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Opaque financial reports and R^2: Revisited

Sudip Datta [a,*], Mai Iskandar-Datta [a], Vivek Singh [b]

[a] Department of Finance, School of Business Administration, Wayne State University, 5201 Cass Avenue, Detroit, MI 48202, USA
[b] Department of Finance and Accounting, College of Business, University of Michigan-Dearborn, Dearborn, MI 48126, USA

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ABSTRACT

In this study, we revisit the link between R^2 (synchronicity) and earnings management (opacity) because of the importance of the ongoing debate on the relation between idiosyncratic risk and earnings management in the finance and accounting literatures. Hutton et al. (J. Financial Economics, 2009) provide evidence of a positive link between opacity and R^2. They interpret their finding to imply that firms with high R^2 (high synchronicity) have less firm-specific information impounded in their stock price. Our results for this relationship fail to unequivocally support the results reported in Hutton et al. (2009). We show that their results are not only time variant but also not robust to the alternative empirical technique recommended for panel data by Petersen (2009) and alternative estimation of discretionary accruals adjusted for firm performance prescribed by Kothari et al. (2005). We also find no support for a convex relation between idiosyncratic risk and opacity. The findings documented in this study substantially revise some of Hutton et al.'s findings in this important and growing area of research.

1. Introduction

Recently, Hutton, Marcus, and Tehranian (2009) (henceforth, HMT) examine the link between stock return synchronicity with the market and the opacity of financial statements. They argue that when less firm-specific information is publicly available, individual stock returns follow the broad market more closely, resulting in higher stock price synchronicity with the market. Synchronicity is measured by R^2 obtained from the market model, which regresses the firm's stock returns on the market returns. Hence, higher R^2 implies higher synchronicity. HMT's evidence shows a positive link between opacity, proxied as earnings management, and synchronicity. They interpret this finding to imply that firms with higher synchronicity have less firm-specific information impounded in the stock price. In addition, they conclude from their analysis that opaque firms are more likely to experience stock price crashes. Given the importance of this topic and the continuing debate on the relationship between synchronicity and the information environment of the firm, we replicate HMT's analysis and also apply prescribed alternative empirical methodologies and estimation techniques to revisit this issue. Our results on the relation between idiosyncratic risk and opacity fail to support the findings documented by HMT. We show that the results and conclusions drawn by HMT are not robust to the application of other empirical estimation techniques, in addition to being time-variant.

The debate initiated by Roll (1988) regarding whether synchronicity or low idiosyncratic volatility is associated with more transparency or more opacity of firm-specific information continues to generate significant research interest. There is empirical evidence supporting both sides of this debate. One strand of research documents support for the view that low R^2 is associated with greater information transparency (see, Durnev, Morck, Yeung, & Zarowin, 2003; Jin & Myers, 2006; Morck, Yeung, & Yu, 2000; Piotroski & Roulstone, 2004).

However, this view is not beyond dispute. There is a significant countervailing body of research that supports the opposite argument of a positive association between information transparency and stock price synchronicity captured by R^2 (e.g. Ashbaugh-Skaife, Gassen, & LaFond, 2006; Bartram, Brown, & Stulz, 2012; Chan & Hameed, 2006; Dasgupta, Gan, & Gao, 2010; Rajgopal & Venkatachalam, 2011). West (1988) attributes low R^2 to a greater level of non-informational noise in stock returns, and Ashbaugh et al. (2006) show that Durnev et al.'s (2003) results are not generalizable in an international setting. Recently, Griffin, Kelley, and Nardari (2010) have shown that countries with better information environments have higher R^2s, contrary to what Morck et al. (2000) suggest. In addition, Teoh, Yang, and Zhang (2009) and Kelly (2007) document that U.S. firms with poor information environments display greater volatility and conclude that low R^2 is not an index for stock price informativeness. Other researchers attribute

* Corresponding author at: Department of Finance - Prentis 216, School of Business Administration, Wayne State University, 5201 Cass Avenue, Detroit, MI 48202, USA. Tel.: +1 313 577 0408; fax: +1 313 577 0058.
E-mail address: sdatta@wayne.edu (S. Datta).

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higher firm- specific uncertainty to rise in speculative trading (Brandt, Brav, Graham, & Kumar, 2010), or heightened global competitive environment (Gaspar & Massa, 2006; Irvine & Pontiff, 2009).[1] Our study contributes to this vibrant, and yet unsettled, debate among researchers on whether information transparency is associated with higher or lower R^2 (see e.g., Kim, Li, & Zhang, 2011).

In addition to replicating HMT's analysis, we also apply the following modifications to HMT's methodology. First, we re-estimate the regression using Petersen's (2009) standard error clustering technique prescribed for pooled data sets. Second, we require 15 firms per year from each industry grouping to estimate the discretionary accruals obtained from the modified-Jones model to increase the reliability of estimates by reducing noise. Third, we employ Kothari, Leone, and Wasley's (2005) performance-adjusted discretionary accruals model as an alternative proxy for earnings management (opacity). Lastly, we extend the sample period and examine whether the results are time variant.

When we apply the first two adjustments, namely invoke Petersen's (2009) technique and impose the 15-firm requirement, we find no evidence of a significant link between idiosyncratic risk and opacity. Further, our results also do not support HMT's finding that the relation between opacity and idiosyncratic risk is convex. When we replicate HMT's analysis, their results regarding the relation between idiosyncratic risk and opacity hold; however, the coefficients and the p-values are much smaller in magnitude.[2] In addition, HMT's finding of convexity on the relation between opacity and idiosyncratic risk is still not supported in any of our findings (including exact replication of HMT's analysis). Our conclusions are maintained when we simulate HMT's sample size and sample composition. In a nutshell, we find that HMT's results are tenuous and sensitive to: i) the number of observations employed to estimate discretionary accruals, ii) the use of Petersen's (2009) clustering technique prescribed for panel data, and iii) the sample period under study as we document that the relation between synchronicity and opacity is highly time variant.

The remainder of the paper is organized as follows. In Section 2, we discuss the empirical issues and alternative estimation techniques that we consider, in addition to those employed in HMT's analysis. In Section 3 we present the sample formation process and research design, including different measures of earnings management (or opacity). In Section 4, we present our empirical findings, based on our replication of HMT's analysis, as well as using alternative, and arguably more appropriate techniques to measure opacity. Section 5 concludes.

2. Empirical refinements and alternative estimation techniques

Although we begin our analysis by replicating HMT's analysis, we believe that their empirical methodology and estimation procedures are subject to potential problems that can have a significant distortive effect on their reported results and conclusions.

In this section, we elaborate on some of the empirical issues inherent in HMT's analysis. First, HMT use the modified-Jones model, as proposed by Dechow, Sloan, and Sweeney (1995), to estimate their opacity variable, OPAQUE. However, HMT do not impose the requirement of a minimum number of firms in their industry groups each year to obtain their estimates of accruals. The norm in the literature (see for example, Gong, Louis, & Sun, 2008; Yu, 2008) is to use about 10–20 observations to estimate Eq. (1) in the HMT article (page 70). This requirement ensures that the regression coefficients are estimated with less noise and resulting standard errors of coefficients. The lack of available information to estimate their Eq. (1) can impact a significant portion of the sample. In this study, in addition to replicating HMT's estimation method, we also present results using the modified-Jones model but with this requirement to reduce the noise in the estimates and the standard errors.

Second, previous research shows that both the Jones (1991) and modified-Jones models are misspecified (e.g., Dechow et al., 1995; Guay, Kothari, Watts, & Watts, 1996). Further, Kothari et al. (2005) develop a discretionary accruals estimation technique that adjusts for firm performance. In their study, they conclude: "… our findings suggest that researchers will be on firmer ground if they used a performance-matched accrual measure. Conversely, researchers who do not use such a measure are likely to draw inferences that are unreliable at best and incorrect at worst." We therefore use the Kothari et al. (2005) specified performance-adjusted discretionary accruals model as an additional alternative estimation of the earnings management variable, OPAQUE.[3]

Third, using panel data, HMT rely on ordinary least squares regressions, and check the robustness of their results using the Fama and MacBeth (1973) approach. However, Petersen (2009) underscores that in panel data sets, the residuals may be correlated across firms and/or across time. Therefore, OLS and Fama–MacBeth standard errors are potentially biased downwards resulting in inflated t-statistics. For unbiased estimates in such situations, Petersen (2009) prescribes estimating clustered standard errors to account for the residual dependence created by firm effect and/or time effect. Thus, HMT's findings may not be significant when the appropriate estimation technique is used. In addition to replicating their analysis, we estimate the models reported by HMT using industry and year fixed effects regressions, as prescribed by Petersen (2009). While the idiosyncratic risk measure used in HMT corrects for industry effects, the right hand side measures lack an adjustment for industry effects. The use of clustered industry standard errors corrects for this concern as well.

3. The sample and measurements of key variables

3.1. Sample formation

We include all firms in the Compustat database during the period 1991–2005 and follow the sample selection process implemented by HMT (page 70). Based on HMT's selection criteria, our sample is composed of a maximum of 44,152 firm-year observations representing 7338 unique firms. Our sample emerges to be somewhat larger than the HMT sample. They report a sample size of 40,882 firm-years. Our larger sample size may be due to (a) backfilling by Compustat database, and/or (b) HMT used other filters not described in their paper.

3.2. Measurement of opacity metric

HMT use discretionary accruals to proxy for opacity of firm's financial reports. To estimate accruals management, accruals have to be separated into *non-discretionary* accruals that are indispensable accounting adjustments and *discretionary* accruals made at the discretion of

[1] An additional argument can be made that to the extent that idiosyncratic volatility can influence investor perception of intrinsic value of the stock, management may be inclined to dampen cash flow fluctuations in order to diminish idiosyncratic volatility. In fact, in support of this view, Graham, Harvey, and Rajgopal's (2005) survey finds that the majority of financial managers admit to smoothing earnings to influence the stock price because they perceive that volatile earnings lead to greater risk premium.

[2] While HMT do not state in their article that they winsorized the variables at 1% and 99%, our direct correspondence with them revealed that they did. Therefore, in our replication of their results we also do the same.

[3] While other accruals estimation methods have been employed (Ettredge, Toolson, Hall, & Na, 1996), the primary techniques in the literature are the modified Jones model and the Kothari et al. (2005) model. More recently, Dechow, Hutton, Kim, and Sloan (2012) developed a new technique to estimate discretionary accruals. However, Gerakos (2012) argues that the Dechow et al. (2012) technique "is incomplete and suffers from many of the same issues that plague the traditional methods used to identify accruals-based earnings management. Most importantly, their method relies on researchers knowing exactly the periods in which accruals are managed and reversed." As a result, the Dechow et al. (2012) method is more appropriate for samples where the earnings management and reversals are easily identifiable such as firms subject to SEC enforcement. So, Gerakos (2012) argues that the Dechow et al. (2012) technique is not necessarily superior or more reliable than previously established techniques.

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managers. The current methodologies first estimate non-discretionary accruals and extract them from total accruals to derive the discretionary component. One of the first models used to capture discretionary accruals is the Jones (1991) model, which was then modified by Dechow et al. (1995) to mitigate the mis-estimation of earnings management due to changes in receivables. HMT employ the Dechow et al. (1995) approach to estimate their OPAQUE variable. Needless to say that when we replicate HMT's analysis we exactly follow their estimation technique as stated in their paper.

Kothari et al. (2005) argue that if a firm's performance exhibits mean reversion or momentum (i.e., performance is not a random walk), then forecasted accruals would be non-zero. Specifically, in situations where firms exhibit unusual performance or when performance deviates from a random walk, such as in firms with earnings momentum (such as, in high growth opportunity firms or in firms with accounting conservatism where there is earnings momentum in the presence of good news and mean reversion in the presence of bad news), Jones and modified-Jones models are problematic because they do not capture the effect of firm performance on accruals. Kothari et al. posit that the correlation between performance and accruals is problematic because the discretionary accruals obtained from Jones and modified-Jones models are severely mis-specified when applied to samples experiencing non-random performance (see Dechow et al., 1995; Guay et al., 1996). To remedy these concerns, they develop a discretionary-accruals estimation approach that adjusts for firm performance based on return on assets. Their results indicate that their estimation approach, which corrects for firm performance, is crucial for obtaining well-specified and powerful tests of earnings management.[4] Other researchers also recommend discretionary accruals models adjusted for performance (see e.g. Barth, Cram, & Nelson, 2001; Dechow, Kothari, & Watts, 1998; Guay et al., 1996; Healy, 1996; Kang & Sivaramakrishnan, 1995; Peasnell, Pope, & Young, 2000).

This methodology derives discretionary accruals (DA) in two stages. First, total accruals variable (defined as the difference between net income and cash flows from operations) is regressed on key variables that are expected to influence it. Specifically, we estimate nondiscretionary accruals from yearly cross-sectional regressions of total accruals (TACC) on changes in sales minus change in receivables, property, plant, and equipment (PPE), and lagged return on assets (ROA) for each of 49 Fama–French industry SIC classifications. The lagged return on assets (ROA) is included as an additional regressor to control for the effect of performance on a firm's accruals (Kothari et al., 2005; Ronen & Yaari, 2008). We run the following yearly cross-sectional OLS regressions using Fama–French industry groupings to estimate the coefficients α_1, α_2, α_3 and α_4. Following the literature, we require a minimum of 15 observations for each year and Fama–French industry combination for the cross-section regression of Eq. (1).

$$\frac{TA_{it}}{A_{it-1}} = \alpha_1 \frac{1}{A_{it-1}} + \alpha_2 \left(\frac{\Delta REV_{it}}{A_{it-1}} - \frac{\Delta AR_{it}}{A_{it-1}} \right) + \alpha_3 \frac{PPE_{it}}{A_{it-1}} + \alpha_4 \frac{Income_{it-1}}{A_{it-1}} + \varepsilon_{it} \tag{1}$$

where i indexes firms, t indexes time, TA_{it} equals income before extraordinary items (Compustat variable IB) minus net cash flow from continuing operations (Compustat variable OANCF), ΔREV_{it} is the changes in sales (Compustat variable, SALE), ΔAR_{it} is the change in receivables (Compustat variable RECT) and PPE is the total property, plant, and equipment (Compustat variable PPEGT). All these variables are scaled by lagged value of assets (Compustat variable AT). We use the estimated coefficients $\widehat{\alpha}_1, \widehat{\alpha}_2, \widehat{\alpha}_3$ and $\widehat{\alpha}_4$ to compute discretionary accrual as follows:

$$DA_{it} \equiv \varepsilon_{it} = \frac{TA_{it}}{A_{it-1}} - \left(\widehat{\alpha}_1 \frac{1}{A_{it-1}} + \widehat{\alpha}_2 \left(\frac{\Delta REV_{it}}{A_{it-1}} - \frac{\Delta AR_{it}}{A_{it-1}} \right) + \widehat{\alpha}_3 \frac{PPE_{it}}{A_{it-1}} + \widehat{\alpha}_4 \frac{Income_{it-1}}{A_{it-1}} \right) \tag{2}$$

3.3. Measuring idiosyncratic risk

We estimate R^2s and residual returns using Eq. (4) in HMT:

$$r_{i,t} = \alpha_1 + \alpha_2 r_{m,t-1} + \alpha_3 r_{m,t} + \alpha_4 r_{m,t+1} + \alpha_5 r_{i,t-1} + \alpha_6 r_{i,t} + \alpha_7 r_{i,t+1} + \varepsilon_{i,t} \tag{3}$$

where, $r_{j,t}$ is the return on stock j in week t, $r_{m,t}$ is the CRSP value-weighted market index, and $r_{i,t}$ is the Fama–French value-weighted industry index. The model includes lead and lag terms for both the market and industry indexes to account for non-synchronous trading.

While $(1 - R^2)$ measures firm-specific volatility, because it is bounded between zero and one, HMT define idiosyncratic risk using a logistic transformation of R^2, where idiosyncratic risk is computed as IDIOSYN $= [\ln[(1 - R^2) / R^2]$. We follow the same procedure in defining idiosyncratic risk.

3.4. Sample description

Table 1 replicates HMT's Tables 3A and 3B describing the main variables used in the study. In Panel A, we provide the mean, median and standard deviation for a set of variables. Given that we define the variables exactly as described in HMT, it is not surprising that the statistics in Table 1 are similar to those reported by HMT in spite of the fact that our sample contains a larger number of firms.[5] Panel B presents the correlations between the variables, showing that an overwhelming majority of the correlations are very similar to those reported by HMT, in terms of sign and significance, confirming that our sample closely resembles that of HMT. These descriptive statistics and correlations are based on winsorized variables at the 1% and 99% levels.

4. Empirical findings

4.1. Relation between idiosyncratic risk and opacity

We first replicate HMT's regression model with IDIOSYN, computed as $\ln[(1 - R^2) / R^2]$, as the dependent variable, following HMT's technique and variable measurements. Similarly, we follow HMT's definition when computing opacity as the moving sum of the past three years of absolute discretionary accruals (as described on pages 70–72 in HMT). The control variables used are: Size (lagged), calculated as natural logarithm of the market value of equity at the beginning of the fiscal year; market-to-book ratio, M to B (lagged), is defined as the market value of equity to the book value of equity measured at the beginning of the fiscal year; leverage, LEV (lagged), is the book value of all liabilities divided by total assets, as of beginning of the fiscal year; and return on equity, ROE, defined as income before extraordinary items scaled by the book value of equity; the variance of the Fama and French weekly industry index, Var (Industry Index), Skewness and Kurtosis of the firm-specific weekly returns.

Our Table 2A replicates HMT's Table 6, Panel A. The main purpose of this table is to identify the relation between opacity and idiosyncratic volatility (or firm-specific information). For side-by-side comparison, we provide in our table HMT's three regression models relating firm-specific information, captured by IDIOSYN, and opacity reported in

[4] Kothari et al.'s (2005) replication of Teoh, Welch, and Wong's (1998) study using their model for discretionary accruals reveals that the positive discretionary accruals in the years preceding the SEOs reported in Teoh et al. disappear, while the pattern of negative discretionary accruals post-SEO is weaker.

[5] Most of these additional observations are of firms that have experienced a crash as defined in HMT.

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Table 1
Descriptive statistics and correlation matrix. This table presents statistics for key variables (measured as in Hutton et al., 2009) and Pearson correlation matrix for a sample of 44,152 firm years between 1991 and 2005. The variables are winsorized at the 1% and 99% levels. ^{a} and ^{b} denote significance at the 99% and 95% levels, respectively.

Panel A: Descriptive statistics

Variables	Mean	Q1	Median	Q3	Std dev
Market value (lagged)	1,655	51.327	186.7	807.934	5.189
Opaque	0.228	0.007	0.159	0.078	0.233
R^2	0.248	0.125	0.206	0.331	0.164
Kurtosis	1.692	0.180	0.918	2.196	2.516
Skewness	0.091	−0.273	0.115	0.502	0.737
ROE	−0.010	−0.006	0.088	0.156	0.431
Market-to-book (lagged)	2.885	1.098	1.903	3.330	3.283
Leverage (lagged)	0.467	0.292	0.474	0.629	0.219
Var (industry index)	0.0009	0.000	0.0007	0.001	0.0009

Panel B: Pearson correlation matrix

Variables	Size	Opaque	R^2	Skewness	Kurtosis	Crash	Jump	ROE	MB	Leverage
Size (lagged)										
Opaque	−0.131^{a}									
R^2	0.618^{a}	−0.064^{a}								
Skewness	−0.210^{a}	0.017^{a}	−0.116^{a}							
Kurtosis	−0.086^{a}	0.033^{a}	−0.193^{a}	−0.108^{a}						
Crash	0.010^{b}	0.025^{a}	−0.049^{a}	−0.412^{a}	0.338^{a}					
Jump	−0.176^{a}	0.030^{a}	−0.162^{a}	0.569^{a}	0.387^{a}	−0.087^{a}				
ROE	0.167^{a}	−0.172^{a}	0.108^{a}	−0.002	−0.073^{a}	−0.074^{a}	−0.052^{a}			
Market-to-book (lagged)	0.254^{a}	0.147^{a}	0.128^{a}	−0.076^{a}	−0.000	0.027^{a}	−-0.050^{a}	−0.087^{a}		
Leverage (lagged)	0.128^{a}	−0.099^{a}	0.091^{a}	0.022^{a}	−0.028^{a}	0.003	0.002	0 .081^{a}	−0.027^{a}	
Var (industry index)	0.061^{a}	0.116^{a}	0.190^{a}	−0.045^{a}	−0.004	0.025^{a}	−0.023^{a}	−0.106^{a}	0.110^{a}	−0.108^{a}

their Table 6 (Panel A) and our corresponding estimates obtained from replicating their results. The regression estimates show that OPAQUE is significantly negative, similar to HMT, but the coefficients are much smaller in magnitude (around a third that of HMT) and the t-statistics are also smaller.[6] Further, contrary to HMT's findings, our corresponding Model 3 results show that OPAQUE^2 is consistently insignificant. We obtain similar findings regarding OPAQUE^2 when the variables are censored. Hence, our replication of their analysis does not support their finding of a convex relation between firm-specific information and their measure of opacity.

In the last three models in Table 2A we conduct another robustness check. We employ an expanded sample from 1991–2010 to estimate the aforementioned three models. This leads to a sizable increase in the number of observations from 40,882 in HMT to 54,946. The evidence shows that both OPAQUE and OPAQUE^2 are statistically insignificant in all three models. The insignificance of OPAQUE for this larger sample suggests that the HMT results may be time variant.[7]

To further explore the results over time, we partition the extended sample into two 10-year periods. The findings are reported in Table 2B. For the first sub-period (1991–2000), the coefficients for OPAQUE are negative in all three models (significant in Models 1 and 2 only), while in the second sub-period (2001–2010), all three estimates are positive (significant in Model 1 only). OPAQUE^2 is insignificant in both sub-periods. We also re-estimate the results using 1991–2002 and 2003–2010 sub-periods. The same pattern of negative link in the pre-SOX period and positive but largely insignificant link in the post-SOX period is maintained. The above findings indicate that any link between synchronicity and opacity is not reliably time invariant.

Table 3A replicates Panel B of Table 6 in HMT, reporting the coefficients and t-statistics for OPAQUE and OPAQUE^2 for a number of robustness check regressions that (1) exclude ROE from the model, (2) require 51 weeks of data per year, (3) use single year discretionary accruals measure instead of the three-year measure, (4) use percentile rank of OPAQUE instead of its numerical value, (5) apply Fama–MacBeth regressions for the full sample, and (6) apply Fama–MacBeth regressions excluding post-2002 data. For parsimony, we only present our results using winsorized variables.

As recommended for panel data (see Petersen, 2009), we provide additional coefficient estimates from the model using firm-level clustering with industry and year fixed effects in the last two rows of the table. In addition, Table 3A reports coefficients for the focus variables for Model 3 (of Table 2A) employing OPAQUE from modified-Jones model, as in Dechow et al. (1995), and performance-adjusted Kothari et al.'s (2005) model, following the accepted practice of using a minimum of 15 observations for reliable estimation with sufficient degrees of freedom. This results in 30,793 firm-year observations.[8]

In columns 3 and 4, where we exactly replicate HMT's reported analysis, we find that the coefficients for the focus variable, OPAQUE, are negative and significant in five of the seven models. OPAQUE is insignificant in two cases: (1) where single-year discretionary accruals variable is used to measure OPAQUE, and (2) when the Fama and MacBeth regression technique is applied excluding post-2002 data. Consistent with our finding in Tables 2A and 2B, OPAQUE^2 is generally insignificant, indicating the absence of convexity in the relation between idiosyncratic risk and opacity.

When we estimate the modified Jones model with a minimum of 15 observations to ensure the reliability of the estimates, (see e.g., Gong et al., 2008; Yu, 2008), the coefficients for OPAQUE are consistently insignificant in all regressions. In the model that employs single-year discretionary accruals, in contrast to HMT's finding, OPAQUE^2 is significantly *negative*. These results highlight the importance of obtaining reliable

[6] For additional robustness, we also censor all the variables at the 1% and 99% levelsquery. While the unreported results for Models 1 and 2 are similar to those obtained when employing winsorized variables, both OPAQUE and OPAQUE^2 are insignificant in Model 3, failing to support HMT's findings.

[7] Another difference between HMT's results and ours is the sign and significance of the leverage variable coefficients which are positive and insignificant in HMT but consistently negative and significant in our results. To examine this issue further, we use total long-term debt to total assets (as opposed to total debt divided by total assets which is employed by HMT and our study). The coefficients are unchanged in sign and significance. Rajgopal and Venkatachalam (2011) also document a negative link between idiosyncratic risk and leverage after controlling for abnormal accruals and other control variables.

[8] While Table 1, Panel B in HMT seems to suggest that there are sufficient observations in different industry groups, the number of observations that are required for estimation of accruals is an *annual* requirement. On average, about 5 industry sectors are impacted by this requirement each year. Our examination indicates that there is no systematic pattern as to which industries are impacted by this requirement from year to year.

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Table 2A
Relation between idiosyncratic risk and opacity.

Variables	HMT's (2009) results (1991–2005)			Replication of HMT's analysis (1991–2005)			Replication of HMT's analysis (1991–2010)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	2.870	2.740	2.782	3.014	2.875	2.881	3.075	2.940	2.937
	(190.22)	(177.52)	(160.66)	(220.83)	(204.92)	(190.75)	(249.35)	(232.80)	(214.92)
OPAQUE	**−0.163**	**−0.167**	**−0.402**	**−0.056**	**−0.063**	**−0.102**	−0.011	−0.016	0.003
	(−8.95)	**(−9.34)**	**(−8.49)**	**(−3.55)**	**(−4.06)**	**(−2.76)**	(−0.76)	(−1.11)	(−0.07)
Var (industry index)	−125.228	−124.669	−123.064	−162.576	−160.497	−160.197	−224.484	−222.625	−222.687
	(−33.49)	(−33.89)	(−33.35)	(−40.15)	(−40.34)	(−40.17)	(−76.89)	(−77.63)	(−77.59)
Size (lagged)	−0.254	−0.247	−0.249	−0.284	−0.277	−0.277	−0.296	−0.290	−0.290
	(−127.44)	(−122.82)	(−121.89)	(−147.34)	(−142.51)	(−141.78)	(−170.77)	(−167.26)	(−166.13)
M to B (lagged)	0.003	0.003	0.003	0.012	0.012	0.011	0.017	0.017	0.017
	(2.51)	(0.35)	(2.67)	(10.66)	(10.43)	(10.48)	(16.54)	(16.26)	(16.18)
LEV (lagged)	0.001	0.006	0.003	−0.088	−0.083	−0.083	−0.107	−0.101	−0.100
	(0.07)	(0.35)	(0.15)	(−5.36)	(−5.13)	(−5.17)	(−7.23)	(−6.92)	(−6.88)
ROE	−0.022	−0.008	−0.006	−0.035	−0.017	−0.017	−0.045	−0.026	−0.026
	(−2.43)	(−0.94)	(−0.67)	(−4.15)	(−2.08)	(−2.07)	(−5.76)	(−3.39)	(−3.39)
Skewness		0.030	0.030		0.024	0.024		0.020	0.020
		(6.17)	(6.06)		(5.04)	(5.01)		(4.54)	(4.55)
Kurtosis		0.051	0.051		0.056	0.056		0.056	0.056
		(37.02)	(37.14)		(40.44)	(40.45)		(45.19)	(45.18)
OPAQUE^2			**0.228**			0.036			−0.018
			(5.35)			(1.08)			(−0.56)
Adjusted R^2	0.335	0.357	0.357	0.380	0.402	0.402	0.435	0.455	0.455
Obs. (firm years)	40,882			44,152			54,946		

This table presents results reported in HMT (2009) (Table 6) and replication of their analysis in this study employing OLS regressions that explain idiosyncratic risk using three-year cumulative measure of discretionary accruals. The analysis first employs HMT's sample period (1991–2005) and for an extended sample that spans 1991–2010. IDIOSYN = $[\ln[(1 - R^2) / R^2]$. Control variables are variability, logarithm of lagged firm size, lagged market-to-book ratio, lagged leverage, return on equity, skewness and kurtosis of residual risk. Focus variables are OPAQUE and OPAQUE^2. Models are estimated using winsorized variables at the 1% and 99% levels. t-statistics are in parentheses.

estimates using a minimum number of observations when measuring accruals. The Fama–MacBeth estimation, using the full sample, shows that the coefficient for OPAQUE is −0.604 (t-statistic = −1.51).

Further, in the last two rows in Table 3A we present additional analysis applying Petersen's (2009) clustering technique for panel data. First we use the absolute value of *one-year* discretionary accruals as the measure of opacity with firm level clustering and industry and year fixed effects. Second, we use the cumulative absolute discretionary accruals for the preceding *three years* as a proxy for opacity and additionally applying firm level clustering and industry and year fixed effects, reported as the last model in the table. Applying this more refined technique reveals no statistical significance for either OPAQUE or OPAQUE^2. Specifically, when using three-year cumulative absolute discretionary accruals and applying Petersen's (2009) technique, we find that the coefficients for OPAQUE and OPAQUE^2 are −0.025 (t-statistic = −0.83) and -0.004 (t-statistic = −0.24) respectively.

These results are reconfirmed, in the next two columns, when we repeat the robustness checks using the performance-adjusted Kothari et al.'s (2005) model to estimate OPAQUE and OPAQUE^2. In this case, the coefficient for OPAQUE when employing Fama–MacBeth (full sample) is negative, −0.785, and significant (t-statistic = −1.84), but it becomes insignificant, −0.027 (t-statistic = −0.74), when Petersen's (2009)

Table 2B
Robustness: sub-period testing of the relation between idiosyncratic risk and opacity. This table splits the sample into two sub-periods of 10 years each. Regression estimates explain idiosyncratic risk using three-year cumulative measure of discretionary accruals. The dependent variable, IDIOSYN, equals $[\ln[(1 - R^2) / R^2]$. Control variables are variability, logarithm of lagged firm size, lagged market-to-book ratio, lagged leverage, return on equity, skewness and kurtosis of residual risk. Focus variables are OPAQUE and OPAQUE^2. t-statistics are in parentheses.

Variables	Replication of HMT's analysis (1991–2000)			Replication of HMT's analysis (2001–2010)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	2.938	2.803	2.756	2.950	2.780	2.773
	(199.85)	(182.78)	(150.61)	(169.59)	(156.39)	(145.32)
OPAQUE	−0.037	−0.038	−0.073	0.035	0.032	0.073
	(−1.82)	(−1.92)	(−1.47)	(1.69)	(1.60)	(1.44)
Var (industry index)	−166.932	−170.574	−170.237	−216.060	−209.792	−209.864
	(−25.93)	(−26.96)	(−26.84)	(−65.27)	(−64.97)	(−64.98)
Size (lagged)	−0.255	−0.246	−0.246	−0.308	−0.301	−0.301
	(−106.99)	(−10.2.25)	(−101.55)	(−120.26)	(−119.27)	(−118.67)
M to B (lagged)	0.003	0.003	0.003	0.025	0.023	0.023
	(2.28)	(2.14)	(2.18)	(15.83)	(14.97)	(14.86)
LEV (lagged)	−0.091	−0.087	−0.088	−0.133	−0.117	−0.116
	(−3.49)	(−3.36)	(−3.39)	(−4.74)	(−4.28)	(−4.23)
ROE	−0.051	−0.034	−0.034	−0.070	−0.048	−0.048
	(−5.12)	(−3.47)	(−3.46)	(−6.06)	(−4.21)	(−4.21)
Skewness		0.021	0.021		0.015	0.016
		(3.56)	(3.54)		(2.60)	(2.62)
Kurtosis		0.056	0.056		0.064	0.064
		(32.37)	(32.38)		(37.47)	(37.47)
OPAQUE^2			0.034			−0.038
			(0.76)			(−0.88)
Adjusted R^2	0.332	0.356	0.356	0.454	0.483	0.482
Obs. (firm years)	29,035			25,911		

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Table 3A
The relation between idiosyncratic risk and opacity. This table reports results from OLS regressions that explain idiosyncratic risk using three-year cumulative measure of discretionary accruals for a sample that spans from 1991–2005. Models are estimated using winsorized variables. Dependent variable IDIOSYN is $\ln[(1 - R^2) / R^2]$. First two columns report HMT's results from their Table 6 (Panel B), the next two columns replicate their results (for Model 3). In columns 5–6, modified-Jones model (Dechow et al., 1995) as applied by HMT but with a minimum of 15 firms is used to estimate OPAQUE, while in columns 7–8 OPAQUE is estimated using Kothari et al. (2005) model, again using a minimum of 15 firms for estimation. We use the same set of control variables used by HMT (suppressed for brevity). Boldfaced figures indicate significance and boldfaced italics indicate significance in the opposite direction to HMT. t-statistics are in parentheses.

	HMT's (2009) results		Replicated results from this study (1991–2005)		Modified-Jones (15 firm minimum) (1991–2005)		Kothari et al. (2005) (15 firm minimum) (1991–2005)	
Description of regression	OPAQ.	OPAQ.^{2}	OPAQ.	OPAQ.^{2}	OPAQ.	OPAQ.^{2}	OPAQ.	OPAQ.^{2}
Baseline regression (as in Panel A)	**−0.402**	**0.228**	−0.102	0.036	−0.043	0.001	−0.061	0.014
	(−8.49)	**(5.35)**	**(−2.76)**	(1.08)	(−0.88)	(0.03)	(−1.25)	(0.36)
Excluding ROE from set of explanatory variables	**−0.401**	**0.230**	**−0.099**	0.037	−0.042	0.003	−0.059	0.016
	(−8.48)	**(5.39)**	**(−2.52)**	(1.10)	(−0.86)	(0.08)	(−1.22)	(0.40)
Requiring 51 weeks of data per year	**−0.391**	**0.223**	**−0.102**	0.036	−0.044	0.002	−0.061	0.015
	(−8.04)	**(5.02)**	**(−2.59)**	(1.09)	(−0.89)	(0.05)	(−1.26)	(0.38)
Measuring opacity using single year accruals	**−0.462**	**0.554**	0.061	−0.147	0.135	**−0.303**	0.102	−0.219
	(−5.66)	**(3.44)**	(0.80)	(−0.98)	(1.54)	***(−1.82)***	(1.19)	(−1.39)
Using percentile rank of OPAQUE instead of value	**−0.099**		**−0.000**		−0.000		**−0.000**	
	(−7.33)		**(−3.29)**		(−1.21)		**(−1.73)**	
Fama–MacBeth: full sample	**−0.189**	0.115	**−0.291**	**0.387**	−0.604	0.607	**−0.785**	1.443
	(−1.72)	(1.53)	**(−2.44)**	**(1.77)**	(−1.51)	(0.67)	**(−1.84)**	(1.55)
Fama–MacBeth: excl. post-2002 data	**−0.333**	**0.211**	1.130	−6.317	11.189	−28.306	−2.25	21.485
	(−3.31)	**(3.16)**	(0.80)	(−1.28)	(1.28)	(−1.42)	(−0.35)	(1.20)
One-year DA — Petersen technique and industry & year fixed effects	Not reported		Not reported		−0.035	**−0.149**	−0.048	−0.097
					(−0.60)	***(−2.09)***	(0.78)	(−1.21)
Three-year DA — Petersen technique and industry & year fixed effects	Not reported		Not reported		−0.025	−0.004	−0.027	−0.002
					(−0.83)	(−0.24)	(−0.74)	(−0.12)

prescribed method is applied. These results highlight the importance of employing Petersen's technique because the Fama–MacBeth standard errors may be biased downwards resulting in inflated t-statistics.

For additional robustness, in Table 3B, we replicate Table 3A for the *expanded* sample (1991–2010) and for a *randomized* sample that restricts the sample size to 40,882 (to simulate HMT's sample size). In columns 3 and 4, the results from replicating HMT using the expanded sample show that none of the OPAQUE and OPAQUE^2 coefficients are significant, with one exception. The next two columns, estimated using modified Jones model for the *expanded* sample, indicate that in five of the nine regressions the link between opacity and R^2 is in fact opposite to that predicted by HMT. These coefficients are positive and significant. In addition, when employing Kothari et al. accruals estimates, all the coefficients for OPAQUE are insignificant except in one instance when it is significantly positive.

Given that our sample size is larger than that of HMT, we also conduct a randomized procedure by randomly selecting a sample of 40,882 observations to simulate the sample size in HMT, as we did not get access to HMT's exact sample. We still require at least 15-firm year observations to estimate discretionary accruals. The unreported results from this robustness check fail to support HMT's conclusions. In most instances, there is lack of a relationship between opacity and

Table 3B
Robustness checks: the relations between idiosyncratic risk and opacity. This table replicates Table 3A for an extended sample period that spans 1991–2010. OLS regressions explain idiosyncratic risk using three-year cumulative measure of discretionary accruals where the dependent variable is IDIOSYN = $\ln[(1 - R^2) / R^2]$. First two columns report HMT's results from their Table 6 (Panel b); the next two columns replicate their results for their Model 3, in columns 5–6, modified Jones model (Dechow et al., 1995) as applied by HMT but with a minimum of 15 firms is used to estimate OPAQUE, while in columns 7–8 OPAQUE is estimated using Kothari et al. (2005) model, again using a minimum of 15 firms for estimation. We use the same of control variables used by HMT. Boldfaced figures indicate significance and boldfaced italics indicate significance in the opposite direction to HMT. t-statistics are in parentheses. Variables are winsorized at 1% and 99%.

	HMT's (2009) results		Replicated results from this study (1991–2010)		Modified-Jones (15 firm minimum) (1991–2010)		Kothari et al. (2005) (15 firm minimum) (1991–2010)	
Description of regression	OPAQ.	OPAQ.^{2}	OPAQ.	OPAQ.^{2}	OPAQ.	OPAQ.^{2}	OPAQ.	OPAQ.^{2}
Baseline regression (as in Panel A)	**−0.402**	**0.228**	0.003	−0.018	**0.082**	**−0.073**	0.048	−0.040
	(−8.49)	**(5.35)**	(−0.07)	(−0.56)	***(1.80)***	***(−1.83)***	(1.08)	(−1.08)
Excluding ROE from set of explanatory variables	**−0.401**	**0.230**	0.008	−0.017	**0.084**	**−0.070**	0.051	−0.038
	(−8.48)	**(5.39)**	(0.22)	(0.54)	***(1.85)***	***(−1.76)***	(1.14)	(−1.01)
Requiring 51 weeks of data per year	**−0.391**	**0.223**	0.002	−0.017	**0.081**	**−0.071**	0.048	−0.040
	(−8.04)	**(5.02)**	(0.07)	(0.55)	***(1.77)***	***(−1.80)***	(1.06)	(−1.05)
Measuring opacity using single year accruals	**−0.462**	**0.554**	0.054	−0.028	**0.141**	−0.197	**0.138**	−0.183
	(−5.66)	**(3.44)**	(0.75)	(−0.19)	***(1.70)***	(−1.20)	***(1.69)***	(−1.17)
Using percentile rank of OPAQUE instead of value	**−0.099**		−0.000		**0.000**		0.000	
	(−7.33)		(−0.12)		***(1.95)***		(1.45)	
Fama–MacBeth: full sample	**−0.189**	0.115	**−0.252**	0.484	−0.378	0.432	−0.516	1.081
	(−1.72)	(1.53)	**(−2.00)**	(1.38)	(−1.07)	(0.56)	(−1.41)	(1.41)
Fama–MacBeth: excl. post-2002 data	**−0.333**	**0.211**	1.130	−6.317	11.189	−28.306	11.189	−28.306
	(−3.31)	**(3.16)**	(0.80)	(−1.28)	(1.28)	(−1.42)	(1.28)	(−1.42)
One-year DA — Petersen technique and industry & year fixed effects	Not reported		Not reported		0.039	**−0.180**	0.026	−0.129
					(0.70)	***(−2.59)***	(0.43)	(−1.54)
Three-year DA — Petersen technique and industry & year fixed effects	Not reported		Not reported		0.017	−0.019	0.041	−0.031
					(0.57)	(−1.16)	(1.23)	(−1.49)

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synchronicity and whenever the relation is statistically significant, it is opposite to that predicted by HMT. When employing the alternative proxy for earnings management (opacity) using the Kothari et al. (2005) performance adjusted discretionary accruals model, the coefficients for OPAQUE and $OPAQUE^2$ variables are insignificant.[9]

Given the totality of our findings that point to the absence of a link between opacity and R^2, we argue that either earnings management is not a good indicator of information opacity, or opacity and firm-specific information are unrelated. It has been documented that, for some firms, earnings management may, in fact, improve information transparency and the price discovery process (see e.g. Francis, LaFond, Olsson, & Schipper, 2005; Kirschenheiter & Melumad, 2002; Ronen & Sadan, 1981; Sankar & Subramanyam, 2001; Tucker & Zarowin, 2006), while for others it may contribute to information opacity. Hence, the net effect of accruals may be driven by the composition of the sample with these two types of firms. Further consolidating this view, researchers also point to the heterogeneity among firms with respect to the use of discretionary accruals, especially in panel data (see e.g. Guay et al., 1996; Healy, 1996). While some researchers document how earnings management, motivated by opportunism, exacerbates information uncertainty, others have shown that managers employ accruals to improve the quality of information revealed in earnings, which results in diminishing of information risk. Finally, other studies, examining broad samples that approximate the population, show that the net effect of discretionary accruals is to enhance earnings as a performance measure (see e.g. Francis et al., 2005; Subramanyam, 1996). Given the above discussion, HMT's primary assumption of greater earnings management being associated with opacity is not categorically irrefutable.

Taken together, our analysis demonstrates that HMT's results relating idiosyncratic risk and opacity are tenuous, and hence, we should exercise caution when generalizing their result that opacity is associated with higher R^2 (less firm-specific information). We also do not find support for convexity in the relation between idiosyncratic risk and opacity.[10] Our results imply that synchronicity cannot be used to proxy for stock price informativeness.

5. Conclusions

One major conclusion reached in Hutton et al.'s (2009) study is that opacity of financial statements is positively related to R^2, i.e., opacity is associated with less firm-specific information. In this study we revisit their analysis and find that their results are not robust. Specifically, our evidence indicates no link between opacity and idiosyncratic risk, except when we ignore the conventional requirement of measuring earnings management with at least 15 firms to increase the reliability of estimates. Furthermore, when we expand the sample to encompass a larger period (1991–2010), replication of HMT's regressions does not yield a significant link between opaqueness and R^2.

Utilizing arguably more robust techniques to measure opacity, including the modified-Jones model and the Kothari et al. model, and employing the regression estimation method prescribed by Petersen (2009), we do not find support for their result of a negative relation between opacity and idiosyncratic risk. In most instances, the relation is not significant. However, when it is significant, the link indicates that opacity positively affects R^2. Similar results are obtained when we employ randomized samples to simulate the size and composition of HMT's sample.

HMT also find convexity in the relation between opacity and idiosyncratic risk. None of our different approaches, including replication of their analysis, indicate convexity in the relation between opacity and idiosyncratic risk. Our study demonstrates that HMT's result relating idiosyncratic risk and opacity is not robust, and hence, it cannot be concluded that opacity is associated with higher R^2 (less firm-specific information). In particular, we show that inferences are sensitive to: i) the number of firms used to estimate discretionary accruals, ii) the use of Petersen's (2009) clustering technique for panel data, and iii) time period under study.

The evidence documented in this study substantially revises the findings in Hutton et al. in this important and growing area of research. To that end, our study contributes to the ongoing debate on the relation between R^2 and the information transparency of the firm. Our analysis implies that the association between opacity and R^2 may be influenced by the heterogeneity among firms with respect to the use of discretionary accruals, especially in panel data. Clearly, further research is needed to resolve how heterogeneity among sample firms, with respect to their use of earnings management resulting in either increased or decreased information transparency, influences the link between synchronicity and opacity.

[9] Since our sample composition differs somewhat from HMT's (it contains a larger number of firms that crash), for additional robustness check we construct a sample that is similar to HMT's in terms of size and type of firms within the sample. We do this by randomly selecting firms from the two types of firms (crash and non-crash firms) from within our sample. When we estimate the three models, the results are similar to those reported in Table 2A when the larger sample is used. Again, the coefficients and t-statistics are much smaller in magnitude than those in HMT. We also estimate Model 3 using the 15-firm minimum requirement for modified Jones and Kothari et al. accruals, and find, as in Table 3A, the coefficients for OPAQUE and $OPAQUE^2$ are insignificant. These tests verify that our results are not due to sample composition.

[10] Further, the rationale for the second part of HMT's paper is based on their finding of a negative relation between opacity and idiosyncratic risk, and hence their narrative on opacity and stock price crash is weakened.

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