The Forecaster's Dilemma
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Abstract:
Forecasts are often influential because a low forecast may cause a firm not to launch a new product so that actual sales are never observed.

This paper considers a dilemma we face as influential forecasters. Our client requests an unbiased forecast but pressures sometimes exist to provide a bias forecast. From theoretical and empirical perspectives, we discuss the impact of these pressures on the quality of forecasts. We find that:

Non-influential forecasts, generally, create no pressure for statistically biased forecasts. As influence increases, the pressures increase. When our forecasts eliminate alternatives, (e.g., product designs, advertising campaigns), not all forecasts are tested. Not validating all forecasts causes two effects: Survivor's Curse and Prophet's Fear.

Survivor's Curse makes statistically unbiased forecasts appear optimistic (i.e., overestimate actual sales) because, often, only optimistic forecasts are tested. Forecasts appearing statistically unbiased or pessimistic might cause concern. Perhaps, some failures are justified.

Prophet's Fear encourages pessimistic forecasts because these forecasts cause hidden opportunity losses while optimistic forecasts cause observable actual losses. Tested forecasts may appear completely unbiased despite a pessimistic pre-launch bias.

Although no perfect solution exists, clients may lessen bias with experimentation and by seeking more accurate forecasts. Forecasters may lessen bias with forecasts conditioned on launching and by seeking more accurate forecasts.
THE FORECASTER'S DILEMMA

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Influential forecasts occur when the forecast itself determines whether the forecast is tested. New product sales forecasts are often influential because a low forecast may cause a firm not to launch a new product so that actual sales are never observed.

This paper considers a dilemma we face as influential forecasters. Our client requests an unbiased forecast but pressures sometimes exist to provide a bias forecast. From theoretical and empirical perspectives, we discuss the impact of these pressures on the quality of forecasts. We find that:

- Noninfluential forecasts, generally, create no pressure for statistically biased forecasts.
- As influence increases, the pressures increase.
- When our forecasts eliminate alternatives, (e.g., product designs, advertising campaigns), not all forecasts are tested.
- Not validating all forecasts causes two effects: Survivor's Curse and Prophet's Fear.
- Survivor's Curse makes statistically unbiased forecasts appear optimistic (i.e., overestimate actual sales) because, often, only optimistic forecasts are tested.
- Forecasts appearing statistically unbiased or pessimistic might cause concern. Perhaps, some failures are justified.
- Prophet's Fear encourages pessimistic forecasts because these forecasts cause hidden opportunity losses while optimistic forecasts cause observable actual losses.
- Tested forecasts may appear completely unbiased despite a pessimistic pre-launch bias.
- Although no perfect solution exists, clients may lessen bias with experimentation and by seeking more accurate forecasts. Forecasters may lessen bias with forecasts conditioned on launching and by seeking more accurate forecasts.

(Forecasting; New Product Research; Channel Relationships; Bias; Brand Management)

1. Introduction

"Every decision is based on a forecast" (Green and Tull 1978). Decision-makers, in marketing, use forecasts to select actions. These forecasts influence actions taken and, subsequently, the nature of forecast testing. We call this influential forecasting. We, for example, may forecast outcomes for two advertising campaigns. Influenced by the forecast, our client selects one campaign. Here, we only test our forecast for the selected campaign. We never observe the latent sales generated by the rejected campaign.

Although market research forecasts are often influential, many forecasts are not. Economic forecasts, for example, seldom influence evaluation. Consider forecasts of next month’s exports, GNP or unemployment rates. Here, we observe forecasted outcomes whatever the forecast. In contrast, influential forecasts can affect observed outcomes.

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Forecasting new product sales is one important class of influential forecasts. Urban and Hauser (1980) explain how these forecasts determine whether to launch a new product. Holbert (1974) finds, “in terms of usefulness,” no other forecast even approached new product forecasting “as the cornerstone of the research effort in the view of the marketing manager.”

After obtaining a new product forecast, we can end the project, gather additional information or launch the new product. Baldinger (1988) finds ending the project is the most common result. He also finds that heavy users of new product forecasting models primarily use these models to eliminate potential failures. Therefore, forecasts can easily kill a new product.

Sometimes forecasts encourage launching (Cafarelli 1980). Beecham Group filed a $24 million suit against market-research giant Yankelovich because of over-optimistic forecasts given by the research company’s Litmus forecasting model in 1985 related to its introduction of Delicare cold water wash (Alter 1987). Beecham needed 30% of the market to recoup its total investment. “Beecham claims it went ahead with Delicare's 1986 introduction only because the research it bought showed the delicate fabric detergent could outsell American Home Products Corp.'s Woollite” (Dagnoli 1987).

As expected, much research tries to improve the accuracy of new product forecasts (Eliashberg and Shugan 1994, Elrod 1988, Hauser and Koppelman 1979, Shugan 1987, Wind and Spitz 1976). For simplicity, these studies, and statisticians such as DeGroot (1970) and Winkler (1972), assume that decision-makers collect information and make new product decisions. Clemen (1987) and others, however, distinguish between forecasters and decision-makers. Boyd and Britt (1965) observe this distinction is routine in practice. Small and Rosenberg (1975) note that forecasters are often external consultants or in different departments than decision-makers. Kean (1969) observes that researchers crave decision-making involvement. Stout (1981) even suggests the market researchers “must make it clear that the decision-making responsibility lies with the line management.”

Clients have information that forecasters do not. Clients have strategic objectives (e.g., Bergen, Dutta, and Shugan 1993), production considerations, political constraints and competitive pressure that correctly or incorrectly influence their decisions. Therefore, clients seldom delegate decision-making to us.

This paper shows that the separation of forecasting and decision-making creates a dilemma for the forecaster. Our client requests an unbiased forecast but sometimes creates pressures to provide a bias forecast. From theoretical and empirical perspectives, we discuss the impact of these pressures on the quality of the forecasts. Indeed, the forecaster and client are a channel of distribution that faces coordination problems (Jeuland and Shugan 1983).

This paper shows that some pressures encourage conservative (pessimistic) forecasts while others encourage high (optimistic) forecasts. In both cases, the pressures increase as forecasts become more influential (Ehrman and Shugan 1988).

Many analysts think the Beecham-Yankelovich suit pressures researchers to adopt defensive measures and become more cautious. Many wonder whether forecasts will be simply based “on play-it-safe, suit-proof conclusions.” Legal damages usually occur only when forecasts over-estimate actual sales (Editorial 1987).

Past research already recognizes the existence of statistical bias in forecasting, (e.g., Wheelwright and Makridakis 1972). Tyebjee (1987), for example, identifies three sources of bias in new product forecasting. Lowe and Shaw (1968), after studying sales managers, conclude “it seems clear that managers were prepared to bias their sales forecasts to suit their own interests as rational economic individuals.”

This paper’s goal is to continue this research. We show parametric conditions when a pressure to bias exists. We identify the problems and pressures we face. We find the
direction of the net bias created by competing pressures. We also examine the impact on our forecasts. We determine that as forecasts become more influential, the pressure to provide some pessimistic forecasts increases.

We derive a result we call Survivor's Curse. Survivor's Curse causes our otherwise statistically unbiased forecasts\(^1\) to appear optimistic. Therefore, actual sales usually disappoint. With Survivor's Curse, truly unbiased forecasts appear optimistic, and the appearance of objectivity may conceal true pessimism. Survivor's Curse may cause conservatism.

We show that statistically unbiased forecasts should appear optimistic because some forecasts remain untested. Tested forecasts should, on average, overstate expected sales. Perhaps, on average, firms should have some new product failures. A lack of new product failures may suggest a downward forecasting bias.

We also show that strong pressures exist to sometimes provide conservative (pessimistic) forecasts though loss functions are symmetric. For example, when forecasting the outcome of multiple alternatives, forecast-variances may differ across alternatives. Here, we seek to encourage validation of low-variance forecasts. We seek to discourage testing high-variance forecasts. In the new product setting, testing is less likely for pessimistic forecasts because these forecasts discourage launching the new product. We also show, when testing occurs, tested forecasts are generally unbiased.

We call this effect Prophet's Fear. Prophet's Fear can occur when the forecast influences observation. For example, suppose an account executive wants a sales forecast for two mutually exclusive advertising campaigns. The first campaign is traditional while the second campaign is extremely innovative. Although our market research suggests the second campaign may be somewhat superior, this research is equivocal. We expect the first campaign forecast to be more accurate and seek testing of it. The account executive, fully aware of potential forecast error, may still choose to consider only the expected outcome, adopt the second campaign, and test our less-accurate forecast.

Given a desire for accurate forecasts, decision theory suggests imposing a certainty equivalent and adjusting the second forecast to reflect extreme uncertainty. Consequently, we adjust the second forecast to make it pessimistic. This is Prophet's Fear, fear of high-variance forecasts. However, if the account executive is risk-seeking our adjustment is inappropriate.

Prophet's Fear is easy to understand. Prophets fear the testing of their forecasts. Testing the forecast "you will like this restaurant's food" is likely because the client will probably try the food. However, testing the forecast "you will not like the chicken here" is less likely because the client probably will not order chicken. Although testing the second forecast is possible, testing is less likely and, therefore, it is a safer forecast.

Note that Prophet's Fear vanishes when the forecast does not influence the outcome because we observe all forecasted outcomes. For example, suppose the account executive uses both advertising campaigns, (e.g., for different markets) and only desires a forecast for planning purposes. Here, it is illogical to adjust the second forecast for our uncertainty. We provide each forecast, and we hope for accuracy.

Prophet's Fear is related to the psychological literature on confirmation. Einhorn and Hogarth (1986), for example, find that individuals often seek confirming evidence for their beliefs rather than falsifying evidence. With Prophet's Fear, the prophet also seeks confirming evidence. However, unlike the individual, who unintentionally avoids all falsification, the prophet only avoids falsification as uncertainty increases.

2. Overview

We organize this paper as follows. We start by developing a theory of how various factors affect the profitability of providing statistically unbiased forecasts. We consider

\(^1\) A statistically unbiased forecast is a forecast whose expected error is zero for finite samples.
many factors including the effect of accuracy on our profit, the potential impact of our forecast on our client’s decisions, our client’s ability to ignore our forecast, the reward associated with verifying our forecast, the ability of clients to use other information beyond our forecast, and the uncertain nature of our profits. Our theory provides conditions for the existence of both Survivor’s Curse and Prophet’s Fear.

To be concrete, we develop our theory in the context of new product introductions. Here, the alternatives are to launch a new product or not. Forecasting for new product introductions may be the most time-honored use for market research (Blattberg and Golanty 1978; Choffray and Lilien 1978; Hauser and Shugan 1980; Pringle, Wilson, and Brody 1982; Silk and Urban 1978). Many marketing and decision-making textbooks introduce the topic of information within the new product paradigm, (e.g., Brown, Kahr, and Peterson 1974).

In that context, we derive the optimal forecast. We find conditions when (1) the optimal forecast is biased, (2) the optimal forecast is unbiased, and (3) no optimal forecast exists.

Following the theoretical development, the paper provides some discussion relating the theory to forecasting in practice. We provide both implications and insights. We then test our implications using four data sources. First, we analyze forecasting data from the ASSESSOR model to show evidence of Survivor’s Curse. Second, we run an experiment to provide evidence of Prophet’s Fear. Third, we analyze presidential newspaper endorsements and find some evidence for Prophet’s Fear. Fourth, we conduct in-depth interviews with several well-known market research firms. Our empirical evidence provides some support for our theoretical implications both within and outside a market forecasting context.

Finally, we propose possible solutions. We suggest clients may lessen bias with experimentation and by seeking more accurate forecasts. Forecasters may lessen bias by seeking more accurate forecasts and with forecasts conditioned on launching. The paper closes with our conclusions and suggestions for future research.

3. Ethics in Forecasting

Before continuing, we have two comments concerning ethics. First, we use the term “bias” in the statistical sense—a biased forecast has an error whose expected value is not zero for finite samples. It is a statistical property. We associate no ethical meaning to the word. As Zellner (1986) notes, “optimal, rational forecasts are often biased.”

Second, this paper explores only the pressures facing market research suppliers and not their actual behavior. These pressures certainly create ethical problems. Hunt et al. (1984) find that “the most difficult ethical problem facing marketing researchers is maintaining the integrity of their research efforts.” Deshpande and Zaltman (1984) find that the “political acceptability of the final [market research] report” is very important.

These empirical findings are consistent with our theoretical results. We should recall, however, that Hunt et al. (1984) also find a perception of “relatively low frequency of unethical behavior” and that “marketing researchers do not believe that unethical behaviors in general lead to success in marketing research.”

We do not suggest that any marketing researchers misrepresent forecasts. Nor do we suggest that forecasters relish the current reward structure. Our paper attempts only to understand the forecasting environment that forecasters face. Ethical people can still face ethical problems.

4. The Theory

4.1 Our Forecast

Our client must decide whether to launch a new product, i.e., make a GO decision. After a launch, new product sales are known. Pre-launch, sales are unknown.
Using market research (any methods necessary) and experience, we gather knowledge about the anticipated sales of the new product. Unless otherwise stated, all equations are pre-launch but post market research. We estimate sales of $\hat{s}$ given by Equation (1).

$$\hat{s} = \mu + \bar{n}$$

(1)

where:

$\hat{s}$ = our pre-launch estimate for new product's sales (random variable)
$\mu$ = the post-launch sales for the new product (a constant)
$\bar{n}$ = the random error in $\hat{s}$.

Here, $\mu$ is a constant that is unknown pre-launch and $\bar{n}$ is the random error in our estimate $\hat{s}$. We assume that $\bar{n}$ has a normal distribution with mean zero and variance $\sigma^2$. Note, $\bar{n}$ reflects our uncertainty about the new product’s sales.

For example, suppose that our pre-launch market research estimates annual sales of 300,000 units for the new product. Here, $\hat{s} = 300,000$. Post-launch, we observe actual new product sales of 100,000 units. Then, $\mu = 100,000$ and $\bar{n} = 200,000$. Pre-launch, our estimate $\hat{s}$ is random because it contains a random error $\bar{n}$. We learn $\bar{n}$ only after a launch.

We supply, to the client, the forecast given by Equation (2).

$$f = \hat{s} + \beta$$

(2)

where:

$f$ = our pre-launch forecast, generally a random variable
$\beta$ = the reporting bias which we may choose to add to $\hat{s}$.

The decision-variable $\beta$ is known to us but not the client. We call $\beta$ the “reporting bias.” It allows forecasts different from $\hat{s}$ when $\beta \neq 0$. So, $f$ has two parts: (1) the unbiased forecast $\hat{s}$ and (2) the reporting bias $\beta$.

Now, $\hat{s} = \mu + \bar{n}$, implies $f = \mu + \bar{n} + \beta$. Hence, $f$ is a random variable because $f$ contains an unknown error, $\bar{n}$. Take our former example. Let $\beta = -50,000$. Then, $f = 250,000$ because $\hat{s} = 300,000$. Post-launch, we learn $\mu = 100,000$ and $\bar{n} = 200,000$. Our client, however, only observes $f - \mu = \bar{n} + \beta$. Post-launch, the client observes an error $250,000 - 100,000 = 150,000$.

Taking expectations, remembering $E[\bar{n}] = 0$, Equation (2) yields Equation (3).

$$E[f] = \mu + \beta$$

(3)

where:

$E[\cdot] =$ expectations operator (here, the forecaster’s expectations).

When $\beta = 0$, our forecast is unbiased because $E[f] = \mu$. When $\beta > 0$, the forecast is optimistic because $E[f] > \mu$. When $\beta < 0$, the forecast is pessimistic because $E[f] < \mu$.

To obtain $f$ pre-launch, our client pays $p$, pre-launch for our new product sales forecast before receiving the forecast. Assume the client requests an unbiased forecast.

4.2 The Client’s Problem

Assume the client truly wants a forecast, and not just internal political justification for a launch. Then, Equation (4) provides the client’s pre-launch estimated profit for a launch.\(^2\)

$$\Pi = m\hat{s}(f) - F$$

(4)

where:

\(^2\) We prohibit client’s use of mixed strategies. This is a limitation but we are aware of no firms actually using mixed strategies.
Π = the client's pre-launch estimate for the new product's profit
S(f) = the client's pre-launch estimate for the new product's sales given our forecast f
m = the new product's per unit profit margin (a constant)
F = the new product's fixed cost (a constant).
We assume the client launches\(^3\) when Π > 0. Equation (4) implies Equation (5).
\[ S(f) > F/m. \] (5)

Solving Equation (5) for f yields Equation (6).
\[ f > \hat{c} \] (6)

where:
\[ \hat{c} = S^{-1}(F/m), \] the critical value for a launch.

We call the nonrandom constant, \( \hat{c} \), the critical value for a launch because \( f > \hat{c} \) implies a launch. As forecasters, we may not know how the client got \( \hat{c} \). We assume, however, that we know \( \hat{c} \). Our extended model partially relaxes this assumption.

The critical value, \( \hat{c} \), can also represent the opportunity cost of money or the expected rewards associated with the next best alternative (e.g., Shore 1978, Cafarelli 1980). Wang (1970) suggests that \( \hat{c} \) should incorporate a "regret" criterion.

Suppose our client uses our forecast to resolve all uncertainty. Then, the client believes \( S(f) = f \). Consequently, \( \hat{c} = F/m \). For example, let the client's fixed costs \( F = 400,000 \) and profit margin \( m = 2 \). The client launches when estimated sales exceed \( F/m = 200,000 \). If the client accepts our forecast of \( f = 250,000 \), the client launches because 250,000 > 200,000.

It may be unreasonable to assume that our client only uses our forecast \( f \) to predict sales. Our client may have a Bayesian Prior Distribution for sales before getting our forecast, and may only use \( f \) to update that distribution. Then, we get Equations (7) and (8). See Appendix A for details.

\[ \hat{c} = (F/m) + k \] (7)
\[ k = (F - \mu_c)\sigma_c^2 / (m\sigma^2) \] (8)

where:
\( k \) is a constant. The constants \( \mu_c, \sigma_c^2 \) and \( \sigma^2 \) are parameters of the client's prior (pre-forecast) distribution for sales.

4.3 The Survivor's Curse Effect

Suppose \( \beta = 0 \), then \( E[f] = \mu \) for every forecast, regardless of whether the client launches. When \( \beta = 0 \), \( f \) is independent of whether \( f \) happens to be above or below \( \hat{c} \). Across several forecasts, however, \( \hat{c} \) determines which outcomes are observed, so average observed error depends on \( \hat{c} \).

Suppose our client applies the same decision rule, i.e., Equation (6), across several launches. It is likely that the average forecast for launched products will exceed the average forecast for all products, because some forecasts may be below \( \hat{c} \). Theorem 1 proves that when that occurs, unbiased forecasts appear biased and optimistic (overstate sales).

**Theorem 1.** Suppose: (1) we supply unbiased sales forecasts (zero reporting bias) for a series of products each having the same expected sales, (2) the client launches some

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\(^3\)This GO–NO GO model and the use of a critical value are very common in the marketing literature. Urban and Hauser (1980), Pittney (1976), Kees (1970) and others use a GO–NO GO model of the new product decision. Saunders (1987), Douglas (1978) and others associate NO GO with low expected sales.
but not all of those products and (3) launched products average higher forecasts than
unlaunched products. Then, the unbiased forecasts, for launched products, appear
optimistic and biased. Mathematically, let \( f_i \) be forecast \( i \), \( f_x \) be the average forecast for
all products and \( f_y \) be the average forecast for launched products. Then, when \( E[f_i] = \mu \) for
all \( i \), then \( E[f_i|f_i > f_x] > \mu \).

**Proof.** See Appendix B.

Theorem 1 implies that even when forecasters make unbiased forecasts, the forecasted
sales for launched products will tend to overstate their actual sales.\(^4\) Remember, when \( \beta = 0 \), the client can not make a forecast biased by not launching. The average forecast is
also unbiased for any random subset of forecasts. However, the client can make the
average forecast biased by removing the smallest forecasts from the average.

Survivor's Curse works as follows. Most forecasts contain some error. Positive errors
enhance the probability of launching and the forecast survives to be tested. Negative
errors enhance the probability of not launching and the forecast remains untested. Those
products surviving the screening process, by exceeding the critical value, are more likely
to have positive errors because products with negative errors may not survive to be tested.
Here, the bias (expected error) across all forecasts is zero, but the bias for tested forecasts
is positive. **Survivors tend to disappoint.**

We will see that the illusion of optimism created by Survivor's Curse makes the pes-
simism of Prophet's Fear difficult to detect. Prophet's Fear causes pessimistic sales forecasts
for subsequently rejected products and thereby causes rejection of potentially successful
products. Survivor's Curse causes over-estimated sales for launched products. Moreover,
Survivor's Curse creates pressure to be conservative. This creates a dilemma for the
forecaster.

### 4.4 Forecasting Error

We assumeCompe that forecasters' reputations depend on accuracy. There are many measures
of accuracy. Here, we adopt the most common measure, i.e., squared error.\(^5\) This is a
natural assumption because most statistical tools automatically use squared error mini-
imization. Clients often expect forecasts from regression analyses to minimize squared
error. Moreover, assuming an asymmetric error might itself cause all forecasts to be
biased. Equation (9) results.

\[
e^2 = (f - \mu)^2
\]  

where:

\( e^2 \) = squared error, a random variable pre-launch.

Note, when \( \beta = 0 \), then \( e^2 = \bar{e}^2 \) because \( f = \mu + \bar{e} \). Also, \( e^2 \) is unknown because \( \mu \) is
unknown.

### 4.5 Our Problem

As a forecaster, we supply a new product sales forecast, \( f \). Consistent with existing
practice, we receive a market price for our forecast before learning the forecast's accuracy.

The market price for our forecast depends on current market conditions, (e.g., com-
petition) and our past reputation. For accounting simplicity, let \( p_i \) represent the market
price net of our forecasting costs. Hence, we receive profit \( p_i \) for our forecast \( f \). Note

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\(^4\) Survivor's Curse resembles "regression to the mean." However, censored observations cause the former and
are unnecessary for the latter.

\(^5\) We get our results with common symmetric error. It would be easy to find biased solutions with an asymmetric
error. Greater penalties for overestimating actual sales only exaggerate our results.
that $p_1$ could be negative for neophyte forecasters, who must build a reputation for accuracy.

Here, $p_1$ is a state variable reflecting our current state, including our reputation and past forecasting accuracy. Assume that past accuracy in forecasting increases $p_1$ while past inaccuracy decreases $p_1$. We allow any monotonic relationship between past forecasts and $p_1$.

We expect our future market prices for forecasts depend on the demonstrated accuracy of our current forecast. We are in stage (1) of the following stages: (1) we supply our forecast to the client and get $p_1$, (2) the client launches or not, (3) we can charge a new price $p_2(f)$ for our next forecast. Here, $p_2(f)$ reflects the market price for our services with any new information about our accuracy. Pre-launch, $p_2(f)$ is a random variable.

It is conceptually possible to extend our analysis to more time periods. However, we multiply $p_2(f)$ by a factor $b$ to capture the effects of our current forecast on the net present value of future revenue streams.

Equation (10) defines our expected profit. Note, forecasters did not choose this objective function nor necessarily like it. The objective comes from the forecasting task.

$$E[\pi(f)] = p_1 + bE[p_2(f)]$$  \hspace{1cm} (10)

where:

- $\pi(f)$ = current and future profits given $f$.
- $p_1$ = current market price net of our forecasting costs.
- $p_2(f)$ = new market price (net costs) given $f$.
- $b$ = factor to reflect impact on future time periods.

Equation (11) defines $p_2(f)$.

$$p_2(f) = p_1 + \{b(R - L(\epsilon^2))\}$$  \hspace{1cm} (11)

where:

- $\delta = 1$ when $f > \bar{c}$ and 0 otherwise
- $R$ = nonnegative constant reflecting an increase in reputation associated with forecast verification
- $L(\epsilon^2)$ = loss function with forecast error $\epsilon^2$.

With a launch, our market price changes by $[R - L(\epsilon^2)]$. We gain $R$ over $p_1$ less a penalty $L(\epsilon^2)$ for forecasting error $\epsilon^2$. For small errors $p_2(f) > p_1$. For large errors, $p_1 > p_2(f)$. Our ability to charge higher fees decreases as our error increases.

We assume that the loss in reputation is continuously differentiable and increases with the error so that $L'(\cdot) > 0$ and $L''(\cdot) > 0$. Without loss in generality, given $R > 0$, we assume $L(\epsilon^2) > 0$. Note, in the special case when $L(\epsilon^2) = \epsilon^2$, we find $L(0) = 0$, $L'(0) = 1$ and $L''(0) = 0$.

Here, $L(\cdot)$ is a general function allowing many interpretations of the objective function. When $L(\epsilon^2) > R$, the market views our next forecast as less valuable than our current forecast. The decreased value comes from the poor accuracy of our current forecast.

Without a launch, our forecast goes untested, $\delta = 0$ and our forecast's market price remains at $p_1$. For many situations, this assumption is only an approximation. Over time, lack of testing might cause $p_1$ to decay. With decay, forecasters might seek firms, who often launch successful new products.

This section ends with a note about the relationship between $\delta$ and $\bar{n}$. Note, $\delta$ is not random because we know $\delta$ pre-launch. Remember, $\delta = 1$ when our forecast $\{f = \delta + \beta\}$ exceeds $\bar{c}$. We do not know the random error $\bar{n}$ pre-launch. Moreover, our distribution of $\bar{n}$ is independent of $\delta$ because we expect sales would be $\delta = \mu + \bar{n}$, regardless of whether the client subsequently launches. Of course, $\delta$ may influence the distribution of observed $\bar{n}$. Removing only low forecasts, causes the expected average forecast to exceed $\mu + \bar{\beta}$.
4.6 The Optimal Forecast

Substituting \( p_2(f) \) from Equation (11) into Equation (10) yields Equation (12).

\[
E[\sigma(f)] = (1 + b)p_1 + b[R - E[L(\epsilon^2)]].
\]  
(12)

Before maximizing \( E[\pi(f)] \), we need Lemma 1. It that shows a value of \( \tilde{s} \), i.e., \( \beta = 0 \), minimizes \( E[L(\epsilon^2)] \).

**Lemma 1.** \( E[L(\epsilon^2)] = E[L(f - \mu)^2] \) is minimized at \( \beta = 0 \), \( f = \tilde{s} \) for \( L[\cdot] \geq 0 \) and \( L'[\cdot] \geq 0 \).

**Proof.** See Appendix B.

When the critical value \( \tilde{c} \) is approached, by definition, \( \delta = 1 \) whatever \( f \). This yields Theorem 2.

**Theorem 2.** The optimal forecast becomes unbiased as it becomes noninfluential. Mathematically, \( \beta = 0 \) is optimal when \( \tilde{c} \) approaches \(-\infty\).

**Proof.** See Appendix B.

Theorem 2 implies that noninfluential forecasts should be unbiased, i.e., \( \beta = 0 \). This result is well known in statistics and follows from the symmetric loss function. The result, however, provides an important baseline for Theorems 3 and 4, which show when pressure exists to bias the forecast.

4.7 The Prophet’s Fear Effect

**Theorem 3.** When the forecast error variance is large, the optimal forecast is no more than the critical value. Hence, an unbiased forecast is optimal only when we estimate sales no more than the critical value. Mathematically, let \( f^* \) be the optimal forecast and \( \sigma^2 = E[L(\epsilon^2)] \). Then, (1) \( f^* \leq \tilde{c} \) when \( \sigma^2 > R \); (2) \( f^* = \tilde{s} \) when \( \tilde{s} < \tilde{c} \) and \( \sigma^2 > R \); (3) \( f^* = \tilde{c} \) when \( \tilde{s} > \tilde{c} \) and \( \sigma^2 > R \).

**Proof.** See Appendix B.

Although multiple optima exist in Theorem 3, later (e.g., Theorem 5) we get uniqueness. Also, when multiple optima exist, we prefer an unbiased forecast to satisfy the client’s request.

Note that we use the term forecast error variance to refer to \( \sigma^2 \), which reflects the expected value of the error adjusted for the loss function \( L(\epsilon^2) \).

Theorem 3 implies that when we have sufficient uncertainty about our forecast, we face the pressure to forecast \( \tilde{c} \) or less. We call this effect Prophet’s Fear. When \( \sigma^2 > R \), we feel pressure to be pessimistic (conservative) and use our influence to discourage a launch. When \( \tilde{s} < \tilde{c} \), we can forecast \( \tilde{s} \) and provide an unbiased forecast. When \( \tilde{s} > \tilde{c} \), however, there is an incentive to be pessimistic and forecast \( \tilde{c} \) rather than \( \tilde{s} \).

We call this effect Prophet’s Fear because prophets fear the testing of forecasts with large error variance.

**Theorem 4.** When the forecast error variance is small, an unbiased forecast is optimal unless: (1) we expect failure and (2) estimated sales are close to the critical value. Here, no solution exists. The optimal forecast is larger than the critical value but as small as possible. Mathematically, let \( \sigma^2 = E[L((\tilde{c} - \mu - \tilde{n})^2)] \). When \( \sigma^2 \leq R \), then \( f^* = \tilde{s} \), unless: (1) \( \tilde{s} \leq \tilde{c} \) and \( \sigma^2 < R \). Here, \( f^* = \tilde{c} + \xi \), where \( \xi > 0 \) but arbitrarily small.

**Proof.** See Appendix B.

Theorem 4 provides yet another situation when we face the pressure to provide a bias forecast. When we are sufficiently confident that sales will be close to the critical value, i.e., \( \sigma^2 < R \), but we expect sales less than the critical value, i.e., \( \tilde{s} < \tilde{c} \), then we face the pressure to forecast slightly above the critical value, \( \tilde{c} + \xi \).

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Now, we compare influential to noninfluential forecasts. Influential forecasts below \( \hat{\xi} \) are not tested while noninfluential forecasts are always tested. Theorem 2 implies that optimal noninfluential forecasts equal \( \hat{\xi} \). The following corollary compares the error variance (i.e., expected accuracy) of influential and noninfluential forecasts for the same new products. Observed influential forecasts appear more accurate.

**COROLLARY 1.** Consider optimal noninfluential and influential forecasts exceeding the critical value (i.e., \( f^* = \hat{\xi} + \xi, \xi > 0 \)) for the same series of new products. Then, we expect, (1) The average error variance of noninfluential forecasts equals that of influential forecasts when the corresponding forecasts (i.e., noninfluential and influential forecast) are always equal. (2) The average error variance of noninfluential forecasts exceeds that of influential forecasts when at least one noninfluential forecast does not equal the corresponding influential forecast.

### 4.8 Summary

The client seeks an unbiased forecast. Although client losses may be inconsistent with an unbiased forecast, it is our client who should apply the suitable loss function and decide whether to launch. Sometimes this situation creates a dilemma for the forecaster.

We, as forecasters, often have the incentive to provide the forecast \( f^* = \hat{\xi} \). But conditions exist when we face the pressure to provide a biased forecast, \( f^* \neq \hat{\xi} \). The first condition is a large forecast error variance, i.e., \( \sigma^2_f > R \), and expected success, i.e., \( \hat{\xi} \geq \hat{\xi} \). The second condition is a small forecast error variance, i.e., \( \sigma^2_f \leq R \), estimated sales close to the critical value, i.e., \( \sigma^2_f \leq R \), and expected failure, \( \hat{\xi} \leq \hat{\xi} \). The first condition encourages a pessimistic forecast, \( f^* < \hat{\xi} \), while the second condition encourages an optimistic pre-launch forecast, \( f^* > \hat{\xi} \). See Table 1.

Table 1 suggests that accurate (or confident) forecasters should provide unbiased forecasts. Occasionally, when estimated sales are slightly below the critical value, optimistic forecasts are optimal. More often, when estimated sales exceed the critical value but error variances are high, Prophet's Fear promotes pessimistic forecasts. This suggests that forecasters should sometimes be pessimistic. Actual pessimism is difficult to detect because all tested forecasts are unbiased. Moreover, Survivor's Curse creates the illusion of optimism.

Unbiased forecasts should appear optimistic. When forecasts accurately reflect actual sales, either all products are launched or the forecaster has removed high variance forecasts by causing rejection of products with large variance forecasts.

We close this section with Equation (13) providing our expected profit for \( f^* > \hat{\xi} \).

We now generalize these results.

\[
E[\pi(f)] = (1 + b)p_i + b(R - \sigma^2_f).
\]  

(13)

**TABLE I**

<table>
<thead>
<tr>
<th>High Expected Error</th>
<th>Low Expected Error near ( \hat{\xi} )</th>
<th>Otherwise</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \sigma^2_f &gt; R )</td>
<td>( \sigma^2_f &lt; R ) and ( \sigma^2_f \leq R )</td>
<td>Unbiased</td>
</tr>
</tbody>
</table>

| We expect Success, \( \hat{\xi} > \hat{\xi} \) | Pessimistic | Unbiased |
| We expect Failure, \( \hat{\xi} \leq \hat{\xi} \) | Unbiased | No Solution |

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4.9 Extensions

Our problems begin with the common assumption of de facto control over the launching decision—forecasting below $\hat{\epsilon}$ stops the launch. We now examine the consequence of diminishing this control. Diminished control agrees with our in-depth interviews with professional market research forecasters. They revealed statisticians seldom make actual decisions. Although forecasts are important, clients retain actual decision-making responsibility. Krum (1969) finds “executive judgment” dominates the decision process.

We, therefore, extend our model by decreasing the influence of $f$. Based on our presentation of the forecast, and information available after the forecast (but pre-launch), clients may reject our forecast. Define $\gamma$ as our subjective probability that our client launches even when our forecast is no more than $\hat{\epsilon}$, i.e., $\delta = 0$. Define $\lambda$ as our subjective probability that our client launches when our forecast exceeds $\hat{\epsilon}$, i.e., $\delta = 1$. Here, $0 \leq \lambda \leq 1$. Note when $\lambda = 1$ and $\gamma = 0$, we obtain our simple model because $f$ again suggests a launch. Consistency requires $\lambda \geq \gamma \geq 0$.

Note an alternate interpretation of the probabilities $\lambda$ and $\gamma$ is that $\lambda$ and $\gamma$ embody our uncertainty about the true level of $\hat{\epsilon}$. Here, $\lambda$ is our subjective probability of $\hat{\epsilon}$ being lower than we thought, and $\gamma$ is our subjective probability of $\hat{\epsilon}$ being higher.

Figure 1 summarizes our problem.

We forecast high ($f > \hat{\epsilon}$) or low ($f \leq \hat{\epsilon}$). Our client, then, decides whether to launch. With a high forecast ($f > \hat{\epsilon}$), our client launches with probability $\lambda$. If we forecast low ($f \leq \hat{\epsilon}$), our client launches with probability $\gamma$. Hence, there is a chance our forecast has no influence.

If our client launches, the forecast error $f - \mu$ is observed. With no launch, our forecast remains untested. Equation (14) generalizes Equation (11).

A model extension could include multiple critical values where the probability of a launch increases with high values.
\[ p_2(f) = p_1 + \{[\delta\lambda + ((1 - \delta)\gamma)](R - L(e^2))\} \]  \hspace{1cm} (14)

where:
\[ \lambda = \text{our subjective probability the client launches when } \delta = 1 \]
\[ \gamma = \text{our subjective probability the client launches when } \delta = 0 \]

**Theorem 5.** Table 2 shows the optimal forecasts in the extended model.

**Proof.** See Appendix B.

Table 2 indicates that no solution exists when \( \delta \leq \hat{c}, \sigma^2 f \leq R \) and \( \lambda(R - \sigma_2) > \gamma(R - \sigma_2) \). This condition requires \( \sigma^2 f \leq R \) because \( \lambda(R - \sigma_2) > \gamma(R - \sigma_2) \geq 0 \). Hence, \( \sigma^2 f \) must be relatively small. Here, it is optimal to forecast just above \( \hat{c} \). It is always possible to increase expected profits by decreasing our forecast provided that our forecast remains larger than \( \hat{c} \). Hence, no optimal solution exists. Forecasting just above \( \hat{c} \) provides higher expected profits than \( f^* = \hat{c} \).

We end this section with Corollary 2.

**Corollary 2.** The optimal non-influential \((\lambda = \gamma)\) forecast is unbiased \((f^* = \hat{c})\).

5. **Discussion**

We see that as our influence over the launch diminishes, with the introduction of \( \lambda \) and \( \gamma \), fewer situations exist with the pressure to bias the forecast. Our dilemma eventually disappears because we more often want to provide a statistically unbiased forecast.

Table 2 shows that in many situations no pressure exists. For example, when our forecast has no influence on the decision \((i.e., \lambda = \gamma)\), our optimal forecast is an unbiased forecast. Hence, when we provide forecasts for general planning activities, economic activities, the weather, forecasting the winner in sports events, stock market prices and GNP, we have no pressure to produce a biased forecast. Note that this is true whatever the functional form of the market response to forecasting error \((i.e., L(\cdot))\).

Equation \((13)\) and Table 2 shows that our expected profits depend on the error variance of the forecast. The more uncertain we are about our forecast, the lower our expected profits. We might even reject or require a higher fee for more difficult assignments that risk our reputation. Moreover, we have an incentive to increase our forecasting accuracy. The desirability, however, of these decisions depends on a cost-benefit analysis and is beyond the scope of this paper.

The pressure to produce a biased forecast increases as our influence over the launch increases. Table 2 shows that we can measure our influence with the ratio \( \lambda/\gamma \), where \( \lambda \approx \gamma \). The more that a low forecast discourages our client from launching, the smaller \( \gamma \). The more that a high forecast encourages our client to launch, the larger \( \lambda \). The ratio,

<table>
<thead>
<tr>
<th>Pre-Launch Optimal Forecasts: Extended Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Expected Error ( \sigma^2 &gt; R ) and ( \lambda/\gamma &gt; (R - \sigma_2)(R - \sigma_2) )</td>
</tr>
<tr>
<td>Expect Success</td>
</tr>
<tr>
<td>( f^* = \hat{c} )</td>
</tr>
<tr>
<td>Otherwise</td>
</tr>
</tbody>
</table>

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\( \lambda / \gamma \), reflects the net influence. For example, when \( \lambda / \gamma \) is large, our forecast has great influence on the launch. When \( \lambda / \gamma = 1 \), the probability of launching is independent of our forecast.

When \( \lambda / \gamma \) is large, pressure exists for a conservative forecast. Suppose that estimated sales are sufficiently large to insure our client launches the product (i.e., \( \hat{x} > \hat{\epsilon} \)). Then, we only want to provide an unbiased forecast (i.e., \( \hat{\epsilon} \)) when our expected error (i.e., \( \epsilon^2 \)) is small. Otherwise, we want to provide a forecast sufficiently small to avoid launching the new product.

We might argue that we are being conservative. Faced with a less accurate forecast, we adjust our forecast downwards to reflect our risk. However, that adjustment should be done by the decision-maker and not us.

We call this pressure Prophet's Fear because a prophet fears the refutation of the prophet's own forecast. Prophets may, therefore, like to make forecasts that remain untested. This is impossible when we have no influence over whether our forecast is tested. Here, actual sales are known regardless of our forecasted sales. Remember, the pressure to be conservative is related to the error variance, not the absolute level of our forecast.

We wish to be conservative when we are uncertain and not necessarily when our forecasted sales are low.

The Prophet's Fear effect causes conservative forecasts anytime a low forecast prevents the testing of the forecast itself. Hence, this effect goes beyond launching new products. For example, pessimistic (i.e., downward biased) forecasts can occur in sales forecasting for production planning when over-production causes observable surpluses and under-production causes unobservable shortages. Here, the number of units that would have been sold in the shortage remains unknown. This prevents testing our forecast. With stock-outs, a forecaster might argue the forecast is very close, if not precisely correct. It can also occur when the forecast determines the best design, the best promotion or the best compensation scheme because the outcome of the next best alternative remains unobserved.

Generally, we see that whenever the forecast influences our client's ability to test the forecast, there is a pressure to be conservative. These biased forecasts may be serious for several reasons. First, it is likely that error variance is large because clients often seek forecasts when more uncertainty exists. Second, uncertainty is likely to be large for products that might be highly successful because highly successful products are often risky.

Now, we might argue that clients would learn that forecasts are conservative and adjust forecasts upwards. However, there are several factors inhibiting client learning. First, unless clients experiment (Little 1976) and deliberately launch products with low expected sales, clients will never test biased forecasts. Remember that all forecasts that suggest a launch (i.e., \( f > \hat{\epsilon} \)) are completely unbiased. Hence, studying these forecasts reveals nothing. Second, Survivor's Curse makes unbiased forecasts appear optimistic.

6. Reporting Confidence Levels

This section shows that giving the client a measure of confidence or expected error, in addition to our forecast, does not alter our previous results.

So far, we have only reported our forecast. We could also report the level of confidence we have in the forecast. When we also report our forecasting confidence, a lower confidence makes our forecast less valuable. A lower confidence, however, also absolves us somewhat from some responsibility for a large forecasting error.

Let \( C_l \) be our reported confidence level and \( \Phi(C_l) \) represent the cost associated with reporting a confidence \( C_l \). Equation (14) provides our price given no reporting of our forecasting confidence. With reporting, see Equation (15).
\[ p_2(f) = p_1 + [(\delta \lambda + (1 - \delta)\gamma)(R - L(e^2))]C_1 - \Phi(C_1) \]  

(15)

where:

- \( C_1 \) is the confidence we report to the client.
- \( \Phi(C_1) \) is the out-of-pocket cost of creating confidence \( C_1 \). Assume \( \Phi(0) = 0, \Phi(C_1) \geq 0, \Phi'(C_1) > 0 \) and \( \Phi''(C_1) > 0 \).

For example, suppose we scale \( C_1 \) between 0 and 1. If we want 100% confidence, then, we must spend ample money on marketing research making our costs \( \Phi(1) \). We tell the client of our 100% confidence and Equation (15) becomes Equation (14) minus \( \Phi(1) \).

Now, suppose we want 10% confidence. Then, we must spend less money on marketing research making our costs only \( \Phi(.1) \). We tell the client of our 10% confidence. Should the client launch, the outcome only has 10% of the effect, i.e., \( 0.1 \times [R - L(e^2)] \), as it would have with 100% confidence, i.e., \( 1.0 \times [R - L(e^2)] \).

Providing 0% confidence is cheap, having no expense, \( \Phi(0) = 0 \). However, the client discards our forecast and Equation (15) becomes \( p_2(f) = p_1 \).

In general, as confidence \( C_1 \) increases, the reporting cost \( \Phi(C_1) \) increases until our gain in profit \( p_2(f) - p_1 \) is zero. Of course, as \( C_1 \) increases, the impact of outcomes, \([R - L(e^2)]C_1\), also increases. Taking the expected value of \( \pi(f) \) we obtain:

\[ E[\pi(f)] = (1 + b)p_1 + [b(\delta \lambda + \gamma - \delta \gamma)(R - \sigma^2)]C_1 - \Phi(C_1) \]

We maximize \( E[\pi(f)] \) by setting \( \partial E[\pi(f)]/\partial C_1 \) equal to zero. We find that,

\[ \Phi'(C_1) = b(\delta \lambda + \gamma - \delta \gamma)(R - \sigma^2). \]

Hence, we set our confidence \( C_1 \) so that the marginal cost, i.e., \( \Phi'(C_1) \), equals the expected reward associated with validation. As the error variance \( \sigma^2 \) increases, our optimal reported confidence decreases.

Our optimal \( f \) remains unaffected by \( C_1 \) because our first-order condition for \( \beta \) is:

\[ 2b(\delta \lambda + \gamma - \delta \gamma)E[L(e^2)(f - \mu)]C_1 = 0. \]

(16)

7. **Empirical Results**

7.1 **Assessor Analysis**

Our empirical findings are preliminary. However, they suggest that both Survivor's Curse and Prophet's Fear exist within and outside a market forecasting context. We start by examining forecasts generated by the new product forecasting model known as ASSESSOR (Silk and Urban 1978). ASSESSOR is a well-established and accurate model for new product forecasting. Urban and Katz (1983) show the model has good validity. Therefore, we expect ASSESSOR forecasts to be good unbiased estimators of actual sales. Consequently, these forecasts should show the Survivor's Curse effect described by Theorem 1.

Although ASSESSOR forecasts are unbiased across all forecasts, the tested forecasts should have an expected positive bias. Table 3 compares shares forecasted by ASSESSOR with the actual post-launch shares for our entire data set, i.e., 44 new products.

Table 4 summarizes the forecasts in Table 3. As with any good forecasting model, the number of optimistic forecasts (68.2%) exceeds the number of pessimistic forecasts (31.8%). A paired sample T-test on the forecasts versus the actual produced a t-statistic that is significant at the 0.05 level. Hence, the ASSESSOR model's forecasts contain the Survivor's Curse effect just as any unbiased forecasting model should.
TABLE 3  
Actual Forecasts and Errors

<table>
<thead>
<tr>
<th>Case</th>
<th>Forecast</th>
<th>Actual</th>
<th>Error</th>
<th>Case</th>
<th>Forecast</th>
<th>Actual</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>26</td>
<td>17.00</td>
<td>22.00</td>
<td>-5.00</td>
<td>21</td>
<td>1.10</td>
<td>0.60</td>
<td>+0.50</td>
</tr>
<tr>
<td>31</td>
<td>13.40</td>
<td>17.20</td>
<td>-3.80</td>
<td>40</td>
<td>7.50</td>
<td>7.00</td>
<td>+0.50</td>
</tr>
<tr>
<td>32</td>
<td>9.30</td>
<td>12.50</td>
<td>-3.20</td>
<td>35</td>
<td>9.00</td>
<td>8.40</td>
<td>+0.60</td>
</tr>
<tr>
<td>39</td>
<td>14.40</td>
<td>17.00</td>
<td>-2.60</td>
<td>4</td>
<td>24.20</td>
<td>23.50</td>
<td>+0.70</td>
</tr>
<tr>
<td>15</td>
<td>0.80</td>
<td>2.50</td>
<td>-1.70</td>
<td>7</td>
<td>3.00</td>
<td>3.00</td>
<td>+0.80</td>
</tr>
<tr>
<td>16</td>
<td>27.10</td>
<td>28.50</td>
<td>-1.40</td>
<td>18</td>
<td>1.23</td>
<td>0.30</td>
<td>+0.93</td>
</tr>
<tr>
<td>12</td>
<td>9.60</td>
<td>10.50</td>
<td>-0.90</td>
<td>19</td>
<td>3.00</td>
<td>2.00</td>
<td>+1.00</td>
</tr>
<tr>
<td>34</td>
<td>10.90</td>
<td>11.50</td>
<td>-0.60</td>
<td>38</td>
<td>4.90</td>
<td>3.80</td>
<td>+1.10</td>
</tr>
<tr>
<td>6</td>
<td>12.60</td>
<td>13.00</td>
<td>-0.40</td>
<td>10</td>
<td>8.40</td>
<td>7.20</td>
<td>+1.20</td>
</tr>
<tr>
<td>30</td>
<td>12.20</td>
<td>12.50</td>
<td>-0.30</td>
<td>36</td>
<td>9.60</td>
<td>8.20</td>
<td>+1.40</td>
</tr>
<tr>
<td>13*</td>
<td>3.00</td>
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<td>6.00</td>
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<td>+1.80</td>
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<td>5.00</td>
<td>-0.10</td>
<td>8</td>
<td>8.40</td>
<td>6.30</td>
<td>+2.10</td>
</tr>
<tr>
<td>33</td>
<td>1.80</td>
<td>1.90</td>
<td>-0.10</td>
<td>28</td>
<td>12.10</td>
<td>9.70</td>
<td>+2.40</td>
</tr>
<tr>
<td>44</td>
<td>0.25</td>
<td>0.13</td>
<td>+0.12</td>
<td>17</td>
<td>13.50</td>
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<td>+2.70</td>
</tr>
<tr>
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<td>2.70</td>
<td>+0.20</td>
<td>14</td>
<td>13.30</td>
<td>10.40</td>
<td>+2.90</td>
</tr>
<tr>
<td>27</td>
<td>7.80</td>
<td>7.60</td>
<td>+0.20</td>
<td>11</td>
<td>5.20</td>
<td>1.60</td>
<td>+3.60</td>
</tr>
<tr>
<td>42</td>
<td>0.43</td>
<td>0.20</td>
<td>+0.23</td>
<td>9</td>
<td>16.50</td>
<td>12.90</td>
<td>+3.60</td>
</tr>
<tr>
<td>29</td>
<td>5.40</td>
<td>5.10</td>
<td>+0.30</td>
<td>5</td>
<td>4.40</td>
<td>0.60</td>
<td>+3.80</td>
</tr>
<tr>
<td>43</td>
<td>0.63</td>
<td>0.28</td>
<td>+0.35</td>
<td>24</td>
<td>8.00</td>
<td>4.20</td>
<td>+3.80</td>
</tr>
<tr>
<td>23</td>
<td>2.60</td>
<td>2.20</td>
<td>+0.40</td>
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<td>3.30</td>
<td>+3.90</td>
</tr>
<tr>
<td>41</td>
<td>0.80</td>
<td>0.30</td>
<td>+0.50</td>
<td>37</td>
<td>5.60</td>
<td>1.50</td>
<td>+4.10</td>
</tr>
</tbody>
</table>

These results agree with past research (Tull 1967). Tull and Rutemiller (1968) compare 41 forecasts with actual new product sales finding that “forecasts of the sales level for new products tend to be biased in an optimistic direction.” Baldinger (1988) inspects 589 new product forecasts, finding only 8% pessimistic and 41% optimistic. Hence, 83.7% of the inaccurate forecasts were higher than actual sales.

7.2 Experimental Analysis

Ethical and data-collection problems prevent testing Prophet’s Fear in actual new product launches. Prophet’s Fear, however, should occur in other forecasting contexts beyond new product launching. So, to demonstrate Prophet’s Fear, we ran an experiment using 200 students at a major midwestern university.

TABLE 4  
Test of Survivor’s Curse

<table>
<thead>
<tr>
<th>ASSESSOR Model Survivor’s Curse</th>
<th>Optimistic (share &gt; actual)</th>
<th>Pessimistic (share &lt; actual)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number</td>
<td>30</td>
<td>14</td>
</tr>
<tr>
<td>Percent</td>
<td>68.2%</td>
<td>31.8</td>
</tr>
<tr>
<td>Total Error</td>
<td>47.3</td>
<td>-20.5</td>
</tr>
</tbody>
</table>

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TABLE 5

| Prediction of the Number of Pennies in a Jar: Statistics for Forecasts over 400 (Actual number = 421) |
|-------------------------------------------------|-----------------|-----------------|
|                                                  | Control         | Experimental    |
| Mean forecast                                   | 568.308         | 455.263         |
| Mean error                                      | 147.308         | 34.263          |
| Squared error                                   | 48,538.846      | 4,246.053       |
| $T$-Statistic                                   | 3.115           | 2.623           |
| $p$-value (2 tail)                              | 0.009           | 0.017           |

After dividing the students into two groups (i.e., control and experimental), we gave them a forecasting task. Students, in both groups, got 5 seconds to estimate (forecast) the number of pennies in a jar. There were 421 pennies in the jar.

Students lacked the opportunity to hold the pennies or to count the 421 pennies in the jar. We told the first group (our control group) that we would count the pennies in the jar. Students, who make forecasts within 25 pennies of the actual number receive $2. Other students receive nothing. We expected students in this group to provide unbiased forecasts, $\beta = 0$, of the number of pennies because their forecasts are always tested (i.e., noninfluential).

We told the second group (our experimental group) that when their forecast was over 400 pennies, a forecast within 25 pennies of the actual number receives $2 while other forecasts receive nothing. Students with forecasts of 400 or less automatically receive $1, whatever the actual number of pennies in the jar. Hence, the experimental group’s forecasts were only tested when the forecasts were over 400 pennies (i.e., influential forecasts).

This task creates conditions required for Prophet’s Fear. The task is conceptually similar to forecasting new product sales. Each student, with similar data, forecasts a total figure.

We do not know $\beta$, so we cannot directly test Theorems 3 and 4. However, we do know $\mu$, so we can directly test Corollary 1. The control group is noninfluential, and the experimental group is influential. Corollary 1 predicts that only those students who are confident about their forecast seek validation of their forecasts. If confidence implies more accuracy (which we implicitly test), then Prophet’s Fear implies that students who seek validation have more accuracy than students who are forced into validation. Students in the experimental group, who were uncertain about the number, could predict 400 (or less) to avoid testing their forecasts. As Corollary 1 predicts, the experimental group forecasts (over 400) should be more accurate than control group forecasts (over 400).

Table 5 compares the two groups’ forecasts (over 400 pennies). See Table 5.

Prophet’s Fear (i.e., Corollary 1) implies more accuracy from those students in the experimental group who sought validation and subsequently forecasted over 400 pennies in the jar. Hence, we expect tested forecasts (i.e., >400) to be more accurate for the experimental group than the control group. Table 5 confirms this expectation. The mean square error of the experimental group (i.e., 4,246.053) is much smaller than the mean squared error of the control group (i.e., 48,538.846). Moreover, the experimental group’s mean error (i.e., 34.263) is 113.045 less than the control group’s mean error (i.e., 147.308). This difference is significant at the 0.011 level.

1 We ran the experiment varying various parts (e.g., a plastic bag vs. a jar, 5 seconds vs. 10 seconds) and found similar results.
Although this experiment supports the Prophet's Fear effect, anchoring on 400 could also cause these results. Therefore, we replicated the experiment without providing any numbers.

This time we used two jars of pennies. Jar one had 230 pennies and Jar two had 210 pennies. We asked participants to estimate the difference in pennies between the two jars. We told the control group that if their estimate (forecast) of the difference is within 25% (25–15), they will receive $2.00. Otherwise, they receive nothing. We told the experimental group that their reward depends on which jar had more pennies. If they estimate the first jar has more pennies, they will receive $3.00 only when their estimate is within 25% of the true difference. Otherwise, they receive nothing. However, if they estimate the second jar has more pennies, they will receive $1.00 regardless of accuracy.

This is similar to the new product gamble and estimating the size of the potential market. A not-to-launch decision removes the risk associated with the forecast. The control group represents estimation without influence on the launch. The experimental group had an incentive to avoid observation and possible refutation when they were uncertain about the true difference. There was a guaranteed payoff of $1.00. Prophet's Fear (Corollary 1) suggests that the experimental group is more likely to estimate a lower difference than the control group.

The results support the existence of Prophet's Fear. A chi-square, using three categories of estimation (Below 15; 15–25; above 25) showed a dependency between control and experimental groups. Chi square is 10.8. Significance is 99.55%. In addition, we used an ANOVA to measure the effect of group on the estimates. The F value is 14.88 and the significance is 0.009. See Table 6. These data strongly support the existence of Prophet's Fear.

Note that most potential confounds with the student population, (e.g., inability to judge accuracy, lack of motivation, lack of understanding the task, different expertise) all work against confirmation of our model. Therefore, these factors all tend to cause statistically insignificant results though we found statistically significant results.

As a limitation, our experiment does not consider the ethical problems facing actual market forecasters.

7.3 Presidential Endorsements

Every four years, we have Presidential elections, and newspapers endorse their favorite candidate. We could interpret an endorsement as a forecast that the endorsed candidate will succeed in office. We could also interpret an endorsement as a forecast that the endorsed candidate will win the election.

For several reasons, we might expect newspapers to endorse the candidate that later wins the election. First, doing so enhances the newspaper's credibility. Second, newspapers

| TABLE 6 |
| Replication of Experiment |
| Prediction of the Difference in the Number of Pennies in 2 Jars Statistics for Forecasted Differences (Actual number = 210 and 230) |
| Control | Experimental |
| Mean | 19.017 | 2.770 |
| Median | 20.000 | 7.000 |
| Standard Error | 3.139 | 2.818 |
| Chi-Square (<15; 15–25; >25) | 10.8 |
| p-value (2 tail) | .0001 |

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like to please their readers and endorsing their reader’s choice sells papers. Third, when newspapers can influence the outcome of the race, endorsement may help the candidate to win. Fourth, post-election, supporters of winners sometimes enjoy more political clout than supporters of the losers.

Polls abound directly before elections. Except for the ’48 race, Dewey vs Truman, it is easy to predict the outcome of a race. Newspapers, therefore, are usually able to predict the winner. Newspapers should be able to almost completely avoid endorsement of losers.

Using the *Ready Reckoner* from Editor and Publisher, we find that in the 50 years 1940–1990, the number of papers picking the winner is only 57%. One would expect the percentage to be much higher. We might wonder why newspapers pick the loser at a ratio of 2:3 rather than a ratio like 1:10. See Table 7.

One possible explanation is that newspapers view endorsements as a means to express their political views, and not a reflection of the outcome of the election. The question remains why newspapers often endorse the losing candidate. It appears that the political views of many newspapers are inconsistent with their readers.

There is another explanation. Endorsing a winner has its dangers. If the politician becomes a very popular individual and assists in the passage of very helpful and constructive legislation, then the endorsement is positive. However, if the politician becomes unproductive, or becomes involved in moral or political scandals, the endorsement can be problematic for the newspaper. Hence, it is safer to endorse the loser. This is the Prophet’s Fear effect.

Prophet’s Fear provides an advantage to endorsing the underdog. Endorsing an underdog lowers the risk of forecast refutation. Of course, other explanations are possible.

### 7.4 In-depth Interviews

A client, who is aware of Prophet’s Fear, will expect pessimistic forecasts and may encourage more optimism from the forecaster. Of course, Prophet’s Fear is undetectable, in our basic model, because all tested forecasts are unbiased and appear optimistic. Still, several factors suggest that some clients may be aware of Prophet’s Fear. First, occasionally launching an expected failure may reveal a bias (our extended model). Second, clients themselves are sometimes in the role of forecasting and are subject to Prophet’s Fear. Finally, clients may understand Equation (10).

#### TABLE 7

<table>
<thead>
<tr>
<th>Year</th>
<th>Winning Candidate</th>
<th>Losing Candidate</th>
<th>Percent of Newspapers Who Endorse the Winner</th>
</tr>
</thead>
<tbody>
<tr>
<td>1944</td>
<td>277</td>
<td>794</td>
<td>.26</td>
</tr>
<tr>
<td>1948</td>
<td>182</td>
<td>771</td>
<td>.19</td>
</tr>
<tr>
<td>1952</td>
<td>930</td>
<td>200</td>
<td>.82</td>
</tr>
<tr>
<td>1956</td>
<td>740</td>
<td>181</td>
<td>.80</td>
</tr>
<tr>
<td>1960</td>
<td>208</td>
<td>731</td>
<td>.22</td>
</tr>
<tr>
<td>1964</td>
<td>440</td>
<td>351</td>
<td>.56</td>
</tr>
<tr>
<td>1968</td>
<td>620</td>
<td>146</td>
<td>.81</td>
</tr>
<tr>
<td>1972</td>
<td>443</td>
<td>126</td>
<td>.78</td>
</tr>
<tr>
<td>1976</td>
<td>753</td>
<td>55</td>
<td>.93</td>
</tr>
<tr>
<td>1980</td>
<td>80</td>
<td>411</td>
<td>.16</td>
</tr>
<tr>
<td>1984</td>
<td>381</td>
<td>62</td>
<td>.86</td>
</tr>
<tr>
<td>1988</td>
<td>195</td>
<td>51</td>
<td>.79</td>
</tr>
<tr>
<td>1992</td>
<td>121</td>
<td>150</td>
<td>.45</td>
</tr>
<tr>
<td>Total</td>
<td>5370</td>
<td>4029</td>
<td>Mean .57</td>
</tr>
</tbody>
</table>
TABLE 8
Quotes from Market Forecasters

"New clients perceive forecasts as giving bad news!"
"If you give a low forecast, your client will go to other sources"
"Brand managers claim [forecasts] are a hindrance."
"When you forecast what the client doesn’t want, the forecast is never validated."
"[Clients] overreact to results."
"There is extreme self-interest in validation."
"Clients decide what you die or die based on the first [forecast]."
"There is lots of pressure to say it’s a good idea."
"There is tremendous pressure to be positive."
"Market research department always sees red light. Sales department always sees green light."

We did in-depth interviews with 15 market forecasters for different size market research firms. This exploratory research suggests that clients regard forecasters as pessimistic. Clients also exert pressure for optimism.\textsuperscript{8} Table 8 provides some representative quotes from our interviews.

Conflicting pressures create ethical and practical problems for market forecasters, particularly when repeat business becomes vital. Nevertheless, our interviews revealed that suppliers did not misrepresent their forecasts. Reputation and ethical concerns dominate.

8. Possible Solutions

We have no perfect solution. Obviously, clients can encourage optimism to avoid Prophet’s Fear, and forecasters can explain Survivor’s Curse. Our theory, however, suggests some directions for possible solutions.

First, Table 2 implies that decreasing $\lambda / \gamma$ can lessen Prophet’s Fear. Hence, the client should do more experimentation (Little 1976). The client needs to occasionally launch products despite unfavorable market research. This solution, however, can be very expensive and politically difficult to implement.

Second, Table 2 implies that decreasing $\sigma^2$ can lessen Prophet’s Fear. Hence, the client should buy more accurate forecasts. Spending more money to lower $\sigma^2$ may result in both more accuracy and less pressure to bias.

Finally, Table 2 implies that decreasing $\hat{c}$ can lessen Prophet’s Fear by making a launch more likely. Clients can announce a low $\hat{c}$, when it is credible to do so. Forecasters can sometimes make a launch more likely. Forecasts often are conditioned on a particular marketing mix (e.g., price, product features, required distribution). Hence, rather than forecasting failure at the planned price or planned features, we may be able to provide the client with an alternative price or alternative features that would make the product successful. Here, launching always occurs making forecasts unbiased.

Maybe when clients kill the messenger, it is better to tell a client how to get desired sales than to provide an accurate but disappointing sales forecast. Of course, this type of forecast is not always possible.

9. Conclusions

This paper considers a dilemma we face as influential forecasters (who influence forecast testing). Our client requests an unbiased forecast, but pressures sometimes exist to provide a bias forecast. Our goal was to identify these pressures. We began by formulating the profit functions of both the forecaster and the client. We derived conditions when

\textsuperscript{8} Another explanation is that these presumed forecasts are not forecasts. See the Future Research section.
forecaster incentives encourage unbiased forecasts. These conditions include: (1) observing all forecasted outcomes and (2) having a small error variance.

Survivor’s Curse and Prophet’s Fear create a pressure to bias forecasts. Survivor’s Curse causes otherwise unbiased forecasts to appear optimistic. Clients may misconstrue our forecasts. With Survivor’s Curse, truly unbiased forecasts appear optimistic because the bias for launched products is positive. A positive bias causes disappointing sales and makes forecasts look optimistic. Not only does Survivor’s Curse create an incentive to be conservative (i.e., pessimistic), it also hides an effect we call Prophet’s Fear.

Prophet’s Fear also encourages conservatism. Prophet’s Fear occurs when both the forecast is influential (i.e., helps determines whether the forecast is tested) and our confidence is low (i.e., variance $\sigma^2$ is large). Here, low forecasts decrease the likelihood of refutation because no launch occurs. With no launch, the sales forecast is never tested. When the forecast itself lessens the likelihood of evaluation and great uncertainty exists, pressure exists to avoid testing. Moreover, in the basic model, untested forecasts are pessimistic but tested forecasts remain unbiased.

We then empirically demonstrated both effects in a variety of situations. In summary, we found the following:

- When our loss function depends on squared error, observing all forecasted outcomes (noninfluential forecasting) creates no pressure to provide biased forecasts, whatever the loss function.
- As influence over testing increases, the pressure to bias increases.
- Survivor’s Curse causes unbiased forecasts to appear optimistic, overestimating actual sales (i.e., sales disappoint).
- High error variance causes Prophet’s Fear, encouraging pessimistic influential forecasts.
- Tested forecasts may appear completely unbiased despite a pessimistic pre-launch bias.
- When forecasts seem unbiased, either all products are launched or the forecaster has removed large variance forecasts by causing rejection of products with high variance forecasts.
- Pessimism is a serious problem because tested forecasts appear optimistic.
- Survivor’s Curse makes pessimistic forecasts difficult to detect.
- Perhaps firms should have some new product failures. A lack of new product failures may suggest a downward forecasting bias.
- Although no perfect solution exists, clients may lessen bias with experimentation and by seeking more accurate forecasts. Forecasters may lessen bias with forecasts conditioned on launching and by seeking more accurate forecasts.

Much research has identified high failure rates associated with new products, (e.g., Urban and Hauser 1980). Perhaps some failures are justified. Only future research can resolve this issue.

10. Future Research

This paper is a first attempt to model influential forecasting. Future research might consider additional issues. Other objective functions are possible. Rothenberg (1989), for example, notes that advertising agencies seek new product forecasting jobs though these jobs don’t “even pay out-of-pocket expenses.” “Agencies seek [these jobs] because, if a new product is brought to market, it can mean a full-scale ad campaign and a commission on the spending.” This situation differs dramatically from the situation in our paper.

Future research might allow decays in reputation. Untested forecasts might diminish reputation. Also, clients might evaluate untested forecasts using expectations about out-
comes. The degree of consistency between forecasts and client expectations might influence the client's evaluation of the forecaster.

Survivor's curse suggests that the strategy for providing multiple forecasts may differ from the strategy of supplying one forecast. It also suggests that making \( \hat{c} \) random would encourage bias forecasting. Future research might investigate this speculation.

Future research might consider the forecasting situation. We might only get forecasting jobs when the error variance is high (Bazerman 1983). This is possible if clients only purchase our forecasts when a great deal of uncertainty exists. Here, we are playing a losing game because our accurate forecasts are seldom validated.

Future research might consider the optimal amount of effort to spend on forecasting using a principal-agent model. Future research might also consider the effect of competition on forecasting and the value of reputation in a competitive environment.

Future research might make \( \lambda \) and \( \gamma \) functions of \( f \). We introduced \( \lambda \) and \( \gamma \) to lessen the influence of \( f \). It is, of course, possible that \( \lambda \) and \( \gamma \) are functions of \( f \). We suspect the result is a more influential forecast.

Finally, forecasts are not always forecasts. Sometimes, forecasts are just supporting confirmation.\(^9\) Keane (1969) notes forecaster complaints about clients' use of marketing research to merely "support a predetermined position." Lee, Acito, and Day (1987) find forecasts confirming managers' pre-launch beliefs are rated higher. Chicago's mayor hired a consultant, Donald Corina, to evaluate the demand for new airport sites and rank possible locations. After previewing the study results, the mayor was unhappy. The mayor first asked Corina not to report site rankings. Later he expressed a "desire to fire Corina and replace him with someone who might be more sympathetic to the city" (Elsner 1991). Future research might consider how these so-called forecasts or testimonial can endure when everyone knows that the number itself is bogus.\(^11\)

Acknowledgments. Authors listed alphabetically. We thank the faculty at the University of Chicago, University of Alberta, Stanford University and University of Florida, particularly Kalpan Raman, for their many helpful comments. We also sincerely thank Glen Urban and Information Resources Incorporated for use of the data contained in this paper.

\(^9\) Piercy (1982) notes that "marketing information is used as a political resource in the struggle for organizational power."

\(^10\) In an editorial for the Journal of Marketing Research, David Hardin (1969) says that "some large companies today readily admit to selecting test markets on the basis of strong local sales efforts or a strong broker—hardly an objective decision input."

\(^11\) This paper was received April 6, 1992, and has been with the authors 4 months for 3 revisions. Processed by Scott Neslin.

Appendix A

Assume the client's prior (pre-forecast) distribution, for the new product's sales, is normally distributed with mean \( \mu_c \) and variance \( \sigma^2_c \). The client gets our forecast \( f \). The client believes that \( f \) is normally distributed with variance \( \sigma^2_f \) that may or may not equal \( \sigma^2_c \). The client updates and obtains posterior distribution \( \tilde{S}_f \). DeGroot 1970 (p. 167) shows that \( E[\tilde{S}_f] = (\sigma_c^2 + \sigma_f^2)/(\sigma_f^2 + \sigma_c^2) \cdot E[S_c] \). Substituting this expression into \( E[\tilde{S}_f] > F/m \) implies \( f > (F \cdot \sigma_f^2 + F \cdot \sigma_c^2 - m \cdot \sigma_c^2)/((m \cdot \sigma_f^2 + m \cdot \sigma_c^2)) \) or \( f > (F/m) + k \) where \( k = (F - m \cdot \sigma_c^2)/(m \cdot \sigma_f^2 + m \cdot \sigma_c^2) \).

Appendix B

PROOF OF THEOREM 1. Let \( \bar{f} \) be the average forecast for products not launched. Since \( \bar{f} \) is the average of independent normal variables, \( \bar{f} \) is normal with mean \( \mu \) and variance \( \sigma^2 \). According to David (1957), \( E[f_0 | f > f_0] = \mu - (\sigma/\sqrt{2}) \). But \( E[f_0 + f_1 | f_1 > f_0] = \mu \), so \( E[f_1 | f_1 > f_0] = \mu + (\sigma/\sqrt{2}) > \mu \). Finally, \( f_0 \) is a convex combination of \( f_1 \) and \( f_0 \), so \( f_0 > f_0 \) requires \( f_1 > f_0 \).

PROOF OF LEMMA 1. Remember that \( d \) is normally distributed with mean 0 and variance \( \sigma^2 \). Also, \( \tau^2 = (f - \mu)^2 \) and \( f = \mu + \tau + \beta \), so \( \tau^2 = (\beta + \tau)^2 \). It follows that:

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\[ E[L(z^2)] = \int_{-\infty}^{\infty} L((x+\beta)^2) \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{(x+\beta)^2}{2\sigma^2}} dx. \]

Taking the derivative with respect to \( \beta \), yields:

\[ \frac{d}{d\beta} E[L(z^2)] = 2 \int_{-\infty}^{\infty} (\beta + \mu) L((x+\beta)^2) \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{(x+\beta)^2}{2\sigma^2}} dx. \]

Letting \( \beta = 0 \) yields:

\[ 2 \int_{-\infty}^{\infty} N(x) dx \quad \text{where:} \quad N(x) = \int_{-\infty}^{x} e^{-\frac{\eta}{2 \sigma^2}} d\eta. \]

The last expression must equal zero for \( \beta = 0 \) to be a minimum. Now, \( L(z^2) > 0 \) for all \( z \). Hence, \( N(-i) = -N(i) \) because:

\[ L'((-\mu)^2) \frac{\eta}{\sqrt{2\pi} \sigma} e^{-\frac{\eta}{2 \sigma^2}} = -L'((\mu)^2) \frac{\eta}{\sqrt{2\pi} \sigma} e^{-\frac{\eta}{2 \sigma^2}}. \]

Then, \( N(i) \) is an odd function which implies:

\[ \int_{-\infty}^{\infty} N(x) dx = 0. \]

The last expression is the required 1st order condition. Hence, \( \beta = 0 \) satisfies the 1st order condition for a minimum. For the 2nd order condition, the second derivative, evaluated at \( \beta = 0 \), is:

\[ 2 \int_{-\infty}^{\infty} L^2(x^2) \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{x^2}{2\sigma^2}} dx + 4 \int_{-\infty}^{\infty} x^2 L^2(x^2) \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{x^2}{2\sigma^2}} dx. \]

Here, the first term is always positive because \( L'[\cdot] > 0 \). The second term is always nonnegative because \( L'[\cdot] \geq 0 \). Therefore, the entire expression is positive, meeting the 2nd-order condition.

**Proof of Theorem 2.** Our expected profits approach \((1 + b)p_i + b[R - E[L(i^2)]].\) From Lemma 1, they are maximized at \( \beta = 0 \).

**Proof of Theorem 3.**

\[ \sigma_i^2 = \int_{-\infty}^{\infty} L(x^2) \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{x^2}{2\sigma^2}} dx. \]

When \( \sigma_i^2 \geq R \), then \((1 + b)p_i + b[R - \sigma_i^2] < (1 + b)p_i \) and the expected profit from a launch is less than the profit from no launch. [Note by Lemma 1, no forecast exists with variance less than \( \sigma_i^2 \), so a no launch is always more profitable.] When \( i \neq \tilde{c} \), \( f^* = \hat{i} \) causes no launch. When \( i = \tilde{c} \), \( f^* = \hat{c} \) causes no launch. Later we impose conditions making \( f^* = \hat{c} \) best.

**Proof of Theorem 4 (Part 1).** We must show the optimal forecast is \( f \) when \( \sigma_i^2 \leq R \) and condition 1 is violated, i.e., \( \sigma_i^2 \leq R \) and \( \sigma_i^2 \). Suppose \( \sigma_i^2 \leq R \), then \((1 + b)p_i + b[R - \sigma_i^2] \leq (1 + b)p_i \) and, from Lemma 1, the optimal forecast is \( f^* = \hat{f} \) and expected profits \( \geq (1 + b)p_i \). Suppose \( \sigma_i^2 < R \), then \((1 + b)p_i + b[R - \sigma_i^2] \leq (1 + b)p_i \) and forecasting \( f^* = \hat{f} \) with \( \sigma_i^2 \leq R \) provides profits of \((1 + b)p_i \).

**Proof of Theorem 4 (Part 2).**

Let \( \sigma_i^2 = \int_{-\infty}^{\infty} L((x - \mu)^2) \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{(x - \mu)^2}{2\sigma^2}} dx. \]

With \( E[L((x - \mu)^2)] < R \), there exists some sufficiently small positive \( \xi \) such that \( E[L((x + \xi - \mu)^2)] < R \). At this \( \xi \), \((1 + b)p_i + b[R - E[L((x + \xi - \mu)^2)]]) > (1 + b)p_i \). Hence, profits at \( f = \xi \) + \( \xi \) are greater than profits for all \( f \leq \xi \) including \( f = \hat{f} \). We now examine \( f > \xi \).

By Lemma 1, \( f = \xi \) maximizes \((1 + b)p_i + b[R - E[L((x - \mu)^2)] which is strictly decreasing in \( f \) for \( f > \xi \). Now, \( f \leq \xi \) so \( [R - E[L((x + \xi - \mu)^2)] \) is strictly decreasing in \( \xi \) for \( \xi > 0 \). Hence, profits at \( f = \xi + \xi \) are greater than profits for all \( f > \xi + \xi \).

But for any \( \xi > 0 \) there exists a smaller \( f > 0 \) producing greater profits because \([R - E[L((x + \xi - \mu)^2)] \) is strictly decreasing in \( \xi \). When \( \xi = 0 \), however, profits are \((1 + b)p_i \) and less than \( \xi > 0 \). Ergo, no solution for \( f \) exists.

**Proof of Corollary 1.** Let \( f^* \) be the optimal influential forecast testing requires \( f^* > \xi \). Let \( f^{**} \) be the optimal noninfluential forecast (i.e., testing always occurs). Note that Theorem 2 implies \( f^{**} = \hat{f} \). Also, note Theorems 3 and 4 imply that the average error variance for \( f^* \) is less than or equal to \( R \). We have four cases.

**Case 1.** \( f^* > \xi \) and \( f^{**} > \xi \). Here, \( f^* = \hat{f} \) (Theorem 3). Both forecasts have the same error variance.
Case 2. $F^* > \epsilon$ and $F^{**} > \epsilon$. Here, $f > \epsilon$ because $F^{**} > \epsilon$. Theorem 3 implies $\epsilon^2 > R$. So, the error variance for $F^{**} > \epsilon$ is greater than $R$. This event raises the average error variance for $F^{**}$ above $F^*$ because the average error variance for $F^* \leq R$.

Case 3. $F^* = \epsilon$ and $F^{**} \leq \epsilon$. Both forecasts are less than $\epsilon$, so the former forecast enters the average.

Case 4. $F^* > \epsilon$ and $F^{**} \leq \epsilon$. Here, $F^{**}$ does not enter the average. Theorem 4 implies this case only occurs when $F^* = \epsilon + \epsilon$. Only using forecasts sufficiently greater than $\epsilon$ ensures that $F^*$ does not enter the average.

Proof of Corollary 2. There are only two bias solutions in Table 2: When $\lambda = \gamma$, solution one requires both $\epsilon^2 > R$ and $(R - \epsilon^2)/(R - \epsilon^2) < 1$. Now, $\epsilon^2 > R$ implies $(R - \epsilon^2)/(R - \epsilon^2) < 1$. Therefore, solution one is not possible.

When $\lambda = \gamma$, solution two requires both $\epsilon^2 < R$ and $(R - \epsilon^2)/(R - \epsilon^2) > 1$. Now, $\epsilon^2 < R$ implies $(R - \epsilon^2)/(R - \epsilon^2) > 1$. Therefore, solution two is not possible. Only unbiased solutions remain.

Proof of Theorem 5 for $\epsilon > \epsilon$. There are two cases, $\epsilon^2 < R$ and $\epsilon^2 > R$.

Case 1. ($\epsilon^2 < R$). From Lemma 1, we know $\epsilon^2 < \epsilon^2$ for any $x$. Hence, profits at $f = \epsilon^2$ exceed $f = x$ for all $x < \epsilon^2$ because $\lambda(R - \epsilon^2) > \lambda(R - \epsilon^2)$. So consider $x < \epsilon$. Again, $R - \epsilon^2 > R - \epsilon^2$. Now when $\epsilon^2 < R$ then $\lambda(R - \epsilon^2) > \lambda(R - \epsilon^2)$ because $\lambda > \gamma$. Hence, profits at $f = \epsilon^2$ exceed $f = x$ for all $x < \epsilon$. Hence, $F^* = \epsilon$ for this case.

Case 2. ($\epsilon^2 > R$). We know $\epsilon^2$ is decreasing in $x$ for $x < \epsilon$. Hence, profits at $f = \epsilon^2$ exceed $f = x$ for all $x < \epsilon$ because $\lambda(R - \epsilon^2) > \lambda(R - \epsilon^2)$. So consider $x > \epsilon$. From Lemma 1, we know $\epsilon^2 < \epsilon^2$ for any $x$. Hence, profits at $f = \epsilon^2$ exceed $f = x$ for all $x > \epsilon$ because $\lambda(R - \epsilon^2) > \lambda(R - \epsilon^2)$. It follows that $F^* = \epsilon$ when $\gamma(R - \epsilon^2) > \gamma(R - \epsilon^2)$ and $F^* = \epsilon$ when $\gamma(R - \epsilon^2) > \gamma(R - \epsilon^2)$.

Proof of Theorem 5 for $\epsilon > \epsilon$. There are two cases, $\epsilon^2 < R$ and $\epsilon^2 > R$.

Case 1. ($\epsilon^2 < R$). From Lemma 1, we know $\epsilon^2 < \epsilon^2$ for any $x$. Hence, profits at $f = \epsilon^2$ exceed $f = x$ for all $x < \epsilon$ because $\lambda(R - \epsilon^2) > \lambda(R - \epsilon^2)$. So consider $x > \epsilon$. Suppose, $\lambda(R - \epsilon^2) > \lambda(R - \epsilon^2)$. Then there exists some sufficiently small positive $\epsilon$ such that for $x = \epsilon + \epsilon$, $\lambda(R - \epsilon^2) > \lambda(R - \epsilon^2)$. Profits at $f = x$, $x = \epsilon + \epsilon$, are $\lambda(R - \epsilon^2)$. We know $\epsilon^2$ is decreasing in $x$ for $x > \epsilon$. Hence, profits at $f = \epsilon + \epsilon$ are greater than profits at $f = \epsilon + \epsilon$ and profits at $f = x$ because $\lambda(R - \epsilon^2) > \lambda(R - \epsilon^2)$. Hence, the conditions $\epsilon < \epsilon$, $\epsilon^2 < R$ and $\lambda(R - \epsilon^2) > \lambda(R - \epsilon^2)$ cause $F^* = \epsilon + \epsilon$. But for any $\epsilon > 0$ there exists a smaller $\epsilon > 0$ providing greater profits because $[R - E[L(I(x + \epsilon + \epsilon^2)])]$ is strictly decreasing in $\epsilon$. When $\epsilon = 0$, however, profits are $\gamma(R - \epsilon^2)$ and less than $\epsilon > 0$. Ergo, no solution for $F^*$ exists.

Case 2. ($\epsilon^2 > R$). From Lemma 1, we know $\epsilon^2 < \epsilon^2$ for any $x$. Hence, profits at $f = \epsilon^2$ exceed $f = x$ for all $x < \epsilon$ because $\lambda(R - \epsilon^2) > \lambda(R - \epsilon^2)$. So consider $x > \epsilon$. Again, $\epsilon^2 > R - \epsilon^2$. Now when $\epsilon^2 > R$ then $\gamma(R - \epsilon^2) > \gamma(R - \epsilon^2)$ because $\lambda > \gamma$. Hence, profits at $f = \epsilon^2$ exceed $f = x$ for all $x > \epsilon$. Hence, $F^* = \epsilon$ for this case. Row 2 follows.

References


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The Forecaster's Dilemma

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KEYWORDS: Forecasting, New Product Research, Channel Relationships, Bias, Brand Management. MS 92 055R3.

SHORT ABSTRACT: Optimal influential forecasts are usually pessimistic, but they often appear optimistic.

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Abstract

Influential forecasts occur when the forecast itself determines whether the forecast is tested. New product sales forecasts are often influential because a low forecast may cause a firm not to launch a new product so that actual sales are never observed.

This paper considers a dilemma we face as influential forecasters. Our client requests an unbiased forecast but pressures sometimes exist to provide a bias forecast. From theoretical and empirical perspectives, we discuss the impact of these pressures on the quality of forecasts. We find that:

- Non-influential forecasts, generally, create no pressure for statistically biased forecasts.
- As influence increases, the pressures increase.
- When our forecasts eliminate alternatives, (e.g., product designs, advertising campaigns), not all forecasts are tested.
- Not validating all forecasts causes two effects: Survivor's Curse and Prophet's Fear.
- Survivor's Curse makes statistically unbiased forecasts appear optimistic (i.e., overestimate actual sales) because, often, only optimistic forecasts are tested.
- Forecasts appearing statistically unbiased or pessimistic might cause concern. Perhaps, some failures are justified.
- Prophet's Fear encourages pessimistic forecasts because these forecasts cause hidden opportunity losses while optimistic forecasts cause observable actual losses.
- Tested forecast may appear completely unbiased despite a pessimistic pre-launch bias.
- Although no perfect solution exists, clients may lessen bias with experimentation and by seeking more accurate forecasts. Forecasters may lessen bias with forecasts conditioned on launching and by seeking more accurate forecasts.

KEYWORDS: Forecasting, New Product Research, Channel Relationships, Bias, Brand Management. MS 92 055R3.
1. Introduction

"Every decision is based on a forecast" (Green and Tull 1978). Decision-makers, in marketing, use forecasts to select actions. These forecasts influence actions taken and, subsequently, the nature of forecast testing. We call this influential forecasting. We, for example, may forecast outcomes for two advertising campaigns. Influenced by the forecast, our client selects one campaign. Here, we only test our forecast for the selected campaign. We never observe the latent sales generated by the rejected campaign.

Although market research forecasts are often influential, many forecasts are not. Economic forecasts, for example, seldom influence evaluation. Consider forecasts of next month's exports, GNP or unemployment rates. Here, we observe forecasted outcomes whatever the forecast. In contrast, influential forecasts can affect observed outcomes.

Forecasting new product sales is one important class of influential forecasts. Urban and Hauser (1980) explain how these forecasts determine whether to launch a new product. Holbert (1974) finds, "in terms of usefulness", no other forecast even approached new product forecasting "as the cornerstone of the research effort in the view of the marketing manager."

After obtaining a new product forecast, we can end the project, gather additional information or launch the new product. Baldinger (1988) finds ending the project is the most common result. He also finds that heavy users of new product forecasting models primarily use these models to eliminate potential failures. Therefore, forecasts can easily kill a new product.

Sometimes forecasts encourage launching (Cafarelli 1980). Beecham Group filed a $24 million suit against market-research giant Yankelovich because of over-optimistic forecasts given by the research company's Litmus forecasting model in 1985 related to its introduction of Delicare cold water wash (Alter 1987). Beecham needed 30% of the market to recoup its total investment. "Beecham claims it went ahead with Delicare's 1986 introduction only because the research it bought showed the delicate fabric detergent could outsell American Home Products Corp.'s Woolite" (Dagnoli 1987).

As expected, much research tries to improve the accuracy of new product forecasts (Eliashberg and Shugan 1994, Elrod 1988, Hauser and Koppelman 1979, Shugan 1987, Wind and Spitz 1976). For simplicity, these studies, and statisticians such as DeGroot (1970) and Winkler (1972), assume that decision-makers collect information and make new product decisions. Clemen (1987) and others, however, distinguish between forecasters and decision-makers. Boyd and Brit (1965) observe this distinction is routine in practice. Small and Rosenberg (1975) note that forecasters are often external consultants or in different departments than decision-makers. Kean (1969) observes that researchers crave decision-making involvement. Stout (1981) even suggests the market researchers "must make it clear that the decision-making responsibility lies with the line management."

Clients have information that forecasters do not. Clients have strategic objectives (e.g., Bergen, Dutta and Shugan 1993), production considerations, political constraints and competitive pressure that correctly or incorrectly influence their decisions. Therefore, clients seldom delegate decision-making to us.

This paper shows that the separation of forecasting and decision-making creates a dilemma for the forecaster. Our client requests an unbiased forecast but sometimes creates pressures to provide a bias forecast. From theoretical and empirical perspectives, we discuss
the impact of these pressures on the quality of the forecasts. Indeed, the forecaster and client are a channel of distribution that faces coordination problems (Jeuland and Shugan 1983).

This paper shows that some pressures encourage conservative (pessimistic) forecasts while others encourage high (optimistic) forecasts. In both cases, the pressures increase as forecasts become more influential (Ehrman and Shugan 1988).

Many analysts think the Beecham-Yankelovich suit pressures researchers to adopt defensive measures and become more cautious. Many wonder whether forecasts will be simply based "on play-it-safe, suit-proof conclusions." Legal damages usually occur only when forecasts over-estimate actual sales (Editorial 1987).

Past research already recognizes the existence of statistical bias in forecasting, (e.g., Wheelwright, S.C. and S. Makridakis 1972). Tyebjee (1987), for example, identifies three sources of bias in new product forecasting. Lowe and Shaw (1968), after studying sales managers, conclude "it seems clear that managers were prepared to bias their sales forecasts to suit their own interests as rational economic individuals."

This paper's goal is to continue this research. We show parametric conditions when a pressure to bias exists. We identify the problems and pressures we face. We find the direction of the net bias created by competing pressures. We also examine the impact on our forecasts. We determine that as forecasts become more influential, the pressure to provide some pessimistic forecasts increases.

We derive a result we call Survivor's Curse. Survivor's Curse causes our otherwise statistically unbiased forecasts\(^1\) to appear optimistic. Therefore, actual sales usually disappoint. With Survivor's Curse, truly unbiased forecasts appear optimistic and the appearance of objectivity may conceal true pessimism. Survivor's Curse may cause conservatism.

We show that statistically unbiased forecasts should appear optimistic because some forecasts remain untested. Tested forecasts should, on average, overstate expected sales. Perhaps, on average, firms should have some new product failures. A lack of new product failures may suggest a downward forecasting bias.

We also show that strong pressures exist to sometimes provide conservative (pessimistic) forecasts though loss functions are symmetric. For example, when forecasting the outcome of multiple alternatives, forecast-variances may differ across alternatives. Here, we seek to encourage validation of low-variance forecasts. We seek to discourage testing high-variance forecasts. In the new product setting, testing is less likely for pessimistic forecasts because these forecasts discourage launching the new product. We also show, when testing occurs, tested forecasts are generally unbiased.

We call this effect Prophet's Fear. Prophet's Fear can occur when the forecast influences observation. For example, suppose an account executive wants a sales forecast for two mutually exclusive advertising campaigns. The first campaign is traditional while the second campaign is extremely innovative. Although our market research suggests the second campaign may be somewhat superior, this research is equivocal. We expect the first campaign forecast to be more accurate and seek testing of it. The account executive, fully aware of potential forecast error, may still choose to consider only the expected outcome,\(^2\)

\(^1\) A statistically unbiased forecast is a forecast whose expected error is zero for finite samples.
adopt the second campaign, and test our less-accurate forecast.

Given a desire for accurate forecasts, decision theory suggests imposing a certainty equivalent and adjusting the second forecast to reflect extreme uncertainty. Consequently, we adjust the second forecast to make it pessimistic. This is Prophet's Fear, fear of high-variance forecasts. However, if the account executive is risk-seeking our adjustment is inappropriate.

Prophet's Fear is easy to understand. Prophets fear the testing of their forecasts. Testing the forecast "you will like this restaurant's food" is likely because the client will probably try the food. However, testing the forecast "you will not like the chicken here" is less likely because the client probably will not order chicken. Although testing the second forecast is possible, testing is less likely and, therefore, it is a safer forecast.

Note that Prophet's Fear vanishes when the forecast does not influence the outcome because we observe all forecasted outcomes. For example, suppose the account executive uses both advertising campaigns, (e.g., for different markets) and only desires a forecast for planning purposes. Here, it is illogical to adjust the second forecast for our uncertainty. We provide each forecast and we hope for accuracy.

Prophet's Fear is related to the psychological literature on confirmation. Einhorn and Hogarth (1986), for example, find that individuals often seek confirming evidence for their beliefs rather than falsifying evidence. With Prophet's Fear, the prophet also seeks confirming evidence. However, unlike the individual, who unintentionally avoids all falsification, the prophet only avoids falsification as uncertainty increases.

2. Overview

We organize this paper as follows. We start by developing a theory of how various factors affect the profitability of providing statistically unbiased forecasts. We consider many factors including the effect of accuracy on our profit, the potential impact of our forecast on our client's decisions, our client's ability to ignore our forecast, the reward associated with verifying our forecast, the ability of clients to use other information beyond our forecast, and the uncertain nature of our profits. Our theory provides conditions for the existence of both Survivor's Curse and Prophet's Fear.

To be concrete, we develop our theory in the context of new product introductions. Here, the alternatives are to launch a new product or not. Forecasting for new product introductions may be the most time-honored use for market research (Blattberg and Golanty 1978; Choffray and Lilien 1978, Hauser and Shugan 1980, Pringle, Wilson and Brody 1982; Silk and Urban 1978). Many marketing and decision-making textbooks introduce the topic of information within the new product paradigm, (e.g., Brown, Kahr and Peterson 1974).

In that context, we derive the optimal forecast. We find conditions when (1) the optimal forecast is biased, (2) the optimal forecast is unbiased, and (3) no optimal forecast exists.

Following the theoretical development, the paper provides some discussion relating the theory to forecasting in practice. We provide both implications and insights. We then test our implications using four data sources. First, we analyze forecasting data from the ASSESSOR model to show evidence of Survivor's Curse. Second, we run an experiment to provide evidence of Prophet's Fear. Third, we analyze presidential newspaper endorsements
and find some evidence for Prophet's Fear. Fourth, we conduct in-depth interviews with several well-known market research firms. Our empirical evidence provides some support for our theoretical implications both within and outside a market forecasting context.

Finally, we propose possible solutions. We suggest clients may lessen bias with experimentation and by seeking more accurate forecasts. Forecasters may lessen bias by seeking more accurate forecasts and with forecasts conditioned on launching. The paper closes with our conclusions and suggestions for future research.

3. Ethics in Forecasting

Before continuing, we have two comments concerning ethics. First, we use the term "bias" in the statistical sense -- a biased forecast has an error whose expected value is not zero for finite samples. It is a statistical property. We associate no ethical meaning to the word. As Zellner (1986) notes, "optimal, rational forecasts are often biased."

Second, this paper explores only the pressures facing market research suppliers and not their actual behavior. These pressures certainly create ethical problems. Hunt et al. (1984) find that "the most difficult ethical problem facing marketing researchers is maintaining the integrity of their research efforts." Deshpande and Zaltman (1984) find that the "political acceptability of the final [market research] report" is very important.

These empirical findings are consistent with our theoretical results. We should recall, however, that Hunt et al. (1984) also find a perception of "relatively low frequency of unethical behavior" and that "marketing researchers do not believe that unethical behaviors in general lead to success in marketing research."

We do not suggest that any marketing researchers misrepresent forecasts. Nor do we suggest that forecasters relish the current reward structure. Our paper attempts only to understand the forecasting environment that forecasters face. Ethical people can still face ethical problems.

4. The Theory

4.1 Our Forecast

Our client must decide whether to launch a new product, i.e., make a GO decision. After a launch, new product sales are known. Pre-launch, sales are unknown.

Using market research (any methods necessary) and experience, we gather knowledge about the anticipated sales of the new product. Unless otherwise stated, all equations are pre-launch but post market research. We estimate sales of $\hat{s}$ given by Equation 0.

$$\hat{s} = \mu + \hat{n}$$

(1)

where:

$\hat{s}$ = our pre-launch estimate for new product's sales (random variable)
$\mu$ = the post-launch sales for the new product (a constant)
$\hat{n}$ = the random error in

Here, $\mu$ is a constant that is unknown pre-launch and $\hat{n}$ is the random error in our
estimate. We assume that \( \bar{n} \) has a normal distribution with mean zero and variance \( \sigma^2 \). Note, \( \bar{n} \) reflects our uncertainty about the new product's sales.

For example, suppose that our pre-launch market research estimates annual sales of 300,000 units for the new product. Here, \( \overline{\mu} = 300,000 \). Post-launch, we observe actual new product sales of 100,000 units. Then, \( \mu = 100,000 \) and \( \bar{n} = 200,000 \). Pre-launch, our estimate is random because it contains a random error \( \bar{n} \). We learn \( \bar{n} \) only after a launch.

We supply, to the client, the forecast given by Equation 0.

\[
\hat{f} = \mu + \beta
\]

where:
- \( \hat{f} \) = our pre-launch forecast, generally a random variable
- \( \beta \) = the reporting bias which we may choose to add to

The decision-variable \( \beta \) is known to us but not the client. We call \( \beta \) the "reporting bias". It allows forecasts different from \( \mu \) when \( \beta \neq 0 \). So, \( \hat{f} \) has two parts: (1) the unbiased forecast and (2) the reporting bias \( \beta \).

Now, \( \overline{\mu} = \mu + \bar{n} \), implies \( \hat{f} = \mu + \bar{n} + \beta \). Hence, \( \hat{f} \) is a random variable because \( \hat{f} \) contains an unknown error, \( \bar{n} \). Take our former example. Let \( \beta = 50,000 \). Then, \( \hat{f} = 250,000 \) because \( \mu = 300,000 \). Post-launch, we learn \( \mu = 100,000 \) and \( \bar{n} = 200,000 \). Our client, however, only observes \( \hat{f} = \mu + \bar{n} + \beta \). Post-launch, the client observes an error 250,000 - 100,000 = 150,000.

Taking expectations, remembering \( E[\bar{n}] = 0 \), Equation 0 yields Equation 0.

\[
E[f] = \mu + \beta
\]

where:
- \( E[\cdot] \) = expectations operator (here, the forecaster's expectations)

When \( \beta = 0 \), our forecast is unbiased because \( E[f] = \mu \). When \( \beta > 0 \), the forecast is optimistic because \( E[f] > \mu \). When \( \beta < 0 \), the forecast is pessimistic because \( E[f] < \mu \).

To obtain \( \hat{f} \) pre-launch, our client pays \( \pi \) pre-launch for our new product sales forecast before receiving the forecast. Assume the client requests an unbiased forecast.

4.2 The Client's Problem

Assume the client truly wants a forecast, and not just internal political justification for a launch. Then, Equation 0 provides the client's pre-launch estimated profit for a launch.

\[
\Pi = m \cdot (\hat{f}) - F
\]

where:
- \( \Pi \) = the client's pre-launch estimate for the new product's profit
- \( (\hat{f}) \) = the client's pre-launch estimate for the new product's sales given our forecast \( \hat{f} \)
- \( m \) = the new product's per unit profit margin (a constant)
- \( F \) = the new product's fixed cost (a constant)

\[\text{We prohibit clients use of mixed strategies. This is a limitation but we are aware of no firms actually using mixed strategies.}\]
We assume the client launches\(^3\) when \(\Pi > 0\). Equation 0 implies Equation 0.

\[
(f) > F/m
\]  
\(\text{(5)}\)

Solving Equation 0 for \(f\) yields Equation 0.

\[
f > -1(F/m), \text{ the critical value for a launch}
\]
\(\text{(6)}\)

where: \(-1(F/m)\) is the critical value for a launch.

We call the non-random constant, \(-1(F/m)\), the critical value for a launch because \(f > -1(F/m)\) implies a launch. As forecasters, we may not know how the client got \(-1(F/m)\). We assume, however, that we know \(-1(F/m)\). Our extended model partially relaxes this assumption.

The critical value, \(-1(F/m)\), can also represent the opportunity cost of money or the expected rewards associated with the next best alternative (e.g., Shore 1978, Cafarelli 1980). Wang (1970) suggests that \(-1(F/m)\) should incorporate a 'regret' criterion.

Suppose our client uses our forecast to resolve all uncertainty. Then, the client believes \((f) = f\). Consequently, \(-1(F/m) = F/m\). For example, let the client's fixed costs \(F=400,000\) and profit margin \(m=2\). The client launches when estimated sales exceed \(F/m=200,000\). If the client accepts our forecast of \(f=250,000\), the client launches because \(250,000 > 200,000\).

It may be unreasonable to assume that our client only uses our forecast \(f\) to predict sales. Our client may have a Bayesian Prior Distribution for sales before getting our forecast, and may only use \(f\) to update that distribution. Then, we get Equations 0 and 0. See appendix A for details.

\[
= (F/m) + k
\]
\(\text{(7)}\)

\[
k = (F- \muC m) \sigma / (m \sigma)
\]
\(\text{(8)}\)

where: \(k\) is a constant. The constants \(\muC\), \(\sigma\) and \(\sigma\) are parameters of the client's prior (pre-forecast) distribution for sales.

### 4.3 The Survivor's Curse Effect

Suppose \(\beta=0\), then \(E[f]=\mu\) for every forecast, regardless of whether the client launches. When \(\beta=0\), \(f\) is independent of whether \(f\) happens to be above or below \(\beta\). Across several forecasts, however, \(\beta\) determines which outcomes are observed, so average observed error depends on \(\beta\).

Suppose our client applies the same decision rule, i.e., Equation 0, across several launches. It is likely that the average forecast for launched products will exceed the average forecast for all products, because some forecasts may be below \(\beta\). Theorem 1 proves that when that occurs, unbiased forecasts appear biased and optimistic (over-state sales).

---

\(^3\) This GO-NO GO model and the use of a critical value is very common in the marketing literature. Urban and Hauser (1980), Fitzroy (1976), Kotler (1970) and others use a GO-NO GO model of the new product decision. Saunders (1987), Douglas (1978) and others associate NO GO with low expected sales.
THEOREM 1. Suppose: (1) we supply unbiased sales forecasts (zero reporting bias) for a series of products each having the same expected sales, (2) the client launches some but not all of those products and (3) launched products average higher forecasts than un-launched products. Then, the unbiased forecasts, for launched products, appear optimistic and biased. Mathematically, let \( f_i \) be forecast \( i \), \( f_A \) be the average forecast for all products and \( f_L \) be the average forecast for launched products. Then, when \( E[f_i] = \mu \) for all \( i \), then \( E[f_L | f_L > f_A] > \mu \).

PROOF. See Appendix B.

Theorem 1 implies that even when forecasters make unbiased forecasts, the forecasted sales for launched products will tend to overstate their actual sales\(^4\). Remember, when \( \beta = 0 \), the client can not make a forecast biased by not launching. The average forecast is also unbiased for any random subset of forecasts. However, the client can make the average forecast biased by removing the smallest forecasts from the average.

Survivor's Curse works as follows. Most forecasts contain some error. Positive errors enhance the probability of launching and the forecast survives to be tested. Negative errors enhance the probability of not launching and the forecast remains untested. Those products surviving the screening process, by exceeding the critical value, are more likely to have positive errors because products with negative errors may not survive to be tested. Here, the bias (expected error) across all forecasts is zero, but the bias for tested forecasts is positive. Survivors tend to disappoint.

We will see that the illusion of optimism created by Survivor's Curse makes the pessimism of Prophet's Fear difficult to detect. Prophet's Fear causes pessimistic sales forecasts for subsequently rejected products, and thereby causes rejection of potentially successful products. Survivor's Curse causes over-estimated sales for launched products. Moreover, Survivor's Curse creates pressure to be conservative. This creates a dilemma for the forecaster.

4.4 Forecasting Error

We assume that forecasters' reputations depend on accuracy. There are many measures of accuracy. Here, we adopt the most common measure, i.e., squared error\(^5\). This is a natural assumption because most statistical tools automatically use squared error minimization. Clients often expect forecasts from regression analyses to minimize squared error. Moreover, assuming an asymmetric error might itself cause all forecasts to be biased. Equation 0 results.

\[
\varepsilon^2 = (f - \mu)^2
\]

\(^4\) Survivor's Curse resembles "regression to the mean". However, censored observations cause the former and are unnecessary for the later.

\(^5\) We get our results with common symmetric error. It would be easy to find biased solutions with an asymmetric error. Greater penalties for overestimating actual sales only exaggerate our results.
where: $\varepsilon^2 = \text{squared error, a random variable pre-launch}$

Note, when $\beta=0$, then $\varepsilon^2 = \hat{\eta}^2$ because $f=\mu+\hat{\eta}$. Also, $\varepsilon^2$ is unknown because $\mu$ is unknown.

4.5 Our Problem

As a forecaster, we supply a new product sales forecast, $f$. Consistent with existing practice, we receive a market price for our forecast before learning the forecast's accuracy.

The market price for our forecast depends on current market conditions, (e.g., competition) and our past reputation. For accounting simplicity, let $p_1$ represent the market price net of our forecasting costs. Hence, we receive profit $p_1$ for our forecast $f$. Note that $p_1$ could be negative for neophyte forecasters, who must build a reputation for accuracy.

Here, $p_1$ is a state variable reflecting our current state, including our reputation and past forecasting accuracy. Assume that past accuracy in forecasting increases $p_1$ while past inaccuracy decreases $p_1$. We allow any monotonic relationship between past forecasts and $p_1$.

We expect our future market prices for forecasts depend on the demonstrated accuracy of our current forecast. We are in stage (1) of the following stages: (1) we supply our forecast to the client and get $p_1$, (2) the client launches or not, (3) we can charge a new price $p_2(f)$ for our next forecast. Here, $p_2(f)$ reflects the market price for our services with any new information about our accuracy. Pre-launch, $p_2(f)$ is a random variable.

It is conceptually possible to extend our analysis to more time periods. However, we multiply $p_2(f)$ by a factor $b$ to capture the effects of our current forecast on the net present value of future revenue streams.

Equation 0 defines our expected profit. Note, forecasters did not choose this objective function nor necessarily like it. The objective comes from the forecasting task.

$$E[p_1(f)] = p_1 + b E[p_2(f)]$$  \hspace{1cm} (10)

where: $\pi(f)$ = current and future profits given $f$.

- $p_1$ = current market price net of our forecasting costs.
- $p_2(f)$ = new market price (net costs) given $f$.
- $b$ = factor to reflect impact on future time periods

Equation 0 defines $p_2(f)$.

$$p_2(f) = p_1 + [\delta \cdot R \cdot L(\varepsilon^2)]$$  \hspace{1cm} (11)

where: $\delta = 1$ when $f > \mu$ and $0$ otherwise

- $R$ = non-negative constant reflecting an increase in reputation associated with forecast verification
- $L(\varepsilon^2)$ = loss function with forecast error $\varepsilon^2$

With a launch, our market price changes by $[R \cdot L(\varepsilon^2)]$. We gain $R$ over $p_1$ less a penalty $L(\varepsilon^2)$ for forecasting error $\varepsilon^2$. For small errors $p_2(f) > p_1$. For large errors, $p_1 > p_2(f)$. Our ability to charge higher fees decreases as our error increases.
We assume that the loss in reputation is continuously differentiable and increases with the error so that $L(\epsilon) > 0$ and $L(\epsilon) = 0$. Without loss in generality, given $R = 0$, we assume $L(\epsilon^2) = 0$. Note, in the special case when $L(\epsilon^2) = \epsilon^2$, we find $L(0) = 0$, $L(0) = 1$ and $L(0) = 0$.

Here, $L(\epsilon)$ is a general function allowing many interpretations of the objective function. When $L(\epsilon^2) > R$, the market views our next forecast as less valuable than our current forecast. The decreased value comes from the poor accuracy of our current forecast.

Without a launch, our forecast goes untested, $\delta = 0$ and our forecast's market price remains at $p_1$. For many situations, this assumption is only an approximation. Over time, lack of testing might cause $p_1$ to decay. With decay, forecasters might seek firms, who often launch successful new products.

This section ends with a note about the relationship between $\delta$ and $\bar{n}$. Note, $\delta$ is not random because we know $\delta$ pre-launch. Remember, $\delta = 1$ when our forecast ($f = \pm \beta$) exceeds $\mu$. We do not know the random error $\bar{n}$ pre-launch. Moreover, our distribution of $\bar{n}$ is independent of $\delta$ because we expect sales would be $\mu + \bar{n}$, regardless of whether the client subsequently launches. Of course, $\delta$ may influence the distribution of observed $\bar{n}$. Removing only low forecasts, causes the expected average forecast to exceed $\mu + \beta$.

4.6 The Optimal Forecast

Substituting $p_2(f)$ from Equation 0 into Equation 0 yields Equation 0.

$$E[\pi(f)] = (1+b)p_1 + b \delta \{ R \ E[L(\epsilon^2)] \}$$

Before maximizing $E[\pi(f)]$, we need Lemma 1. It shows a forecast of $\beta = 0$, minimizes $E[L(\epsilon^2)]$.

**LEMMA 1.** $E[L(\epsilon^2)] = E[L(f \mu^2)]$ is minimized at $\beta = 0$, $f = \mu$ for $L(\epsilon) > 0$ and $L(\epsilon) = 0$.

**PROOF.** See Appendix B.

When the critical value approaches $\mu$, by definition, $\delta = 1$ whatever $f_i$. This yields Theorem 2.

**THEOREM 2.** The optimal forecast becomes unbiased as it becomes non-influential. Mathematically, $\beta = 0$ is optimal when $\mu$ approaches $\mu$.

**PROOF.** See Appendix B.

Theorem 2 implies that non-influential forecasts should be unbiased, i.e., $\beta = 0$. This result is well known in statistics and follows from the symmetric loss function. The result, however, provides an important baseline for Theorems 3 and 4, which show when pressure exists to bias the forecast.
4.7 The Prophet’s Fear Effect

**THEOREM 3.** When the forecast error variance is large, the optimal forecast is no more than the critical value. Hence, an unbiased forecast is optimal only when we estimate sales no more than the critical value. Mathematically, let \( f^* \) be the optimal forecast and \( \sigma = E[L(\hat{n}^2)] \). Then, (1) \( f^* \) when \( \sigma > R \); (2) \( f^* = R \) when \( \sigma > R \); (3) \( f^* = \) when \( \sigma > R \).

**PROOF.** See Appendix B.

Although multiple optima exist in Theorem 3, later (e.g., Theorem 5) we get uniqueness. Also, when multiple optima exist, we prefer an unbiased forecast to satisfy the client's request.

*Note that we use the term forecast error variance to refer to \( \sigma \), which reflects the expected value of the error adjusted for the loss function \( L(\hat{\varepsilon}^2) \).*

Theorem 3 implies that when we have sufficient uncertainty about our forecast, we face the pressure to forecast \( R \) or less. We call this effect Prophet’s Fear. When \( \sigma > R \), we feel pressure to be pessimistic (conservative) and use our influence to discourage a launch. When \( \sigma < R \), we can forecast \( R \) and provide an unbiased forecast. When \( \sigma > R \), however, there is an incentive to be pessimistic and forecast \( R \) rather than \( R \).

We call this effect Prophet’s Fear because prophets fear the testing of forecasts with large error variance.

**THEOREM 4.** When the forecast error variance is small, an unbiased forecast is optimal unless: (1) we expect failure and (2) estimated sales are close to the critical value. Here, no solution exists. The optimal forecast is larger than the critical value but as small as possible. Mathematically, let \( \sigma = E[L((\mu - \hat{n})^2)] \). When \( \sigma < R \), then \( f^* = \), unless: (1) \( \sigma < R \). Here, \( f^* = + \xi \), where \( \xi > 0 \) but arbitrarily small.

**PROOF.** See Appendix B.

Theorem 4 provides still another situation when we face the pressure to provide a bias forecast. When we are sufficiently confident that sales will be close to the critical value, i.e., \( \sigma < R \), but we expect sales less than the critical value, i.e., \( \sigma < R \), then we face the pressure to forecast slightly above the critical value, \( + \xi \).

Now, we compare influential to non-influential forecasts. Influential forecasts below are not tested while non-influential forecasts are always tested. Theorem 2 implies that optimal non-influential forecasts equal \( R \). The following Corollary compares the error variance (i.e., expected accuracy) of influential and non-influential forecasts for the same new products. Observed influential forecasts appear more accurate.

**COROLLARY 1.** Consider optimal non-influential and influential forecasts exceeding the critical value (i.e., \( f^* = \) \( + \xi \), \( \xi > 0 \)) for the same series of new products. Then, we expect,
(1) The average error variance of non-influential forecasts equals that of influential forecasts when the corresponding forecasts (i.e., non-influential and influential forecast) are always equal.
(2) The average error variance of non-influential forecasts exceeds that of influential forecasts when at
least one non-influential forecast does not equal the corresponding influential forecast.

4.8 Summary

The client seeks an unbiased forecasts. Although client losses may be inconsistent with an unbiased forecast, it is our client who should apply the suitable loss function and decide whether to launch. Sometimes this situation creates a dilemma for the forecast.

We, as forecasters, often have the incentive to provide the forecast \( f^* \). But conditions exist when we face the pressure to provide a biased forecast, \( f^\dagger \). The first condition is a large forecast error variance, i.e., \( \sigma > R \), and expected success, i.e., \( \pi > \). The second condition is a small forecast error variance, i.e., \( \sigma < R \), estimated sales close to the critical value, i.e., \( \bar{\sigma} < R \), and expected failure, \( \pi < \). The first condition encourages a pessimistic forecast, \( f^* < \), while the second condition encourages an optimistic pre-launch forecast, \( f^* > \). See 0.

<table>
<thead>
<tr>
<th></th>
<th>High Expected Error ( \sigma &gt; R )</th>
<th>Low Expected Error near ( \bar{\sigma} ) ( \sigma &lt; R ) and ( \sigma &gt; R )</th>
<th>Otherwise</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>We expect Success, ( \pi &gt; )</strong></td>
<td>Pessimistic ( f^* = )</td>
<td>Unbiased ( f^* = )</td>
<td>Unbiased ( f^* = )</td>
</tr>
<tr>
<td><strong>We expect Failure, ( \pi &lt; )</strong></td>
<td>Unbiased ( f^* = )</td>
<td>No Solution ( f^* = +\xi, \xi &gt; 0 )</td>
<td>Unbiased ( f^* = )</td>
</tr>
</tbody>
</table>

0 suggests that accurate (or confident) forecasters should provide unbiased forecasts. Occasionally, when estimated sales are slightly below the critical value, optimistic forecasts are optimal. More often, when estimated sales exceed the critical value but error variances are high, Prophet’s Fear promotes pessimistic forecasts. This suggests that forecasts should sometimes be pessimistic. Actual pessimism is difficult to detect because all tested forecasts are unbiased. Moreover, Survivor’s Curse creates the illusion of optimism.

**Unbiased forecasts should appear optimistic.** When forecasts accurately reflect actual sales, either all products are launched or the forecaster has removed high variance forecasts by causing rejection of products with large variance forecasts.

We close this section with Equation 0 providing our expected profit for \( f^* > \). We now generalize these results.

\[
E[\Pi(f)] = (1+b)p_1 + b \left\{ R \quad \sigma \right\} 
\] (13)
4.9 Extensions

Our problems begin with the common assumption of de facto control over the launching decision -- forecasting below stops the launch. We now examine the consequence of diminishing this control. Diminished control agrees with our in-depth interviews with professional market research forecasters. They revealed statisticians seldom make actual decisions. Although forecasts are important, clients retain actual decision-making responsibility. Krum (1969) finds "executive judgment" dominates the decision process.

We, therefore, extend our model by decreasing the influence of \( f \). Based on our presentation of the forecast, and information available after the forecast (but pre-launch), clients may reject our forecast. Define \( \gamma \) as our subjective probability that our client launches even when our forecast is no more than \( \hat{y} \), i.e., \( \delta = 0 \). Define \( \lambda \) as our subjective probability that our client launches when our forecast exceeds \( \hat{y} \), i.e., \( \delta = 1 \). Here, \( 0 \leq \lambda \leq 1 \). Note when \( \lambda = 1 \) and \( \gamma = 0 \), we obtain our simple model because \( f \) again suggests a launch\(^6\). Consistency requires \( \lambda \gamma \geq 0 \).

Note an alternate interpretation of the probabilities \( \lambda \) and \( \gamma \) is that \( \lambda \) and \( \gamma \) embody our uncertainty about the true level of \( \hat{y} \). Here, \( \lambda \) is our subjective probability of \( \hat{y} \) being lower than we thought, and \( \gamma \) is our subjective probability of \( \hat{y} \) being higher.

1 summarizes our problem.

<FIGURE 1 ABOUT HERE>

We forecast high (\( f > \)) or low (\( f < \)). Our client, then, decides whether to launch. With a high forecast (\( f > \)), our client launches with probability \( \lambda \). If we forecast low (\( f < \)), our client launches with probability \( \gamma \). Hence, there is a chance our forecast has no influence.

If our client launches, the forecast error \( \hat{f} - \mu \) is observed. With no launch, our forecast remains untested. Equation 0 generalizes Equation 0.

\[
\begin{align*}
p_2(f) &= p_1 + \{ [\delta \lambda + ((1 - \delta)\gamma)] [R \ L(\varepsilon^2)] \}\end{align*}
\]

where:
- \( \lambda \) = our subjective probability the client launches when \( \delta = 1 \)
- \( \gamma \) = our subjective probability the client launches when \( \delta = 0 \)

THEOREM 5. 0 shows the optimal forecasts in the extended model.

0. Pre-Launch Optimal Forecasts: Extended Model

<table>
<thead>
<tr>
<th>High Expected Error ( \sigma &gt; R ) and ( \lambda/\gamma &gt; (R - \sigma)/(R - \sigma) )</th>
<th>Low Expected Error near ( \hat{y} ) ( \sigma &lt; R ) and ( \gamma/\lambda &lt; (R - \sigma)/(R - \sigma) )</th>
<th>Otherwise</th>
</tr>
</thead>
</table>

\(^6\) A model extension could include multiple critical values where the probability of a launch increases with high values.
<table>
<thead>
<tr>
<th>Expect Success</th>
<th>Pessimistic $f^*=\text{Unbiased}$</th>
<th>Unbiased $f^*=$</th>
<th>Unbiased $f^*=$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expect Failure</td>
<td>Unbiased $f^*=$</td>
<td>No Solution $f^*=+\xi, \xi&gt;0$</td>
<td>Unbiased $f^*=$</td>
</tr>
</tbody>
</table>

PROOF. See Appendix B.

0 indicates that no solution exists when $\sigma \leq R$ and $\lambda(R \sigma) > \gamma(R \sigma)$. This condition requires $\sigma \leq R$ because $\lambda(R \sigma) > \gamma(R \sigma) > 0$. Hence, $\sigma$ must be relatively small. Hence, it is optimal to forecast just above $\sigma$. It is always possible to increase expected profits by decreasing our forecast provided that our forecast remains larger than $\sigma$. Hence, no optimal solution exists. Forecasting just above $\sigma$ provides higher expected profits than $f^*=$.

We end this section with Corollary 2.

COROLLARY 2. The optimal non-influential ($\lambda=\gamma$) forecast is unbiased ($f^*=$).

5. Discussion

We see that as our influence over the launch diminishes, with the introduction of $\lambda$ and $\gamma$, fewer situations exist with the pressure to bias the forecast. Our dilemma eventually disappears because we more often want to provide a statistically unbiased forecast.

0 shows that in many situations no pressure exists. For example, when our forecast has no influence on the decision (i.e., $\lambda=\gamma$), our optimal forecast is an unbiased forecast. Hence, when we provide forecasts for general planning activities, economic activities, the weather, forecasting the winner in sports events, stock market prices and GNP, we have no pressure to produce a biased forecast. Note that this is true whatever the functional form of the market response to forecasting error (i.e., $L(\eta)$).

Equation 0 and 0 shows that our expected profits depend on the error variance of the forecast. The more uncertain our forecast, the lower our expected profits. We might even reject or require a higher fee for more difficult assignments that risk our reputation. Moreover, we have an incentive to increase our forecasting accuracy. The desirability, however, of these decisions depends on a cost-benefit analysis and is beyond the scope of this paper.

The pressure to produce a biased forecast increases as our influence over the launch increases. 0 shows that we can measure our influence with the ratio $\lambda/\gamma$, where $\lambda \geq \gamma$. The more that a low forecast discourages our client from launching, the smaller $\gamma$. The more that a high forecast encourages our client to launch, the larger $\lambda$. The ratio, $\lambda/\gamma$, reflects the net influence. For example, when $\lambda/\gamma$ is large, our forecast has great influence on the launch. When $\lambda/\gamma=1$, the probability of launching is independent of our forecast.

When $\lambda/\gamma$ is large, pressure exists for a conservative forecast. Suppose that estimated sales are sufficiently large to insure our client launches the product (i.e., $\sigma > \sigma$). Then, we only want to provide an unbiased forecast (i.e., $f^*=$) when our expected error (i.e., $\sigma$) is small.
Otherwise, we want to provide a forecast sufficiently small to avoid launching the new product.

We might argue that we are being conservative. Faced with a less accurate forecast, we adjust our forecast downwards to reflect our risk. However, that adjustment should be done by the decision-maker and not us.

We call this pressure Prophet's Fear because a prophet fears the refutation of the prophet's own forecast. Prophets may, therefore, like to make forecasts that remain untested. This is impossible when we have no influence over whether our forecast is tested. Here, actual sales are known regardless of our forecasted sales. Remember, the pressure to be conservative is related to the error variance not the absolute level of our forecast. We wish to be conservative when we are uncertain and not necessarily when our forecasted sales are low.

The Prophet's Fear effect causes conservative forecasts anytime a low forecast prevents the testing of the forecast itself. Hence, this effect goes beyond launching new products. For example, pessimistic (i.e., downward biased) forecasts can occur in sales forecasting for production planning when over-production causes observable surpluses and under-production causes unobservable shortages. Here, the number of units that would have been sold in the shortage remains unknown. This prevents testing our forecast. With stock-outs, a forecaster might argue the forecast is very close, if not precisely correct. It can also occur when the forecast determines the best design, the best promotion or the best compensation scheme because the outcome of the next best alternative remains unobserved.

Generally, we see that whenever the forecast influences our client's ability to test the forecast, there is a pressure to be conservative. These biased forecasts may be serious for several reasons. First, it is likely that error variance is large because clients often seek forecasts when more uncertainty exists. Second, uncertainty is likely to be large for products that might be highly successful because highly successful products are often risky.

Now, we might argue that clients would learn that forecasts are conservative and adjust forecasts upwards. However, there are several factors inhibiting client learning. First, unless clients experiment (Little 1976) and deliberately launch products with low expected sales, clients will never test biased forecasts. Remember that all forecasts that suggest a launch (i.e., \( f > \)) are completely unbiased. Hence, studying these forecasts reveals nothing. Second, Survivor's Curse makes unbiased forecasts appear optimistic.

6. Reporting Confidence Levels

This section shows that giving the client a measure of confidence or expected error, in addition to our forecast, does not alter our previous results.

So far, we have only reported our forecast. We could also report the level of confidence we have in the forecast. When we also report our forecasting confidence, a lower confidence makes our forecast less valuable. A lower confidence, however, also absolves us somewhat from some responsibility for a large forecasting error.

Let \( C_1 \) be our reported confidence level and \( \Phi(C_1) \) represent the cost associated with reporting a confidence \( C_1 \). Equation 0 provides our price given no reporting of our forecasting confidence. With reporting, see Equation 0.

\[
p_2(f) = p_1 + \left\{ \delta \lambda + (1 - \delta) \gamma \right\}[R \cdot L(\epsilon^2)] C_1 \cdot \Phi(C_1)
\]  
(15)
where: \( C_1 \) = the confidence we report to the client.  
\( \Phi(C_1) \) = the out-of-pocket cost of creating confidence \( C_1 \).  
Assume \( \Phi(0)=0, \Phi(C_1) > 0 \) and \( \Phi(C_1) > 0 \).

For example, suppose we scale \( C_1 \) between 0 and 1. If we want 100% confidence, then, we must spend ample money on marketing research making our costs \( \Phi(1) \). We tell the client of our 100% confidence and Equation 0 becomes Equation 0 minus \( \Phi(1) \).

Now, suppose we want 10% confidence. Then, we must spend less money on marketing research making our costs only \( \Phi(.1) \). We tell the client of our 10% confidence. Should the client launch, the outcome only has 10% of the effect, i.e., .1 \( [R \ L(\epsilon^2)] \), as it would have with 100% confidence, i.e., 1.0 \( [R \ L(\epsilon^2)] \).

Providing 0% confidence is cheap, having no expense, \( \Phi(0)=0 \). However, the client discards our forecast and Equation 0 becomes \( p_2(f) = p_1 \).

In general, as confidence \( C_1 \) increases, the reporting cost \( \Phi(C_1) \) increases until our gain in profit \( p_2(f) - p_1 \) is zero. Of course, as \( C_1 \) increases, the impact of outcomes, \( [R \ L(\epsilon^2)] C_1 \), also increases. Taking the expected value of \( \pi(f) \) we obtain:

\[
E[\pi(f)] = (1+b)p_1 + [b(\delta \lambda + \gamma \delta \gamma) (R \ \sigma) C_1 ] \Phi(C_1)
\]

We maximize \( E[\pi(f)] \) by setting \( E[\pi(f)] / C_1 \) equal to zero. We find that,

\[
\Phi(C_1) = b(\delta \lambda + \gamma \delta \gamma)(R \ \sigma)
\]

Hence, we set our confidence \( C_1 \) so that the marginal cost, i.e., \( \Phi(C_1) \), equals the expected reward associated with validation. As the error variance \( \sigma \) increases, our optimal reported confidence decreases.

Our optimal \( f \) remains unaffected by \( C_1 \) because our first-order condition for \( \beta \) is:

\[
2b(\delta \lambda + \gamma \delta \gamma) E[L(\epsilon^2)(f - \mu)] C_1 = 0
\]  

(16)

7. Empirical Results

8.1 Assessor Analysis

Our empirical findings are preliminary. However, they suggest that both Survivor's Curse and Prophet's Fear exist within and outside a market forecasting context. We start by examining forecasts generated by the new product forecasting model known as ASSESSOR (Silk and Urban 1978). ASSESSOR is a well established and accurate model for new product forecasting. Urban and Katz (1983) show the model has good validity. Therefore, we expect ASSESSOR forecasts to be good unbiased estimators of actual sales. Consequently, these forecasts should show the Survivor's Curse effect described by Theorem 1.

Although ASSESSOR forecasts are unbiased across all forecasts, the tested forecasts should have an expected positive bias. \( \sigma \) compares shares forecasted by ASSESSOR with the actual post-launch shares for our entire data set, i.e., forty-four new products.
0 summarizes the forecasts in 0. As with any good forecasting model, the number of optimistic forecasts (68.2%) exceeds the number of pessimistic forecasts (31.8%). A paired sample T-test on the forecasts versus the actual produced a t-statistic that is significant at the .05 level. Hence, the ASSESSOR model's forecasts contain the Survivor's Curse effect just as any unbiased forecasting model should.

These results agree with past research (Tull 1967). Tull and Rutemiller (1968) compare 41 forecasts with actual new product sales finding that "forecasts of the sales level for new products tend to be biased in an optimistic direction." Baldinger (1988) inspects 589 new product forecasts, finding only 8% pessimistic and 41% optimistic. Hence, 83.7% of the inaccurate forecasts were higher than actual sales.
## 0. Actual Forecasts and Errors

### ASSESSOR Model: Forecasts and Errors

<table>
<thead>
<tr>
<th>Case</th>
<th>Forecast</th>
<th>Actual Share</th>
<th>Error</th>
<th>Case</th>
<th>Forecast</th>
<th>Actual Share</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>26</td>
<td>17.00</td>
<td>22.00</td>
<td>5.00</td>
<td>21</td>
<td>11.00</td>
<td>0.60</td>
<td>+0.50</td>
</tr>
<tr>
<td>31</td>
<td>13.40</td>
<td>17.20</td>
<td>3.80</td>
<td>40</td>
<td>7.50</td>
<td>7.00</td>
<td>+0.50</td>
</tr>
<tr>
<td>32</td>
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<td>12.50</td>
<td>3.20</td>
<td>35</td>
<td>9.00</td>
<td>8.40</td>
<td>+0.60</td>
</tr>
<tr>
<td>39</td>
<td>14.40</td>
<td>17.00</td>
<td>2.60</td>
<td>4</td>
<td>24.20</td>
<td>23.50</td>
<td>+0.70</td>
</tr>
<tr>
<td>15</td>
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<td>2.50</td>
<td>1.70</td>
<td>7</td>
<td>3.80</td>
<td>3.00</td>
<td>+0.80</td>
</tr>
<tr>
<td>16</td>
<td>27.10</td>
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<td>1.40</td>
<td>18</td>
<td>1.23</td>
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<td>+0.93</td>
</tr>
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<td>10.50</td>
<td>0.90</td>
<td>19</td>
<td>3.00</td>
<td>2.00</td>
<td>+1.00</td>
</tr>
<tr>
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<td>11.50</td>
<td>0.60</td>
<td>38</td>
<td>4.90</td>
<td>3.80</td>
<td>+1.10</td>
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<td>12.60</td>
<td>13.00</td>
<td>0.40</td>
<td>10</td>
<td>8.40</td>
<td>7.20</td>
<td>+1.20</td>
</tr>
<tr>
<td>30</td>
<td>12.20</td>
<td>12.50</td>
<td>0.30</td>
<td>36</td>
<td>9.60</td>
<td>8.20</td>
<td>+1.40</td>
</tr>
<tr>
<td>13</td>
<td>3.00</td>
<td>3.20</td>
<td>0.20</td>
<td>25</td>
<td>6.00</td>
<td>4.40</td>
<td>+1.60</td>
</tr>
<tr>
<td>3</td>
<td>2.00</td>
<td>2.20</td>
<td>0.20</td>
<td>20</td>
<td>9.00</td>
<td>7.20</td>
<td>+1.80</td>
</tr>
<tr>
<td>22</td>
<td>4.90</td>
<td>5.00</td>
<td>0.10</td>
<td>8</td>
<td>8.40</td>
<td>6.30</td>
<td>+2.10</td>
</tr>
<tr>
<td>33</td>
<td>1.80</td>
<td>1.90</td>
<td>0.10</td>
<td>28</td>
<td>12.10</td>
<td>9.70</td>
<td>+2.40</td>
</tr>
<tr>
<td>44</td>
<td>0.25</td>
<td>0.13</td>
<td>+0.12</td>
<td>17</td>
<td>13.50</td>
<td>10.80</td>
<td>+2.70</td>
</tr>
<tr>
<td>2</td>
<td>2.90</td>
<td>2.70</td>
<td>+0.20</td>
<td>14</td>
<td>13.30</td>
<td>10.40</td>
<td>+2.90</td>
</tr>
<tr>
<td>27</td>
<td>7.80</td>
<td>7.60</td>
<td>+0.20</td>
<td>11</td>
<td>5.20</td>
<td>1.60</td>
<td>+3.60</td>
</tr>
<tr>
<td>42</td>
<td>0.43</td>
<td>0.20</td>
<td>+0.23</td>
<td>9</td>
<td>16.50</td>
<td>12.90</td>
<td>+3.60</td>
</tr>
<tr>
<td>29</td>
<td>5.40</td>
<td>5.10</td>
<td>+0.30</td>
<td>5</td>
<td>4.40</td>
<td>0.60</td>
<td>+3.80</td>
</tr>
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<td>0.63</td>
<td>0.28</td>
<td>+0.35</td>
<td>24</td>
<td>8.00</td>
<td>4.20</td>
<td>+3.80</td>
</tr>
<tr>
<td>23</td>
<td>2.60</td>
<td>2.20</td>
<td>+0.40</td>
<td>1</td>
<td>7.20</td>
<td>3.30</td>
<td>+3.90</td>
</tr>
<tr>
<td>41</td>
<td>0.80</td>
<td>0.30</td>
<td>+0.5</td>
<td>37</td>
<td>5.60</td>
<td>1.50</td>
<td>+4.10</td>
</tr>
</tbody>
</table>

## 0. Test of Survivor's Curse

<table>
<thead>
<tr>
<th>Optimistic (share&gt;actual)</th>
<th>Pessimistic (share&lt;actual)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number</td>
<td>30</td>
</tr>
<tr>
<td>Percent</td>
<td>68.2%</td>
</tr>
<tr>
<td>Total Error</td>
<td>47.3</td>
</tr>
</tbody>
</table>

### 8.2 Experimental Analysis
Ethical and data-collection problems prevent testing Prophet's Fear in actual new product launches. Prophet's Fear, however, should occur in other forecasting contexts beyond new product launching. So, to demonstrate Prophet's Fear, we ran an experiment using 200 students at a major midwestern university.

After dividing the students into two groups (i.e., control and experimental), we gave them a forecasting task. Students, in both groups, got 5 seconds to estimate (forecast) the number of pennies in a jar\(^7\). There were 421 pennies in the jar.

Students lacked the opportunity to hold the pennies or to count the 421 pennies in the jar. We told the first group (our control group) that we will count the pennies in the jar. Students, who make forecasts within 25 pennies of the actual number, receive $2. Other students receive nothing. We expected students in this group to provide unbiased forecasts, \(\beta=0\), of the number of pennies because their forecasts are always tested (i.e., non-influential).

We told the second group (our experimental group) that when their forecast was over 400 pennies, a forecast within 25 pennies of the actual number receives $2 while other forecasts receive nothing. Students with forecasts of 400 or less automatically receive $1 whatever the actual number of pennies in the jar. Hence, the experimental group's forecasts were only tested when the forecasts were over 400 pennies (i.e., influential forecasts).

This task creates conditions required for Prophet's Fear. The task is conceptually similar to forecasting new product sales. Each student, with similar data, forecasts a total figure.

We do not know \(\beta\), so we cannot directly test theorems 3 and 4. However, we do know \(\mu\), so we can directly test Corollary 1. The control group is non-influential and the experimental group is influential. Corollary 1 predicts that only those students, who are confident about their forecast, seek validation of their forecasts. If confidence implies more accuracy (which we implicitly test), then Prophet's Fear implies that students, who seek validation, have more accuracy than students who are forced into validation. Students in the experimental group, who were uncertain about the number, could predict 400 (or less) to avoid testing their forecasts. As Corollary 1 predicts, the experimental group forecasts (over 400) should be more accurate than control group forecasts (over 400). \(\text{See 0.}\)

Prophet's Fear (i.e., Corollary 1) implies more accuracy from those students in the experimental group who sought validation and subsequently forecasted over 400 pennies in the jar. Hence, we expect tested forecasts (i.e., >400) to be more accurate for the experimental group than the control group. \(\text{See 0.}\) confirms this expectation. The mean square error of the experimental group (i.e., 4,246.053) is much smaller than the mean squared error of the control group (i.e., 48,538.846). Moreover, the experimental group's mean error (i.e., 34.263) is 113.045 less than the control group's mean error (i.e., 147.308). This difference is significant at the 0.011 level.

\(^7\) We ran the experiment varying various parts (e.g., a plastic bag vs. a jar, 5 seconds vs. 10 seconds) and found similar results.
0. Test of Prophet's Fear

Prediction of the Number of Pennies in a Jar: Statistics for Forecasts over 400
(Actual number = 421)

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Experimental</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean forecast</td>
<td>568.308</td>
<td>455.263</td>
<td>113.045</td>
</tr>
<tr>
<td>Mean error</td>
<td>147.308</td>
<td>34.263</td>
<td>113.045</td>
</tr>
<tr>
<td>Squared error</td>
<td>48538.846</td>
<td>4246.053</td>
<td>44292.793</td>
</tr>
<tr>
<td>T-Statistic</td>
<td>3.115</td>
<td>2.623</td>
<td>2.695</td>
</tr>
<tr>
<td>p-value (2 tail)</td>
<td>.009</td>
<td>.017</td>
<td>0.011</td>
</tr>
</tbody>
</table>

Although this experiment supports the Prophet's Fear effect, anchoring on 400 could also cause these results. Therefore, we replicated the experiment without providing any numbers.

This time we used two jars of pennies. Jar one had 230 pennies and Jar two had 210 pennies. We asked participants to estimate the difference in pennies between the two jars. We told the control group that if their estimate (forecast) of the difference is within 25% (25 15), they will receive $2.00. Otherwise, they receive nothing. We told the experimental group that their reward depends on which jar had more pennies. If they estimate the first jar has more pennies, they will receive $3.00 only when their estimate is within 25% of the true difference. Otherwise, they receive nothing. However, if they estimate the second jar has more pennies, they will receive $1.00 regardless of accuracy.

This is similar to the new product gamble and estimating the size of the potential market. A not-to-launch decision removes the risk associated with the forecast. The control group represents estimation without influence on the launch. The experimental group had an incentive to avoid observation and possible refutation when they were uncertain about the true difference. There was a guaranteed payoff of $1.00. Prophet's Fear (Corollary 1) suggests that the experimental group is more likely to estimate a lower difference than the control group.

The results support the existence of Prophet's Fear. A chi-square, using three categories of estimation (Below 15; 15 25; above 25) showed a dependency between control and experimental groups. Chi Square is 10.8. Significance is 99.55%. In addition, we used an ANOVA to measure the effect of group on the estimates. The F value is 14.88 and significance is .999. See 0. These data strongly support the existence of Prophet's Fear.

Note that most potential confounds with the student population, (e.g., inability to judge accuracy, lack of motivation, lack of understanding the task, different expertise) all work against confirmation of our model. Therefore, these factors all tend to cause statistically insignificant results though we found statistically significant results.

0. Replication of Experiment

Prediction of the Difference in the Number of Pennies in 2 Jars
Statistics for Forecasted Differences
(Actual number = 210 and 230)

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Experimental</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>19.017</td>
<td>2.770</td>
</tr>
<tr>
<td>Median</td>
<td>20.000</td>
<td>7.000</td>
</tr>
<tr>
<td>Standard Error</td>
<td>3.139</td>
<td>2.818</td>
</tr>
<tr>
<td>Chi-Square</td>
<td></td>
<td>10.8</td>
</tr>
<tr>
<td>(15; 25; &gt;25)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-value (2 tail)</td>
<td></td>
<td>.0001</td>
</tr>
</tbody>
</table>

As a limitation, our experiment does not consider the ethical problems facing actual market forecasters.

8.3 Presidential Endorsements

Every 4 years, we have Presidential elections, and newspapers endorse their favorite candidate. We could interpret an endorsement as a forecast that the endorsed candidate will succeed in office. We could also interpret an endorsement as a forecast that the endorsed candidate will win the election.

For several reasons, we might expect newspapers to endorse the candidate that later wins the election. First, doing so enhances the newspaper's credibility. Second, newspapers like to please their readers and endorsing their reader's choice sells papers. Third, when newspapers can influence the outcome of the race, endorsement may help the candidate to win. Fourth, post-election, supporters of winners sometimes enjoy more political clout than supporters of the losers.

Polls abound directly before elections. Except for the '48 race, Dewey vs Truman, it is easy to predict the outcome of a race. Newspapers, therefore, are usually able to predict the winner. Newspapers should be able to almost completely avoid endorsement of losers.

Using the Ready Reckoner from Editor and Publisher, we find that in the 50 years 1940–1990, the number of papers picking the winner is only 57%. One would expect the percentage to be much higher. We might wonder why newspapers pick the loser at a ratio of 2:3 rather than a ratio like 1:10. See 0.

0. Newspaper Candidate Endorsements

<table>
<thead>
<tr>
<th>Year</th>
<th>Winning Candidate</th>
<th>Losing Candidate</th>
<th>Percent of Newspapers who Endorse the Winner</th>
</tr>
</thead>
<tbody>
<tr>
<td>1944</td>
<td>277</td>
<td>794</td>
<td>.26</td>
</tr>
<tr>
<td>1948</td>
<td>182</td>
<td>771</td>
<td>.19</td>
</tr>
<tr>
<td>1952</td>
<td>930</td>
<td>200</td>
<td>.82</td>
</tr>
<tr>
<td>1956</td>
<td>740</td>
<td>181</td>
<td>.80</td>
</tr>
</tbody>
</table>
One possible explanation is that newspapers view endorsements as a means to express their political views, and not a reflection of the outcome of the election. The question remains why newspapers often endorse the losing candidate. It appears that the political views of many newspapers are inconsistent with their readers.

There is another explanation. Endorsing a winner has its dangers. If the politician becomes a very popular individual and assists in the passage of very helpful and constructive legislation, then the endorsement is positive. However, if the politician becomes unproductive, or becomes involved in moral or political scandals, the endorsement can be problematic for the newspaper. Hence, it is safer to endorse the loser. This is the Prophet’s Fear effect.

Prophet’s Fear provides an advantage to endorsing the underdog. Endorsing an underdog lowers the risk of forecast refutation. Of course, other explanations are possible.

8.4 In-Depth Interviews

A client, who is aware of Prophet’s Fear, will expect pessimistic forecasts and may encourage more optimism from the forecaster. Of course, Prophet’s Fear is undetectable, in our basic model, because all tested forecasts are unbiased and appear optimistic. Still, several factors suggest that some clients may be aware of Prophet’s Fear. First, occasionally launching an expected failure may reveal a bias (our extended model). Second, clients themselves are sometimes in the role of forecasting and are subject to Prophet’s Fear. Finally, clients may understand Equation 0.

We did in-depth interviews with 15 market forecasters for different size market research firms. This exploratory research suggests that clients regard forecasters as pessimistic. Clients also exerted pressure for optimism. 0 provides some representative quotes from our interviews.

0. Quotes from Market Forecasters

"New clients perceive forecasts as giving bad news!"
"If you give a low forecast, your client will go to other sources"
"Brand managers claim [forecasts] are a hindrance."

Another explanation is that these presumed forecasts are not forecasts. See the Future Research section.
Conflicting pressures create ethical and practical problems for market forecasters particularly when repeat business becomes vital. Never-the-less, our interviews revealed that suppliers did not misrepresent their forecasts. Reputation and ethical concerns dominate.

8. Possible Solutions

We have no perfect solution. Obviously, clients can encourage optimism to avoid Prophet's Fear and forecasters can explain Survivor's Curse. Our theory, however, suggests some directions for possible solutions.

First, $\lambda/\gamma$ implies that decreasing $\lambda/\gamma$ can lessen Prophet's Fear. Hence, the client should do more experimentation (Little 1976). The client needs to occasionally launch products despite unfavorable market research. This solution, however, can be very expensive and politically difficult to implement.

Second, $\lambda/\gamma$ implies that decreasing $\sigma$ can lessen Prophet's Fear. Hence, the client should buy more accurate forecasts. Spending more money to lower $\sigma$ may result in both more accuracy and less pressure to bias.

Finally, $\lambda/\gamma$ implies that decreasing $\lambda/\gamma$ can lessen Prophet's Fear by making a launch more likely. Clients can announce a low $\lambda/\gamma$, when it is credible to do so. Forecasters can sometimes make a launch more likely. Forecasts often are conditioned on a particular marketing mix (e.g., price, product features, required distribution). Hence, rather than forecasting failure at the planned price or planned features, we may be able to provide the client with an alternate price or alternate features that would make the product successful. Here, launching always occurs making forecasts unbiased.

Maybe when clients kill the messenger, it is better to tell a client how to get desired sales than to provide an accurate but disappointing sales forecast. Of course, this type of forecast is not always possible.

9. Conclusions

This paper considers a dilemma we face as influential forecasters (who influence forecast testing). Our client requests an unbiased forecast but pressures sometimes exist to provide a bias forecast. Our goal was to identify these pressures. We began by formulating the profit functions of both the forecaster and the client. We derived conditions when forecaster incentives encourage unbiased forecasts. These conditions include: (1) observing all forecasted outcomes and (2) having a small error variance.

Survivor's Curse and Prophet's Fear create a pressure to bias forecasts. Survivor's Curse causes otherwise unbiased forecasts to appear optimistic. Clients may misconstrue our
forecasts. With Survivor's Curse, truly unbiased forecasts appear optimistic because the bias for launched products is positive. A positive bias causes disappointing sales and makes forecasts look optimistic. Not only does Survivor's Curse create an incentive to be conservative (i.e., pessimistic), it also hides an effect we call Prophet's Fear.

Prophet's Fear also encourages conservatism. Prophet's Fear occurs when both the forecast is influential (i.e., helps determines whether the forecast is tested) and our confidence is low (i.e., variance $\sigma$ is large). Here, low forecasts decrease the likelihood of refutation because no launch occurs. With no launch, the sales forecast is never tested. When the forecast, itself, lessens the likelihood of evaluation and great uncertainty exists, pressure exists to avoid testing. Moreover, in the basic model, untested forecasts are pessimistic but tested forecasts remain unbiased.

We then empirically demonstrated both effects in a variety of situations. In summary, we found the following:

- When our loss function depends on squared error, observing all forecasted outcomes (non-influential forecasting) creates no pressure to provide biased forecasts, whatever the loss function.
- As influence over testing increases, the pressure to bias increases.
- Survivor's Curse causes unbiased forecasts to appear optimistic, overestimating actual sales (i.e., sales disappoint).
- High error variance causes Prophet's Fear, encouraging pessimistic influential forecasts.
- Tested forecasts may appear completely unbiased despite a pessimistic pre-launchbias.
- When forecasts seem unbiased, either all products are launched or the forecaster has removed large variance forecasts by causing rejection of products with high variance forecasts.
- Pessimism is a serious problem because tested forecasts appear optimistic.
- Tested forecast may appear completely unbiased despite a pessimistic pre-launch bias.
- Survivor's Curse makes pessimistic forecasts difficult to detect.
- Perhaps, firms should have some new product failures. A lack of new product failures may suggest a downward forecasting bias.
- Although no perfect solution exists, clients may lessen bias with experimentation and by seeking more accurate forecasts. Forecasters may lessen bias with forecasts conditioned on launching and by seeking more accurate forecasts.

Much research has identified high failure rates associated with new products, (e.g., Urban and Hauser 1980). Perhaps, some failures are justified. Only future research can resolve this issue.

10. Future Research

This paper is a first attempt to model influential forecasting. Future research might consider additional issues. Other objective functions are possible. Rothenberg (1989), for example, notes that advertising agencies seek new product forecasting jobs though these jobs
don't "even pay out-of-pocket expenses." "Agencies seek [these jobs] because, if a new product is brought to market, it can mean a full-scale ad campaign and a commission on the spending." This situation differs dramatically from the situation in our paper.

Future research might allow decays in reputation. Untested forecasts might diminish reputation. Also clients might evaluate untested forecasts using expectations about outcomes. The degree of consistency between forecasts and client expectations might influence the client's evaluation of the forecaster.

Survivor's curse suggests that the strategy for providing multiple forecasts may differ from the strategy of supplying one forecast. It also suggests that making random would encourage bias forecasting. Future research might investigate this speculation.

Future research might consider the forecasting situation. We might only get forecasting jobs when the error variance is high (Bazerman 1983). This is possible if clients only purchase our forecasts when a great deal of uncertainty exists. Here, we are playing a losing game because our accurate forecasts are seldom validated.

Future research might consider the optimal amount of effort to spend on forecasting using a principal-agent model. Future research might also consider the effect of competition on forecasting and the value of reputation in a competitive environment.

Future research might make $\lambda$ and $\gamma$ functions of $f$. We introduced $\lambda$ and $\gamma$ to lessen the influence of $f$. It is, of course, possible that $\lambda$ and $\gamma$ are functions of $f$. We suspect, the result is a more influential forecast.

Finally, forecasts are not always forecasts$^9$. Sometimes, forecasts are just supporting confirmation$^{10}$. Keane (1969) notes forecaster complaints about clients' use of marketing research to merely "support a predetermined position." Lee, Acito and Day's (1987) find forecasts confirming manager's pre-launch beliefs are rated higher. Chicago's mayor hired a consultant Donald Corinna to evaluate the demand for new airport sites and rank possible locations. After previewing the study results, the mayor was unhappy. The mayor first asked Corinna not to report site rankings. Later he expressed a "desire to fire Corinna and replace him with someone who might be more sympathetic to the city" (Elsner 1991). Future research might consider how these so-called forecasts or testimonials can endure when everyone knows that the number itself is bogus.

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$^9$ Piercy (1982) notes that "marketing information is used as a political resource in the struggle for organizational power."

$^{10}$ In an Editorial for the *Journal of Marketing Research*, David Hardin (1969) says that "some large companies today readily admit to selecting test markets on the basis of strong local sales efforts or a strong broker—hardly an objective decision input."
Appendix A

Assume the client’s prior (pre-forecast) distribution, for the new product’s sales, is normally distributed with mean $\mu_C$ and variance $\sigma$. The client gets our forecast $f$. The client believes that $f$ is normally distributed with variance $\sigma^2$ that may or may not equal $\sigma^2$. The client updates and obtains posterior distribution $p$. DeGroot 1970 (p.167) shows that $E[p] = (\mu_C \sigma + f \sigma^2) / (\sigma^2 + \sigma)$. Substituting this expression into $E[p] > F/m$ implies $f > (F \sigma + F \sigma^2 m \mu_C \sigma^2) / (m \sigma^2)$ or $f > (F/m) + k$ where $k = (F \mu_C m) / (m \sigma^2)$.

Appendix B

PROOF OF THEOREM 1. Let $f_N$ be the average forecast for products not launched. Since $f_N$ is the average of independent normal variables, $f_N$ is normal with mean $\mu$ and variance $\sigma^2$. According to David (1957), $E[f_N | f_l > f_N] = \mu - (\sigma^2 / 2)$. But $E[f_N + f_l | f_l > f_N] = \mu$, so $E[f_l | f_l > f_N] = \mu + (\sigma^2 / 2) > \mu$. Finally, $f_A$ is a convex combination of $f_l$ and $f_N$, so $f_l > f_N$ requires $f_l > f_A$.

PROOF OF LEMMA 1. Remember that, $\bar{n}$ is normally distributed with mean 0 and variance $\sigma^2$. Also, $\varepsilon^2 = (f - \mu)^2$ and $f = \mu + \bar{n} + \beta$, so $\varepsilon^2 = (\bar{n} + \beta)^2$. It follows that:

$$E[L(\varepsilon^2)] = \int_{-\infty}^{+\infty} L((\eta + \beta)^2) \frac{1}{\sqrt{2\pi}\sigma} e^{-\eta^2/2\sigma^2} d\eta$$

Taking the derivative with respect to $\beta$, yields:

$$\frac{d}{d\beta} E[L(\varepsilon^2)] = 2 \int_{-\infty}^{+\infty} (\beta + \eta)L'((\beta + \eta)^2) \frac{1}{\sqrt{2\pi}\sigma} e^{-\eta^2/2\sigma^2} d\eta$$

Letting $\beta = 0$ yields:

$$2 \int_{-\infty}^{+\infty} N(\eta) d\eta \text{ where: } N(\eta) = \int_{-\infty}^{+\infty} \eta L'((\eta + \beta)^2) \frac{1}{\sqrt{2\pi}\sigma} e^{-\eta^2/2\sigma^2} d\eta$$

The last expression must equal zero for $\beta=0$ to be a minimum.

Now, $L[\varepsilon^2] > 0$ for all $t$. Hence, $N(t) = N(0)$ because:

$$L'((-\eta)^2) \frac{-\eta}{\sqrt{2\pi}\sigma^2} e^{-\eta^2/2\sigma^2} = -L'(\eta^2) \frac{\eta}{\sqrt{2\pi}\sigma^2} e^{-\eta^2/2\sigma^2}$$

Then, $N(t)$ is an odd function which implies:

$$\int_{-\infty}^{+\infty} N(\eta) d\eta = 0$$

The last expression is the required 1st order condition. Hence, $\beta=0$ satisfies the 1st order condition for a minimum. For the 2nd order condition, the second derivative, evaluated at $\beta=0$, is:

$$2 \int_{-\infty}^{+\infty} L'((\eta^2)^2) \frac{1}{\sqrt{2\pi}\sigma} e^{-\eta^2/2\sigma^2} d\eta + 4 \int_{-\infty}^{+\infty} \eta^2 L'' \left[ \eta^2 \right] \frac{1}{\sqrt{2\pi}\sigma} e^{-\eta^2/2\sigma^2} d\eta$$

Here, the first term is always positive because $L[\cdot] > 0$. The second term is always non-negative because $L[\cdot] > 0$. Therefore, the entire expression is positive, meeting the second-order condition.

PROOF OF THEOREM 2. Our expected profits approach $(1+b)p_1 + b[R \ E[L(\varepsilon^2)]$. From Lemma 1, they are maximized at $\beta=0$. 
PROOF OF THEOREM 3.

When, \( \sigma > R \), then \((1+b)p_1 + b[R - \sigma] < (1+b)p_1 \) and the expected profit from a launch is less than the profit from no launch. [Note: by lemma 1, no forecast exists with variance less than \( \sigma \), so a no launch is always more profitable.] When, \( \sigma = \) causes no launch. When \( \sigma > \), \( \sigma \) causes no launch. Later we impose conditions making \( \sigma \) best.

PROOF OF THEOREM 4 (PART 1). We must show the optimal forecast is \( \sigma \) when \( \sigma > R \) and condition 1 is violated, i.e., \( \sigma > R \). Suppose \( \sigma > R \), then \((1+b)p_1 + b[R - \sigma] > (1+b)p_1 \) and forecasting \( \sigma \) provides profits \( (1+b)p_1 \).

PROOF OF THEOREM 4 (PART 2).

Let \( \sigma^2 = \int_{-\infty}^{\infty} L[(\hat{\xi} - \mu)^2] \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{1}{2\sigma^2} d\eta} \)

With \( E[L((\hat{\xi} - \mu)^2)] < R \), there exists some sufficiently small positive \( \xi \) such that \( E[L((\hat{\xi} + \xi - \mu)^2)] < R \). At that \( \xi \), \((1+b)p_1 + b[R - E[L((\hat{\xi} + \xi - \mu)^2)]] > (1+b)p_1 \). Hence, profits at \( \sigma = \) are greater than profits for all \( \sigma \) including \( \sigma = \). We now examine \( \sigma > \) and \( \xi \).

By Lemma 1, \( \sigma = \) maximizes \( (1+b)p_1 + b[R - E[L((\hat{\xi} + \xi - \mu)^2)] \) which is strictly decreasing in \( \xi \) for \( \xi > 0 \). Hence, profits at \( \sigma = \) are greater than profits for all \( \sigma > \) and \( \xi \).

But for any \( \xi > 0 \) there exists a smaller \( \xi > 0 \) producing greater profits because \( E[L((\hat{\xi} + \xi - \mu)^2)] \) is strictly decreasing in \( \xi \) for \( \xi > 0 \). When \( \xi = 0 \), however, profits are \((1+b)p_1 \) and less than \( \xi > 0 \). Ergo, no solution for \( \sigma \) exists.

PROOF OF COROLLARY 1. Let \( \sigma \) be the optimal influential forecast (testing requires \( \sigma > R \)). Let \( \sigma'' \) be the optimal non-influential forecast (i.e., testing always occurs). Note that, Theorem 2 implies \( \sigma'' = \). Also note, theorem 3 and 4 imply that the average error variance for \( \sigma \) is less than or equal to \( R \). We have four cases.

Case 1. \( \sigma > \) and \( \sigma'' > \).

Here, \( \sigma = \) (theorem 3). Both forecasts have the same error variance.

Case 2. \( \sigma > \) and \( \sigma'' > \).

Here, \( \sigma > \) because \( \sigma'' > \). Theorem 3 implies \( \sigma > R \). This event raises the average error variance for \( \sigma'' \) above \( \sigma \) because the average error variance for \( \sigma'' \) is greater than \( R \).

Case 3. \( \sigma > \) and \( \sigma'' \). Both forecasts are less than \( \sigma \) and neither forecast enters the average.

Case 4. \( \sigma > \) and \( \sigma'' \). Here, \( \sigma'' \) does not enter the average. Theorem 4 implies this case only occurs when \( \sigma = \). Only using forecasts sufficiently greater than \( \sigma \) insures that \( \sigma \) does not enter the average.

PROOF OF COROLLARY 2. There are only two bias solutions in \( 0 \). When \( \lambda = \nu \), solution one requires both \( \sigma > R \) and \( (R - \sigma)/(R - \sigma < 1) \). Now, \( \sigma > R \) implies \( (R - \sigma < 0) \). But, if \( \sigma > \sigma \) implies \( (R - \sigma < 0) \) and \( (R - \sigma)/(R - \sigma > 1) \). Therefore solution one is not possible.

When \( \lambda = \nu \), solution two requires both \( \sigma < R \) and \( (R - \sigma)/(R - \sigma > 0) \). Now, \( \sigma < R \) implies \( (R - \sigma < 0) \). So, if \( \sigma > \)
implies \((R \circ)/(R \circ) < 1\). Therefore solution two is not possible. Only unbiased solutions remain.

**PROOF OF THEOREM 5 FOR \(\circ >\) \(\cdots\)** There are two cases, \(\circ < R\) and \(\circ > R\).

**Case 1.** \((\circ < R)\). From Lemma 1, we know \(\circ < \circ\) for any \(x\). Hence, profits at \(f=\) exceed \(f=x\) for all \(x > \) because \(\lambda(R \circ) > \lambda(R \circ)\). So consider \(x > \). Again, \(\circ > R \circ\). Now when \(\circ > R\) then \(\lambda(R \circ) > \gamma(R \circ)\) because \(\lambda > \gamma\). Hence, profits at \(f=\) exceed \(f=x\) for all \(x > \). Hence, \(f=\) for this case.

**Case 2.** \((\circ > R)\). We know \(\circ\) is decreasing in \(x\) for \(x < \). Hence, profits at \(f=\) exceed \(f=x\) for all \(x < \) because \(\gamma(R \circ) > \gamma(R \circ)\). So consider \(x > \). From Lemma 1, we know \(\circ < \circ\) for any \(x\). Hence, profits at \(f=\) exceed \(f=x\) for all \(x > \). It follows that \(f=\) when \(\gamma(R \circ) \lambda(R \circ)\) and \(f=\) when \(\gamma(R \circ) > \lambda(R \circ)\).

**PROOF OF THEOREM 5 for \(\circ \cdots\)\(\circ\)** There are two cases, \(\circ < R\) and \(\circ > R\).

**Case 1.** \((\circ < R)\). From Lemma 1, we know \(\circ < \circ\) for any \(x\). Hence, profits at \(f=\) exceed \(f=x\) for all \(x > \) because \(\gamma(R \circ) > \gamma(R \circ)\). So consider \(x > \). Suppose, \(\lambda(R \circ) > \gamma(R \circ)\). Then there exists some sufficiently small positive \(\xi\), such that for \(x = +\xi\), \(\lambda(R \circ) > \gamma(R \circ)\). Profits at \(f=x\), \(x = +\xi\), are \(\lambda(R \circ)\). We know \(\circ\) is decreasing in \(x\) for \(x > \). Hence, profits at \(f=+\xi\) are greater than profits at \(f=+\xi\) and profits at \(f=\) because \(\lambda(R \circ) > \gamma(R \circ)\). Hence, the conditions \(\circ < R\) and \(\lambda(R \circ) > \gamma(R \circ)\) cause \(f=+\xi\). But for any \(\xi > 0\) there exists a smaller \(\xi > 0\) providing greater profits because \([R \ E[L(( + \xi \ 1))]\) is strictly decreasing in \(\xi\). When \(\xi=0\), however, profits are \(\gamma(R \circ)\) and less than \(\xi > 0\). Ergo, no solution for \(f\) exists.

**Case 2. (\(\circ > R\)).** From Lemma 1, we know \(\circ < \circ\) for any \(x\). Hence, profits at \(f=\) exceed \(f=x\) for all \(x > \) because \(\gamma(R \circ) > \gamma(R \circ)\). So consider \(x > \). Again, \(\circ > R \circ\). Now when \(\circ > R\) then \(\gamma(R \circ) > \lambda(R \circ)\) because \(\lambda > \gamma\). Hence, profits at \(f=\) exceed \(f=x\) for all \(x > \). Hence, \(f=\) for this case. Row 2 follows.
References


FIGURE 1: Our Problem