STRENGTHENING QUANTITATIVE RESEARCH IN INTERNATIONAL BUSINESS: BEST PRACTICES FOR METHODS AND RESULTS SECTIONS

Abstract

Purpose: This article discusses best practices for the methods and results sections in quantitative international business (IB) studies, with emphasis on data collection, analytical techniques, and additional robustness tests to improve the replicability and reproducibility in the research area.

Design/methodology/approach: The paper reviews best practices in quantitative IB research, focusing on three key themes: research design, data transparency, and rigor. It analyzes exemplar studies in IB research and discusses specific challenges in emerging market contexts.

Findings: This paper identifies ways researchers can strengthen quantitative IB research, including (1) the importance of thorough research design documentation and justification, (2) the need for increasing transparency in data collection and analytical procedures, (3) the value of triangulation across methods, data sources, and analytical techniques, and (4) guidelines for reporting results, including presentation of moderating effects and robustness tests.

Research implications: The best practices and recommendations discussed have important implications for scholars developing quantitative studies – increased transparency and rigor which can improve the quality of a study. More broadly, they help researchers to enhance the credibility and replicability of quantitative research, particularly in dealing with cross-cultural and emerging market contexts. This includes specific recommendations for handling data collection, analysis, and presenting results.

Originality/value: This paper provides guidelines for strengthening quantitative research methods in IB. It addresses current challenges in research credibility and replicability while offering specific guidance for emerging market contexts. We combine methodological best practices with practical examples from exemplar studies.

Key words: quantitative research methods; best practices

Paper type: Viewpoint

Introduction

Recent studies have suggested that there is a crisis of credibility that plagues academia – a very high percentage of studies are unable to be replicated (Aguinis, Cascio, & Ramani, 2017; Bergh, Sharp, Aguinis, & Li, 2017). Some IB scholars have challenged the academic community by questioning whether or not we can trust research findings (Cuervo-Cazurra, Andersson, Brannen, Nielsen, & Reuber, 2016; Sinkovics, Penz, & Ghauri, 2008). Cuervo-Cazurra et al. further asserted that "inclusion of the wrong controls, or exclusion of relevant controls, may seriously affect empirical results and cast in doubt the validity of a study" (2016: 889). Others have pointed to concerns regarding data transparency, HARKing and P-hacking, which undermine research integrity (Beugelsdijk, van Witteloostuijn, & Meyer, 2020; Meyer, van Witteloostuijn, & Beugelsdijk, 2017). To address these concerns, for example, increased transparency in reporting and furthered contextuality of findings have been suggested as possible techniques to enhance replicability and trustworthiness (Reuber & Fischer, 2022; Welch, Paavilainen-Mäntymäki, Piekkari, & Plakoyiannaki, 2022). Sinkovics et al. (2008) underscored the importance of "reliability, validity, generalizability and objectivity" for quantitative research methods. Therefore, this article seeks to discuss some best practices for the methods and results sections in quantitative international business (IB) studies.

Best Practices Quantitative Research Methods Section

Research design. A solid research design lies at the heart of rigorous research. Miller, Moore and Eden (2024) suggested that in studies that use quantitative methods, the research design influences data selection and analytical techniques to test hypotheses (also see Šilenskytė & Smale, 2021). However, many quantitative studies entail 'mismatches' – e.g., with respect to (1) research question and methods and (2) data-theory.[1] The former involves inappropriate selection

of a method – in particular analytical technique(s) relative to the research question asked. The latter is especially prevalent – e.g., poor measures that raise construct validity concerns (e.g., dummy variables to capture key constructs such as institutional differences). Another concern pertains to the use of static measures/cross-sectional data that capture dynamic theoretical relationships. Thus, the analysis does not test the phenomenon in question – such as how firms learn over time and reduce liability of foreignness as they expand abroad. These research design issues can stir ethical concerns in the IB research community.

Miller et al. (2024) urged IB scholars to carefully consider data needs/requirements and identify data quality issues. Moreover, they suggested that a solid research design addresses potential analytical concerns. For both archival and survey data, IB researchers need to anticipate cultural issues with respect to measurements and ensure that those measurements capture the constructs under study. They need to explain why the chosen analytical technique is suitable for hypothesis testing and provide a theoretical rationale for potential econometric issues such as endogeneity. Surveys need to be developed with best practices in mind (see Chidlow, Ghauri, Yeniyurt, & Cavusgil, 2015) and all steps (e.g., pre-testing procedures and psychometric properties) need to be disclosed in the methods section. Belderbos, Lee, Mudambi, Du, and Somers (2024) provide an exemplary research design. These authors provided a detailed explanation of the data sources and a detailed discussion with respect to defining and classifying "global cities". They allude to their conceptualization and theory and efforts to "improve the alignment" of their theory and empirical tests (2024: 5). They were transparent concerning the distribution of R&D investments across global cities and the measurement of all variables. They provide an extensive discussion of why they use a random parameter (mixed) logit model

including advantages over other types of logit models. Their robustness tests sought to address endogeneity concerns.[2]

Data transparency. Aguinis, Ramani and Alabduljader defined transparency as the "degree of detail and disclosure about the specific steps, decisions, and judgment calls made during a scientific study" (2018: 83). Scholars need to be transparent in terms of data collection and analysis. For data transparency, we urge scholars to disclose fully the sources of archival data. If it is a new data set, we strongly recommend disclosing the procedures undertaken to collect the data and measure each item. It is important to discuss the time period selected, justify the range, and explain if major events (e.g., a pandemic) occurred during the period under study and how such events may influence the results. Moreover, researchers need to discuss how they arrived at the final sample.

An exemplar study regarding data transparency is Dai, Eden and Beamish (2017). These scholars clearly described their data sources and the data collection process for identifying the locations of subsidiaries and wars using geographic coordinates. They also provide detailed explanations of the variables and choice of statistical analysis - in their case, a Cox Proportional hazard model. Moreover, they sought to 'accurately gauge rates of exit in response to war, they incorporated multiple "onsets of risk"' into their hazard models in order "to capture true periods of war" (2017: 1486). Similarly, the Xu, Hitt and Dai (2020) study demonstrates transparency with respect to data sources. Demonstrating completeness, clarity and credibility in the methods section (Zhang & Shaw, 2012), the Xu et al. study was thorough in terms of explaining measurement of key variables and use of a generalized estimating equation (GEE) model. For example, they provided detailed explanations of the computation of variables such as the breadth (and depth) of international diversification.

Triangulation. Jick (1979) provided one of the early calls for researchers to use triangulation, which can be effective for "controlling for errors, biases, and omissions of particular methods and techniques" (Nielsen et al., 2020: 1492). More recently, Nielsen et al. (2020) broadened the scope of triangulation. Specifically, they encourage IB researchers to consider (1) method triangulation, which refers to "Combining two or more methods (multimethod) within the same study";[3] (2) data triangulation, which is described as "Combining multiple data sources or multiple techniques for data collection within a single method study"; (3) analytical triangulation, which reflects to "Using different analytical techniques on the same dataset within a single-method study". In addition, they urge the use of contextual triangulation (i.e., "Building in differences in setting, location, unit, and time during data collection and analysis") and investigator triangulation (i.e., "Using more than one researcher to collect data and/or interpret results") (2020: 1493).[4] One opportunity for triangulation involves using natural experiments such as event study methodology (ESM). Interestingly, most ESM software packages include parametric and non-parametric test statistics, which is another form of analytical triangulation. In terms of opportunities of data triangulation, we recommend interviewing (1) subjects/executives who understand causality with respect to the study and the use of accounting and market data and (2) key local actors who may help with gathering survey data and identifying suitable measures for key variables in a particular country. In emerging markets, we strongly recommend checking data sources and comparing them with local market observations and expectations.

Despite calls for triangulation in research involving quantitative methods, exemplary studies tend to appear in other fields (e.g., see Foss & Ellefsen, 2002; Homburg, Klarmann, Reimann, & Schilke, 2012)[5] or concerning qualitative methods in IB (e.g., Hurmerinta &

Nummela, 2011). However, Kurokawa, Iwata and Roberts (2007) used qualitative and quantitative approaches for data collection. Specifically, they used survey data from R&D subsidiaries of Japanese MNCs in the United States as well as interviews of subsidiary and headquarter managers. Wolfolds and Siegel (2019) triangulated with respect to analytical techniques in their study of the performance implications of foreign market entry via acquisition or greenfield. When feasible or appropriate (Wellman, Tröster, Gromes, Roberson, Rink, & Gruber, 2023), we recommend triangulation (e.g., data or analytical triangulation) to enhance the quality and rigor of a study.

Pursuing rigor. Nielsen et al. defined methodological rigor as "a scholarly community's standards regarding all aspects of the research process: the design, data collection, analysis, and reporting of the study." (2020: 1479). A key aspect of any quantitative study is drawing attention to potential biases and demonstrating that the study has taken the necessary precautions to eliminate or neutralize their effect on the results. Biases can arise from the nature of the research question, during the data collection process, or from the analytical techniques selected. For example, in survey-based studies, scholars need to disclose all steps taken for data gathering involving human subjects (e.g., pretesting, response rates). They also need to discuss procedures undertaken to ensure equivalence (Hult et al., 2008).[6] If the study involves constructs that have been known to produce social desirability bias, then we urge scholars to consider alternative data techniques that can mitigate the bias, such as best-worst scaling (see Auger, Devinney, & Louviere, 2007).

Some quantitative IB studies tend to involve a high degree of complexity (Eden & Nielsen, 2020). In these situations, IB scholars can mitigate biases by using non-traditional analysis techniques that may be unfamiliar to the scholar. Failure to do so can create biased

coefficients and standard errors, both of which can produce incorrect results. In these situations, we recommend that researchers consult a methods expert. Alternatively, where possible, we suggest authors to collaborate with a research methods expert on a particular analytical technique in order to ensure it is performed correctly.

Conducting research across different countries poses language challenges for researchers. This is particularly difficulty in emerging markets and regions with linguistic diversity. In those contexts, researchers face high translation costs and distribution constraints to make questionnaires accessible across such diverse populations, which can undermine data collection, threatening data reliability, validity, and comparability (Ghauri & Chidlow, 2017). Hult et al. (2008) asserted that data collection and sampling procedures are critical to ensure equivalence across different markets. Researchers have to establish measures to safeguard data comparability in cross-cultural research. Achieving data equivalence – ensuring that survey questions hold consistent meaning and interpretation across all countries and cultures (Craig & Douglas, 2001) – requires researchers to take specific actions. The lack of information can compromise the trust and quality of the data collected, as participants from different linguistic backgrounds may interpret questions and numerical scales differently. For example, scales measuring satisfaction or agreement may not carry the same weight or meaning in every language or culture, leading to responses that researchers may be unable to standardize. Constructs and definitions may also vary across markets and require special attention from researchers. Such differences threaten data comparability across regions, demanding more research on language-sensitive methodologies in quantitative studies. Craig and Douglas (2001) urged researchers to introduce measures to safeguard the comparability of results, such as a multi-national team with researchers from the countries involved in the study, who will participate in all stages of the

research and contribute to the development of the questionnaire, sampling procedures, data collection, and interpretation of results. Moreover, Hult et al. (2008) argued that to achieve data collection equivalence, researchers are required to recruit parallel respondents in each country, align sampling frame techniques and procedures, and minimize time gaps between data collection across different countries.

In a slight twist using archival data, Solarino and Buckley (2023) provide an equivalence example using performance data from Mainland China, Hong Kong SAR, and Singapore. Their thoughtful approach discussed construct equivalence (i.e., "the extent to which a construct is valid and reliable across countries" (2023: 555)), method equivalence (i.e., the degree of similarity in data collection method across countries), and item equivalence (the extent to which "measures behave similarly across countries" (2023: 557)). After justifying the sample countries, the authors provided detailed explanations of the different approaches used to test for equivalence. Their article provided a persuasive argument that equivalence analysis is suitable for survey-based IB research as well as archival data-oriented IB research.

Reporting results in quantitative papers

For the presentation of results in studies using quantitative research methods, it is essential to provide summary statistics with correlations. Moreover, it is important to address high correlations and explain if they influence the results by providing test results for evidence of multicollinearity (variance inflation factor test). Studies that use panel data need to report results on the appropriateness of fixed or random effects. Also, the study needs to provide test results for outliers and discuss whether alternative analytical techniques are warranted. IB studies that use surveys need to be transparent in terms of pre-testing, data equivalence tests and procedures to

alleviate common method variance. Also, the study needs to explain the choice of analytical technique and justify its suitability for testing the hypotheses.

When feasible, we recommend the use of a hierarchical regression approach in which the first model includes only control variables. The study needs to assess this model (e.g., f statistic) to determine if the chosen controls provide a suitable baseline. The second model needs to include the control variables plus the main effects and a test as to whether the main effects improved the explanatory power of the model (i.e., the change in r-squared or change in log likelihood). For studies with moderators, the third model adds the moderator variables or squared terms (for hypotheses that predict non-linear relationships). If one variable moderates multiple variables, then consider estimating models that include each moderator separately and discuss whether or not the results are similar to the full model that includes all the moderator variables. Again, examine the change in r-squared (or change in log likelihood) to determine if the model increases the predictive power of the model relative to the model without interactions and consider including a simple slopes test.

Although we emphasized data transparency above, it is also important to be transparent with respect to the analysis, reported results and robustness tests (e.g., Zhang, Li, & Li, 2014). Some scholars have advocated for disclosing *degrees of freedom*, which "reflect the difference between the unique pieces of summary information provided by the data…and the number of parameters that the data are being used to estimate…" (Cortina, Green, Keeler, & Vandenberg, 2017: 351) and *effect sizes*, which "estimate the magnitude of effect or association between two or more variables" (Ferguson, 2009: 532). Failure to disclose the degrees of freedom makes it impossible for the scholarly community to "determine whether the correct model was tested", especially with multi-level modeling.[7] Acknowledging recent work that challenges the scholarly

community's preoccupation with p-value <0.05 as an indication of statistical significance (Meyer et al., 2017), disclosure of effects sizes can provide insights about a study's quantitative results, especially when samples are small or very large.

Some analytical techniques have their own idiosyncrasies in terms of reporting results. For instance, hierarchical linear modeling (Lindner, Puck & Doh, 2021) and structural equation modeling (SEM). For the former, scholars provide results for intraclass correlation coefficients as well as a model's fit – e.g., root mean square error of approximation (RMSEA) and comparative fit index (CFI); normed fit index (NFI); goodness of fit index (GFI) and Tucker-Lewis index (TLI) as shown in Lee, Yang and Ghauri (2023). For the latter, scholars provide test results for reliability and validity of measurement models. Relatedly, IB studies involving mediation need to report the total effect, indirect and direct effects (e.g., see Tolstoy, Nordman, & Vu, 2022). For example, consider meta-analysis. IB scholars have also used meta-analysis to summarize a field's research base (Steel, Beugelsdijk, & Aguinis, 2021; Wan, Sousa, Lengler, & Tan, 2023) and evaluate and analyze quantitative research findings (Kirca & Yaprak, 2010) in the area. In a commentary article, Steel et al. (2021) provided guidelines for authors who conduct meta-analysis, including data collection, data preparation, data analysis, and reporting. When reporting their results, authors of meta-analysis must emphasize transparency and replicability, meaning that all steps taken should be described in such a way that any researcher could achieve the same results (Steel et al., 2021). This will ensure that these studies are able to be subjected to rigorous scrutiny to verify the validity of conclusions. An exemplary study for reporting meta-analysis results is Dong, He, and Blut's (2024) article. In their study, the authors describe the results of effect size integration, subgroup analysis, and meta-regression analysis. Moreover, they used subgroup analysis and meta-regression to assess the moderating influence of effect

sizes. For other types of analysis, if idiosyncrasies exist – as we showed with SEM and meta-analysis – then the authors need to follow best practices and demonstrate transparency.

We encourage IB scholars to plot interactions (+/- 1 standard deviation, and if necessary, +/- 2 standard deviations), which helps to visualize the findings in the table. Quantify the interaction effect at different levels of the moderator. We discourage rescaling the y-axis to a very small range to give the illusion of different slopes when the interaction effect may be driven by low standard errors arising from a large sample. Kingsley, Noordwier and Vanden Bergh (2017) discussed concerns about overstating and understating moderator effects and urged IB scholars to engage in "better testing and interpretation of interaction models" by examining the range within which a moderator is significant and not significant (2017: 288). In an exemplar study that examines country level IP protection, Jandhyala (2015) identified the ranges of statistical significance and thus avoided overstating the moderating effect of domestic health and understating the moderating effect of domestic interest group on the relationship between WTO commitment and IP protection.

The nonlinear nature of logit/probit models (also hazard models) makes the interpretation of coefficients more challenging, and thus scholars need to consider the marginal effects (Hoetker 2007). In a study of Japanese alliance dissolution, Hu, Jain, and Delios (2021) provide an exemplar on plotting marginal effects – not only for the main effect of centrality asymmetry but also for the moderating effects of cooperation intensity and external competition (2021: 69, 71). Collectively, these studies show that a more comprehensive approach to analyzing moderators can provide valuable insights and more precise contributions (e.g., conditional support for moderator hypotheses).

As a demonstration of rigor, we support the use of various robustness tests (e.g., other proxies for selected variables), and tests for reverse causality (Cordero & Miller, 2019), as well as alternative specifications to alleviate concerns about a potential problem – e.g., potential sources of endogeneity (see Lavie & Miller, 2008).[8] Dai, Eden and Beamish (2023) provide an exemplary discussion of measures as well as endogeneity. They motivate the use of instrumental variable simultaneous equations and provide a detailed discussion of what constitutes a strong instrument. Moreover, they test and provide results for under- and over-identification as well as clear analysis of effect sizes.

Data in Emerging and Developing Countries

Emerging market (EM) data transparency issues pose significant challenges for scholars conducting research in those settings. These challenges can stem from government interference that can lead to biased or incorrect data. The use of indices (e.g., International Monetary Fund), and the methodologies used by these organizations may bias data, while economic forecasts often remain subjective. Local governments can also overestimate economic aggregates, such as growth, demand, and employment rate, to present favorable economic conditions.

IB researchers collecting data through surveys in EM may face low response rates due to the low engagement of participants with surveys. To address this issue, researchers have employed third-party organizations to collect data, which demands attention to and scrutiny of the methods and data collection techniques applied in each country. This requires researchers to have a clear understanding of the sample selection and data collection techniques used to ensure comparability, consistency and accuracy.

Due to the constraints for obtaining data from emerging markets, we urge IB researchers to survey local executives on topics such as firm performance relative to peers, industry conditions, and top management team attributes and consider the use of new measures to provide contextually relevant insights (Rosenberg & Goodwin, 2016). However, the use of those measures must be justified in each research context, ensuring they capture complex phenomena accurately. Dikova and van Witteloostuijn (2007) represent an exemplar for data collection in emerging markets – namely European transition economies. Their study provided a detailed discussion of survey languages, as well as translation/back-translation and pilot testing procedures.

Big Data Issues in Emerging and Developing Countries

Big data has significantly impacted the IB research field. According to George, Osinga, Lavie and Scott, researchers can "leverage big data that are generated from a plurality of sources, including mobile transactions, wearable technologies, social media, ambient networks, and business transactions" for their studies (2016: 1493). This can be achieved by the three core elements of big data: volume, variety, and velocity. Studying emerging markets, Chandy, Hassan, & Mukherji (2017) demonstrate how big data can be used to leapfrog from data poverty to large quantities of data. The large volumes of digital information available present IB researchers with opportunities to develop new studies, especially in contexts where other sources of data might be scant or difficult to obtain. These new studies can focus on relevant themes for large and neglected populations, including poverty, migration, and corruption. However, these new opportunities can be limited in emerging markets due to the scarcity of human resources, infrastructure shortages, and institutional constraints (Joubert, Murawski, & Bick, 2023). Examining big data readiness in African countries, Joubert et al. (2023) revealed that countries

can present significantly different scenarios in terms of volume, variety, and velocity of data available. Those disparities may threaten cross-country data comparison. In this case, researchers must safeguard the comparability of data by triangulating the results of each country involved in the study vis-a-vis consulting local experts.

AI/Machine learning

In the digital age, advances in technology have enabled some scholars to use artificial intelligence (AI) into the research process. AI provides IB researchers with opportunities yet many challenges and ethical issues (Miller et al., 2024). Many of the challenges arise from the researchers' inability to explain fully the data generation process, to understand all biases of the research and programming teams, or to the ability to misuse AI during the research process. For example, machine learning involves biases – e.g., ethical issues that stem from the programmer's biases or from the data used to train computers to learn.[9] Work by Budhwar, Chowdhury and Wood (2023), for example, calls us to exercise caution in the use of AI/machine learning – as well as to be aware of ethical concerns – while adhering to the aforementioned guidelines with respect to research design, transparency, triangulation, rigor, and reporting.

CONCLUSION

The present article seeks to improve the way in which IB studies discuss data collection, analytical techniques, and additional robustness tests in quantitative IB studies in order to address growing concerns about replicability and reproducibility. We focus on three key themes: research design, data transparency, and rigor. We also discuss best practices in the reporting of results. The themes do not operate separately, but are intertwined. For instance, data equivalence is more than conducting tests. It needs to be incorporated into the research design as

well as the sampling, surveying procedures, and analysis; all of which, need to be comprehensively disclosed in the methods and results sections.

We are unable to address every quantitative research methods situation, but strongly recommend that IB scholars consult with more current 'best practice' articles with respect to data collection and analytical techniques (e.g., Eden, Nielsen, & Verbeke, 2020).[10] It is critical to adhere completely "to the prescribed practices"…rather than "cherry picking from recommended practices without disclosing" (Kreamer, Albritton Tonidandel, & Rogelberg, 2023: 387). Moreover, IB scholars need to refrain from "inaccurately following the methodological best practices" (2023: 387), which compromises the rigor of a study and introduces ethical issues. Throughout the article, we draw attention to some examples of exemplary studies. Lastly, we highlight some issues with emerging and developing countries – which present challenges, yet offer great opportunity for IB scholars in the years ahead. We hope this article helps to strengthen the quality of IB scholarship.

REFERENCES

Aguinis, H., Cascio, W., & Ramani, R. 2017. Science's reproducibility and replicability crisis: International business is not immune. *Journal of International Business Studies*, 48: 653-663.

Aguinis, H., Ramani, R., & Alabduljader, N. 2018. What you see is what you get? Enhancing methodological transparency in management research. *Academy of Management Annals*, 12, 83-110.

Auger, P., Devinney, T., & Louviere, J. 2007. Using best–worst scaling methodology to investigate consumer ethical beliefs across countries. *Journal of Business Ethics,* 70: 299-326.

Belderbos, R., Lee, G., Mudambi, R., Du, H., & Somers, D. 2024. When does international knowledge connectivity of global cities attract R&D investments? The role of concentrated ownership through organizational pipelines. *Research Policy*, 53: 105083.

Bergh, D., Sharp, B., Aguinis, H., & Li, M. 2017. Is there a credibility crisis in strategic management research? Evidence on the reproducibility of study findings. *Strategic Organization*, 15: 423-436.

Beugelsdijk, S., van Witteloostuijn, A., & Meyer, K. 2020. A new approach to data access and research transparency (DART). *Journal of International Business Studies*, 51: 887-905.

Budhwar, P., Chowdhury, S., Wood, G., et al. 2023. Human resource management in the age of generative artificial intelligence: Perspectives and research directions on *ChatGPT*. *Human Resource Management Journal*, 33: 606-659.

Chandy, R., Hassan, M., & Mukherji, P. 2017. Big data for good: Insights from emerging markets. Journal of Product Innovation Management, *34*: 703-713.

Chidlow, A., Ghauri, P., Yeniyurt, S., & Cavusgil, S.T. 2015. Establishing rigor in mail-survey procedures in international business research. *Journal of World Business,* 50: 26-35.

Cordero, A., & Miller, S.R. 2019. Political party tenure and MNE location choices. *Journal of International Business Studies* 50: 973-997.

Cortina, J., Green, J., Keeler, K., & Vandenberg, R. 2017. Degrees of freedom in SEM: Are we testing the models that we claim to test? *Organizational Research Methods*, 20: 350-378.

Craig, C. S., & Douglas, S.P. 2001. Conducting international marketing research in the twenty-first century. *International Marketing Review*, 18: 80-90.

Cuervo-Cazurra, A., Andersson, U., Brannen, MY, Nielsen, B., & Reuber, A.R. 2016. From the Editors: Can I trust your findings? Ruling out alternative explanations in international business research. *Journal of International Business Studies*, 47: 881-897.

Dai, L., Eden, L., & Beamish, P. 2017. Caught in the crossfire: Dimensions of vulnerability and foreign multinationals' exit from war-afflicted countries. *Strategic Management Journal*, 38: 1478-1498.

Dai, L., Eden, L., & Beamish, P. 2023. The timing and mode of foreign exit from conflict zones: A behavioral perspective. *Journal of International Business Studies*, 54: 1090-1104.

Dikova, D., & Van Witteloostuijn, A. 2007. Foreign direct investment mode choice: Entry and establishment modes in transition economies. *Journal of International Business Studies*, 38: 1013-1033.

Dong, Y., He, X., & Blut, M. 2024. How and when does digitalization influence export performance? A meta-analysis of its consequences and contingencies. *International Marketing Review*, 41:1388-1413.

Eden, L., & Nielsen, B. 2020. Research methods in international business: The challenge of complexity. *Journal of International Business Studies*, 51: 1609.

Eden, L., Nielsen, B., & Verbeke, A. 2020. *Research methods in international business*. Palgrave Macmillan.

Ferguson, C. 2009. An effect size primer: A guide for clinicians and researchers. *Professional Psychology: Research and Practice*, 40: 532-538.

Foss, C., & Ellefsen, B. 2002. The value of combining qualitative and quantitative approaches in nursing research by means of method triangulation. *Journal of Advanced Nursing*, 40: 242-248.

George, G., Osinga, E., Lavie, D., & Scott, B. 2016. Big data and data science methods for management research. *Academy of Management Journal*, 59: 1493-1507.

Ghauri, P., & Chidlow, A. 2017. Data collection procedure equivalence in emerging economy market research. In M. Marinov (ed.), *Research Handbook of Marketing in Emerging Economies* (9-29). Edward Elgar Publishing.

Goerzen, A., Asmussen, C., & Nielsen, B. 2013. Global cities and multinational enterprise location strategy. *Journal of International Business Studies,* 44: 427-450.

Hoetker, G., 2007. The use of logit and probit models in strategic management research: Critical issues. *Strategic Management Journal*, 28: 331-343.

Homburg, C., Klarmann, M., Reimann, M., & Schilke, O. 2012. What drives key informant accuracy? *Journal of Marketing Research*, 49: 594-608.

Hu, T., Jain, A. & Delios, A. 2021. Centrality asymmetry and partner complementarity as influences on alliance dissolution. *British Journal of Management*, 32: 59-79.

Hult, G.T.M., Ketchen, D.J., Griffith, D.A., Finnegan, C.A., Gonzalez-Padron, T., Harmancioglu, N., Huang, Y., Talay, M.B. and Cavusgil, S.T., 2008. Data equivalence in cross-cultural international business research: assessment and guidelines. *Journal of International Business Studies*, 39: 1027-1044.

Hurmerinta, L., & Nummela, N., 2011. Mixed-method case studies in international business research. In R. Marschan-Piekkari & C. Welch (Eds.), *Rethinking the case study in international business and management research*. Edward Elgar Publishing, 210-228.

Jandhyala, S. 2015. International and domestic dynamics of intellectual property protection. *Journal of World Business*, 50: 284-293.

Jick, T.D. 1979. Mixing qualitative and quantitative methods: Triangulation in action. Administrative *Science Quarterly*, 24: 602–611.

Joubert, A., Murawski, M., & Bick, M. 2023. Measuring the big data readiness of developing countries–index development and its application to Africa. *Information Systems Frontiers*, 25: 327-350.

Kingsley, A., Noordewier, T., & Bergh, R. 2017. Overstating and understating interaction results

in international business research. *Journal of World Business*, 52: 286-295.

Kirca, A., & Yaprak, A., 2010. The use of meta-analysis in international business research: Its current status and suggestions for better practice. *International Business Review*, 19: 306-314.

Kurokawa, S., Iwata, S. & Roberts, E. 2007. Global R&D activities of Japanese MNCs in the US: A triangulation approach. *Research Policy*, 36: 3-36.

Lavie, D., & Miller, S.R. 2008. Alliance portfolio internationalization and firm performance. *Organization Science*, 19: 623-646.

Lee. J.Y., Yang, Y.S., & Ghauri, P. 2023. E-commerce policy environment, digital platform, an international of Chinese new ventures: Th moderating effects of Covid-19 pandemic. *Management International Review*, 63: 57-90.

Lindner, T., Puck, J., & Doh, J. 2021. Hierarchical modelling in international business research: Patterns, problems, and practical guidelines. *Journal of World Business*, 56: 101224.

Meyer, K., van Witteloostuijn A., & Beugelsdijk, S. 2017. What's in a p? Reassessing best practices for conducting and reporting hypothesis-testing research. *Journal of International Business Studies*, 48: 535-551.

Miller, S.R., Moore, F., & Eden, L. 2024. Ethics and international business research: Considerations and best practices. *International Business Review*, 33: 102207.

Nielsen, B.B., Welch, C., Chidlow, A., Miller, S.R., Aguzzoli, R., Gardner, E., Karafyllia, M., & Pegoraro, D. 2020. Fifty years of methodological trends in JIBS: Why future IB research needs more triangulation. *Journal of International Business Studies,* 51: 1478-1499.

Reuber, A.R., & Fischer, E. 2022. Putting qualitative international business research in context (s). *Journal of International Business Studies*, 53: 27-38.

Rosenberg, A., & Goodwin, L. 2016. The dos and don'ts of working with emerging-market data. *Harvard Business Review*. https://hbr.org/2016/07/the-dos-and-donts-of-working-with-emerging-market-data.

Šilenskytė, A., & Smale, A. 2021. Multilevel theorizing in international business: The case of research on strategy implementation in MNCs. *Critical Perspectives on International Business*, 17: 502-521.

Sinkovics, R., Penz, E., & Ghauri, P. 2008. Enhancing the trustworthiness of qualitative research in international business. *Management International Review*, 48: 689-714.

Solarino, A., & Buckley, P. 2023. Equivalence in international business research: A three-step approach. *Journal of International Business Studies,* 54: 550-567.

Steel, P., Beugelsdijk, S., & Aguinis, H. 2021. The anatomy of an award-winning meta-analysis: Recommendations for authors, reviewers, and readers of meta-analytic reviews. *Journal of International Business Studies*, 52, 23-44.

Tolstoy, D., Nordman, E., & Vu, U. 2022. The indirect effect of online marketing capabilities on the performance of e-commerce SMEs. *International Business Review*, 31: 101946.

Wan, C., Sousa, C., Lengler, J., & Tan, Q., 2023. Entry mode choice: a meta-analysis of antecedents and outcomes. *Management International Review*, 63: 193-246.

Welch, C., Paavilainen-Mäntymäki, E., Piekkari, R., & Plakoyiannaki, E. 2022.Reconciling theory and context: How the case study can set a new agenda for international business research. *Journal of International Business Studies,* 53: 4-26.

Wellman, N., Tröster, C., Grimes, M., Roberson, Q., Rink, F. and Gruber, M. 2023. Publishing multimethod research in AMJ: A review and best-practice recommendations. *Academy of Management Journal*, 66: 1007-1015.

Wolfolds, S., & Siegel, J. 2019. Misaccounting for endogeneity: The peril of relying on the Heckman two-step method without a valid instrument. *Strategic Management Journal*, 40: 432-462.

Xu, K., Hitt, M., & Dai, L. 2020. International diversification of family-dominant firms: Integrating socioemotional wealth and behavioral theory of the firm. *Journal of World Business*, 55: 101071.

Zhang, Y.A., Li, H., Hitt, M., & Cui, G. 2007. R&D intensity and international joint venture performance in an emerging market: Moderating effects of market focus and ownership structure. *Journal of International Business Studies*, 38: 944-960.

Zhang, Y.A., Li, Y., & Li, H., 2014. FDI spillovers over time in an emerging market: The roles of entry tenure and barriers to imitation. *Academy of Management Journal*, 57: 698-722.

Zhang, Y.A., & Shaw, J. 2012. From the editor: Publishing in AMJ – Part 5: Crafting the methods and results. *Academy of Management Journal*, 55: 8-12.

Table 1: Exemplars in Quantitative RM in IB

RM issues	Motivational articles	Exemplary articles
Research Design	Šilenskytė and Smale (2021)	Goerzen, Asmussen and Nielsen (2013); Belderbos, Lee, Mudambi, Du and Somers (2024)
Data transparency	Cortina et al. (2017); Beugelsdijk, van Witteloostuijn and Meyer (2020); Miller, Moore and Eden (2024); Zhang and Shaw (2012)	Dai, Eden and Beamish (2017); Xu, Hitt and Dai (2020)
Triangulation	Homburg et al. (2012); Jick (1979); Nielsen et al. (2020)	Kurakawa, Iwata and Roberts (2007); Wolfolds and Siegel (2018)
Pursuing rigor	Ghauri and Chidlow (2017)	Dai, Eden and Beamish (2023); Zhang, Li, and Li (2014)
Reporting results	Meyer, van Witteloostuijn, and Beugelsdijk (2017); Zhang and Shaw (2012)	Hu, Jain and Delios (2021); Jandhyala (2015); Zhang, Li and Li (2014); Zhang, Li, Hitt and Cui (2007)
Emerging markets and data	Eden and Nielsen (2020); Rosenberg and Goodwin (2016)	Dikova and van Witteloostuijn (2007)
Big data in issues in emerging and developing countries	George, Osinga, Lavie, and Scott (2016)	Chandy, Hassan and Mukherji (2017); Joubert, Murawski and Bick (2023)

See Eden, Nielsen and Verbeke (2020) for additional guidance.

ENDNOTES

[1] We thank the reviewer for this comment.

[2] Another paper with exemplary research design – that by coincidence is on the same topic – is Georzen, Asmussen and Nielsen (2013).

[3] It includes mixed-method designs that involve qualitative and quantitative research methods.

[4] They also mention theoretical triangulation, which is not discussed in the present methods article.

[5] Homburg et al. (2012) examined construct-specific attributes and informant attributes that increase or decrease informant reliability. Their study underscores the importance of triangulation by showing that it is especially beneficial in conditions when key informant response accuracy is likely to be low as well as when there is limited or no prior support of key informant response reliability for a specific research setting.

[6] The key themes are not independent. Thus, the topics – such as equivalence – could have been introduced in the discussion of research design or data transparency.

[7] We thank a reviewer for sharing this insight.

[8] The Zhang et al. (2014) study also demonstrates rigor with its extensive supplemental analysis. In each supplemental analysis, the authors exhibited transparency with procedures and findings (even when a supplemental finding was not statistically significant).

[9] See Miller, Moore and Eden (2024) for additional discussion on the ethical issues.

[10] Also see Organizational research Methods for excellent research methods articles and for IB specific editorials on methods, see https://link.springer.com/collections/efhbejagjh).