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Editorial

The Anna Karenina Bias: Which Variables to Observe?

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The opening of Count Lev Nikolayevich (Leo) Tolstoy's novel inspired linguist, molecular physiologist and biogeographer Jared M. Diamond's eponym for the Anna Karenina principle (Diamond 1997). The principle suggests that no one property guarantees success but many guarantee failure. The Anna Karenina (TAK) bias is a logical consequence. TAK bias is more insidious than the kindred Survivor bias, which cautions that measured variables for passively observed survivors often differ from easily overlooked nonsurvivors. TAK bias, in contrast, cautions that the observed variables themselves might differ for survivors. The most revealing variables might exhibit negligible variation among survivors because survivors are necessarily alike. Perhaps variability is inversely related to the variable's importance for survival. TAK bias is more problematic for descriptive research, in contrast to normative (i.e., prescriptive) research, which seeks the true causal variables. Normative research only offers conditional aid to the decision maker on specific variables. To avoid TAK bias, we must not passively let accountants decide which variables we observe. We must actively collect data guided by predictions from deductive theory.

Key words: Anna Karenina bias; Survivor bias; descriptive research; inferential research; active data collection; statistical biases

Passive Data Collection

Many researchers employ passive data collection. When doing business research, passive data collection by researchers in finance, marketing, and production often involves accepting the routine variables present in extant accounting data. Hence, accountants ultimately dictate the relevant variables usually based on criteria related to monitoring and reporting requirements. These accounting variables might, of course, differ from the theoretical variables associated with a thoughtful descriptive theory designed to answer relevant research questions.

Accounting data are useful and can reveal a great deal. However, the accounting task is descriptive and not necessarily consistent with inferential analysis. Accountants only intend to convey objective data (possibly at the cost of relevancy) to describe that state of an organization. When attempting to use these data for inferential tasks (e.g., making inferences about relationships beyond the current firm, current time-period, the currently observed variables), we must contend with several precarious biases.

Data Collection Biases

Passive data collection can suffer from myriad, but related, biases. Most of these biases endanger only inferential research (in contrast to descriptive research) because inference necessarily assumes that observed data represent a sample from a population of interest. Consider some examples. Random samples of managed financial funds might overestimate earnings from the population of all financial funds because observed funds might over-represent survivors by excluding nonsurvivors (Bleiberg 1986). When an organization's new product forecasting model provides unbiased sales forecasts, tested forecasts will more often overestimate observed sales because the organization might fail to launch products with under estimated sales (Ehrman and Shugan 1995). The advertising campaign with the best anticipated effectiveness will likely disappoint because the forecasted best of any set most likely has an upward error and, although the forecasts remain unbiased, the campaigns with large downward errors remain unobserved. Customer satisfaction computed from the current users of a service is often overestimated because dissatisfied past customers may no longer be users. A random sample of extant firms will more often overestimate the profit advantage of the first entrant because the sample omits past first entrants who failed to survive (Golder and Tellis 1993).

Parenthetically, the sometimes serious biases associated with only studying survivors have caused tragic public misperceptions and misguided policy. The public may not understand when an industry requires highly profitable surviving products to compensate for large losses associated with potential nonsurvivors.

Although the precise biases (survivor, censoring, influential, etc.) differ, their underlying cause is the same. The sample of observations represents a different population than intended. Although some methods claim to mitigate the impact of these biases, those methods often require direct assumptions about what we do not, and often cannot, observe (e.g., error terms, omitted variables, unobserved parameters). The ability of statistical technologies to mitigate the impact of many of these biases is severely limited.

Because it is difficult to detect these biases from any inferential procedure relying only on the observed data, we must actively seek observations capable of detecting such biases. With a strong deductive theory that involves knowledge well beyond the observed data we can predict the nature and direction of the potential bias. Statistical technologies are very good at estimating unknown parameters in known relationships (Shugan 2006). However, those technologies are less helpful for determining which variables to observe and what relationships to expect.

Let us now consider one potentially insidious bias associated with passive data collection.

The Anna Karenina Bias

A brilliant book by linguist, molecular physiologist and biogeographer Jared M. Diamond (1997), popularized the Anna Karenina principle inspired by the opening of Count Lev Nikolayevich (Leo) Tolstoy's novel. The principle suggests that while no feature guarantees success, many guarantee failure. This principle is related to the well-known conjunctive decision rule (Gilbride and Allenby 2004, Shugan 1980) in marketing and psychology that involves choosing only objects that satisfy minimum standards on a series of criteria (e.g., safety standards in various product categories).

Professor Diamond uses the Anna Karenina principle to explain why different societies or civilizations survive, prosper, and conquer while others do not. In accordance with the principle, his theory develops several necessary conditions for a successful civilization, all of which are related to geography. His argument involves the necessity for cultures to adopt sophisticated agricultural skills to allow efficiencies in food production which, in turn, allows specialization of labor. With specialization of labor, some people can forgo food production and advance the interests of the society by improving technology, waging war, engaging in trade, and so on. Of course, the ability to develop a productive and efficient agrarian society is intimately related to geography.

However, the Anne Karenina principle has a far more insidious implication, which we will call the Anne Karenina (TAK) bias. If we only observe survivors and survivors share the critical properties necessary for survival, then there will be little or no variation on the key variables (or constants) related to these properties. Hence, it will be difficult to infer the descriptive theory leading to success from the passive observation of survivors. We would need to actively observe nonsurvivors.

Moreover, variables exhibiting the highest levels of variance in survivors might be unimportant for survival because all observed levels of those variables have resulted in survival. One implication is a possible inverse correlation between the importance of a variable for survival and the variable's observed variability.

For example, frequently purchased packaged goods show considerable variation on potentially unimportant attributes (i.e., at least those attributes related to survival) such as their price, frequency of price promotions, and advertising budgets. The more critical variables might be constants such as a predictable shelf life, reliable delivery, and theft-resistant packaging. Because researchers have fundamentally different objectives and reasons for using data (Shugan 2002), the TAK bias will impact some objectives more than others.

Implications for Normative (i.e., Prescriptive) Deductive Research

Normative (i.e., prescriptive) deductive research starts with a series of conditions and derives logical consequences that hopefully aid decision makers. For example, Liu and Zhang (2006) deduce conditions when retailers should employ personalized pricing. Normative deductive research is successful when it improves decisions by revealing previously unknown relationships between the specified conditions, some decision variables, and predicted outcomes.

Although normative theories implicitly rely on a descriptive theory, they resemble technologies more than scientific theories. This is because normative theories need only help decision makers rather than replace them in full or in part. Hence, normative deductive theories focus on part of the decision and deliberately avoid a complete descriptive theory with regard to the decision environment.

Moreover, deductive normative theories are by definition deductive—not inferential. Consequently, scientific falsification is less of an issue. We test a deductive theory or technology by comparing its utility with competing technologies rather than seeking disconfirming tests. The superiority of different technologies often depends on the needs of a particular decision maker in a particular situation, rather than on a true underlying causal theory. An optimization model relying only on a reasonable and exogenous response function, for example, might reveal hidden compromises without any theory that explains the origin of the response function.

Although all research is potentially susceptible to TAK bias, normative deductive research is the least susceptible for two reasons. First, it is not highly dependent on inference; thus, having a nonrepresentative sample is less problematic. Second, it can establish superiority, under at least some conditions, over extant technologies without establishing an absolute claim to the understanding of the underlying process.

As TAK bias suggests, one can often accomplish tasks by observing and mimicking every behavior of accomplished practitioners—just as children mimic their parents. Many novices intuitively seek experienced practitioners as role models because it might be sufficient to mimic every possible aspect of past successes. Analogously, once a mine field has been successfully navigated, one need only follow in the same footsteps to achieve the same success. Of course followers must be careful to step in all the same steps as the leader. Some of these steps will be critical to the successful navigation of the mine field. However, some will also be needless diversions that lengthen the duration of the trip. For that reason, prescriptive guides tend to provide long checklists of purportedly critical variables without attempting to prioritize them.

Implications for Normative Inferential Research

Normative inferential research attempts to aid decision makers by providing them with inferences from a sample. For example, we might predict the market share of a product in a particular population from a sample of consumers (e.g., Hauser et al. 2006). Because the variables analyzed from our sample might exhibit little variation on the key properties necessary for success, TAK bias might doom our predictions. However, normative inferential research is rarely the only source of information available to the decision maker. Our research provides only one input. For example, a conjoint analysis model might provide market share predictions conditional on the competency of the decision maker in other domains. Analogously, a tax consultant might only advise on the tax implications of a particular investment, while the decision maker has other information about expected returns, potential exposure to risk, synergies, and peripheral effects. Most seasoned decision makers know the properties necessary for survival. So specialized models need only focus on another part of the decision. In fact, decision makers might seek market share predictions only after many strategic, tactical, and managerial conditions have been satisfied.

Similar to normative deductive research, the best way to judge normative inferential research is by whether it outperforms competing technologies in aiding the decision maker. It is often unnecessary to understand the deeper underlying process. (One can drive a car without understanding how the brakes, power train or steering mechanism works.) A time series model can often forecast better than causal models without explicitly assuming a particular underlying causal theory.

Implications for Descriptive Deductive Research

TAK bias can produce misleading conclusions, which is far more serious for descriptive modelers than normative modelers. Unlike normative modelers seeking only to advise decision makers on some variables, descriptive modelers want to identify the key variables that explain observed phenomena and deduce observable implications. For example, Guo (2006) deduces a descriptive theory of price competition with consumer uncertainty about future preferences. However, when attempting to make observed decisions endogenous, descriptive modelers must know the decisions and all the information required to make them. When we passively observe survivors, we may overlook the key variables that explain the observed decisions and the underlying environment. This puts the entire descriptive theory at risk.

For all types of deductive research, we would like the implications to be far stronger than the assumptions. In fact, we could measure the value added by the deductive theory by conceptually subtracting the specificity of the assumptions from the specificity of the implications. We would hope for weak assumptions that approximate many situations and strong implications that are very precise, easily falsified, and more than the sum of the assumptions.

Fortunately, descriptive deductive research only requires observations to inspire the theory and, hence, is less dependent on the comprehensiveness of the observations. Nevertheless, TAK bias could mislead some researchers into deducing descriptive theories with little predictive capability. Researchers can overcome TAK bias by actively observing nonsurvivors.

Implications for Descriptive Inferential Research

TAK bias may have the most dramatic impact on descriptive inferential research. Unlike normative research that can focus only on selected variables and rely on the decision maker's knowledge, descriptive inferential research must claim that it captures the primary variables that explain the observed behavior. For example, Mitra and Golder (2006) infer serveral important findings that describe the impact of objective quality changes for perceived quality. Moreover, if the contribution relies on inference from a sample, the sample must be representative. TAK bias makes both the sample and the observed variables unrepresentative. It also threatens inference by masking the most critical variables as simply common properties of all the observations.

We must use great care when limiting our analysis to variables exhibiting large amounts of variation. Because variables related to critical properties will show little or no variance, it is essential that observed data include nonsurvivors.

Conclusion

When our empirical observations include only those from existing organizations, products, and processes, then these observations could easily exhibit the Anna Karenina bias. Like the Survivor bias, the Anna Karenina bias results from observations of survivors being different than the missing observations of nonsurvivors. However, Survivor bias focuses on the impact of missing observations on the values of observed variables.

The Anna Karenina bias takes Survivor bias one step farther. Not only are survivors different on observed variables, but also focusing only on existing organizations, products, and processes leads us to observe different variables. Potentially critical variables might appear unimportant because of their extremely low variance. Indeed, all survivors may show little or no variance, almost by definition, on the most critical requisites for survival, which may cause us to overlook the most important variables necessary for survival. Hence, the critical requisites are not variables at all, but constants.

If we make passive observations, we risk overlooking the critical variables necessary to understand and influence the phenomena of interest. The Anna Karenina bias tells us that the lowest variance attributes might be the most important variables because a low variance implies a necessary condition for survival. Moreover, the Anna Karenina bias suggests that we must observe many nonsurvivors before we can uncover all of the relevant variables associated with survival.

We need more active observation. We should not restrict ourselves to accounting data. We should not let accountants decide the variables to explain phenomena and extend marketing theory. Although inferential analysis is an important research step, we can only achieve active observation from deductive analysis. Only with strong (i.e., unambiguous and specific) deductive theory can we know which variables to observe.

In the end, the most revealing part of a data set might be what we fail to observe.

References

Bleiberg, S. D. 1986. The nature of the universe. *Financial Analysts J.* **42**(2) 13–14.

Diamond, J. M. 1997. *Guns, Germs, and Steel: The Fates of Human Societies*. W. W. Norton, New York.

Ehrman, C. M., S. M. Shugan. 1995. The forecaster's dilemma. *Marketing Sci.* **14**(2) 123–147.

Gilbride, T., G. M. Allenby. 2004. A choice model with conjunctive, disjunctive, and compensatory screening rules. *Marketing Sci.* **23**(3) 391–406.

Golder, P. N., G. J. Tellis. 1993. Pioneer advantage: Marketing logic or marketing legend? *J. Marketing* **30**(2) 158–170.

Guo, L. 2006. Consumption flexibility, product configuration, and market competition. *Marketing Sci.* **25**(2) 116–130.

Hauser, J., G. J. Tellis, A. Griffin. 2006. Research on innovation: A review and agenda for marketing science. *Marketing Sci.* **25**(6) 687–717.

Liu, Y., Z. J. Zhang. 2006. The benefits of personalized pricing and a channel. *Marketing Sci.* **25**(1) 97–105.

Mitra, D., P. N. Golder. 2006. How does objective quality affect perceived quality? Short-term effects, long-term effects, and asymmetries. *Marketing Sci.* **25**(3) 230–247.

Shugan, S. M. 1980. The cost of thinking. *J. Consumer Res.* **7**(2) 99–111.

Shugan, S. M. 2002. In search of data: An editorial. *Marketing Sci.* **21**(4) 369–377.

Shugan, S. M. 2006. Errors in the variables, unobserved heterogeneity, and other ways of hiding statistical error. *Marketing Sci.* **25**(3) 203–216.