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Why Baseline Modelling is Better than Null-Hypothesis Testing: Examples from International Business Research

Andreas Schwab
Iowa State University, aschwab@iastate.edu

William H. Starbuck
University of Oregon

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Why Baseline Modelling is Better than Null-Hypothesis Testing: Examples from International Business Research

Abstract
• Purpose – This chapter reports on a rapidly growing trend in data analysis – analytic comparisons between baseline models and explanatory models. Baseline models estimate values for the dependent variable in the absence of hypothesized causal effects. Thus, the baseline models discussed in this chapter differ from the baseline models commonly used in sequential regression analyses.

Baseline modeling entails iteration: (1) Researchers develop baseline models to capture key patterns in the empirical data that are independent of the hypothesized effects. (2) They compare these patterns with the patterns implied by their explanatory models. (3) They use the derived insights to improve their explanatory models. (4) They iterate by comparing their improved explanatory models with modified baseline models.

• Methodology/approach – The chapter draws on methodological literature in economics, applied psychology, and the philosophy of science to point out fundamental features of baseline modeling. Examples come from research in international business and management, emerging market economies, and developing countries.

• Findings – Baseline modeling offers substantial advantages for theory development. Although analytic comparisons with baseline models originated in some research fields as early as the 1960s, they have not been widely discussed or applied in international management.

• Practical implications – Baseline modeling takes a more inductive and iterative approach to modeling and theory development.

• Originality/value of paper – Because baseline modeling holds substantial potential, international-management scholars should explore its opportunities for advancing scientific progress.

Keywords
Baseline model, model comparison, theory development, hypothesis testing

Disciplines
Entrepreneurial and Small Business Operations | Finance and Financial Management | International Business | Marketing | Other Business

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WHY BASELINE MODELING IS BETTER THAN NULL-HYPOTHESIS TESTING: EXAMPLES FROM RESEARCH ABOUT INTERNATIONAL BUSINESS AND MANAGEMENT, DEVELOPING COUNTRIES, AND EMERGING MARKET ECONOMIES

by

Andreas Schwab
3315 Gerdin Business Building
Iowa State University
Ames, IA 50011-1350
Phone: (515) 294-8119
aschwab@iastate.edu

and

William H. Starbuck
420 Lillis Hall 1208
Lundquist College of Business
University of Oregon
Eugene, OR 97403-1208
Phone: (541) 346-0751
starbuck@uoregon.edu

Published in
Advances in International Management

Reference:
Schwab, A. & Starbuck, W. H. (2013). Why Baseline Modeling is Better than Null-Hypothesis Testing: Examples from Research about International Management, Developing Countries, and Emerging Markets. In T. Devinney, T. Pedersen & L. Tihanyi (eds.), *Advances in International Management*, Vol. 26, 171-195. Bingley, UK: Emerald.

Running head: Baseline modeling

Key words: Baseline model, model comparison, theory development, hypothesis testing

Footnote: This chapter builds on our earlier chapter published in *Research Methodology in Strategy and Management* (Schwab and Starbuck, 2012). However, the earlier chapter did not consider research about international management and this chapter includes some new data about research into developing countries and emerging markets.

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ABSTRACT

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INTRODUCTION

This chapter describes the methodology of baseline modeling and its advantages for the analysis of empirical data and theory development. Baseline modeling is a rather new methodology that has begun to spread rapidly. In the social sciences, empirical studies that applied baseline modeling first appeared around 1960, the earliest users being economists and political scientists. Usage remained infrequent until the latter part of the 1990s, and then began to grow at exponential rates. Figure 1 compares three fields of studies in terms of the numbers of papers that involved some form of baseline modeling. Studies of emerging market economies have been the most frequent users, followed by studies of developing countries. So far, few studies in international management have used baseline modeling.

[Insert Figure 1 here]

Baseline modeling has received increasing attention throughout the social and biological sciences. In various research fields, baseline modeling began to grow more popular as early as 1980 and as late as 2000. In many research fields, baseline modeling shifted into exponential growth during the 2000s. Bioecologists played an important early role in exploring the usefulness of baseline modeling. Although baseline modeling remains far from being a dominant methodology, it is occurring often enough to deserve discussion in all methodology training.

It appears that international-management researchers have made much less use of baseline modeling than have researchers in other fields. Thus, one goal of this chapter is the bringing of this methodology to the attention of researchers in international business and management. The chapter suggests reasons for the methodology's growing popularity and describes its use in other fields.

While research that has used baseline modeling mainly discusses what specific models the researchers considered and what inferences they drew, it often does not state the philosophies that such thinking embodies. However, baseline modeling raises more general methodological issues related to the nature of scientific inquiries and how researchers develop theories. Among the scholars who have discussed these more general implications, the economist George C. Archibald has expressed especially relevant ideas. Most of these ideas are discussed in the discussion section of this chapter, but the next section describes how Archibald's ideas evolved from model testing to model comparison. Then the ensuing sections outlines how baseline models facilitate model comparison and describe the types of baseline models that researchers have used in studies of international management, developing countries and emerging market economies. The chapter concludes by outlining the potential of baseline modeling for enabling more fruitful inductive approaches to

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theory development -- approaches that international-management researchers should consider for future studies.

WHY ARCHIBALD LOST FAITH IN POPPER'S IDEAS

Baseline modeling is a product of many social and biological scientists who have struggled with the meaning and validity of their work over the last half century. One of these was a Scottish economist, George Christopher Archibald (1926-1996), whose mental voyage profoundly changed his beliefs about scientific knowledge and research achievements (Lipsey, 1996). In the early 1960s, Archibald subscribed to the ideas of Karl Popper (1959), who had argued that a proposition is not scientifically meaningful unless it is empirically falsifiable. Thus, for a theoretical statement to be "scientific", researchers must be able, at least in principle, to find evidence that the statement is false. If there is no possible way to find or produce such evidence, the statement does not deserve to be classified as "scientific."

Popper's ideas about falsification induced Archibald to challenge the theories about perfect competition and monopolistic competition on the ground that proponents of these theories refuse to accept discrepancies between theory and observation as evidence that the theories are wrong. He (1961, pp. 4-5) argued, "If we accept the new methodology, and propose to judge a hypothesis by the correspondence of its predictions with facts, and if one (or more) of its predictions does not correspond, can we say anything but "the hypothesis is refuted? (Popper, 1959, p. 33)"

However, Archibald continued to wrestle with the usefulness of Popper's ideas, and he gradually came to see Popper's ideas as an unrealistic basis for scientific progress (Archibald, 1967). For example, he perceived that some statements in economic theories are worthy of empirical investigation even though researchers have no way to prove these statements are false. In addition, he recognized that empirical studies make somewhat ambiguous tests of theories because they entail measurement errors and sampling errors. The measured values of variables are never exactly the same as the abstract theoretical concepts they are supposed to represent, which creates the possibility that a theoretical statement may be true but measurement errors make it appear false, or vice versa. When the available data are samples as opposed to complete populations, observed events may differ from those not observed. Past events may differ from future events. Furthermore, theories have many dimensions, such as their elegance, parsimony, generality, usefulness for prediction, or time horizon. As a result, a theory may perform excellently on dimensions A and B, but poorly on dimensions C and D, whereas an alternative theory may perform excellently on dimensions A and C, but poorly on dimensions B and D .

In 1967, Archibald published a seminal article "Refutation or comparison?" that presents his insights about the limitations and opportunities of empirical investigations. Archibald's

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reformulation has two central properties: Firstly, in place of Popper's sharply dichotomous classification of theoretical statements as true or false, Archibald characterized truth probabilistically. A theoretical statement has a probability of being true. Secondly, instead of theoretical statements being testable, Archibald characterized them as comparable. One theoretical statement can be compared with another in terms of the probabilities that they are true. He (1967, p. 293) said, "I suggest . . . *that we call a statement—or hypothesis—scientific if we may, at least in principle, compare its probable truth or falsity with that of another statement by appeal to observation* (*reference to facts*)."

BASELINE MODELING

This notion that researchers should compare theories instead of testing them is Archibald's signal insight, and he was an early and thoughtful advocate. However, Archibald is by no means the originator of comparing theories and his article has not been widely cited. Other social scientists were having similar thoughts about methodology during the 1960s. Economists and political scientists began comparing their explanatory theories with baseline models several years before Archibald's article appeared in print (Ando and Modigliani, 1963; Arrow, Chenery, Minhas, and Solow, 1961; Boness, 1964; Deutsch, 1960; Savage and Deutsch, 1960). In 1968 and 1969, a debate among agricultural economists ended with mutual agreement that comparing theories is more useful than testing null hypotheses (Johnson, 1968, 1969; Lianos, 1969; Wise and Yotopoulos, 1968; Yotopoulos and Wise, 1969a, 1969b).

Recent users of baseline modeling say little about their reasons for adopting this methodology; presumably they are adopting it because they have seen it in published work and they found it informative. Early users, on the other hand, justified their use of this methodology. They usually explained that they found comparisons with baseline models to offer more challenge for their explanatory theories than did tests of null hypotheses and that comparisons with their specific baseline models offered better guidance for future research and theory development.

Baseline models

Baseline modeling entails comparisons between an explanatory model and a baseline model. However, 'baseline model' has been a developing concept with fuzzy boundaries. The character of baseline models has changed a bit over time as researchers have developed more sophistication and as baseline modeling has migrated to different fields of research. Consequently, researchers have used the term 'baseline model' in diverse ways, and researchers have used other terms – especially 'naïve model' and 'null model' – to denote the entities that other researchers have called baseline models.

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Although the term 'baseline model' implies comparison with an alternative that is more complex than a no-effect hypothesis, the terms 'naïve model' and 'null model' better indicate the kinds of models that researchers have used as baselines so far. Some of baseline models have described studied phenomena as inertial. The models say that current situations are very likely to continue unchanged, or that current trends are very likely to persist, or that people's behavior adheres to stable traditions and norms. Other baseline models have described studied phenomena as utterly random. They say that resources or activities have frequency distributions that exhibit statistical independence or that situations change randomly over time. The researchers have explained that they used such baseline models because they wanted to find out whether their explanatory models actually said something that requires real understanding of causal processes. Biologists, who have standardized on the label 'null model', have engaged in lively debate about the degree to which a null model should take account of the properties of observed data (Gotelli and Graves, 1996).

The idea that a baseline model should not describe causal processes in detail has appeared in many subfields throughout the biological and social sciences. This idea may have spread widely because behavioral studies of decision making and perceptual biases made most researchers conscious of their humanity – their attributional biases, their propensities to search for confirmatory data, their blind spots generated by their hypotheses and theories, and their retrospective sensemaking (Beach, 1966; Calhoun and Starbuck, 2003; Erev and Barron, 2005; Hansen, 1980; Kahneman and Tversky, 1973; Lichtenstein, Fischhoff, and Phillips 1982; Phillips, Hays, and Edwards 1966; Slovic, 1991). Use of a non-causal baseline model is a way for researchers to demonstrate to themselves as well as others that they are trying to guard against self-deception and hubris.

Two other factors may also have contributed to the spreading popularity of simple baseline models that do not describe causal processes in detail. Firstly, the accumulating body of research findings has reinforced awareness that inertia is pervasive. For example, during the 1960s, four teams of economists undertook to produce models that could make short-range forecasts about the US economy; the availability of computers and very large budgets allowed these economists to build models of great complexity. Later, Elliott (1973) compared these complex computer-simulation models with two naive models. Three of the simulation models turned out about as accurate as the naive model that said no change will occur over the next three months. The fourth and most accurate simulation model predicted about as accurately as the naive model that said "the trend over the last three months will continue through the next three months.

Second, most researchers have studied statistics, which presents many examples of random events and stochastic processes, so researchers have become aware that random events can mimic causal events. For example, bioecologists plunged into a major

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methodological debate during the 1980s, after Connor and Simberloff (1983, 1986) argued that conventional null-hypothesis tests have no value because interactions within ecological communities make simple no-effect null hypotheses very unrealistic. They proposed that bioecologists should replace null hypotheses with non-causal 'null models' that generated random distributions for studied variables. Connor and Simberloff (1983) showed that such a 'null model' could accurately describe the numbers of species pairs on each of the Galapagos Islands, a topic that had roused debate among bioecologists for decades.

Advancements in computer software enable researchers to simulate the effects of different types of inertia and random processes with increasing ease. This development, however, has also encouraged researchers to use more complex baseline models. Later sections of this chapter discuss the pros and cons of making baseline models more complex, and possibly incorporating explicit causation into baseline models. However, it is clear that the originators of baseline modeling intentionally restricted explicit causation to their explanatory models, which they compared with non-causal baseline models.

When a baseline model is not a baseline model

It is important for researchers to understand that baseline modeling, as this chapter uses this term, is quite different from labeling the first calculation in a sequence of regression calculations as a 'baseline model". Many studies in international business and management make a series of increasingly complex regression calculations, which they call models, and they frequently apply the label 'baseline model' to the first calculation in such a sequence. Some of these 'baseline models' include only independent variables that the researchers describe as 'control variables'; others include both 'control variables' and other variables. Researchers have every right to use the label baseline model as they wish, but these 'baseline models' differ from those discussed in this chapter.

The 'baseline models' in these regression sequences differ in five significant ways from the baseline models discussed in this chapter. First, researchers often do not explain why they categorize specific variables as 'control variables' and include them in a baseline model. Although researchers probably select control variables based on prior research and characteristics of the empirical setting, explanations for such selections are scarce. Second, researchers leave unclear whether the baseline variables have causal effects on dependent variables, but it often appears that some control variables have rather direct causal effects. Thirdly, researchers do not explain how the baseline variables interact with each other to constitute a coherent model. Fourthly, each calculation in a sequence recalculates the coefficients of the baseline variables, so the baseline model changes with each calculation. Fifthly, the comparisons between models on these calculation sequences are limited to binary statements about statistical significance.

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In the kind of baseline modeling that this chapter discusses, a baseline model offers a single coherent explanation for the dependent variable(s). Each variable fits into the baseline model, and there are usually very few variables. The baseline model proposes an explanation for how the dependent variables might behave in the absence of explicit causation. The baseline model is stable; it does not change when researchers change their explanatory theory. Comparisons between baseline models and explanatory models should not be binary; they should be multidimensional and more continuous than discrete.

There is also a more general issue of whether a regression analysis generates a theoretical model. Regression calculations can be very useful tools for inductive analyses. However, regression coefficients are subject to corrupting influences, such as collinearity among the independent variables and the effects of outliers. When researchers ignore such sources of corruption, regression coefficients are unreliable indicators of the importance of independent variables, and the significance levels associated with coefficient estimates are unreliable or irrelevant criteria for decisions about what variables and relationships to include in theories. Statistical significance is often a poor or deceptive indicator of theoretical or practical importance (Schwab, Abrahamson, Starbuck, and Fidler, 2011; Starbuck, 2006, p. 137). Probably the most important issue is conceptual coherence. Lists of statistically significant variables that emerge from series of regression calculations often lack an overall conceptual framework that warrants calling them a theory.

The next section describes some common baseline models and provides illustrative examples of their applications. Schwab and Starbuck (2012) introduced a general framework that classified different types of baseline models, and this chapter extends these types. The next section highlights six types of baseline models that seem likely to prove useful in studies of international business and management. Researchers have used four of these types in international business and management studies. A literature search produced no examples of international business and management research applying the other two types of baseline models, but they offer promise. Although these six examples represent very simple models, various researchers have used them for revealing comparisons with their explanatory theories.

SIX USEFUL TYPES OF BASELINE MODELS

Equal-weight factors

During the 1950s and 1960s, applied psychologists discovered that multiple regression analyses are likely to yield unreliable predictions for employee selection and college admissions (Starbuck, 2006, pp. 53-55, 131-136). Before 1950, the tradition had been to evaluate applicants for jobs or for college admission by checking off their characteristics on lists. These lists had not resulted from careful studies; they were rooted in the feelings, experiences, and prejudices of human resources or admissions personnel. Evaluators

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counted the numbers of positive checkmarks to measure applicants' suitability. The counting process generally gave every item on a list equal weight.

Starting in the 1950s, psychometricians began to use squared-error regression to assign weights to items (Perloff, 1951). They reasoned that regression would assign higher weights to more important items and would assign low weights to redundant or uninformative items. It appeared that statistical theory said regression weights would minimize prediction errors. However, the ensuing two decades of experience produced evidence that the use of regression weights made predictions less accurate. Prediction scores computed with regression-derived weights correlated less highly with students' or employees' actual performances than had scores generated by equally-weighted a priori items (Boyce, 1955; Lawshe and Schucker, 1959; Wesman and Bennett, 1959).

During the 1970s, psychometricians used computer simulation to investigate reasons for this surprising phenomenon. Their studies assumed an ideal situation – perfect normal distributions and independent variables with no measurement errors. They represented the idea of equally-weighted a priori items by saying the standardized value of a dependent variable equals 1/Sqrt(K) times the sum of the standardized values of K independent variables. They assumed that all of the independent variables related positively to the dependent variable. The psychometricians discovered that sampling errors cause regression calculations to produce incorrect estimates, so the results of regressions generate unreliable predictions unless samples are quite large. Indeed, with small samples, researchers could make more accurate predictions if they would gather no data and make no regression calculations. The psychometricians also found that even when regressions are based on large samples, predictions based on regressions are only modestly more reliable than predictions based on equal weights (Claudy, 1972; Dorans and Drasgow, 1978; Einhorn and Hogarth, 1975; Schmidt, 1971).

One implication of these studies is that researchers can use equally weighted independent variables as a baseline model for any explanatory model that is intended to be applicable to future data. This baseline model assumes a standardized dependent variable (StdY) and standardized independent variables (StdX); it says:

$$\text{StdY} = (\text{StdX}_1 + \text{StdX}_2 + \text{StdX}_3 + \ldots \text{StdX}_n)/\text{Sqrt}(\text{VarSum})$$

where VarSum is the variance of the sum of the standardized independent variables. If the independent variables are uncorrelated, VarSum equals the number of independent variables. This correction assures that the total variance on the right-hand side equals 1.

Such a baseline model has some substantive content, so it is not purely non-causal. Firstly, researchers choose variables to include in their regressions, so the baseline model incorporates whatever insights induce researchers to use specific independent variables.

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Secondly, researchers have to define the independent variables so that all of the regression coefficients in the baseline model have the same signs as they do in the explanatory model(s). The baseline model will be more accurate if the independent variables are uncorrelated.

Comparisons between baseline models that use equally-weighted independent variables and explanatory regressions yield clues about the functional form of causal effects and the potential impact of sampling errors. Hypothetically, sampling errors should be more problematic with smaller samples, and the errors should cause less distortion with large samples. Of course, a regression calculation with any model will give coefficients that fit the sample data more closely than this baseline model, for a regression calculation is defined to minimize the sum of squared errors. However, the fitted data do not provide a relevant comparison for theorizing about future research. The important comparison is how accurately the baseline model and the explanatory model each predict values of the dependent variable when using new data that were not included in the regression analyses to determine the factor weights for the proposed independent variables.

Although this type of baseline modeling had significant influence on methodology in applied psychology, international business and management scholars seem to have not used such baseline models.

Log-linear changes of scale

International business and management studies frequently investigate causal effects across different countries and different organizations engaged in international business. So, how should scholars compare large countries with small ones? Or small organizations with large ones? How does a small country or organization change when it grows larger? As a baseline model, many researchers have used the assumption that inputs and outputs relate proportionately: if the inputs double, the outputs should double . . . approximately.

One frequently used representation of this idea is the Cobb-Douglas production function:

$$Q = AL^{\alpha}C^{(1-\alpha)}$$

Where Q is the total output (or consumption) of an economy or organization, L is the labor (or employment) input, C is the capital input, and A and α are constants. A is usually interpreted as an indicator of technological effectiveness. Logarithmic transformations produce a convenient linear function:

$$\log Q = \log A + \alpha \log L + (1-\alpha) \log C$$

The Cobb-Douglas function has a long history and many theoretical and empirical analyses have used it. In recent years, some researchers have started to treat the Cobb-Douglas

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function as a baseline model to compare with less simple formulations. They have used it for analyses of both cross-sectional one-time data and changes over time. Comparisons tend to ask whether observed phenomena depart from logarithmic linearity, either by depending on other factors than capital, labor, and technology, or by exhibiting curvilinearity. The transcendental-logarithmic model adds curvature by assuming:

$$\log Q = \beta_1 \log L + \beta_2 \log C + \beta_3 (\log L)^2 + \beta_4 (\log C)^2 + \beta_5 \log L * \log C + \text{Error}$$

For example, Triebs and Kumbhakar (2012) used Cobb-Douglas functions as baselines in their study of the effects of management on production efficiency. Their study used data about management practices in 3140 medium-sized firms from half a dozen countries. They fitted data to transcendental-logarithmic models in order to assess the degrees to which actual productivities deviate from Cobb-Douglas functions. They inferred that management practices generally exert more influence on the productivity of labor than on the productivities of technology or capital. However, they pointed out that this finding might reflect their measures of management practices. They also discovered variations in the effects of management in different countries.

Statistical independence

The concept of statistical independence among variables assumes that the values of one variable do not correlate with the values of another variable. Tables 1 and 2 show portions of the tables reported by Schmidt and Vandenborre (1970) in their analysis of favored-nation biases for trade among 14 nations and regions. The cells on the major diagonals are empty because countries do not export to or import from themselves. Schmidt and Vandenborre (1970) explained:

> [Table 2] develops a set of expected data from assumptions of complete indifference among the trading partners and thus allows one to measure the plus or minus differences between these base values and the actual amounts of transactions in each direction for every pair of countries or regions. The method removes gross size effects by taking into account the actual volumes of trade as registered by every country (exports as well as imports) and locates departures from the null-model which could then be examined in a subsequent investigation. The causes for the departures from the null-model could be prices, transportation costs, formally established preference policies, etc. . . . The no-preference assumption is made without regard for reality, insofar as expected data deviate from the actual data will a system of preferences be revealed. (pp. 8-9)

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Table 1. Portion of observed flows of grain in 1965						
		Exports				
		From Eastern Europe	From USSR	From US	From EFTA	From Africa
Imports	To Eastern Europe		1010	416	60	
	To USSR					
	To US				1	
	To EFTA	305	95	3616		509
	To Africa			318	8	

Table 2. Portion of Schmidt and Vandenborre's baseline model that assumes statistically independent flows of grain						
		Exports				
		From Eastern Europe	From USSR	From US	From EFTA	From Africa
Imports	To Eastern Europe		108	860	32	33
	To USSR	1		43	1	1
	To US	12	22		13	13
	To EFTA	129	496	3943		151
	To Africa	7	25	200	8	

The Chi-square statistic is a familiar metric for evaluating the differences between two tables such as Tables 1 and 2. The tables might show the observed data (e. g., Table 1), a baseline model (e. g., Table 2), or an explanatory model. Schmidt and Vandenborre did not propose an explanatory model, but they did use their baseline model to spot deviations from statistical independence that matched to trade agreements, cultural similarities, and price differentials.

Thomsen and Pedersen (1996) investigated national differences in large firm ownership across six European countries. A visual evaluation of the data in Table 3 convinced them that substantial differences exist, so they investigated whether these differences reflect nationality, industry composition, or firm size. They used a variety of calculations that included comparing observed frequencies with expected frequencies in baseline models that assumed statistical independence. They inferred that there are nation-specific differences in large-firm ownership between the six countries.

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Table 3. Ownership of the 100 largest companies in six nations						
	Dispersed	Dominant	Family	Foreign	Cooperative	State
Britain	61	11	6	18	1	3
Denmark	10	9	30	23	17	11
France	16	28	15	16	3	22
Germany	9	30	26	22	3	10
Netherlands	23	16	7	34	13	7
Sweden	4	31	18	14	12	21

No-change and no-change-in-trend

Many baseline models for longitudinal theories start by capturing assumptions about period-to-period changes. A majority of social processes, practices and norms change rather slowly. They exhibit inertia in both their magnitudes and their rates of change. This allows simple baseline models that assume values of the dependent variable will not change over time to fit most time-series data very well.

For instance, Ozsoz, Rengifo, and Salvatore (2010) investigated the effects of interventions into foreign currency markets by the central banks of Croatia, Czech Republic, and Slovakia. They compared their explanatory model with what they labeled a “naïve” model. This naive baseline model assumed the banks’ interventions had no effects. Table 4 compares their explanatory model with their naïve model for the events in Slovakia. Comparison between the models basically removes the “no action” events from consideration, and draws attention to the three instances in which the explanatory model predicted correct actions.

Table 4. Interventions by Slovakia’s central bank, 1998-2006						
	Explanatory model			Naïve model		
Intervention	Sell	No action	Buy	Sell	No action	Buy
Total events	6	80	11	6	80	11
Correct predictions	2	80	1	0	80	0
% Correct	33	100	9	0	100	0
% Incorrect	67	0	91	100	0	100

Coën and Desfleurs (2004) compared a similar “naïve” baseline model with the accuracy of earnings forecasts between 1990 and 2000 by financial analysts in Hong Kong, Korea, Indonesia, Malaysia, Thailand, Singapore, Taiwan and the Philippines. Their naïve model said that earnings next year will be the same as earnings this year. Coën and Desfleurs decided that analysts have learned little from their errors during a period of financial crisis, have not been improving the accuracy of forecasts in general, and have been particularly poor at forecasting turning points.

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Lee, Trimi, and Kim (2013) used a no-change baseline model when they investigated the impact of cultural differences on technology adoption. Based on Hofstede's cultural dimensions, they hypothesized that people in individualistic cultures seek out information sources for their adoption decisions, whereas people in collectivist cultures rely more on the evaluations of like-minded individuals who have adopted the innovation. They compared these expectations with actual mobile phone adoption in the US and Korea and with a baseline model that said adoptions are the same year after year.

A slightly more complicated baseline model for time series assumes that variables continue to change at constant rates. Arora and Smyth (1990), for example, compared economic forecasts made by the International Monetary Fund with a naïve baseline model that said economies would change next year by the same percentage that they changed this year. The data consisted of nine time series for each of five international regions: Africa, Asia, Europe, the Middle East, and the Western Hemisphere. Comparison of IMF's forecasts with the baseline model convinced the researchers that errors in IMF's forecasts are not systematic. By one measure, the baseline model produced more accurate forecasts in 27 out of 45 instances, and by another measure, the baseline model produced more accurate forecasts in 42 out of 80 instances. Although Arora and Smyth found that these differences were not statistically significant, they inferred that their "no-change-in-trend" baseline model would have been more accurate than the actual forecasts.

In general, no-change baseline models help researchers to evaluate the inertial tendencies associated with their dependent variable and focus their investigation of proposed causal effects on period-to-period changes, either absolute changes or percentages. Alternatively, researchers could limit their investigation to effects on period-to-period change model by redefining their dependent variables as period-to-period changes. The explicit estimation of inertial tendencies using baseline models, however, provides potentially valuable information for the interpretation of observed effects – and this may be one of the reasons why researchers have tended not to limit their dependent variables to measuring only period-to-period changes. When baseline models capture that trends do not change, researchers are enabled to identify and evaluate accelerations or decelerations in rates of change.

Random walks

Our literature search has found no examples of baseline models that explicitly simulated random-walk processes in studies of developing countries, emerging markets, or international business. Some researchers, such as Lee et al. (2013) introduced earlier, described their no-change model or their no-change-in-trend models as "random walks" because random-walk processes can be one of many factors contributing to inertial tendencies. The focus in this section, however, is rather on baseline models that explicitly

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simulate random walk effects and try to predict more complex change trajectories over time or difference between alternative empirical settings.

In other fields of management research, the value of random-walk baseline models has been well-established. In research into the population ecology of organizations, for example, Levinthal (1991) compared random walks with data about the growth and survival of business firms. He started from a model in which organizational wealth changes according to a random walk, and he surmised:

> This paper shows that such a process generates the familiar pattern of negative duration dependence that has been observed in nearly all empirical analyses of age dependence in organizational mortality. The process is also consistent with the presence of an initial honeymoon period and a liability of adolescence . . . in which the risk of death for an individual organization is initially quite low and increases with time, reaching a peak at a point referred to as adolescence, and then subsequently declines. This more complex pattern of organizational mortality has been observed at an aggregate level in several empirical studies (Singh, Tucker and House, 1986; King and Wicker, 1988; Brüderl and Schüssler, 1990). . . . In the model developed here, there is no direct relationship between age and mortality. The negative relationship between age and mortality rates is due to the fact that older, surviving organizations tend to be organizations that have been successful, and this prior success buffers them from subsequent selection pressures. . . . The basic random-walk model demonstrates the importance of heterogeneity that emerges stochastically over time. (p. 401)

Levinthal saw random walks as baseline models that challenge contemporary explanatory models and expose issues for exploration. He pointed out that the ability of a random-walk model to generate data very similar to the observed data does not prove that more subtle and interesting processes are occurring. It does, however, draw attention to the possibility that random events can mimic causal processes.

Random-walk baseline models have also been very successfully applied in organizational studies of labor markets. Zuckerman et al. (2003), for example, investigated the effects of identity building and type casting on the repeated collaboration patterns and careers in the Hollywood movie industry. For their investigation, they had to develop baseline models to capture differences between the number of movies produced in a specific genre (e.g., drama, comedy, action) in order to estimate the corresponding random probability of working on a future film project in the same genre. Corresponding baseline model comparisons represented an important part of their very meticulous empirical investigation that identified complex and contingent type casting patterns.

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Clearly, organizational survival and labor markets processes are phenomena also of interest to international business and management scholars. In addition, similar random-walk processes may be highly relevant for the investigation of other phenomena. Advancements in available computer technology have also created new opportunities to estimate and simulate random-walk processes. Consequently, random-walk baseline models deserve more attention in future studies.

Markov chains

Some researchers make more complex assumptions by creating baseline models or explanatory models that are Markov chains. In the Markov chain framework, each possible state of a stochastic variable defines a distinct probability distribution for the next state of the variable. The states can have complex definitions that take account not only of variables' current values but also their past values. Thus, a researcher might use a simpler Markov chain as a baseline model to compare with a more complex Markov chain as an explanatory model.

Liu, Wang and Wei (2009) used a Markov chain as a baseline model in their study of the effects of foreign direct investment on Chinese manufacturing. They used Markov chains because previous research revealed undesirable properties of least-squares estimates. As a first step, they estimated the parameters of industry-specific Cobb-Douglas production functions on the assumption that these parameters change following specified Markov chain processes. Then, Liu et al. used these industry-specific production functions as baseline models to analyze the data in search of effects attributable to horizontal, forward, and backward linkages between the Chinese firms and foreign firms. They inferred that the effects of foreign direct investment differ by regions and the kinds of foreign and Chinese firms.

Again, available computer technology has created new opportunities to simulate and model such potentially relevant stochastic processes. Related baseline modeling applications promise more comprehensive empirical investigations that maybe of interest to international-management scholars.

DISCUSSION

A small, but increasing, number of international-management researchers are using baseline modeling. They are experimenting with a range of models, but the opportunities are vast for developing new approaches and the potential benefits may be large.

Stronger tests for deductive theories

Most of the international-management researchers who have used the term "baseline model" did not engage in the kind of baseline modeling that this chapter discusses. Instead,

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they have developed baseline models as the first stage in a sequence of regression analyses. Most often, they then used dichotomized decision rules based on null-hypothesis statistical significance tests to add variables to the regression calculations. Null hypotheses propose no effect of a causal variable or treatment in an experiment of field data. Methodologists have long argued that null hypotheses are highly unlikely to be true, as most treatments or causal variables have some effects. Consequently, null-hypothesis tests set very low thresholds for evaluating hypotheses and they have high likelihoods of false inferences.

Baseline modeling asks researchers to pose stronger challenges to their explanatory theories than do null hypotheses. From a hypothesis-testing perspective, such baseline modeling "raises the bar" and promises more meaningful analyses. Methodological tradition says that baseline models should not incorporate causal processes that researchers see as meaningful explanations for their dependent variables. However, researchers, especially bioecologists, have debated the degrees to which baseline models should take into account properties of studied contexts.

Inductive iterative model development.

In a debate among sociologists about the value of baseline models, Turner and Hanneman (1984, pp. 283-288) argued against the use of baseline models only for simple one-shot dichotomous comparisons with proposed explanatory models. Instead, researchers can use models for much broader and more detailed comparisons of the data patterns implied by both the baseline models and the causal models. Such comparisons promise a much deeper understanding not only of the theoretical constructs and their causal relationships, but also of the specific empirical contexts. Researchers can then revise or propose alternative causal models and alternative baseline models.

Multi-dimensional comparisons and parsimonious theorizing

Comparisons that involve multiple evaluation dimensions promise a deeper understanding that supports theory development. Archibald highlighted the usefulness of multidimensional comparisons between models. He (1967, p.295) remarked, “when we compare theories with observation, we commonly find more than one criterion. Thus we may ask which better accounts for, e.g. total variance, or for turning points, or for amplitude of fluctuations. Once again, we should not be surprised if the theory which does better by some criteria does worse by others.”

Comparison across multiple dimensions and multiple baseline models implies new challenges for the interpretation of observed empirical patterns because it is unusual for one theory to prove superior on all dimensions. In particular, strong baseline models can demonstrate the power of very simple assumptions. Comparisons with very simple

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baseline models then challenge researchers to demonstrate that complicated explanatory theories perform sufficiently better to justify their complexity.

Contemporary social research norms have been placing low value on theoretical parsimony. The use of null-hypothesis significance tests and the ease of collecting larger samples has induced researchers to add more and more variables to their explanatory models. Journal reviewers frequently propose that researchers should add more variables or interactions. One result has been models that fit the data too closely.

When researchers add more independent variables, regression calculations climb and descend Ockham's hill, an effect named for William Ockham, a 14th century advocate of parsimonious theorizing (Schwab et al., 2011). Although a model that includes too few independent variables fails to capture important variation and it makes inaccurate inferences about the population, additional variables have diminishing returns. A model that includes too many independent variables is likely to describe random noise or idiosyncratic properties of a studied context that do not generalize. Gauch (2006) found that the models that give the most accurate generalizations are quite parsimonious.

Earlier, this chapter introduced two empirical studies that illustrate how researchers can use simple baseline models to challenge more complex causal explanations. Elliott's (1973) study discovered that "no-change" and "no-change-in-trend" baseline models performed as well as the far more sophisticated economic models developed independently by several think tanks. Levinthal (1991) showed how simple random walk processes lead to firm survival patterns that are very similar to those explained by the theories of population ecology. In both cases, these studies changed the directions of future research by showing that complex causal explanations are not better than simple non-causal explanations.

A fundamentally different methodological paradigm

Using baseline models for multi-dimensional model comparison and iterative model development has implications for the nature of scientific inquiry because it implies a fundamental departure from our current research paradigm based on deductive falsification of hypotheses. In his "Logic of Scientific Discovery", Popper (1959) argued that true science is based on falsification and not on verification. In contrast, Archibald and others have advocated a more inductive approach to identify best-fit hypotheses through an iterative process of empirical comparison and refinement of alternative models and hypotheses. This approach builds on the fundamental philosophy of science arguments of inductive logic as proposed by Bacon (1620) and Chamberlin (1897), who recommended the investigation of multiple opposing hypotheses. Such an approach replaces the idea of a test that conclusively rejects a hypothesis, with the idea that continuing analysis and refinement of hypotheses lead toward more likely hypotheses. Instead of judging hypotheses to be important or unimportant, true or false, iterative comparisons search for

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hypotheses that are better on some of many dimensions – likely, useful, effective, accurate, terse, general.

Archibald (1967, pp. 295-296) envisioned:

> … we compare rival theories by reference to such criteria as scope, generality, elegance, etc.: we ask, e.g. If one is 'above more things' than another or carries excess baggage in the form of unnecessary elements, or connects more satisfactorily with other parts of our theoretical structures. We should not be surprised if a theory which is superior on some counts is inferior on others! The case of vector-dominance is the rare and lucky one in which one theory at last wins all down the line, so that we may reject its rival without waiting for the refutation that never occurs. … The new paradigm is accepted, not because it passes tests which refuted the old, but because it does strikingly better on a number of crucial comparisons.

It will thus be seen that comparisons are frequently indecisive, not merely because each comparison is itself indecisive, being a probabilistic rather than deterministic, but because the complexity of theory and observation give rise to multiple criteria for comparison. Thus when we say that one theory is 'doing better' than a rival, we refer specifically to that set of (individually indecisive) comparisons that has already been carried out. It is this complexity of comparisons, rather than pig-headedness, that accounts for the well-known circumstances that we frequently disagree over theories even after a good deal of relevant empirical work has been done!

CONCLUSION

Baseline modeling if implemented as an iterative and multi-dimensional process of model comparison, model improvement, and theory development addresses fundamental methodological issues of scientific inquiry. These ideas also resonate with arguments for more systematic inductive reasoning based on the notions (a) that similar approaches have proven very useful in other fields of science, such as atomic physics, molecular chemistry, and chemistry (Platt, 1964), and (b) that researchers should focus on detecting useful regularities in observed phenomena instead of simplistic null-hypothesis tests (Starbuck, 2006; Nord and Connell, 2011).

The examples of baseline modeling in the international business and management literature did not explicitly describe how researchers engaged in iterative model comparison and model development. The absence of such description, however, may be deceptive, as research reports are always incomplete and as authors may have tried to increase their odds for publication by emphasizing their conformity to the hypothesis testing paradigm. An iterative and multi-dimensional process of model comparison seems to be the most promising form of baseline modeling to support theory development.

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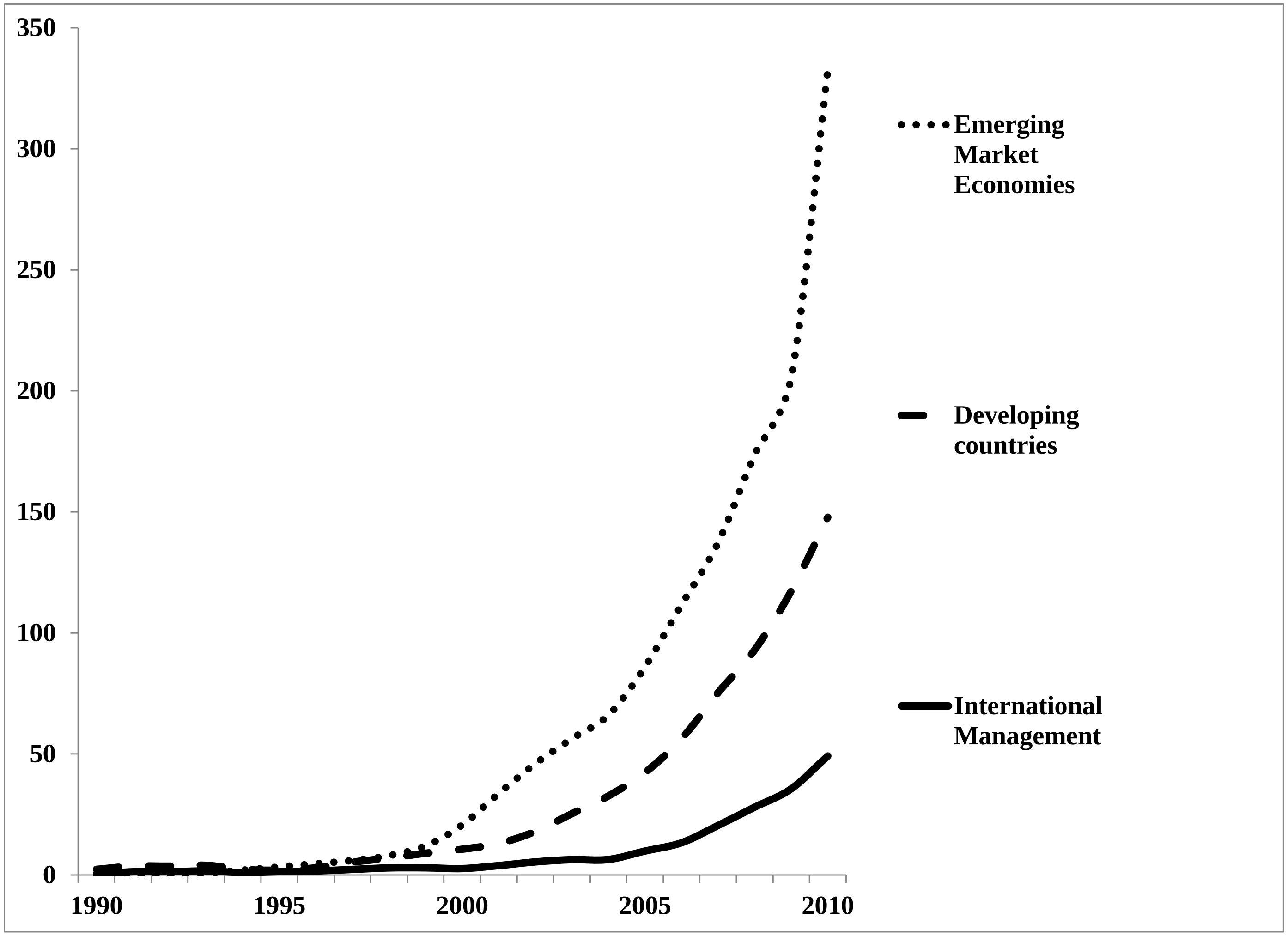

Fig. 1. Numbers of studies that used baseline modeling (3-year moving averages)

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