the results of a mixed modes experiment* [ISER Working Paper Series, (No. 2015-18)]. https://www.econstor.eu/bitstream/10419/126482/1/836342755.pdf

Cornesse, C., Blom, A., Marie-Sohnius, L., González Ocanto, M., Rettig, T., & Ungefucht, M. (2023). Experimental evidence on panel conditioning effects when increasing the surveying frequency in a probability-based online panel. *Survey Research Methods*, *17*(3), 323–339. https://doi.org/10.18148/srm/2023.v17i3.7990

Dong, Y., & Dumas, D. (2020). Are personality measures valid for different populations? A systematic review of measurement invariance across cultures, gender, and age. *Personality and Individual Differences*, *160*, 109956. https://doi.org/10.1016/j.paid.2020.109956

Emerson, S. D., Guhn, M., & Gadermann, A. M. (2017). Measurement invariance of the satisfaction with life scale: Reviewing three decades of research. *Quality of Life Research*, *26*, 2251–2264. https://doi.org/10.1007/s11136-017-1552-2

Groves, R. M., Fowler Jr, F. J., Couper, M. P., Lepkowski, J. M., Singer, E., & Tourangeau, R. (2011). *Survey methodology*. Wiley.

Kish, L. (1995). *Survey sampling*. Wiley.

Kohler, U. (2019). Possible uses of nonprobability sampling for the social sciences. *Survey Methods: Insights from the Field*. https://doi.org/10.13094/SMIF-2019-00014

Kohler, U., Kreuter, F., & Stuart, E. A. (2019). Nonprobability sampling and causal analysis. *Annual Review of Statistics and its Applications*, *6*, 149–172. https://doi.org/10.1146/annurev-statistics-030718-104951

Kopycka, K., Kiersztyn, A., Sawiński, Z., Bieńkowski, S., & Sovpenchuk, V. (2023). Use of panel surveys to measure employment precarity in a cross-national framework. *Survey Research Methods*, *17*(3), 353–393. https://doi.org/10.18148/srm/2023.v17i3.7989

Kraemer, F., Silber, H., Struminskaya, B., Bernd Weiß, M., Bosnjak, Koßmann, J., & Sand, M. (2023). Satisficing response behavior across time: Assessing negative panel conditioning using an experimental design with six repetitions. *Survey Research Methods*, *17*(3), 269–300. https://doi.org/10.18148/srm/2023.v17i3.7986

Leitgöb, H., Seddig, D., Asparouhov, T., Behr, D., Davidov, E., De Roover, K., Jak, S., Meitinger, K., Menold, N., Muthén, B., Rudnev, M., Schmidt, P., & van de Schoot, R. (2023). Measurement invariance in the social sciences: Historical development, methodological challenges, state of the art, and future perspectives. *Social Science Research*, *110*, 102805. https://doi.org/10.1016/j.ssresearch.2022.102805

Liu, A. C., Scholtus, S., & De Waal, T. (2022). Correcting selection bias in big data by pseudo-weighting. *Journal of Survey Statistics and Methodology*, smac029. https://doi.org/10.1093/jssam/smac029

Martin, P., & Lynn, P. (2011). *The effects of mixed mode survey designs on simple and complex analyses* [ISER Working Paper Series, No. 2011-28]. https://www.europeansocialsurvey.org/sites/default/files/2023-06/The%5C%20effect%5C%20of%5C%20mixed%5C%20mode%5C%20survey%5C%20designs.pdf

Meitinger, K., Davidov, E., Schmidt, P., & Braun, M. (2020). Measurement invariance: Testing for it and explaining why it is absent. *Survey Research Methods*, *14*(4), 345–349. https://doi.org/10.18148/srm/2020.v14i4.7655

Nakamura, T. (1990). Corrected score function for errors-in-variables models: Methodology and application to generalized linear models. *Biometrika*, *77*(1), 127–137.

Paccagnella, O., & Guidolin, M. (2023). Question order and panel conditioning analysing self-reported data. *Survey Research Methods*, *17*(3), 341–352. https://doi.org/10.18148/srm/2023.v17i3.7993

Pforr, K., Blohm, M., Blom, A. G., Erdel, B., Felderer, B., Fräßdorf, M., Hajek, K., Helmschrott, S., Kleinert, C., Koch, A., Krieger, U., Kroh, M., Martin, S., Saßenroth, D., Schmiedeberg, C., Trüdinger, E.-M., & Rammstedt, B. (2015). Are incentive effects on response rates and nonresponse bias in large-scale, face-to-face surveys generalizable to Germany? Evidence from ten experiments. *Public Opinion Quarterly*, *79*(3), 740–768. https://doi.org/10.1093/poq/nfv014

Rettig, T., & Struminskaya, B. (2023). Memory effects in online panel surveys: Investigating respondents' ability to recall responses from a previous panel wave. *Survey Research Methods*, *17*(3), 301–322. https://doi.org/10.18148/srm/2023.v17i3.7991

Rutkowski, L., & Svetina, D. (2014). Assessing the hypothesis of measurement invariance in the context of large-scale international surveys. *Educational and Psychological Measurement*, *74*(1), 31–57. https://doi.org/10.1177/0013164413498257

Vandenberg, R. J., & Lance, C. E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods*, *3*(1), 4–70. https://doi.org/10.1177/109442810031002

Vannieuwenhuyze, J., Loosveldt, G., & Molenberghs, G. (2010). A method for evaluating mode effects in mixed-mode surveys. *Public Opinion Quarterly*, *74*(5), 1027–1045. https://doi.org/10.1093/poq/nfq059