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# A COMPARISON OF ALTERNATIVE MEASURES OF ORGANIZATIONAL ASPIRATIONS

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*Research on organizational aspirations has used various representations of firm-level aspirations and based those representations on various performance measures. To advance our understanding of the measurement of aspirations, we empirically compare three different aspiration models defined using six different performance measures to explain three different firm outcomes (financial misrepresentation, R&D spending, and income-stream uncertainty). The results moderately support a model with separate historical and social aspirations over a model of aspirations that systematically switches between the two. The results strongly support both the separate and switching models over a model where aspirations constitute a weighted average of historical and social comparisons, the model associated most directly with Cyert and March's original specification. We discuss the implications of these results and highlight directions for future research.*


## INTRODUCTION

How do managers evaluate their own firm's performance? Some theoretical paradigms, such as the behavioral theory of the firm (or BTOF; Cyert and March [1963] 1992) tackle this question explicitly. Other approaches largely ignore how managers assess success, implicitly assuming they use either accounting or capital market performance measures. Yet, paradigms that attempt to explain strategic behavior must make some assumptions about how managers evaluate firm performance; even profit-maximizing models implicitly assume firms know their profits and understand how it compares to optimal profits.

The BTOF argues that managers compare expected firm performance to aspiration levels that depend on prior aspirations, prior performance, and the performance of comparable firms. A large literature demonstrates that performance relative to aspirations (or "attainment discrepancy") influences risk taking (Bromiley, 1991; Fiegenbaum, 1990; March and Shapira, 1987; Miller and Chen, 2004; Miller and Leiblein, 1996; Singh, 1986). Attainment discrepancy also influences research and development (R&D) spending (Antonelli, 1989; Bromiley and Washburn, 2011; Chen and Miller, 2007; Palmer and Wiseman, 1999), capital structure (Miller and Bromiley, 1990), actual and intended firm growth (Greve, 2008; Wicklund and Shepherd, 2003), large-scale organizational change (Greve, 1998), alliance choices (Baum *et al.*, 2005), innovation (Greve, 2003a), diversification (Palmer and Wiseman, 1999), capital investment (Greve, 2003b), divestment of business units (Shimizu, 2007), safety initiatives (Baum and Dahlin, 2007), bank lending practices

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(McNamara and Bromiley, 1999), product quality (Rhee, 2009), acquisitions (Iyer and Miller, 2008), and organizational misconduct (Harris and Bromiley, 2007).

Despite abundant research using attainment discrepancy to explain firm behavior, differences in measuring aspirations demonstrate an insufficient level of theoretical and empirical understanding of organizational aspirations leading to two major problems. First, aspirations studies adopt one of several functional forms for aspirations without discussing the theoretical assumptions or methodological merits of the alternative forms. Second, most studies examining organizational aspirations measure performance using one measure without considering other performance measures. To address these problems, we compare functional forms for aspirations measures defined using a number of different performance measures.

The issue we address, comparing a set of measures, differs from the standard measurement issue of validating or assessing the reliability of a single measure. The many extant studies employing one of these three measures collectively demonstrate nomological validity but do not resolve the problem of having several competing measures for the same construct, especially when each measure embodies a slightly different theoretical nuance about how organizational aspirations function. Using three different datasets, we directly compare the measures using archival corporate data on three organizational outcomes: variability in analyst forecasts of earnings for firms (a measure of income-stream uncertainty), R&D expenditures, and financial misrepresentation. We examine R&D expenditures and income-stream uncertainty because researchers have often attempted to explain these using aspirations models. We include financial misrepresentation—a less commonly examined behavior in aspirations research—because it offers a very different behavior, giving a contrast to the two more traditionally examined outcomes. This allows us to better assess the generalizability of our findings.

This paper extends our understanding of aspirations by empirically comparing the three most prominent models of aspirations and firm behavior using six different measures of firm performance and predicting three different corporate behaviors. We use separate datasets for each of the predicted corporate behaviors. The empirical results presented below, therefore, both advance empirical work by comparatively assessing actual measures well established in the literature and shed light on the relative merits of the three different approaches.

Previous research has demonstrated that performance relative to aspirations influences all three of these organizational actions; hence our research question is not a reexamination of *whether* aspirations predict these particular behaviors. Rather, our analysis employs three different variables to assess the relative merits of the alternative representations of aspirations and measures of firm performance, contributing to our understanding of *how* firms set aspirations. Figure 1 summarizes the three “levers” (alternative dependent variables, aspirations representations, and performance measures) our empirical analysis investigates.

The paper proceeds as follows. First, we summarize and evaluate theoretical issues associated with aspirations. This theoretical discussion leads to an explanation of the three models of aspirations. Next, we describe the data used, empirically compare the different aspiration models, and present empirical results. Finally, we discuss the theoretical and empirical implications of the findings.

## BACKGROUND

For more than 50 years, the behavioral theory of the firm has been a prominent paradigm in strategic management (Argote and Greve, 2007; Cyert and March [1963] 1992). Following Singh (1986) and Bromiley (1991), much of the work has examined the theory’s argument that firms performing below aspirations search for ways to improve performance to a satisfactory level. The theory proposes that unsatisfactory performance relative to aspirations drives search.

The literature sometimes conflates two usages of the term *aspirations*. While aspirations in March and Simon (1993) have a psychological connotation and refer at least partially to individuals, aspirations in the BTOF refer strictly to organizational phenomena. The BTOF uses the terms goals, objectives, targets, and aspirations referring to the same construct (see, Cyert and March [1963] 1992, section 3.2.3). The BTOF presentation of the aspiration model most commonly cited by researchers (see



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**Theoretical Specification Employed**

*Weighted average* model
One aspiration variable based on a weighted combination of internal (self) and external (social) targets. Optimal weighting is either stipulated or endogenously determined using the data. Variable is split above and below the social reference point.

*Separate* model
Separate self and social aspirations, assuming that internal and external reference points are both salient, but operate as independent influences. Investigates the widest variety of combinations, without imposing a single objective function.

*Switching* model
One aspiration variable imposing a theoretical switching of attention from the external to the internal reference point. Performance target is assumed to be (1.05 * self) if the firm's performance is above industry average performance; otherwise, beating the industry average is the salient performance target.

**Performance Measure Employed**

*Return on assets (ROA)*
Net income / total assets

*Cash flow ROA*
EBITDA / gross assets

*Composite accounting*
Composite of ROA, ROS, ROE

*Stockholder returns*
Dividends plus change in stock price divided by prior year's stock price

*Composite accounting & stock returns*
Composite ROA, ROS, ROE, stock returns

*Net income*
Unscaled net income

**Firm Outcome Predicted**

*Financial misconduct*
The presence of an accounting restatement triggered by material accounting irregularities, as described by the GAO and analyzed in Harris & Bromiley (2007) and O'Connor et al. 2006.

*Risk (income stream uncertainty)*
The square root of standard deviation in analyst forecasts of earnings for firms, measuring the riskiness oftheir strategic decisions, as analyzed in Bromiley (1991) and Wiseman and Bromiley (1996).

*R&D spending*
The ratio of R&D expenditures to sales, as a measure of R&D spending, as analyzed in Chen & Miller (2007) and Greve (2003a).

Figure 1. Three empirical "levers" in aspiration models

Equation 1 below) uses the term "goal" whereas subsequent researchers have said "aspiration." While individual aspirations may require that the individual internalize the aspiration, organizational aspirations or targets do not. Organizational units often react to externally imposed objectives in a manner that fits the aspiration-search process. Managers often feel pressure to reach objectives even if the managers consider the objectives misguided; a manager may not like the budget targets but usually faces pressures to meet them.

Both the theory and existing empirical results suggest that firm aspirations adapt to two factors: the firm's own historical performance and the performance of other referent firms (Cyert and March [1963] 1992; March and Simon [1958] 1993). Generally, aspirations rise when a firm exceeds its past aspirations and fall when it does not.

However, scholars have measured firm aspirations in different ways. Almost all empirical work claims a foundation in Cyert and March's ([1963] 1992: 172) original model:

$$A_{i,t} = a_1 A_{i,t-1} + a_2 P_{it-1} + a_3 C_{i,t-1} \qquad (1)$$

where $A_{i,t}$ is aspirations in year t; $P_{i,t-1}$ is firm performance in year t-1; $C_{i,t-1}$ is the performance of comparable firms in t-1; and $a_1 + a_2 + a_3 = 1$.

Repeatedly substituting appropriately lagged versions of Equation 1 in place of $A_{i,t-1}$ results in aspirations in year $t$ equaling an exponentially weighted infinite sum of prior values of $P_{i,t-j}$ and $C_{i,t-j}$: $\mathrm{A_{i,t}} = \sum_{j=0}^{\infty} a_1^j \left(a_2 \; P_{i,t-1-j} + a_3 \; C_{i,t-1-j}\right)$.

Most organizational studies using aspirations do not have direct measures of aspirations. They typically use factors that *influence* aspirations in place of actual measures of aspirations. They use a measure of the difference between performance and aspirations (termed attainment discrepancy or relative performance) in the analysis. For example, if one used the aspirations equation presented in Equation 1, the researcher would create an attainment discrepancy measure as $AttainmentDiscrepency_{i,t} = P_{it} - (a_1 A_{i,t-1} + a_2 P_{it-1} + a_3 C_{i,t-1})$ or $AttainmentDiscrepency_{i,t} = P_{it} - \sum_{j=0}^{\infty} a_1^j \left(a_2 P_{i,t-1-j} + a_3 C_{i,t-1-j}\right)$, in which the summation is typically limited to one to three lags. Then, the researchers use the attainment discrepancy measure in a model that attempts to explain the phenomenon of interest.

The details of aspirations measures vary widely across studies. While some use a weighted average of self and social-referent measures to give one aggregate measure (Greve, 2003a; Mezias, Chen, and Murphy, 2002), others use an aspiration measure that equals the self-reference point for firms above their social comparison levels and the social comparison level for firms below that level (Bromiley, 1991; Wiseman and Catanach, 1997). Some studies use only social comparisons (Fiegenbaum and Thomas, 1986; Miller and Bromiley, 1990), and others include separate measures of social and self aspirations rather than blending them into one aggregate measure (Baum *et al.*, 2005; Greve, 2003b; Harris and Bromiley, 2007). Along with the growing number of studies about aspirations and search, formulations of aspirations measures have proliferated with little evidence to suggest the most appropriate representation of aspirations.

No existing research directly compares different representations of organizational aspirations using a common set of publicly available corporate data. Prior methodological studies on aspirations have used internal, direct measures of aspirations. Lant (1992) and Mezias *et al.* (2002) both estimate models with actual aspirations measures but do not compare multiple aspirations formulations. In addition, their results may not generalize to corporate data. Lant (1992) used data from experiments using business school students. Mezias *et al.* (2002) used branch bank budget targets. Washburn and Bromiley (2012) use internal targets from an auto manufacturer to compare alternative aspiration models, but the implications of their results for aggregate studies on archival data are unclear. While these papers make important contributions, an explicit comparison of different aspiration models employing the kind of historical data most studies use is long overdue.

We attempt to address the lack of consensus on the appropriate measure of aspirations by comparing three different aspiration measures, each well established in prior research. With aggregate analyses using common sets of archival data, we directly compare the different measures' abilities to explain a particular behavior. The results of the comparison here serve to refine our theoretical and practical understanding of attainment discrepancy.

## ASPIRATION MEASURES

We begin by outlining the three primary models of aspirations in the literature and consider their features. While our primary evaluation depends on statistical analyses, our discussion addresses two qualitative criteria for evaluation of aspiration measures. First, how well do the information processing demands of the measure align with what researchers know about information processing in firms (Bromiley, 1986; Eliasson, 1976)? Second, how well do the qualitative features of the model's predictions fit with what researchers know about firms?

The aspirations measures in the literature generally fall into one of three categories. Many studies use weighted averages of firm past performance and industry performance to generate a single aspiration measure. Other studies use separate measures for aspirations determined by the firm's past performance (self comparison) and average performance in the firm's industry (social comparison). A third set of models systematically switch between self- and social-reference points to generate a single aspirations measure. We next outline these three types of aspiration measures, consider their qualitative fit with organizational actions, and then describe how we will compare them. Figure 2 summarizes the models.

### Weighted-average model

Researchers often combine self- and social-referent aspirations into a single measure of aspirations. For instance, Greve (2003a) assumes a single-aspiration measure influences behavior and assumes this aspiration balances social and self-referent aspirations. For firm i, he calculates social aspiration ($SocialA_{i,t}$) as the average of performance for all other firms in the industry in year t,

$$SocialA_{i,t} = \left( \sum_{i \neq j} P_{j,t} \right) \Big/ (N-1) \qquad (2)$$

where $P_{j,t}$ is performance for firm j in period t, and N is the number of firms in the industry. For convenience, we will refer to $SocialA_{i,t}$



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| Model | Number of Parameters | Aspiration Level | Use in Structural Model |
|---|---|---|---|
| | | | |
| Switching Model | 1 | $A_{i,t}$ = $IndustryPerformance_{i,t-1}$ if $P_{i,t-1}$ < $IndustryPerformance_{i,t-1}$<br><br>$A_{i,t}$ = 1.05 * $P_{,t-1}$ if $P_{i,-1}$ > $IndustryPerformance_{i,t-1}$ | $Y_{i,t} = b_1 (P_{i,t-1} - A_{i,t-1}) + \ldots$ |
| | | | |
| Weighted-Average Model | 4 | $A_{i,t} = a_1 IndustryPerformance_{i,t} + (1-a_1)(1-a_2)\sum_{j=0}^{\infty} a_2^j \; P_{i,t-1-j}$ | $Y_{i,t} = b_1 D_1 * (P_{i,t-1} - A_{i,t-1}) + b_2 D_2 * (P_{i,t-1} - A_{i,t-1}) + \ldots$<br><br>*Where:*<br>$D_1$=1 if $P_{i,t-1}$ > $IndustryPerformance_{i,t}$, 0 otherwise<br>$D_2$=1 if $P_{i,t-1}$ < $IndustryPerformance_{i,t}$, 0 otherwise |
| | | | |
| Separate Model | 4 | $Self_t = P_{t-1}$<br><br>$Social_t = IndustryPerformance_t$ | $Y_{i,t} = b_1 D_1 * (P_{i,t-1} - Self_{i,t-1}) + b_2 D_1 * (P_{i,t-1} - Social_{i,t-1}) + b_3 D_2 * (P_{i,t-1} - Self_{i,t-1}) + b_4 D_2 * (P_{i,t-1} - Social_{i,t-1}) + \ldots$<br><br>*Where:*<br>$D_1$=1 if $P_{i,t-1}$ > $IndustryPerformance_{i,t}$, 0 otherwise<br>$D_2$=1 if $P_{i,t-1}$ < $IndustryPerformance_{i,t}$, 0 otherwise |

Figure 2. Three models of aspirations

as $IndustryPerformance_{i,t}$. Greve (2003a) models self-referent aspirations as a function of past self-referent aspirations and performance:

$$SelfA_{i,t} = a_2 SelfA_{i,t-1} + (1 - a_2) \quad P_{i,t-1} \qquad (3)$$

Overall aspirations then equal a weighted average of the two:

$$A_{i,t} = a_1 IndustryPerformance_{i,t} + (1 - a_1)\, SelfA_{i,t} \qquad (4)$$

Replacing $SelfA_{it}$ and solving for lagged values of performance give:

$$A_{i,t} = a_1 IndustryPerformance_{i,t} + (1 - a_1)(1 - a_2)\sum_{j=0}^{\infty} a_2^j P_{i,t-1-j} \qquad (5)$$

Greve's (2003a) aspirations model has two parameters, $a_1$ and $a_2$. He estimates the parameters by creating aspiration measures for various values for $a_1$ and $a_2$ and estimating his structural model with each of the various measures. He selects the values of $a_1$ and $a_2$ that give the highest likelihood in the full-model estimation. Greve (2003a) estimates $a_1 = 0.8$ and $a_2 = 0.2$. With $a_1 = 0.8$, industry comparisons dominate this blended measure of aspirations. In addition, within the summation in Equation 5, j = 0 gives $P_{i,t-1}$ a weight of 1, while the remainder of the summation ($\sum_{j=1}^{n} a_2^j$, with $\alpha_2 = 0.2$) only adds to 0.25. This implies that performance in t-1 dominates the self-referent aspirations component.

Greve subtracts aspirations from performance and splits the result into positive and negative values (i.e., performance − aspirations when performance > aspirations and performance − aspirations when performance < aspirations). The approach provides for empirical estimation of two separate influences (positive and negative attainment discrepancy). This aspiration representation results in a model that has four parameters; $a_1$ and $a_2$ estimated by trying out alternative values for each attainment discrepancy and two in the final estimation.

Theoretically, this approach embodies several ideas. First, it assumes that organizations have a single aspiration level for a performance dimension. This aligns well with corporate practice: firms usually retain only one set of stated goals for a given activity at a given time, though those goals may reflect various factors (e.g., a sales target based on input from both sales and other managers). Second, this single-aspiration level depends on a balance of the organization's self- and social-referent aspirations. The weights used in studies blending self and social components come from straightforward empircs with no theoretical reason for the relative importance of the self- and social-reference points. This aspirations



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formulation imposes a zero-sum structure; as the influence of social-referent aspirations increases, the influence of self-referent aspirations must decrease, and vice-versa.

This representation has some drawbacks. Unlike the original BTOF specification, the model treats self- and social-referent aspirations differently. Historical values of self-referent aspirations matter, but only current values of social. This requires a somewhat unlikely pattern of organizational information processing where the firm retains a past self-referent aspiration—used in the calculation of current self-referent aspirations in Equation 3 but not past social aspiration—and acts only on some overall aspiration level that combines social and self (Equations 4 and 5). The model also can create implausible aspirations. For example, employing Greve's coefficients that weight industry 80 percent and weight self 20 percent, the weighted average between self- and social-referents implies that a firm with performance consistently above the industry will aspire to lower performance than it has recently experienced. It seems unlikely that a firm with a long history of high performance would "aspire" to lower-than-historical performance. Nevertheless, of the three models we consider, this model conforms most closely with the original model of Cyert and March ([1963] 1992); empirical work advancing this model appears to be the most consistent with the original model.

### Separate social and self measures

Instead of aggregating social and self into one aspiration level, several studies have used separate measures of aspirations and attainment discrepancies for social- and self-referents (Baum and Dahlin, 2007; Baum *et al.*, 2005; Greve, 1998, 2003b; Harris and Bromiley, 2007). Baum and Dahlin's (2007) study of railroad accidents used a weighted moving average of historical performance for self-referent aspirations, and current mean industry performance for social-referent aspirations. Greve (1998, 2003b) models self-referent aspirations as an exponentially weighted moving average of prior performance and social-referent aspirations as current industry performance. Harris and Bromiley (2007) measure self-referent aspirations by the prior year's performance, and social-referent aspirations by the prior year's industry average performance. Baum *et al.* (2005) used a weighted moving average of historical performance for self-referent aspirations, and two different measures for social-referent aspirations that are particularly salient for their chosen industry setting (current-year market share and "status" as measured by network centrality).

These examples illustrate that models sharing a common approach to measuring aspirations—separate self-referent and social-referent aspirations—can still differ in details of measurement. Most of these models take the form

$$SocalA_{i,t} = a_1 IndustryPerformance_{i,t}$$

$$SelfA_{i,t} = \sum_{j=1}^{n} a_2^j Performance_{i,t-j} \tag{6}$$

Measuring separate attainment discrepancies based on self- and social-referent aspirations differs theoretically from the blended approach discussed previously. Unlike models that combine social- and self-referent aspirations in one measure, models with separate self and social variables allow for social aspirations versus performance to have a different influence when social aspirations exceed performance than when they fall below performance, and likewise self-referent aspirations can have a different influence when performance exceeds social aspirations than when it does not. Allowing these separate influences provides for the possibility that firms vary their referents depending on their performance versus industry.

The increased flexibility of this model comes with a logical complexity. Using separate social- and self-referent attainment discrepancies employs two indicators for the same construct. Because the attainment discrepancies from the separate measures use different referents, they do not necessarily align closely with the weighted model results. Empirically, this may not create as much a problem as one might imagine; with a heavy (e.g., 80%) weight on social comparison, the weighted model strongly resembles the industry-based aspiration measure.

Qualitatively, if we assume only a one-period structure for both social- and self-referents, then it is plausible that managers know both, but firms seldom create two sets of formal goals for the same thing. While managers might refer to both referent points in setting goals, management systems rarely carry two explicit target values for the same metric. The separate measure approach also has a less obvious underlying mechanism than the other two approaches. With both the weighted and switching models, the firm has one operational aspiration level and searches when performance falls below that level. With the separate social and self measures, if firm performance falls below both aspiration levels we would also expect search, but have no clear theory whether the satisficing works primarily toward the social or self aspiration level. Furthermore, the process employed when the firm exceeds the social aspiration but falls below the self aspiration, or vice versa, remains unclear (see Plambeck and Weber, 2009, 2010). While in aggregate statistical results a researcher might interpret both as tendencies that change the likelihood of particular behaviors, this does not clarify a mechanism.

### Switching model

Bromiley (1991) offers a model with a single aspiration level that systematically switches from one referent to the other (see also Deephouse and Wiseman, 2000; Park, 2007; Wiseman and Bromiley, 1996). These papers argue that firms with performance below the industry average would not be satisfied with simply improving performance over the prior year while remaining below the industry, and firms with performance above the industry would not be satisfied with lower performance than last year even if they remained above the industry average. Any aspiration model where aspirations equal a weighted sum of social and self-referent values has these problems. Instead, this approach suggests a theoretically-derived aspiration measure that equals industry performance for firms below industry performance, and slightly better than prior performance for firms performing above industry performance. Bromiley (1991) used a value of 1.05 times prior performance and claims his results were insensitive to moderate variation in this parameter. This approach explicitly extends the switching of attention - another theoretical mechanism central to the BTOF - to aspirations. Stated formally:

$$\begin{aligned} A_{i,t} &= IndustryPerformance_{i,t-1} \\ &\quad \text{if } \mathrm{P}_{\mathrm{i,t-1}} < IndustryPerformance_{i,t-1} \\ A_{i,t} &= 1.05 * P_{i,t-1} \\ &\quad \text{if } \mathrm{P}_{\mathrm{i,t-1}} > IndustryPerformance_{i,t-1} \qquad (7) \end{aligned}$$

The switching mechanism in this model increases parsimony and assumes less information processing, while still allowing both social and self-referents to influence aspirations. This parsimony comes at the expense of flexibility, by imposing an a priori, theory-based rationale for what managers attend to and why. Methodologically, because the switching model forces a particular relation between social- and self-referent relative performances to create a single aspiration model, it does not introduce the two free parameters used by the weighted average model. Further, it does not provide for different influences when performance exceeds aspirations versus when it does not.

Qualitatively, this model is certainly plausible. Actual organizational debates over firm goals could easily include both referent points, and the switching mechanism requires less information processing than either of the two other approaches. Much of the BTOF addresses switching attention (Ocasio, 1997); the switching model of aspirations extends the attention focus so central to the BTOF to the formation of aspirations, another key aspect of the BTOF. The switching model gives a single aspiration level and thus a single measure of attainment discrepancy.

We now turn to the statistical comparison of the measures using multiple performance dimensions along with multiple dependent variables.

## DATA AND ESTIMATION

In an attempt to analyze the models, variables, and measures in the cleanest and most precise way possible, we employ original data to compare the models directly, rather than conducting a meta-analysis of previously-published, disparate empirical results. This follows Lipsey and Wilson (2001: 2), who suggest that if original data is available, “it will generally be more appropriate and informative to analyze them directly using conventional procedures rather than meta-analyze summary statistics.” By using common data to compare the models directly, we achieve better control over the comparisons and more precise interpretation of the results.

In comparing the aspirations models, we vary both the performance dimension on which aspirations are defined and the outcome explained by



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aspirations. Since the estimation samples and techniques vary across dependent variables, we discuss the data and estimation together.

We examine three dependent variables used in prior studies of aspirations, giving us a range of empirical "coverage" on the kinds of outcomes demonstrated to be driven by aspirations and search: financial misrepresentation, variation in analyst forecasts of earnings, and R&D expenditures.

To employ the best available data for each dependent variable, we constructed slightly different datasets for each of the dependent variables, although some firms may appear in more than one of the datasets. For example, the models predicting financial restatements use data from firms identified by the Government Accountability Office in a report on financial cheating (U.S. General Accounting Office, 2002), along with a corresponding set of matched firms that had not restated their financials. Due to the number of small firms in the GAO data and lack of small firm coverage of small firms in Execucomp, we hand collected data on compensation for some of these firms. In contrast, for the models predicting R&D spending, we use all firms with available data from COMPUSTAT and Execucomp. For income-stream uncertainty, we use all firms with available data from COMPUSTAT, Execucomp, and IBES.

### Income restatement dependent variable

We relied on a widely-used inventory of firms identified by the Government Accountability Office as materially misrepresenting their financial statements (U.S. General Accounting Office, 2002). The GAO list of firms identified restatements triggered by egregious misrepresentation and not restatements triggered by mergers, accounting method changes, or bookkeeping errors.[1]

Given a low frequency event in the dependent variable, we followed the standard practice of using a matched-sample design. Matched-sample designs have been extensively used in our field, both in other studies of these same financial restatements (Aier *et al.*, 2005; Arthaud-Day *et al.*, 2006; Kinney *et al.*, 2004; O'Connor *et al.*, 2006), and in studies of other similarly infrequent phenomena (Cannella *et al.*, 1995; Daily and Dalton, 1994; Erickson *et al.*, 2006; Hambrick and D'Aveni, 1988). Our estimation of the matched sample uses conditional logit, a standard procedure for estimating models with matched case-control samples and zero/one dependent variables (Bowen and Wiersema, 2004; Holford, 2002). Conditional logit estimates a logit with a fixed effect for each matched pair.

In constructing our own sample for this analysis, we matched each misrepresenting firm with a firm of close to the same size in the same 4-digit Standard Industrial Classification (SIC) code industry that had not restated its financials. In a few cases where no appropriate firm could be found in the 4-digit industry, we used a match from a closely related industry. Where a firm had multiple restatements, the analysis only considered the first instance. The dependent variable in these analyses equals zero if the firm did not restate earnings and one if it did. The models were estimated using Stata's conditional logit procedure thus including fixed effects for each pair. We merged the GAO data with financial data from COMPUSTAT and compensation data from Execucomp, and—where Execucomp did not provide it— hand-collected compensation data from firm proxy statements filed with the Securities and Exchange Commission (SEC). Since the winsorized data replaces extreme values by a less extreme value, the winsorized and full-sample analyses (explained below) have the same number of observations. While the GAO list included 845 restatements, due to missing data and repeated misstatements, our winsorized and full samples estimates used 870 observations (i.e., 435 restating firms and 435 non-restating matched firms), while the Cook's D had 814 observations.

### Income-stream uncertainty dependent variable

The earliest large-sample applications of an aspirations model to corporate data (Bromiley, 1991; Wiseman and Bromiley, 1996) attempted to explain the coefficient of variation in analyst forecasts of firm earnings, an indicator of uncertainty about the firms' future earnings. However, the coefficient of variation is not a good measure of

[1] The GAO restatement data is the definitive, well-accepted sample of cheating firms that has been used not only in numerous studies in strategy and organization theory (e.g., Arthaud-Day *et al.* 2006; Dunn, 2004; Harris and Bromiley, 2007; O'Connor *et al.*, 2006), but also in finance (e.g., Burns and Kedia, 2006) and accounting (e.g., Desai *et al.*, 2006; Erickson *et al.*, 2006; Srinivasan, 2005).



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uncertainty when the mean of the variable can take both positive and negative values or is near zero, as is the case for some analyst forecasts of firm income. Therefore, to reduce outliers, we measured uncertainty about future earnings by the square root of the standard deviation of analysts' forecasts and dropped observations where fewer than three analysts offered forecasts. Consequently, our analysis uses analyst forecasts available from IBES, combined with financial data from COMPUSTAT and compensation data from Execucomp. Merging data on all firms available from these sources gave roughly 11,046 usable observations covering 1,618 firms from 1994 to 2007 (with some firms missing in some years) for the estimations where outliers were identified using Cook's D, and 11,267 observations covering 1,625 firms for the full and winsorized samples. These models were estimated using regression procedures that included fixed effects for each firm along with controls for the log of sales and the proportions of CEO income from options and bonuses.

### R&D dependent variable

Several studies use aspirations models to explain R&D spending, or the ratio of R&D expenditures to sales (Bromiley and Washburn, 2011; Chen and Miller, 2007; Greve, 2003a). We examine R&D spending rather than the ratio of R&D spending to sales because firms choose R&D spending levels, while R&D to sales depends partially on revenue. Our analysis used financial data on all firms available from COMPUSTAT and compensation data on all firms available from Execucomp. The results in Tables 2 and 3 use 8,466 observations covering 1,264 firms from 1994 to 2007 (with some firms missing in some years) for the estimations where outliers were identified using Cook's D, and 8,855 observations covering 1,287 firms from 1994 to 2007 with the full sample and the winsorized data. Our fixed effects regression estimator eliminated firms that reported no R&D spending in the observed period. The models included controls for the log of sales and the proportions of CEO income from options and bonuses.

### Control variables

Across the existing studies examining these aspirations measures, a wide variety of control variables appear. Given the moderate size of the financial restatement dataset, we wanted to restrain the number of control variables. With fixed effects, we did not need control variables that did not vary over time. As such, we chose to include the control variables originally employed in Harris and Bromiley (2007): the proportion of CEO income from options, the proportion of CEO income from bonuses, and the log of sales. A substantial literature demonstrates that CEO incentives and firm size both influence behavior.

We address outliers two ways; (1) winsorizing all variables (replacing values in the bottom or top 2 percent by the value of the second or 98th percentile with variables bounded by zero winsorized only at the top) and (2) deleting observations with Cook's D values over 4/N (Bollen and Jackman, 1990). In addition, we also report full sample results.

Having discussed our alternative outcome measures, we now consider the three different aspirations models compared in the estimations:

### The weighted average model

Following Greve (2003a), we tried values for $a_1$ and $a_2$ from 0 to 1 by increments of 0.1 to calculate the aspirations variables, estimated the structural model, and selected the $a_1$ and $a_2$ that gave the highest log likelihood value (which also gave the lowest AIC and BIC). The best weights for $a_1$ and $a_2$ were 0.1 and 0.9 for analyst forecasts, 0.6 and 0.4 for R&D, and 0.1 and 0.9 for financial misrepresentation. We examined models using one (performance$_{t-2}$) and two lagged values of firm past performance (performance$_{t-2}$ and performance$_{t-3}$). The one-lag model had higher AIC and BIC statistics so we report the results using one lag. The models are fit as spline functions allowing the regression to change coefficients at the reference point.

### The separate model, with independent self-referent and social-referent aspirations

Following Greve (2003b) and Harris and Bromiley (2007), we construct separate measures of self and social aspirations. The models include a dummy variable to indicate positive versus negative performance relative to aspirations. Here we represented self aspiration by firm performance and social aspirations by industry average performance (excluding the firm of interest) in t-1. We considered additional lags, but they resulted in lower fit indices, so as with the weighted average approach, we report results on the one lag model. Following Harris and Bromiley (2007), we include a dummy variable for each (social and self) reference point, to allow discontinuities when aspirations minus performance switches signs from negative to positive.

### The switching model with 1 year of industry and firm data

Following Bromiley (1991), for firms performing below the industry average the industry average functions as the focal reference point. For firms performing above the industry average, the reference point equals 1.05 times the firm's performance in the previous year. Following Bromiley (1991), attainment discrepancy has the same influence for positive and negative values.

### Model comparison

We compare both the alternative performance measures and the three aspiration models based on their Akaike information criterion (AIC) and Bayesian information criterion (BIC) values. AIC and BIC are "penalized model selection criteria" that trade off goodness of fit and parsimony (Kuha, 2004: 189). As such, both information criteria consist of the sum of two terms—the likelihood ratio statistic and a function of the degrees of freedom that declines with additional parameters, thus penalizing increases in model size. The two terms "pull in opposite directions" and trade off fit and complexity (Kuha, 2004: 190). These information criteria can be used to compare both nested and non-nested models. AIC and BIC are generally defined as:

$$AIC = 2\left[l\left(\widehat{\theta_2}\right) - l\left(\widehat{\theta_1}\right) - 2\left(p_2 - p_1\right)\right] \quad (8)$$

$$BIC = 2\left[l\left(\widehat{\theta_2}\right) - l\left(\widehat{\theta_1}\right) - (\log n)\left(p_2 - p_1\right)\right] \quad (9)$$

where $p_1$ and $p_2$ are the number of parameters in the two models being compared; $n$ is the number of observations; and the first term $(2[l(\widehat{\theta_2}) - l(\widehat{\theta_1})])$ is the likelihood ratio test statistic, asymptotically distributed as $\chi^2$ with $p_2 - p_1$ degrees of freedom. Since these statistics vary with the sample, to increase comparability, we report estimates using only the observations that could be estimated under all three models.

Lower values of either AIC or BIC indicate better model fit (Long and Freese, 2000). Although some researchers (e.g., Raftery, 1986; Weakliem, 1999) consider BIC the superior test,[2] researchers commonly use both AIC and BIC. AIC and BIC have different penalties for model size so they may produce different findings (i.e., an AIC test may show one model to be superior, while a BIC test may support another). However, when the two criteria agree on the best model, this constitutes a particularly robust indication of model superiority (Kuha, 2004).

In addition to the fit indices, we calculate a series of J-tests (Davidson and Mackinnon, 1982, 2002; Greene, 2008). These model specification tests allow comparison of non-nested models. The test compares two models:

H0: $y = X\ B_1 + e$ and H1: $y = Z\ B_2 + e$

The test estimates whether a predicted y from the model in H1 is statistically significant when it is added to the model in H0: $Y = X\ B_1 + c\ \hat{y} + e$.

If the coefficient on $\hat{y}$ is statistically significant, it rejects the hypothesis H0 in favor of a model that includes the variables in H1. The test can be reversed to test whether the model that appeared in H0 above adds to the model labeled H1 above.

### Performance measures

Aspirations need to be defined with respect to a particular dimension of performance. While most studies using firm-level aspirations have relied on accounting measures—often return on assets (ROA)—studies have not addressed whether other measures of performance might be superior, nor have they considered the problems that may be inherent in the use of a single accounting measure such as ROA. To evaluate the use of different performance measures in constructing aspirations measures, analyzed the following measures of performance:

[2] The degrees-of-freedom adjustment term is derived theoretically for BIC but is essentially arbitrary for AIC.



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1. ROA, defined as net income divided by total assets, the conventional measure of return on assets in the literature.
2. Cash flow ROA, defined as income before depreciation, interest, and taxes divided by gross assets (assets plus accumulated depreciation). This measure avoids some of the accounting issues associated with recognition of discretionary items and depreciation.
3. Stockholder returns, defined as dividends plus change in stock price divided by the stock price in the previous year.
4. A composite accounting measure that included ROA, return on stockholder equity (ROE), and return on sales (ROS). The composite measure equaled the sum of standardized values of the three variables. The measure was constructed using the Stata alpha procedure. Variables created from a confirmatory factor analysis gave similar results.
5. A larger composite that included ROA, ROE, ROS, and stockholder returns. The composite measure equaled the sum of standardized values of the four variables. The measure was constructed using the Stata alpha procedure.
6. Unscaled net income, by far the simplest performance measure. Management researchers seldom use net income as a performance measure, but managers pay attention to it.

## ANALYSIS AND RESULTS

Let us first consider the measures of performance. Table 1 presents the two summary statistics (AIC and BIC) for the six alternative measures of performance estimated using each of the three models. For comparability, we used the set of observations for which we could estimate all the performance measures so each entry in a given row was estimated with the same number of observations, but the number of observations varies across rows. Because the techniques for deleting outliers dropped different numbers of outliers for the different performance measures, outliers were not deleted in this initial analysis. Table 1 indicates that, surprisingly, the net income measure had the best fit for the majority (10 out of 18) of the dependent variable-aspiration model combinations, while stock returns had the next best fit in one third (6 out of 18) of the combinations. Cash flow ROA had the best fit for the remaining two combinations. Thus, the empirical results favor the net income measure over the others.

Given the fit results of the performance measure comparison, two alternatives appeared reasonable. We could either use the performance measure with the best fit for each performance measure-dependent variable pair so the performance

Table 1. Comparing performance dimensions for measuring aspirations

| | Dependent variable | Aspirations representation | Composite accounting & stock return | Stock return | Composite accounting | Cash flow ROA | Traditional ROA | Net income |
|---|---|---|---|---|---|---|---|---|
| AIC | Analyst forecasts | Separate | 79,535 | 79,539 | 79,536 | 79,531 | 79,533 | **79,507** |
| | Analyst forecasts | Switching | 85,293 | **82,573** | 85,293 | 85,290 | 85,292 | 85,295 |
| | Analyst forecasts | Weighted average | 78,415 | 78,420 | 78,412 | **78,408** | 78,411 | 78,419 |
| | R&D | Separate | 90,151 | 90,172 | 90,145 | 90,099 | 90,156 | **89,386** |
| | R&D | Switching | 96,453 | **94,043** | 96,453 | 96,455 | 96,448 | 96,458 |
| | R&D | Weighted average | 88,405 | 88,421 | 88,405 | 88,385 | 88,412 | **88,063** |
| | Misrepresentation | Separate | 384 | 380 | 382 | 381 | 379 | **374** |
| | Misrepresentation | Switching | 391 | **389** | 391 | 390 | 390 | 391 |
| | Misrepresentation | Weighted average | 383 | 381 | 383 | 379 | 383 | **378** |
| BIC | Analyst forecasts | Separate | 79,681 | 79,685 | 79,682 | 79,677 | 79,679 | **79,653** |
| | Analyst forecasts | Switching | 85,413 | **82,692** | 85,412 | 85,410 | 85,411 | 85,415 |
| | Analyst forecasts | Weighted average | 78,533 | 78,538 | 78,530 | **78,526** | 78,529 | 78,537 |
| | R&D | Separate | 90,294 | 90,314 | 90,287 | 90,241 | 90,298 | **89,528** |
| | R&D | Switching | 96,569 | **94,159** | 96,569 | 96,571 | 96,565 | 96,574 |
| | R&D | Weighted average | 88,520 | 88,536 | 88,519 | 88,500 | 88,527 | **88,177** |
| | Misrepresentation | Separate | 424 | 420 | 422 | 421 | 418 | **413** |
| | Misrepresentation | Switching | 409 | **407** | 409 | 408 | 408 | 409 |
| | Misrepresentation | Weighted average | 405 | 403 | 405 | 401 | 405 | **400** |

Bold indicates lowest value in row.

measure would vary across models, or we could use one performance measure for all the comparisons. The latter approach seemed most useful for comparative purposes. To reduce the number of varying factors, and given the surprisingly strong results on net income in Table 1, we present the comparative analysis of the aspiration models using net income (see Table 2).

AIC and BIC summary statistics are best compared when applied to the same samples. AIC does not include sample size in its calculation. While BIC includes sample size in its calculation, its results still vary with sample size. Consequently, we ran the analyses on the maximum sample size for which we could estimate *all* the models.

Table 2 presents the AIC and BIC statistics for the different aspirations representations and the three dependent variables. The results do not unanimously support a specific model, but across all the estimates, the weighted average model has a poorer fit than the other two models. The BIC criterion preferred the switching model in seven of the nine estimates across the three sets of results with the other two favoring the separate model. This model had the fewest free parameters (see Figure 2), and so this result is in some ways unsurprising, but nevertheless a consistent strong result. The AIC criterion supported the separate model for seven of the nine results, and the switching and weighted average models for one each of the remaining two results. Overall, these comparisons favored the separate model (best in 9 of 18) and switching model (best in 8 of 18 estimates) over the weighted average (best in only 1 of 18).

In addition to the AIC and BIC tests, we ran J-tests comparing the models (see Table 3). The column headings refer to the model that is taken as H0, and the rows refer to the models taken as H1. Here, the results are somewhat more complex; we discuss the J-test results for each dependent variable sequentially.

All three estimates for variation in analyst forecasts demonstrate that the separate model adds explanatory power to that provided by both the switching model (b = 1.001, $p < 0.001$; b = 0.950, $p < 0.001$; b = 0.946, $p < 0.05$ for Cook's D, winsorized and full samples, respectively) and weighted average model (b = 0.973, $p < 0.001$; b = 1.034, p < 0.00; b = 1.018, p < 0.05). The switching model only adds to the weighted average model with the winsorized data (b = 1.026, p < 0.001). The weighted average model only adds to the switching model (b = 0.877, $p < 0.01$) and

Table 2. Fit indices for alternative aspirations models

| Fit index | dv | Separate | Switching | Weighted average |
|---|---|---|---|---|
| Full Sample | | | | |
| AIC | Analyst | **118,221** | 118,223 | 118,231 |
| AIC | R&D | **121,778** | 122,826 | 122,238 |
| AIC | Restate | **526** | 539 | 542 |
| BIC | Analyst | 118,375 | **118,347** | 118,378 |
| BIC | R&D | **121,927** | 122,946 | 122,380 |
| BIC | Restate | 564 | **558** | 576 |
| Cook's D | | | | |
| AIC | Analyst | **88,919** | 88,927 | 88,931 |
| AIC | R&D | **94,491** | 95,142 | 94,647 |
| AIC | Restate | **486** | 498 | 503 |
| BIC | Analyst | 89,072 | **89,052** | 89,077 |
| BIC | R&D | **94,639** | 95,262 | 94,788 |
| BIC | Restate | 524 | **517** | 536 |
| Winsorized | | | | |
| AIC | Analyst | 95,535 | 95,537 | **95,532** |
| AIC | R&D | 104,141 | **104,140** | 104,148 |
| AIC | Restate | **527** | 535 | 539 |
| BIC | Analyst | 95,689 | **95,662** | 95,679 |
| BIC | R&D | 104,198 | **104,168** | 104,197 |
| BIC | Restate | 565 | **554** | 573 |

Bold indicates lowest value in row.



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Table 3. J-Tests among models

| H0: | Cook's D Switching | Cook's D Separate | Cook's D Weighted average | Winsorized Switching | Winsorized Separate | Winsorized Weighted average | Full sample Switching | Full sample Separate | Full sample Weighted average |
|---|---|---|---|---|---|---|---|---|---|
| H1: | | | | | | | | | |
| DV: Square root of standard deviation of Analyst Forecasts | | | | | | | | | |
| b for separate | 1.001*** | . | 0.973*** | 0.950*** | . | 1.034*** | 0.946* | . | 1.018* |
| Std error for separate | 0.277 | . | 0.300 | 0.295 | . | 0.218 | 0.418 | . | 0.42 |
| b for switching | . | −0.020 | 0.100 | . | 0.160 | 1.026 | . | 5.609 | 2.062 |
| Std error for switching | . | 0.924 | 0.826 | . | 0.446 | 0.262 | . | 5.883 | 2.645 |
| b for weighted average | 0.949 | 1.253 | . | 0.877*** | 1.816* | . | −1.204 | 37.668 | . |
| Std error for weighted average | 0.618 | 2.177 | . | 0.252 | 0.868 | . | 2.083 | 41.274 | . |
| DV: R&D | | | | | | | | | |
| b for separate | 0.975** | . | 0.976** | 0.920 | . | 1.033* | 1.004 | . | 0.807 |
| Std error for separate | 0.379 | . | 0.369 | 0.591 | . | 0.468 | 0.533 | . | 0.644 |
| b for switching | . | 4.247* | 3.615 | . | 1.086 | 1.049 | . | 14.789 | 2.144 |
| Std error for switching | . | 1.959 | 2.411 | . | 1.548 | 0.564 | . | 21.728 | 23.544 |
| b for weighted average | 0.774 | 5.486 | . | −0.080 | −0.128 | . | 1.000 | 4.364 | . |
| Std error for weighted average | 1.474 | 3.225 | . | 1.318 | 1.565 | . | 0.827 | 3.131 | . |
| DV: Financial misrepresentation | | | | | | | | | |
| b for separate | 0.595 | . | 0.502 | 0.604 | . | 0.478 | 0.724 | . | 0.542 |
| Std error for separate | 0.705 | . | 0.717 | 0.726 | . | 0.731 | 0.732 | . | 0.745 |
| b for switching | . | −1.091 | −0.756 | . | −0.483 | −0.236 | . | −0.659 | −0.410 |
| Std error for switching | . | 1.088 | 1.058 | . | 1.000 | 0.995 | . | 1.05 | 1.036 |
| b for weighted average | −0.445 | −1.036 | . | 0.035 | −0.460 | . | −0.008 | −0.621 | . |
| Std error for weighted average | 1.013 | 1.065 | . | 0.964 | 0.983 | . | 0.984 | 1.021 | . |

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

separate model ($b = 1.868$, $p < 0.001$) with winsorized data.

Only four of the 18 J-tests for R&D spending were statistically significant. We find the separate model adds explanatory power to both the switching model ($b = 0.975$, $p < 0.01$) and to the weighted average model ($b = 0.976$, $p < 0.01$), using the Cook's D sample, and to the weighted average model using the winsorized data ($b = 1.033$, $p < 0.05$). The switching model only adds explanatory power to the separate model with the Cook's D sample ($b = 4.247$, $p < 0.05$).

Finally, examining the results for financial misrepresentation, we find that none of the variables are statistically significant. This is likely due to the smaller sample size.

The J-test results strongly favor the separate model over the two others. Of the 12 statistically significant J-tests, 9 involved the separate model adding to other models. Nevertheless, interpreting the J-test results is somewhat complicated; for example, in the winsorized sample of analyst forecasts, we see that the weighted average adds to the separate model and the separate model adds to the weighted average model. These kinds of J-statistic results are not uncommon particularly when both models have good fits. Under such conditions, the J-test 'over rejects' the null (Davidson and Mackinnon, 1982). As such, the AIC and BIC criteria may be preferable tools for model comparison.

Nevertheless, the J-test analysis supports the findings of the AIC and BIC criteria. All in all, across the three dependent variables, the J-tests rank the fit of the different models as follows: the separate model is best (significant in 9 of 18 estimates), followed by the switching model (2 of 18), and the weighted average model (2 of 18). Hence the J-test results suggest the superiority of the separate model and only weakly support the other two models.

Taken together, the fit indices rate separate and switching models approximately equal and the J-tests strongly favor the separate model over the others. Across all the estimates, the separate model receives the most support, as it ties the switching model on the AIC/BIC fit indices and performs best on the J-tests. Across the metrics, the weighted average model is clearly inferior to the two other models of organizational aspirations.

## DISCUSSION

To our knowledge, this is the first comparison of different models of organizational aspiration representations using publicly-available archival data. Most empirical applications of aspirations models use a single measure of corporate attainment discrepancy to explain a firm-level behavior. This includes almost all the studies explaining risk and R&D, but also applies to studies explaining less studied firm behaviors such as financial misrepresentation and a wide range of other dependent variables. Our comparative analysis of the aspiration models across three different dependent variables constitutes a robust way to test a methodological effect: to horse-race each model of aspirations in three different sets of estimations, testing three very different managerial behaviors, each analyzed in the way most appropriate for examining that particular behavior. Our study starts to give some indication on the metric on which aspirations should be defined and the appropriate representation for aspirations. Let us consider some of our findings.

Our analysis used several performance measures, as well as composites of some of the measures, to address possible biases inherent in often-employed measures like ROA. Researchers have criticized the use of accounting measures of firm performance like ROA for being dependent on firm accounting choices. For example, a firm's total assets (the denominator) depend on the firm's depreciation policies, inventory valuation techniques, policies on booking "goodwill", and other factors. Likewise, reported net income (the numerator) reflects firm choices regarding tax strategies, inventory valuation, and other factors that management can manipulate without substantively changing the underlying business activities. Consequently, many scholars (e.g., Benston, 1985) have argued for measuring firm performance by stock market returns or the market value of the company relative to its replacement cost (Tobin's Q).

Surprisingly, our comparison of performance measures strongly favored unscaled net income, the simplest of the accounting performance measures and one of the measures potentially most subject to measurement bias. Why would this flawed measurement of firm performance serve the best in our comparative analysis? The answer lies in what we are actually testing in these models of managerial behavior. Researchers often want a performance metric to represent "real" firm performance and as such may favor metrics less sensitive to managerial manipulation and measurement bias. However, if we want to explain managerial behavior prompted by firm performance relative to aspirations, the construct of performance *as perceived by the managers* is of primary interest (see, for instance, March and Simon, [1958] 1993). Aspirations models attempt to explain the behavior of firms as a result of *perceived* attainment discrepancy.

Viewed this way, our comparative results on the performance measures support the conventional wisdom that managers pay attention to reported net income. Firm plans and budget control systems emphasize accounting measures of performance like net income. Stock analysts predict firm earnings per share, and the firm's stock suffers greatly if the firm misses analyst predictions. Indeed the literature demonstrating that firms manipulate accounting to raise reported income over analyst predictions shows the importance managers place on net income. Press coverage of firm earnings announcements routinely reports earnings per share and net income, often with a comparison to analyst forecasts and prior earnings per share or income, but such coverage only infrequently reports return on assets or more sophisticated measures like Tobin's Q. With the exception of the most senior managers in an organization, managerial incentives often depend heavily on accounting measures of performance. Even if managers



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considered net income or earnings per share a poor measure of performance, the importance placed on earnings by the business press, stock analysts, and organizational incentive systems would force managers to care about them. Indeed, anecdotal experience with managers—consistent with the statistical results reported here—suggests that managers do rely on reported income as a primary measure of firm performance.

Therefore, one of the contributions of this analysis is evidence that research on attainment discrepancy should seriously consider using net income as a performance measure. While perhaps a flawed measure of "true" firm performance, managers use it as an important metric. The use of income in these models has interesting ties to both the estimation procedure and the literature on how managers assess their firms and their environments. When estimating models with fixed effects, the estimation uses the variation within firms over time to determine the parameters. That is, the fixed effects remove any stable cross-firm variation. Part of the reason to divide income by assets or use other normalizations is to make measures comparable across firms, a problem ameliorated, but not solved, by fixed effects models.

However, while net income may work well as a performance measure for aspirations models that use fixed effects estimation techniques to look at within-firm variation, it may not work in models that compare across firms. Obviously, firms cannot directly compare their income to the income of firms of different sizes, although they may compare rates of change. Our results in favor of net income suggest a need for additional research on how particular metrics gain primacy, both within organizations and when comparing organizational performance to the performance of other firms. For example, future research could examine whether managers use different metrics to compare their current performance to past performance than to compare their performance to that of other firms. Undoubtedly, incentives play a role in focusing managerial attention on particular metrics, as may regulatory requirements and attention paid to particular metrics by outside consultants or analysts. Additional qualitative or survey research might explore how managers come to ascribe the importance they do to different performance measures and how they use these measures in both longitudinal and cross-sectional comparisons.

The second thrust of the analysis is the comparison of the aspiration models. Regarding the best model of aspirations, across the various organizational actions and comparison techniques, our results clearly favor the separate and switching models over the weighted average model and moderately favor the separate model over the switching model. Note that each of the models apparently is a good enough representation to give statistically significant results when analyzed alone; the models generally had significant parameters on attainment discrepancy. However, our study demonstrates that they are not all *equally* good.

The empirical support of the separate and switching models over the weighted average model is notable because the weighted average model of aspirations ties most closely to the BTOF's original model, which has only one comprehensive aspiration for a specific outcome, and that aspiration equals a weighted sum of social- and self-referent factors.

While it would be premature to go so far as to suggest that the comparative analysis reported here justifies the outright rejection of the weighted average model, further research should more thoroughly examine the aspiration models and their theoretical underpinnings to draw broader theoretical conclusions. Although Cyert and March's formal model (equation 1) explicitly invokes the weighted average approach, alternative aspirations like the separate and switching models are not entirely inconsistent with the BTOF; indeed a careful reading of Cyert and March allows for the possibility that social and self aspirations might not aggregate:

> In some cases, we will want to define two values for $\alpha_3$—one for when comparative experience exceeds the organization's goal and a different one for when it is below the goal. Similarly, we may want to allow for the effect of the organization's experience to depend on whether it exceeds or is below the goal (Cyert and March, [1963] 1992: 172).

This opens the door to less-constrained aspiration models; given that our findings favor the separate model, future work should further explore alternative models of aspirations on theoretical grounds. The literature has largely ignored Cyert & March's argument that managers routinely attend to several different objectives. A more



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theoretically-grounded examination of separate aspirations would have implications for our understanding of managerial attention (Ocasio, 1997) as well as for assertions that firms should possess single objectives (Jensen, 2002).

Given the substantial number of papers that use a single performance metric to measure firm aspirations, we focused on such measures, but we recognize that such measures have problems. For some kinds of behaviors (e.g., safety initiatives), other measures may be appropriate. One could easily envision a case where the importance of performance metrics varied across decisions depending on who in the company makes the decisions of interest.

However, our dependent variables in this analysis reflect a variety of corporate actions taken by different individuals in corporations, and the findings have striking consistency. For instance, many corporate decisions made by many managers in a variety of situations influence overall corporate performance and income-stream uncertainty. In contrast, top management often sets a target for R&D spending in the budget process. Financial misrepresentation can come from the top or mid-levels of the organization. Our examination of all three dependent variables finds consistent results but does not rule out the possibility that the important metrics vary with decision maker and type of decision. The determinates of aspirations also might vary with industry, time period, firm size, or other factors (Short and Palmer, 2003). A finer-grained analysis could consider such variation across decision makers and decision types.

Indeed, firms sometimes *intentionally* focus aspirations on a specific reference point. For example, in place of incremental improvements in quality targets, quality experts taught firms that they should aspire to and search for substantial quality improvements (e.g., Deming, 1993; Juran, 1995). Alternatively, instead of comparing a firm's overall performance to its industry, benchmarking advocates instructed firms to aspire to raise performance in specific activities to the level of the best firms at those activities. Such examples demonstrate that firms sometimes *consciously* and *purposefully* manipulate the referents on which they build their aspiration levels.

Cyert and March's original discussion proposed that firms have aspiration levels defined on numerous dimensions (e.g., sales, overhead, cost per unit, etc.) and that the focus of search efforts depended on the dimension on which the firm failed to meet aspirations. To make models tractable, almost all aspiration-related studies have defined aspirations solely in terms of one aggregate performance measure (see Greve, 2008 and Baum and Dahlin, 2007 for exceptions). If search in different dimensions depends on aspirations defined on those specific dimensions, findings using overall corporate performance metrics could simply reflect corporate performance acting as a proxy for various other outcome measures. If researchers examine within-firm variation over time, then sales, income, earnings per share, and a variety of other performance variables will correlate highly, making it feasible for one performance metric to proxy for another. Further research should attempt to better understand the dimensionality of aspirations within firms.

While some studies measure aspirations using several years of prior performance data, our results suggest one year works better. Although the one-year lag may reflect something idiosyncratic in the dependent variables examined, we suspect that the orientation to the most recent year's performance reflects something more general about an unstated assumption about the BTOF model. The model in Equation 1 refers to time t, but does not specify the appropriate units for measuring t. Calculating a weighted sum on annual financial data implicitly assumes t stands for years. With this implicit assumption, the idea that a firm pays little attention to anything more than 1 year previous seems short sighted. Yet, this agrees with corporate practice; most firms do not pay much attention to the past beyond the previous year, and old plans, initiatives, and documents disappear quickly. Managers live day in and day out with the prior year's performance for an entire year. The prior year's performance figures in planning, budgeting, and numerous comparisons. In contrast, performance two years previous seldom, if ever, appears in budgeting and control documents. Given management practices, it makes sense that the prior year's performance matters, but two years previous does not.

In short, in place of the model where a weighted average of social and historical performance determines a single aspiration level, the theory needs to embrace both the possibility that both social and historical performance directly—and independently—influence behavior,



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*and* the possibility of switching attention between social and historical referents.

Researchers might also want to distinguish between top-level choices and those lower down in the organization. At lower levels, managers often face explicit goals in the budget. Perhaps, at the highest level of the corporation, attainment discrepancy comes from individuals using different reference points when discussing specific issues rather than a comparison of performance with a specific budget target. Instead of past performance or a competitor's performance influencing an aspiration level that then figures into attainment discrepancy, managers may specifically compare firm performance to the competitor's performance or the firm's past performance. This might explain the results on both the switching and separate models.

This expanded conception does not require significant additional computation or analysis by the firm and fits nicely within several of the BTOF's major themes. The BTOF is largely a theory of the allocation of attention, yet the original aspiration model has no such attention allocation explicitly built into it. In contrast, the switching and separate model results fit well with varying attention. The BTOF also recognizes the influence of organizational politics. One way managers can influence perceptions is by selective choice of the referents they use for comparisons. By varying between historical and social referents, and even across firms in social comparison, managers might manipulate whether a given outcome is above or below the reference level. The BTOF recognizes political behavior in both determining the dimensions of goals and setting some goals (as a compromise within the dominant coalition) but has typically not extended this recognition when talking about aspiration levels. Our methodological analysis suggests the potential value in such theoretical extensions.

In addition to the future research directions already discussed, several limitations of this study offer additional directions for future research. As previously mentioned, this study combines data across industries, but aspiration-related mechanisms may differ systematically across industries; industry-specific social phenomena could influence firm aspirations. Future research might examine interindustry differences and attempt to explain such differences.

Although our study includes an analysis of financial restatements, we have not explored Harris and Bromiley's (2007) findings on the nonlinearity of the influence of attainment discrepancy. Demonstrating that attainment discrepancy has a nonlinear impact on firm behavior, they found that the probability of misrepresentation did not increase in the linear fashion most modeling assumes but rather stayed low until firms performed far below their competitors. We are not sure whether this nonlinearity applies solely to firm misconduct or might appear in other areas. Furthermore, does such evidence indicate nonlinearity in the formulation of aspirations, or nonlinearity in firm responses to performance relative to aspirations?

Future research might also more fully explore how firms interpret equivocal or ambivalent attainment discrepancy signals (Plambeck and Weber, 2009, 2010). Work in social psychology suggests that individuals interpret performance or reward disparities differently whether they perceive such disparities as their being *disadvantaged*, versus their competitors being *advantaged* (e.g., Lowery, Chow, and Crosby, 2009). If individual aspirations depend on context and framing, do *organizational* aspirations similarly depend on framing, say by the media or other contextual influences? Additional research investigating such questions could answer a call to "update" the behavioral theory of the firm with recent insights from psychology and social psychology (Gavetti, Levinthal, and Ocasio, 2007).

Because we lacked direct measures of aspirations, we did not address differences between direct and indirect measures of aspirations. Greve (2003c: 48) argues that direct measures of aspirations have primarily been explored in the goal-setting literature (e.g., Locke and Latham, 1990) rather than in work grounded in the BTOF although Lant (1992), Mezias, Chen and Murphy (2002) and Bromiley and Washburn (2012) do use direct measures. However, future research might compare the results using public archival data to results using direct measures of aspirations.

## CONCLUSION

Overall, this study provides a comparative analysis of three different models of aspirations and does so in the context of multiple measures of performance and three different outcome variables. Methodologically, the analysis compared the abilities of these measures and models to describe organizational responses to attainment discrepancy. The results offer some concrete findings for future research: (1) accounting measures such as net income—while biased measures of true performance—may be salient measures to analyze for aspirations-based work; (2) modeling aspirations separately appears to be superior to other models of aspirations; and (3) the least effective way to model aspirations is by aggregating self and social factors into one weighted average.

These methodological contributions also point the way to greater theoretical exploration of aspirations models. The ease by which researchers can obtain archival accounting data has resulted in aspirations researchers emphasizing such analyses and, with a consequent lack of research, using internal firm targets and other methods. A greater variety of empirical studies could advance our theoretical understanding of aspirations and attainment discrepancy as a motivation for organizational action. Such research could deepen our understanding of the processes underlying aspirations but also might lead to models that better explain which aspiration models apply, and when. Research in this area should strive to develop a richer theory and expand empirical modeling, rather than generating additional studies showing the simple influence of aspirations on another dependent variable.

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