Behavioral Reasons for New Product Failure: Does Overconfidence Induce Over-forecasts?

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Abstract

We empirically investigate one specific cognitive distortion heretofore neglected in studies of new product commercialization—overconfidence, commonly defined in the literature as excessive belief in own abilities to generate superior performance. To lay the groundwork for our study, we develop a behavioral model which both organizes well-understood new product performance determinants and illuminates others heretofore not studied, namely, incentive alignment and cognitive limitations and biases. The model summarizes extant research and allows us to develop research hypotheses related to overconfidence. We find that decision makers' overconfidence is associated with a higher likelihood of over-forecasting new product sales. The observed effect is fully mediated by tactical decisions that dampen demand, namely elevated product pricing. We conclude with a discussion of our results and provide specific recommendations for practice.

Keywords: overconfidence, new product development, innovation, new product performance, failure, managerial decision making, cognitive biases

Introduction

Reducing high new product failure rates remains one of the greatest challenges of new product research (e.g., Barczak, Griffin, and Kahn, 2009; Wind and Mahajan, 1997). In response, a number of scholars have identified and categorized various determinants of new product success or failure (e.g., Cooper and Kleinschmidt, 1990; Henard and Szymanski, 2001; Montoya-Weiss and Calantone, 1994). Although those studies have greatly expanded our understanding of what drives new product performance, they tend to explore a relatively constant subset of drivers. In particular, these frameworks have not considered classes of factors that pertain to the decision unit's incentive structures and cognitive limitations. Studies in marketing, economics, finance, and management consistently demonstrate that managers' incentives and characteristics, including cognitive limitations, affect firm decisions and performance (e.g., Currim, Lim, and Kim, 2012; Graham, Harvey, and Puri, 2013; Hirshleifer, Low, and Teoh, 2012). In this paper, we investigate one specific cognitive bias heretofore neglected in studies of new product commercialization—overconfidence.

Overconfidence is commonly defined in the literature as excessive belief in own abilities to generate superior performance (Clark and Friesen, 2009; Hirshleifer, Low, and Teoh, 2012; Malmendier and Tate, 2005; Moore and Healy, 2007). Assessment of confidence and its impact on human decision making has been a prominent area of research in cognitive psychology over the past half-century (Benabou and Tirole, 2002; Moore and Healy, 2007). In the past decade, its importance has filtered into business disciplines, as evidenced by a veritable explosion of research on overconfidence in the management and finance literatures. The newly formed "Judgment and Decision Making" department in the journal *Management Science* highlights a need for more business research on "assessments of confidence" in its current editorial statement (Management Science, 2014).

Simply put, the heightened emphasis on overconfidence in business research is motivated by greater appreciation of its impact in decision making. Researchers associate overconfidence, in particular, with serious judgment errors in various domains of human activity, including corporate investments (Malmedier and Tate, 2005, Roll, 1986, Malmedier and Tate, 2008, Gervais, Heaton, and Odean, 2011, Odean, 1999). Summarizing the relevant evidence, Plous (1993, p. 217) states: “No problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence.”

We address two research questions about the impact of this bias on new product commercialization activities. First, we explore whether overconfidence is associated with over-forecasting new product demand. Second, we investigate two complementary mechanisms that may account for overconfidence-induced over-forecasts. Our findings are based on data generated in the course of management simulation workshops conducted among graduate students at three leading business schools in India.

To lay the groundwork for our study, we develop a model which both organizes well-understood new product performance determinants and illuminates others heretofore not studied, namely, incentive alignment and cognitive limitations and biases. We summarize extant research in this behavioral model intended to facilitate general hypothesis development. We then use the model to develop research hypotheses related to the portion of the model that addresses overconfidence.

In the next section, we present our model that summarizes nine established and two newly-proposed categories of new product performance determinants by linking them to key behaviors in the new product development (NPD) process. This model contextualizes the hypothesized impact of overconfidence and other cognitive limitations. We then state our research hypotheses followed by the empirical investigation. We conclude with a discussion of our results and their implications for research and practice.

Generalized Model of New Product Failure

Multiple factors contribute to a new product's performance in the marketplace. Extant literature groups those factors in a large number of similar categories (e.g., Cooper and Kleinshmidt, 1990; de Brentani, 1991; Di Benedetto, 1999; Henard and Szymanski, 2001). We summarize this literature in the form of a generalized framework (shown schematically in Figure 1 and further detailed in Table 1) that incorporates both previously identified and our newly proposed determinants of new product failure (the latter are flawed incentive structures and decision unit limitations) in a multi-level structure. We frame new product outcomes in terms of failure rather than success to provide for a more pointed discussion. Superior performance on at least one key antecedent is a necessary, but not sufficient condition for success. Adequate performance on most antecedents is also required for new product success. In contrast, failure on a single antecedent can often prove decisive. For the purposes of the current research, we define failure broadly as the inability to meet previously set objectives (e.g., Cooper, 1979; Maidique and Zirger, 1985).

<< Insert Figure 1 about here >>

We hierarchically arrange new product performance antecedents according to their longitudinal sequence, whereby some conditions and activities precede and influence or serve as inputs for subsequent activities. The spine of the model reflects the behavioral sequence of steps in the NPD process: analysis and interpretation, decision response, execution. Although NPD is commonly treated as a multi-stage process, the aggregate three-step representation captures the distinct behavioral dimensions of NPD activities in the following fashion. Managers look to their business environment for new product ideas. Information about market needs, trends, and competitive offerings serves as input for decisions to modify existing products or develop new ones. The *environmental analysis and interpretation* serves as the basis for a managerial *decision response* with respect to project selection, continuation and launch. In the latter step, the firm also specifies a new product offering together with a business model through which the offering is to be commercialized. The firm then *executes* these decisions in the development process and commercialization. Because NPD and eventual launch are learning processes, firms routinely consider both internal and external feedback and update analysis, decisions, and execution as these (and subsequent) steps unfold.

As such, most determinants of failure flow through the three "spinal" activities in Figure 1. "Foundational" determinants, listed above the spine, are those inputs and structural elements that support (or inhibit) the spinal activities (e.g., faulty market research or resource limitations). They provide the foundation for the underlying NPD behavioral process, i.e., analysis and interpretation, decision response, and execution. "Byproduct" determinants, listed below the spine, are the byproducts of inadequate analysis and interpretation, decision response, or execution that form more proximate causes of marketplace failure (i.e., those marketing and operations missteps that prevent the product from thriving).

It is worth noting that the execution step represents a very broad behavioral category. We keep it in the aggregated form for the sake of parsimony. Also, the managerial steps, or sets of activities, in the spine of the model map closely, but not one-to-one, to the three components of the market orientation concept (e.g., Kohli and Jaworski, 1990): (1) activities to gather information on customer wants and needs; (2) the use of cross-functional teams to analyze the information; and (3) value creation.

We group the foundational and byproduct determinants into the five categories above and below the spine, respectively, shown in Figure 1. The locus of their proposed impact is indicated by the dashed arrows.[1] To keep the model tractable, we do not postulate relationships among determinants at the same level of the hierarchy in Figure 1. Some

[1] The proposed arrows reflect what we view as primary flows. While other linkages are possible, they are likely to be of more indirect nature.

determinants may be linked by moderating or mediating relationships (as we demonstrate empirically with respect to pricing and over-forecasts). We accommodate this extra complexity by placing byproduct determinants within a general flow (represented in the wide arrow) that leads towards new product failure. The proposed categories are sufficiently general to capture most known and newly-proposed antecedents. For example, most issues pertaining to a new product (e.g., mis-specification, no reason to be, or flawed design) will fall in one of our two product-related categories: “Weak Value Proposition” or “Low Product Quality.”

The model reflects the idea that weaknesses in resources or structure impact analysis, decision, and/or execution. Flaws in analysis, decision, and/or execution in turn produce marketing and/or operational missteps that lead to a higher likelihood of new product failure. For example, managers’ cognitive limitations, such as overconfidence, may induce a systematic bias in the “analysis and interpretation” step that produces excessive expectations for new product performance (i.e., over-forecasts) and overproduction. This view casts the foundational determinants as the root cause of new product failure. The seeds of failure are planted there. They grow through the behavioral components of the spine and emerge as the weeds that are the byproduct determinants of new product failure. Stated differently, the model postulates that the key to preempting most marketing or operational missteps is in ensuring that the foundational determinants are properly addressed.

Additional failure determinants that are outside a firm’s control include a group of environmental factors, such as adverse competitive and market forces, that affect a new product’s performance after commercialization. This group of factors generally occurs late in the temporal sequence of NPD activities and may moderate the impact of the other byproduct determinants on marketplace outcomes (Calantone, Schmidt, and Di Benedetto, 1997). As such, we place these factors in proximity to the outcome in Figure 1. We note that other adverse forces can also directly impact byproduct determinants. For example, the effectiveness of distribution efforts and product quality or reliability may be impaired by unanticipated component shortages or perturbations in the supply chain, such as disputes or strikes.

<< Insert Table 1 about here >>

Most of the antecedents implicit in Figure 1 have been discussed in prior literature, either through conceptual frameworks, hypotheses advanced, or empirical study. We summarize that research in Table 1 (that is organized around the categories postulated in Figure 1). In Table 1, we pay particular attention to those antecedents that have been confirmed through meta-analyses or replication in multiple studies.

In addition to reframing and summarizing the impact of new product failure determinants in a longitudinal behavioral form, we argue that models and research into new product performance determinants should consider two important classes of factors—a decision unit's limitations and incentive incompatibility between firm owners and managers as well as between layers of managers. We summarize cross-disciplinary research that points to one of our new failure determinants, incentive incompatibility in Table 1. However, owing to its focus in our empirical work, we provide a more developed rationale for considering decision unit limitations as foundational new product performance antecedents in the next section. We substantiate our arguments by developing and testing specific hypotheses about how managerial overconfidence may produce flawed (byproduct) decisions that would hinder a new product's performance after launch.

Managerial Overconfidence and Errors in the NPD Process

Like all humans, managers suffer from limited information processing capacity (e.g., Kahneman, 2003; Simon, 1957). To cope, managers routinely resort to intuition- and heuristics-based decision-making processes (e.g., Bazerman and Moore, 2012; Kahneman and Tversky, 1979). In day-to-day activities, judgmental heuristics generally produce satisfactory outcomes (e.g., Gigerenzer and Selten, 2001). Unfortunately, heuristics also make decision makers susceptible to a variety of cognitive biases that often degrade decision quality in more complex situations. The literature documents dozens of such biases (Bazerman and Moore, 2012; Sutherland, 2007). In particular, research has implicated overconfidence bias as an important factor in flawed decisions in contexts directly relevant to NPD, such as risk taking, resource allocation, and forecasting.

Overconfidence arises as a side effect of cognitive processes engaged in the maintenance and enhancement of self-esteem and self-confidence that are key factors in human motivation to act (Anderson et al., 2012; also, see Benabou and Tirole, 2002 for an overview). Empirical research shows that most individuals, including experts, are overconfident in general, but there is considerable variation among individuals (Biais et al., 2005; Kahneman and Tversky, 1992; Odean, 1999). Overconfidence also varies over time and across tasks (Benabou and Tirole, 2002).

Overconfidence reflects a systematic miscalibration of one's judgment and beliefs that results in more positive assessments of self and situation than is justified by the facts. Overconfident managers tend to view challenges in an optimistic light (Lovallo and Kahneman, 2003), in part, because they overestimate the amount of control they have over outcomes (Moore and Healy, 2007; Presson and Benassi, 1996) and because they ignore risks (March and Shapira 1987). Voluminous research shows that individuals display a greater degree of overconfidence when faced with higher problem complexity (Alba and Hutchinson, 2000; Griffin and Tversky, 1992; Moore and Healy, 2007), suggesting that NPD (O'Connor, 2008), may present fertile ground for decisions tinged with this bias. In the only published research on overconfidence in the NPD domain known to us, Simon and Houghton (2003) report a field study showing that overconfidence is associated with a higher likelihood of launching more pioneering (i.e., riskier) high-technology products that are less successful on average than more incremental innovations.[2]

Overconfidence manifests itself in overestimation of the accuracy and depth of one's own knowledge (Alba and Hutchinson, 2000; Bazerman and Moore, 2012; Benabou and Tirole, 2002). This may arise from individuals' tendency to underweight or ignore those aspects of a problem with which the decision maker is less familiar (Brenner, Koehler, and Tversky, 1996). As a result, overconfident individuals tend to over-rely on their basic knowledge and experience, and be relatively less engaged in evaluating new (or disconfirming) information that would allow them to further reduce uncertainty in a situation (Russo and Shoemaker, 1992). Such over-reliance on one's basic knowledge and experience can be particularly problematic in the NPD context, because NPD activities often require perspectives that are novel and different from one's past experience (O'Connor, 2008).

This research implies that overconfidence may lead to flawed inputs for important NPD decisions and activities through inaccurate forecasts. Accurate forecasting is predicated on effective information acquisition and use (Kahn, 2006). It also requires effective updating of one's prior beliefs as new information becomes available. However, the literature shows that overconfidence may hinder one's ability to process and incorporate new information (Russo and Shoemaker, 1992). Multiple studies confirm that overconfidence affects individuals' predictions of events in which the individuals participate. In particular, these predictions/forecasts tend to be positively biased (e.g., Alba and Hutchinson, 2000; Camerer and Lovallo, 1999; Pulford and Colman, 1996). In sum, this literature suggests that managers may issue positively-biased new product forecasts as a direct byproduct of their overconfidence. Stated formally,

[2] Hirshleifer, Low, and Teoh (2012) find that greater CEO overconfidence is associated with higher R&D expenditure and patenting output. Unfortunately, research sheds little light on how a firm's patenting output relates to new product performance specifically, since firms patent their inventions for various strategic reasons.

H1: Overconfidence produces a higher likelihood of over-forecasting new product sales.

The preceding discussion implicates additional mechanisms that may mediate the effect of overconfidence in producing mis-forecasts. Specifically, to the extent that overconfidence is associated with blind spots in assessing the limits of one's knowledge in a situation (Bazerman and Moore, 2012; Russo and Shoemaker, 1992), overconfident managers may be more prone to prematurely curtail data acquisition. As a result, overconfident managers may be inadequately informed given the complex information-intensive demands of the NPD process. We state this in the following testable hypothesis:

H2: Low information acquisition (negatively) mediates the impact of decision makers' overconfidence on the likelihood of over-forecasting new product sales.

NPD managers who rely relatively more on their intuition and guesswork are also likely to be more prone to errors in the specification of a new product's price. In particular, to the extent that overconfident managers fail to consider customer feedback or competitors' reactions (Zajac and Bazerman, 1991), they may be more likely to over-forecast consumer demand (e.g., Cooper and Kleinshmidt, 1990; de Brentani, 1991). Anecdotal evidence shows that managerial overconfidence and failure to consider customer price sensitivity may lead to overpricing a new product and subsequent sales shortfall. The original iPhone provides a case in point. Apple's Steve Jobs who personally oversaw the iPhone through development and commercialization is known for supreme confidence (Hirshleifer, Low, and Teoh, 2012; Koontz and Weihrich, 2007, p. 331), which prompted him, among other things, to downplay the value of market research (Isaacson, 2013). In spite of getting product features right and creating avid desire among consumers, Apple initially failed to translate iPhone's mass-market appeal into commercial success. Apple grossly overpriced the original iPhone relative to consumer willingness to pay and was forced into a 33% price cut only two months after launch, when sales started coming in below expectations (Hafner and Stone, 2007). Although

Apple was able to recover fully on the strength of its revolutionary smartphone, other (less notable) products that are overpriced at launch may have less ability to recover from a poor start. We summarize this discussion in the following hypothesis:

> *H3: Flawed marketing decisions, in particular elevated pricing, negatively mediate the impact of decision makers' overconfidence on the likelihood of over-forecasting new product sales.*

Empirical Investigation

Data and Setting

We generated data for this research through four standardized workshops conducted at three top-tier business schools in India. In the course of the workshops, each of the 330 graduate business students (MBA and MS) managed a virtual firm in a custom management simulation called the Strategic Innovation Game (SIG). The simulation consisted of four decision periods, and lasted five hours, including short breaks between periods. Prior to the exercise, participants received an extensive briefing on all aspects of the SIG. Each participant managed a virtual firm in competition against the firms of five other participants in a simulated industry. Participants were instructed to make decisions so as to maximize shareholder value. The workshops had an explicit educational objective centered on decision making under uncertainty and, therefore, participants did not focus on the fact that the data captured in the course of the exercise may also be used for research purposes.

Since we study decision-making in NPD, we focus on the subset of firm-period observations that include a new product introduction. Following the convention, we treat both product reformulations and products developed from scratch as new products. Our final sample included observations from 330 participants, of whom 69 did not launch new products and 271 collectively launched 444 new products. Only three of the 271 product launching participants launched four or five products, the rest launched three of fewer new products.

The two key benefits of simulation-based data are their generally high internal validity arising from a controlled setting and the research setting's realism and complexity that capture important aspects of the business context in which the focal processes usually unfold. Dating back to the 1960's (e.g., Babb, Leslie, & Skyke, 1966), the use of data from management simulations has a rich history in behavioral decision research (e.g., Abramson, Currim, & Sarin, 2005; Clark and Friesen, 2009; Glazer, Steckel, and Winer 1992), including research in the NPD domain (e.g., Green and Ryans, 1990; Jespersen, 2012; Spanjol et al., 2011).

The SIG specifically possesses desirable features that make it well-suited for our investigation. Most notably, this simulation provides extensive opportunities for information acquisition. Participants have free access to detailed time-varying reports on industry performance, market demand, market segment characteristics and preferences, brand perceptions by segment, and competitor actions and perceptions. Therefore, financial constraints do not impact information acquisition.

The SIG also enables participants to conduct NPD activities by modifying existing products or creating new ones. Products in the SIG, which are paints and coatings, are created by choosing from various grades of pigment, binder, and additive mix, and setting a price. Various combinations of these four inputs determine products with widely different performance profiles on the dimensions of durability, appearance, non-toxicity and cost-efficiency. Participants do not know the exact relationships between product characteristics and performance, but they can ascertain these relationships at specific levels of product characteristics by using a dynamic what-if analysis tool. Reflecting an important aspect of reality, demand in the SIG is calibrated in such a way that buyers have the option of purchasing imported products (i.e., not buy from any of the suppliers) if the supplier products fail to meet buyer requirements. Finally, the SIG incorporates a full range of marketing mix decisions, including resource allocation and pricing.

Measurement

We report scale items and components of the variable constructs discussed below in Appendix A.

Independent variables

Consistent with prior research (e.g., Kennedy, Anderson and Moore, 2013; Miller and Geraci, 2011), we operationalize *Overconfidence* as a 0/1 variable based on participants' forecast of own performance in the SIG relative to actual performance. We classify as overconfident those participants who forecast their performance in the top quintile, but ranked in the bottom quintile on our focal measure of performance—average market valuation over four periods of the SIG. (Using more stringent cutoffs produces too few observations for analysis.) It is not crucial for our investigation to know how participants measure on confidence in general. Our tests rely only on *differences* in the extent of confidence across the participants. Overconfident individuals in our data launched 81 of 444 new products, or 18% of the total.

Our additional independent variables are the *Price* of a new product and the number of decision support system tools and reports (collectively referred to as *DSS*) accessed in a period. These reports include: market share report, customer analysis report, competitor analysis report, advertising performance report, income statement, cash flow statement, investment report, firm valuation report, product attributes calculator, and profit-and-loss calculator. (All participants also had *automatic* access to the industry performance report, production report, and the balance sheet, that we did not count in the *DSS* total.) Appendix A provides a description of these DSS tools. (As part of our robustness checks, we also consider the impact of participants using a subset of the most relevant DSS tools.)

Dependent variables

We operationalize our *Overforecast* variable by relating a new product's actual production quantity to quantity sold as follows: *Overforecast* = 1 – Sales/(Production*ForecastAdjustment). The ForecastAdjustment factor is participants' sales forecast (in percent) issued to optimize logistics and transportation (which affects the firm's total logistics costs). This factor helps to account for instances where participants strategically overproduce a product in an effort to minimize unit variable cost. (Like in real life, this is not a costless strategy in the SIG, because it ties up capital, increases inventory carrying cost, and involves downside risk if the product fails to meet market expectations.) Because the continuous *Overforecast* variable is not normally distributed, we also evaluate an ordinal variable, *OverforecastOrd*, with three levels that have an intuitive interpretation. *OverforecastOrd* takes the value of 1 if *Overforecast* is between 0 and 0.33 (conceptually, a forecast that may be viewed as reasonable); there are 319 observations in this category, including 50 new product launches by overconfident participants. *OverforecastOrd* takes the value of 2 if *Overforecast* is greater than 0.33 but less than 0.67 (i.e., a considerable miss); there are 43 observations in this category, including 11 new product launches by overconfident participants. Finally, *OverforecastOrd* equals 3 if *Overforecast* is greater than 0.67 (effectively, a complete miss); 82 observations fall in this category, including 20 new product launches by overconfident participants.

Control variables

Our model includes three classes of control variables capturing firm decisions, the competitive environment and participant characteristics. Firm decisions include aggregate marketing expenditure (salesforce and advertising) on all products, *FirmMktSpend*. (Unfortunately we are not able to evaluate marketing spending on new products specifically.)

The controls for industry competitiveness include average marketing expenditure by the launching firm's five industry competitors *IndMktSpend*; the average price charged in the industry, excluding the price of the new product, *IndAvgPrice*; and the number of products marketed in the industry, *IndProducts*. We include the launching firm in the latter two computations because its existing products may compete with the new product. (Like in real life, the SIG segments prefer products that best match their preferences, but they may purchase from multiple sources to the extent that other products dominate on important dimensions.) This variable class also includes the final average market valuation of the launching firm's five industry competitors, *IndAvgValuation*. This variable is based on the Capital Asset Pricing Model rather than a relative measure of value creation. Its purpose is to control for different quality of competition across industries. The distributions of *FirmMktSpend*, *IndMktSpend*, *IndAvgPrice*, and *IndAvgValuation* exhibit various degrees of skewness. To ensure normally distributed variables, we use logarithm of these variables in our analyses.

The participant-level controls include years of work experience, *WorkExp*; educational background at the bachelor's level, *STEM*, that takes the value of 1 if a participant had a BS in science, technology, engineering, mathematics or medicine and 0 otherwise (95% of the non-STEM observations have a business degree); and dispositional *Optimism*. By using the latter control, we seek to separate the effect of situational optimism that arises with overconfidence from enduring optimism that is dispositional and, as such, conceptually distinct from overconfidence. To measure dispositional optimism, we employ the standard six-item Revised Life Orientation Test (LOT-R) scale (Scheier, Carver, and Bridges, 1994) embedded in the simulation registration form. We use a seven-point response scale anchored by "Strongly disagree" = 1, "Neither agree nor disagree" = 4, and "Strongly disagree" = 7. We compute *Optimism* as the sum of individuals' responses on the six LOT-R items scaled by 1/6 for interpretability.

Analysis

Our primary analysis involves regressing our ordinal dependent variable, *OverforecastOrd*, on the independent and control variables using ordinal logistic regression. We compare these results with those for the continuous *Overforecast* variable that we estimate using ordinary least squares regression (OLS). To test for mediation, we use the Sobel test (Baron and Kenny, 1986; Iacobucci, 2012). We additionally conduct a number of robustness checks reported in the "Additional Analyses" section.

<< Insert Table 2 and Table 3 about here >>

Results

Table 2 shows the descriptive statistics and correlations in the full sample and sub-samples of new products launched by overconfident and non-overconfident participants. These statistics provide preliminary evidence that the hypothesized relationships exist in our data. Most notably, over-forecasting appears to be more pronounced among overconfident participants, with their new product forecasts exceeding demand by 32 percent on average versus 22 percent among non-overconfident participants. Although overconfident individuals do not seem to differ from non-overconfident individuals in the extent of information search, the prices they charge for new products are 11.43 percent higher on average. We explore these initial insights further in a regression framework.

Table 3 shows results of ordinal logit regressions of *OverforecastOrd* (Models 1-3) and OLS regressions of *Overforecast* (Models 4-6). Models 1 and 4 include only the controls. Models 2 and 5 additionally include *Overconfidence*. Models 3 and 6 further include the hypothesized mediator variables *DSS* and *Price*. All models are statistically significant at $p < .1$ (Models 4) or better (Models1, 2, 3, 5, and 6). Both estimation methods—ordinal logit and OLS—produce substantively identical results. Of central interest to this research, *Overconfidence* is shown to have a statistically significant impact on overforecasts ($p < .065$ in the logit regression; in OLS, $p < .05$). The R^2 in Model 2 and Model 5 which include *Overconfidence* but exclude the moderators is 0.054 and .041, respectively, in line with other studies of cognitive phenomena (e.g., Cooper, Woo, and Dunkelberg, 1988; Garland, 1990; Keil et al., 1995). The F-change statistic associated with adding *Overconfidence* in the OLS regression is significant at the .05 level. On balance, this set of results confirming H1 suggests that *Overconfidence* is one factor that may influence faulty forecasts. There are likely other factors, including mediating effects. Although the effect of *DSS* is not significant, thus failing to support H2 that overconfidence may result in low information search, our Model 3 and Model 6 evidence full mediation of *Overconfidence* on *Overforecast* via *Price*. We use the Sobel test to assess mediation. We observe that *OverconfidenceOrd* has a significant positive effect as a predictor of *Price* ($p < .05$). The coefficient on *OverconfidenceOrd* loses its significance in the presence of *Price* (Models 3 and 6). The Sobel Z statistic is significant at the .05 level (shown at the bottom of Table 3). These results are replicated for *Overconfidence*. Overall, these results support H3.

<< Insert Table 4 about here >>

Additional Analyses

We conduct several additional analyses to assess the sensitivity of our results to alternative variable operationalizations and to test our assumptions. First, we assess the impact of using an alternate *DSS* measure that includes a subset of DSS inputs that are particularly important for making informed decisions in the SIG, *KeyDSS*. Accessing only key DSS tools may be a rational strategy under time constraints. We operationalize *KeyDSS* as the sum of reports included in *DSS* (as detailed in Appendix A) less the cash flow statement and the investment report. Using *KeyDSS* instead of *DSS* has no substantive effect on our results. We show results of this regression as Model 7 in Table 4. As part of this investigation, we also evaluate whether including the number of trials run on the two dynamic calculators—the product attributes calculator and profit-and-loss calculator—would impact our results. Neither variable is statistically significant.

Next, we test our implicit assumption that the observed positive relationship between overconfidence and price is more consistent with "optimistic" pricing rather than overconfident participants launching higher-cost products with superior features. We, therefore, regress *Price* on *Overconfidence* and a new product's unit variable cost, *UVC*, which is a close measure of product quality in the SIG. We show this regression as Model 8 in Table 4. As expected, *UVC* is highly significant in predicting *Price*. However, *Overconfidence* remains statistically significant ($p < .05$) with *UVC* in the model. This supports the view that overconfidence likely induces optimistic pricing.

Additionally, we address whether overconfidence is associated with optimistic forecasts primarily, which is our central assumption, or if it tends to influence misforecasts in both directions. To this end, we evaluate the absolute forecast error as the dependent variable, *AFE*, operationalized as the absolute value of the difference of a new product's adjusted production (i.e., production scaled by the $\text{ForecastAdjustment}_i$ factor discussed in the "Dependent Variables" section) and the product's total demand rather than actual sales. We take log of *AFE* to normalize its distribution. This regression excludes *DSS* and *Price* that may mediate the impact of overconfidence on demand. Therefore, the resultant regression (shown as Model 9 in Table 4) is directly comparable to Model 2 and Model 5 in our main analyses. The obtained coefficient on *Overconfidence* is not significant. Therefore, we cannot conclude that overconfidence is associated with misforecasts in general.

Finally, we consider whether overconfidence is associated with a flawed NPD effort overall, as evidenced by low demand, holding all else constant, including product pricing and information search. Because this variable's distribution is right-skewed, we use a square root transformation of demand (that is preferred to log-transformation in this case). This regression (shown as Model 10 in Table 4) demonstrates a number of significant relationships in our data that provide a cross-check of its face validity. Namely, there is a significant positive relationship between a new product's demand and a firm's total marketing expenditure, *FirmMktSpend*. (This variable is not a direct measure of marketing spending on the new product, but it is likely correlated. As such, we view it as a useful proxy.) The number of DSS reports used in constructing a new product offering is directionally positive, but not significant. (Incidentally, using *KeyDSS* instead of *DSS* in the regression produces a significant result on this variable, showing that using a subset of key information under time constraints is beneficial.)

As expected, a new product's demand is negatively related to its price and the number of new products marketed in an industry (that produce demand fragmentation). The one counterintuitive result in this regression involving a positive impact of total marketing expenditure in an industry can be explained by moderate initial buyer awareness of the different product offerings in the SIG. Therefore, industry marketing expenditure stimulates overall industry demand by increasing brand awareness and providing information about product attributes and performance. Most notably, however, the impact of *Overconfidence* on *Demand* is not significant at the conventional level. Therefore, we find no evidence that overconfidence is directly associated with the development of less competitive new product offerings in our research context.

Discussion and Conclusions

Efforts to organize and integrate research findings on new product performance determinants have lagged since the last significant overview paper appeared over a decade ago (Henard and Szymanski, 2001).[3] Importantly, this literature has not considered entire categories of factors that are known to affect managerial decisions and behavior, namely, those that pertain to decision makers' cognitive limitations and incentive structures. To make progress on this front, we present a model of new product failure determinants that summarizes extant research and highlights under-explored areas. The model organizes new product performance determinants in a hierarchical structure. The foundational marketing inputs and conditions serve as inputs to or influences on the analysis and interpretation of the business environment, decision response and execution in a manner that produces strategic and tactical missteps. We conceptualize the latter as byproduct antecedents of new product performance to the extent that they flow from foundational determinants and form more proximate causes of failure. We view the model as a useful framework for theory development and empirical research into new product performance antecedents. In particular, the model can serve as a basis for exploring a wide range of moderating and mediating relationships.

We proceed to explore a specific set of linkages postulated by the model. We study how one pervasive exemplar of decision unit's cognitive limitations—managerial overconfidence—can lead to undesirable outcomes in the NPD process. We show that decision makers' overconfidence is associated with a higher likelihood of over-forecasting new product sales. Over-forecasts can be detrimental to new product performance in several ways. To the extent that forecasts influence decisions pertaining to project selection, continuation, and launch, overly optimistic forecasts may result in failure to screen out projects that are particularly risky or have low potential. This implies sub-optimality in the affected firm's new product pipeline and a higher baseline failure rate among such products. To the extent that forecasts impact managerial expectations, they may also result in excessive

[3] Although there have been more recent classification attempts since that research, all were published in peripheral journals. Conversely, the influential PDMA surveys (the most recent one conducted in 2003, reported in Barczak et al., 2009), provide an in-depth assessment of best practices in a sample of participating firms, but do not attempt to summarize the literature.

performance goals for a new product. Failure to meet elevated expectations may then be interpreted more negatively than it would be if related to more realistic performance objectives. Equally problematic, to the extent sales forecasts are used to schedule production, overconfidence-induced bias in forecasts will lead to overproduction. Overproduction and elevated inventory levels may, in turn, produce additional pressures on the product. This can interfere with the new product's commercialization strategy or send ambiguous signals through the channels and to customers.

Our empirical investigation shows that overconfidence may produce over-forecasts via flawed tactical decisions. In our research context, overconfidence induced what we call "optimistic" pricing at above-market-average levels. In price-sensitive markets (which includes most industrial markets) elevated pricing may result in depressed new product demand. This illustrates one specific route through which overconfidence can impact new product outcomes. It is also worth noting that we find no evidence implicating overconfident individuals as poor "innovators" per se (as reflected in new product demand). This result is consistent with related research on overconfidence that used a different lens. Hirshleifer, Low, and Teoh (2012) use Compustat data on over 10,000 firm-year observations to show that firms led by overconfident CEOs (classified so based on holdings of company stock options deeply in-the-money) spend more on research and development and generate more patents than firms with non-overconfident CEOs.

Although our data fail to support H2, which postulates that overconfident individuals tend to engage in less information search, we consider this null result valuable. Since flawed decisions do not seem to arise from more limited information acquisition, they are, therefore, more likely to arise from flaws in information processing and use. This is consistent with related empirical research showing that NPD managers involved with a project may be slow to update their prior beliefs as new information becomes available (Biyalogorsky, Boulding and Staelin, 2006). In particular, if managers start with an overly optimistic assessment of a new product's prospects (i.e., over-forecast), they may persist with the product beyond a rational stopping point. This may explain instances of escalating commitment in the NPD process (Biyalogorsky, Boulding and Staelin, 2006; Boulding, Morgan, and Staelin, 1997).

Managerial Implications

Practitioners will find this research beneficial in two important respects. First, the proposed behavioral model invites a different way of looking at new product failure as the likely result of an inter-temporal sequence of specific inputs and outcomes mediated by organizational and individual behaviors in the NPD process. Due to its dynamic longitudinal nature, the novel framework may stimulate sensitivities towards the development of new routines specifically directed at the foundational determinants of new product failure. In other words, we hope to stimulate managers' search for the root causes of new product failure rather than the symptoms.

Possible examples of steps implied by our model managers might take include:

- Focus on a sound decision-making process that follows a predetermined sequence of steps as a precursor to sound decisions;
- Include the search and consideration of disconfirming information on the NPD process "checklist;"
- Set up a culture that makes questioning and criticism of all developments the norm to mitigate overconfidence;
- Consider using project teams with diverse, but relevant NPD experience. Having (industry) outsiders may be beneficial to introduce unconventional perspectives and more balanced information assessment;
- Conduct market research to inform pricing decisions, as this is an important area in which overconfidence may lead managers astray;

- Focus on organizational risk tolerance. Too low a target failure rate discourages innovation. Too high a target failure rate may encourage speculative projects. Managerial incentive structures that tie rewards and consequences to project characteristics and risk may prove effective at discouraging undesirable behaviors.

Limitations and Further Research

Our paper's limitations present opportunities for related research. Empirical research on decision unit limitations, such as ours, concerns basic unobservable human decision processes and behaviors that are difficult to study in-vivo or ex-post (e.g., using methods that rely on key informants' recollection of past events). To achieve internal validity, our approach and sample sacrifice a measure of external validity. Despite the importance of context in NPD activity, basic human decision making often persists across contexts. Without intervention, behavior in the laboratory can approximate behavior in the organization. In fact, one of the objectives of laboratory research is to find interventions that will prevent certain basic behaviors from manifesting itself in applied contexts.

Likewise, we hope that our findings will give impetus to additional laboratory research and field studies that can corroborate our results, further expand our understanding of the role of managerial overconfidence in producing undesirable NPD outcomes, and suggest effective debiasing strategies. This research can be extended even further to enhance external validity once the intervention is actually implemented by analyzing decision quality pre- and post- implementation. Such a path demonstrates the complementary nature of in-vivo and laboratory research approaches.

An additional important limitation of our research arises from our data constraints. It would be instructive to explore the impact of overconfidence on a full range of marketing decisions, including resource allocations to new product commercialization, and the innovativeness of new product configurations launched by overconfident managers. It would also be very valuable to explore other possible mechanisms that may mediate or moderate the impact of overconfidence in the NPD context.

Finally, the principal-agent literature points to incentive incompatibility between managers and owners and between layers of management as a potential source of bias in NPD decisions (e.g., those that pertain to project selection, continuation and launch). We highlight this gap in the literature on new product performance antecedents, but do not explore it empirically, as it involves a theoretical lens and relationships that are distinct from those we focus on in the current study. We believe this important research opportunity presents a unique set of challenges that can be addressed equally well by means of a traditional survey or management simulation, like the one used in our research.

References

Abramson, C., Currim, I., and Sarin, R. 2005 An experimental investigation of the impact of information on competitive decision making. *Management Science* 51:195-207.

Anderson, C., Brion, S., Moore, D. A., and Kennedy, J. A. 2012. A status-enhancement account of overconfidence. *Journal of Personality and Social Psychology*, 103: 718-735.

Babb, E., Leslie, M., and Van Slyke, M. 1966. The potential of business-gaming methods in research. *The Journal of Business*, 39(4): 465-472.

Barczak, G., Griffin, A., and Kahn, K. 2009. Trends and drivers of success in NPD practices: Results of the 2003 PDMA best practices study. *Journal of Product Innovation Management,* 26(1): 3-23.

Barnett, B. D., and Clark, K. B. 1996. Technological newness: An empirical study in the process industries. *Journal of Engineering and Technology Management*, 13(3/4): 263.

Bazerman, M. H., and Moore, D. A. 2012. *Judgment in managerial decision making*. Eighth Edition. Hoboken, NJ: John Wiley and Sons, Inc.

Benabou, R., and Tirole, J. 2002. Self-confidence and personal motivation., *Quarterly Journal of Economics*, 117, 871-915.

Biais, B., Hilton, D., Mazurier, K. and Pouget, S. 2005. Judgmental overconfidence, self-monitoring and trading performance in an experimental financial market," *Review of Economic Studies*, 72: 287-312.

Biyalogorsky, E., Boulding, W., and Staelin, R. 2006. Stuck in the past: Why managers persist with new product failures. *Journal of Marketing*, 70(2): 108-121.

Bonabeau, E., Bodick, N., and Armstrong, R. W. 2008. A more rational approach to new-product development. *Harvard Business Review*, 86(3): 96-102.

Boulding, W., Morgan, R., and Staelin, R. 1997. Pulling the plug to stop the new product drain. *Journal of Marketing Research,* 34(1): 164-176.

Brass, D. J., and Burkhardt, M. E. 1993. Potential power and power use: An investigation of structure and behavior. *Academy of Management Journal,* 36(3): 441-470.

Brown, S. L., and Eisenhardt, K. M. 1995. Product development: Past research, present findings, and future directions. *Academy of Management Review*, 20(2): 343-378.

Calantone, R. J., Harmancioglu, N., and Droge, C. 2010. Inconclusive innovation 'returns:' A meta-analysis of research on innovation in new product development. *Journal of Product Innovation Management,* 27(7): 1065-1081.

Calantone, R. J., Schmidt, J. B., and Di Benedetto, C. A. 1997. New product activities and performance: The moderating role of environmental hostility. *Journal of Product Innovation Management,* 14(3): 179-189.

Calantone, R. J., Schmidt, J. B., and Song, X. M. 1996. Controllable factors of new product success: A cross-national comparison. *Marketing Science,* 15(4): 341-358.

Camerer, C., and Lovallo, D. 1999. Overconfidence and excess entry: An experimental approach. *American Economic Review,* 89(1): 306-318.

Clark, J., and Friesen, L. 2009. Overconfidence in forecasts of own performance: An experimental study," *Economic Journal*, 119(534): 229-251.

Cooper, R. G. 1979. The dimensions of industrial new product success and failure. *Journal of Marketing,* 43(3): 93-103.

Cooper, M. J., Gulen, H., and Rau, P. R. 2005. Changing names with style: Mutual fund name changes and their effects on fund flows. *Journal of Finance,* 60(6): 2825-2858.

Cooper, R. G., and Kleinschmidt, E. J. 1987. New products: What separates winners from losers? *Journal of Product Innovation Management,* 4(3): 169-184.

Cooper, R. G., and Kleinschmidt, E. J. 1990. *New products: The key factors in success*. Chicago: American Marketing Association.
Cooper, A. C., Woo, C. Y., and Dunkelberg, W. C. 1988. Entrepreneurs' perceived chances for success. *Journal of Business Venturing*, 3(2): 97-108.
Crawford, C. M. 1977. Marketing research and the new product failure rate. *Journal of Marketing,* 41(2): 51-61.
Currim, I. S., Lim, J., and Kim, J.W. 2012. You get what you pay for: The effect of top executives' compensation on advertising and R&D spending decisions and stock market return. *Journal of Marketing*. 76(5): 33-48.
De Brentani, U. 1991. Success factors in developing new business services. *European Journal of Marketing,* 25(2): 33-59.
Di Benedetto, C. A. 1999. Identifying the key success factors in new product launch. *Journal of Product Innovation Management,* 16(6): 530-544.
Dutta, S., Narasimhan, O., and Rajiv, S. 1999. Success in high-technology markets: Is marketing capability critical? *Marketing Science*, 18(4): 547-568.
Ehrman, C. M., and Shugan, S. M. 1995. The forecaster's dilemma. *Marketing Science,* 14(2): 123-147.
Ernst, H., Hoyer, W. D., Rübsaamen, C. 2010. Sales, marketing, and research-and-development cooperation across new product development stages: Implications for success. *Journal of Marketing*, 74(5): 80-91.
Fischhoff, B., Slovic, P., and Lichtenstein, S. 1977. Knowing with certainty: The appropriateness of extreme confidence. *Journal of Experimental Psychology,* 3(4): 552-564.
Garland, H. 1990. Throwing good money after bad: The effect of sunk costs on the decision to escalate commitment to an ongoing project. *Journal of Applied Psychology*, 75(6): 728-731.
Gigerenzer, G., and Selten, R. 2001. *Bounded rationality: The adaptive toolbox*. Cambridge, MA: MIT Press.
Glazer, R., Steckel, J., and Winer, R. 1992. Locally rational decision making: The distracting effect of information on managerial performance. *Management Science*, 38(2): 212-226.
Green, D. H., and Ryans, A. B. 1990. Entry strategies and market performance: Causal modeling of a business simulation. *Journal of Product Innovation Management*, 7: 45-58.
Griffin, A., and Page, A. L. 1996. PDMA success measurement project: recommended measures for product development success and failure. *Journal of Product Innovation Management,* 13(6): 478-496.
Hafner, K., and Stone, B. 2007. iPhone owners crying foul over price cut. *New York Times*, September 6. http://www.nytimes.com/2007/09/07/technology/07apple.html. Accessed May 2, 2011.
Harris, M., Kriebel, C. H., and Raviv, A. 1982. Asymmetric information, incentives and intrafirm resource allocation. *Management Science*, 28(6): 604-620.
Henard, D. H., and Szymanski, D. M. 2001. Why some new products are more successful than others. *Journal of Marketing Research*, 38(3): 362-375.
Hirshleifer, D., Low, A., and Teoh, S. H. 2012 'Are overconfident CEOs better innovators? *Journal of Finance*, 67(4): 1457-1498.
Houston, M. B., Walker, B. A., Hutt, M. D., and Reingen P. H., 2001. Cross-unit competition for a market charter: The enduring influence of structure. *Journal of Marketing,* 65(2): 19-34.

Hultink, E. J, and Atuahene-Gima, K. 2000. The effect of salesforce adoption on new product selling performance. *Journal of Product Innovation Management,* 17(6): 435-450.

Imai, K. I., Nonaka, I., and Takeuchi, H. 1985. Managing the new product development process: How Japanese companies learn and unlearn. In *The Uneasy alliance: Managing the productivity-technology dilemma*. Hayes, R. H., K. B. Clark, C. Lorenz, Eds. Boston, MA: Harvard Business School Press, 337-75.

Jacobson, R., and Aaker, D. A. 1987. The strategic role of product quality. *Journal of Marketing*, 51(4): 31-44.

Jensen, M. C., and Meckling, W. H. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics,* 3(4): 305-360.

Johnson, D. D. P. 2004. *Overconfidence and war: The havoc and glory of positive illusions*. Cambridge, MA: Harvard University Press.

Kahn, K. B. 2006. *New product forecasting: An applied approach*. Armonk, NY: M.E. Sharpe.

Kahneman, D. 2003. Maps of bounded rationality: Psychology for behavioral economics. *American Economic Review,* 93(5): 1449-1475.

Kahneman, D., and Tversky, A. 1979. Prospect theory: An analysis of decision under risk. *Econometrica,* 47(2): 263-291.

Keil, M., Mixon, R., Saarinen, T., and Tuunainen, V. 1995. Understanding runaway information technology projects: Results from an international research program based on escalation theory. *Journal of Management Information Systems*, 11(3): 67-87.

Kennedy, J. A., Anderson, C., and Moore, D. A. 2013. When overconfidence is revealed to others: Testing the status-enhancement theory of overconfidence. *Organizational Behavior and Human Decision Processes,* 122(2): 266-279.

Klayman, J., Soll, J. B., Gonzalez-Vallejo, V. C., and Barlas, S. 1999. Overconfidence: It depends on how, what and whom you ask. *Organizational Behavior and Human Decision Processes,* 79(3): 216-247.

Kohli, A. K., and Jaworski, B. J. 1990. Market orientation: The construct, research propositions and managerial implications. *Journal of Marketing,* 54(2): 1-18.

Koontz, H., and Weihrich, H. 2007. *Essentials of management: An international perspective*. New Delhi: Tata McGraw-Hill.

Lovallo, D., and Kahneman, D. 2003. Delusions of success: how optimism undermines executives' decisions. *Harvard Business Review*, 56: 56–63.

Maidique, A. M., and Zirger, B. J. 1984. A study of success and failure in product innovation: The case of the US electronics industry. *IEEE Transactions on Engineering Management,* EM-31(4): 192-203.

Maidique, A. M., and Zirger, B. J. 1985. The new product learning cycle. *Research Policy,* 14(6): 299-313.

Malmendier, U., and Tate, G. 2005. CEO overconfidence and corporate investment. *Journal of Finance*, 60(6): 2661-2700.

Management Science. 2014. Editorial Statements and Abridged Policies. Retrieved from http://pubsonline.informs.org/page/mnsc/editorial-statements.

March, J. G., and Shapira, Z. 1987. Managerial perspectives on risk and risk taking. *Management Science*, 33(11): 1404-1418.

Marquis, D. G. 1969. The anatomy of successful innovations. *Innovation*, 1: 28-37.

Miller, T. M., and Geraci, L. 2011. Unskilled but aware: Reinterpreting overconfidence in low-performing students. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 37(2): 502-506

Montoya-Weiss, M. M., and Calantone, R. 1994. Determinants of new product performance: A review and meta-analysis. *Journal of Product Innovation Management*, 11(5): 397-417.
Nevins, J., and Whitney, D. E. 1989. *Concurrent Design of Products and Processes: A Strategy for the Next Generation in Manufacturing*. New York, NY: McGraw-Hill.
O'Connor, G. C. 2008. Major innovation as a dynamic capability: A systems approach. *Journal of Product Innovation Management*, 25(4): 313-330.
Ottum, B. D., and Moore, W. L. 1997. The role of market information in new product success/failure. *Journal of Product Innovation Management*, 14(4): 258-273.
Owen, D. 1986. Welcome to McMath's museum of marketing. *Management Review,* 75(10): 19.
Page, A. L. 1993. Assessing new product development practices and performance: Establishing crucial norms. *Journal of Product Innovation Management*, 10(4): 273-290.
Phillips, L. W., Chang, D. R., and Buzzell, R. D. 1983. Product quality, cost position and business performance: A test of some key hypotheses. *Journal of Marketing,* 47(2): 26-43.
Plous, S. (1993). *The psychology of judgment and decision making*. New York: McGraw-Hill.
Presson, P. K., and Benassi, V. A. (1996). Illusion of control: A meta-analytic review. *Journal of Social Behavior and Personality,* 11(3): 493-510.
Pulford, B. D., and Colman, A. M. 1996. Overconfidence, base rates and outcome positivity/ negativity of predicted outcomes. *British Journal of Psychology*, 87(3): 431-445.
Quelch, J. A., and Jocz, K. E. 2009. How to market in a downturn. *Harvard Business Review*, 87(4): 52–62.
Redmond, W. H. 1995. An ecological perspective on new product failure: The effects of competitive overcrowding. *Journal of Product Innovation Management*, 12(3): 200-213.
Rothwell, R. 1972. *Factors for Success in Industrial Innovations from Project SAPPHO—A Comparative Study of Success and Failure in Industrial Innovation*. Brighton, Sussex: S.P.R.U.
Russo, J. E., and Schoemaker, P. J. H. 1992. Managing overconfidence. *Sloan Management Review,* 33(2): 7-17.
Scheier, M. R., Carver, C. S., and Bridges, M. W. 1994. Distinguishing optimism from neuroticism: A reevaluation of the life orientation test. *Journal of Personality and Social Psychology*, 5: 1063-1078.
Schmidt, J. B., and Calantone, R. J. 2002. Escalation of commitment during new product development. *Journal of the Academy of Marketing Science,* 30(2): 103-118.
Simon, H. A. 1957. *Models of man: Social and rational*. New York: Wiley.
Simon, M., and Houghton, S. M. 2003. The relationship between overconfidence and the introduction to risky products: Evidence from a field study. *Academy of Management Journal,* 46(2): 139-149.
Smith, T. J. 2012. *Pricing strategy: Setting price levels, managing price discounts and establishing price structures*. South-Western Cengage Learning. Mason, OH.
Song, X. M., and Parry, M. E. 1994. The dimensions of industrial new product success and failure in state enterprises in the people's republic of China. *Journal of Product Innovation Management*, 11(2): 105-118.
Song, X. M., Souder, W. E., and Dyer, B. 1997. A causal model of the impact of skills, synergy, and design sensitivity on new product performance. *Journal of Product Innovation Management*, 14(2): 88-101.

Spanjol, J., Tam, L. Qualls, W. J., and Bohlmann, J. D. 2011. New product team decision making: Regulatory focus effects on number, type, and timing decisions. *Journal of Product Innovation Management*, 28(5): 623–640.

Staw, B. M. 1976. Knee-deep in the big muddy: A study of escalating commitment to a chosen course of action. *Organizational Behavior and Human Performance*, 16(1): 27-44.

Sutherland, S. 2007. *Irrationality*. Pinter and Martin Ltd., UK.

Troy, L. C., Hirunyawipada, T., and Paswan, A. K. 2008. Cross-functional integration and new product success: An empirical investigation of the findings," *Journal of Marketing*, 72(6): 132-146.

Ulwick, A. W. 2002. Turn customer input into innovation. *Harvard Business Review*, 80(1): 91-97.

Urban, G. L., and Hauser, R. 1993. *Design and Marketing of New Products*. Englewood Cliffs, NJ: Prentice Hall.

Whyte, G. 1991. Decision failures: Why they occur and how to prevent them. *Academy of Management Executive*, 5(3): 23-31.

Wind, J., and Mahajan, V. 1997. Issues and opportunities in new product development: An introduction to the special issue. *Journal of Marketing Research,* 34(1): 1-12.

Yoon, E., and Lilien, G. L. 1985. New industrial product performance: The effects of market characteristics and strategy. *Journal of Product Innovation Management*, 2(3): 134-144.

Zajac, E. J., and Bazerman, M. H. 1991. Blind spots in industry and competitor analysis: Implications of interfirm (mis):perceptions for strategic decisions. *Academy of Management Review*, 16(1): 37-56.

Zinkhan, G. M., and Martin, J. C. R. 1987. New brand names and inferential beliefs: Some insights on naming new products. *Journal of Business Research,* 15(2): 157-172.

Zirger, B. J., and Maidique, M. A. 1990. A model of new product development: An empirical test. *Management Science*, 36(7): 867-883.

Table 1. Known and Proposed Antecedents of New Product Failure[1]

Antecedent	Description and Examples	Literature sources
Faulty market research		
- Flawed market research planning or execution	Inappropriate research methods or sampling may bias inferences or sales forecasts.	Henard & Szymanski 2001; Marquis 1969; Ottum & Moore 1997; Urban & Hauser 1993
Resource limitations		
- Financial constraints	Insufficient funding may lead to harmful compromises in execution, such as skipping or curtailing important steps, e.g., testing.	Page 1993
- Low senior management support	Low senior management support may deprive project teams of critical inputs, such as help formulating new product strategies or developing a clear vision of objectives; funding, resources and cover so that work can continue unobstructed; and help incubating new-to-the-world technologies.	Brown & Eisenhardt 1995; Henard & Szymanski 2001; Imai, Nonaka, & Takeuchi 1985; O'Connor 2008
- Incompatible engineering skills[2]	Incompatible engineering skills and know-how can hamper a firm's effort to specify a new product correctly and to develop it defect-free, on time and within budget.	Cooper & Kleinschmidt 1990; Henard & Szymanski 2001; Maidique & Zirger 1985
- Incompatible production process knowledge[3]	Lack of process knowledge increases the likelihood of manufacturing defects and hurts product quality	Barnett & Clark 1996; Nevins & Whitney 1989
- Lack of marketing synergy	A firm's brand strength, supply chain and corporate reputation may provide minimal leverage in an unrelated product category, e.g., newcomers to a product category do not have a supportive network of supplier, distributor and customer relationships that facilitate new product development, sourcing and commercialization.	Calantone, Schmidt, & Song 1996; Di Benedetto 1999; Dutta, Narasimhan, & Rajiv 1999; Henard & Szymanski 2001; Hultink & Atuahene-Gima 2000
Incentive Incompatibility		
	The principal-agent literature postulates that organizations are made up of individuals who act in their own self-interest while pursuing organizational goals.	Jensen & Mekling 1976
	Besides goal divergence between owners and managers, goals (and investment preferences) may differ among layers of management.	Harris, Kriebel, & Raviv 1982
	Managers compete with each other in various domains. A high number of NPD projects may allow a business unit to draw greater resources from the parent corporate entity that can be used not only for those projects but also to grow the business unit and increase its organizational influence.	Brass & Burkhardt 1993; Houston, Walker, Hutt, & Reingen 2001
	Sales managers are willing to "bias their sales forecasts to suit their own interests as rational economic individuals."	Lowe and Shaw 1968

Structural Impediments		
- Low cross-functional participation or integration	Greater participation or integration of key functions in the NPD process, including sales and marketing has a positive impact on new product success.	Di Benedetto 1999; Ernst, Hoyer, & Rübsaamen 2010; Troy, Hirunyawipada, & Paswan 2008
Misforecasts		
	New product sales forecasts are particularly influential, because they impact project selection, continuation and launch. Misforecasts may lead to suboptimalities in a firm's NPD pipeline and costly commercialization missteps.	Ehrman & Shugan 1995; Kahn 2006
Weak value proposition		
- Weak value proposition	To the extent that value proposition is a key consideration in product purchase, a weak value proposition handicaps product sales.	Cooper & Kleinschmidt 1990; Henard & Szymanski 2001; Maidique & Zirger 1984
Flawed marketing programs		
- Flawed product tactics	Weakness in salient product details, such as poor appearance, brand name or packaging, have a negative impact on buyer behavior.	Cooper, Gulen, & Rau 2005; Owen 1986; Zinkhan & Martin 1987
- Flawed pricing tactics	Price-level decisions impact both product profitability and value to customers. Mispricing a product in either direction, thus, can greatly diminish its financial performance.	Smith 2012
- Flawed distribution approaches, including poorly trained or incentivized sales force	A flawed distribution approach or sales effort impairs a firm's ability to reach target markets effectively or generate sales. In contrast, a sound distribution strategy may also benefit new product performance through synergies with other elements of commercialization strategy, such as pricing.	Di Benedetto 1999; Hultink & Atuahene-Gima 2000
- Flawed promotion tactics	Flawed promotion tactics impair a firm's ability to reach target markets, communicate the value of a new product offering or stimulate purchasing	Calantone, Schmidt, & Song 1996; Di Benedetto 1999; Song & Parry 1994
- Weak launch effort	Because new products compete with incumbents for limited distribution space and share of wallet, they require considerable marketing support over time to penetrate a market	Cooper 1979; Maidique & Zirger 1984
- Low product quality	Lack of overall quality, or excellence on dimensions, such as appearance, performance, ease of use, workmanship, materials, reliability, durability and safety has a negative impact on market success over time	Jacobson & Aaker 1987; Phillips, Chang, & Buzzell 1983; Song, Souder, & Dyer 1997
Adverse market conditions		
- Small or stagnant markets	Larger markets offer the possibility of greater sales, whereas expanding markets are frequently characterized by competitive instability that may favor new products.	Brown & Eisenhardt 1995; Cooper & Kleinschmidt 1987; Zirger & Maidique 1985
- Many competitors	New industrial products have been shown to enjoy a higher success rate in markets with a small number of competitors	Yoon & Lilien 1985

- Hostile markets	Environmental hostility moderates the impact of NPD proficiency on success	Calantone, Schmidt & Di Benedetto, 1997
Adverse market conditions (cont'd)		
- Markets with frequent new product introductions[3]	Frequent new product introductions drive demand fragmentation and oversaturation of distribution. Industries characterized by a historically high rate of new product introductions, such as consumer packaged goods, offer inherently less fertile ground for new products.	Redmond 1995

[1] The list of references cannot claim to be comprehensive. Where possible, it includes review papers where the reader can find additional references.
[2] Henard and Szymanski's meta-analysis shows the factor to be marginally not significant. However, other important studies rank it as highly important.
[3] Hypothesis lacks empirical evidence in the context of new product performance.

Table 2. Descriptive Statistics and Correlations for Key Constructs in the Full Sample (n=444) and Subsets of New Product Launches by Overconfident (n=81) and Non-overconfident (n=363) Decision Makers

	Full Sample		Overconf.=0		Overconf.=1										
	Mean	SD	Mean	SD	Mean	SD	1	2	3	4	5	6	7	8	9
*st**	.24	.37	.22	.35	.32	.41									
ence	.18	.39	.00	.00	1.00	.00	.10								
	4.91	2.22	4.93	2.20	4.81	2.30	-.04	-.02							
	19.91	7.76	19.50	7.30	21.73	9.38	.49	.11	-.02						
end	8.43	5.70	8.41	5.84	8.57	5.07	-.07	.01	.04	-.11					
d	8.64	3.92	8.77	3.97	8.08	3.68	-.12	-.07	.02	-.23	.21				
	18.41	2.19	18.35	2.18	18.68	2.23	.07	.06	-.12	.29	-.21	-.33			
	21.51	2.48	21.58	2.48	21.20	2.47	-.06	-.06	.01	-.23	.50	.46	-.31		
ation	411.34	107.47	407.81	106.60	430.60	110.03	-.03	.08	-.02	-.05	.29	.29	-.02	-.08	
	2.15	4.31	2.19	4.70	2.00	1.73	.04	-.02	-.03	.04	.02	.01	.01	-.06	-.0
	.60	.49	.61	.49	.56	.50	.00	-.05	-.05	.00	.05	-.10	.08	.01	.1
	4.88	.79	4.81	.79	5.22	.71	.02	.20	.00	.07	-.02	.00	.03	-.02	-.0

* Correlations with OverforecastOrd (not shown for parsimony reasons) are identical in magnitude and significance to those for Overforecast.
Firm and industry-average expenditure data, as well as firm market valuations, are in millions.
Correlations with absolute values greater than .08, .09 and .12 are significant at p < .1, p < .05 and p < .01, respectively.

Table 3. Results for Cumulative Logit (Models 1-3), OLS (Models 4-5) Regressions, and Sobel Test

	Model 1 OverforecastOrd		Model 2 OverforecastOrd		Model 3 OverforecastOrd		Model 4 Overforecast		Model 5 Overforecast		(
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	(
	-.226	.206	-.254	.205	-.296	.227	-0.045	0.033	-.048	.032	-.
	-1.151***	.399	-1.100***	.400	-1.006**	.432	-0.160***	0.060	-.149**	.060	-.
	.676	.955	.637	.959	-1.704	1.099	0.072	0.156	.066	.156	-.2
	.060	.053	.060	.053	.108*	.057	0.007	0.009	.007	.009	
	.001	.001	.001	.001	.001	.001	0	0	0	0	
	.026	.023	.027	.023	.019	.025	0.005	0.004	.005	.004	
	.090	.220	.117	.221	.011	.239	0.015	0.036	.017	.036	-
	.140	.137	.086	.140	.050	.154	0.014	0.022	.006	.022	-
			.490*	.265	.330	.297			.090**	.046	
					-.046	.054					-
					.143***	.018					.02
	444		444		444		444		444		
	8		9		11		8		9		
	.044		.054		.262						
	16.09**		19.41**		101.6***						
							.031		.041		
							1.75*		2.03**		13.5
			.010		.204				.010		
c									3.89**		50.1
					2.24**						2.

* p < .1; ** p < .05; *** p < .01
The models included an intercept (cumulative logit fits an intercept for each variable class) that are not shown.

Table 4. Results of Additional Analyses

	Model 7		Model 8		Model 9		Model 10	
dent variable:	OverforecastOrd		Price		AFE		Demand	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	
ktSpend	-.294	.227			.244**	.105	263.567***	5
:Spend	-1.018**	.431			.366*	.193	280.592***	1C
ıPrice	-1.678	1.101			-.920*	.504	60.695	26
ducts	.108*	.057			.003	.028	-38.567***	1
ıValuation	.001	.001			.000	.001	.027	
:xp	.019	.025			.012	.013	-5.738	
	.015	.239			-.003	.116	2.943	6
sm	.052	.154			-.092	.072	-17.683	3
onfidence	.328	.297	1.596**	.690	.139	.149	39.101	7
		.062					21.307	1
	.143***	.018					-47.127***	
;S	-.037							
			.654***	.033				
	444		444				444	
	11		2				11	
i-sq	101.27***							
:scaled R^2	.261							
			.478		.059		.342	
stic			203.40***		2.99***		20.22***	

* p < .1; ** p < .05; *** p < .01.
The models included an intercept (cumulative logit fits an intercept for each variable class) that are not shown.

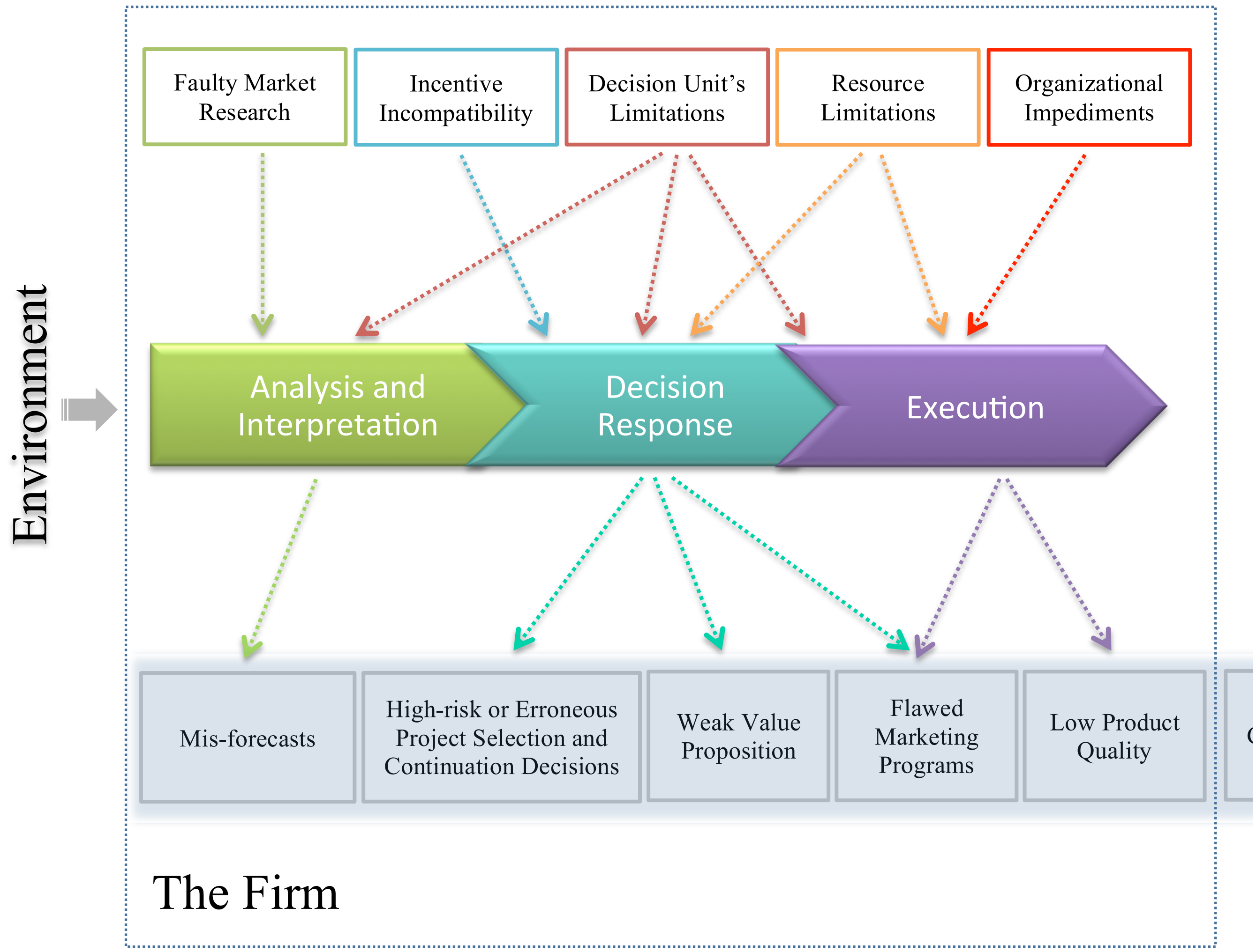

Figure 1. A General Model of Antecedents of New Product Failure in the Marketplace

APPENDIX A.

Items Used to Measure Key Constructs

1. Overconfidence:

This simulation exercise involves managing a virtual firm in competition against firms managed by other participants. To this end, you will be required to make a full spectrum of business decisions pertaining to operations, marketing and finance. Given your current level of preparedness, how do you expect to perform relative to the other participants beginning the exercise with you today?

☐ Bottom 20%
☐ Lower 21-40%
☐ Middle 41-60%
☐ Upper 61-80%
☐ Top 20%

2. Dispositional Optimism based on the Revised Life Orientation Test scale

Please indicate your agreement or disagreement with the following statements. (The 7-point scale is anchored by “Strongly disagree” = 1, “Neither agree nor disagree” = 4, and “Strongly agree” = 7.

a. In uncertain times, I usually expect the best
b. If something can go wrong for me, it will (reverse coded)
c. I am always optimistic about my future
d. I hardly ever expect things to go my way (reverse coded)
e. I rarely count on good things happening to me (reverse coded)
f. Overall, I expect good things to happen to me rather than bad

*3. Decision Support System (DSS) reports and tools**

a. Market share report (shows market share by product by market segment for all products)
b. Customer analysis report (shows segment characteristics, preferences and projected evolution)
c. Competitor analysis report (shows competitors’ pricing, market awareness about each product, and customer perceptions of all products on key attributes)
d. Advertising performance report (shows the effectiveness of the firm’s advertising campaigns relative to actual performance and perceptual objectives)
e. Income statement
f. Cash flow statement
g. Investment report (shows the net present value of firm investments)
h. Valuation report (shows firm market valuation over time)
i. Product attributes calculator (a dynamic tool that allows participants to estimate product performance attributes given various levels product characteristics)**
j. Profit-and-loss calculator (a dynamic tool that allows participants to estimate profit or loss given the firm’s sales projections and current cost structure)**

* The SIG provides automatic display of the Industry performance report, Production report and Balance sheet. To the extent that all participants see these baseline reports, we do not include them in the *DSS* variable.
** Our treatment of the two dynamic tools is categorical (used/not used), similar to how we treat the other reports. We separately consider the number of estimates run in each calculator in our robustness checks.