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EVA versus Earnings: Does it matter which is more highly correlated with stock returns?[1]

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Abstract

Dissatisfaction with traditional accounting-based performance measures has spawned a number of alternatives, of which Economic Value Added (EVA) is clearly the most prominent. How can we tell which performance measures best capture managerial contributions to value? There is currently a heated debate among practitioners as to whether the new performance measures have a higher correlation with stock values and returns than do traditional accounting earnings. Academic researchers have instead relied on the variance of performance measures to gauge their relative accuracy.

Our analysis pits EVA against earnings as two candidate performance measures. We use a relatively standard principal-agent model, but recognize that while the variability of each measure is observable, their exact information (signal) content is not. The model provides a formal method for ascertaining the relative value of such measures based on two distinct uses of the stock price. First, as is well-known, prices provide a noisy measure of managerial value-added. Our novel insight is that stock prices can also reveal the signal content of alternative accounting-based performance measures. We then show how to combine stock prices, earnings, and EVA to produce an optimally weighted compensation scheme. Surprisingly, we find that the simple correlation between EVA or earnings and stock returns is a reasonably reliable guide to their value as an incentive contracting tool. This is not because stock returns are themselves an ideal performance measure, rather it is because correlation places appropriate weights on both the signal and noise components of alternative measures.

We then calibrate the theoretical improvement in incentive contracts from optimally using EVA in addition to accounting earnings at the firm and industry level. That is, we empirically estimate the "value-added" of EVA by firm and industry. These estimates are positive and significant in predicting which firms have actually adopted EVA as an internal performance measure.

1 Introduction

There is near unanimity in the belief that performance-based compensation is a critically important corporate governance mechanism. Opinions of *how* to design the compensation contract differ widely. Some argue that managers should simply be paid according to stock price performance (Jensen and Murphy (1990b) and Rappaport (1986)). However, others argue that stock-based compensation imposes excessive risk on the manager, owing to market-wide movements (Sloan (1993)) and because even firm-specific returns reflect factors beyond managers' control (Lambert, 1993). Paul (1992) points out an additional weakness with stock prices; they tend to aggregate relevant information inefficiently for compensation purposes. These latter arguments imply that firms may be able to improve incentives by relying directly on other measures of performance which more accurately reflect the manager's marginal contribution to firm value. But which measures accomplish this task, and how should they be combined to produce the best possible incentive contract?

Practitioner interest in the above question has outstripped even the academic interest. A large number of major consulting firms produce and aggressively market their own accounting-based performance measures. Examples include Stern Stewart's EVA (Economic Value Added), Holt's CFROI (Cash Flow Return on Investment), Boston Consulting Group's TBR (Total Business Return), McKinsey's Economic Profit, and LEK/Alcar's SVA (Shareholder Value Added).[1] Intense competition has arisen among these various firms for the lucrative business of designing and implementing compensation schemes aimed at increasing shareholder wealth. In marketing their services, all of the above firms provide a list of major successful clients. Stern Stewart, Boston Consulting Group, and LEK/Alcar also make the claim that their proprietary performance measure correlates more closely with stock returns than do either traditional accounting measures or the measures of rival firms, allegedly making it a more desirable compensation tool.[2] The correlation-rationale appears to carry some weight in practice, judging from examples such as the Crane Company's March 1995 Proxy Statement disclosing new executive pay based on EVA:

> Compared to such common performance measures as return on capital, return on equity, growth in earnings per share, and growth in cash flow, EVA has the highest statistical correlation with the creation of value for shareholders.[3]

[1] See Randy Myers, "Measure for Measure", *CFO Magazine*, November 1997.

[2] See O'Byrne (1997) Boston Consulting Group (1996), and LEK/Alcar (1998). A recent academic literature has emerged to critically examine such claims. Biddle et al (1997) perform the most systematic study and find that, in stark contrast to O'Byrne (1997), earnings appear to "outperform" EVA in explaining stock price movements.

[3] Reported in Wallace (1998). Companies such as Boeing, Clorox, and National Semiconductor also mention the importance of a high correlation between performance measures and stock prices (see Davis (1996)).

Since the avowed goal of the new performance measures is to increase shareholder wealth, the correlation of such measures with stock returns has an obvious appeal. However, as originally shown by Gjesdal (1981), a strong statistical correlation with stock returns does *not* establish that a performance measure adds value. No measure of performance could ever have a higher statistical correlation with stock returns than the return itself. Thus, if correlation was the only goal, firms should *solely* use their stock price for compensation and ignore all other measures. However, as argued above, stock returns might be an excessively noisy and even misleading measure of managers' value-added.[4]

These arguments seem to suggest that an ideal performance measure would not be too closely related to the stock price. However, if this is the goal, there are an infinite number of truly irrelevant and inappropriate measures that fit the criterion of being unrelated to the stock price. In light of these conflicting arguments, how are we then to judge the value of alternative performance measures?

To answer this question, we use an explicit incentive contracting and valuation model. This allows us to go beyond the polar cases, since no actual performance measure has an R^2 of either zero or one.[5] The model reminds us that what matters for compensation is the signal-to-noise ratio (see Banker and Datar (1989)). Our first contribution is to incorporate the fact that while it is relatively easy to measure the volatility or "noise" content of alternative performance measures, the "signal" content of such measures is not directly observable by researchers and, most likely, by the firms that use them. We simply assume that we don't know all of the relevant attributes of the available performance measures, and show that a performance measure's correlation with the stock price indirectly reveals some of these features.[6] Therefore, we show how to use alternative accounting-based performance measures together along with stock returns to empirically determine their signal-to-noise ratio. Consequently, we are able to state the value-added of each performance

[4]An alternative argument is that, unlike stock prices, EVA and other measures can be decomposed to the divisional level and beyond. It can then be argued that EVA serves as a divisional surrogate for the (nonexistent) stock price. Unfortunately, the *firm-level* correlation between an performance measure and stock prices cannot establish its value at lower levels of the organization. The divisional level measures could be extremely biased and dysfunctional, but as long as these biases "wash-out" at the firm level, we will be unable to detect them. Additionally, the Paul (1992) argument implies that even a perfect division-level surrogate for the stock price would not necessarily be ideal for incentive compensation.

[5]A theoretically ideal performance measure would measure effort without noise *and* allow a forcing contract. Such a measure would have zero variability in equilibrium, but would also be extremely sensitive to any changes in managers' value-added. The R^2 of such a measure is either zero or undefined.

[6]There are other examples in the literature where the firm learns from the capital market or other performance measures. Dye and Sridhar (1998) examine how firms' strategic decision making can be improved by observing stock market reactions to proposed strategic initiatives. Dye (1999) builds a formal model that helps us interpret popular management concepts, such as TQM and the "Balanced Scorecard". He argues that when there exists uncertainty about what drives firm value, managers should experiment with various measures of performance as a means of learning about which one is most critical to the value creation process.

measure, *entirely in terms of observables*. The relative variance of alternative measures is clearly a poor measure of their value since this ignores differences in the signal content of each measure. The value-added is also not equivalent to the relative size of the coefficient obtained by regressing stock returns on the accounting measures, echoing Paul's (1992) results. Surprisingly, the relative ability of each measure to explain abnormal stock returns (i.e., its R^2) fares far better. While it is not a perfect measure of the incremental value-added of a performance measure, it has the right ordinal properties. Holding the noise content fixed, an increase in the signal will increase the R^2. And holding the signal content fixed, an increase in noise will decrease the R^2. This turns out to be nearly enough for the purpose of determining the relative value of two accounting measures. Thus, our model suggests that despite its rather obvious weaknesses, there is substantial value in the debate over which performance measure has the larger R^2.

Following the above, we attempt to integrate the theory and empirical tests in a meaningful way. We test our approach by computing the value-added by using EVA according to our theory, along with the relative R^2 for over 500 US firms between 1979-98. Consistent with the findings of Biddle et al (1997) and our results on the value of R^2 weightings, EVA adds little or no value for a large number of firms. However, there are significant differences across firms and industries. For example, the percentage reduction of the variance of an optimal compensation plan using both EVA and earnings relative to a plan written only on earnings is just 2.2% for the Tobacco Products industry (SIC two-digit code 21). However, this same variance reduction is 32.6% for the Food and Kindred Products industry (SIC 20).[7]

This heterogeneity in the value-added of EVA raises the question of whether EVA and related measures are in fact more likely to be adopted by firms for which EVA's marginal value is greater. To investigate this, we use the lists of firms that have adopted EVA or a related "economic profit" measure for incentive purposes from the studies of Wallace (1997), Hogan and Lewis (1999), and Kleiman (1999). Our model does surprisingly well. For example, no firm in the Tobacco Products industry has formally adopted EVA in our sample, whereas 11.5% of the firms in the Food and Kindred Products industry have adopted EVA. In our analysis of actual EVA adoption decisions, we also control for other plausible determinants of the value-added of EVA, including capital intensity, size, leverage, prior performance, and Tobin's q. Any capital-intensive firm would seem an obvious candidate to adopt EVA. Large firms, for which the agency problems may be most pronounced and fixed costs of adoption loom less large, may find EVA more valuable, as would

[7] These results can be found in *Tables 6* and *7*

any firm that has suffered from poor historical performance. On the other hand, firms that are highly leveraged may need EVA less as debt provides its own incentives to operate efficiently (see Jensen (1989)). However, our empirical analysis shows that only capital-intensity is associated with the adoption decision; measures such as size, leverage, past performance, or Tobin's q have little ability to distinguish those firms that do and those that do not adopt EVA. Thus, our method for measuring the value-added of EVA appears itself to add value.

The rest of the paper is organized as follows. Section 2 develops the model and characterizes the problem we explore. Section 3 presents the formal empirical structure for testing our formal model of compensation when performance measures have unknown attributes. Section 4 provides our empirical results. Section 5 concludes. All proofs are in the Appendix.

2 Model Setup

In this section, we develop a model of managerial compensation design. Our goal is to determine the marginal value of adding the EVA performance measure to an existing earnings-based compensation plan.[8] As is standard, we require all measures to be used optimally. Less standard is our ability to express the results in terms of observable quantities.

We model a single firm run by a risk-averse manager. Fundamental firm value is determined by both the manager's effort choices and randomness, where this latter component represents elements beyond the manager's control. We assume that there are two dimensions of managerial effort, denoted a_c and a_f. Strictly speaking, the action a_c can be captured by (accounting) performance measures, while the action a_f is not revealed by our candidate accounting measures. This action will be captured by another performance measure, then revealed through stock prices. We introduce these two types of effort in order to distinguish between two uses of the stock price. First, it represents a direct measure of a_f, and second, it serves as an additional source of information about the competing accounting measures of a_c. The firm's terminal value is given by

$$X_c + X_f = (a_c + \theta_c) + (a_f + \theta_f),$$

where $a_i \in [0, \infty)$, for $i \in \{c, f\}$, are the manager's (unobservable) effort choices across a_c and a_f, and θ_i is noise, with $\theta_i \sim N(0, \sigma_i^2)$ for $i \in \{c, f\}$. The terms θ_c and θ_f are independent shocks

[8] It is important to note that our analysis is directly amenable to any pair-wise comparison of performance measures. We focus on only two accounting measures since we are interested in characterizing the battle over which accounting measure – EVA or earnings – is better for incentive compensation.

to the manager's efforts, with variances σ_c^2 and σ_f^2, respectively. Naturally, these need not have zero mean, but are so modelled here for convenience. Observe that we have set the unadjusted sensitivities of the manager's two action choices both equal to one. This is just a normalization as we will allow the cost of the different types of effort, and therefore their value marginal products, to vary arbitrarily.

The manager has utility that is separable in wealth and effort, and has a reservation utility level normalized to zero. We assume that the manager has negative exponential utility over wealth, with a coefficient of risk-aversion given by r. Further, the general cost of effort is given by $C(a_c, a_f)$.[9] Risk neutral shareholders design the manager's compensation contract to maximize their wealth, subject to the participation and incentive compatibility constraints. Given the unobservability of both effort decisions, shareholders must rely on performance-based compensation arrangements. Hampering these efforts in our model is the assumption that the underlying value of the firm (X_c+X_f) is *not* directly observable. Rather, there exists a set of observable performance measures which offer noisy, yet informative estimates of the individual components of firm value.

2.1 Available Performance Measures and the Stock Price

We assume that there are two competing (accounting) measures of a_c, Y_1 and Y_2, and one measure of a_f given by Y_f. The two accounting performance measures are observable to all and contracts can be written on them directly. These measures are given by

$$\begin{aligned} Y_1 &= \lambda_1 X_c + \varepsilon_1 \\ Y_2 &= \lambda_2 X_c + \varepsilon_2, \end{aligned}$$

where $\varepsilon_1 \sim N(0, \omega_1^2)$ and $\varepsilon_2 \sim N(0, \omega_2^2)$. For generality, we allow these errors to have a (possibly) non-zero covariance given by $Cov(\varepsilon_1, \varepsilon_2) = \rho_{\varepsilon_1\varepsilon_2}\omega_1\omega_2$.

The parameters λ_1 and λ_2 are positive, deterministic scalars that represent the *marginal value* of the performance measure. In particular, they determine what proportion of the manager's contribution to firm value through a_c is successfully captured by the performance measure. At the heart of our paper is the acknowledgment that these parameters need not be *known* a priori. The motivation for this specification is as follows. It is apparent that in the performance specification of

[9] These assumptions are made solely for simplicity. Since our focus is on relative, rather than absolute performance weights, we can ignore differences in risk aversion or effort costs. Any differences would simply carry through to our Banker and Datar (1989) ratio of optimal performance weights. However, for interesting work on the effects of manager risk aversion on optimal compensation contracts, see Haubrich (1994) and Garen (1994).

$Y_j = \lambda_j X_c + \varepsilon_j$, "false" value creation is potentially registered in either measure by the error term ε_j. Naturally, these errors could differ across performance measures. Similarly, the unknown and potentially nonequal λ_j's capture the fact that our accounting measures might also fail to register value-increases that have in fact occurred. That is, these measures can, and most likely do, have differential "signal content" as well. Thus, we model a situation where performance measures are freely available for contracting purposes, yet their value in this regard may be uncertain.

The above formulation is in part an attempt to capture the implicit logic behind the "R^2 debate". If all practitioners agreed on the properties of alternative performance measures, there would be no reason to argue about which is most closely related to stock prices. One would simply demonstrate that EVA (or a competing measure) is consistent with basic valuation principles while accounting earnings are not. However, actual performance measurement involves both noise and judgement. As Stern Stewart and other practitioners have implicitly recognized, the theoretical argument in favor of EVA or related measures needs buttressing by empirical evidence, such as the relationship between the performance measure and stock prices. Our model indicates exactly what kind of evidence is needed and how it should be used.

For the case of earnings, it is well-known that earnings changes have a substantially lower variance than do stock returns, even after removing market effects from the stock returns. But if earnings had a λ value of one, then they would be more variable than fundamental value due to the noise term ε. While this can be explained away by assuming that this effect stems solely from variations in future value (Y_f) or simple stock price noise, it is equally likely that earnings reports suppresses *information*, as well as noise. A similar argument can be made for EVA. First, changes in EVA are far less volatile than abnormal stock returns in Biddle et al's (1997) sample, as well as in our sample. Second, EVA's adjustments to reported earnings are unlikely to undo all of the conservativeness in accounting earnings. Finally, and perhaps most important, the equity cost of capital used in Stern Stewart's capital charge is estimated with a great deal of noise.[10] In response, Stern Stewart appear to advocate smoothing the capital charge across firms and over time, as evidenced by the following excerpt:

> Coca-Cola, (a prominent Stern Stewart client), uses 12% as its single cost of capital worldwide, expressed in dollars. Why 12%? Because it's 1% a month.[11]

Our formulation resembles that used by Sloan (1993) in allowing accounting numbers to be

[10] See Fama and French (1997) for an examination of the time-variation in industry costs of capital.

[11] See Ehbar (1999).

related to fundamental value by a multiplicative constant. However, his approach critically relied on the extreme assumption that abnormal stock returns are a *noiseless* measure of X_c. We allow for a more realistic setting in which *all* measures are noisy and at the outset of the analysis, we don't know all of the relevant attributes of the available performance measures of a_c. However, we do allow for the possibility that there exists another valuable piece of information. In addition to the two current value performance measures, there is a measure of a_f given by

$$Y_f = X_f + \varepsilon_f,$$

where $\varepsilon_f \sim N(0, \omega_f^2)$. We assume that Y_f is observed by capital market investors and hence, revealed through the stock price. In equilibrium, the stock price (P) is set by competitive, risk-neutral traders who observe Y_1, Y_2 and Y_f, and understand the statistical properties of each measure.[12] This specification implies that the capital market participants are able to obtain accurate estimates of the variances Y_1 and Y_2. Access to a sufficiently long time-series of observations on Y_1 and Y_2 would be sufficient for such a purpose.

The measure Y_f could very well represent information that is privately observed by some capital market investors. However, it should be noted that our analysis could readily accommodate the assumption that the firm's shareholders (who design the manager's wage contract) could also observe Y_f. In fact, they could also observe the λ_1 and λ_2 parameters. What is implicit in our analysis is that the shareholders design a contract using the two accounting measures and stock price, and treat Y_f as noncontractible. Our contribution builds on the reality that as empirical researches, *we* cannot observe λ_1, λ_2, or Y_f.

Given this information structure, the stock price is

$$P = E(X_c + X_f \mid Y_1, Y_2, Y_f) + \phi, \tag{1}$$

where $\phi \sim N(0, \sigma_\phi^2)$ captures the possibility that market prices have additional errors that are independent of fundamentals.[13] Note that since expected returns are zero, any non-zero returns are abnormal returns reflecting innovations in the measures Y_1, Y_2, Y_f or the error term ϕ.

2.2 Optimal Contracts

For incentive contracting purposes, the firm's shareholders are interested in the manager's contributions to firm value through a_c and a_f. If λ_1 and λ_2 were known, the stock price would not provide

[12]We assume that the discount rate is zero.

[13]For simplicity, we are ignoring the fact that the manager's pay comes out of the stock price. Inclusion of this does not qualitatively alter the results, although the algebra becomes increasingly tedious.

a valuable signal of the manager's choice of a_c. The reason is that the stock price's estimate of a_c is based only on measures Y_1 and Y_2, which can already be used directly for contracting purposes. In this case, the stock price is only a useful surrogate for the manager's choice of a_f.

In the case that λ_1 and λ_2 were known, we could transform the reported Y_i measures to

$$\Psi_i = \frac{Y_i}{\lambda_i}, \tag{2}$$

for $i \in \{1, 2\}$. Restricting the set of feasible wage contracts to be linear, we can then write an optimal contract directly on the transformed performance measures by solving for

$$w(Y_1, Y_2, P_f) = W + \gamma_1 \Psi_1 + \gamma_2 \Psi_2 + \alpha \left[P - E[P|Y_1, Y_2, Y_f]\right], \tag{3}$$

where W represents the fixed wage.[14] 4

Naturally, the absolute weights in this wage contract depend on the explicit functional form for the manager's cost of effort and risk-aversion coefficient. However, as we know from Banker and Datar (1989) for the case where the manager has a single effort decision (here a_c), the optimal *relative* weights on the two accounting measures Y_1 and Y_2 are independent of these considerations. Their result carries over to our multi-task setting since we assume that both Y_1 and Y_2 are noisy measures of the same action on the part of the manager.[15] More importantly, the relative weights can be easily computed from the second moments of the two measures when λ_1 and λ_2 were known, and these are

$$\frac{\gamma_1^*}{\gamma_2^*} = \frac{Var(\Psi_2) - Cov(\Psi_1, \Psi_2)}{Var(\Psi_1) - Cov(\Psi_1, \Psi_2)}. \tag{4}$$

3 Extracting Information from Stock Prices

There is, however, a fundamental difference between the optimal relative weights when we do not observe λ_1 and λ_2. We do *not* observe the additional information λ_1 and λ_2 necessary to construct the measures Ψ_1 and Ψ_2 in the first place. In this section, we develop our formal framework for using stock market information to elicit estimates of each performance measure's signal content, as well as estimate a performance measure's marginal value in being added to an existing compensation contract.

[14] We will only consider linear compensation contracts. See Holmstrom and Milgrom (1987) for justification of this approach.

[15] See Feltham and Xie (1994) for a characterization of the more general case where measures capture multiple aspects of effort.

We can obtain an estimate of λ_i, for $i \in \{1, 2\}$, through the regression

$$Y_i = k_i + \chi_i P,$$

where

$$\begin{aligned} \chi_i &= \frac{Cov(Y_i, P)}{Var(P)} \\ &= \frac{\lambda_i \sigma_c^2}{Var(P)}. \end{aligned} \tag{5}$$

This regression provides an estimate of λ_i in the form of the coefficient χ_i. It is important to recognize that χ_i understates the true λ_i because $Var(P) > \sigma_c^2$. This is apparent given that the stock price depends not just on X_c (as captured by Y_1 and Y_2), but also on X_f (revealed through Y_f) and additional noise, given by the variance of ϕ. Sloan (1993) undertook an analysis similar to that above but assumed that the variance of abnormal stock returns were in fact equal to σ_c^2 (which is the variance of X_c). Under that strict assumption, χ offered an unbiased estimate of λ. As pointed out by Lambert (1993), this assumption is unrealistic and in fact undercuts the entire exercise since it immediately implies that the abnormal return should be the only performance measure used.

Naturally, since we don't observe λ_i, our estimate of $\chi_i = \frac{Cov(Y_i,P)}{Var(P)}$ remains less than ideal. Moreover, we should state clearly that we do not claim to solve the above errors-in-variables problem and obtain unbiased estimates of the λ_i. When the errors $(\varepsilon_1, \varepsilon_2)$ in our accounting performance measures are correlated ($\rho_{\varepsilon_1 \varepsilon_2} \neq 0$), we are unable to completely decompose the variance of the stock price into the components that reflect a_c, a_f, and noise. Fortunately, as we now show, we do not need to solve the errors-in-variables problem to obtain an unbiased measure of the relative optimal weights on our accounting performance measures. The reason is simply that the degree of underestimation is *equivalent* across both performance measures. Hence, we denote

$$g \equiv \frac{Var(P)}{\sigma_c^2},$$

which offers us an estimate of λ_i, denoted $\widehat{\lambda}_i$,

$$\widehat{\lambda}_i = g\chi_i, \tag{6}$$

for $i \in \{1, 2\}$, that carries the same constant g in both $\widehat{\lambda}_1$ and $\widehat{\lambda}_2$. This allows us to express the optimal Banker and Datar (1989) relative weights given by (4) completely in terms of observable correlations,

$$\begin{aligned}
\frac{\gamma_1^*}{\gamma_2^*} &= \frac{Var(\Psi_2) - Cov(\Psi_1, \Psi_2)}{Var(\Psi_1) - Cov(\Psi_1, \Psi_2)} \\
&= \frac{\chi_1}{\chi_2}\left(\frac{\chi_1 Var(Y_2) - \chi_2 Cov(Y_1, Y_2)}{\chi_2 Var(Y_1) - \chi_1 Cov(Y_1, Y_2)}\right) \\
&= \frac{\rho_{Y_1P}}{\rho_{Y_2P}}\left(\frac{\rho_{Y_1P} - \rho_{Y_1Y_2}\rho_{Y_2P}}{\rho_{Y_2P} - \rho_{Y_1Y_2}\rho_{Y_1P}}\right),
\end{aligned} \tag{7}$$

where ρ denotes the simple correlation coefficient.

The last two expressions are stated entirely in terms of observables. While there is no single statistical concept that captures all the elements of the optimal compensation ratio, it is quite closely related to the ratio of the simple R^2 obtained from regressing stock returns on the two accounting measures, which can be written as $\left(\frac{\rho_{Y_1P}}{\rho_{Y_2P}}\right)^2$. By contrast, the ratio of relative variances is *not* fundamentally related to the optimal weights, and later we show that this is true empirically as well. Similarly, if the firm were to ignore the accounting performance measures and tie the managers' pay exclusively to the stock price, the two measures would implicitly receive weights of χ_1 and χ_2, respectively. The problem with the stock market weights is that they place too much emphasis on relative variance. To see this, observe that the ratio $\frac{\chi_1}{\chi_2}$ can be written as $\frac{\rho_{Y_1P}\sigma_{Y_2}}{\rho_{Y_2P}\sigma_{Y_1}}$. This is a special case of Paul's (1992) general demonstration that the stock market need not aggregate information efficiently for incentive purposes.

3.1 EVA's Contribution to Efficient Contracting

We now use our methodology from above to predict which firms will explicitly adopt EVA or a related measure. For this purpose, we need to characterize the marginal value (or value-added) of using EVA in an optimal wage contract versus not using it all. In general, the value-added of using a second performance measure in conjunction with an existing measure in an incentive-based wage contract is a function of the difference between the variance of the existing measure and the variance of the optimally weighted composite measure. For our purposes, we wish to assess the marginal contribution of adding EVA (Y_1) to a compensation plan written only on earnings (Y_2). The resulting plan would essentially be written on a composite measure, given by $\Psi_c^* \equiv \frac{\gamma_1^*}{\gamma_1^*+\gamma_2^*}\Psi_1 + \frac{\gamma_2^*}{\gamma_1^*+\gamma_2^*}\Psi_2$, where γ_1^* and γ_2^* are given by (7). The marginal contribution is then strictly increasing in the difference between the variance of the transformed earnings measure ($Var(Y_2/\lambda_2) = Var(\Psi_2)$) and the variance of the optimal composite measure ($Var(\Psi_c^*)$). With this hand, we have the following result.

Proposition 1

The value-added of adding EVA to a compensation plan written on earnings is given by $Var(\Psi_2) - Var(\Psi_c^*)$. *While this expression includes the unobservable term* $g = Var(P)/\sigma_c^2$, *the percentage value-added,* $\frac{(Var(\Psi_2) - Var(\Psi_c^*))}{Var(\Psi_2)}$, *can be expressed entirely in terms of the simple correlations* ρ_{Y_2P}, ρ_{Y_1P}, *and* $\rho_{Y_1Y_2}$.

The above result translates the relative weighting characterized in (7) into the total value-added of the alternative measures. This reflects the extent to which the firm can reduce the risk imposed on executives without sacrificing incentives.

There is one remaining difficulty with using *Proposition 1* to predict the decision to adopt EVA. In our framework, we envision the firms optimally combining the new performance measures with their existing ones. Stern Stewart advocate that EVA be used *to the exclusion* of traditional measures such as earnings. However, it is certainly possible that in the process of customizing EVA for each client, they end up with a measure like ours that retains the valuable portions of earnings and combines it optimally with the unique features of EVA. While the result on the value of using either earnings or EVA in isolation in an optimal wage scheme is informative, one could argue that our optimal weighting scheme of $\Psi_c^* \equiv \frac{\gamma_1^*}{\gamma_1^* + \gamma_2^*}\Psi_1 + \frac{\gamma_2^*}{\gamma_1^* + \gamma_2^*}\Psi_2$ is closely akin to what firms might do in reality. For example, in deciding how to handle their R&D expenses, Federal-Mogul corporation debated between expensing them (as is done in traditional Earnings) or capitalizing them (as is advocated by Stern Stewart in EVA). In the end, they chose to capitalize them as this method offered the highest correlation (R^2) with stock price changes. We would interpret this as giving low weight to earnings (i.e., low γ_1^*) and giving more weight to EVA (i.e., high γ_2^*) in Ψ_c^*.

Unfortunately, with the exception of a few stylized examples, we have no way to ascertain when such weighting takes place when firms adopt EVA. Fortunately, as we now show, there is a close relationship between the value-added of EVA as part of an optimal performance measure, and its value when used to the exclusion of earnings.

Proposition 2

The value to the firm from using EVA (Y_1) *on its own, relative to that of using earnings* (Y_2) *on its own, can be expressed in terms of observables as*

$$\frac{Var(\Psi_2)}{Var(\Psi_1)} = \frac{\rho_{Y_1P}^2}{\rho_{Y_2P}^2}.$$

Proposition 2 conveys two important messages, one direct and another indirect. The direct message is that the comparison of relative R^2 is exactly the right question for a firm that is considering replacing earnings with EVA in its performance measurement and incentive system. The more subtle message is that while this simple approach gives an incorrect quantitative assessment of the value of using earnings and EVA together, it generally gives the right *ordinal* message about whether or not EVA is valuable as a performance measure in isolation. The reason is that the two approaches differ only in that the optimal weighting approach takes account of the correlation between the two measures, an issue that is of course irrelevant if only one measure will be used. In addition, the two approaches give similar *rankings* of EVA versus earnings because the correlation between the two measures has the same effect on the value of each.

4 Empirical Analysis

4.1 Hypotheses tested

There are two fundamentally different approaches to empirically testing the theory. The first would be to test whether firms pay their managers as if they understood and applied the theory independently of whether or not they had explicitly chosen to adopt EVA or a related performance measure. This would be related to recent empirical work by Bushman et al (1998) and Krolick (1998) who compare the importance of standard accounting measures in explaining stock prices and in explaining compensation. Both studies find evidence consistent with our model in that measures which are more important in determining stock prices are also more important in compensation. As the authors recognize, the results of Gjesdal (1981) imply that the relationship need not hold in theory. Our *Proposition 2* provides a credible theoretical rationale for why the Gjesdal (1981) critique need not hold in practice, so that the value of accounting numbers in valuation and stewardship can in fact be closely related.

Both Bushman et al (1998) and Krolick (1998) use well-established measures such as return on assets, earnings, and so forth. By contrast, we focus on a relatively novel development in performance measurement, EVA. A conceptual problem with a compensation test of our theory is that we would be estimating the sensitivity of pay to measures, such as EVA, which many firms do not explicitly use in compensation. While one could defend the test by asserting that firms should nonetheless act "as if" they were using EVA, we adopt the more direct approach of explaining which firms explicitly adopt EVA or a related performance measure. We begin with the lists of adopters from Wallace (1997) and Hogan and Lewis (1999). These researchers searched text databases, including Lexis/Nexis, ABI/Inform, and The Wall Street Journal Ondisc databases over 1985-1994 (Wallace) and 1986-1994 (Hogan and Lewis) for keywords including Economic Value Added, Residual Income, Economic Value Management, Economic Profit, Value Based Management, and Market Value Added. We add to these lists the adopting firms identified by Kleiman (1999), who searched the Compact Disclosure database for the words EVA and Economic Value Added. The three lists had an overlap of over 80%, and we only require a firm to appear in one of the sets to be deemed an "adopter".

Hogan and Lewis (1999) and Kleiman (1999) look for evidence of performance improvements following the adoption of EVA or a related measure; Kleiman (1999) finds strong evidence of stock return improvement but Hogan and Lewis (1999) find no evidence of operating performance improvements relative to the industry mean. By contrast, we wish to explain why firms adopt or do not adopt such performance measures in the first place. We ask whether firms are more likely to adopt EVA or a related measure when our theory suggests it will be an efficient tool for incentive contracting in that particular firm. Hogan and Lewis (1999) suggest an alternative view based on their finding that performance improvements appear to be no better than for similar firms that did not adopt the measures. They also argue that firms may simply time the adoption of these measures to coincide with exogenous anticipated increases in performance. This hypothesis is intriguing, but incomplete, as it does not explain why those other firms whose performance improved similarly, did not also adopt EVA or a related measure.

4.2 Data

This section presents results from firms over the years 1986-97. Our longest possible time-period starts in 1978 and our results are similar with this longer time-series. We use the shorter series to reduce the chance of an underlying structural break. To derive our prior expectations for the value-weight placed on alternative performance measures, we use standard accounting and stock price data from Standard and Poors' Compustat and CRSP. These data were augmented with estimates of Economic Value Added secured from the Stern Stewart Performance 1000. It is worth noting at this point that we use the *publicly reported* EVA numbers from Stern Stewart to capture the value of such measures. This may understate the value of these measures, as we miss the detailed firm-specific adjustments that Stern Stewart performs for its clients.

Table 1 provides basic descriptive statistics of our sample. Abnormal stock returns are estimated assuming a beta of one and using the NYSE value-weighted index as the market portfolio as in Biddle et al (1997). Results are essentially identical using firm-specific betas from CRSP. The sample size is just under 6800 observations, which represents the universe of firms which appear in the Stern Stewart Performance 1000 list as well as CRSP and COMPUSTAT for at least two years of our sample period. Two years are required because we use changes in both stock values and accounting performance measures to compute our optimal weights. We do this in order to remove (as far as possible) the effect of anticipated performance from stock returns, and also to avoid the non-stationarity of data in levels.

As is common with panel data on large companies, *Table 1* indicates some large outliers in both accounting performance measures and stock returns. To reduce the effects of such extreme observations, we first removed all firms with less than five years of data.[16] We then winsorize all our values at the 1% tails before performing our statistical analyses. That is, if an observation falls outside the 1% confidence interval at either tail, we set it equal to the upper or lower bound of that interval.

4.3 Firm-Level Data

To compute the correlations that underlie our calculation of the value-added by EVA, we use abnormal stock returns and innovations in EVA and earnings. We follow Biddle et al (1997) in dividing our accounting measures by lagged market value of equity as this provides consistent scaling with stock returns. Finally, we use an AR1 specification to identify innovations in the accounting numbers, similar to Biddle et al (1997). As expected, our results are similar but noisier if we use simple first differences to proxy for unexpected changes in earnings or EVA.

Standard contract theory requires that performance measures be tailored to each firm's specific circumstances. Moreover, the decision to adopt or not to adopt EVA is certainly a firm-level decision. As Kleiman (1999) reports, EVA adoption shows some clustering in the manufacturing sector (industry codes 2000-3999). However, even at the 4-digit industry level, there are only three industries in which more than 90% of the firms (weighted by sales or assets) have adopted EVA. In our theory, the weights that are to explain the decision to adopt EVA are in turn computed using firm-specific statistical correlations. With at most 12 years of data on each firm, we will inevitably have noisy measures of the relevant correlations and variances. We can extend the series to 19 years for a subsample of firms, but this heightens the prospect of an underlying structural break.

[16] Our results are similar if we increase the required number of years to ten, or reduce them to four.

Our results are similar with our full sample.

Table 2 presents the summary statistics for our firm-level data. The first two rows present results similar to Biddle et al (1997); earnings tend to have a higher correlation with stock returns than does EVA. The third row shows that the two measures are significantly correlated with one another on average, indeed somewhat more so than with the stock price. In terms of our model, this last finding implies that the measurement errors ε_1 and ε_2 tend to covary positively, an issue which is accounted for explicitly in our computation of the value of EVA. It is also important to note that a non-trivial number of our correlations are negative, an issue that does not appear in previous studies which estimate the relationship between EVA, earnings and abnormal returns for large pooled cross-section and time-series of data. While the theory does not restrict the correlations to be positive, we describe below how we handle these values in computing the value of EVA.

The next row in *Table 2* summarizes our dummy variable indicating whether or not a firm has adopted EVA. The low average value reflects first the fact that previous research has identified 78 total adopters, of which 47 had six years of full data from COMPUSTAT, CRSP, and Stern Stewart. The year of adoption is also indicated in the previous studies, but we were unable to exploit this information because of (a) a lack of sufficient data on either side of the adoption year, and (2) a lack of a dynamic theory indicating exactly when firms should be expected to adopt EVA. The next two rows of *Table 2* summarize our alternative *a priori* measures of the relative contracting value of EVA versus earnings. The average percentage reduction in contracting noise from using EVA is over 15%, but the median value is zero. Since most firms have not in fact adopted EVA, the large proportion of firms for which the value-added of EVA is zero provides the first piece of evidence that is consistent with the prediction of our model. Moreover, the average fraction of EVA adopters in the 283 firms where our theory says EVA is of no value is just under 2.5% while it is nearly 14% in the remaining 257 firms. This suggests that actual adoption decisions bear some relation to our theoretical predictions, an issue we investigate systematically in the next section.

There are three reasons for our conclusion that the median firm gains nothing from using EVA. First, there are many cases where earnings has a higher correlation with stock returns than does EVA, and the two are not themselves highly correlated. Second, there are a significant number of cases where EVA has a small or even negative correlation with stock returns and a relatively high correlation with earnings. In this case, the theoretically optimal response would be to place negative weight on EVA, using it in much the same way one would use an industry performance index. While the intuition is compelling, it is difficult to imagine firms using EVA or earnings in this way; for this reason we restrict the weights on earnings and EVA to fall between zero and one. There are also cases where EVA has only a small or negative correlation with earnings, but a negative correlation with abnormal returns. In these cases, we set the value-added of EVA to zero as it is a perverse performance measure.[17] Finally, in the 17 cases where EVA is positively correlated to stock returns but earnings are negatively correlated, we set the fraction of value-added of EVA to 100%. We adopt similar conventions for the computation of relative R^2 values.

The last five rows of *Table 2* summarize a set of control variables which may also affect the decision to adopt EVA. Size may affect the adoption decision if there are fixed costs, but it is readily confirmed that there are very few small firms that satisfy all our data requirements. It is also worth noting that the organizational costs of adopting EVA should also increase with size so the effect of size is *a priori* ambiguous. More highly leveraged firms may have less demand for EVA since a larger fraction of their capital costs are in the form of interest payments. Put another way, highly levered firms may already run a "tight ship" (see Jensen (1989)) and so gain little from additional performance incentives. High values of Tobin's q may either reflect good performance, in which case the demand for EVA may be less, or may capture growth firms for whom the measurement of EVA is more problematic. Finally, firms with more tangible assets may gain more from careful management of capital, or it may be in more mature industries in which EVA is more valuable. We also experimented with a set of operating and stock market performance measures to allow for the possibility that firms with poor recent performance are motivated to adopt EVA. Consistent with the findings of Hogan and Lewis (1999) and Kleiman (1999), there is little difference in the prior performance of adopters and their industry counterparts.[18]

4.4 Theoretical and actual adoption of EVA

Table 3 presents simple correlations between the alternative measures and the adoption of EVA or a related performance measure. None of our explanatory variables shows a significant univariate Pearson correlation coefficient with the decision to adopt EVA. As expected from the expressions in *Propositions 1* and *2*, the value of EVA under the optimal weighting scheme is positively correlated with the relative R^2 of the two measures. The correlation is barely significant at the 10% level, however. This is problematic because as argued earlier (see *Proposition 2*), relative R^2 is the right measure if firms truly abandon all other performance measures when adopting EVA, while

[17] A direct application of our theoretical formula mis-handles such cases because all correlations are squared.

[18] Kleiman (1999) finds that stock price performance improves *after* the adoption of EVA, but there is no difference before adoption or in operating performance.

our percentage value-added is the right measure if firms manage to combine EVA with previously available earnings-based measures. The mathematical expressions for the two different measures suggest that their ranking may be more highly correlated than their numerical values, and this is buttressed by the problem of some major outliers in the R^2 measure. Consistent with this, the Spearman rank correlation between relative R^2 and percentage value-added is over 85%. Since we wish to allow for the possibility that firms can either adopt EVA exclusively, or combine it with existing measures, we adopt an approach similar to that of Aggarwal and Samwick's (1999) study of the relationship between the variance of stock returns and their use in CEO compensation. Specifically, we use the cumulative distribution function of the percentage value-added by EVA as our primary dependent variable. Firms for whom EVA adds zero value thus receive a value of zero and those for whom EVA improves incentive efficiency by 100% receive a weight of 1. As Aggarwal and Samwick (199) stress, this approach has the useful property of being less sensitive to outliers in either method of gauging the value of EVA.

Both of our cardinal measures of the value of EVA are positively correlated with both firm size and leverage and negatively correlated with Tobin's q and the fraction of tangible assets. None of these correlations are large enough to raise much of a multicollinearity issue and none of our key results are sensitive to the choice of regression controls. The remaining correlations in *Table 3* are fairly standard; leverage is positively related to size and negatively related to Tobin's q, and Tobin's q is significantly lower with greater firm size. The only surprising correlations are with the fraction of tangible assets being negatively related to leverage and positively related to Tobin's q. The correlations are generally not large and probably reflect the fact that we are estimating a univariate relationship over a large sample of firms covering essentially all industries.

Table 4 presents regression estimates of the relationship between our estimates of the value added by EVA and actual adoption decisions. The first two columns present logit estimates of the probability that the firm adopts EVA with an indicator variable for adoption as the dependent variable. The data present problems of both heteroskedasticity and correlated errors. To reduce heteroskedasticity, we first weight the data by the square root of the number of observations we have for each firm. We compute our standard errors using the Huber-White sandwich estimator available on the Stata® Statistical package. We also allow for the residuals to be correlated within SIC industries; the reported results only allows correlation at the 4-digit level, but results are minimally affected by using either the 2- or 3-digit level.

The results tend to support the theory that firms take account of the signal and noise content of

EVA in deciding to adopt this measure for performance evaluation and compensation. Firms that have a relatively high value-added of EVA are significantly more likely to be those among firms that adopt the system. The only other significant determinant of adoption is the fraction of tangible assets. None of the other controls have any discernible effect on the adoption decision, perhaps partly due to correlation between them and to the fact that we have a large and heterogeneous sample. We also experimented with non-linear specifications of the controls (including their rank) with similar results.

The overall explanatory power of the regressions is modest, delivering the realistic message that we still have much to learn about the value of EVA and firms motivations for adopting it. As noted by Kleiman (1999), there are some industry patterns to adoption and to control for these effects we used 25 industry dummies; 6 for industries outside manufacturing (SIC 2000-2999) and the remainder making finer distinctions between the industries in manufacturing that comprise the bulk of EVA adopters. As expected, these dummies raise the explanatory power of the estimate and they also tend to *strengthen* the marginal effect of our estimated value-added of EVA.

The last column of *Table 4* pursues further the issue of industry effects. In this table we group the data by 4-digit SIC industry. We use the sales-weighted fraction of adopters in each industry as the dependent variable, and then add one and take the log to provide a continuous measure that is not heavily influenced by outliers. We pool all the return and accounting data by industry in computing the correlations and variances that underlie our estimate of the value-added of EVA, and average the remaining controls over each firm-year in each industry. We have over 200 industries, and with 540 firms this implies that many industries will have only a single firm. While our results are similar for coarser industry groupings, significance levels fall as we lose degrees of freedom. As with the firm-level estimates, we weight the data by the square root of the number of observations underlying each industry estimate and compute robust standard errors. The results are consistent with the previous firm-level results.

The economic significance of our key result is not immediately apparent due to the logistic transformation of the adopt/not adopt dummy variable. At the median level of EVA value-added, the probability of adoption is just under 8%. Using the estimated coefficient from the first column, a firm that is in the upper quartile of value-added by EVA will adopt it with probability 13.4%. A firm in the lower quartile will adopt with a probability of only 4.64%. The results carry through more strongly for more extreme values; firms at the 95th percentile of value-added according to our theory will adopt with a probability over 30%, while those at the lowest 5 percentile will adopt with probability less than 1.7%. These effects are particularly gratifying given the design of our experiment. First, our estimates of the value-added of EVA are just that, estimates. They involve a non-linear transformation of three correlations and three variances estimated from particularly small samples. Thus, the value of EVA is estimated with an error that is not zero, but is otherwise difficult to characterize. Second, our controls do not seem to do a very good job in accounting for differences in the costs of adopting EVA. These costs may even be time-varying, as more is learned about the value and properties of EVA over time. Even a simplistic "follow-the-leader" theory would predict the clustering of EVA-adoption by industries that we observe in the data (see Bikhchandani, Hirshleifer, and Welch (1992)). Unlike our model, however, such a story would not predict *which* industries should feature EVA adopters and which should not. Nonetheless, our predictive power could presumably be improved with a more complete dynamic model.

While some of our empirical problems are inevitable given the theory and the subject under study, we hope to achieve improved estimates by including relevant controls. While we have controlled for the "usual suspects" of firm size, Tobin's q, leverage and so forth, we would like to identify variables which test the hypothesis that EVA is adopted by firms based on fads or on the opportunistic timing on the part of managers, as suggested by Hogan and Lewis (1999). Our theory focuses exclusively on the use of EVA in an efficient incentive contract, and it would be extremely valuable to test this idea against plausible alternatives.

4.5 Additional information on adopters versus non-adopters

Tables 5-7 present some evidence intended to supplement the statistical work and to suggest alternative hypotheses and controls. For *Table 5*, we select eight prominent firms for which we have the full 12 years of data, two in each of the following categories: (i) firms which the model correctly classifies as adopters, (ii) firms which the model correctly classifies as non-adopters, (iii) firms which the model incorrectly classifies as adopters, and (iv) firms which the model incorrectly classifies as non-adopters. These firms are particularly influential in our results, meaning that they either fit our theory very well or very poorly. It is important to note that none of the statistical conclusions are fundamentally changed by the inclusion or exclusion of these or any other specific firm.

In *Table 5*, *Subsample A* presents four firms that our theory classifies correctly. Olin is a diversified chemicals company that we correctly classify as an adopter given the high correlation between EVA and returns, coupled with a low correlation between earnings and returns. The other firm in Olin's 4-digit industry is Monsanto, also an EVA-adopter that shows a substantial (39%)

improvement from using EVA. The other correctly identified adopter gives some sense of the range of firms that we identify; the telephone service provider Sprint shows a nearly 60% reduction in performance measurement noise from using EVA. For Sprint, the correlation between earnings and returns is about average but that with EVA is extremely high, and the correlation between the two measures is high but not as high as might be expected.

Our theory correctly identifies Amgen as a company where EVA should *not* be adopted. It is highly correlated with earnings and is far less able to explain stock returns. As might be expected for such a heavily traded biotech company, neither accounting measure is particularly highly correlated with stock returns. In terms of the model, this means either that forward-looking value captured by Y_f is very important, or the stock price is moved by the non-fundamental factors summarized in our price error ϕ. Our theory also correctly identifies Boeing as a non-adopter since EVA is actually negatively related to stock returns. Interestingly, Davis (1996) reports that Boeing considered adopting EVA but decided that it was incapable of taking account of their long production lead times and large, lumpy order flows. The data certainly are consistent with Boeing's impression that EVA might penalize their managers for value-adding decisions.

The next four firms in *Table 5*, reported as *Subsample B*, are incorrectly classified by the model. We include them to provide a sense of balance and also to suggest new theoretical directions that might be followed. First, our data strongly suggest that Office Depot should be an EVA adopter, which it is not. The reason is clear; EVA is a fairly good predictor of returns while earnings surprises move in the wrong direction. To remind us that industry effects are not the sole or even the primary driver, we note that Sterling Software is also an incorrectly classified non-adopter. Both these firms are small relative to the sample average, but this pattern does not seem to be a sample-wide phenomenon. There is also an outstanding 3-digit industry (331) that we incorrectly classify as one that should be full of adopters. This is the Steel Manufacturing industry, and includes Bethlehem Steel and US Steel. None of the firms in this industry have adopted EVA despite the fact that EVA has a positive and significant relationship with returns, while earnings is small and negative.

The next two incorrectly classified firms reminds us that correlation with returns is not the sole reason why firms adopt EVA. According to our estimates, EVA is a perverse performance measure for Hewlett-Packard but they are nonetheless recent EVA adopters. It is possible that performance declines pushed this move, but we were unable to detect any systematic pattern of this sort in the data. Finally, Tektronix is a firm that despite its high-tech industry classification is actually one where stock returns are closely related to earnings innovations but not to positive surprises in EVA.

Tables 6 and *7* complete our picture of how EVA varies by industry. Two conclusions can be drawn from these data. First, the value of EVA as derived from our incentive model (see *Propositions 1* and *2*) varies significantly across firms. Second, and more importantly, the adoption or non-adoption of EVA is not driven by any obvious industrial characteristic such as capital-intensity or maturity. We take a different tack; we start with basic incentive theory, build in some real-world complications, and use the information contained in stock prices. To this end, we have some success in predicting and isolating instances where EVA is used. The industry-level data in *Tables 6* and *7* do not reveal any obvious alternatives.

5 Concluding Remarks

Not surprisingly, given the dollar amounts at stake, there is now a substantial practitioner and applied literature attempting to assess the value of EVA and related "shareholder value-based" performance measures. Most such studies focus on the strength of the statistical relationship between alternative measures and the firm's stock price. This paper begins with the more fundamental, and previously unaddressed, question: What is a good objective measure of the value of these new performance metrics? We first confirm that it is easy to construct models, and easier still to provide verbal arguments, in which the practice of relating accounting measures to stock returns is misguided or useless (a point originally made in Gjesdal (1981)). We show, however, that this conclusion is driven at least in part by a common and implausible assumption of formal agency theory that all the relevant attributes of alternative performance measures are known and directly observable. When we relax this assumption, we find substantial value in the debate over which measure is more closely related to stock prices. We also find important heterogeneity in the statistical relationship, a heterogeneity which bears some relationship to firms' decisions to adopt or not to adopt one of the new performance measures. Thus, the relevant applied question appears to be not so much whether EVA beats earnings per se, but under what circumstances does EVA beat earnings, and why?

Our paper also presents a formal empirical structure for testing the model of Paul (1992). Past research, such as Sloan (1993), find that accounting measures of performance continue to explain changes in compensation even when stock returns are included as an explanatory variable. This is consistent with the Paul (1992) model in that firms do not use exactly the same weights as the stock market in determining compensation. We advance the literature by ascertaining the relative weights that firms should use in a realistic setting where we do not know all of the relevant attributes of alternative performance measures *a priori*. More surprisingly, we show that the apparently simplistic idea of comparing the relative ability of alternative measures to explain stock returns, is both theoretically defensible and a reasonable representation of practice.

6 Appendix

6.1 Proof of Proposition 1

To simplify the analysis, denote by Ψ_k the scaled measure that the firm chooses to use. In the case where the firm uses only earnings, $\Psi_k = \Psi_2$, and in the case where the firm optimally uses EVA in addition to earnings, $\Psi_k = \Psi_c^*$. Finally, denote by α_c the weight that the firm places on this scaled measure, and α the weight on the (filtered) price. Since the performance measures are freely contractible, it is convenient to orthogonalize the stock price to the accounting measures of performance. We construct a "filtered price" P_f as in Kim and Suh (1993):

$$P_f = P - E(X_c + X_f \mid Y_1, Y_2)$$

so that P_f is orthogonal to our two measures of current performance. The firm then chooses the contract weights to solve the following modified problem:

$$\underset{\alpha_c,\alpha}{Max}\, \Gamma = a_c^* + a_f^* - C(a_c^*, a_f^*) - \frac{r}{2}\left(\alpha_c^2 Var(\Psi_k) + \alpha^2 Var(P_f)\right).$$

The first-order conditions for the optimal choices are:

$$\frac{\partial \Gamma}{\partial \alpha_c} = \frac{\partial a_c^*}{\partial \alpha_c}\left(1 - \frac{\partial C}{\partial a_c}\right) + \frac{\partial a_f^*}{\partial \alpha_c}\left(1 - \frac{\partial C}{\partial a_f}\right) - r[\alpha_c Var(\Psi_k)] = 0$$

$$\frac{\partial \Gamma}{\partial \alpha} = \frac{\partial a_c^*}{\partial \alpha}\left(1 - \frac{\partial C}{\partial a_c}\right) + \frac{\partial a_f^*}{\partial \alpha}\left(1 - \frac{\partial C}{\partial a_f}\right) - r[\alpha Var(P_f)] = 0.$$

The first part of the Proposition is that the value of using EVA (Y_1) monotonically increases in the difference $Var(\Psi_2) - Var(\Psi_c^*)$. A sufficient condition for this is that maximized firm value $\Gamma(\alpha_c^*, \alpha^*)$ monotonically decreases in the variance of Ψ_k. This condition in turn follows from:

$$\frac{\partial \Gamma(\alpha_c^*, \alpha^*)}{\partial Var(\Psi_k)} = -\frac{r}{2}\alpha_c^2 + \frac{\partial \alpha_c^*}{\partial Var(\Psi_k)}\frac{\partial \Gamma}{\partial \alpha_c} + \frac{\partial \alpha^*}{\partial Var(\Psi_k)}\frac{\partial \Gamma}{\partial \alpha}$$

and the fact that both α_c and α are optimally chosen so that $\frac{\partial \Gamma}{\partial \alpha_c} = \frac{\partial \Gamma}{\partial \alpha} = 0$. Thus we have:

$$\frac{\partial \Gamma(\alpha_c^*, \alpha^*)}{\partial Var(\Psi_k)} = -\frac{r}{2}\alpha_c^2 < 0$$

The remaining parts of the Proposition refer to expressing the difference in variance in terms of observables. First, recall that $\Psi_j = \frac{Y_j}{\lambda_j} = \frac{Y_j}{g\chi_j} = \frac{Y_j}{g\rho_{Y_j P}\frac{\sigma_{Y_j}}{\sigma_P}}$, $j \in \{1, 2\}$. We can therefore write, for $j \in \{1,2\}$,

$$\begin{aligned} Var(\Psi_j) &= \frac{Var(Y_j)}{[g\rho_{Y_jP}\frac{\sigma_{Y_j}}{\sigma_P}]^2} \\ &= \frac{Var(P)}{g^2}\frac{1}{\left(\rho_{Y_jP}\right)^2} \end{aligned}$$

and

$$Cov(\Psi_1,\Psi_2) = \frac{Var(P)}{g^2}\frac{\rho_{Y_1Y_2}}{\rho_{Y_1P}\rho_{Y_2P}}.$$

The level of value-added from using EVA can be expressed as $Var(\Psi_2) - Var(\Psi_c^*)$, where

$$\begin{aligned} Var(\Psi_2) - Var(\Psi_c^*) &= \left[\begin{array}{c} Var(\Psi_2) - \left(\frac{\gamma_1^*}{\gamma_1^*+\gamma_2^*}\right)^2 Var(\Psi_1) \\ -\left(\frac{\gamma_2^*}{\gamma_1^*+\gamma_2^*}\right)^2 Var(\Psi_2) - \left(\frac{\gamma_1^*\gamma_2^*}{(\gamma_1^*+\gamma_2^*)^2}\right) Cov(\Psi_1,\Psi_2) \end{array}\right] \\ &= \frac{Var(P)}{g^2}\left[\begin{array}{c} \frac{1}{\left(\rho_{Y_2P}\right)^2} - \left(\frac{\gamma_1^*}{\gamma_1^*+\gamma_2^*}\frac{1}{\rho_{Y_1P}}\right)^2 \\ -\left(\frac{\gamma_2^*}{\gamma_1^*+\gamma_2^*}\frac{1}{\rho_{Y_2P}}\right)^2 - \left(\frac{\gamma_1^*\gamma_2^*}{(\gamma_1^*+\gamma_2^*)^2}\right)\frac{\rho_{Y_1Y_2}}{\rho_{Y_1P}\rho_{Y_2P}} \end{array}\right]. \end{aligned} \qquad (8)$$

It can also be shown that the optimal weights γ_1^* and γ_2^*, from

$$w(Y_1,Y_2,P_f) = W + \gamma_1\Psi_1 + \gamma_2\Psi_2 + \alpha\left[P - E[P|Y_1,Y_2,Y_f]\right],$$

depend only on simple correlations. First, recall that with wages written as above, we need to estimate each of the components in

$$\frac{\gamma_1^*}{\gamma_2^*} = \frac{Var(\Psi_2) - Cov(\Psi_1,\Psi_2)}{Var(\Psi_1) - Cov(\Psi_1,\Psi_2)}.$$

First, we now know from (2) that

$$\begin{aligned} Var(\Psi_i) &= \frac{Var(Y_i)}{\lambda_i^2} \\ &= \frac{Var(Y_i)}{\chi_i^2 g^2}, \end{aligned}$$

where the second equality follows from (6). In a similar manner, we can also derive

$$\begin{aligned} Cov(\Psi_1,\Psi_2) &= \frac{Cov(Y_1,Y_2)}{\lambda_1\lambda_2} \\ &= \frac{Cov(Y_1,Y_2)}{\chi_1\chi_2 g^2}. \end{aligned}$$

Combining terms, we see that

$$\begin{aligned} Var(\Psi_2) - Cov(\Psi_1,\Psi_2) &= \frac{1}{\chi_2 g^2}\left(\frac{Var(Y_2)}{\chi_2} - \frac{Cov(Y_1,Y_2)}{\chi_1}\right) \\ &= \frac{1}{\chi_2 g^2}\frac{\chi_1 Var(Y_2) - \chi_2 Cov(Y_1,Y_2)}{\chi_1\chi_2} \\ &= \frac{\chi_1}{\chi_1^2\chi_2^2 g^2}\left(\chi_1 Var(Y_2) - \chi_2 Cov(Y_1,Y_2)\right) \end{aligned}$$

and

$$\begin{aligned}
Var(\Psi_1) - Cov(\Psi_1, \Psi_2) &= \frac{1}{\chi_1 g^2}\left(\frac{Var(Y_1)}{\chi_1} - \frac{Cov(Y_1, Y_2)}{\chi_2}\right) \\
&= \frac{1}{\chi_1 g^2}\frac{\chi_2 Var(Y_1) - \chi_1 Cov(Y_1, Y_2)}{\chi_1 \chi_2} \\
&= \frac{\chi_2}{\chi_1^2 \chi_2^2 g^2}\left(\chi_2 Var(Y_1) - \chi_1 Cov(Y_1, Y_2)\right).
\end{aligned}$$

Upon taking the ratio, the term g cancels out and leaves us with

$$\begin{aligned}
\frac{\gamma_1^*}{\gamma_2^*} &= \frac{Var(\Psi_2) - Cov(\Psi_1, \Psi_2)}{Var(\Psi_1) - Cov(\Psi_1, \Psi_2)} \\
&= \frac{\chi_1}{\chi_2}\left(\frac{\chi_1 Var(Y_2) - \chi_2 Cov(Y_1, Y_2)}{\chi_2 Var(Y_1) - \chi_1 Cov(Y_1, Y_2)}\right).
\end{aligned}$$

This expression can be posed in terms of correlations, yielding

$$\begin{aligned}
\frac{\chi_1}{\chi_2}\left(\frac{\chi_1 Var(Y_2) - \chi_2 Cov(Y_1, Y_2)}{\chi_2 Var(Y_1) - \chi_1 Cov(Y_1, Y_2)}\right) &= \frac{\rho_{Y_1P}\sigma_{Y_1}}{\rho_{Y_2P}\sigma_{Y_2}}\left(\frac{\frac{\rho_{Y_1P}\sigma_{Y_1}Var(Y_2)}{\sigma_P} - \frac{\rho_{Y_2P}\sigma_{Y_2}\rho_{Y_1Y_2}\sigma_{Y_1}\sigma_{Y_2}}{\sigma_P}}{\frac{\rho_{Y_2P}\sigma_{Y_2}Var(Y_1)}{\sigma_P} - \frac{\rho_{Y_1P}\sigma_{Y_1}\rho_{Y_1Y_2}\sigma_{Y_1}\sigma_{Y_2}}{\sigma_P}}\right) \\
&= \frac{\rho_{Y_1P}\sigma_{Y_1}}{\rho_{Y_2P}\sigma_{Y_2}}\left(\frac{\sigma_{Y_1}Var(Y_2)\left(\rho_{Y_1P} - \rho_{Y_2P}\rho_{Y_1Y_2}\right)}{\sigma_{Y_2}Var(Y_1)\left(\rho_{Y_2P} - \rho_{Y_1P}\rho_{Y_1Y_2}\right)}\right) \\
&= \frac{\rho_{Y_1P}}{\rho_{Y_2P}}\left(\frac{\rho_{Y_1P} - \rho_{Y_1Y_2}\rho_{Y_2P}}{\rho_{Y_2P} - \rho_{Y_1Y_2}\rho_{Y_1P}}\right).
\end{aligned}$$

The expression above is helpful in addressing the validity of using R^2 to assess a performance measure's value in incentive-based compensation.

With γ_1^* and γ_2^* expressed in terms of observables, we see that the only other terms in the value-added expression are $Var(P)$, which is observable, and g, which is not. However, using (8), we see that the percentage value-added from using EVA is

$$\frac{Var(\Psi_2) - Var(\Psi_c^*)}{Var(\Psi_2)} = 1 - \frac{1}{\left(\rho_{Y_2P}\right)^2}\left[\begin{array}{c} \left(\frac{\gamma_1^*}{\gamma_1^*+\gamma_2^*}\frac{1}{\rho_{Y_1P}}\right)^2 + \left(\frac{\gamma_2^*}{\gamma_1^*+\gamma_2^*}\frac{1}{\rho_{Y_2P}}\right)^2 \\ + \left(\frac{\gamma_1^*\gamma_2^*}{(\gamma_1^*+\gamma_2^*)^2}\right)\frac{\rho_{Y_1Y_2}}{\rho_{Y_1P}\rho_{Y_2P}} \end{array}\right],$$

which depends only on simple and observable correlations. ■

6.2 Proof of Proposition 2

If we re-define $\Psi_k = \Psi_1$, which is EVA, *Proposition 1* immediately implies that the value of using EVA as a replacement for earnings is:

$$\frac{Var(\Psi_2)}{Var(\Psi_1)}.$$

We also know from *Proposition 1* that we can write

$$Var(\Psi_j) = \frac{Var(P)}{g^2 \rho^2_{Y_j P}}.$$

Thus, we can write the value-added of EVA used in exclusion as:

$$\frac{Var(\Psi_2)}{Var(\Psi_1)} = \frac{\frac{1}{\rho^2_{Y_2 P}}}{\frac{1}{\rho^2_{Y_1 P}}} = \frac{\rho^2_{Y_1 P}}{\rho^2_{Y_2 P}}.$$

Observe that this is simply the ratio of the individual R^2's between each of the candidate measures and the stock price. ■

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Table 1: Descriptive Statistics for Raw Data

	Mean	Median	SD	Min	Max
Total Assets	3.27	1.34	15.7	0.0854	1175
Market Value of Equity	5.14	1.83	11.3	0.0696	240
Earnings before Extraordinary Items	0.0578	0.0677	0.254	-7.99	3.65
EVA	-0.0452	-0.006	0.261	-8.53	1.17
Raw stock returns %	23.6	17.5	44.5	-89.4	1396
Abnormal stock returns %	7.49	3.47	36.2	-91.6	1015

Notes: Sample is 7031 firm-years, from 1986-1997. All dollar figures are in billions. Stock returns are in percentages. Abnormal stock returns are raw returns less the contemporaneous return on the S&P 500 value-weighted index.

Table 2: Descriptive Statistics at the Firm Level

	n	Mean	Median	SD	Min	Max
$\rho_{Earn,AR}$	540	0.331	0.383	0.332	-0.678[19]	0.884
$\rho_{EVA,AR}$	540	0.126	0.126	0.344	-0.815[20]	0.854
$\rho_{EVA,Earn}$	540	0.389	0.484	0.431	-0.896[21]	0.978
EVA Adoption Dummy	540	0.0870	0	0.271	0	1
Percentage value-added from adopting EVA	540	0.167	0	0.282	0	1
Relative $R^2, \rho^2_{EVA,AR}/\rho^2_{Earn,AR}$	540	855	0.167	1004	0	24078
Number of Observations for each firm	—	10	11	1.53	6	11
Total Assets ($ millions)	540	8457	2307	22517	115	240783
$\frac{\text{Long-Term Debt}}{\text{Total Assets}}$ (Leverage)	540	0.597	0.584	0.184	0.103	0.993
$\frac{\text{MV of Equity + BV of L-T Debt +Preferred Stock}}{\text{Total Assets}}$ (q)	540	1.38	1.213	0.852	0.847	6.48
$\frac{\text{Property, Plant and Equipment}}{\text{Total Assets}}$ $(Tangible)$	540	0.478	0.508	0.243	0	0.942

Notes: $\rho_{EVA,AR}$ denotes the Pearson correlation coefficient between innovations in EVA as a fraction of lagged market value of equity, and abnormal stock returns. $\rho_{Earn,AR}$ is defined the same way for earnings in place of EVA, and $\rho_{EVA,Earn}$ is the correlation between innovations in EVA and in earnings. The percentage reduction in variance is computed with weights on EVA and on earnings restricted to be nonnegative. Total Assets, Leverage, q, and Tangible are all averaged over all available years for each firm. Lastly, MV stands for Market Value and BV stands for Book Value.

[19] 9% of correlations are negative.

[20] 24% of corrrelations are negative.

[21] 10% of correlations are negative.

Table 3: Pearson Correlation Coefficients

	Adoption Dummy	Value-Added by EVA	Relative R^2 of EVA	Log Assets	Leverage	Tobin's q	Tangible Assets
Adoption Dummy	1						
Value-Added by EVA	0.0357	1					
Relative R^2 of EVA	-0.0129	0.130	1				
Log Assets	0.0144	0.0817	0.0398	1			
Leverage	0.0106	0.119	0.0759	0.588	1		
Tobin's q	-0.413	-0.0262	-0.0626	-0.447	-0.650	1	
Tangible Assets	0.0876	-0.0791	-0.0791	-0.198	-0.323	0.121	1

Notes: Sample drawn from 540 firms.

Table 4: Regression Results Explaining the Adoption Decision

Logit Regressions Explain Firm-Level Adoption Dummy, OLS explains log of (1+sales-weighted fraction of adopters) at 4-digit SIC level

Explanatory variable	Logit	Logit, 25 Industry Dummies	OLS, log(Fraction of Adopters)
Constant	-4.207* (0.961)	-5.53* (1.04)	-0.247 (0.263)
C.D.F of Value-Added by EVA	2.315* (0.519)	2.543* (0.579)	0.000247** (0.000120)
Total Assets	-1.55 E-5 (1.68 E-5)	-1.24 E-5 (1.64 E-5)	3.20 E-6 (5.20 E-6)
Tobin's q	-0.286 (0.322)	-0.390 (0.296)	0.00470 (0.0134)
Leverage	0.259 (1.17)	0.839 (1.17)	0.0428 (0.0438)
Prop., Plant & Equip to Total Assets	1.542** (0.718)	2.20* (0.739)	0.0902*** (0.486)
Number of observations	540	540	201
R^2 (pseudo-R^2 for logit)	0.0725	0.128	0.0442

Notes: Sample is 540 firms, weighted by the square root of the number of observations for each firm. Robust standard errors in parentheses. For the logit analysis we allow errors to be correlated within 4-digit industries but not across industries. * indicates different from zero at 1%, ** at 5%, *** at 10%.

Table 5: Some Illustrative Cases

Subsample A: Some Firms Correctly Classified by the Theory

Firm	SIC	% Value-Added by EVA	$\rho_{EVA,AR}$	$\rho_{Earn,AR}$	$\rho_{Earn,EVA}$	Assets	Leverage	Tobin's q
Olin Corporation	2800	93.2	0.480	0.158	0.792	1995	0.627	0.838
Sprint	4813	57.7	0.543	0.353	0.637	12438	0.702	1.05
Amgen Company	2836	0	0.180	0.294	0.972	1374	0.291	3.97
Boeing Corporation	3771	0	-0.253	0.401	0.011	19660	0.562	1.03

Subsample B: Some Firms Incorrectly Classified by the Theory

Firm	SIC	% Value-Added by EVA	$\rho_{EVA,AR}$	$\rho_{Earn,AR}$	$\rho_{Earn,EVA}$	Assets	Leverage	Tobin's q
Office Depot	5940	93.2	0.251	-0.405	-0.425	1821	0.590	1.71
Sterling Software	7372	57.7	0.840	0.017	0.243	541.3	0.530	1.29
Hewlett-Packard	3570	0	-0.120	0.418	-0.162	16632	0.457	1.48
Tektronix Corporation	3825	0.912	0.171	0.605	-0.034	1068	0.512	0.899

Table 6: Value and Adoption of EVA

Percentage Reduction in Variance and Percentage of Adopters by 1-Digit SIC Industry

1-Digit SIC	Industry Description	# of Firms	% Reduction in Variance	% of Adopters
0100-0199	Agriculture, Forestry, Fishing	4	25.2	0
1000-1999	Mining, Construction	31	10.2	6.45
2000-3999	Manufacturing	294	14.3	10.1
4000-4999	Transportation, Utilities	37	13.8	10.8
5000-5999	Wholesale & Retail Trade	71	22.5	7.04
6000-6999	Financial Services	57	26.0	2.23
7000-8999	Miscellaneous Services	46	12.2	9.0

Table 7: Value and Adoption of EVA

Percentage Reduction in Variance and Percentage of Adopters by 2-Digit SIC Industry

2-Digit SIC	Industry Description	# of Firms	% Reduction in Variance	% of Adopters
20	Food and Kindred Products	26	32.6	11.5
21	Tobacco Products	1	2.2	0
22	Textile Mill Products	6	17.6	0
23	Apparel and Other Fabrics	3	9.5	0
24	Lumber and Wood	4	17.8	0
25	Furniture and Fixtures	5	13.4	9.1
26	Paper and Allied Products	19	11.6	10.5
27	Printing, Publishing and Allied	20	18.4	10.0
28	Chemical and Allied	53	14.6	5.6
29	Petroleum Refining	13	23.0	7.3
30	Rubber and Plastics	9	18.0	22.2
32	Stone, Clay, Glass and Concrete	3	6.1	0
33	Primary Metal	10	31.6	10.0
34	Fabricated Metal	9	5.9	11.1
35	Industrial and Commercial Machinery and Computer Equipment	34	18.6	14.7
36	Electronic and Other Electrical	27	5.4	7.4
37	Transportation Equipment	22	17.7	9.1
38	Measuring, Analyzing, and Controlling	27	11.1	18.5
39	Miscellaneous Manufacturing	3	26.0	0