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THE QUANTITATIVE DISCOVERY: WHAT IS IT AND HOW TO GET IT PUBLISHED

For most management scholars, the term "induction" is nearly antithetical with quantitative research. Social scientists learn early on in their career that in contrast to qualitative research, which by nature is "inductive and interpretive," quantitative research is grounded upon a "hypothetical-deductive model" driven by the testing of general *a priori* propositions (Gephart, 2004: 455). But might there not be some middle ground?

In this FTE, we argue that the application of quantitative approaches to describe and examine organizational problems, anomalies, and management-related phenomena lying beneath the radar may serve as a critical means of laying the groundwork for theory generation. This is not a new idea. Indeed, in arguing our position below, we highlight well-known studies that used numbers rather than words to call attention to anomalies requiring new theoretical formulations, providing empirically driven insights to guide theoretical development along the way. Moreover, we also highlight some of the unique demands made of researchers when using quantitative data and methods in the interests of discovery such as the collection of data from unconventional contexts and the use of analytics specifically designed to uncover atypical and unexpected patterns. Specifically, quantitative data collection and analyses in *AMD* articles are undertaken for the purpose of revealing, describing, and diagnosing interesting phenomena that are poorly understood, as distinct from purposes in other journals of testing hypotheses or filling gaps in established research areas. After defining the nature and purpose of quantitative discovery in management, we highlight how it has been used in the past, and then conclude with several suggestions as to how scholars can more effectively capture, demonstrate, and ultimately diffuse their quantitatively driven discoveries.

QUANTITATIVE DISCOVERY IN MANAGEMENT: ITS NATURE AND PURPOSE

Nineteenth century discussions in the philosophy of science framed "discovery" as a "eureka" experience resulting in a major, paradigm-shifting insight or innovation such as the identification of a previously unknown element or the cause of a disease (Schickore, 2014). However, more contemporary perspectives on discovery frame it as "an analyzable reasoning process, not just as a creative leap," the ultimate purpose of which is to generate new ideas and theories with meaningful implications (Schickore, 2014). In many fields, quantitative data often provide a critical basis for this analytical reasoning process, which is neither inductive nor deductive in nature. Indeed, as noted by Van de Ven and his editorial team in an earlier FTE (2015), discovery is grounded on the logic of abductive reasoning elicited by the observation of "astonishing phenomena" or empirical anomalies (Hanson 1960: 104). Capturing these phenomena or anomalies in the form of quantitative data, the process of discovery is therefore structured around activities aimed at inferring preliminary theory from numbers and numerical patterns, and using quantitative findings to modify and enhance the predictive utility and explanatory potential of such theory (Kulkarni & Simon, 1988).

Moreover, this contemporary perspective on discovery suggests that incremental, data-driven insights (i.e., discoveries with a small "d") are no less significant than the big leaps (i.e., Discoveries with a big "D"). Indeed, what may *appear* to be "sudden," big leaps may, in actuality, emerge from a stream of smaller, incremental advances (Study 1, Study 2, etc. . .) as investigators identify an interesting anomaly and then use empirical observation to "tweak" it and learn more about its properties and effects. For example, while goal setting serves as one of the most important "big D" discoveries in management, it is difficult to discern this big-D discovery from the chain of small "d," incremental advances ("discoveries") on which it is based (Latham & Locke, 2002).

Similarly, this contemporary perspective suggests that we avoid defining "discovery" on the basis of the magnitude of explanation or statistical effect size. Indeed, our literature is rife with examples of small effects having robust theoretical implications (such as the findings of Karasek et al. [1981] regarding the link between job characteristics and heart disease) and broad practical impact (such as the effect of rudeness on doctors' diagnostic accuracy and speed; Riskin et al. [In Press]). Accordingly, when making the case for a discovery, statistical significance should be considered necessary but not sufficient. The emphasis must be placed on the rigorous and comprehensive description of phenomenon whose magnitude of *practical* effects are indisputably important and impactful. Indeed, theoretical advancement is impossible in the absence of such description and is meaningless unless a case can be made for its practical implications.

But just as small effect sizes may represent important insights on phenomena, many statistically significant findings can be obtained on effect sizes that are trivial and do not advance knowledge. In this age of access to big datasets often consisting of thousands of observations, statistically significant findings are easy to obtain on minute magnitudes of effects that are not practically important. Unfortunately, too many management researchers examining secondary databases are losing sight of reality through the numbers. Obviously, a firm grounding in the subject matter is necessary to determine what effect size is large enough to lead other researchers and practitioners to pay attention to and change their way of thinking about the finding.

TYPES OF QUANTITATIVE DISCOVERY

There is little doubt that quantitative data can rarely compete with qualitative data in offering rich and meaning-embedded descriptions of management-related phenomenon or organizational anomalies. However, quantitative data are likely to be the "data of choice" for a number of discovery-oriented research activities and objectives. One of these activities has to do with classification. Quantitatively driven taxonomies and classification systems provide a basis for description on the basis of phenomenological distinctiveness. Quantitative data can facilitate the identification of repeating patterns and commonalities, as well as the preliminary testing of hunches about the clustering of phenomenon and the distinctions among emergent types. Using such an approach, Lee et al. (2015) derived a framework for distinguishing among team types thus facilitating the generation of more nuanced and parsimonious theories of work teams.

Similarly, quantitative data are essential for scholars seeking to transform poorly understood phenomenon into distinct and measurable constructs. Indeed, as the literatures on cultural intelligence and abusive supervision suggest (Ang, Van Dyne, Koh, Ng, Templer, Tay-Lee & Chandrasekar, 2007; Tepper, 2000), new research areas and entire literatures typically depend on construct-driven, quantitative discovery. For example, Ang and colleagues (2007) relied on quantitative data from 2,154 individuals across seven samples comprising Singaporean and American undergraduate students and culturally diverse working professionals to validate a measure of cultural intelligence. This measure provided scholars struggling to conceptualize intercultural competence with a theoretically coherent and measurable construct. In turn, having a validated measure ignited empirical research and theory development in the area of cultural intelligence.

Quantitative methods further facilitate theory development by providing the means to assess both the internal and external validity of such findings. While qualitative data allow for idiographic discovery, statistical analyses provide scholars with a basis for assessing the degree to which the findings accurately and reliably reflect what the authors say they do, and for determining the degree to which the findings may be generalizable to similar phenomenon or different contexts. In this sense, discovery on the basis of quantitative data serves as an important basis for the generation of nomothetic theory.

Additionally, scholars can apply quantitative methods to uncover and describe key emergent processes in and across organizations. Once strictly the domain of qualitative research, advances in data analytic techniques now allow us to use statistical means to model trends and emergent patterns, and lay the ground work for process theories (Mohr, 1982). The ability to quantitatively model how a variety of antecedents may differentially interact under varying conditions to precipitate the emergence of one or more alternative outcomes is an important addition to the toolkit of management scholars. Applying such tools to "big data" may allow scholars to detect patterns of emergence that are only "visible" in large numbers and impossible to detect on the basis of even the most sensitive qualitative techniques. For example, one might use sophisticated data analytics to discern from mountains of compensation data differential shifts in pay form (e.g., benefits as a proportion of total compensation) across different types of enterprises and markets. Findings from such analyses might challenge or extend current theories (e.g., agency theory, human capital theory) and even lay the groundwork for new theoretical development.

Other types of quantitative modes of discovery may involve meta-analysis, replication research, and evaluation studies. Meta-analyses account for sampling error variance of individual studies and help us discover contextual boundary conditions of empirical phenomena. For example, de Wit, Greer, and Jehn (2012) discovered through meta-analysis that task conflict is negatively associated with group performance ($p = -.21$) in non-top management teams but unrelated with group performance ($p = .09$) in top management teams. This finding suggests that organizational level presents a contextual boundary condition for the negative effect of task conflict on group performance. More importantly, however, this finding may lay the groundwork for further theory generation aimed at explaining why and how status or leadership may moderate the consequences of conflict.

Similar to meta-analyses, replication studies play a crucial role in discovering boundary conditions for management-related phenomena. Replication studies may lead to discoveries when they (a) replicate an existing finding in a different population or (b) fail to replicate an existing finding in the same population. Whereas the former replication finding contributes to empirical generalization (Tsang & Kwan, 1999), the latter replication finding contributes to the discovery of boundary conditions (Brandt et al., 2014). Makino, Isobe, and Chan (2004) provide an empirical example for both. These authors replicated prior studies that had compared the relative impact of industry, corporate, and business unit effects on business unit performance within a single country for multinational corporations. As in single-country studies, Makino and colleagues found that business unit effects explained the largest portion of variance in business unit performance. Hence, their study contributed to empirical generalization. At the same time, Makino et al. also discovered country-effects as an important boundary condition. In particular, results showed that corporate and business unit effects played a stronger role in explaining business unit performance in developed countries, whereas industry effects were more crucial in developing countries.

Finally, evaluation studies may discover boundary conditions when evaluating interventions in new contexts. Using this approach, Sia and Soh (2002) uncovered limits to the universality of enterprise resource planning (ERP) software solutions. Specifically, these authors observed 179 cultural misfits when a patient care ERP system based on industry best practices from the West was implemented in an Asian hospital. In doing so, they shifted conceptualizations of end-users of ERP systems from passive functional experts to active change agents.

HOW TO MAKE DISCOVERIES OFF OF QUANTITATIVE DATA

Having described types of quantitative discoveries, we now turn our attention to some suggestions for how to make discoveries off of quantitative data. Perhaps, the most obvious suggestion is to follow up on hunches or ideas about discovered anomalies to test these new insights. For example, Sutton and Rafaeli (1988) initially expected a positive relationship between employee's display of pleasant emotions to customers and organizational sales. Contrary to their expectation, however, empirical results showed a negative association between displayed emotions and organizational sales. However, a modest positive correlation between line length and sales, as well as a negative relationship between line length and displayed emotions, sparked a hunch that the business of the store might explain their unexpected finding. The authors then collected additional data (including interviews, observations, direct working experience, and site visits) to substantiate this hunch. These data led to the discovery that norms for emotion expression differed significantly between busy and slow times. Norms for displaying positive emotion in busy settings evoked only neutral emotion displays, whereas these same norms in slow settings were associated with positive emotion displays. Finally, Sutton and Rafaeli reanalyzed the original quantitative data to confirm that store pace, as indicated by total sales and average line length, negatively predicted the display of positive emotions.

The second suggestion is to examine data patterns with an eye toward potentially important anomalies. The series of experiments reported by Latham, Erez, and Locke (1988) provides an instructive example for how discoveries can be made through the search for patterns that explain inconsistent findings. Latham et al. had initially conducted similar experiments on the role of participation in goal setting, which suggested divergent conclusions. The authors then came together and brainstormed possible differences in their procedures that might explain their results. From this discussion, Latham et al. designed a series of studies that tested the impact of nine procedural differences and substantially clarified the boundary conditions for participation effects in goal setting.

Third, scholars may use unconventional quantitative methods to statistically uncover critical latent patterns or structural dimensions embedded in longitudinal data. This may include the application of stochastic modeling to identify random processes or flows, as well as nonlinear dynamic models to uncover patterns in time series data that are neither orderly nor random. For example, Cheng and Van de Ven (1996) used a combination of linear regression, stochastic and nonlinear dynamic modeling to diagnose from real data on innovation events the degree to which random, chaotic, or periodic patterns govern innovation development. Such a discovery is critical to accurately model the system that explains innovation processes and events.

Fourth, researchers should consider drawing on big data to make quantitative discoveries, particularly when the domain of discovery involves phenomenon with a low base rate or low sensitivity. For example, Barnes and Wagner (2009) drew on a massive data base of 23 years of workplace injury data to demonstrate that the sleep deprivation induced by daylight saving switch increases the probability of workplace injury. In particular, Barnes and Wagner compared workplace injuries on days following daylight saving switch with injuries occurring the rest of the year. Using this quasi-experimental design, they discovered that on average, 3.6 (5.7 percent) more injuries occurred and 2,649 (67.6 percent) more days of work were lost due to injury on days following daylight saving switch compared to regular days. Similarly, following a hunch that sleep deprivation may be associated with subsequent cyberloafing, Wagner, Barnes, Lim, and Ferris (2012) compared the relative percentage of Internet searches related to entertainment on Mondays after the switch to daylight saving time—a proxy for lost sleep—with the Mondays preceding and following it from 2004 to 2009 across 203 metropolitan areas in the United States. Findings showed that Google users indeed searched for over 3.1 percent more entertainment-related websites on the Monday following the switch to daylight saving time compared to the Mondays preceding the switch.

Finally, we suggest that scholars take advantage of methodological innovations to uncover phenomena previously deemed inaccessible or difficult to measure or capture. For example, using random coefficient modeling (RCM), Chen, Ployhart, Thomas, Anderson, and Bliese (2011) obtained empirical Bayes parameter estimates from an RCM analysis to model the trajectory of job satisfaction over time. They then used these findings to demonstrate that job satisfaction trajectories contribute above and beyond static job satisfaction level in explaining turnover. Similarly, Liu, Bamberger, Wang, Shi, and Bacharach (2014), using heavy drinking with customers as an empirical referent, applied growth mixture modeling to identify empirically alternative patterns of newcomer behavior. They then demonstrated that the classification of newcomers to one pattern or the other was contingent on veteran peer (but not supervisor) socialization, and that these alternative patterns of behavior had diverging consequences on job performance, work-family conflict, and turnover. In this way, both studies used sophisticated statistical techniques to explore emergent attitudinal and behavioral patterns and discover associations that previously were difficult if not impossible to model.

KEY SUCCESS FACTORS FOR GETTING QUANTITATIVE DISCOVERIES PUBLISHED

Quantitative discovery is well understood by most of us. This is because it is what many of us do before engaging in the theoretical contortionism and retrofitting required for publishing important and interesting findings in most of the leading management journals. *Discoveries* was created to allow scholars to report and describe their findings as they emerged in a more authentic manner.

But because quantitative discovery follows the logic of abductive reasoning, it demands that scholars tell their "story" in a different way. Structuring an article according to the logic of abductive reason suggests that scholars try to follow four basic guidelines. First, as explained in greater detail in an earlier FTE (Van de Ven et al., 2015), authors need to clearly describe and "problematize" the issue, phenomenon, or anomaly they wish to explore, highlighting the potential theoretical and practical implications of doing so. That is, authors should be sure to position the issue their study addresses within literature(s) likely to be theoretically or practically impacted by their findings.

Second, rather than offering *a priori* hypotheses, authors should draw from the extant literature to review alternative options about the nature of the phenomenon or relationships their study examines. In doing so, authors should strive to be authentic, focusing on the ideas they developed *a priori* when embarking on their journey, rather than the conclusions they reached post-hoc. Here, authors are cautioned to avoid reliance on the somewhat restrictive medical model (i.e., the differential diagnosis approach made famous by Dr. House in the TV series of the same name), which involves the systematic testing of hypotheses from a set of known alternatives (Schaffner, 1993). Instead, they are encouraged to use a more creative and open approach, drawing hunches from alternative domains and fields, or deriving them on the basis of thought experiments in the manner made famous by Albert Einstein (Isaacson, 2007).

Third, authors should apply the same standards of rigor applied for publishing research in other top-tier journals. In particular, authors should highlight how the design and methods they adopted allowed them to capture and describe the phenomena or anomaly in all of its (surprising) dimensions. However, because some argue that abductive reasoning is by its very nature overly permissive (Schickore, 2014), in attempting to distill theory from their findings, authors must also be careful to explain how their design and methods allowed them to rule out "the usual suspects" (i.e., the alternative explanations suggested by extant theory or the method itself), and drill down their characterization of the phenomenon. In many cases, this may require the collection of additional data. Indeed, authors of some of the best articles submitted to *Discoveries* to date have been asked to conduct additional studies and collect additional data as a condition for further evaluation. Thus, for example, readers should not be surprised to see that while scenario-based studies are published in *Discoveries*, they are nearly always one of multiple studies presented.

Finally, because the logic of abductive reasoning calls for propositions to be inferred and evaluated on the basis of empirical findings and thus use of data to rule out alternative explanations (Hanson, 1960), theoretical insights can only truly be drawn in the discussion. Accordingly, while theoretical contribution is no less important in *Discoveries* than in other theory-driven management journals, authors should be aware that unlike these other journals, the assessment of the study's theoretical value added is based on an analysis of the article's "back-end" rather than its "front-end." In making their claim in the study's back-end, authors should be careful to remember that their data suggest only exploratory hypotheses or what might be deemed "pre-theory." The purpose of the discussion is therefore to (a) assess the merits and promise of such data-derived propositions; (b) contrast these propositions to extant theory, highlighting their similarity and uniqueness; and (c) speculate as to the implications that this theoretical extension or innovation may have for directly and distally related management literatures.

CONCLUSION

Quantitative approaches play a crucial role in discovering organizational and social anomalies that require new theoretical formulations. The various types of quantitative discoveries reviewed above attest to the multitude of possibilities scholars have for using quantitative analyses to stimulate theory generation and even initiate new lines of research in management. We hope that the delineation of these possibilities and opportunities will motivate quantitative researchers give greater consideration to exploring their datasets for potentially theory-rich anomalies and atypical/non-intuitive phenomena and patterns.

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