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Measuring Reporting Conservatism using the Dichev-Tang (2008) Model

Abstract

This paper provides a critical evaluation of an alternative measure of reporting conservatism introduced by Dichev and Tang (2008). Although there is substantial interest in research on accounting conservatism, there is no consensus among researchers on the most appropriate measure of conservatism in empirical studies. Dichev and Tang (2008) introduce a new measure of conservatism, which they believe to be a "natural and practical measure of conservatism (p. 1441)." However, the econometric properties of this measure have not been fully evaluated, and previous studies have not provided evidence of this measure's construct validity. Based on a parsimonious model of conservatism, I find that the Dichev and Tang (2008) measure is increasing in the conservatism parameter. However, although this measure produces well-specified test statistics that generate Type 1 errors according to researchers' specifications, it generates tests of low power that lead to relatively high Type 2 errors. Next, I use actual data to provide evidence consistent with the construct validity of this measure. Finally, I suggest an alternative measure by using the reverse regression specification of the Dichev and Tang (2008) model. Results from simulations suggest that this alternative measure is feasible and is slightly superior to the Dichev and Tang (2008) measure in terms of test power.

Key words: Measure of Accounting Conservatism, Construct Validity Tests

1. Introduction

Financial reporting conservatism is one of the most prominent qualitative attributes of accounting, and its economic role and continued existence have been a focus of debate and research attention among regulators, practitioners and academics (e.g., FASB, 2005; Watts, 2003). As a result of extensive interest in this important topic, researchers wanting to test various theories and hypotheses of accounting conservatism have attempted to quantify and operationalize the notion of conservatism in their studies. Basu (1997) introduced a market-based measure of conservatism that has been widely used in the literature. However, various studies examine the econometric properties of this measure and highlight its shortcomings and limitations (e.g., Dietrich, Mueller & Riedl, 2007; Givoly, Hayn & Natarajan, 2007; Patatoukas & Thomas, 2010). Given the documented deficiencies of this measure and the limitations of other measures (e.g., the market-to-book ratio), there is no consensus among researchers on the most appropriate measure of conservatism in empirical studies.

The purpose of this paper is to provide a critical evaluation of an alternative measure of reporting conservatism introduced recently by Dichev and Tang (2008) in their matching model. The authors develop a model of matching expenses to the associated revenue and examine how the amount of matching success affects various properties of accounting earnings. In their model, Dichev and Tang (2008) characterize the mismatching of expenses as introducing noise over and above economics-driven volatility in the process of earnings measurement, and they demonstrate that poor matching leads to lower contemporaneous correlation between revenue and expenses, higher volatility of earnings and lower persistence of earnings. The authors corroborate their model's findings by examining the relationship between revenue and expenses over the last 40 years, and they conclude that the temporal decline in matching success contributes to increased earnings volatility and reduced earnings persistence over time.

The analysis of Dichev and Tang (2008) that is particularly relevant to this study is their empirical examination of the relationship between revenue and past, present and future expenses. In particular, they estimate the following empirical model:

$$Revenues_t = \alpha_0 + \alpha_1 Expenses_{t-1} + \alpha_2 Expenses_t + \alpha_3 Expenses_{t+1} + Error_t$$

The coefficient of interest to the authors is α_2, which measures the relationship between revenue and contemporaneous expenses. Perfect matching of expenses to the associated revenue for a profitable entity implies $\alpha_2 > 1$, and both α_1 and α_3 equal 0. Dichev and Tang (2008) document a trend of declining α_2 in annual cross-sectional regressions from 1967 to 2003, which they interpret as a decline in matching over time.

In this model, α_1 measures the extent to which expenses are recognized ahead of the associated revenue. Dichev and Tang (2008) suggest that α_1 can be used as a "natural and practical measure of conservatism," especially in light of the growing research interest in reporting conservatism and the limitations of existing empirical measures of conservatism (Dichev & Tang, 2008, p. 1441). They document a trend of increasing α_1 over the same sample period, which they suggest is evidence of increased conservatism over time. This latter finding is consistent with Givoly and Hayn (2000), who conclude an upward trend of reporting conservatism using a different empirical methodology over a comparable sample period.

However, this measure suggested by Dichev and Tang (2008) has its limitations. First, the econometric properties of this measure have not been fully evaluated in prior work. For instance (to be elaborated in greater detail later), the observed current expenses are incurred to earn past, current and future revenue and thus there is an errors-in-variables problem. It is not obvious whether this measurement error affects the suitability of using α_1 as a measure of reporting conservatism. Second, prior studies have not provided evidence of this measure's construct validity. This paper addresses these gaps in the current literature.

Based on certain model assumptions, I propose that researchers can determine the unobserved level of reporting conservatism by analyzing the Dichev and Tang (2008) measure. However, although this measure produces well-specified test statistics that generate Type 1 errors according to researchers' specifications, it generates tests of low power that lead to relatively high Type 2 errors. Next, I use actual data to support the construct validity of this measure. Finally, I explore an alternative measure of conservatism using a reverse regression specification. Results from simulations suggest that this measure is feasible and is slightly superior to the Dichev and Tang (2008) measure in terms of test power.

The remainder of this paper is organized as follows. In section 2, I explore a simple model of matching, highlight how the concept of conservatism relates to the model, and assess whether the estimated α_1 coefficient from the Dichev and Tang (2008) model can be utilized to measure reporting conservatism analytically. In section 3, I conduct simulations to test the specification and power of the model. In section 4, I provide construct validity tests of this measure of conservatism using actual data. I then examine an alternative measure of conservatism using a reverse regression specification in Section 5. Section 6 offers conclusions.

2. Model of Matching and the Concept of Conservatism

2.1 Basic Model of Matching

I consider a simple model of revenue and expenses for an economic entity. First, I define the following generating process for expenditures incurred to generate revenue in time t (E_t):[1]

$$E_t = \mu_0 + \mu_1 E_{t-1} + \upsilon_t \quad (1)$$

where υ_t denotes a random shock in expenditures, and is modeled as mean-zero white noise.[2] In this process, there could be time-series dependence between current and past expenditures, depending on the value of μ_1. When $\mu_1 = 0$, expenditures are independent and identically distributed (i.i.d.), whereas when $\mu_1 = 1$, expenditures follow a random walk process. μ_0 represents a constant term (or a drift in expenditures when $\mu_1 = 1$) , which I include here for completeness, but this is not crucial to my analysis that is presented later.

In this model, the relationship between revenue (R_t) and expenditures (E_t) is assumed to be the following:

$$R_t = \varphi_0 + \varphi_1 E_t + \omega_t \quad (2)$$

[1] Throughout this paper, I use the expression "expenditures" and "costs" synonymously to refer to the true economic costs incurred to earn revenue in a particular time period.

[2] That is, $E[\upsilon_t] = 0, E[\upsilon_t^2] = \sigma_\upsilon^2$ and $E[\upsilon_t, \upsilon_s] = 0\ \forall t \neq s$.

where ω_t denotes a random shock in revenue, and is also modeled as a mean-zero white noise. $\varphi_1$represents the contemporaneous relationship between expenditures incurred to generate revenue in period t and that period's revenue. For a profitable entity, $\varphi_1 > 1$ and $(\varphi_1 - 1)$ can be interpreted as the profit margin of the firm. φ_0 represents a constant term, which again is included for completeness. Consistent with Dichev and Tang (2008), I view the firm as an entity that continually incurs costs to reap revenues and earnings, and the success of the firm is measured by its ability to earn revenue in excess of costs that are incurred to obtain that revenue (that is, having higher profit margin or φ_1).

At the end of every fiscal period, the firm observes expenditures and attempts to match expenditures to the associated revenue. In principle, the goal of accounting matching is to reflect business reality and hence to match costs incurred to earn revenue in the same reporting period.[3] The relationship between reported expenses at time t (e_t) and true economic costs incurred to earn revenue at time t (E_t) is expressed in a two-period matching model as follows:[4]

$$e_t = (1 - \gamma)E_t + \gamma E_{t+1} \tag{3}$$

In the case of perfect matching, $e_t = E_t$ and $\gamma = 0$, which means that the firm is able to recognize all costs incurred to earn the corresponding revenue in the same reporting

[3] The principle of matching is obviously subjected to certain practical limits. For example, certain costs incurred like research and development expenditure is difficult, if not impossible, to match accurately to a specific revenue.

[4] Dichev and Tang (2008) model the relation between true expenditures and recognized expenses in a slightly different way. In particular, they modeled recognized expenses as $e_t = E_t + \xi_t$, where $\xi_t = \tau_t - \tau_{t-1}$. In this specification, τ is a random variable that represents matching error, which self-corrects in the following period. The authors do not model γ as I do in equation (3) because the focus of their paper is on the additional volatility to earnings due to poor matching, and not on the propensity to recognize expenditures early (reporting conservatism).

period. In the case of imperfect matching, $e_t \neq E_t$ and $\gamma > 0$, which indicates that the firm recognizes some proportion of expenditures that are related to time t in the current period, and recognizes the remainder of expenditures that are related to time t in the following fiscal period. In this model of matching, γ denotes reporting conservatism because γ measures the extent to which expenditures are recognized ahead of the associated revenue. In this model, conservatism is a manifestation of a lack of matching.

Note that I only consider a two-period instead of a three-period matching model as studied by Dichev and Tang (2008) because the focus of my paper is on reporting conservatism that is estimated from α_1 in their empirical model. Considering a three-period model will add more complexity to the analysis without providing significant insights beyond that obtained by examining a two-period model. Furthermore, Dichev and Tang (2008) provide evidence that the temporal decline in the matching of expenses with the associated revenue is the consequence of increased advancing of rather than delaying of expense recognition over time, which suggests that analyzing a two-period model is sufficient in the context of this paper.

The success of matching across different firms (that is, $(1-\gamma)$) is affected by various factors, including cost structure (e.g., the extent of fixed versus variable costs and the traceability of costs); accounting rules (e.g., rules relating to research and development expenses); and managerial discretion. In examining the econometric properties of this model, I do not separately consider these determinants of matching success in order to keep the model simple and tractable. This simplification does not prevent me from drawing reasonable conclusions from this basic model.

In order to estimate the level of reporting conservatism using the Dichev and Tang (2008) model, the researcher estimates the following empirical equation:

$$R_t = \alpha_0 + \alpha_1 e_{t-1} + \alpha_2 e_t + \varepsilon_t \tag{4}$$

In this equation, α_1 measures the relationship between current revenue and past expenses, which Dichev and Tang (2008) suggest to be consistent with the notion of reporting conservatism. As mentioned in the preceding discussion, I define the unobserved true level of reporting conservatism as γ in the matching model (equation 3). Hence, the key to evaluating the appropriateness of using α_1 as a measure of conservatism is to first assess whether we can infer γ from estimating α_1 in empirical equation (4). Once I have demonstrated the correspondence between γ and α_1, I can then evaluate the estimation efficiency of using α_1 to measure reporting conservatism.

It is important to note that the empirical researcher can observe only recognized expenses (e) but not true expenditures and their components (E). In the following sub-sections, I will explore three scenarios of matching and observability of costs to illustrate if the estimated α_1 coefficient of the model can be utilized to measure the magnitude of reporting conservatism in the sample population.

2.2 Perfect Matching with Perfect Observation of Cost Components

First, I begin with the scenario where there is perfect matching of revenue with contemporaneous costs incurred to earn that revenue. This implies:

$$e_t = E_t; \gamma = 0 \tag{5}$$

An example of perfect matching is the case of a firm where all costs are directly traceable to revenue (e.g., cost of goods sold and variable sales commission). In this scenario, estimating empirical equation (4) is similar to estimating the revenue model (2) because the researcher is able to infer true expenditures (E_t) from observing recognized expenses (e_t). If the researcher estimates empirical equation (4), $E[\alpha_1] = 0$ and $E[\alpha_2] = \varphi_1$. Conservatism is nonexistent in this scenario of perfect matching because firms are always able to match expenditures to their associated revenue. Hence, the only information derived from estimating the Dichev and Tang (2008) model is the profit margin φ_1, based on the assumption of perfect matching with perfect observation of cost components.

2.3 Imperfect Matching with Perfect Observation of Cost Components

Next, I consider a case where there is imperfect matching of revenue with contemporaneous costs incurred to earn that revenue. Hence, the recognized expenses are expressed as follows (similar to equation (3)):

$$e_{t-1} = (1-\gamma)E_{t-1} + \gamma E_t \qquad \text{(3a')}$$

$$e_t \quad = (1-\gamma)E_t + \gamma E_{t+1}; \gamma > 0 \qquad \text{(3b')}$$

In this scenario, perfect observability by the researcher is assumed, and she can observe all the individual cost components. In other words, the researcher can perfectly observe the amount of expenditures that are mismatched across the two time periods (that is, both γE_t and $(1-\gamma)E_t$). Suppose the researcher uses her perfect observation of individual cost components to estimate equation (4), but she only extracts the true expenditures pertaining to time t in her empirical estimation:

$$e'_{t-1} = \gamma E_t \qquad \text{(6a)}$$

$$e'_t \quad = (1-\gamma)E_t \qquad \text{(6b)}$$

With perfect observation of cost components, estimating empirical equation (4) with the mismatched true expenditures is equivalent to estimating:

$$R_t = \alpha_0 + \alpha_1 e'_{t-1} + \alpha_2 e'_t + \varepsilon_t$$
$$= \alpha_0 + \alpha_1(\gamma E_t) + \alpha_2((1-\gamma)E_t) + \varepsilon_t \quad (7)$$

In principle, it can be shown that in this case, $E[\alpha_1] = E[\alpha_2] = \varphi_1$.[5] Consider a simple firm where all types of costs are variable and exhibit similar profit margin (e.g., a cost-based pricing arrangement). In this scenario, when a firm imperfectly matches expenditures across different time periods that correspond to revenue at time t, the profit margin that is associated with each dollar of expense recognized in each time period should be similar, hence $E[\alpha_1] = E[\alpha_2] = \varphi_1$. Consider a numerical example where a firm with only variable costs effects a mark-up of 50% for pricing purposes and which recognizes costs incurred for contemporaneous revenue at time t-1 and time t using the following proportion: 20% and 80% respectively. In this example, even though total expenses recognized in time t-1 and time t may differ, $E[\alpha_1] = E[\alpha_2] = \varphi_1$ = 1.5.

The above scenario assumes every dollar of cost (on average) has the same marginal productivity in generating revenue and the only issue lies in the mismatch between revenue and expenditures in different time periods.[6] In this scenario, α_1 provides no information about how conservative a firm is relative to other firms because α_1 measures

[5] From an empirical standpoint, the researcher will not be able to estimate equation (7) because both explanatory variables in the equation can be expressed as a linear combination of the other variable, which results in perfect collinearity.

[6] While not the focus of this model, it could be the case that different expenses recognized in different time periods have different marginal productivity in generating revenue. However, without a clear theory to explain why expenses recognized in time t-1 systematically have greater (or lesser) marginal productivity than expenses recognized in time t, I abstract away from this scenario in the above discussion.

only profit margin. To measure conservatism in this model of perfect observability, the researcher is better off using the relative weight of $e'_{t-1}$and e'_t to estimate the magnitude of conservatism across firms. The reason is that this relative weight indicates the extent to which expenses are advanced or mismatched in the preceding time period of the associated revenue, and thus this alternative measure is consistent with the notion of conservatism γ.[7]

In sum, based on the scenario of imperfect matching with perfect observation of cost components, the α_1 coefficient is inappropriate for measuring the extent of reporting conservatism, and a more feasible measure is considering the relative weight of $e_{t-1}$and e_t. In practice, it is unlikely that the empirical researcher can perfectly observe the mismatched expenditures that the firm observes. The case of imperfect matching and imperfect observability of cost components is examined next.

2.4 Imperfect Matching with Imperfect Observation of Cost Components

Third, I consider a case where there is imperfect matching of revenue with contemporaneous costs incurred to earn that revenue as well as a researcher's imperfect observation of cost components. In particular, the researcher observes:

$$e_{t-1} = (1-\gamma)E_{t-1} + \gamma E_t \qquad (8a)$$

$$e_t \quad = (1-\gamma)E_t \quad + \gamma E_{t+1} \qquad (8b)$$

In this setting, in addition to imperfect matching by the firm, there is also imperfect observation of cost components by the empirical researcher. For instance, instead of

[7] In particular, $\frac{e'_{t-1}}{e'_{t-1}+e'_t} = \frac{\gamma E_t}{\gamma E_t+(1-\gamma)E_t} = \gamma$.

observing mismatched cost components $(1-\gamma)E_t$ and γE_t associated with revenue at time t individually, the researcher observes only expenses reported in time t (e_t), which include costs incurred to earn revenue in time t and t+1 (that is, $(1-\gamma)E_t$ and γE_{t+1} respectively, see expression 8b). Hence, there is a measurement error in the observed expenses e_{t-1} and e_t, and the issue is whether the α_1 coefficient from estimating empirical equation (4) is an appropriate measure of reporting conservatism in the sample population.

To determine whether I can infer the true measure of conservatism γ from estimating the $\alpha_1$coefficient, I first derive an expression for the probability limit of the Ordinary Least Squares (OLS) estimate of α_1 . Because $Var(E_t)$ is non-stationary for various values of $Var(E_t)$,[8] I provide a solution for the specific case where I can take the limit of $Var(E_t)$ over time such that $Var(E_t) = \frac{Var(v_t)}{(1-\mu_1^2)}$ and $Var(E_t)$ becomes stationary. The OLS estimate of α_1 is then expressed as follows (derived in detail in Appendix A):

$$plim(\alpha_1^{OLS})$$
$$= \varphi_1 \cdot \left[\frac{\mu_1 k\gamma^2(1-\mu_1^2) + \gamma^3(1-\mu_1^2)^2}{(1-\mu_1^2)^2(\gamma^4 - k^2\gamma^2) + (1-\mu_1^2)(2k^2\gamma^2 - 2\mu_1 k^3\gamma) + (k^4 - \mu_1^2 k^4)}\right]$$

where $k = (1-\gamma+\gamma\mu_1)$.

Dichev and Tang (2008) suggest that the estimated α_1 coefficient is positively associated with reporting conservatism. The key to corroborating the authors' claim is to demonstrate that the estimated α_1 coefficient is increasing in reporting conservatism (γ). In the above expression, it is sufficient to show that the bracketed term is increasing in γ.

[8] That is, $Var(E_t) = \mu_1^2 Var(E_{t-1}) + Var(v)$, where E_{t-1} is again a function of E_{t-2} and so on.

Note that the bracketed term varies with reporting conservatism (γ) and the time-series correlation in expenditures (μ_1). To determine whether α_1 is increasing in γ, I plot the solution to the bracketed term against values of γ from 0 to 1 (in 0.01 increments), holding μ_1 constant at various levels between 0 and 0.99 (μ_1 = 0, 0.25, 0.5, 0.75 and 0.99).[9] Figure 1 plots the solution to α_1 (vertical axis) against reporting conservatism γ (horizontal axis), conditional on various values of μ_1 and assuming φ_1=1.2.

As shown in Figure 1, the probability limit of the OLS estimate of α_1 is generally increasing in reporting conservatism (γ) at various assumed values of μ_1 between 0 and 1. For smaller assumed values of μ_1 (that is, μ_1 = 0 and 0.25), α_1 is increasing only monotonically in γ until the point where γ is approximately 0.75. However, this is not a crucial issue empirically because firms are unlikely to practice such high levels of reporting conservatism and the time-series correlation in expenditures (μ_1) is usually larger than 0.5. Hence, based on the scenario of imperfect matching and imperfect observability of cost components, the OLS estimate of α_1 can be utilized to infer the firm's true level of reporting conservatism (γ).

2.5 Discussion

In sum, an examination of the econometric properties of Dichev and Tang's (2008) matching model suggests that $\alpha_1$can be a feasible measure of reporting conservatism in empirical studies based on certain model assumptions. Even though the researcher cannot

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[9] I do not examine the case where expenditures follow a random walk process ($\mu_1 = 1$) because the limit of $Var(E_t) = \frac{Var(v)}{1-\mu_1^2}$ is undefined when $\mu_1 = 1$.

perfectly observe the mismatched expenditures pertaining to a particular revenue, the researcher can infer the firm's level of reporting conservatism from estimating the α_1 coefficient. Based on the analyses in this section, the α_1 coefficient from the Dichev-Tang (2008) model measures only reporting conservatism because of the measurement error (or imperfect observability) in expenses, whereas based on the assumption of perfect observability (section 2.3), the α_1 coefficient measures profit margin and thus provides no information about reporting conservatism.

Although I have established the relationship between the α_1 coefficient and the unobserved level of reporting conservatism (γ), I have not evaluated the estimation efficiency of using the α_1 coefficient as a measure of conservatism. In the following section, I conduct simulations to assess the specification and power of the test statistics using the conservatism measure based on the Dichev and Tang (2008) model.

3. Simulations

In this section, I conduct simulations to test the power of the Dichev and Tang (2008) model to determine if the null hypothesis can be rejected when the alternative hypothesis is true. To do so, I create simulated data based on the model outlined in section 2.4 detailing the case of imperfect matching and imperfect observability of cost components. For each simulated firm-year, I create 20 time-series observations to mimic the researcher's estimation of α_1 coefficient from a set of time-series data. I assume the following parameters for the model:

1. Random shock in expenditures $\upsilon_t \sim N(0,1)$

2. Random shock in revenue $\omega_t \sim N(0,1)$
3. Profit margin $\varphi_1 = 1.2$
4. Correlation in expenditures $\mu_1 \in [0,1)$ in increments of 0.25, up to a value of 0.99
5. Reporting conservatism $\gamma \in [0,1]$ in increments of 0.1, up to a value of 1

For each firm-year with 20 time-series observations, I run a regression of equation (4) to obtain the α_1 coefficient. I then use a one-tailed test level of 5% to test whether the α_1 coefficient is greater than 0. For each combination of different values of μ_1 and γ (5 x 11 combinations), I simulate a dataset of 10,000 firm-years to compute the frequency of rejecting the null hypothesis of no reporting conservatism (γ = 0). Note that for these simulations, I do not assume stationary variance of expenditures as I did when deriving the probability limit of the OLS estimate of α_1 in section 2.4. The results of these simulations are plotted in Figure 2 and 3, where the estimated α_1 coefficient and the frequency of rejecting the null hypothesis (vertical axis in Figure 2 and 3 respectively) is plotted against the magnitude of reporting conservatism (horizontal axis), conditional on various values of μ_1.

As shown in Figure 2, based on simulated data, the plot of the estimated α_1 coefficient is similar to the plot of the solution to $plim(\alpha_1^{OLS})$ in Figure 1. Figure 3 indicates that the frequency of rejecting the null hypothesis when there is no reporting conservatism (γ = 0) is approximately 5%, which is not significantly different from 5% based on a two-tailed binomial test (results untabulated). This suggests that the frequency of Type 1 error (rejecting the null hypothesis when the null is true) is the same as the specified test level.

When there is reporting conservatism ($\gamma > 0$), the frequency of rejecting the null hypothesis gradually increases to only about 20% when γ is approximately between 0.35 and 0.4. In fact, the frequency of rejection is relatively low when $\gamma < 0.5$. This suggests that the frequency of Type 2 error (not rejecting the null hypothesis when the null is false) is relatively high when we use the estimated α_1 coefficient to measure reporting conservatism.

In sum, the results from the simulations suggest that using the estimated α_1 coefficient to measure reporting conservatism produces well-specified test statistics that generate Type 1 errors according to researchers' specifications. However, using this measure to test the magnitude and incidence of conservatism generates tests of low power that require a relatively large magnitude of reporting conservatism in order to accurately reject the null hypothesis of no conservatism. Obviously, the above tests of the model's power are based on explicit assumptions of the expenditures and revenue generating processes and the process by which expenditures are matched to revenue. To the extent that the assumptions are not representative of actual revenue, expenditures and matching processes, the above tests may lack external validity and hence, the results of the simulations should be interpreted with consideration of the model's assumptions.

In the following section, I describe and present the results of construct validity tests of this measure of conservatism using actual data.

4. Construct Validity Tests

4.1 Empirical Predictions of the Model

Based on the expression for the probability limit of the OLS estimate of α_1 in section 2.4, I can derive several empirical predictions from the model that I can test to see if the estimated α_1 coefficient correlates with other variables using actual data based on these expectations. In the model, the probability limit of the OLS estimate of α_1 is expressed as follows:

$$plim(\alpha_1^{OLS})$$

$$= \varphi_1 \cdot \left[\frac{\mu_1 k\gamma^2(1-\mu_1^2) + \gamma^3(1-\mu_1^2)^2}{(1-\mu_1^2)^2(\gamma^4 - k^2\gamma^2) + (1-\mu_1^2)(2k^2\gamma^2 - 2\mu_1 k^3\gamma) + (k^4 - \mu_1^2 k^4)}\right]$$

where $k = (1 - \gamma + \gamma\mu_1)$.

As observed from the above expression, $plim(\alpha_1^{OLS})$ varies with γ, μ_1 and φ_1. In what follows, I describe empirical proxies for these variables that I use to test the predictions of the model.

4.1.1 Reporting conservatism ($\boldsymbol{\gamma}$). From section 2.4, I demonstrated that the estimated α_1 coefficient can be utilized to measure reporting conservatism, which I define to be an unobserved value of γ in the model. Empirically, α_1 should vary with accounting practices that are expected *a priori* to be associated with conservative reporting. The first empirical proxy for reporting conservatism is research and development (R&D) and advertising expense intensity (ADV).[10] R&D and advertising expenses are incurred to drive sales revenue, but because of the difficulty in matching these expenses to their

[10] Detailed descriptions of all variables used in this paper are included in Appendix C.

associated revenue and the complexity involved in verifying their future economic benefits, these expenses are not capitalized and are expensed as incurred.[11] Therefore, I expect R&D and advertising expense intensity to be positively associated with the estimated α_1 coefficient.

The second empirical proxy for reporting conservatism is the rate of depreciation for fixed assets (DPRATE). Firms are required to depreciate the value of their fixed assets over the assets' estimated useful life. However, firms have reasonable discretion in determining the estimated useful life when depreciating the value of the assets. Firms that depreciate the value of their assets over a shorter useful life are regarded as reporting more conservatively, and hence, I expect the rate of depreciation for fixed assets to be positively associated with the estimated α_1 coefficient.

The third empirical proxy for reporting conservatism is the market-to-book ratio (MB). In prior research (e.g., Beaver & Ryan, 2000; Feltham & Ohlson, 1995), it is suggested that accounting conservatism is manifested in higher market-to-book ratio because equity values reflect expectations of future cash flows -- expectations that are not reflected in book values that are understated as a result of reporting conservatism. Hence, I expect the market-to-book ratio to be positively associated with the estimated α_1 coefficient.

The final empirical proxy for reporting conservatism is the extent of fixed costs versus variable costs in the firm's cost structure (FIXED). This proxy is related to R&D, advertising and depreciation (manufacturing unrelated) expenses because these expenses

[11] See Statements of Financial Accounting Standards (SFAS) No. 2 for precise accounting rules relating to research and development expenses.

are difficult to trace and are usually considered fixed or period costs. Even though this proxy is not directly associated with reporting conservatism, I include this proxy because based on the model, γ is positively associated with matching difficulty, and the latter is affected by the cost structure of the firm. Therefore, I expect the extent of fixed costs in the cost structure to be positively associated with the estimated α_1 coefficient.

4.1.2 Time-series correlation in expenditures (μ_1). Based on the model, the OLS estimate of α_1 varies with the time-series correlation in expenditures μ_1. The empirical proxy for μ_1 will be the estimated coefficient from a regression of expenses on past expenses (EXPCORR). From the solution plotted in Figure 1, the relationship between the estimated α_1 and μ_1 is indeterminate because when γ is approximately less than 0.4, α_1 is increasing in μ_1 but when γ is greater than 0.4, α_1 is decreasing in μ_1. Therefore, I expect the time-series correlation in expenses to be associated (positively or negatively) with the estimated α_1 coefficient.

4.1.3 Profit margin (φ_1). From the solution to $plim(\alpha_1^{OLS})$, I determine α_1 to be increasing in profit margin φ_1. Because I cannot determine the true expenditures incurred to earn the corresponding revenue, I also cannot determine the firm's economic profit margin. Therefore, I use the firm's reported profit margin as an empirical proxy for φ_1, which is defined as income before extraordinary items divided by sales (MARGIN). I expect the profit margin to be positively associated with the estimated α_1 coefficient.

4.1.4 Random noise in expenditures (ν_t) and revenue (ω_t). Finally, I analyze the empirical relationship between the estimated α_1 coefficient and the random noise in expenditures (ν_t) and revenue (ω_t). As indicated by the solution to the OLS estimate of α_1, random noise in expenditures and revenue should not affect the magnitude of the α_1

coefficient when I assume stationarity of expenditures at the limit. Empirically, noise in expenses and revenue may lead to greater difficulty in matching. Hence, reporting conservatism, which in essence is a manifestation of lack of matching, is expected to increase in noise. Therefore, I expect noise in expenditures and revenue to be positively associated with the estimated α_1 coefficient. I estimate the noise in expenditures (ν_t) and revenue (ω_t) using the volatility in recognized expenses (EXPVOL) and revenue (SALEVOL) respectively.

4.2 Empirical Results

I obtain my initial sample of firm-year observations from 1971 – 2007 from COMPUSTAT. I include firms that are incorporated in the US, listed in the US stock exchanges (EXCHG code between 11 and 19), and with stock returns data from CRSP. I also exclude financials (SIC 6000-6999) and utilities (SIC 4900-4999) because these regulated firms are likely distinctive in their financial reporting activities. My main sample, after data requirements are met, consists of 58,650 firm-years. To mitigate the influence of outliers, I discard observations where the value of the continuous variables is lower (higher) than the 1% (99%) levels.

Table 1 presents the descriptive statistics for the main sample. The firms in my sample are generally larger than the COMPUSTAT universe in the corresponding sample period. The sample median of total assets is $180 million whereas the COMPUSTAT median of total assets is $86 million (untabulated). This size difference is due to my firm-year specific measurement of reporting conservatism (α_1) that requires data from the previous 10 fiscal years. Therefore, my sample is composed of only larger firms that have survived at least 10 years.

Table 2 presents the Pearson correlation between the estimated α_1 coefficient and other variables. Consistent with the model's predictions, α_1 is positively correlated with various empirical proxies of reporting conservatism γ, which include research and development expense intensity (R&D, Pearson correlation = 0.16); rate of depreciation for fixed assets (DPRATE, Pearson correlation = 0.09); the market-to-book ratio (MB, Pearson correlation = 0.10); and the extent of fixed versus variable costs in the firms' cost structure (FIXED, Pearson correlation = 0.17). However, I do not find evidence of a significant positive relationship between α_1 and advertising expense intensity (ADV, Pearson correlation = 0.01).

Next, I find that the empirical proxy for time-series correlation in expenditures μ_1 (EXPCORR) is negatively correlated with α_1 (Pearson correlation = -0.03), which is consistent with the model's prediction that μ_1 is related to α_1. However, I find that profit margin φ_1 is negatively correlated with α_1 (MARGIN, Pearson correlation = -0.12), which is contrary to the model's predictions. A possible explanation for this surprising result is that profit margin is a proxy for a firm's performance, and a firm with poor performance is also more likely to recognize expense ahead of the associated revenue ("big bath").

Finally, expense volatility (EXPVOL) is positively correlated with α_1 (Pearson correlation = 0.03), which is consistent with the earlier prediction that noise can lead to poor matching and hence results in a higher estimated α_1 coefficient.

The earlier discussion is based on pairwise univariate correlations, and to confirm my results based on multivariate analysis, I also run a regression of α_1 on all other variables. Table 3 presents the results of this regression. As shown in this table, most of the regression coefficients are consistent with the univariate analysis except for advertising expense intensity (ADV), which is now found to be negative and significant (coefficient = -0.183, *t*-statistic = -2.41), whereas it is positive and insignificant (Pearson correlation = 0.01) in the correlation table. Also, due to the high correlation between sales volatility (SALEVOL) and expense volatility (EXPVOL, Pearson correlation = 0.94), there is a potential issue with multi-collinearity (Variance Inflation Factor (VIF) > 10, untabulated). When I include only either SALEVOL or EXPVOL in the regression, both coefficients are positive but only the coefficient of EXPVOL is significant, a finding that is consistent with the univariate analysis. Overall, the results of the regression are largely consistent with the univariate analysis.

From section 2.4, I conclude that the $plim(\alpha_1^{OLS})$ is strictly increasing over certain values of reporting conservatism (γ). It is interesting to examine the sample properties of the empirical estimate of γ to see if the sample γ falls in the range of values where α_1 is strictly increasing as predicted by the model. To do so, I estimate the sample γ by computing the sum of research and development expenses, advertising expenses and depreciation expenses, divided by total expenses in the fiscal year. The sample mean (median) of γ is 0.08 (0.06) and the first (third) quartile value of γ is 0.03 (0.10). Although this estimation suggests that the sample γ falls in the range where α_1 is strictly increasing, it also indicates that the α_1 coefficient is likely to generate tests of low power at such low values of γ.

In sum, the empirical results in this section generally support the predictions of the model. Therefore, the empirical findings provide some support for the use of α_1 as an empirical proxy for the unobserved level of reporting conservatism (γ) as recommended by Dichev and Tang (2008). Moreover, the empirical findings indicate that other variables unrelated to reporting conservatism (e.g., proxies of μ_1, φ_1 and ν_t) may be correlated with the estimated α_1. Hence, it is important to control for these variables in the empirical model for hypothesis testing. Finally, the empirical estimation of γ confirms earlier results from simulations that the α_1 coefficient is likely to generate tests of low power to detect conservatism in the sample population.

5. Alternative Measure of Conservatism using a Reverse Regression Specification

The findings in the earlier sections suggest that the α_1 coefficient from the Dichev and Tang (2008) model is a feasible measure of conservatism. However, results from simulations also indicate that this measure generates tests of relatively low power. In this section, I explore an alternative measure of conservatism using a reverse regression specification to determine if this measure is statistically superior to the α_1 coefficient.

In the Dichev and Tang (2008) model, I measure reporting conservatism based on the estimated $\alpha_1$coefficient from the following empirical equation:

$$R_t = \alpha_0 + \alpha_1 e_{t-1} + \alpha_2 e_t + \varepsilon_t \qquad (4)$$

Based on the matching model (section 3.2), expenditures are matched to the associated revenue. Therefore, the matching process can also be expressed empirically as a reverse regression where I estimate reporting conservatism based on the estimated β_2 coefficient from the following empirical equation:

$$e_t = \beta_0 + \beta_1 R_t + \beta_2 R_{t+1} + \varepsilon_t \tag{9}$$

In the above expression, the estimated β_2 coefficient measures the relationship between current recognized expenses and future revenue, a relationship that is consistent with the notion of conservatism represented by the α_1 coefficient. The above expression seems natural because it reflects how the revenue earned in time t and time t+1 determine the amount of expense recognized in time t. In a way, this specification (equation 9) focuses on the matching process, which emphasizes revenue driving recognized expenses, whereas the original specification (equation 4) focuses on the revenue generating process, which emphasizes expenditures driving revenue. Both specifications can be interpreted as opposite sides of the same coin, and the empirical specification chosen depends on the needs and interests of the researcher. For purposes of this paper, I am interested in deriving an empirical measure of reporting conservatism (α_1 or β_2 coefficient) and hence both specifications are appropriate. The key question is which measure (α_1 or β_2 coefficient) exhibits superior statistical properties. In the following sub-sections, I will first evaluate whether the estimated β_2 coefficient measures the unobserved level of reporting conservatism (γ). I will then conduct simulations to assess the specification and power of the test statistics of the β_2 coefficient and compare them with the test statistics generated by the α_1 coefficient.

5.1 Probability Limit of the OLS Estimate of β_2

To derive the probability limit of the OLS estimate of β_2, I use the model assumptions provided in section 2.4 in the case of imperfect matching and imperfect observability of cost components. As in section 2.4, I provide a solution for the specific case where I take the limit of $Var(E_t)$ over time such that $Var(E_t) = \frac{Var(\upsilon_t)}{(1-\mu_1^2)}$ and $Var(E_t)$ becomes stationary. Based on these assumptions, the probability limit of the OLS estimate of β_2 is given by (derived in detail in Appendix B):

$$plim(\beta_2^{OLS}) = \frac{\varphi_1[\mu_1(1-\gamma)+\gamma]Var(\omega) + \varphi_1^3\gamma Var(\upsilon)}{\varphi_1^4 Var(\upsilon) + 2\varphi_1^2 Var(\omega) + (1-\mu_1^2)\frac{[Var(\omega)]^2}{Var(\upsilon)}}$$

To determine whether β_2 is increasing in γ, I plot the solution to $plim(\beta_2^{OLS})$ against values of γ from 0 to 1 (in 0.01 increments), holding μ_1 constant at various levels between 0 and 0.99 ($\mu_1 =$ 0, 0.25, 0.5, 0.75 and 0.99). Additionally, because the solution is also dependent on φ_1, $Var(\omega)$ and $Var(\upsilon)$, I arbitrarily set φ_1 equals to 1.2 and both $Var(\omega)$ and $Var(\upsilon)$ equal to 1. Figure 4 plots the solution to $plim(\beta_2^{OLS})$ (vertical axis) against reporting conservatism γ (horizontal axis), conditional on various values of μ_1 and assuming φ_1 = 1.2 and $Var(\omega)$ = $Var(\upsilon)$ = 1.

As shown in Figure 4, the probability limit of the OLS estimate of β_2 is strictly increasing in reporting conservatism (γ) at various assumed values of μ_1 between 0 and 1. This result compares favorably to the solution to $plim(\alpha_1^{OLS})$ (Figure 1) where $plim(\alpha_1^{OLS})$ is increasing only monotonically in γ until the point where γ is approximately larger than 0.75. However, note that for values where μ_1 > 0, $plim(\beta_2^{OLS})$ does not start from the origin when γ = 0. Intuitively, when γ = 0,

$e_t = E_t$

$R_{t+1} = \varphi_0 + \varphi_1 E_{t+1} + \omega_{t+1}$

Therefore, the β_2 coefficient, which measures the relationship between e_t and R_{t+1} in equation (9), also captures the relationship between E_t and E_{t+1}, and this relationship is increasing in the time-series correlation in expenditures μ_1.

This result may present a problem in statistical tests because the β_2 coefficient is positive even in the absence of conservatism (γ = 0). To determine whether this issue is problematic for test statistics, I conduct simulations to assess the specification and power of the test statistics of the β_2 coefficient. Findings are presented in the following sub-section.

5.2 Test Statistics of the β_2 Coefficient

To assess the specification and power of the test statistics of the β_2 coefficient, I conduct simulations using the same parameters outlined in section 3.3. The results of these simulations are plotted in Figure 5 and 6, where the estimated β_2 coefficient and the frequency of rejecting the null hypothesis (vertical axis in Figure 5 and 6 respectively) is plotted against the magnitude of reporting conservatism (horizontal axis), conditional on various values of μ_1.

Figure 5 indicates that the estimated β_2 coefficient is strictly increasing in reporting conservatism (γ), which is consistent with the plot of the solution to $plim(\beta_2^{OLS})$ in Figure 4. As shown in Figure 6, when there is no reporting conservatism (γ = 0) and no time-series correlation in expenditures (μ_1 = 0), the frequency of rejecting the null hypothesis is approximately 5%, which is consistent with the specified test level.

However, when $\mu_1 > 0$, the frequency of rejecting the null hypothesis monotonically increases as μ_1 increases, even in the absence of conservatism ($\gamma = 0$). In fact, when $\mu_1 = 0.99$, the frequency of rejecting the null hypothesis when $\gamma = 0$ is very high at approximately 61%. This suggests that the frequency of a Type 1 error (rejecting the null hypothesis when the null is true) is greater than the specified test level when $\mu_1 > 0$.

When there is reporting conservatism ($\gamma > 0$), the frequency of rejecting the null hypothesis increases to more than 90% when $\gamma > 0.5$. Figure 7 provides a comparison of test power between α_1 and β_2 at various values of μ_1, and the figure suggests that the β_2 coefficient generates tests of greater power than does the $\alpha_1$coefficient. In terms of test power, the β_2 coefficient is clearly more powerful than the $\alpha_1$coefficient. However, the β_2 coefficient appears to over-reject the null hypothesis when $\mu_1 > 0$.

As highlighted in the preceding sub-section, the issue of an upward biased coefficient of β_2 is due to the time-series correlation in expenditures μ_1. A possible means of controlling for μ_1 in the estimation of the β_2 coefficient is to include future recognized expenses in the regression. That is, instead of estimating equation (9), I estimate the following equation:

$$e_t = \beta_0 + \beta_1 R_t + \beta_2 R_{t+1} + \beta_3 e_{t+1} + \varepsilon_t \quad (10)$$

The purpose of including e_{t+1} in equation (10) is to control for the time-series correlation in expenditures μ_1 in the estimation of the β_2 coefficient. To assess if this methodology mitigates the upward bias in the β_2 coefficient, I conduct simulations to assess the test statistics of the β_2 coefficient estimated from equation (10). The results of these simulations are plotted in Figure 8 and 9.

As observed from Figure 8, the estimated β_2 coefficient is still strictly increasing in reporting conservatism (γ) at various values of μ_1 after I control for e_{t+1} in equation (10). However, note that the estimated β_2 coefficient is slightly above 0 in the absence of conservatism (γ = 0) at all values of μ_1. Further investigation reveals that the upward biased coefficient is due to multicollinearity from having both R_{t+1} and e_{t+1} as explanatory variables in equation (10), and a short time-series of 20 observations in the simulations appears to exacerbate the bias.[12]

With respect to test statistics, the frequency of rejecting the null hypothesis when there is no conservatism (γ = 0) ranges from 6% to 8%, and these frequencies are significantly different from the specified test level of 5% based on a two-tailed binomial test (results untabulated). This suggests that the test statistics are misspecified after controlling for e_{t+1}, albeit with a much smaller bias than is presented in the original β_2 coefficient specification.

Figure 9 indicates that the test power declines after I control for e_{t+1} in equation (10). When there is reporting conservatism ($\gamma > 0$), the frequency of rejecting the null hypothesis gradually increases to only about 20% when γ is approximately 0.3. If we compare the test power of α_1 and β_2 after controlling for e_{t+1}, as shown in Figure 10, the β_2 coefficient is slightly superior to the α_1 coefficient in terms of test power. The results suggest that by controlling for e_{t+1} in equation (10), I am able to obtain a β_2 coefficient that has fewer Type 1 errors and more Type 2 errors than the original β_2 coefficient specification.

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[12] In separate simulations, I confirm that the bias becomes smaller as I increase the number of time-series observations in the regression (results untabulated).

5.3 Discussion

In summary, in this section, I evaluate an alternative measure of reporting conservatism using a reverse regression specification of the Dichev and Tang (2008) model. Analytical derivation indicates that the solution to $plim(\beta_2^{OLS})$ strictly increases in reporting conservatism (γ), which compares favorably to the solution to $plim(\alpha_1^{OLS})$, which only strictly increases over certain values of γ. Results from the simulations demonstrate that although the β_2 coefficient generates tests of relatively high power, it also appears to over-reject the null hypothesis when conservatism is absent. After I control for e_{t+1} in the estimation of the β_2 coefficient, the resulting coefficient is slightly superior to the α_1 coefficient in terms of test power. Overall, the results in this section suggest that the β_2 coefficient is a feasible alternative to the α_1 coefficient when maximizing test power is an important consideration for the empirical researcher.

6. Conclusion

In conclusion, this paper provides a critical evaluation of the econometric properties of the measure of reporting conservatism introduced recently by Dichev and Tang (2008). I find that in the case of imperfect matching and imperfect observability of cost components, the measurement error in the recognized expenses allows the researcher to infer the true level of conservatism from the estimated α_1 coefficient in the Dichev and Tang (2008) model. Although the estimated α_1 coefficient produces well-specified test statistics that generate Type 1 errors according to researchers' specifications, I find that this measure generates tests of low power that lead to relatively high Type 2 errors. Next, I find empirical results that are consistent with the model's predictions. Although the empirical findings generally provide support for using the estimated α_1 coefficient as a measure of conservatism, the researcher is also advised to include other correlated variables in the empirical model to mitigate the omitted correlated variables problem, which may lead to spurious inferences in hypothesis testing. Finally, I explore an alternative measure of conservatism using a reverse regression specification. Results from simulations suggest that this alternative measure is feasible and is slightly superior to the α_1 coefficient in terms of test power.

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APPENDIX A

Derivation of $plim(\alpha_1^{OLS})$ under Imperfect Matching with Imperfect Observation of Cost Components

Define a firm with the following generating process for expenditures:

$$E_t = \mu_0 + \mu_1 E_{t-1} + \upsilon_t$$

Expenditures are incurred to generate revenue based on the following process:

$$R_t = \varphi_0 + \varphi_1 E_t + \omega_t$$

Firms vary in different levels of reporting conservatism. Conservatism is defined as the extent to which expenditures are recognized before the associated revenue. From a modeling view, expenses recognized in time t (e_t) is defined as follows:

$$e_t = (1-\gamma)E_t + \gamma E_{t+1}$$

Hence, based on the above relation between true expenditures (E) and recognized expenses (e), γ measures the proportion of true expenditures in time t+1 (E_{t+1}) that is recognized in advance in time t (e_t). This notion is consistent with reporting conservatism, and I define conservatism in this model to be increasing in γ. The empirical researcher can only observe recognized expenses (e) but not true expenditures (E). The issue is whether we can infer a firm's level of reporting conservatism γ by examining the relation between revenue and past and present recognized expenses as suggested by Dichev and Tang (2008):

$$R_t = \alpha_0 + \alpha_1 e_{t-1} + \alpha_2 e_t + \varepsilon_t$$

Without loss of generality, assume $\mu_0 = 0$. Under this assumption,

$$e_{t-1} = (1-\gamma)E_{t-1} + \gamma E_t$$

$$= (1-\gamma)E_{t-1} + \gamma(\mu_1 E_{t-1} + \upsilon_t)$$

$$= (1-\gamma+\gamma\mu_1)E_{t-1} + \gamma\upsilon_t$$

$$e_t = (1-\gamma+\gamma\mu_1)E_t + \gamma\upsilon_{t+1}$$

Because υ_t is modeled as a mean-zero white noise, the following statistical properties apply:

$$Var(\upsilon_t) = Var(\upsilon) \ \forall \ t;$$

$$Cov(\upsilon_t, \upsilon_s) = 0 \qquad \forall \ t \neq s$$

Let $k = (1-\gamma+\gamma\mu_1)$, therefore, the probability limit of the OLS estimate of α_1 is given by:

$$plim(\alpha_1^{OLS})$$

$$= \frac{Cov(R_t, e_{t-1})Var(e_t) - Cov(R_t, e_t)Cov(e_{t-1}, e_t)}{Var(e_{t-1})Var(e_t) - [Cov(e_{t-1}, e_t)]^2}$$

$$= \frac{Cov(\varphi_0 + \varphi_1 E_t + \omega_t, kE_{t-1} + \gamma\upsilon_t)Var(kE_t + \gamma\upsilon_{t+1})}{Var(kE_{t-1} + \gamma\upsilon_t)Var(kE_t + \gamma\upsilon_{t+1}) - [Cov(kE_{t-1} + \gamma\upsilon_t, kE_t + \gamma\upsilon_{t+1})]^2}$$

$$- \frac{Cov(\varphi_0 + \varphi_1 E_t + \omega_t, kE_t + \gamma\upsilon_{t+1})Cov(kE_{t-1} + \gamma\upsilon_t, kE_t + \gamma\upsilon_{t+1})}{Var(kE_{t-1} + \gamma\upsilon_t)Var(kE_t + \gamma\upsilon_{t+1}) - [Cov(kE_{t-1} + \gamma\upsilon_t, kE_t + \gamma\upsilon_{t+1})]^2}$$

$$= \frac{[\varphi_1 kCov(E_t, E_{t-1}) + \varphi_1\gamma Var(\upsilon)][k^2 Var(E_t) + \gamma^2 Var(\upsilon)]}{[k^2 Var(E_{t-1}) + \gamma^2 Var(\upsilon)][k^2 Var(E_t) + \gamma^2 Var(\upsilon)] - [k^2 Cov(E_{t-1}, E_t) + k\gamma Var(\upsilon)]^2}$$

$$- \frac{\varphi_1 kVar(E_t)[k^2 Cov(E_{t-1}, E_t) + k\gamma Var(\upsilon)]}{[k^2 Var(E_{t-1}) + \gamma^2 Var(\upsilon)][k^2 Var(E_t) + \gamma^2 Var(\upsilon)] - [k^2 Cov(E_{t-1}, E_t) + k\gamma Var(\upsilon)]^2}$$

$$= \frac{\varphi_1 k\gamma^2 Cov(E_t, E_{t-1})Var(\upsilon) + \varphi_1\gamma^3 [Var(\upsilon)]^2}{[k^2 Var(E_{t-1}) + \gamma^2 Var(\upsilon)][k^2 Var(E_t) + \gamma^2 Var(\upsilon)] - [k^2 Cov(E_{t-1}, E_t) + k\gamma Var(\upsilon)]^2}$$

To simplify the above expression, I first derive a representation for $Var(E_t)$:

$$Var(E_t) = \mu_1^2 Var(E_{t-1}) + Var(\upsilon)$$

Note that the variance of E_{t-1} is again a function of E_{t-2} and so on. Using recursive substitution, $Var(E_t)$ can be expressed as:

$$Var(E_t) = Var(\upsilon)[1 + \mu_1^2 + \mu_1^4 + \cdots]$$

The limit of $Var(E_t)$ can be simplified as:

$$\lim\{Var(E_t)\} = \frac{Var(\upsilon)}{(1-\mu_1^2)}$$

I then derive a representation of $Cov(E_t, E_{t-1})$ as follows:

$$Cov(E_t, E_{t-1}) = Cov(\mu_0 + \mu_1 E_{t-1} + \upsilon_t, E_{t-1})$$

$$= \mu_1 Var(E_{t-1})$$

$$= \mu_1 Var(E_t)$$

$$= \frac{\mu_1 Var(\upsilon)}{(1-\mu_1^2)}$$

Hence, the probability limit of the OLS estimate of α_1 becomes:

$plim(\alpha_1^{OLS})$

$$= \frac{\varphi_1\mu_1 k\gamma^2 \frac{[Var(\upsilon)]^2}{(1-\mu_1^2)} + \varphi_1\gamma^3[Var(\upsilon)]^2}{\left[k^2\frac{Var(\upsilon)}{(1-\mu_1^2)} + \gamma^2 Var(\upsilon)\right]\left[k^2\frac{Var(\upsilon)}{(1-\mu_1^2)} + \gamma^2 Var(\upsilon)\right] - \left[\mu_1 k^2\frac{Var(\upsilon)}{(1-\mu_1^2)} + k\gamma Var(\upsilon)\right]^2}$$

$$= \frac{\varphi_1\mu_1 k\gamma^2 \frac{[Var(\upsilon)]^2}{(1-\mu_1^2)} + \varphi_1\gamma^3[Var(\upsilon)]^2}{k^4\left[\frac{Var(\upsilon)}{(1-\mu_1^2)}\right]^2 + 2k^2\gamma^2\frac{[Var(\upsilon)]^2}{(1-\mu_1^2)} + \gamma^4[Var(\upsilon)]^2 - \mu_1^2k^4\left[\frac{Var(\upsilon)}{(1-\mu_1^2)}\right]^2 - 2\mu_1k^3\gamma\frac{[Var(\upsilon)]^2}{(1-\mu_1^2)} - k^2\gamma^2[Var(\upsilon)]^2}$$

$$= \frac{\varphi_1\mu_1 k\gamma^2 \frac{1}{(1-\mu_1^2)} + \varphi_1\gamma^3}{k^4\left[\frac{1}{(1-\mu_1^2)}\right]^2 + 2k^2\gamma^2\frac{1}{(1-\mu_1^2)} + \gamma^4 - \mu_1^2k^4\left[\frac{1}{(1-\mu_1^2)}\right]^2 - 2\mu_1k^3\gamma\frac{1}{(1-\mu_1^2)} - k^2\gamma^2}$$

$$= \frac{\varphi_1\mu_1k\gamma^2(1-\mu_1^2) + \varphi_1\gamma^3(1-\mu_1^2)^2}{k^4 + 2k^2\gamma^2(1-\mu_1^2) + \gamma^4(1-\mu_1^2)^2 - \mu_1^2k^4 - 2\mu_1k^3\gamma(1-\mu_1^2) - k^2\gamma^2(1-\mu_1^2)^2}$$

$$= \varphi_1 \cdot \left[\frac{\mu_1k\gamma^2(1-\mu_1^2) + \gamma^3(1-\mu_1^2)^2}{(1-\mu_1^2)^2(\gamma^4 - k^2\gamma^2) + (1-\mu_1^2)(2k^2\gamma^2 - 2\mu_1k^3\gamma) + (k^4 - \mu_1^2k^4)}\right]$$

APPENDIX B

Derivation of $plim(\beta_2^{OLS})$ using a Reverse Regression Specification

In the Dichev and Tang (2008) model, I measure reporting conservatism based on the estimated $\alpha_1$coefficient from the following empirical equation:

$$R_t = \alpha_0 + \alpha_1 e_{t-1} + \alpha_2 e_t + \varepsilon_t$$

I can also use a reverse regression and estimate reporting conservatism based on the estimated β_2 coefficient from the following empirical equation:

$$e_t = \beta_0 + \beta_1 R_t + \beta_2 R_{t+1} + \varepsilon_t$$

As before, I first evaluate if I can infer the unobserved level of reporting conservatism (γ) based on the estimated β_2 coefficient. I use the same model assumptions based on section 2.4 in the case of imperfect matching and imperfect observability of cost components. Because ω_t is also modeled as a mean-zero white noise, the following statistical properties apply:

$$Var(\omega_t) = Var(\omega)\ \forall\ t;$$

$$Cov(\omega_t, \omega_s) = 0 \qquad \forall\ t \neq s$$

Therefore, the probability limit of the OLS estimate of β_2 is given by:

$$plim(\beta_2^{OLS})$$

$$= \frac{Cov(e_t, R_{t+1})Var(R_t) - Cov(e_t, R_t)Cov(R_t, R_{t+1})}{Var(R_t)Var(R_{t+1}) - [Cov(R_t, R_{t+1})]^2}$$

$$= \frac{Cov\big((1-\gamma)E_t + \gamma E_{t+1}, \varphi_0 + \varphi_1 E_{t+1} + \omega_{t+1}\big)Var(\varphi_0 + \varphi_1 E_t + \omega_t)}{Var(\varphi_0 + \varphi_1 E_t + \omega_t)Var(\varphi_0 + \varphi_1 E_{t+1} + \omega_{t+1}) - [Cov(\varphi_0 + \varphi_1 E_t + \omega_t, \varphi_0 + \varphi_1 E_{t+1} + \omega_{t+1})]^2}$$

$$- \frac{Cov\big((1-\gamma)E_t + \gamma E_{t+1}, \varphi_0 + \varphi_1 E_t + \omega_t\big)Cov(\varphi_0 + \varphi_1 E_t + \omega_t, \varphi_0 + \varphi_1 E_{t+1} + \omega_{t+1})}{Var(\varphi_0 + \varphi_1 E_t + \omega_t)Var(\varphi_0 + \varphi_1 E_{t+1} + \omega_{t+1}) - [Cov(\varphi_0 + \varphi_1 E_t + \omega_t, \varphi_0 + \varphi_1 E_{t+1} + \omega_{t+1})]^2}$$

$$= \frac{[\varphi_1(1-\gamma)Cov(E_t, E_{t+1}) + \varphi_1\gamma Var(E_{t+1})][\varphi_1^2 Var(E_t) + Var(\omega)]}{[\varphi_1^2 Var(E_t) + Var(\omega)][\varphi_1^2 Var(E_{t+1}) + Var(\omega)] - [\varphi_1^2 Cov(E_t, E_{t+1})]^2}$$

$$- \frac{[\varphi_1(1-\gamma)Var(E_t) + \varphi_1\gamma Cov(E_t, E_{t+1})][\varphi_1^2 Cov(E_t, E_{t+1})]}{[\varphi_1^2 Var(E_t) + Var(\omega)][\varphi_1^2 Var(E_{t+1}) + Var(\omega)] - [\varphi_1^2 Cov(E_t, E_{t+1})]^2}$$

As before, I derive a representation for $Var(E_t)$ to simplify the above expression:

$$Var(E_t) = \mu_1^2 Var(E_{t-1}) + Var(v)$$

Note that the variance of E_{t-1} is again a function of E_{t-2} and so on. Using recursive substitution, $Var(E_t)$ can be expressed as:

$$Var(E_t) = Var(v)[1 + \mu_1^2 + \mu_1^4 + \cdots]$$

The limit of $Var(E_t)$ can be simplified as:

$$\lim\{Var(E_t)\} = \frac{Var(v)}{(1-\mu_1^2)}$$

I then derive a representation of $Cov(E_{t+1}, E_t)$ as follows:

$$Cov(E_{t+1}, E_t) = Cov(\mu_0 + \mu_1 E_t + v_{t+1}, E_t)$$

$$= \mu_1 Var(E_t)$$

$$= \frac{\mu_1 Var(v)}{(1-\mu_1^2)}$$

Hence, the probability limit of the OLS estimate of β_2 becomes:

$plim(\beta_2^{OLS})$

$$= \frac{\left[\varphi_1\mu_1(1-\gamma)\frac{Var(v)}{(1-\mu_1^2)} + \varphi_1\gamma\frac{Var(v)}{(1-\mu_1^2)}\right]\left[\varphi_1^2\frac{Var(v)}{(1-\mu_1^2)} + Var(\omega)\right]}{\left[\varphi_1^2\frac{Var(v)}{(1-\mu_1^2)} + Var(\omega)\right]\left[\varphi_1^2\frac{Var(v)}{(1-\mu_1^2)} + Var(\omega)\right] - \left[\varphi_1^2\mu_1\frac{Var(v)}{(1-\mu_1^2)}\right]^2}$$

$$- \frac{\left[\varphi_1(1-\gamma)\frac{Var(v)}{(1-\mu_1^2)} + \varphi_1\mu_1\gamma\frac{Var(v)}{(1-\mu_1^2)}\right]\left[\varphi_1^2\mu_1\frac{Var(v)}{(1-\mu_1^2)}\right]}{\left[\varphi_1^2\frac{Var(v)}{(1-\mu_1^2)} + Var(\omega)\right]\left[\varphi_1^2\frac{Var(v)}{(1-\mu_1^2)} + Var(\omega)\right] - \left[\varphi_1^2\mu_1\frac{Var(v)}{(1-\mu_1^2)}\right]^2}$$

$$= \frac{\varphi_1\mu_1(1-\gamma)\frac{Var(\upsilon)Var(\omega)}{(1-\mu_1^2)} + \varphi_1^3\gamma\left[\frac{Var(\upsilon)}{(1-\mu_1^2)}\right]^2 + \varphi_1\gamma\frac{Var(\upsilon)Var(\omega)}{(1-\mu_1^2)} - \varphi_1^3\mu_1^2\gamma\left[\frac{Var(\upsilon)}{(1-\mu_1^2)}\right]^2}{\varphi_1^4\left[\frac{Var(\upsilon)}{(1-\mu_1^2)}\right]^2 + 2\varphi_1^2\frac{Var(\upsilon)Var(\omega)}{(1-\mu_1^2)} + [Var(\omega)]^2 - \varphi_1^4\mu_1^2\left[\frac{Var(\upsilon)}{(1-\mu_1^2)}\right]^2}$$

$$= \frac{\varphi_1[\mu_1(1-\gamma)+\gamma]\frac{Var(\upsilon)Var(\omega)}{(1-\mu_1^2)} + \varphi_1^3\gamma(1-\mu_1^2)\left[\frac{Var(\upsilon)}{(1-\mu_1^2)}\right]^2}{\varphi_1^4(1-\mu_1^2)\left[\frac{Var(\upsilon)}{(1-\mu_1^2)}\right]^2 + 2\varphi_1^2\frac{Var(\upsilon)Var(\omega)}{(1-\mu_1^2)} + [Var(\omega)]^2}$$

$$= \frac{\varphi_1[\mu_1(1-\gamma)+\gamma]\frac{Var(\omega)}{(1-\mu_1^2)} + \varphi_1^3\gamma\frac{Var(\upsilon)}{(1-\mu_1^2)}}{\varphi_1^4\frac{Var(\upsilon)}{(1-\mu_1^2)} + 2\varphi_1^2\frac{Var(\omega)}{(1-\mu_1^2)} + \frac{[Var(\omega)]^2}{Var(\upsilon)}}$$

$$= \frac{\varphi_1[\mu_1(1-\gamma)+\gamma]Var(\omega) + \varphi_1^3\gamma Var(\upsilon)}{\varphi_1^4 Var(\upsilon) + 2\varphi_1^2 Var(\omega) + (1-\mu_1^2)\frac{[Var(\omega)]^2}{Var(\upsilon)}}$$

APPENDIX C

Variables Definition[13]

α_1 — Defined as α_1 in the following firm-year specific time series regression in the prior ten-year rolling window:

$$REVENUE_t = \alpha_0 + \alpha_1 * EXP_{t-1} + \alpha_2 * EXP_t + \alpha_3 * EXP_{t+1} + \varepsilon_t$$

where REVENUE is sales (SALE) and EXP is expenses (SALE – IB).

ADV — Advertising expenditure (XAD) scaled by sales (SALE) in the fiscal year. This variable is set to zero if missing.

ASSETS — Total assets (AT) at the end of the fiscal year.

DPRATE — Rate of depreciation for fixed assets, defined as depreciation expense for the fiscal year (DP) divided by the gross property, plant and equipment (PPEGT) at the end of the fiscal year.

EXPCORR — The time-series correlation in expenditures, defined as the estimated coefficient from a firm-year specific time-series regression of expenses on past expenses (SALE – IB) in the prior ten-year rolling window.

EXPVOL — Volatility of expenses (SALE - IB), measured over at least 3 years in the prior ten fiscal years.

FIXED — The extent of fixed costs in the firm's cost structure, defined as total expenses (SALE – IB) less cost of goods sold (COGS), divided by total expenses in the fiscal year.

MARGIN — Profit margin, defined income before extraordinary items (IB) divided by sales (SALE) in the fiscal year.

[13] COMPUSTAT variables in parentheses, unless otherwise noted.

MB	The market-to-book ratio at the end of the fiscal year, defined as the sum of the book value of debt (AT – CEQ) and market value of equity (CSHO*PRCC_F) divided by total assets (AT).
R&D	Research and development expenditure (XRD) scaled by sales (SALE) in the fiscal year. This variable is set to zero if missing.
SALEVOL	Volatility of sales (SALE), measured over at least 3 years in the prior ten fiscal years.

Table 1
Sample and Descriptive Statistics

Variables	Obs.	Mean	Median	Std. Dev.	Q1	Q3
α_1	58,650	0.059	0.026	0.164	-0.028	0.118
R&D	59,217	0.024	0.000	0.055	0.000	0.023
ADV	59,245	0.009	0.000	0.020	0.000	0.011
DPRATE	58,202	0.084	0.072	0.045	0.057	0.097
MB	58,431	1.502	1.223	0.879	0.969	1.700
FIXED	58,598	0.311	0.280	0.163	0.195	0.400
EXPCORR	58,650	0.534	0.568	0.310	0.333	0.759
MARGIN	58,598	0.017	0.036	0.149	0.010	0.065
SALEVOL	58,636	0.230	0.182	0.166	0.116	0.289
EXPVOL	58,636	0.233	0.179	0.182	0.110	0.292
ASSETS	58,650	1,185.9	179.6	3,127.1	49.1	780.9

The sample consists of 58,650 US-incorporated firm-years from 1971 – 2007 and excluding financials (SIC 6000-6999) and utilities (SIC 4900-4999). α_1 is the estimated coefficient of past expenses in the firm-year specific time-series regression of revenue on past, present and future expenses, estimated over the prior ten fiscal years. R&D is research and development expenditure scaled by sales for the fiscal year. ADV is advertising expenditure scaled by sales for the fiscal year. DPRATE is the rate of depreciation for fixed assets for the fiscal year. MB is the market-to-book ratio at the end of the fiscal year. FIXED is the extent of fixed costs versus variable costs in the firm's cost structure for the fiscal year. EXPCORR is the time-series correlation in expenses estimated over the prior ten fiscal years. MARGIN is the firm's profit margin for the fiscal year. SALEVOL is the volatility of sales measured over at least 3 years in the prior ten fiscal years. EXPVOL is the volatility of expenses measured over at least 3 years in the prior ten fiscal years. ASSETS is the total assets of the firm at the end of the fiscal year.

Table 2

Pearson Correlation Table

	α_1	R&D	ADV	DPRATE	MB	FIXED	EXPCORR	MARGIN	SALEVOL	EXPVOL
α_1	1.00									
R&D	0.16	1.00								
ADV	**0.01**	-0.01	1.00							
DPRATE	0.09	0.24	**0.01**	1.00						
MB	0.10	0.29	0.07	0.19	1.00					
FIXED	0.17	0.41	0.22	0.24	0.33	1.00				
EXPCORR	-0.03	-0.02	0.05	-0.03	0.02	**-0.01**	1.00			
MARGIN	-0.12	-0.27	0.03	-0.15	0.02	-0.14	0.07	1.00		
SALEVOL	**0.01**	0.01	-0.07	0.21	**0.01**	-0.15	0.20	-0.13	1.00	
EXPVOL	0.03	0.05	-0.07	0.23	0.04	-0.10	0.15	-0.19	0.94	1.00

The sample consists of 58,650 US-incorporated firm-years from 1971 – 2007 and excluding financials (SIC 6000-6999) and utilities (SIC 4900-4999). α_1 is the estimated coefficient of past expenses in the firm-year specific time-series regression of revenue on past, present and future expenses, estimated over the prior ten fiscal years. R&D is research and development expenditure scaled by sales for the fiscal year. ADV is advertising expenditure scaled by sales for the fiscal year. DPRATE is the rate of depreciation for fixed assets for the fiscal year. MB is the market-to-book ratio at the end of the fiscal year. FIXED is the extent of fixed costs versus variable costs in the firm's cost structure for the fiscal year. EXPCORR is the time-series correlation in expenses estimated over the prior ten fiscal years. MARGIN is the firm's profit margin for the fiscal year. SALEVOL is the volatility of sales measured over at least 3 years in the prior ten fiscal years. EXPVOL is the volatility of expenses measured over at least 3 years in the prior ten fiscal years. All correlations except those in bold are statistically significant at the 0.05 level or better.

Table 3
Empirical Test of the Model's Predictions

	α_1			
	Pred.	*Coef.*	*t-stats*	
R&D	+	0.212	4.47	***
ADV	+	-0.183	-2.41	**
DPRATE	+	0.071	1.80	*
MB	+	0.008	3.27	***
FIXED	+	0.130	9.85	***
EXPCORR	+/-	-0.008	-1.94	*
MARGIN	+	-0.132	-6.08	***
SALEVOL	+	-0.138	-3.04	***
EXPVOL	+	0.150	3.39	***
CONSTANT		0.002	0.19	
Adjusted R^2		0.053		
Observations		52,053		

The sample for the regression consists of 52,053 US-incorporated firm-years from 1971 – 2007 and excluding financials (SIC 6000-6999) and utilities (SIC 4900-4999). α_1 is the estimated coefficient of past expenses in the firm-year specific time-series regression of revenue on past, present and future expenses, estimated over the prior ten fiscal years. R&D is research and development expenditure scaled by sales for the fiscal year. ADV is advertising expenditure scaled by sales for the fiscal year. DPRATE is the rate of depreciation for fixed assets for the fiscal year. MB is the market-to-book ratio at the end of the fiscal year. FIXED is the extent of fixed costs versus variable costs in the firm's cost structure for the fiscal year. EXPCORR is the time-series correlation in expenses estimated over the prior ten fiscal years. MARGIN is the firm's profit margin for the fiscal year. SALEVOL is the volatility of sales measured over at least 3 years in the prior ten fiscal years. EXPVOL is the volatility of expenses measured over at least 3 years in the prior ten fiscal years. Standard errors are corrected for cross-sectional and time-series dependence (Gow, Ormazabal & Taylor, 2010; Petersen, 2009). ***, **, and * indicate statistical significance at the 0.01, 0.05 and 0.10 level or better, respectively (two-tailed test).

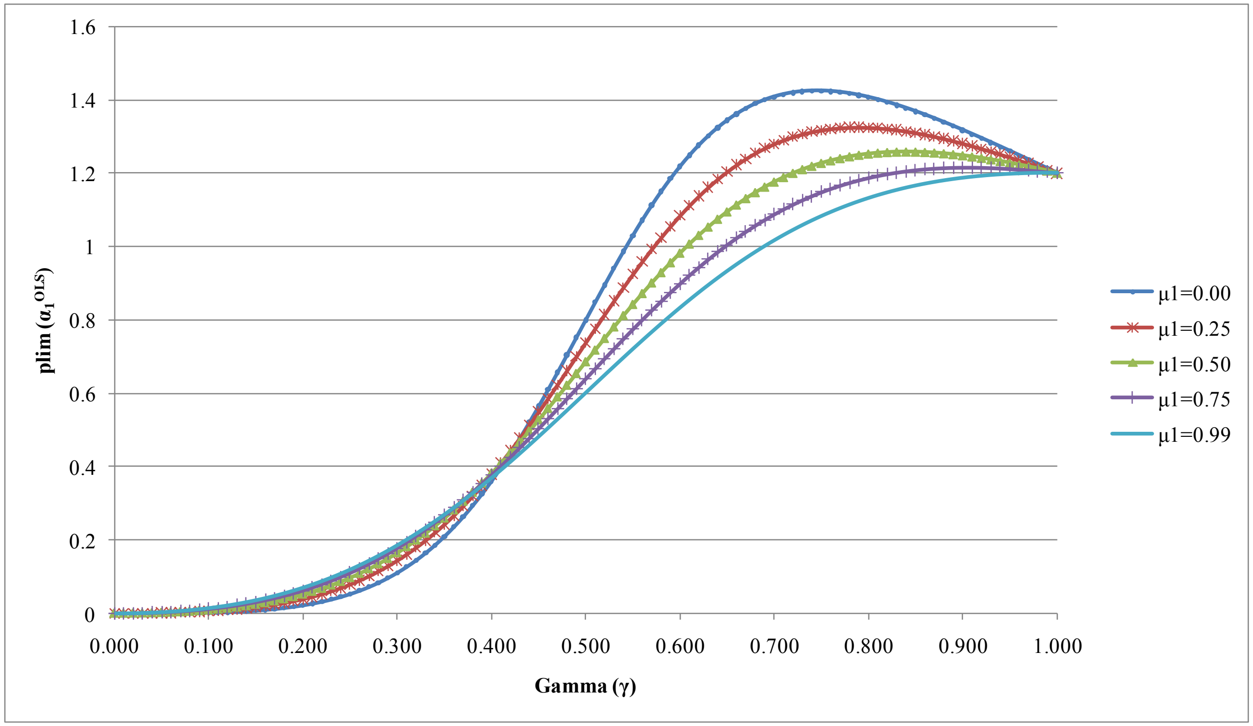

Figure 1. $\boldsymbol{plim(\alpha_1^{OLS})}$ **Conditional on** $\boldsymbol{\gamma}$ **and** $\boldsymbol{\mu_1}$

The above graph plots the solution to $plim(\alpha_1^{OLS})$ against reporting conservatism (γ), assuming φ_1=1.2 and μ_1 taking on various values between 0 and 1. The probability limit of the OLS estimate of α_1 is expressed as follows:

$$plim(\alpha_1^{OLS}) = \varphi_1 \cdot \left[\frac{\mu_1 k\gamma^2(1-\mu_1^2) + \gamma^3(1-\mu_1^2)^2}{(1-\mu_1^2)^2(\gamma^4 - k^2\gamma^2) + (1-\mu_1^2)(2k^2\gamma^2 - 2\mu_1 k^3\gamma) + (k^4 - \mu_1^2 k^4)}\right]$$

where $k = (1 - \gamma + \gamma\mu_1)$.

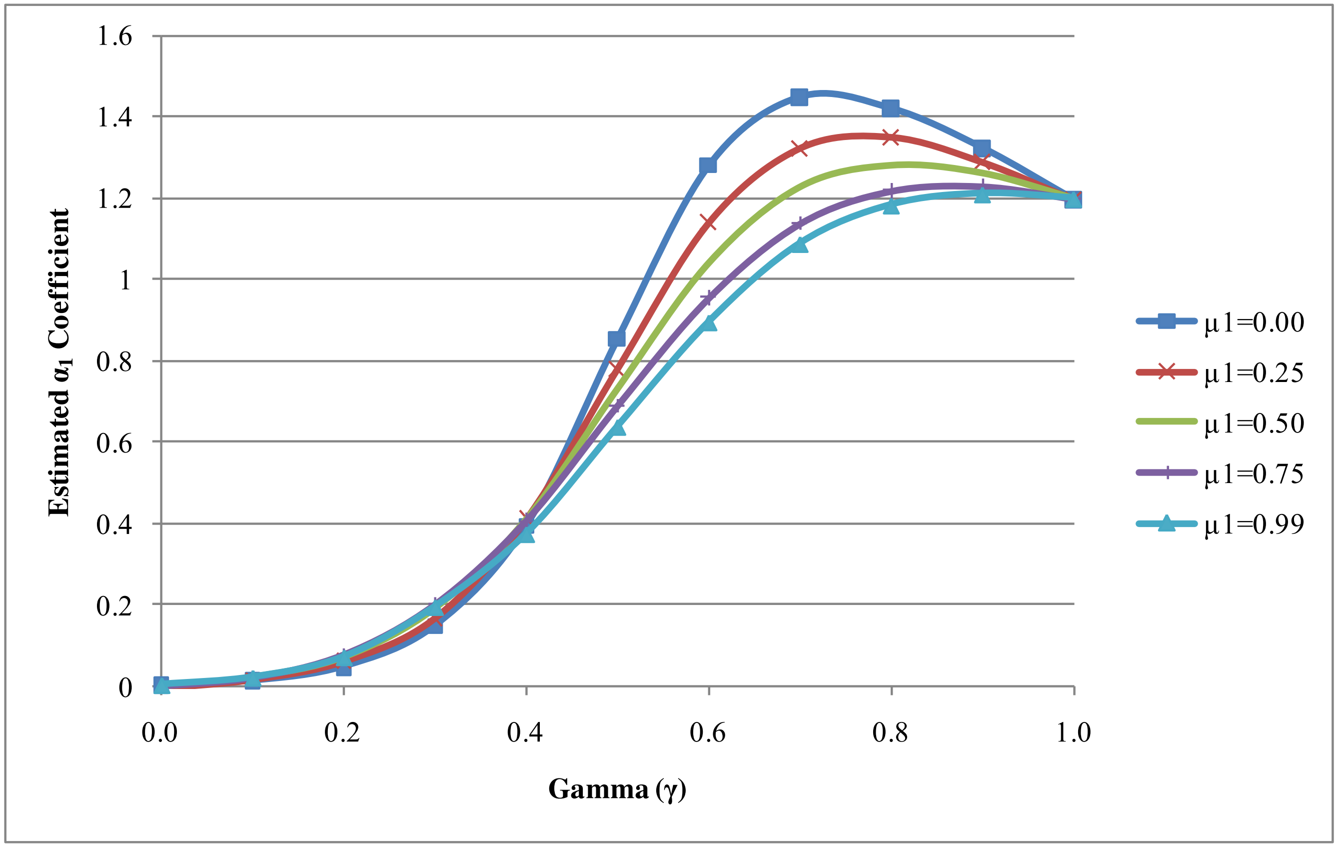

***Figure 2*. Estimated α_1 Coefficient Conditional on γ and μ_1**

The above graph plots the magnitude of the estimated α_1 coefficient against the assumed levels of conservatism (γ) ranging from 0 to 1. Each simulation uses 10,000 firm-years, and each firm-year consists of 20 time-series observations of revenue and expenses

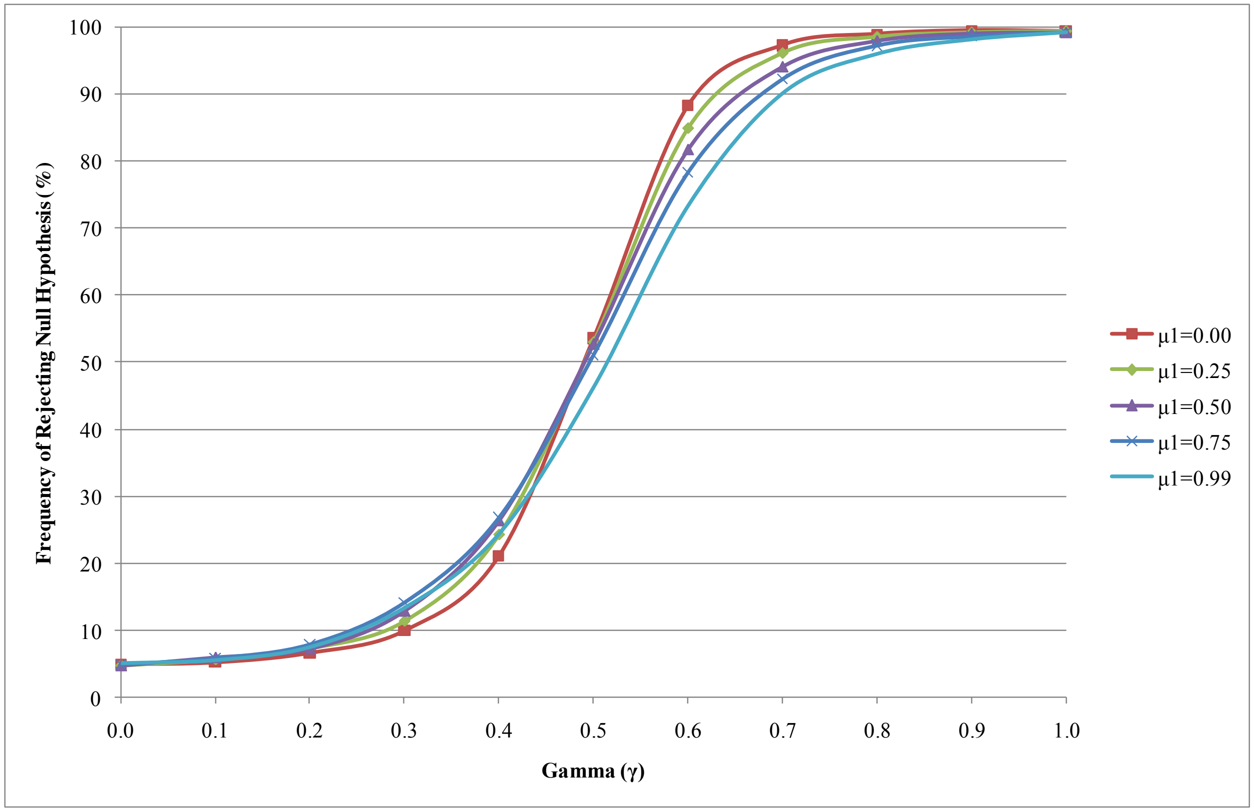

***Figure 3*. Estimated Rejection Rates for α_1 Conditional on γ and μ_1**

The above graph plots the frequency of rejecting the null hypothesis of no reporting conservatism against the assumed levels of conservatism (γ) ranging from 0 to 1 and uses a one-sided test level of 5% for rejecting the null hypothesis. Each simulation uses 10,000 firm-years, and each firm-year consists of 20 time-series observations of revenue and expenses

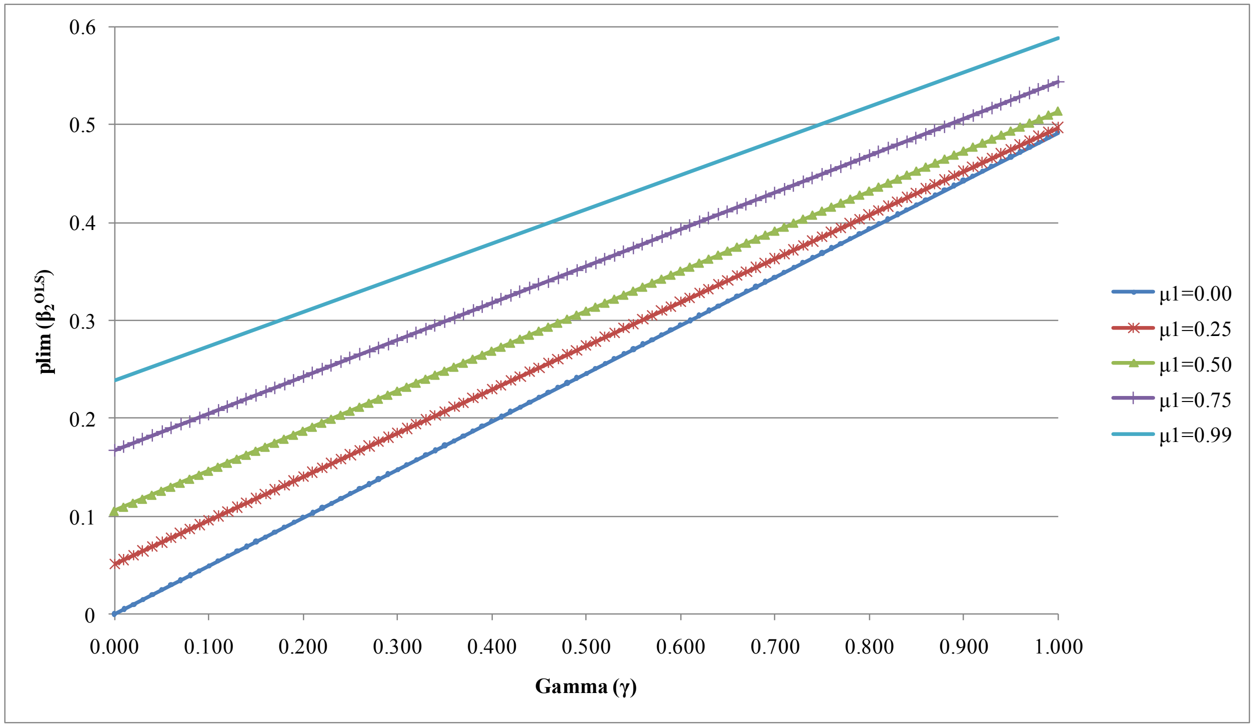

Figure 4. $\boldsymbol{plim(\beta_2^{OLS})}$ **Conditional on** $\boldsymbol{\gamma}$ **and** $\boldsymbol{\mu_1}$

The above graph plots the solution to $plim(\beta_2^{OLS})$ against reporting conservatism (γ), assuming φ_1=1.2, $Var(\upsilon)$ = 1, $Var(\omega)$ = 1 and μ_1 taking on various values between 0 and 1. The probability limit of the OLS estimate of β_2 is expressed as follows:

$$plim(\beta_2^{OLS}) = \frac{\varphi_1[\mu_1(1-\gamma)+\gamma]Var(\omega)+\varphi_1^3\gamma Var(\upsilon)}{\varphi_1^4 Var(\upsilon)+2\varphi_1^2 Var(\omega)+(1-\mu_1^2)\dfrac{[Var(\omega)]^2}{Var(\upsilon)}}$$

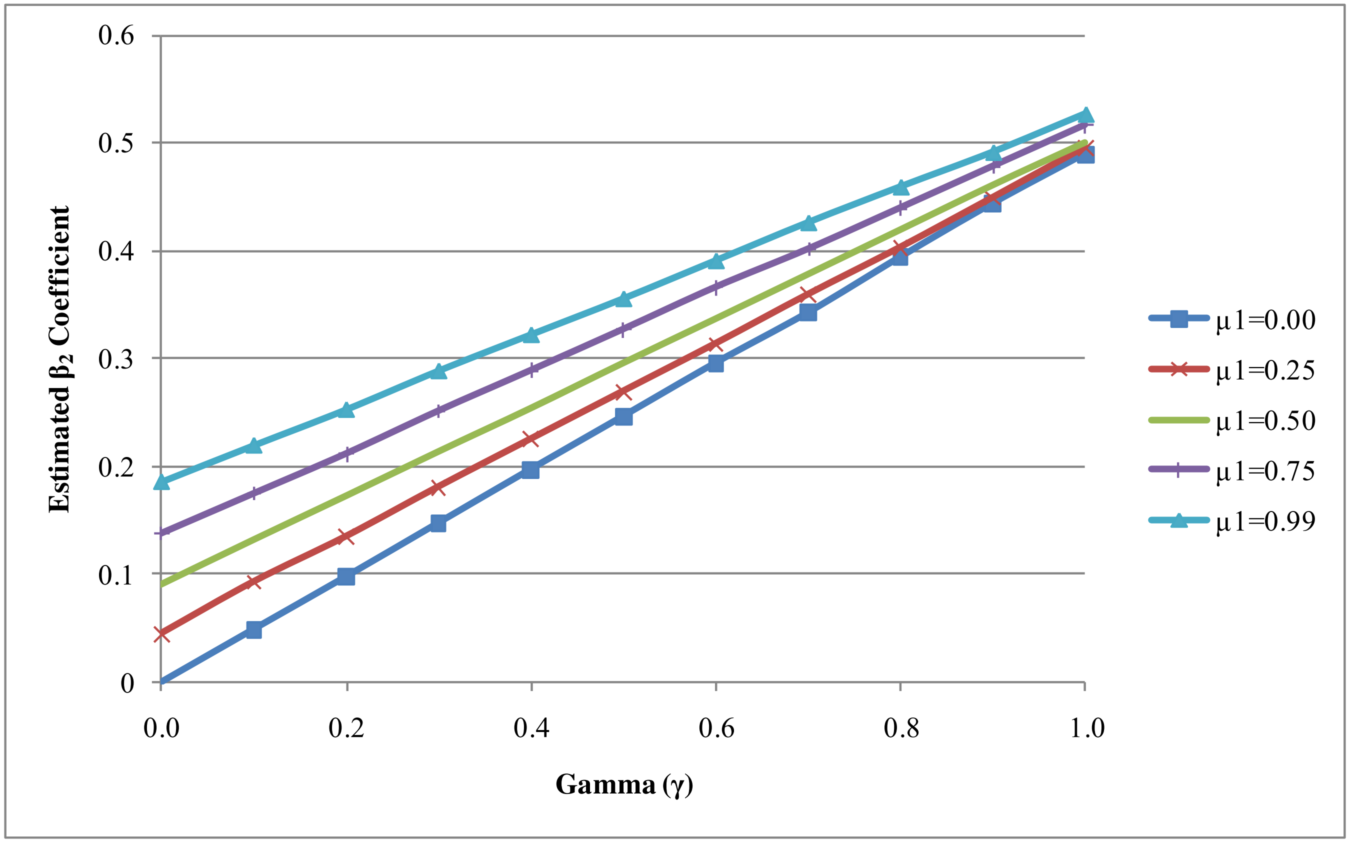

***Figure 5*. Estimated β_2 Coefficient Conditional on γ and μ_1**

The above graph plots the magnitude of the estimated β_2 coefficient against the assumed levels of conservatism (γ) ranging from 0 to 1. Each simulation uses 10,000 firm-years, and each firm-year consists of 20 time-series observations of revenue and expenses.

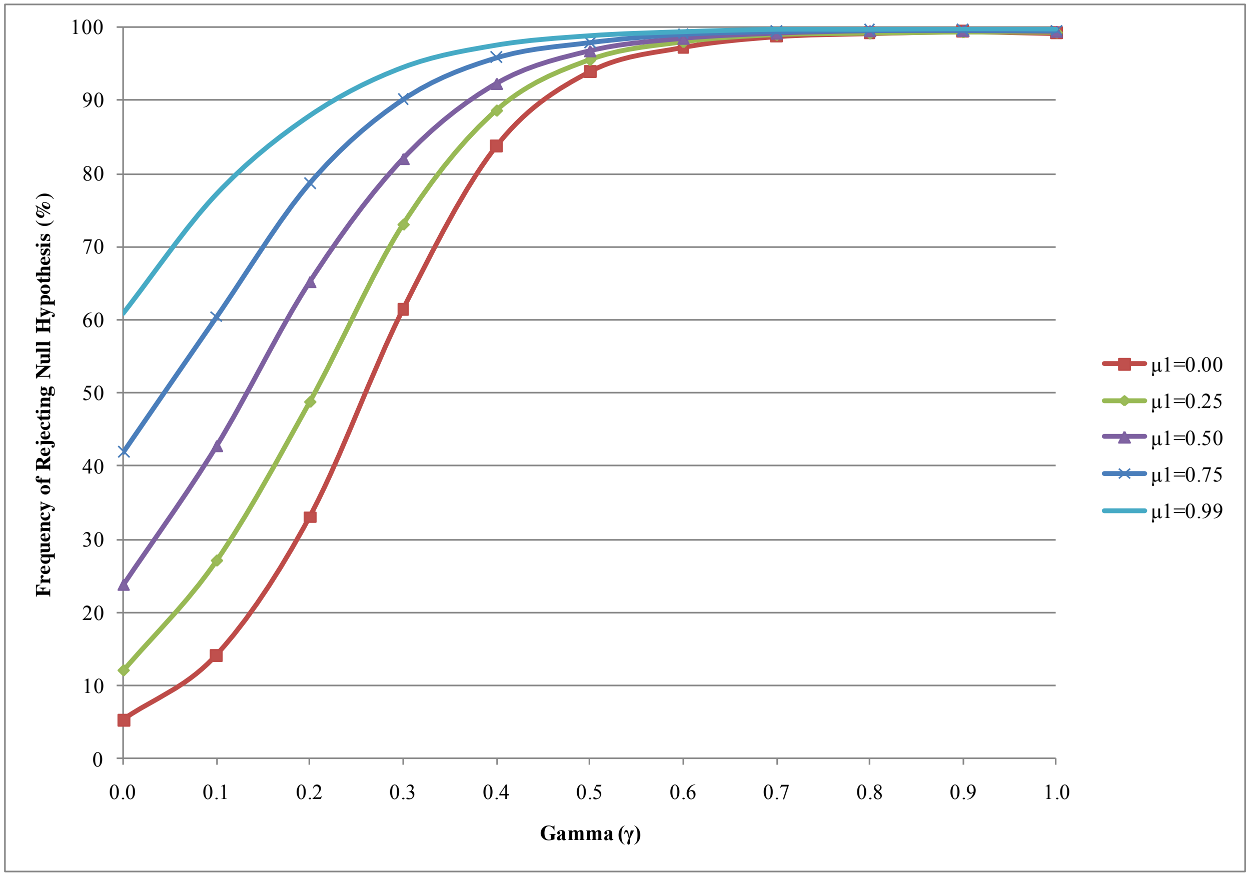

***Figure 6*. Estimated Rejection Rates for β_2 Conditional on γ and μ_1**

The above graph plots the frequency of rejecting the null hypothesis of no reporting conservatism against the assumed levels of conservatism (γ) ranging from 0 to 1 and uses a one-sided test level of 5% for rejecting the null hypothesis. Each simulation uses 10,000 firm-years, and each firm-year consists of 20 time-series observations of revenue and expenses

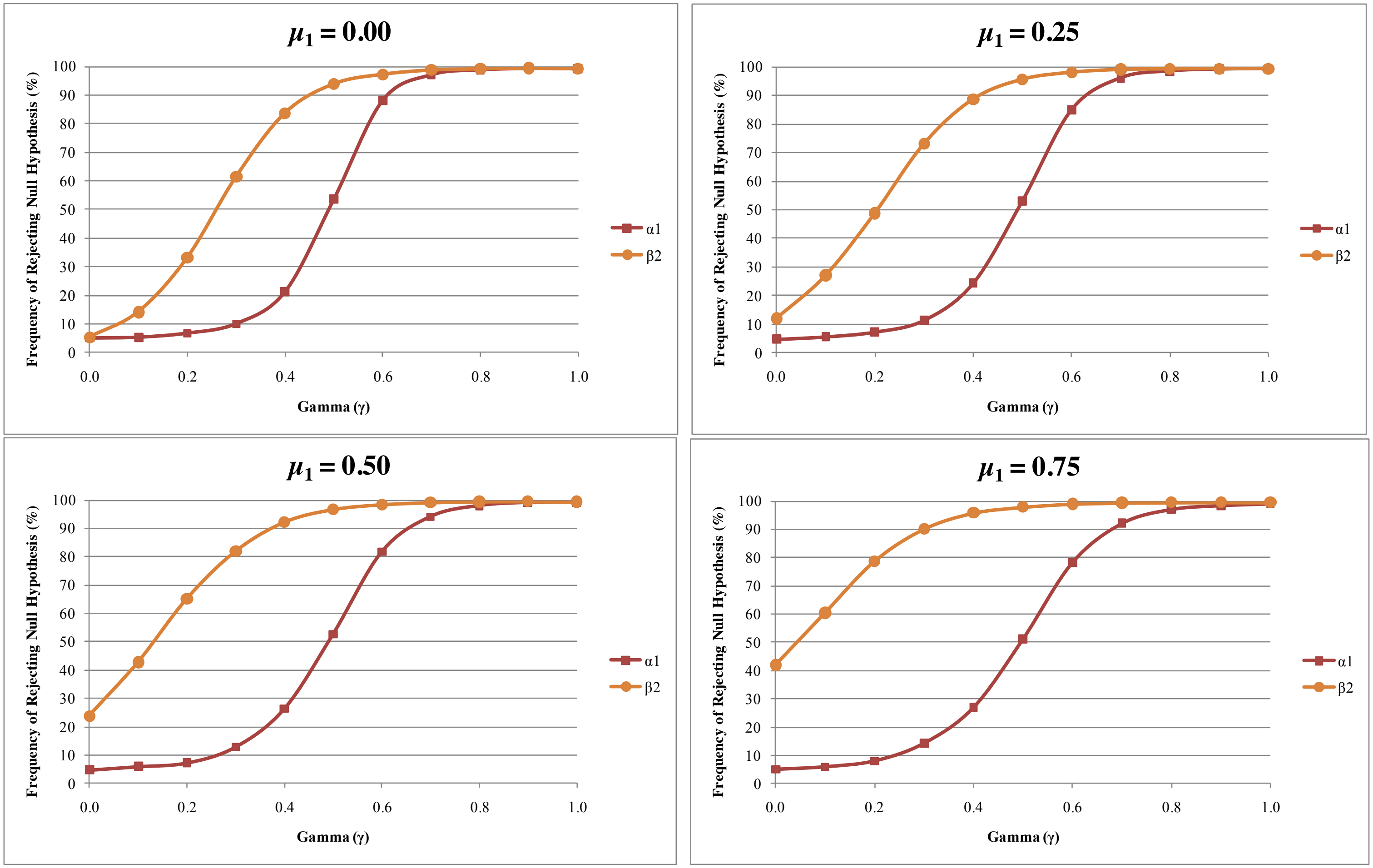

Figure 7**. Comparison of Estimated Rejection Rates for α_1 and β_2**

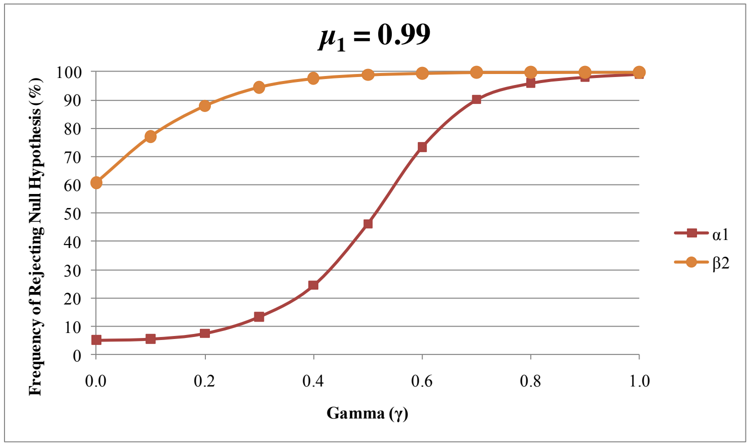

***Figure 7*. Comparison of Estimated Rejection Rates for α_1 and β_2 (continued)**
The above graphs plots the frequency of rejecting the null hypothesis of no reporting conservatism against the assumed levels of conservatism (γ) ranging from 0 to 1 and uses a one-sided test level of 5% for rejecting the null hypothesis. Each simulation uses 10,000 firm-years, and each firm-year consists of 20 time-series observations of revenue and expenses

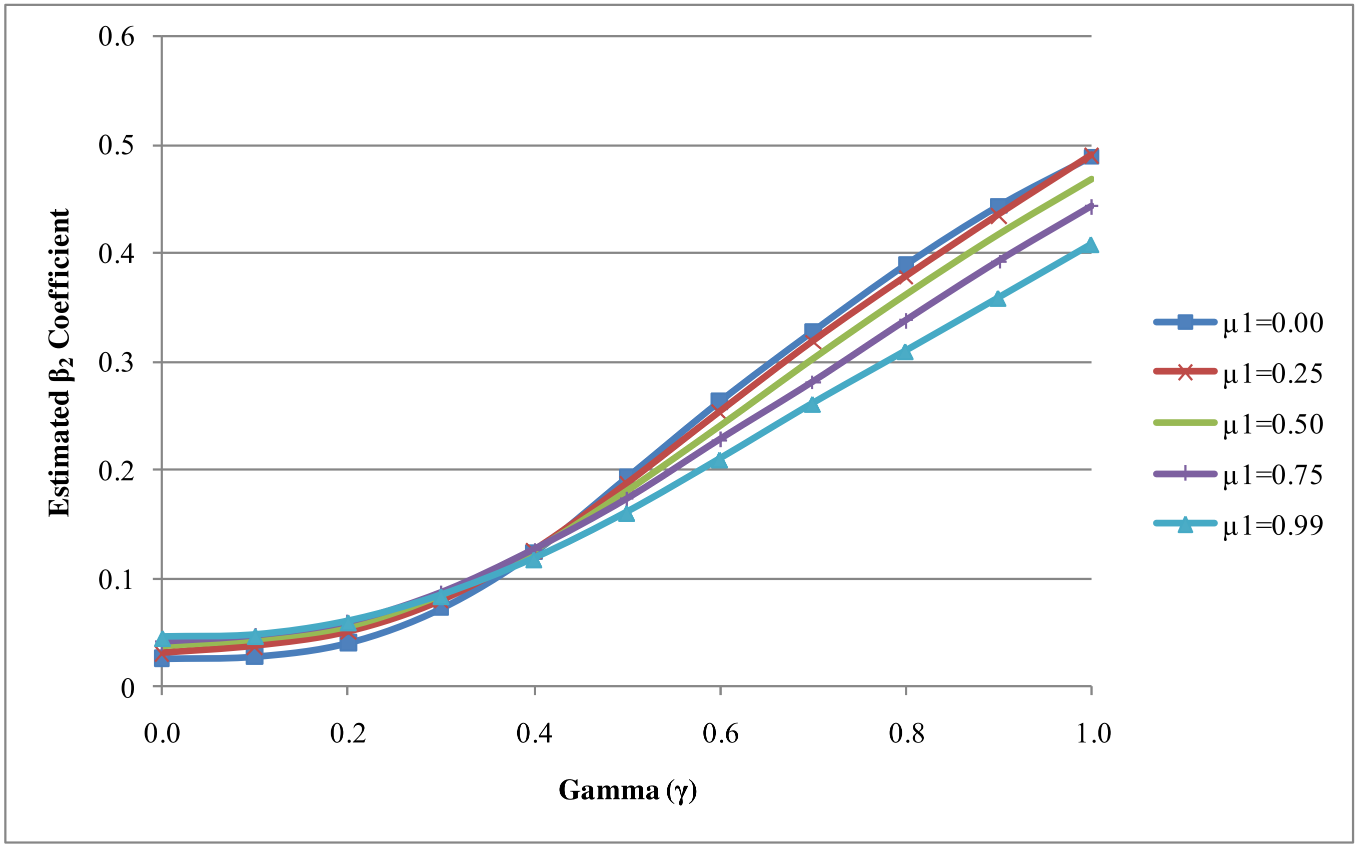

***Figure 8*. Estimated β_2 Coefficient (controlling for e_{t+1}) Conditional on γ and μ_1**

The above graph plots the magnitude of the estimated β_2 coefficient against the assumed levels of conservatism (γ) ranging from 0 to 1. Each simulation uses 10,000 firm-years, and each firm-year consists of 20 time-series observations of revenue and expenses

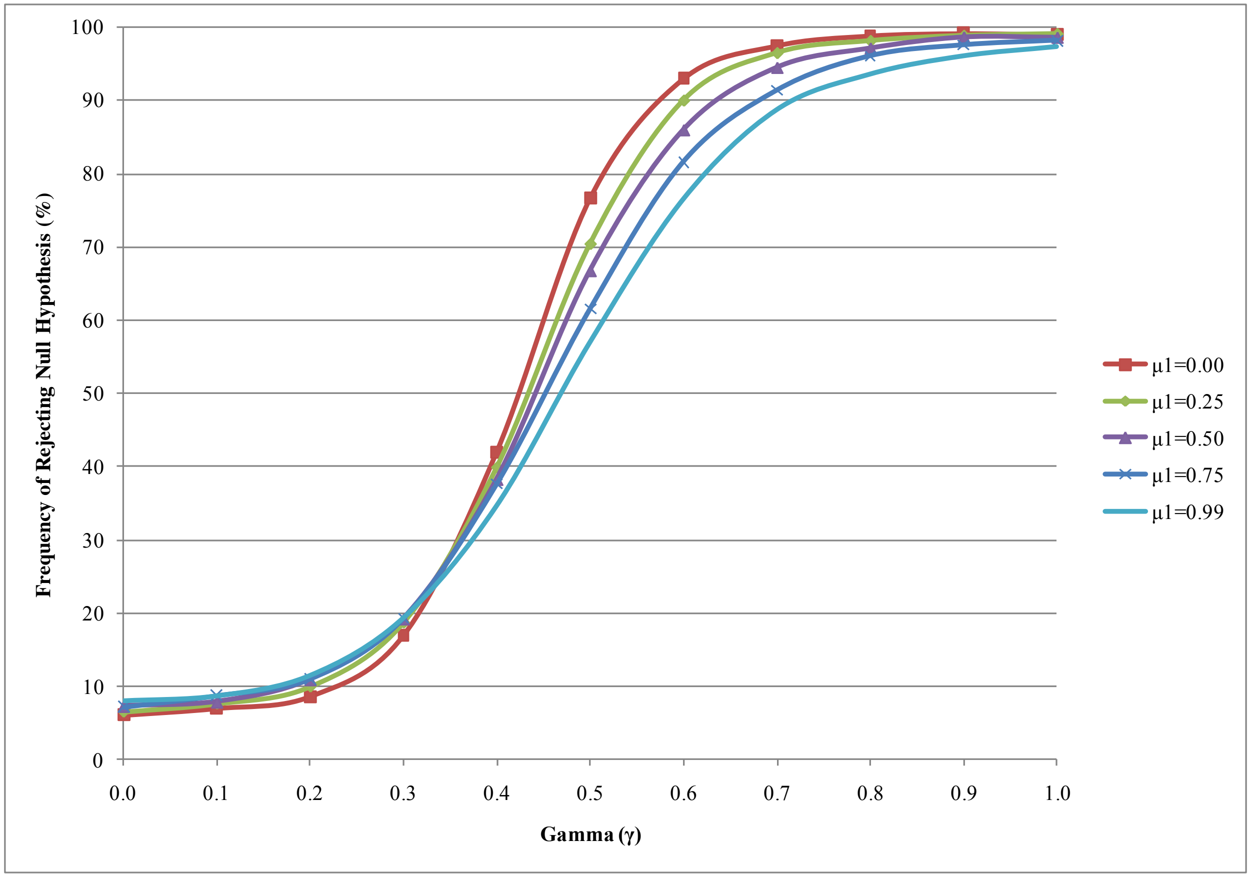

***Figure 9*. Estimated Rejection Rates for β_2 (controlling for e_{t+1}) Conditional on γ and μ_1**

The above graph plots the frequency of rejecting the null hypothesis of no reporting conservatism against the assumed levels of conservatism (γ) ranging from 0 to 1 and uses a one-sided test level of 5% for rejecting the null hypothesis. Each simulation uses 10,000 firm-years, and each firm-year consists of 20 time-series observations of revenue and expenses

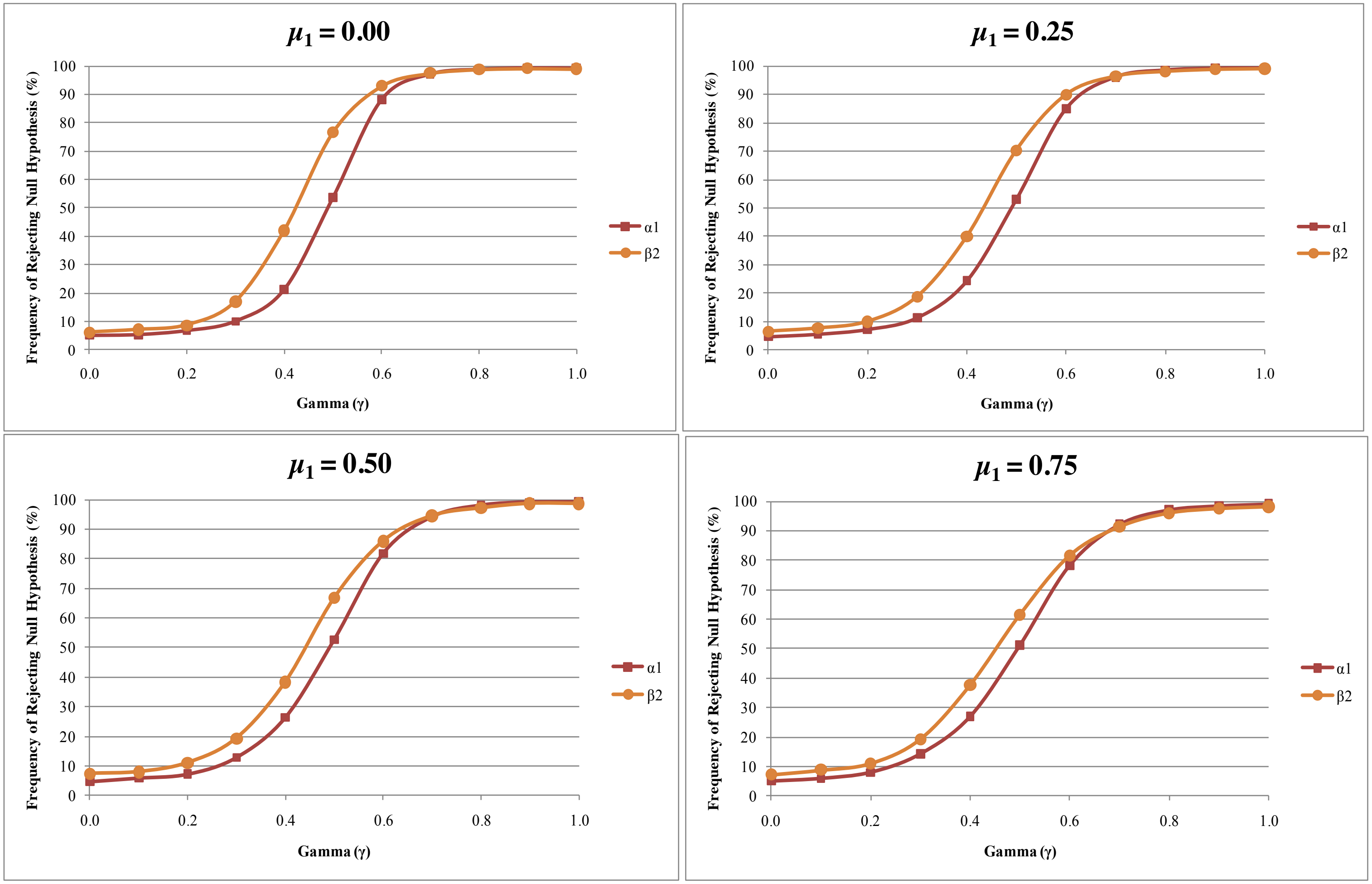

Figure 10. **Comparison of Estimated Rejection Rates for α_1 and β_2 (controlling for e_{t+1})**

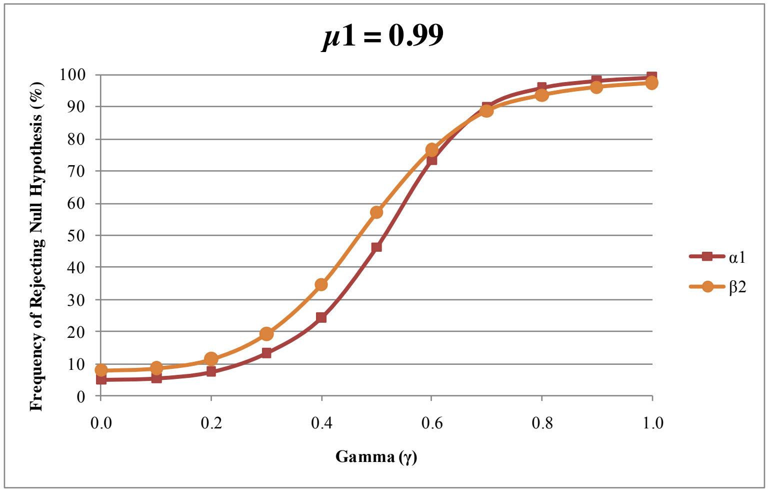

***Figure 10*. Comparison of Estimated Rejection Rates for α_1 and β_2 (controlling for e_{t+1}) (continued)**

The above graphs plots the frequency of rejecting the null hypothesis of no reporting conservatism against the assumed levels of conservatism (γ) ranging from 0 to 1 and uses a one-sided test level of 5% for rejecting the null hypothesis. Each simulation uses 10,000 firm-years, and each firm- year consists of 20 time-series observations of revenue and expenses