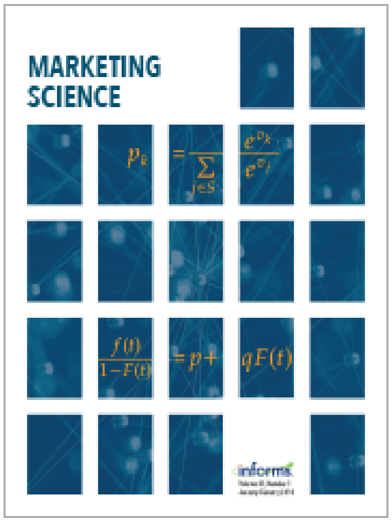

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In Search of Data: An Editorial

Steven M. Shugan,

In Search of Data: An Editorial

Steven M. Shugan*
Warrington College of Business Administration, University of Florida,
201 Bryan Hall, Campus Box 117155, Gainesville, Florida 32611-7155
http://mktsci.pubs.informs.org

We argue that: (1) whether articles contain numeric data should be irrelevant to the evaluation process; (2) the desirability of numeric real, numeric synthetic, or nonnumeric data depends on the research objective; (3) assumptions can and should sometimes substitute for additional data; and (4) equal scrutiny should be given to data collection procedures, regardless of whether the researcher influences the collection or not. Finally, rather than focusing on data, evaluation of research should focus on whether the research provides compelling evidence for the conclusions.
(*Numeric Data; Nonnumeric Data; Synthetic Data; Marketing Theory*)

Worshipping Data

Observations, often called data, have become a cause célèbre. Data obviously play a pivotal role in the publication process in every discipline, but data play a special role in ours. Data are the fuel for the popular "falsification" engine of science that allows refinement and rejection of hypotheses and research models (e.g., the numerous works of Kuhn, Popper, and Lakatos). Data are the foundation for popular decision-support systems that provide guidance for better decisions by better organizing and structuring data (Little 1979). The goal of many of our popular and sophisticated methods of analysis is to more efficiently extract more information from data. However, because our methods, our techniques, our technologies, and our philosophies often originate from diverse disciplines and varied research streams, our approaches to data sometimes have conflicting objectives. Given these conflicts, we suffer a greater tension concerning the use of data than disciplines that have more uniform objectives and more shared sources of data. In the last year, one of our leading journals has refused to accept so-called purely theoretical articles that lack numeric data.

Another troubling development has been the conflicts arising over sources for numeric data. Some researchers claim numeric data from experiments have inherent defects, including an inability to always generalize to "real-world" environments (Winer 1999) and an inability to account for heterogeneity (Hutchinson et al. 2000). Some researchers claim that aggregate data have inherent defects. The problems of endogeneity of marketing activities and heterogeneous consumers are well known (e.g., Chintagunta 2001). Simultaneity is a problem (Bound et al. 1995). Often, aggregate data lack observations in relevant regions, contain ambiguity created by multicolinearity, cause overidentification, and lack sufficient individual level information (Griliches 1985). Some researchers claim that natural experiments are the answer, because they contain truly exogenous manipulations (e.g., Meyer 1995); how-

*Steven M. Shugan is the Russell Berrie Foundation Eminent Scholar of Marketing.

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ever, other researchers find fault with that data (Rosenzweig and Wolpin 2000). Some researchers claim that questionnaire data are inherently flawed, because they often rely on recall and a willingness to return the questionnaire (Leeflang and Wittink 2000). However, some econometricians yearn for data collected by the researcher, rather than by another party who may have objectives different from those of the researcher (Griliches 1985). Some researchers prefer cross-section data, while other researchers find them deficient (Bronnenberg and Mahajan 2001). While many econometricians seek "objective" or revealed data, others suggest using data from psychometric experiments (e.g., McFadden 1986). Of course, no source of data goes unscathed (Wedel et al. 2000).

It has now become commonplace to classify contributions by their relationship to numeric data. We say research has a substantive contribution if we learn from the numeric data and focus on the information extracted from the data. We say research has a methodological contribution if we learn how to better extract or manipulate information from the numeric data. We say research has a theoretical contribution if it makes no use of numeric data.

Obviously, after mustering considerable effort to compile a large database, researchers may attempt to mine (i.e., look for correlations or possible hypotheses) within the database and develop research questions based on what is found. Data mining can be an important initial phase in a research effort. Data mining might be the modern and glamorous version of old-fashion exploratory analysis (Jeffers 1994). Data mining occurs when the research analyst goes to great lengths to obtain a good fit, including the use of data-specific searches (Chatfield 1995). However, adopting a research strategy in which the data determine the research agenda is a difficult and perilous strategy to follow. Existing data both provide and limit the potentially available information, rather than providing the relevant research questions. Producing meaningful substantive results from a data-driven research strategy often requires more creativity and luck than a research strategy that starts with a research question and then collects data (e.g., survey, experimental, secondary) to answer the research question. In the end, every research effort must find an important research question and make meaningful progress toward an answer. This is true whether the research question proceeds or follows the data collection. Answering a research question is the ultimate goal, whether the research question dictates an action for a decision maker, reveals a previously unknown relationship, or provides a tool for answering the questions of how to do something better.

In recent years, to the dismay of many researchers, the journals and many reviewers are moving away from classifying research by using research objectives and research questions. Many researchers are beginning to classify articles by the type of data they use. Research is often branded as based on "laboratory data," "secondary data," "opinion data," "survey data," "nonnumeric data," or "lacking-data." Some researchers consider the presence of secondary data in a modeling effort as a signal of external validity. Some researchers consider the collection of data in a real-world application as a signal of a model's merit and applicability. It seems that our discipline may be dividing based on whether research uses experimental data, secondary data, survey data, or nonnumeric data. It has been said that some researchers develop research agendas around databases rather than research questions. It has been said that the unavailability of data has prevented the investigation of some critical research questions. It has been said that data availability, rather than research questions, actually drives research programs (Allenby and Rossi 1999). It has been said that the outcome of the review process for a manuscript often depends on the type of data used by that manuscript. A few researchers have suggested defining the discipline around the type of data we use. (Of course, one wonders, for example, how that is possible. We might wonder whether purchasing and sales data belong to finance, marketing, accounting, operations, economics, public policy, or statistics.) At present, the role of data has become so critical in the review process that it is time to explicitly recognize the issues and develop some general guidelines on the use of data.

Appropriate Data and Synthetic Data

We must remember that manuscripts can have different objectives. Some researchers seek to develop tools to help decision makers make improved decisions. Some researchers seek to develop qualitative strategies to help decision makers identify or eliminate courses of action. Some researchers seek to develop methods that provide decision makers with better information. Some researchers seek to develop theories that will ultimately lead to better applications. We must recognize that the appropriate type and use of data vary by objective. We should avoid blindly applying "rules of thumb" about the appropriate use of data given one objective to other objectives.

For example, so-called "scanner data" are extraordinarily useful for decision making involving consumer promotions, trade promotions, and pricing. However, Bucklin and Gupta (1999) find that "scanner data" seem deficient (at least, historically) for decision making involving product strategy, advertising, and distribution management. Although purchase history data have been less useful in developing new products, when combined with demographic data, they have been very useful for targeting customers (Rossi et al. 1996).

For a more detailed example, consider the use of simulated or synthetic data (Tippett 1927, Lerman and Manski 1981) that was pioneered by E. S. Pearson in the 1930s. Synthetic data are invaluable for testing methods that claim to recover information more efficiently from data (e.g., Sudharshan et al. 1987, Van den Bulte and Lilien 1997). When the objective is the recovery of true underlying parameters, it is ideal to use data simulated with known true underlying parameters and a known error-generating process. Although real data often also contain noise, we can only infer the nature of that noise. With synthetic data, we know the true underlying parameters. We can directly determine how well different methods recover those parameters. More importantly, we can also vary the coherent introduction of noise or vary the degree to which each method's underlying assumptions are violated. Varying these factors allows us to determine directly when each method performs better at the recovery of the known true underlying parameters or process. Moreover, synthetic data can accurately approximate complex analytical functions (Fishman 1996). With advancing computer technology, barely workable ideas about simulation are now facile (Metropolis et al. 1953). Finally, synthetic data allow quick and efficient replication. Other researchers at other times given different objectives can immediately replicate the findings with different data generated under the same circumstances.

Diametric reasoning applies when our objective is proving a demonstrable conclusion from a series of explicit assumptions. Then, the use of simulated data is a permissible but an inferior route. It is best to use analytic methods of proof to show that a result always follows from our explicit assumptions or conditions. Proofs avoid tacit and hidden conditions and show that our result is always true, given those conditions. Deductive analytical methods are more precise. They can provide us, for example, with precise conditions when one estimator has smaller standard errors than another estimator. Analytical methods, for example, can provide us with precise conditions as to when a firm should share its customer knowledge with a rival so as to improve its rival's ability to target specific customers (Chen et al. 2001). Analytical methods can provide us with precise conditions about when sales signs will be effective and can reveal the conditions impacting their effectiveness (Anderson and Simester 2001).

Analytical methods also enjoy the advantage of being replicable. Any reviewer, reader, or critic can usually completely replicate an analytical finding without obtaining omitted details or other missing information from the authors of the research. It is often impossible to publish sufficient detail about a data analysis to make replication easy.

Of course, when analytic methods seem intractable and implementing them seems to be beyond our capability, then we may resort to simulated data to show that a result is true under many conceivable possibilities or under specific prespecified conditions.

The use of simulated data as an alternative to proof is permissible, given intractability, but it remains a qualitatively inferior technique because simulated data only provide results for a finite number of cases while analytical methods of proof provide results for all infinite cases.

Finally, consider the use of synthetic data to provide substantive findings. This use of synthetic data for that objective is obviously inferior. Through use of simulated data, we can show, for example, that a new product's sales growth curve (given specific trial and repeat rates) can sometimes peak and decline before achieving a steady-state plateau. However, simulated data are unable to tell us whether these peaks frequently occur or occur at all. Moreover, analytical methods of proof can certainly provide more precise methods for determining the specific conditions when those growth peaks do occur.

The Absence of Data

Obviously, some research questions are best answered without real or synthetic numeric data. Numeric data are irrelevant to some research objectives. For example, we can derive and compare the property of two statistical estimators without numeric data. We can determine the optimal strategy, given a set of market conditions without numeric data. We can determine the optimal advertising budget for a particular response function without numeric data. Research questions involving consistency between stylized facts (i.e., previously found observed or estimated regularities) may not warrant use of specific numeric data. We can often logically deduce the testable implications of any set of assumptions without numeric data.

In fact, although data may be present in some parts of a research study, data may be absent from other parts of the study. Indeed, most articles that focus on data analyses require some form of formal deductive logic preceding the analysis. This is particularly true of articles with traditional objectives such as hypothesis "falsification" and "decision support." The early key assumptions involving which variables to measure and the relationship between those variables have a profound impact on data analysis and the ultimate conclusion.

The purpose of a research study is to answer research questions, and making observations is only a means to this end. It must follow that the presence of numeric data per se should be largely irrelevant to the evaluation of a research article. The key focus should be on the research question. When answering the research question requires specific information, it is necessary to make observations or collect data that contain the necessary information. Moreover, it is necessary to use methods capable of extracting the relevant information from the data. When numeric data are irrelevant to answering the research question, numeric data may only be a distraction. Rather than focusing on data, evaluation of research should focus on whether the research provides compelling evidence for the conclusions.

The demarcation of all research as theoretical and empirical is somewhat nonsensible. This demarcation ignores the basic issue that all research requires information. That information, whether from numeric data or not, requires meticulous observations. That information also depends on observations made in past research. The focal issue should be the research question and its answer, rather than whether the information is numeric. Simple observations about emerging technologies (e.g., Xie and Shugan 2001) or firm behavior (e.g., that retailers only advertise some products, that promotions correspond to seasons, and that capacity constraints dictate service strategy) can provide more information for answering some research questions than large longitudinal datasets. Answering other research questions (e.g., what the precise shape of a service's response function is) absolutely requires large longitudinal datasets. Answering still other research questions (e.g., how to sell products more effectively) may require entirely new radical methods of analyzing more nonnumeric data. Finally, as the quality of data increases and databases become comprehensive, statistical theories of noise and inference become less relevant and, possibly, qualitative theories of future reality become more germane.

Substituting Assumptions for Data

All research starts with assumptions (a better term is probably "conditions"). The assumptions define the scope of the research and the conditions when the research is claimed to be valid. Although findings may be more general than claimed, the researcher avoids an onerous burden of validation by using assumptions to forfeit this claim of generality.

Assumptions may be explicitly stated, implicitly shared by all research in a field, or hidden in the procedures followed in the research. The assumptions may be innocuous or they may be highly restrictive, but they are always present. Data and assumptions are substitutes. With more assumptions, we often require less data and can exploit the data we have more efficiently. With fewer assumptions, we require more data, and we often produce weaker conclusions from our data.

For example, the powerful and usually desirable assumption of linearity removes many nuisance parameters associated with higher-order functions. The assumption that some variables are irrelevant avoids prohibitively costly data collection and possible colinearity problems. The assumption of specific probability distributions allows more efficient estimation and provides the desirable properties of our estimators. The assumption that certain properties are superior allows comparison of different estimators.

In the extreme, we can eliminate the need for any new data by making explicit assumptions or by exploiting observations found in prior research. The explicit assumptions do restrict the set of situations when the conclusions are justified. Of course, conclusions are always limited by factors including the generality of the assumptions, the representativeness of the data, and the extent to which the data represent future reality.

The intention of this argument is not to diminish the role in research of meticulous observations and, specifically, numeric data. Exact observations are a natural and vital part of research. However, we seek information rather than observations per se. We hope that observations and their interpretation will reveal previously unknown information. We hope to find actions and alternatives that were previously overlooked. Hence, the value of observations derives from the value of the extracted information rather than from the quantity or uniqueness of the observations. Extracting unique and revealing information from a dataset is a contribution while merely collecting a unique dataset is not inevitably a contribution.

Moreover, let us avoid marginalizing the role of nonnumeric data. Careful documentation of nonnumeric observations can reveal as much or more information as numeric data would reveal. Obviously, because traditional statistical tools have focused on numeric data, a journal focusing on mathematical models often favors numeric data that can be manipulated with arithmetic tools. However, we can exaggerate the importance of amenability to arithmetic operations. There is nothing sacrosanct about numeric data. In fact, future methods using recent advances in computer technology may allow more analyses of nonnumeric qualitative data.

We must find clever ways of extracting the information from both numeric and nonnumeric data. We must remember that we are unable to extract information that is not there. When data lack the relevant information, assumptions will drive the conclusions. Sometimes, data become a distraction. Critical assumptions in the analysis, rather than the data, can produce the research results (e.g., see Sudhir 2001).

Data as Deception

Authors of truly empirical manuscripts do learn from the data and go beyond their assumptions. Sometimes, however, assumptions within a data analysis dictate the manuscript's findings rather than the data itself. The implicit assumptions deceive the researcher into believing that the finding originated from the data rather than from the postulated model specification. Making assumptions such as an S-shaped response function, a concave response function, a specific prior distribution, or which variables to exclude in the analysis can each dictate specific findings regarding optimal policies. Moreover, when these assumptions are embedded within a complex estimation on an extensive database, the findings may appear to result from the data rather than from the modeling assumptions.

In the area of litigation, for example, I often found that Logit models seem to favor plaintiffs with failed new products while regression models seem to favor aggressive monopolistic defendants. The reason appears to be that as data become noisier, Logit models seem to inflate the estimated shares for new brands (giving them the same share as existing brands with similar attributes). Linear regression models (which fail to fit well as noise increases) give these new brands an insignificant share.

It is well known that results of a data analysis can be very sensitive to the assumed structure or model specification, making falsification difficult if not impossible (Leamer 1983). Sometimes, hidden implicit assumptions cause the results. An implicit assumption of independence, for example, can result in a finding of independence. An implicit assumption of optimal behavior can result in a finding of optimal behavior. Implicitly assuming that manufacturers fail to respond to retail price changes may cause an empirical analysis to conclude that retail prices are lower than optimal. Implicitly assuming that long-term goodwill is irrelevant may cause an author of an empirical analysis to conclude that service levels are higher than optimal. Implicitly assuming that all firms are equally diligent in decision making may lead to the false conclusion that diverse marketing strategies are successful, when many strategies often end in failure.

This argument's intention is not to advocate more complex models. More inclusive models are sometimes inferior. As argued elsewhere, parsimony is desirable (Shugan 2002). We should, instead, conclude that assumptions are a virtue of research and, although data is a good substitute for some assumptions, there is a necessary optimal balance. We must remain vigilant about assumptions in every analysis and about their potential impact on research results. We must find clever ways of efficiently extracting the relevant information from the data. We must also remember that we are unable to extract information that is absent from the data. Data should be a source of information rather than either an interesting sideshow or, worse, a deceptive distraction.

Why Data Are Revered

We might wonder why the mere presence or absence of numeric data in an article, whether appropriate or inappropriate, is sufficiently decisive to classify an article as being in a different class. Perhaps, the answer is our focus on answering important research questions in marketing, using mathematical modeling, which are particularly apt for analyzing numeric data. Perhaps, the answer is that the mere presence of numeric data is an indication or signal by the author. It signals that the author aspires to applicability, has concern for realism, has velleity for practicality, and respects empiricism. Although how the data are used reveals far greater information, it appears that reviewers and readers sometimes forget to delve that deep. Using data for illustrative purposes differs from discovering new relationships in the data. Let us revere the elegant, compelling, and influential research, rather than the data.

The Need for Data

Often, empirical researchers who rely on derived observations or experiments may remain skeptical of purely theoretical research. There are legitimate reasons for this skepticism, but they are unrelated to the presence of numeric data. Possession of numeric data should not mitigate these concerns.

One concern is the ultimate contribution of the research. For example, it is unclear whether, in the short term, theory can help prediction, invention, or application. Faulhaber and Baumol (1988) note, for example, that the record of adoption of theoretic economic innovations is spotty. Ehrenberg (1995) argues that it is sometimes better to consider empirical generalizations separately from theory so that we discover new links to theory. Cobb (1928) argues that advances come from accretion of data rather than from excogitation of theory.

Theory may be unable to help prediction and may sometimes hinder predictions. Theory restricts the set of admissible models to those consistent with the theory. It is unclear whether one model from this smaller set of theory-consistent models can produce more accurate predictions than models found from trial and error from the larger unrestricted class of all possible models. This reasoning may explain why models based on historic data with few or no explanatory variables (e.g., time series, neural network models, models of random walks) often predict better than models with considerable theoretical structure. Hopefully, in the long run, theory will help find models we would not otherwise try.

Theory may not help invention and may hurt it. It is unclear whether great inventors made better use of existing theory or whether serendipity, creativity, and necessity played greater roles. Indeed, theory may hinder invention and innovation because it discourages the pursuit of clever but atheoretical ideas. Existing theories may hurt application by discouraging trial of theoretically inferior alternatives. Trial and error could be as effective, in the short run, as the loyal application of theory.

Finally, beyond being ultimately useful, theories should be ultimately testable and be ultimately rigorously verified. We should avoid casual excuses for not collecting data to test theory. Despite the difficulties involved in procuring data or quantitatively measuring phenomena, we should keep some perspective. Certainly, if Olaus Romer could crudely measure the speed of light with the technology of 1676 and if Albert Michelson could provide precise measurements of that speed with 19th century technology, we should be somewhat humble about the difficulties in measurement that we face.

Perhaps theory, application, and technology are so intertwined that it is impossible to tell whether improved theoretical understanding allows better decisions or whether better decisions lead to improvements in understanding. In the long run, we must hope that the advancement of theory, empirical research, and application to practice are synergistic. Of course, this argument is independent of numeric data.

Primary, Secondary, and Good Data

Sometimes, as reviewers, we quickly find fault with the procedures used to collect primary data (e.g., survey, experimental, quasiexperimental) but ignore the procedures used for the collection of secondary data (e.g., purchased data, data collected by a second party). Data collection procedures profoundly affect the course of research, regardless of whether the researchers have any influence over them or not. Primary data collected with recognized defects may still be vastly superior to secondary data collected through unknown procedures beyond any influence by the research. We must apply the same standards to all data collection procedures.

Hurling onerous critiques of primary data collection procedures and paying only cursory attention to secondary data collection procedures gives researchers the wrong incentives. Rather than attempting to collect fresh data with potentially new information, we give researchers the wrong incentive. We encourage them to squeeze still more information from an already extensively analyzed dataset. The attention of researchers may become focused on the already measured variables rather than on pivotal yet-to-be-measured variables outside the dataset. Each subsequent research effort may become more incremental as each subsequent effort reveals less new information about the same variables in the same context under the same conditions in the same time frame.

Significant problems develop when researchers share a small number of common datasets (De Long and Lang 1992). We should avoid worshipping data only because a second party publishes the data. We need to be more forgiving of primary data collections. Equal scrutiny should be applied to all data collections. There will always be defects in the collection effort. The important issue is not whether there are defects but how (or whether) those defects impact the qualification of the research findings.

Although data analysis tools from many disciplines, including statistics, market research, econometrics, biometrics, psychometrics, and management science, can correct some defects, there is no free lunch. It is impossible to extract information from data that are absent from the data. As noted earlier, we usually use assumptions to compensate for all defects in data, including defects in the collection effort. When assumptions replace data, we must wonder whether the assumptions cause the results. A variable may, for example, become important only because of an assumption about the way to allocate ambiguous variance. A variable may become important only because we have overlooked a more important variable (i.e., by implicit assumption). In the end, the same issue remains; we must be sure the research findings are justified, given the data and the data analysis.

The discussion of defects naturally leads to the issue of how to evaluate data. Good data should have certain properties. Let us consider just a few very desirable properties of data. These properties are only necessary because the nature of the data analysis will require still stronger properties. Moreover, these properties are only a highly abridged conceptual guideline. A comprehensive treatment of this topic is well beyond the scope of this short essay.

The first desirable property of data is the consistency of the data. Taking any appropriately large subset of observations from the original data should produce the same information. Some observations should not appear to be from different underlying realities. Although we tolerate coherent error, the same underlying error generating process should taint every observation. Consistency of the data and consistency of the analysis are both required for statistical validity (Cook and Campbell 1979). Of course, development of theory, which includes causality and the extrapolation to future real-world settings, requires far more than traditional statistical validity. See Lynch (1983) for a discussion of these requirements in a marketing context. See Lynch (1999) and Winer (1999) for a debate on whether combining data sources (e.g., scanner and experimental) produces findings that are more easily generalized.

Note that when we are blessed with a large quantity of numeric data (possibly a census of the entire publication), error theories become less important. In that case, the usefulness of techniques for inference to a larger population diminishes. All predictions are to the future, and external validity is the critical issue (Griliches 1985).

The second desirable property of data is inclusiveness. The data must contain the information we need. Data should be more than an interesting sidebar or a distraction from the central research question. The findings must originate from observations, rather than from speculation or imperious assumptions made in the method of analysis. The data collection procedure must have been capable of producing observations that refute the tenet of the underlying research. When the data lack the information necessary to answer the central research question, then the data are irrelevant. When there is no natural (i.e., exogenous) variation on a variable, then only assumptions allow us to fully estimate the influence of that variable. If colinearity is extreme, we will be unable to completely decipher the influence of the variables with the shared variance. These are examples of defects in the data rather than in the analysis. Although research results are still possible, research results will follow from the assumptions rather than from the data.

A third property is replicability. Given the reported details of a research effort, another researcher must be able to reproduce the collection of data with the same information. One of the primary advantages of deductive research, which is predicated on explicitly stated assumptions, is that replication should be straightforward. The opposite situation occurs with numeric data collected with unclear procedures and without a clear research objective.

We conclude with one final property—extractability. We must be capable of extracting the information from the data (e.g., by developing our own tools or using tools from elsewhere). Currently, there are large quantities of nonnumeric data available (e.g., consumer descriptions of products, professional reviews, advertising copy); we currently lack sufficiently powerful tools to extract the embedded information. Currently, there are different forms of data from different sources (e.g., experimental, survey, aggregate sales) collected for the same research question (e.g., which form of advertising has the greatest impact). However, we lack tools for integrating these data sources (Wedel et al. 2000).

Consistent, inclusive, replicable and extractable (CIRE) data are good data.

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