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USING BAYESIAN METHODS IN STRATEGY RESEARCH: AN EXTENSION OF HANSEN *et al.*

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Hansen, Perry, and Reese (2004) recently argued for and demonstrated the utility of Bayesian methods for research associated with the resource-based view (RBV) of the firm. In this paper, we propose that Bayesian approaches are highly relevant not only for strategy problems based on the RBV, but also to its extensions in the areas of dynamic capabilities and co-evolution of industries and firms. Further, we argue that Bayesian methods are equally applicable for a wide range of strategy research questions at both the micro- and macro-level. Bayesian techniques are especially useful in addressing specific methodological challenges related to firm- and individual-level effects, firm-level predictive results, precision with small samples, asymmetric distributions, and the treatment of missing data. Moreover, Bayesian methods readily permit the engineering and updating of more realistic, complex models. We provide a specific illustration of the utility of Bayesian approaches in strategy research on entry order and pioneering advantage to show how they can help to inform research that integrates micro- and macro-phenomena within a dynamic and interactive environment.

INTRODUCTION

Recently, Hansen, Perry, and Reese (2004) (hereafter HPR) described how empirical research using the theoretical perspectives of the resource-based view (RBV) of the firm may be usefully examined through Bayesian hierarchical modeling. They argued that aspects of RBV research, notably estimation of detailed findings at the individual firm level, are especially well informed by Bayesian methods. HPR showed how information about the full distribution of firm-level parameters afforded by the Bayesian perspective can be used to go beyond the typical overall point estimates and aggregate confidence intervals generated from standard statistical analyses. In particular, detailed information may be readily estimated such as the probability that the outcome of a particular firm initiative will be positive or within some particular range.

In this paper, we argue that the Bayesian approach has utility for a broader range of strategy research. More specifically, the ability of Bayesian hierarchical models to 'borrow strength' across firm-level activities (possibly in separate markets or at separate points in time) allows for the same kind of detailed findings described in HPR to be obtained in research relying on a wide range of theoretical traditions in strategy. Indeed, Bayesian methods have had a major impact on other business management fields such as marketing precisely because of their ability to deliver observation-specific results (see Allenby, Bakken, and Rossi, 2004, for an overview).

Bayesian techniques are helpful in informing both micro- and macro-level strategy research

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questions. For example, Bayesian methods offer approaches that assist in overcoming challenges associated with incorporating firm- and individual-level variables in their models. In addition, Bayesian approaches are appropriate for macro-level research related to the context and external dynamics of entry order, pioneering advantage, and first mover strategies, particularly in environments characterized by rapid change. Research on pioneering advantage offers mixed normative guidance as to the conditions under which early or later entry is preferable. From a Bayesian perspective, those conditions often change and evolve; requiring updating that includes a re-evaluation and incorporation of prior conditions into future testing (see also Hahn, 2006, and HPR for additional discussion regarding the incorporation of prior information in a Bayesian framework as well as HPR for an introduction to Bayesian concepts).

This paper is organized as follows. First, we summarize and comment on the main contributions of HPR regarding the utility of a Bayesian approach in RBV-based strategy research. Then, we move beyond the special case of RBV to show more generally how Bayesian methods can inform approaches to and findings of strategy research at both the micro- and macro-levels. Next, we illustrate these points with a specific application to entry order and pioneering advantage research, an application that complements the RBV focus of HPR. Finally, we summarize these contributions and draw conclusions about the potential impact of Bayesian methods in strategic management research more broadly.

A BAYESIAN APPROACH TO RBV STRATEGY RESEARCH AND ITS EXTENSIONS

In developing the background to their research, HPR discussed several reasons to consider a Bayesian approach to strategy research. We briefly review some of those reasons and summarize HPR's results and findings that were obtained using a Bayesian approach. We then argue that Bayesian methods are also relevant for recent extensions of the RBV, notably the dynamic capabilities and co-evolutionary streams of strategy research.

The contributions of Bayesian approaches to RBV strategy research

HPR proposed that the theoretical and the practical utility of the RBV may be enhanced by operationalizing the theory in a manner that is more consistent with the original framework as developed by Penrose (1959). They suggested that a more complete understanding of the RBV should reflect the explicit recognition of two classes of resources: administrative resources and productive resources. The addition of administrative resources shifts focus to discretionary managerial decisions and therefore individual-level effects, the measurement of which is well suited to the application of Bayesian methods. Further, they argued that the RBV's emphasis on exceptional performance, that is, statistical outliers, constitutes another condition that makes Bayesian approaches especially effective.

Hence, according to HPR, one of the most interesting reasons to consider a Bayesian approach in strategy research is the ability to obtain individual-level effects that derive from administrative—as well as productive—capabilities. In HPR, this allows for firm-specific findings to be determined by the estimation of additional intercepts nested at the firm level. These intercepts can be thought of as offsets or deviations from the overall population intercept. Thus, firms that are underperforming with regard to an outcome variable because of internal variation in resources or capabilities will have a specific offset that reflects their level of underperformance. Conversely, overperforming firms will have offsets that capture their resource-based advantage.

Individual-level effects have several uses in strategy research. First, they allow for more direct comparisons of the unique capabilities of the units of analysis under examination. For example, firms can be sorted from highest to lowest according to the distributions of their effects and these distributions of these effects can be plotted on a common graph. The firms may then be clustered into peer groups or subdivided into above-average vs. below. In a related analysis, HPR obtained the average industry-level effect and then compared the firm-specific effect for Micron (their principal focal firm) to it. Their analysis showed that Micron was not only likely to outperform the industry on average, but also that Micron's market performance effect was more consistently and closely centered around a central value (63%). By contrast, the industry performance effect was lower and had a much wider dispersion, indicating a lower level of consistency and a higher rate of variability at the industry level. Second, it is important to note that these comparisons are adjusted for any other covariates in the model. For example, if firm size had been entered in the model as an aggregate-level covariate, the firm-specific comparisons would be adjusted to account for firm size. This may be helpful to a researcher investigating underlying assumptions such as constant returns to scale. Conversely, the aggregate-level parameters will be estimated in manner that permits controlling for firm-level effects.

Third, these individual effects can be used in conjunction with aggregate-level effects to provide more specific predictions or forecasts about out-of-sample events. For example, it may be of interest to examine what performance would be like for a particular firm if it increased in size but otherwise retained its unique characteristics. Such an analysis would be straightforward in the Bayesian context. By contrast, classic regression approaches rely exclusively on aggregate-level parameters, so they can only estimate how an average firm's performance would change if it moved from one size to another. Thus, a Bayesian approach allows for more detailed examinations of the impacts of strategic endeavors. In turn, this should lead to improved understanding of the factors that influence firm performance-related outcomes. Individual-level effects, however, need not be associated exclusively with firms per se but can also be associated with other relevant units of analysis under consideration. For example, the units of analysis may be individuals (as is often the case in marketing), departments, plants, industries, states, regions, countries, or entities at many other levels of analysis. Multiple levels of effects (such as plants within firms) may also be incorporated.

Bayesian approaches, extensions of the RBV, and the boundaries of the firm

Although HPR provide an effective argument as to why the Bayesian approach is particularly useful for RBV research, and they undertake a rigorous and insightful application of that approach, the potential for Bayesian methods to inform strategy research is much broader than in the RBV alone. Indeed, Bayesian approaches may be more useful in other areas of strategy research. Here we begin with a brief discussion of the potential for Bayesian methods to inform more contemporary variants of the RBV framework before moving on to a wider range of potential applications.

Recent extensions of the RBV literature have offered a dynamic capabilities perspective on strategy. The RBV had been criticized for lacking sufficient focus on how and why certain firms have competitive advantage in situations of rapid and unpredictable change (Eisenhardt and Martin, 2000) and for overlooking the managerial coordinative processes by which firms assemble and leverage knowledge assets. In response, building on the administrative and productive capabilities of the RBV, strategy researchers have offered an extension of the RBV and other strategy perspectives in the form of a 'dynamic capabilities' view of competitive strategy (Kogut and Zander, 1992; Teece, Pisano, and Shuen, 1997). Dynamic capabilities refer to capabilities by which managers 'integrate, build, and reconfigure internal and external competencies to address rapidly changing environments' (Teece *et al*., 1997: 516). Kogut and Zander (1992) refer to 'combinative capabilities' as the ability to acquire and synthesize knowledge resources and build new applications from those resources, especially in a changing environment. The focus of the dynamic capabilities perspectives on rapid change captures the environment in which firms consider—often under intense pressure from competitors and the external environment—how and where to deploy and redeploy assets across geographic space.

In a related vein, the strategic management literature has struggled with how best to apply resource-based perspectives on strategy in environments characterized by turbulence and change. Moreover, strategy researchers are now expanding their focus beyond the boundaries of the firm as reflected in conceptual development and empirical testing of co-evolutionary theory. In particular, recent work in the area of dynamic, co-evolutionary processes in organizations (Volberda and Lewin, 2003) is relevant to the challenges for the firm of maintaining competitive advantage in the face of pressures to reduce costs and shift production brought about by changing technology, markets, and competition, and Bayesian methods can be of use in capturing these more dynamic and complex relationships.

In the next section, we offer a more specific accounting of the particular benefits of Bayesian methods to strategy research at different levels of analysis and using different types of variables. We then broaden the discussion to show that Bayesian methods are important for grappling with more expansive issues associated with new and evolving theoretical paradigms in strategy research, such as co-evolution and strategic renewal.

THE CONTRIBUTION OF BAYESIAN METHODS TO METHODOLOGICAL AND CONCEPTUAL CHALLENGES IN STRATEGY RESEARCH

Beyond the persuasive argument for application of a Bayesian approach to strategy research based upon the RBV and its extensions in the areas of dynamic capabilities and co-evolution, there are a range of additional reasons to consider Bayesian methods within strategy research. Bayesian approaches are relevant for both micro- and macro-level phenomena and may be especially useful in studies that attempt to integrate variables at multiple levels and under dynamic conditions. We summarize these considerations and the situations to which they apply in Table 1.

Strategy research and the Bayesian perspective

Two of the main frameworks that have characterized economic approaches to strategy research are the industrial organization (I/O) perspective and the RBV. The I/O perspective (Bain, 1956; Porter, 1980) has focused on the interaction of firms within industries characterized by particular structures and dynamics, while the RBV (Barney, 1991; Penrose, 1959; Nelson and Winter, 1982) has focused on the resources firms possess and deploy. These two perspectives have defined and constrained many of the methodological approaches to strategy problems over the last three decades. In addition to the economic approaches to strategy research, social and behavioral theory have been used to shed insights into institutional, organizational, group, and individual decision making and its implications for strategic competitiveness. There are several variables and context-based conditions that pose challenges to research within economic, social, and behavioral traditions, and at the macro- and micro-levels of analysis.

In addition to industry- and macro-level analysis, there is a long tradition of firm-level research addressing the role and influence of CEOs and top management teams (TMTs), beginning with the early research focused on dominant coalitions (Cyert and March, 1963), managerial theories and analyses (Mintzberg, 1973), and demography (Pfeffer, 1972; Hambrick and Mason, 1984). More recently, TMT research has turned toward process and decision making (Eisenhardt, 1989; Wally and Baum, 1994; Lawrence, 1997). Recently there have been calls for improved methods of investigation (West and Schwenk, 1996; Lawrence, 1997), incorporation of additional explanatory variables

Table 1. Strategy research challenge areas using traditional methods and contributions of Bayesian approaches

Context/situation	Challenge for traditional methods	Contributions of Bayesian approach
Firm- and individual-level effects	Individual effects often ignored or averaged out. Only limited information potentially available from EM estimation	Permits full estimation of distribution of individual effects terms
Firm-level predictive results	Estimation of firm-level in-sample and out-of-sample results difficult especially as model complexity increases	Estimation of full predictive results straightforward, even in complex models
Precision with small samples and asymmetric distributions	Large-sample approximations may not hold when samples are small or data are skewed	Distributional results exact under skew and/or small samples
Missing data	Case deletion and mean substitution known to generate bias, EM algorithm only provides point estimates	Full results and distributions available via techniques such as data augmentation or Gibbs sampling

(Finkelstein and Hambrick, 1996), and investigation of additional outcomes of TMTs (Collins and Clark, 2003).

Methodological challenges associated with research of TMTs and CEO characteristics include the presence of a large number of potentially influential factors that may occur at a variety of levels, including unmeasured but important CEO characteristics, actions of competitors, business cycle fluctuations, industry developments, changing consumer tastes, and even macroeconomic and/or political events occurring at the national and international level. Despite the proliferation of factors, it is unlikely that all such factors are equally relevant and so instead attention should be appropriately focused on a key subset of these. Such a subset would most likely include, *inter alia*, CEO- and firm-specific characteristics.

Here we review how Bayesian approaches can improve these approaches, using illustrations of research on industry and firm performance, and CEO and top management teams, as examples of variables of interest.

Firm- and individual-level effects

Much of strategy is concerned with firm- and individual-level effects, only some of which are captured by the RBV. Estimating firm- and individual-level effects allows a clearer picture of the true relationship between an independent and dependent variable to emerge, because in estimating these effects we isolate their impacts from the impact of the true variable of interest. Other firm variables at the individual level that are of concern to strategy researchers generally, and to those studying strategic leadership and top management characteristics in particular (see Finkelstein and Hambrick, 1996), include demographic characteristics such as CEO education, age, tenure, and network relationships.

A Bayesian approach to study of the independent influence of these variables can illuminate strategy research in a number of ways. In the typical fixed-effects model, it may be difficult to disentangle the impact of a CEO (and his/her characteristics) on performance from the impact of other aspects of the firm (such as organizational culture). In part, this difficulty arises because a CEO is an individual who brings many characteristics to the position, some of which may be more easily measurable (such as education, age, tenure, and network relationships) and some of which may be less easily measurable but nevertheless highly relevant (such as charisma or innate leadership abilities). Hence, both firm-specific and CEO-specific effects must be controlled for simultaneously. To examine this issue in more detail, firm-specific effects could be eliminated by following only one specific firm over a time period in which multiple CEOs had come and gone (note that this decision eliminates the existence of differing firm-specific effects at the cost of drastically reducing the sample size and perhaps the generalizability of the research). Dummy variables for each CEO could be used to try to capture the impact of the unmeasured CEO characteristics so as to permit a clearer examination of the impact of the measured characteristics. However, there will be a trade-off associated with the turnover rate of CEOs in the firm. High-turnover firms will have many CEOs with short tenures, allowing for a wider range of CEO characteristics such as education and age to be analyzed. However, the short CEO tenures will result in a proliferation of dummy variables that will lead to a highly overparameterized model for which the usual statistical assumptions may not hold. This is because the sample size per parameter will be very low.

In this situation, individual-level random effects at the level of the CEO will allow for the pooling of information across CEOs for more reliably estimated coefficients. For example, suppose that y_{it} is the performance measure of the firm under CEO i during time period t of his or her tenure, and that x_{it} is the CEO characteristic of interest, say CEO age. Then, the classical ordinary least-squares regression equation can be written as

$$y_{it} = \alpha + \beta x_{it} + \varepsilon_{it} \tag{1}$$

where α is the intercept, β is the slope of the relationship between x and y, and ε represents the error term. Here, unmodeled characteristics of the CEO such as charisma appear in the error term and thus contribute additional random noise to the analysis. This error term can be examined more closely by breaking it into an intercept-like term for each CEO and letting the remainder be the random noise component. The intercept for the CEO i can be written as b_i, and the remainder can be written as ε^*_{it}. Thus, we have $\varepsilon_{it} = b_i + \varepsilon^*_{it}$.

Now we can rewrite the regression equation as

$$y_{it} = \alpha + \beta x_{it} + b_i + \varepsilon^*_{it} \qquad (2)$$

The model formulation can be completed by considering the variance of the error terms in more detail. In Equation 1, the regression model requires that the error terms have a normal distribution with variance σ^2. In Equation 2, however, we are splitting the error term into two parts. The variance will also be split into two variance components: σ_b^2 and $\sigma_{\varepsilon*}^2$. Because the b_i terms have a common normal distribution with their own variance, σ_b^2, these terms can borrow strength from one another so that they are estimated more accurately. Phrased differently, since the b_i terms are drawn from a common distribution, learning about one of them assists in learning about the rest. As a brief example, suppose we were to discover an entirely new industry, never before examined, perhaps in some remote region of a developing country. Suppose further there are 15 small business 'firms' that comprise this industry. As we learn about the business performance of Firm 1, we may have an inkling of an idea of what to expect regarding Firms 2 through 15. By the time Firms 1 through 10 have been analyzed, we may know a good deal about the industry and should be in a better position to make some basic predictions about Firms 11 through 15 because of our updated knowledge about the mean and variance of the distribution. For example, we might expect that the performance of those firms is likely to lie in a particular range. Of course, we would continue our study by examining the remaining firms, but it should be clear that the existence of a common parameter set that governs the behavior of individual-level parameters in effect allows for information about the units of analysis to be propagated or shared with the other units, a phenomenon often termed 'borrowing strength' in the modeling literature.

Once this framework is established, the extension to additional levels is straightforward. Recall that the focus on one firm was to eliminate any firm-specific effects from the analysis. We may now wish to add more firms to our sample so that we have a total of j firms in total. Here again, we would take our y_{ijt} and partition the error term so that we had three variance components, the new one included to reflect the random firm-specific terms. These terms at the firm level can be employed to account for firm-specific heterogeneity, which would otherwise be manifested as noise in the model. The benefit of including terms to capture these kinds of firm- or individual-level effects is not confined to strategy research but has also been used in other fields. For example, in marketing this approach was employed to inform the process of tailoring a marketing campaign away from one-size-fits-all generic coupon mailings toward the level of the individual consumer household and its specific marketing characteristics (Rossi and Allenby, 1993).

Firm-level predictive results

Strategy research is often concerned with measuring firm-specific results and outcomes. In a Bayesian approach, results can be disaggregated to the firm or even individual level, a technique that can be valuable in terms of offering normative firm-level recommendations. For example, consider the development of an experimental drug. Regulators or the drug's developer may be interested in the average impact of the drug. By contrast, the patient will care less about the average effect of the drug and instead care much more deeply about the possible (unique) impact of the drug on him or her. Regulators and the drug's developer should also be interested in individual-level experiences with the drug because this information would allow them to monitor whether there are any outliers or extreme responses that would preclude the drug's wider usage. With a Bayesian approach, the individual-level effects can provide more information to the 'patient' about what he/she should specifically expect to have as an outcome and also to the developer about what responses are like. Thus, a potential source of spurious findings will be removed as predictions or recommendations will not be based on 'average performance' but instead be reflective of individual performance.

In the TMT research and its related application in the study of board composition and influence, Bayesian methods would allow disaggregation of the impact of different board member characteristics on decisions about compensation and strategy in a manner similar to those described at the CEO level. Here, the model can be extended such that the board-specific effects were conceptualized as being a function of covariates associated with the board. For example, the size of the board or the amount of time the board had been in existence with its current set of members could be incorporated into the model. The model could be further extended by examining covariate information regarding the board's members. Here, we might again consider characteristics such as the age or the amount of experience of board members. Bayesian methods are especially helpful in facilitating updating of conditions. For example, in studying the ability of a CEO to manage the integration of an acquired firm into the focal firm, Bayesian approaches would allow for updating to take into account the accumulated experience of the CEO in integrating prior acquisitions. In essence, such an empirical inquiry amounts to estimating regression-type relationships at a more aggregate level of analysis (the board level) that are partially a function of relationships that occur at a more disaggregate level (the member level). In turn, we may wish to examine how factors at these two different levels resulted in impacts or outcomes at yet another level of analysis (e.g., such as at the even more aggregate firm level). The flexibility of a hierarchical modeling approach allows for these kinds of inquiries.

Predictive results for an in-sample firm can be obtained by considering the distribution of the terms relevant for the firm of interest. For example, suppose we estimate a regression model with individual-level intercepts to account for firm-specific effects, and that firm i is our firm of interest. Our model can be written as

$$y_i = \alpha + \beta x_i + b_i + \varepsilon_i \tag{3}$$

The model terms that are relevant to firm i can then be collected to obtain the predictive distribution for this firm. If we use Markov chain Monte Carlo (MCMC) techniques, which are simulation-based methods commonly used in Bayesian modeling (see, for example, HPR for a review), obtaining the predictive distribution is straightforward. Here, terms can be collected to form the linear predictor for firm i, $\eta_i = \alpha + \beta x_i + b_i$, and we then sample from the posterior distribution for η_i by monitoring it during the MCMC run. Then, we can estimate the expected value, standard deviation, and 95 percent probability interval of η_i so that we can draw inferential conclusions. While we have focused on an in-sample firm here, for out-of-sample firms the predictive distribution is also readily available (e.g., Gill, 2002: 179–181). We return to the topic of out-of-sample predictive distributions below.

Controlling for firm-level effects in entry research is a major challenge. Doh (2000) suggests that success (or failure) in entering markets may be due to a latent manifestation of an underlying positive relationship between a (possibly unobservable) firm-level characteristic such as entrepreneurial orientation and an observable action (i.e., a more or less aggressive move into a market). The flexibility in model building afforded by the Bayesian approach could permit an empirical examination of this conceptualization as follows. First, the underlying characteristic could be estimated from indicators using a latent trait model. Then, latent measurement of the firm's value could be used to predict firm propensity to engage in more aggressive market entry tactics. Later in this paper we describe the application of a very similar model-building process in which theory suggests the use of a more complex model based on the conjunction of a transition matrix model and a latent class model.

Precision with small samples and asymmetric distributions

Strategy research seeking to measure individual, firm, and industry variables is often challenged by low sample size. For example, surveys of CEOs often result in relatively small samples, due to the limited number of CEOs and their lack of response to surveys. Moreover, extrapolating individual responses to firm-level behaviors can be dangerous if there are not additional respondents from individual firms in order to ensure inter-rater reliability. In entry order research, the problem of small sample sizes is pervasive, especially for entry into highly concentrated industries such as those that are formerly state-owned or regulated such as energy, electric utilities, and telecommunications (Doh, 2000). In co-evolutionary studies, the subject may be a small group of firms interacting with the broader environment. Outside of the strategy field, recent research on the role of nongovernmental organizations (NGOs) in global governance and value creation has called for the inclusion of NGOs in research in international business–government relations (Teegen, Doh, and Vachani, 2004). Such research might include interactions among a single firm, host government, and influential NGO, just three organizational actors that also feature fundamentally different characteristics. A Bayesian approach to strategy and other managerial research can permit modeling to proceed despite the existence of small sample sizes and possibly non-normal parameter distributions by eliminating the need to appeal to large-sample results.

Bayesian approaches can offer more exacting and precise findings within small samples because, unlike classical models, they do not rely on the large-sample properties of estimators. Students in most introductory courses on classical statistics learn various rules of thumb about the sample sizes necessary for reasonably reliable parameter estimation. For example, in the classical approach a sample size of 30 is often used as a rule of thumb to assess whether a sample mean may be reliably estimated. This rule of thumb draws its justification from the Central Limit Theorem, which describes the behavior of estimators in large samples. The properties of the normal distribution are well understood, and so the normal distribution (or in other instances, the *t* distribution) is used as an approximation to avoid more complex computations.

A particular advantage of the normal distribution (and its heavier-tailed relations) is that it is symmetric. This allows a simple formula to be used for confidence intervals that, because of symmetry, extend the same distance in both directions around the central value. Specifically, confidence intervals can be constructed using the form: *parameter estimate* ± *constant* × *standard error*, where *constant* is a value indicating the coverage level of the confidence interval (i.e., constant = 1.96 for the two-sided normal 95% confidence interval). In most traditional approaches to multivariate statistical analysis, there is an assumption of symmetric distributions across the sample. As a result of natural artifacts within a sample, these distributions are rarely symmetric, making it necessary to test for—and often attempt to adjust—distributions that violate these rules. If it turns out that such assumptions of symmetry are incorrect, substantial incorrectness of classical standard errors and confidence intervals may be observed (for examples, see Brown and Prescott, 1999; Raudenbush and Bryk, 2002).

As a point of contrast, the Bayesian approach usually involves the direct evaluation of the integrals associated with the probability distributions under consideration. This is typically more computationally demanding but is exact at all sample sizes and moreover does not require an assumption of symmetry. Given the increasing prevalence of more complex and highly parameterized models in strategy research, the issue of sample size adequacy should be of increasing concern. Yet guidelines for adequate sample sizes can vary widely. In the structural equation modeling literature, for example, in some cases adequacy was achieved at a ratio of five subjects per variable (Bentler and Chou, 1987), while in other cases even a sample size of 5000 may be insufficient (Hu, Bentler, and Kano, 1992) Of course, the reason for the variety in recommendations is that the behavior of the estimators depends on the properties of the data, and so for any particular data set the adequacy of large-sample approximations may be unknown or unknowable. Bayesian methods, by contrast, provide the exact distributions of parameters, eliminating concern over whether a normal approximation is adequate.

Missing data

Missing observations regularly pose challenges when working with real-world data (Little and Rubin, 1987). As in the case of most empirical studies, strategy researchers must also deal with missing data (e.g., Leiblein and Miller, 2003). In research on the co-evolution of firms and industries, there is considerable missing data that must be addressed in some fashion. In some cases, data may be unavailable or unobserved. There are a variety of *ad hoc* approaches for handling missing data. These range from mean substitution, which is known to create bias such that the covariance matrix tends toward zero, to pairwise deletion which may cause the covariance matrix to no longer be positive definite. Perhaps the most commonly used approach is casewise deletion, wherein observations are thrown out if they have even one missing data point on any of the variables of interest. Casewise deletion is predicated on specific assumptions about the pattern of missing data, and it can be shown to bias the estimates so that incorrect conclusions are drawn (Ibrahim *et al*., 2005). Missing data problems can often be addressed with the EM algorithm (Dempster, Laird, and Rubin, 1977; see also McLachlan and Krishnan, 1997), and the resulting estimates can usually be shown to have desirable properties. However, the EM algorithm gives a single summary point estimate of the missing value, and so in effect ignores or averages over the uncertainty about the missing value. In the Bayesian framework, however, missing data are merely other unknown quantities to be estimated, just like regression coefficients. Indeed, MCMC estimation techniques used in Bayesian inference can be shown to be related to the EM algorithm (Schafer, 1997), and Bayesian approaches to missing data problems have been shown to have attractive properties (Rubin, 1996) and are used in demanding environments such as in the context of public-use samples at the U.S. Census Bureau (Clogg *et al*., 1991).

Unfortunately, more appropriate treatments for missing data have yet to become commonplace in management research, despite the fact that the validity of results may depend on the methods used. For example, in the case of survey research involving CEO characteristics, some CEOs may elect not to respond to a few questions. Using a simple strategy of casewise deletion, these CEO respondents would have to be dropped from the analysis even though most of their information is available. Because those CEOs are now lost, the sample size and the researcher's ability to uncover hypothesized relationships both decrease. It may turn out that findings will disappear because of the inflation of standard errors, or the coefficient values may be biased far away from their true values. In the latter case, incorrect results may be reported and even published. At a minimum, additional work will need to be undertaken to justify the validity of the data by testing for differences between the complete-data respondents and the incomplete-data respondents.

In summary, missing data have long been a challenge associated with empirical work. However, the tools to handle this problem are becoming widely available. From the Bayesian perspective, applications-oriented approaches for missing data are covered by Congdon (2001; §6.4–6.6), while from a classical perspective popular software packages such as SPSS have recently begun providing for missing value analysis using approaches based on the EM algorithm. Thus, we expect use of more sophisticated and appropriate missing data techniques to grow in popularity in the near future. Recent calls for more rigorous demonstration of validity and reliability in management research (Hubbard, Vetter, and Little, 1998) would be well served by best-practice methods for missing data. The adoption of such practices will positively affect research validity and rigor, improve the quality of the body of knowledge in management, and enhance journal stature.

To obtain results for missing data, we can use the out-of-sample predictive distribution mentioned earlier. In principle, we could work directly with the analytic formula for the distribution;[1] however, it is often easier to use MCMC simulation techniques to obtain results. For example, using the MCMC technique of data augmentation (Tanner and Wong, 1987), we iteratively use the parameters and the completely observed data to estimate the missing data, and then we use the estimated missing data and the completely observed data to better estimate the parameters. The technique is very similar to that of the EM algorithm in that we iteratively refine our estimates with the information available. The attractiveness of data augmentation as compared to EM is that we obtain the full posterior predictive distribution of the missing data and so we can calculate the expected values, standard deviations, and 95 percent probability intervals for them. By contrast, EM will identify the modes of the missing data points only. Note that if we only simulate one sample value of each missing datum per iteration, we obtain as a special case the widely used MCMC technique called Gibbs sampling.

Bayesian approaches and emerging issues in strategy research: co-evolution and strategic renewal

Volberda and Lewin (2003: 2129) have called for 'fundamentally new empirical research strategies and approaches' to strategy research. Compared to traditional methodological approaches to strategy research, Bayesian techniques have the potential to incorporate variables that would otherwise go unobserved or unmeasured, reveal relationships that would not necessarily have been made evident or explicit, provide new approaches to test existing theory (such as HPR demonstrated), and offer the prospect of more thorough testing of new and evolving theoretical paradigms. For example, Flier, van den Bosch, and Volberda (2003) proposed metrics associated with three dimensions of strategic renewal: an exploration/exploitation

[1] In general, this means evaluating an integral of the form $\int p(y_M|y_O,\theta)\,d\theta$, where y_M is the missing data, y_O is the observed data, and θ is the parameter vector.

ratio, an external/internal strategic renewal actions ratio, and a temporal metric of strategic renewal formed from the timing, frequency, and volatility of strategic renewal actions. Bayesian approaches can provide the basis for examination of how the first two of these measures are affected by factors such as industry composition or managerial characteristics through the use of logistic regression models with random effects (e.g., Zeger and Karim, 1991). Such an approach would permit the estimation of firm-specific effects. In addition, the propositions derived by Flier *et al*. (2003) from single-lens and co-evolutionary theories seem well suited for empirical examination using Bayesian methods as were the RBV propositions investigated in HPR. Here we provide two examples.

First, from their review of the knowledge-based and dynamic capability perspectives on managerial intentionality, Flier *et al*. suggest that 'From a managerial intentionality approach, renewal actions of incumbent firms will show firm-specific patterns regarding the temporal dimension of strategic renewal behaviour' (Flier *et al*., 2003: 2167). Here, the authors indicate that renewal actions will have a strongly firm-specific component, indicating that an empirical perspective based on averages obtained from ordinary regression approaches will not be ideally suited for empirical inquiries. Second, using a co-evolutionary approach, they propose that 'From a co-evolutionary perspective, interaction effects of industry selection, country institutional effects and managerial intentionality at firm level explain deviations of strategic renewal behaviour of incumbent firms from predictions derived from single-lens theories' (Flier *et al*., 2003: 2168). In sum, firm-level interaction effects, including the evolution, co-evolution, and broader dynamic interactions between the firm and its environment, are hypothesized to explain the behavior of firms that would otherwise be viewed as unexplained deviations from the more specific single-lens theories. Bayesian methods are well suited to reveal these potentially latent relationships.

In summary, Bayesian methods are useful for addressing many pervasive challenges associated with empirical research. Yet perhaps the most interesting benefit of Bayesian methods is their flexibility; they allow more realistic and complex models to be built using well-known existing models as building blocks, a concept that can be thought of as incremental engineering. As such, new models can be engineered so that they are closely tailored to a strategy research issue. This permits the researcher to reflect more accurately the underlying reality in these circumstances. In the following section, such a model is presented. The model described involves the combination of a latent class model and a model for transition matrices.

APPLICATION: BAYESIAN APPROACHES TO RESEARCH ON ENTRY ORDER AND PIONEERING ADVANTAGE

In this section, we provide a specific application of a Bayesian approach to a circumstance that requires both macro- and micro-level analyses within a complex, dynamic environment.

Research on entry order and pioneering advantage

Strategy research on entry order has identified a number of salient variables at the environmental, industry, company, and individual level that must be considered when determining the preferred entry into a new sectoral or geographic market. These include various measures of time in relation to order entry, the resource commitments both incumbent and new entrants bring to their entry, the configuration—often evolving—and concentration of industries and markets during the entry period, the reaction of consumers and regulators to that evolving configuration, and the dynamic interactions among new entrants and incumbents and among all industries and participants during the period of analysis. Research in entry order has focused on country, market, and industrial organization variables as partial determinants of the conditions under which early entrants have the potential to internalize advantages that might be difficult for later entrants to appropriate (Kerin, Varadarajan and Peterson, 1992; Lieberman and Montgomery, 1988; Mascarenhas, 1992). First-mover benefits are substantial when one-time discontinuities create generous rent streams for the early entrant, with little left for followers (Doh, 2000). In other circumstances, later entrants may be advantaged because they are able to learn from the mistakes of first movers (Smith, Grimm, and

Gannon, 1992; Tellis and Golder, 1996) and the competitive dynamics among firms may result in the first mover overpaying for its initial position, a situation analogous to the 'winner's curse', a problem that is particularly acute in bidding for items of uncertain value, resulting in below-normal or even negative average profits for winners (Thaler, 1991). The challenge, of course, is determining, *ex ante*, which of the conditions exist to support early versus later entry.

Doh (2000) provides an interesting synthesis of industrial organization (macro) and RBV (micro) perspectives on strategies by firms in response to newly privatized and subsequently liberalized infrastructure markets such as electricity and telecommunications in developing countries. This circumstance suggests an integration of macro- and micro-level variables within a dynamic, unpredictable environment (Eisenhardt and Martin, 2000) and the need for dynamic capabilities to respond to that environment (Kogut and Zander, 1992; Teece *et al*., 1997). In addition, the interaction between entrants and the evolution of the privatizing and liberalizing markets suggest a dynamic, co-evolutionary process (Volberda and Lewin, 2003).

Methodological and variable challenges

In examining the impacts of entry order into markets, a number of variables and conditions lend themselves well to Bayesian methods. Entry order research has been challenged by the definition and measurement of time from first entry and the need to measure it at multiple points (Mitchell, 1989, 1991; Luo and Peng, 1998), the measurement of stage in product life-cycle and specification of performance by incumbent and new entrants (Mascarenhas, 1992), and the role of local context and the reaction of local firms. Researchers have also been concerned with the interactions among entry timing and firm asset advantages (Delios and Makino, 2003), the questions of survivor bias, the influence of resource commitments and technology transfer and on timing of entry and performance (Isobe, Makino, and Montgomery, 2000). Other issues of study have included the trade-offs between risk reduction and returns during initial and subsequent entry (Luo, 1998; Pan and Chi, 1999) and the benefits of different entry modes to entry order advantage (Pan, Shaomin, and Tse, 1999).

Specific illustration: The Bogner, Thomas, and McGee study of entry paths of European firms into the U.S. pharmaceutical industry

Bogner, Thomas, and McGee (1996) undertook a longitudinal study of the competitive positions and entry paths of European firms in the U.S. pharmaceutical market. The data upon which this study is based are rich and comprehensive, yet the study is primarily approached from a qualitative vantage as opposed to a more formal statistical one. While many qualitative insights were derived from the data, we see the potential for additional empirical insights, especially from the application of a Bayesian methodology. For example, the authors present an appendix that shows the composition of strategic groups in the U.S. pharmaceutical market. This information could actually be structured as a transition matrix which is amenable to empirical inquiry. An example of a model that might be considered is a comparison of movers and stayers (e.g., Fougere and Kamionka, 2003). Given the relatively small sample size of firms considered, a Bayesian approach might be better suited for the data. We begin our discussion below by first providing additional details regarding the data set. We then describe the model and examine the results with an emphasis on the new findings that our approach generates.

In an appendix, Bogner *et al.* (1996) track the evolution of the pharmaceutical industry by means of a qualitative graphical method in which they chart with arrows the transitioning movement of firms across time periods. In particular, they show firms in 1969 as being in one of four industry categories: medium-size limited research, medium-size moderate research, broad organic chemistry focus, and early diversification pursuit. In the period 1970–77, firms were again in one of four categories: medium-size limited research, traditionally antibiotics, broad organic chemistry focus, and generic-like firms. Additionally, there is a fifth category that can be derived from the two sets of results: market entrants and market withdrawers. Market entrants are those firms that were not classified in one of the four categories in 1969 but were classified in 1970–77. The converse description applies to market withdrawers.

We very briefly apply a Bayesian model for transition matrices to Bogner *et al.*'s data. Our model is simplified for expository purposes but extensions are straightforward. We suppose there is heterogeneity in the data such that there are distinct sets of market evolution strategies for the different firms. This corresponds to the notion that there are multiple latent classes of firms in the data with different strategies. Here, we posit that there are two latent classes and so for firm i we may write a latent variable, l_i, that takes on the values 1 and 2. Depending on a firm's latent class, its market evolution strategy will differ. That is, the market position of firm i in period 2 (1970–77), M_{i2}, will depend on its market position in period 1 (1969), M_{i1}, as well as its latent class. The latent class in turn is determined via logistic regression with an identifying intercept of 1 and a parameter α. Similarly, M_{i2} depends on the transition probabilities that are obtained from logistic regressions with identifying intercepts and parameters β_{11} to β_{55}, which capture the changes from the five states in M_{i1} to the five states in M_{i2}.

The model is estimated via MCMC which, as discussed previously, allows us to obtain the full distributions of the parameters of interest through simulation. In the Bayesian approach, prior distributions must be placed on parameters. Here, locally uniform noninformative normal priors (mean = 0, variance = 100) were used throughout. Noninformative priors, commonly used in contemporary Bayesian work, generally ensure that results are robust and the impact of the prior is minimal. Here, sensitivity analyses indicated that alternative noninformative prior specifications had no substantive effects on the results. We allowed 5000 iterations to elapse to give the simulation time to reach its final steady state. The parameter estimates were then based on the results from an additional 50,000 simulations from each parameter distribution. We present a few select results here. We find the posterior probability of a firm being in latent class 1 to be 34.3 percent and the probability of a firm being in latent class 2 to be 65.7 percent. Thus, we have two latent classes of differing prevalences, with strategies of firms in latent class 2 being the more dominant in the industry. Table 2 contains the transition probabilities for the medium-size limited research firms.

Two distinct strategies emerge. In latent class 1, firms typically elect to stay in their original category; i.e., a no-change strategy is adopted. This can be seen by the relatively high probability (0.700) of a firm that is originally a medium-size limited research firm (market category 2) remaining in category 2; hence, $p(2,2) = 0.700$. In the second latent class, evidence of switching occurs and specifically the trajectory is toward becoming a generic-like firm with high probability ($p(2,5) = 0.761$). We note that the other strategies (including market exit, which is category '1', traditionally antibiotics which is category '3', and broad organic chemistry focus which is category '4') are not adopted with any regularity. Bogner *et al.* (1996: 107) have graphically identified the cluster of firms that appears as latent class 2. These firms appear in the top of the leftmost column and are connected by an arrow to a cluster appearing at the bottom of column 2. However, the no-change group in latent class 1 is not explicitly identified there, despite the relative prevalence of the strategy. As for firm-level results, we may simulate directly from the predictive distribution to determine what transition strategy a firm will take. Overall, medium-size limited research firms are estimated to exit with probability 0.008, to remain as medium-size limited research firms with probability 0.354, to switch to the traditionally antibiotics category with probability 0.008, to switch to a broad organic chemistry focus with probability 0.008, and to switch to be a generic-like firm with probability 0.622.

Table 2. Transition probability estimates for medium-size limited research firms

Class 1		Class 2	
$p(2,1)$	0.010	$p(2,1)$	0.006
$p(2,2)$	0.700	$p(2,2)$	0.220
$p(2,3)$	0.016	$p(2,3)$	0.007
$p(2,4)$	0.016	$p(2,4)$	0.006
$p(2,5)$	0.258	$p(2,5)$	0.761

In Table 3, we consider the strategies of entering firms (category '1'). The strategies of these firms are not as explicitly delineated in the graphical approach of Bogner *et al*. Here, we find that no single strategy truly dominates for firms in

Table 3. Transition probability estimates for market entrants

Class 1		Class 2	
$p(2,1)$	0.021	$p(2,1)$	0.017
$p(2,2)$	0.344	$p(2,2)$	0.175
$p(2,3)$	0.028	$p(2,3)$	0.015
$p(2,4)$	0.280	$p(2,4)$	0.614
$p(2,5)$	0.328	$p(2,5)$	0.179

latent class 1. Firms in latent class 1 enter as medium-size limited research firms with probability $p(1, 2) = 0.344$. This is closely followed by entry as a generic-like firm ($p(1, 5) = 0.328$) and then as a broad organic chemistry focus firm ($p(1, 4) = 0.280$). We also see in latent class 2 that the typical decision is to enter as a broad organic chemistry focus firm (with probability $p(2, 4) = 0.614$). We note here that Bogner *et al*. discussed different entry paths such as these in their analyses of the findings. However, the model presented here helps extend these findings by demonstrating that there is one class of firms with a focused primary strategy (latent class 2) and that there is another class with a more eclectic strategy. As for firm-level results, direct simulation results indicate entrants are estimated to exit with probability 0.019, to become medium-size limited research firms with probability 0.224, to enter the traditionally antibiotics category with probability 0.017, to adopt a broad organic chemistry focus with probability 0.516, and to become a generic-like firm with probability 0.224.

In summary, our modeling approach illustrates the flexibility of the Bayesian paradigm. It is relatively straightforward to engineer more complex combinations of simpler models. Here, we combined a latent class model with a transition matrix analysis. We also benefit from the ability to derive estimations from a small sample size, an important consideration as only 34 firms were in the sample. Further, we see how the Bayesian approach quantitatively reinforces the initial conclusions drawn by Bogner *et al*. through a qualitative approach, while providing additional insights from the same basic data set. Finally, Bayesian methods allow the researcher to raise and answer new questions with the results that would be inferred less clearly from the original analysis.

BAYESIAN METHODS AND NEW FRONTIERS IN STRATEGY RESEARCH

Volberda and Lewin's (2003) proposal for new and fundamentally different approaches to strategy research suggests a re-examination of the traditional empirical approaches to managerial problems. In this paper, we have sought to provide a general argument for how the application of Bayesian methods to strategy problems responds to this challenge, and we have offered a series of particular examples for how this application can be accomplished in practice. In rich complex business environments increasingly characterized by change and uncertainty, Bayesian methods may be a more useful, flexible, and accurate methodological approach to strategy problems. One feature of the Bayesian approach involves the need to place prior distributions on all parameters to reflect prior beliefs. The use of priors that are noninformative is very common in contemporary Bayesian analyses. Such priors are either uniform or approximately uniform distributions across the range of realistically observable coefficient values (and often extend well beyond what might realistically be observed as a 'just in case' measure). The use of these priors typically produces results regarding the coefficients which closely resemble their classical counterparts. Moreover, it is easy to perform sensitivity analyses regarding the impact of certain priors to determine whether they have any meaningful influence on results.

When standard conditions are met, standard research questions are posed, and standard models applied, the Bayesian and classical approaches generally provide similar results about parameters, particularly when noninformative priors are used. This is because both Bayesian and classical approaches rely on the concept of likelihood to characterize the data (e.g., Gelman *et al*., 2004). Here, the standard conditions include large sample sizes and well-behaved data that conform to assumptions made about them, the standard questions revolve around the behavior of average firms and the coefficients of their associated distributions, and the standard models are the familiar long-utilized ones such as ordinary linear regression. Thus, in these circumstances research studies would likely be well served by both classical and Bayesian methods. As such, standard approaches will undoubtedly continue to be useful in establishing core relationships between key concepts. However, when there is a need to move outside the standard frameworks to accommodate richer but perhaps less well-behaved data, or when there is a need for a new research vantage point to examine important managerial phenomena at a more fine-grained level of analysis, Bayesian methods have useful characteristics that make their application increasingly attractive. With regard to mainstream strategy research, Bayesian approaches can shed new insights into previously well-considered areas (such as in the cases we describe here or those of HPR). By contrast, in newly emerging areas of research interest, fundamental issues will be unresolved by definition. In light of the benefits described in Table 1, Bayesian models have much promise for adding value in these contexts, either in their own right or as a starting point for extending or revisiting results derived from classical approaches.

The HPR contribution is an important milestone in strategy research in that it demonstrates that the well-established RBV could be profitably reexamined and perhaps even reinvigorated by approaching it from a new methodological vantage. HPR showed that new insights were possible in the extant RBV context and that the implications of established strategy theories still contained many areas for further growth in terms of our understanding of management phenomena. We contend that the potential for Bayesian methods has much broader implications for strategy research. Other well-worked areas, such as TMT decision making, governance structure, and entry order literature can be revisited from a new perspective in order to deepen understanding of important management concepts, and emerging contemporary issues can be examined in more realistic and illuminating ways. Bayesian techniques provide the potential to expand the boundaries of strategy research by offering new and different approaches to existing strategy questions and by opening up new research avenues and areas of inquiry.

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APPENDIX: BAYESIAN REFERENCES FOR STRATEGY RESEARCH

Over the past decade, Bayesian methods have been used with increasing frequency in a range of disciplines. Interestingly, Bayesian approaches are infrequently used in management and strategy research. Several works have been introduced recently that can provide helpful guidance regarding the use of the Bayesian approach. Berry (1996), Albert (1996), and Bolstad (2004) provide elementary introductions. At a higher level (and in an approximately increasing order of overall technical exposition), Buck, Cavanagh, and Litton (1996) is quite readable, Gelman *et al*. (2004) is a well-regarded comprehensive treatment, and Gill (2002) focuses on the social and behavioral sciences. The texts by Congdon (2001, 2003) describe and provide sample code for numerous kinds of models that may be considered using a Bayesian approach. Technical details are kept to a minimum.