The Differential Predictive Ability of Opaque and Transparent Firms' Earnings Numbers

Kenneth S. Lorek
Northern Arizona University

Mary S. Stone
University of Alabama

G. Lee Willinger
University of Oklahoma

We partition a sample of firms into those with earnings that depend primarily on the realization of investment opportunities (i.e., opaque*) and those with earnings that depend more on the effective use of assets in place (i.e.,* transparent*). Because opaque firms may be more difficult for shareholders to monitor, this provides an opportunity for opaque firm managers to smooth earnings. Our empirical results reveal that the quarterly earnings series of opaque firms are significantly more autocorrelated and are easier to predict than those of transparent firms. These findings support the notion that the time-series properties and predictive ability of firms' reported earnings numbers are different for opaque and transparent firms. Specifically, we provide new evidence on the time-series properties of quarterly earnings, refine statistically based modeling of quarterly earnings, and uncover a useful screening device for financial analysts interested in deriving accurate earnings for covered firms.*

Introduction

Zeckhauser and Pound (1990) argue that it is more difficult for shareholders to monitor managers' investment decisions whenever the firm's earnings depend more on the realization of unrecorded investment opportunities than on the effective deployment of assets in place. Zeckhauser and Pound refer to firms that are more dependent on investment opportunities as *opaque* and those that are more dependent on assets in place as *transparent*. Zeckhauser and Pound argue that the shareholders of opaque firms are less able to detect actions taken by management to enhance short-term earnings at the expense of future earnings. The inability of shareholders to easily undo earnings management practices using publicly available information creates the opportunity for

0747-5535/99/1400/0003/$2.00

manipulation (Schipper, 1989) and to increase firm value by reducing earnings volatility (Trueman and Titman, 1988).

Although difficult for investors to detect as it is occurring, opportunistic earnings management may be inferred using time-series data. Managers behaving as predicted by Zeckhauser and Pound would reduce volatility in the earnings stream of opaque firms relative to that of transparent firms thereby inducing higher levels of autocorrelation. We examine the sample autocorrelations (SACFs) of the earnings series of opaque and transparent firms to determine whether systematic differences in autocorrelation exist. The linkage between autocorrelation levels and predictive ability of earnings numbers is established by Beaver (1970), who provides analytical findings, and by Bathke et al. (1989), who show empirically that increased levels in SACFs of the earnings series enhance the ability to forecast future observations of that same series. In the current study, we assess whether the opacity or transparency of the firm affects the predictive ability of future earnings numbers.

Our results provide new evidence regarding the time-series properties of the quarterly earnings series of opaque and transparent firms. Major results include:

- Consistent with the potential opportunistic earnings management by opaque firm managers, the quarterly earnings of opaque firms are more highly autocorrelated than are those of transparent firms;
- Opaque firms also demonstrate enhanced levels of earnings predictive ability relative to transparent firms when using univariate autoregressive integrated moving average (ARIMA) prediction models.

Related Research

What Increases the Cost of Monitoring?

The separation of management from share ownership that characterizes the modern corporation results in information asymmetries (Myers, 1977). The asymmetry arises because management knows more about the investment opportunities and going concern value of a firm than do its shareholders. How much more management knows depends on the sources of the firm's going concern value (e.g., Myers and Majluf, 1984). If the firm's value is primarily dependent on the effective use of assets in place, which will require minimal additional discretionary investment, management's informational advantage is less than if firm value depends more on management's future investments. The latter would be the case for firms dependent on the outcome of ongoing R&D projects. For such firms, the value of yet-to-be discovered products depends on management's ability to make sufficient future discretionary investments to produce and successfully market the new products. Because management knows its plans for future discretionary expenditures, it is in a better position than are outsiders to predict the future earnings from ongoing projects. Unfortunately, management cannot reliably convey its private information because such disclosure would inform competitors as well as current shareholders and therefore would reduce either the value of assets in place or the net present value of the investment opportunities.

Because information asymmetry is greater, shareholders in firms that are more heavily involved in R&D find it more difficult to monitor the investment decisions of the managers of those firms. Zeckhauser and Pound refer to these more difficult to monitor firms as *opaque* and easier to monitor firms as *transparent*. They posit that it is more difficult for the shareholders of opaque firms to detect actions taken by management to enhance short-term earnings at the expense of future earnings.

Trueman and Titman (1988) demonstrate that such situations provide an opportunity to shift earnings across periods to give the appearance of a less volatile earnings process and thereby reduce outsiders' assessments of the probability of bankruptcy. This opportunity occurs because claim holders are unsure whether the reported earnings they observe come from firms with low volatility and limited manipulation of earnings across periods or from firms that appear less volatile because earnings have been manipulated across periods. Because of this uncertainty, managers of firms with the flexibility to shift earnings across periods can project lower volatility in earnings than can managers of firms without flexibility. Shareholders observing the lower volatility may perceive that the firm's cash flows are less volatile and therefore lower their demanded rate of return, which increases the market value of the firm's common stock.[1]

Such efforts by management to reduce the variability in reported earnings across time are sometimes referred to as *smoothing* (Gaver, Gaver, and Austin, 1995). Asserted benefits of smoothing include reporting earnings that are closer to market expectations (Hand, 1989), maximizing earnings-based bonus compensation over time (Healy, 1985), and providing information on the degree of future persistence in the unexpected component of current earnings (Hand, 1989).

The literature suggests that managers of opaque firms have greater opportunities to smooth earnings, but does not indicate whether their incentives to smooth also would be greater. The existing literature on the incentive effects of debt and earnings-based compensation contracts provides limited guidance. Evidence in Myers (1977) suggests that firms with more assets in place (i.e., transparent firms) find it easier to borrow and thus tend to be more highly levered. In turn, the accounting literature (Sweeney, 1994) argues that more levered firms are closer to binding debt covenant constraints and therefore have greater incentives to increase (but not necessarily smooth) income.

The compensation literature (Gaver and Gaver, 1995) indicates that managers of firms with higher market-to-book ratios (arguably, opaque ones that are more dependent

[1] The scenario we present would provide incentives for managers of transparent firms to take costly actions to signal investors that risk is lower than suggested by the variability of the firm's unsmoothed earnings. Such managers, for example, might issue additional fixed rate debt to indicate its assessment that the probability of bankruptcy is low. Further discussion of managers' use of financial policy to signal firm type can be found in Healy and Palepu (1993).

on taking advantage of growth opportunities) have more of their compensation based on stock appreciation than on accounting earnings. To the extent that income smoothing increases firm value (Trueman and Titman, 1988), managers of opaque firms would have greater incentives as well as greater opportunities to smooth earnings.

Identifying Opaque and Transparent Firms

Zeckhauser and Pound classify firms as opaque or transparent based on the R&D-to-sales ratio. They reason that firms with higher ratios have more closed information structures that make it more difficult for shareholders to monitor management's investment decisions and to "make detailed assessments of the corporation's likely future performance" (p. 167).

The R&D-to-sales ratio also has been used in studies of the effect of the investment opportunities versus assets in place dichotomy on executive compensation (Skinner, 1993; Gaver and Gaver, 1993; and Smith and Watts, 1992). Our justification for using this proxy and for positing that firms with high R&D-to-sales ratios are more difficult to monitor follows Skinner (1993). Skinner argues that investments in R&D yield expected payoffs that form part of managers' private information and that their value is difficult for outsiders to monitor. In a related context, R&D expenditures are similar to the investment opportunities discussed by Myers (1977). Other researchers who have used the R&D proxy for investment opportunities include Dechow and Sloan (1991) and MacKie-Mason (1990).

As a sensitivity check on the above partitioning of opaque and transparent firms, we also employ the ratio of the book value of gross property, plant, and equipment to the value of the firm (i.e., PPE/MV). Skinner (1993) suggests that past investments in PPE can be characterized as assets in place and that the PPE/MV ratio is increasing in the proportion of assets in place to value.

Research Hypotheses

The first hypothesis that we test is a descriptive one that concerns the respective autocorrelation levels of the quarterly earnings series of opaque and transparent firms. To the extent that managers of opaque firms recognize the inability of outsiders to easily undo earnings management, they have more opportunity to time accounting, financing, and investing decisions to portray a more highly autocorrelated earnings series. On the other hand, managers of transparent firms may have less incentive to engage in earnings management because such actions are relatively easier for outsiders to monitor. This generates the first prediction:

H1: The level of autocorrelation in the quarterly earnings series of opaque firms is greater than that of transparent firms.

The second hypothesis is predictive. Because statistically based earnings expectation models track the autocorrelation in the earnings stream, firms exhibiting higher levels of autocorrelation in earnings (i.e., opaque firms) will exhibit, ceteris paribus, higher levels of predictive ability than firms that do not (i.e., transparent firms). This generates the second prediction.

H_2: Using time-series models, earnings predictions of opaque firms are significantly more accurate than the earnings predictions of transparent firms.

Data Acquisition and Sample Characteristics

Sampling Procedures

The primary sample comprises all calendar year-end firms on the quarterly Compustat tape that had an uninterrupted, quarterly time series across 1976 to 1991 for the following series:

- Undeflated net income numbers before extraordinary items;
- R&D expenditures; and
- Sales revenue.[2]

The overall length of the database was determined based on the time-series data requirements for ARIMA prediction models. Stringent time-series data requirements necessary to partition our sample into opaque and transparent subsets and estimate the parameters of earnings time-series models reduced the sample size. These sampling filters resulted in 189 firms having complete quarterly time-series data. Our final sample of firms is affected by a survivorship bias that limits the generalizability of our findings because failed firms and newly formed firms do not enter our sample.

Consistent with Zeckhauser and Pound, we employ the R&D-to-sales ratio to partition the 189 firm sample into opaque and transparent firm subsamples. We compute the R&D-to-sales ratio at three points in time for each sample firm. These points correspond to the beginning, middle, and end of the identification test period: 1976-1988 (i.e., last day of the fourth quarter of 1976, last day of the fourth quarter of 1982, and last day of the fourth quarter of 1988). We withheld 12 quarters in the 1989-1991 interval to serve as a holdout test period to assess predictive ability. Sample firms are classified into three subsets:

- Opaque (n = 74) if firms consistently exhibit R&D-to-sales ratios above the respective median values at the beginning, middle, and end of the identification test period;
- Transparent (n = 76) if such ratios are consistently below the sample medians; and
- Inconsistent (n = 39) if such ratios are not consistently above or below the sample medians.[3]

[2] Additionally, we require all sample firms to have sufficient data to construct the PPE/MV ratio to partition firms into opaque and transparent subsets.

[3] As a sensitivity check, we use the PPE/MV ratio to classify firms as well. The PPE/MV ratio is computed at the same three points in time as the R&D-to-sales ratio. Firms are classified into opaque (n = 59), transparent (n = 57), and inconsistent (n = 73) subsets where firms that exhibit

Table 1 - Industry Composition of Test Sample R&D-to-Sales Partitions

Two Digit SIC Code	Description	Number of Firms
Panel A. Opaque Firms: (n = 74)		
28	Chemicals	28
35	Machinery	12
37	Transportation	9
36	Electrical Equipment	8
38	Test Instruments & Equipment	8
Other	Seven Different Two Digit SIC Codes	9
Total		74
Panel B. Transparent Firms: (n = 76)		
29	Petroleum Refining	11
26	Paper Products	7
33	Primary Metals	7
34	Hardware, Sheet Metal	7
28	Chemicals	6
37	Transportation	5
20	Food	4
30	Rubber & Plastic	4
35	Machinery	4
36	Electrical Equipment	4
Other	13 Different Two Digit SIC Codes	17
Total		76

Industry Representation

Table 1 presents a breakdown of the opaque and transparent firms in our sample by two digit SIC codes using the R&D-to-sales ratio.[4] While we observe a marked difference in industry representation for the opaque and transparent subsamples, our procedures allow firms within a given industry (e.g., SIC codes 28, 35, 36, and 37) to be classified differently. For example, while most firms in the chemical industry (SIC code 28) are classified as opaque (n = 28), several chemical firms (n = 6) are nevertheless classified as transparent. Recent research indicates that R&D efficacy varies with firm size and strategy. Evidence presented in Baldwin (1997), for example, indicates that small firms can be categorized into two groups. Firms in the first group resemble large firms because they perform R&D and generate new products and processes primarily through their own efforts. Those in the second spend little on R&D and instead rely on customers and suppliers as their sources of ideas for innovation. Therefore, it is not surprising that firms in the same industry may be classified differently. In contrast, Zeckhauser and Pound classify entire industries. If an industry's average R&D-to-sales ratio is greater (less) than 1 percent, they classify that industry as opaque (transparent). Because our focus is testing for levels of autocorrelation and

PPE/MV ratios above (below) the median are classified as transparent (opaque). Firms whose ratios are not consistently above or below the median are classified as inconsistent.

[4] Because no additional insights are provided using the PPE/MV ratio, we suppress SIC code analyses for this partitioning scheme.

predictive ability on a firm-specific basis, we classify individual firms rather than entire industries.

Profiles of Sample Firms

Panel A of Table 2 provides a profile analysis of the opaque (n = 74), transparent (n = 76), and inconsistent (n = 39) firm subsamples using the R&D-to-sales ratio. The median values of the market value of common stock of the opaque and transparent firm subsamples are substantially different at the end of the identification test period. Specifically, the median size of opaque firms ($3,195.4 million) is two and one-half times larger than the median size of transparent firms ($1,251.8 million). The inconsistent firms exhibit the smallest median size value ($602.0 million). Panel A also provides median and range values for the R&D-to-sales ratio for the three subsamples. Due to the sample construction procedures we employ, the opaque firms exhibit relatively higher R&D-to-sales values (.044) than either the transparent (.009) or

Table 2-Profile and Distribution of Opaque/Transparent Firms versus Large/Small Firms

Panel A: Profile Analysis (R&D-to-Sales Partitions)

Sample	Market Value of Common Stock at 12/31/88 (in $ millions) Median	R&D-to-Sales Ratio at 12/31/88 Median	Range
Opaque (n = 74)	$3,195.4	.044	.0224 to .1382
Transparent (n = 76)	1,215.8	.009	.0000 to .0216
Inconsistent (n = 39)	602.0	.023	.0098 to .0506

Panel B: Profile Analysis (PPE/MV Partitions)

Sample	Market Value of Common Stock at 12/31/88 (in $ millions) Median	PPE/MV Ratio at 12/31/88 Median	Range
Opaque (n = 59)	$1,834.6	.208	.0699 to .4297
Transparent (n = 57)	2,543.5	1.027	.4473 to 26.0136
Inconsistent (n = 73)	646.4	.449	.2065 to 3.0057

Panel C: Opaque/Transparent Firms Versus Large/Small Firms (R&D-to-Sales Partitions)

	Large	Small	Inconsistent	Total
Opaque	44	21	9	74
Transparent	28	35	13	76
Inconsistent	10	25	4	39
Total	82	81	26	189

Panel D: Opaque/Transparent Firms Versus Large/Small Firms (PPE/MV Partitions)

	Large	Small	Inconsistent	Total
Opaque	26	25	8	59
Transparent	35	16	6	57
Inconsistent	21	40	12	73
Total	82	81	26	189

inconsistent firms (.023). Panel B provides similar descriptive information on the opaque, transparent, and inconsistent subsamples as determined by the PPE/MV ratio. In contrast, we note that the median size of opaque firms ($1,834.6 million) is smaller than the median size of transparent firms ($2,543.5 million). We discuss this more fully in our presentation of the predictive findings for the above firms.

While the linkage between predictive ability and the opaque/transparent firm-effect has not been examined previously, Bathke et al. (1989) have documented that greater accuracy exists in the earnings forecasts of larger firms versus smaller firms. Panels C and D of Table 2 provide information on the degree of overlap between firm size and opaque/transparent classifications. Panel C partitions firms into opaque, transparent, and inconsistent subsets using R&D-to-sales partitions while Panel D employs the PPE/MV ratio. We partition the sample into large (n = 82), small (n = 81), and inconsistent (n = 26) firms based on the market value of common stock at the beginning, middle, and end of the identification period (1976-1988). All sample firms are ranked from largest to smallest at three points in time: the beginning (last day of the fourth quarter of 1976), middle (last day of the fourth quarter of 1982), and end (last day of the fourth quarter of 1988). We classify a firm as large (small) if it consistently ranks in the upper (lower) half of the size distributions at each of the above time points. Otherwise, the firm is classified as inconsistent. Panel C's firm size results suggest a potential clustering of large and opaque firm classifications as well as a clustering of small and transparent ones. We find that 44 of 82 large firms (53.6 percent) are opaque and 35 of 81 small firms (43.2 percent) are transparent. Panel D's results reveal less clustering. Only 26 of 82 large firms (31.7 percent) are opaque, and 16 of 81 small firms (19.8 percent) are transparent. This suggests that while our proxies for firm size and opaqueness/transparency do overlap, each proxy may provide incremental information potentially useful in a predictive ability context. We will compare the predictive performance of large-opaque firms versus large-transparent firms, as well as small-opaque firms versus small-transparent ones, in a later section.

Descriptive Time Series Properties

We construct cross-sectional SACFs for the opaque and transparent firm subsamples using the R&D-to-sales ratio.[5] These SACFs, as well as the respective partial autocorrelations (PACFs), are computed individually for each sample firm and are averaged across firms within each subsample. We compute these figures using the quarterly earnings numbers of sample firms within the identification period. Similar to Bathke et al. (1989), Panel A of Table 3 presents the SACFs and PACFs for the undifferenced data (d = 0, D = 0). We hypothesize that the quarterly earnings numbers of opaque firms will be more highly autocorrelated than will those of transparent firms

[5] Similar findings are obtained when the PPE/MV ratio is used to classify firms. We drop inconsistent firms from subsequent tables to concentrate on comparisons between opaque and transparent firms.

Table 3-Cross-Sectional Sample Autocorrelations and Partial Autocorrelations: 1976-1988 (means and standard deviations)

	Lags											
	1	2	3	4	5	6	7	8	9	10	11	12
Panel A. Levels of Series (d = 0, D = 0)												
Opaque (n = 74)												
SACF	.526	.439	.381	.383	.238	.190	.149	.174	.101	.065	.054	.075
	(.288)	(.288)	(.265)	(.251)	(.250)	(.240)	(.222)	(.214)	(.188)	(.182)	(.164)	(.163)
PACF	.526	.128	.072	.089	-.133	-.025	-.005	.008	-.036	-.029	.004	.001
	(.288)	(.174)	(.158)	(.181)	(.166)	(.108)	(.122)	(.129)	(.125)	(.083)	(.087)	(.107)
Transparent (n = 76)												
SACF	.454	.362	.317	.333	.193	.125	.096	.125	.045	-.010	-.015	.015
	(.283)	(.261)	(.229)	(.243)	(.208)	(.196)	(.185)	(.212)	(.182)	(.169)	(.166)	(.195)
PACF	.454	.114	.084	.106	-.096	-.052	.001	-.001	-.040	-.042	-.026	-.013
	(.283)	(.150)	(.168)	(.196)	(.169)	(.088)	(.078)	(.098)	(.111)	(.105)	(.109)	(.106)
Panel B. Consecutively Differenced Series (d = 1, D = 0)												
Opaque (n = 74)												
SACF	-.350	-.051	-.083	.261	-.140	-.033	-.090	.185	-.081	-.036	-.062	.141
	(.214)	(.277)	(.246)	(.302)	(.189)	(.254)	(.192)	(.279)	(.190)	(.205)	(.186)	(.234)
PACF	-.350	-.251	-.221	.103	-.045	-.085	-.076	-.021	-.027	-.061	-.050	-.038
	(.214)	(.195)	(.238)	(.236)	(.148)	(.130)	(.154)	(.147)	(.090)	(.104)	(.121)	(.101)
Tansparent (n = 76)												
SACF	-.374	-.057	-.060	.190	-.088	-.052	-.066	.136	-.032	-.051	-.040	.125
	(.179)	(.230)	(.197)	(.268)	(.162)	(.197)	(.149)	(.244)	(.171)	(.177)	(.162)	(.223)
PACF	-.374	-.270	-.239	.003	-.036	-.095	-.084	-.029	-.009	-.033	-.052	-.007
	(.179)	(.165)	(.214)	(.196)	(.130)	(.093)	(.116)	(.136)	(.115)	(.123)	(.110)	(.100)

Table 3 (cont.)-Cross-Sectional Sample Autocorrelations and Partial Autocorrelations: 1976-1988 (means and standard deviations)

	Lags											
	1	2	3	4	5	6	7	8	9	10	11	12
Panel C. Seasonally Differenced Series (d = 0, D = 1)												
Opaque (n = 74)												
SACF	.374	.244	.142	-.183	-.033	-.030	-.048	-.048	-.022	-.013	-.012	-.017
	(.268)	(.216)	(.213)	(.281)	(.193)	(.176)	(.158)	(.184)	(.166)	(.130)	(.134)	(.127)
PACF	.374	.023	-.019	-.307	.081	.001	-.019	-.186	.045	-.012	.012	-.123
	(.268)	(.172)	(.180)	(.186)	(.155)	(.113)	(.132)	(.145)	(.127)	(.106)	(.101)	(.128)
Transparent (n = 76)												
SACF	.300	.201	.099	-.255	-.042	-.042	-.045	-.054	-.008	-.026	-.015	-.013
	(.249)	(.182)	(.149)	(.212)	(.146)	(.149)	(.145)	(.142)	(.136)	(.112)	(.126)	(.117)
PACF	.300	.050	-.023	-.347	.105	.012	-.001	-.222	.076	-.019	-.019	-.138
	(.249)	(.135)	(.132)	(.166)	(.133)	(.105)	(.131)	(.137)	(.112)	(.092)	(.112)	(.140)
Panel D. Consecutive and Seasonal Differences of Series (d = 1, D = 1)												
Opaque (n = 74)												
SACF	-.299	-.008	.140	-.343	.060	.011	-.014	-.021	.007	.009	.008	-.010
	(.220)	(.124)	(.205)	(.213)	(.191)	(.146)	(.143)	(.185)	(.150)	(.087)	(.118)	(.145)
PACF	-.299	-.179	.085	-.301	-.155	-.116	.050	-.177	-.097	-.103	.034	-.123
	(.220)	(.165)	(.184)	(.189)	(.135)	(.137)	(.106)	(.150)	(.122)	(.110)	(.119)	(.122)
Transparent (n = 76)												
SACF	-.357	.004	.177	-.395	.099	-.009	-.004	-.038	.050	-.006	.005	.027
	(.189)	(.085)	(.148)	(.150)	(.159)	(.128)	(.135)	(.145)	(.127)	(.121)	(.131)	(.142)
PACF	-.357	-.199	.115	-.346	-.189	-.149	.070	-.210	-.090	-.087	.034	-.109
	(.189)	(.139)	(.140)	(.136)	(.124)	(.120)	(.114)	(.138)	(.122)	(.113)	(.132)	(.116)

due to the alleged earnings management opportunities of opaque firm managers. Consistent with our expectations, the results in Panel A of Table 3 indicate that the opaque firms' SACFs for the undifferenced series exhibit consistently larger SACF values (e.g., .526, .439, .381, .383) than those of the transparent firms (e.g., .454, .362, .317, .333).

We also perform autocorrelation tests on the consecutively differenced earnings series (e.g., Panel B of Table 3) of the opaque and transparent firms. These tests provide a control against the possibility that the above findings on autocorrelation are an artifact of nonstationary earnings levels. We employ the Box-Ljung Q-statistic to capture residual autocorrelation across lags of the consecutively differenced SACF.[6] The Box-Ljung Q-statistic tests whether the entire residual SACF is different from that expected of a random series. Based upon a nonparametric Mann-Whitney U-test, the median Q-statistic for the opaque firms (32.84) is significantly greater than the corresponding value for the transparent firms (22.32) at p = .016. These findings suggest that the consecutively differenced earnings numbers of opaque firms are more highly autocorrelated than the earnings numbers of transparent firms. Moreover, they are consistent with the results reported above on the undifferenced series. Finally, we also include the SACFs and PACFs of the seasonally differenced series in Panel C and the consecutively and seasonally differenced series in Panel D of Table 3.

Modeling Procedures

Bathke et al. (1989) and Griffin (1977), among others, detail the advantages of using parsimonious, cross-sectionally derived ARIMA models for quarterly earnings data versus potentially more complex, firm-specific alternatives. Such models reduce the possibility of search bias due to sampling variation. Once the optimum model structure is determined from the cross-sectionally derived SACF and PACF, model parameters are estimated on a firm-specific basis. We employ the customary (pdq) × (PDQ) notation where (p, P) variables represent the number of autoregressive or seasonal autoregressive parameters, (d, D) represent the levels of consecutive or seasonal differencing, and (q, Q) represent the number of moving-average or seasonal moving-average parameters.

Analysis of the patterns of autocorrelation in Panel D of Table 3 reveals that the (011) × (011) ARIMA model provides an excellent descriptive fit for all three sub-samples of firms.[7] Specifically, the spike at lags one and four in the SACFs of the consecutively and seasonally differenced series suggest the (011) × (011) ARIMA structure. This model contains both regular and seasonal moving-average parameters

[6] The Box-Ljung Q-statistic is distributed as a chi-square with k-p-q degrees of freedom, where k = number of lags, p = number of autoregressive parameters, and q = number of moving average parameters.

[7] The (011) × (011) ARIMA model also fits all firms when the PPE/MV ratio is used to partition firms.

and is consistent with previous work on the time-series properties of quarterly earnings by Griffin (1977), among others.

The median Box-Ljung Q-statistic for the (011) × (011) ARIMA model for opaque (9.70) and transparent (7.57) subsamples is well below the critical value for the (011) × (011) ARIMA model which is 18.31 ($\alpha = .05$, df = 10). This suggests that the residuals of the (011) × (011) ARIMA model behave, on average, as a white noise series, and that this model is appropriate for our sample of firms. We also identify and estimate a competing ARIMA model attributed to Brown and Rozeff (1979) [(100) × (011)]; however, its descriptive fit is inferior to the (011) × (011) ARIMA model. It is interesting that the alleged smoothing activities of opaque firm managers are not of sufficient magnitude to alter the structure of the ARIMA model vis-à-vis transparent firms. Had the effect been of greater magnitude, a different ARIMA structure would have been identified for each subsample. This finding is consistent with a considerably more subtle and contextual form of earnings management. Finally, the mean values of the regular and seasonal moving-average parameters for the opaque and transparent firm subsets are systematically different. When employing the R&D-to-sales ratio, the mean regular moving average parameter for the opaque (transparent) firms is .427 (.658) while the mean seasonal moving-average parameter for the opaque (transparent) firms is .502 (.697), respectively.[8]

Predictive Hypothesis

One-step-ahead quarterly earnings predictions are generated in an ex-ante fashion using the (011) × (011) ARIMA time-series model for the opaque and transparent firm subsamples. The original model estimation period began with the first quarter, 1976, and ended with the fourth quarter, 1988. The twelve quarters within the 1989-1991 interval are used as the holdout period. The parameters of the (011) × (011) ARIMA model are estimated over the 1976-1988 period to generate predictions for the first quarter, 1989. Parameters are reestimated prior to making each additional one-step-ahead prediction over the 1989-1991 interval. In summary, the forecast profile is based on one-step-ahead quarterly earnings forecasts over 12 quarters for 189 test sample firms yielding 2,268 origin date forecasts. These forecasts test the predictive hypothesis regarding the differential earnings predictive ability of opaque and transparent firms.

Table 4 presents summary statistics on the MAPE metrics for our test sample firms partitioned using the R&D-to-sales ratio. Similar to Foster (1977), all forecast errors greater than 100 percent are truncated to 100 percent prior to statistical testing to mit-

[8] Likewise, use of the PPE/MV ratio results in partitions of firms that also exhibit such parameter differences. Specifically, the mean regular moving-average parameter for the opaque (transparent) firms is .407 (.526) while the mean seasonal moving-average parameter for the opaque (transparent) firms is .600 (.788), respectively.

Table 4–Mean Absolute Percentage Errors of One-Step-Ahead Quarterly Earnings Predictions (1989-1991) R&D-to-Sales Criterion

Panel A: MAPEs

Quarter				Year			
1st	2nd	3rd	4th	1989	1990	1991	Pooled
Opaque (n = 74)							
.388	.334	.365	.464	.351	.393	.421	.388
Transparent (n = 76)							
.467	.396	.392	.514	.371	.442	.515	.442

Panel B: Mann-Whitney U-Tests on Paired Comparisons

Comparison	p-value
Opaque – Transparent	.001

Note: Prior to computing mean absolute percentage errors (MAPEs), all forecast errors greater than 100 percen were truncated to 100 percent. For opaque firms, this resulted in 185 truncations on 888 forecast errors (74 firms × 12 quarters). For transparent firms, this resulted in 218 truncations on 912 forecast errors (76 firms 12 quarters)

igate the effect of potentially explosive errors.[9] This avoids explosive error problems when the denominator of the MAPE is either negative or small. Bathke, Lorek, and Willinger (1989) report a frequency of truncation of MAPEs across quarterly earnings prediction models of 20.0 percent for their lower strata firms. Moreover, Lorek and Willinger (1996) use an identical truncation procedure in the prediction of quarterly cash flows. Their frequency of truncations varies from a low of 21.4 percent for the MULT model to a high of 47.7 percent for the W model. The results in Panel A of Table 4 are partitioned by quarter (first, second, third, fourth), year (1989, 1990, and 1991), subsample (opaque and transparent) as well as across all quarters and years on an aggregate (pooled) basis. The MAPE values are systematically lower for the opaque firms versus for the transparent ones. This dominance in predictive performance of opaque firms is highlighted by the pooled results where the opaque firms' MAPEs (.388) are lower than those of the transparent (.442) firms. Moreover, this dominance is not confined to particular quarters or years in the forecast horizon because opaque firms exhibit the lowest MAPEs in all individual quarter and year comparisons in Table 4.[10]

Panel B of Table 4 provides results of the Mann-Whitney U-test used to determine whether the paired comparisons were significant. The results indicate that the MAPEs of the opaque firms (.388) were significantly smaller than those of the transparent (.422) firms (p = .001). Thus, we provide descriptive evidence demonstrating higher

[9] The bottom of Tables 4-6 discloses the frequency of such truncations for opaque and transparent firms.

[10] We also test the (100) × (011) ARIMA model to assess whether the findings are sensitive to the (011) × (011) ARIMA model structure. Use of the (100) × (011) ARIMA model provides predictive performance that is qualitatively similar to the (011) × (011) ARIMA model. See Brown and Rozeff (1979) and Griffin (1977) for detailed descriptions of both ARIMA models.

levels of autocorrelation as well as predictive evidence pertaining to superior earnings predictive ability for opaque versus transparent firms.

Table 5 presents a similar predictive profile to that displayed in Table 4 except that the PPE/MV ratio is used to partition the sample into opaque (n = 59) and transparent (n = 57) subsets. Using this criterion, even greater dominance in predictive performance is evident. Specifically, the pooled MAPEs for opaque firms (.264) are substantially smaller than those of the transparent (.507) firms. This dominance pertains to all quarters and years in the forecast horizon. Panel B of Table 5 indicates that the MAPEs of opaque firms (.264) are significantly smaller than those of the transparent (.507) firms (p = .0001).

Table 5-Mean Absolute Percentage Errors of One-Step-Ahead Quarterly Earnings Predictions (1989-1991) PPE/MV Criterion

Panel A: MAPEs

Quarter				Year			
1st	2nd	3rd	4th	1989	1990	1991	Pooled
Opaque (n = 59)							
.285	.214	.239	.319	.230	.273	.289	.264
Transparent (n = 57)							
.487	.473	.452	.613	.412	.512	.596	.507

Panel B: Mann-Whitney U-Tests on Paired Comparisons

Comparison	p-value
Opaque – Transparent	.0001

Note: Prior to computing MAPEs, all forecast errors greater than 100 percent were truncated to 100 percent For opaque firms, this resulted in 86 truncations on 708 forecast errors (59 firms × 12 quarters). For transparen firms, this resulted in 196 truncations on 684 forecast errors (57 firms × 12 quarters)

Extant literature [i.e., Skinner (1993), among others] implies that the R&D-to-sales and the PPE/MV ratios are substitutes in that either may be used to differentiate opaque and transparent firms with respect to firm characteristics such as assets in place versus growth opportunities. Closer inspection of Tables 4 and 5, however, reveals that there is a relatively modest overlap between classifications using these ratios.[11] The R&D-to-sales ratio classifies the sample into 74 opaque and 76 transparent firms. On the other hand, the PPE/MV ratio classification results in 59 opaque and 57 transparent firms. It appears that the PPE/MV ratio discriminates more precisely between firms with respect to predictive ability. The difference in pooled MAPEs between opaque and transparent firms when using the PPE/MV ratio is .243 (.507-.264) versus only .054 (.442-.388) when R&D-to-sales ratio is used.

[11] Skinner (1993) shows insignificant findings for the PPE/MV variable contrasted with significant findings for the R&D/sales variable for firms without a bonus plan. Varying results also persist for these variables for firms with a discretionary bonus plan and an incentive bonus plan. Because these ratios are not perfect proxies in this setting, it is not surprising that they partition our sample firms differently.

Table 6 provides information on the joint application of the R&D-to-sales and PPE/MV ratios. The intersection of these criteria uses a classification scheme that labels a firm opaque (transparent) only if it is classified opaque (transparent) by both ratios. This results in 32 opaque and 29 transparent firms. We find a small pooled MAPE for opaque firms (.254) coupled with a relatively large MAPE for transparent firms (.512). Mann-Whitney U-tests on paired comparisons reveal a significant difference in predictive ability with opaque firms' MAPEs (.254) being significantly smaller (p = .0001) than those of transparent (.512) firms.

Table 6-Mean Absolute Percentage Errors of One-Step-Ahead Quarterly Earnings Predictions (1989-1991) Intersection of R&D-to-Sales and PPE/MV Criteria

Panel A: MAPEs

Quarter				Year			
1st	2nd	3rd	4th	1989	1990	1991	Pooled
Opaque (n = 32)							
.271	.210	.199	.336	.227	.255	.281	.254
Transparent (n = 29)							
.507	.485	.439	.616	.417	.528	.590	.512

Panel B: Mann-Whitney U-Tests on Paired Comparisons

Comparison	p-value
Opaque – Transparent	.0001

Note: Prior to computing MAPEs, all forecast errors greater than 100 percent were truncated to 100 percent For opaque firms, this resulted in 47 truncations on 384 forecast errors (32 firms × 12 quarters). For transparen firms, this resulted in 95 truncations on 348 forecast errors (29 firms × 12 quarters)

Given the relationship between firm size and classification (i.e., opaque and transparent) documented in Table 2, we compare the predictive ability of large, opaque firms versus large, transparent firms. Similarly, we compare small, opaque firms versus small, transparent ones. These comparisons provide an indirect control against the concern that firm size may be driving the predictive findings.

Table 7 provides MAPE results on the above comparisons using both ratios. Panel A partitions firms using the R&D-to-sales ratio. It reveals that large, opaque firms (.331) have significantly smaller (p = .0001) MAPEs than do large, transparent firms (.451). Small, opaque firms (.522), however, have MAPEs that are insignificantly different from small, transparent firms (.468). Panel B reports similar analyses using the PPE/MV ratio. We observe that large, opaque firms (.226) have significantly smaller (p = .0001) MAPEs than do large, transparent firms (.478). Moreover, small, opaque firms (.313) also have MAPEs significantly (p = .0001) smaller than small, transparent firms (.595). Once again, the PPE/MV criterion appears to discriminate more precisely between firms on the basis of predictive ability. These results are impressive in light of Panel B of Table 2, which indicates that opaque firms are, on average, smaller than their transparent firm counterparts. The superior predictive ability of opaque firms persists despite the fact that the transparent firms are, on average, larger.

Table 7-Pooled MAPEs, Controlling for Size Effect

Panel A: R&D-to-Sales Criterion

	Large-Opaque (n = 44)	Large-Transparent (n = 28)	Mann-Whitney U-Test
Pooled MAPE	.331	.451	p = .0001
	Small-Opaque (n = 21)	Small-Transparent (n = 35)	Mann-Whitney U-Test
Pooled MAPE	.522	.468	p = .165

Panel B: PPE/MV Criterion

	Large-Opaque (n = 26)	Large-Transparent (n = 35)	Mann-Whitney U-Test
Pooled MAPE	.226	.478	p = .0001
	Small-Opaque (n = 25)	Small-Transparent (n = 16)	Mann-Whitney U-Test
Pooled MAPE	.313	.595	p = .0001

Concluding Remarks

The current research provides findings that are of potential interest to a diverse group of financial statement users and/or academic researchers. Of course, the generalizability of our findings is limited, given the survivorship bias induced by our sample selection criteria. Therefore, our findings pertain only to firms that possess the time-series data requirements employed in our sampling procedures. Financial analysts may find either the PPE/MV ratio or the R&D-to-sales ratio to be convenient screening devices to help partition firms that they cover into opaque and transparent subsets. Our findings suggest that opaque (transparent) firms exhibit significantly greater (lesser) autocorrelation in their quarterly earnings numbers as well as significantly more (less) accurate earnings predictions. These findings persist even after controlling for firm size which suggests that analysts should place more (less) reliance on the earnings forecasts derived from univariate, statistically based, ARIMA models for opaque (transparent) firms. The findings also suggest that analysts may need to experiment with additional qualitative and/or multivariate statistical forecasting methods to enhance the accuracy of the earnings forecasts of transparent firms. Further, we find that the PPE/MV ratio is a more powerful screening tool than the R&D-to-sales ratio. That is, PPE/MV ratio discriminates more precisely between firms with respect to predictive ability.

The descriptive and predictive findings that we present also contribute to the growing body of literature documenting linkages between firm characteristics and accounting behavior. These results add to the time-series literature in accounting by identifying the opaque/transparent dichotomy as a new firm characteristic affecting the predictive ability of quarterly earnings. Such evidence is important to researchers who may need to investigate the opaque versus transparent composition of test samples when employing statistically based earnings expectation models in capital market tests. At a minimum, the presence of transparent firms may lead to less precision in the expectation model employed. Moreover, the potential linkage of earnings predictions to earnings management activities of managers suggests a possible explanation for the differential forecasting results for opaque and transparent firms. Further research is necessary to establish definitively whether income smoothing causes increased autocorrelation and enhanced predictive ability.

References

1. Baldwin, J., "The Importance of Rsearch and Development for iInovation in Small and Large Canadian Manufacturing Firms," *Statistics Canada Analytical Studies* Paper 107 (1997).

2. Bathke, A.W., K.S. Lorek, and G.L. Willinger, "Firm Size and the Predicative Ability of Quarterly Earnings Data," *The Accounting Review*, 64 (1989), pp. 49-68.

3. Beaver, W.H., "The Time Series of Earnings," *Journal of Accounting Research*, 8, (Supplement 1970), pp. 62-99.

4. Brown, L.D., and M.S. Rozeff, "Univariate Time Series Models of Quarterly Accounting Earnings Per-Share: A Proposed Model," *Journal of Accounting Research*, 17 (1979), pp. 179-189.

5. Dechow, P.M., and R.G. Sloan, "Executive Incentives and the Horizon Problem: An Empirical Investigation," *Journal of Accounting and Economics*, 14 (1991), pp. 51-89.

6. Foster, G., "Quarterly Accounting Data: Time Series Properties and Predictive Ability Results," *The Accounting Review* (1977), pp. 1-21.

7. Gaver, J.J., and K.M. Gaver, "Additional Evidence on the Association Between the Investment Opportunity Set and Corporate Financing, Dividend, and Compensation Policies," *Journal of Accounting & Economics*, 16 (1993), pp. 125-160.

8. Gaver, J.J., and K.M. Gaver, "Compensation Policy and the Investment Opportunity Set," *Financial Management*, 24 (1995), pp. 19-32.

9. Gaver, J.J., K.M. Gaver, and J.R. Austin, "Additional Evidence on Bonus Plans and Income Management," *Journal of Accounting and Economics*, 18 (1995), pp. 3-28.

10. Griffin, P.A., "The Time-Series Behavior of Quarterly Earnings: Preliminary Evidence," *Journal of Accounting Research*, 15 (1977), pp. 71-83.

11. Hand, J.R.M., "Did Firms Undertake Debt-Equity Swaps for an Accounting Paper Profit or True Financial Gains?" *The Accounting Review*, 64 (1989), pp. 587-623.

12. Healy, P.M., "The Effect of Bonus Schemes on Accounting Decisions" *Journal of Accounting & Economics*, 7 (1985), pp. 85-107.

13. Healy, P.M., and K.G. Palepu, "The effect of Firms' Financial Disclosure Strategies on Stock Prices," *Accounting Horizons* (1993), pp. 1-11.

14. Lorek, K.S., and G.L. Willinger, "A Multivariate Time-Series Prediction Model for Cash-Flow Data. *The Accounting Review* (1996), pp. 81-101.

15. MacKie-Mason, J.K., "Do Taxes Affect Corporate Financing Decisions?" *Journal of Finance*, 45 (1990), pp. 1471-1493.

16. Myers, S.C., "Determinants of Corporate Borrowing," *Journal of Financial Economics*, 5 (1977), pp. 147-175.

17. Myers, S.C., and Majluf, N., "Corporate Financing and Investment Decisions When Firms Have Information that Investors Do Not Have," *Journal of Financial Economics*, 13 (1984), pp. 187-221.

18. Schipper, K., "Earnings Management," *Accounting Horizons* (1989), pp. 91-102.

19. Skinner, D.J., "The Investment Opportunity Set and Accounting Procedure Choice," *Journal of Accounting & Economics*, 16 (1993), pp. 407-455.

20. Smith, C.W., and Watts, R.L., "The Investment Opportunity Set and Corporate Financing, Dividend and Compensation Policies. *Journal of Financial Economics*, 32 (1992), pp. 264-292.

21. Sweeney, A.P., "Debt-Covenant Violations and Managers' Accounting Responses," *Journal of Accounting and Economics* (1994), pp. 281-308.

22. Trueman, B., and S. Titman, "An Explanation for Accounting Income Smoothing," *Journal of Accounting Research*, 26, (Supplement 1988), pp. 127-139.

23. Zeckhauser, R.J., and J. Pound, "Are Large Shareholders Effective Monitors?: An Investigation of Share Ownership and Corporate Performance," *Asymmetric Information. Corporate Finance, and Investment*, 1990 (University of Chicago Press: Chicago, IL) pp. 149-180.