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R^2 and Idiosyncratic Risk Are Not Interchangeable

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ABSTRACT: A growing literature investigates the association between stock return variation and several aspects of information and governance structures, in both a cross-country setting and a cross-firm setting within the U.S. Papers use either idiosyncratic stock return volatility (σ_e^2) or R^2 as interchangeable measures of firm-specific return variation but report inconsistent results. An important reason for the differing interpretations is the assumption about whether lower R^2 (or higher σ_e^2) captures firm-specific news or noise. We document that higher σ_e^2 (or equivalently, lower R^2) resembles noise. In addition, we show, analytically and empirically, that different results obtain when using R^2 or σ_e^2 because the systematic risk inherent in the R^2 metric is also correlated with the independent variable of interest. Therefore, we recommend that when assessing the association between R^2 (or σ_e^2) and some independent variable, researchers (1) control for elements of systematic risk and (2) triangulate their findings with other measures of information environment.

Keywords: *return variation; idiosyncratic risk; systematic risk; R^2; information; noise; arbitrage*.

Data Availability: *The data in this study are available from commercial providers, e.g., WRDS, Compustat, CRSP, I/B/E/S.*

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I. INTRODUCTION

A growing literature exists in both finance and accounting on the association between firm-specific variation in stock returns and several aspects of the firm's information or governance environment. Appendix A, Part 1 lists 21 published papers in top-tier finance and accounting journals and the Social Sciences Research Network (SSRN) reports at least 75 working papers. These studies rely on one of two proxies for firm-specific return variation as the dependent variable: (1) idiosyncratic risk, often measured as the variance of the residual (σ_e^2) from a regression of firm's stock return on the market return; and (2) the synchronous movement of a firm's stock return with the market's stock return. The latter is often operationalized as R^2 from the market model or a transformed R^2 variable that captures the inverse of return synchronicity (Φ), labeled "asynchronicity." Several of these studies treat lower σ_e^2 as equivalent to higher R^2 and *vice versa*.[1] The objective of this paper is to demonstrate that such presumed equivalence between these seemingly comparable dependent variables is problematic, both from an econometric and an economic perspective.

The issue of whether R^2 or idiosyncratic risk (σ_e^2) is a more appropriate proxy for firm-specific return variation is related to a larger debate on whether greater firm-specific return variation captures value-relevant firm-specific information or noise (Roll 1988). A long stream of literature, starting with Morck, Yeung, and Yu (2000) assumes that lower R^2, or greater firm-specific return variation, reflects stock prices with more information and less noise.[2] In contrast, a parallel body of research argues that more firm-specific return variation captures greater pricing errors in stocks and, hence, less informative stock prices.[3] Campbell, Lettau, Malkiel, and Xu (2001) and Bartram, Brown, and Stulz (2012) conjecture that greater firm-specific return variation can capture both noise and information.

Morck, Yeung, and Yu (2013) review this extensive but contradictory literature and posit that greater σ_e^2, or lower R^2, can simultaneously reflect both noise and news via a complicated feedback loop. They characterize firm-specific return volatility as the intensity with which firm-specific news events occur ("firm-specific return event intensity") and argue that "if firm-specific fundamentals event intensity encourages informed arbitrage, the stock market might become more informationally and functionally efficient" (Morck et al. 2013, 36). At the same time, "if the elevated firm-specific fundamentals event intensity instead discourages arbitrage, the stock market might become less informationally and functionally efficient" (Morck et al. 2013, 36). In sum, the issue of whether lower R^2 or greater σ_e^2 on average captures stock prices with more information or noise remains an empirical question.

We posit that if lower R^2 or higher σ_e^2 is associated with an informationally efficient market, then it should be correlated with better firm-specific information environments. However, we find

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[1] Four examples that treat synchronicity as a substitute measure of idiosyncratic return volatility are: (1) Hutton, Marcus, and Tehranian's (2009, 73) Section 3.3 is titled "Measuring Idiosyncratic Risk" but the paper uses "$\ln[(1-R^2)/R^2]$" as a natural measure of firm-specific volatility or (lack of) market synchronicity; (2) Bartram, Brown, and Stulz (2012, 1334) state that "following Morck, Yeung, and Yu (2000), the literature has paid considerable attention to R^2 as a way to assess the importance of idiosyncratic risk"; (3) Irvine and Pontiff (2009, 1174) state that "the second stream of idiosyncratic risk literature investigates differences in the cross-country levels of R^2"; and (4) Chen, Huang, and Jha (2012, 891) state that "since idiosyncratic volatility is inversely related to R^2, and transparency, in general, means high information quality, one can deduce from this strand of the literature that idiosyncratic volatility is positively related to information quality."

[2] This stream of literature includes Wurgler (2000), Durnev, Morck, Yeung, and Zarowin (2003), Durnev, Morck, and Yeung (2004), Piotroski and Roulstone (2004), Jin and Myers (2006), Bakke and Whited (2006), Ferreira and Laux (2007), and Hutton et al. (2009).

[3] Examples of such research include Xu and Malkiel (2003), Hou, Peng, and Xiong (2005), Mashruwala, Rajgopal, and Shevlin (2006), Pontiff (2006), Ashbaugh-Skaife, Gassen, and LaFond (2006), Chan and Hameed (2006), Griffin, Kelly, and Nardari (2007), and Teoh, Yang, and Zhang (2008).

that both σ_e^2 and Φ, the logarithmic inverse of R^2, are higher in firms with poorer information environments. These environments are represented by firms with higher probability of informed trading (PIN), higher bid-ask spreads, greater price delay, greater levels of illiquidity and liquidity risk, and more zero return days. Therefore, the evidence is more consistent with σ_e^2 and Φ capturing noise instead of firm-specific news. More important, these findings are inconsistent with the common interpretation that, on average, firms with higher Φ or lower R^2 have more firm-specific information impounded into stock prices.

If both σ_e^2 and Φ capture the same underlying economic construct of noise, then why do researchers observe contradictory findings when they use Φ versus σ_e^2 as the dependent variable of interest? To address this issue, we analyze the individual components of return asynchronicity, Φ. Using the market model, it can be shown that a firm's return asynchronicity is additively increasing in idiosyncratic return volatility, σ_e^2, but decreasing in both the inter-temporal variation in the market returns, σ_{rm}^2, and the stock's β, the individual stock return's co-movement with the market return. Therefore, contradictory results could be obtained from the use of Φ versus σ_e^2 as the dependent variable in empirical tests if σ_{rm}^2 and β, the two components of Φ, are also strongly related to the independent variable of interest.

We provide evidence on this assertion using cross-sectional return variation within the U.S. and cross-country return variation. We predict that in the U.S. setting the contradictory results are more likely attributable to differences in β across firms, because by definition market-wide return variation (σ_{rm}^2) for the U.S. market is a cross-sectional constant for any given year. For this setting, we consider a set of papers that correlate firm-specific return variation and earnings quality within the U.S. but report contradictory findings. For example, Rajgopal and Venkatachalam (2011; hereafter, RV) and Chen et al. (2012) document that poor earnings quality is related to greater idiosyncratic risk. Contrary to these papers, Durnev et al. (2003), Ferreira and Laux (2007), and Hutton et al. (2009; hereafter HMT) conclude that poor earnings quality is associated with lower firm-specific return variation, measured as Φ. At the same time, other research, including Fernandes and Ferreira (2008) and Gul, Ng, and Srinidhi (2011), reports an insignificant association between earnings quality and R^2.

We select HMT as representative of studies that use R^2 or variants of R^2 as the dependent variable, and RV for studies that use σ_e^2. To capture firm-specific return variation, HMT use the asynchronicity measure Φ, where $\Phi = \ln[(1 - R^2)/R^2]$, and RV use σ_e^2.[4] Although these two measures are intended to capture the same underlying construct, HMT report a negative relation between inverse earnings quality and Φ, whereas RV find a positive relation between inverse earnings quality and σ_e^2.[5]

Based on the predictions from a decomposition of Φ, we show that HMT obtain different results because the correlation between inverse earnings quality and σ_e^2 is swamped by the correlation between inverse earnings quality and β. As expected, the association between earnings quality and market-wide return variation, σ_{rm}^2, is insignificant. To address the confounding effect of β, we re-estimate the RV and HMT specifications after including β as an additional regressor. After incorporating β, the evidence from the RV model with idiosyncratic risk, σ_e^2, as the dependent

[4] HMT and RV make different assumptions about what Φ and σ_e^2 captures. HMT assume that Φ captures firm-specific news, whereas RV assume that σ_e^2 captures noise.

[5] We consider inverse earnings quality as a measure for which higher values represent poorer quality. HMT use *OPAQUE,* computed as the three-year sum of absolute abnormal accruals from a modified Jones (1991) model. RV use *DD* that is derived from the Dechow and Dichev (2002) model. RV also consider a variant of the *OPAQUE* variable and find no qualitative differences in their findings. Because the two variables *DD* and *OPAQUE* are highly correlated and the association between firm-specific return variation and earnings quality is robust to alternative proxies of earnings quality, differences in the earnings quality measures do not appear to be the source of the ambiguous inferences.

variable remains unchanged. However, inferences from the HMT model when inverse return synchronicity, Φ, is the dependent variable become consistent with RV in that the relation between Φ and inverse earnings quality becomes positive. This suggests that the HMT inferences, under their maintained assumption that Φ captures firm-specific information, would have changed if they had controlled for firm-specific β in their regressions.

Next, we consider a cross-country setting and replicate the findings in Morck et al. (2000), using both cross-country Φ and cross-country idiosyncratic risk, σ_e^2, as the dependent variables. Specifically, we follow Morck et al. (2000) and examine how these two variables correlate with the good government index and the anti-director rights index. In the cross-country setting, the unit of analysis is a country, and the decomposition of country-level return volatility implies different predictions. At the country level, by definition the countrywide β is 1 in any given year. Therefore, any association between cross-country variation in Φ and an independent variable could be attributable only to the association of such a variable with cross-country differences in market-wide return variation, σ_{rm}^2, or the average idiosyncratic return variation, σ_e^2, across countries, or both. Thus, unlike the within-country analysis in which market-wide return variation, σ_{rm}^2, did not play a role, in the cross-country analysis market-wide return variation assumes importance.

Consistent with Morck et al. (2000), we find that countries with better government have lower stock return synchronicity or higher Φ. That is, Φ and the good government index are positively correlated. This finding contrasts with the weak negative association between the idiosyncratic return variation, σ_e^2, and the good government index. The dissonance stems from the Morck et al. (2000) assumption that greater idiosyncratic risk is associated with more informative stock prices, not noise. If this assumption were descriptive of the data, then we would expect a positive coefficient on the good government index when σ_e^2 is the dependent variable because countries with better respect for property rights ought to encourage market participants to generate more firm-specific value-relevant information.

We are again able to explain this inconsistency by decomposing Φ. We find that countries with better governments are associated with a higher Φ because the negative association between market-wide variation, σ_{rm}^2, across countries and the good government index swamps the negative association between the cross-country idiosyncratic variation, σ_e^2, and the good government index.[6] Furthermore, as with the cross-sectional setting, the inconsistency in these findings disappears when we account for the two components of systematic risk, σ_{rm}^2 across countries and country-specific β. Thus, the intuition behind the decomposition of Φ documented in the cross-sectional U.S. setting applies to the cross-country setting as well.

Based on the collective evidence, we make two non-mutually exclusive recommendations. First, we suggest that researchers relying on R^2 or Φ should analyze which of the three components of R^2 drives the association between R^2 and the independent variable of interest and whether these components are consistent with *ex ante* predictions. Second, when R^2 or Φ is the preferred dependent variable, and the researcher is interested in assessing the association between firm-specific return variation and some independent variable, controls should be included for country-level market return variation, σ_{rm}^2, in cross-country settings, and for firm-specific β in cross-sectional settings within a single country.[7] Most important, our empirical analysis suggests that lower R^2 resembles noise and researchers ought to be cautious about assuming that R^2 predominantly captures news.

Section II provides a brief discussion of the literature on R^2 and the alternative interpretations of the information environment, followed by empirical tests of whether R^2 captures news or noise.

[6] Recall that Φ is increasing in σ_e^2 but decreasing in σ_{rm}^2.

[7] In cross-country settings, where the sample of firms in each country is not representative of the market portfolio, or when using panel data of country-years, it is important to control for the average country-level beta in the empirical specification as well.

Section III takes a closer look at the three determinants of R^2 and illustrates the impact of these factors on research outcomes in both the U.S. and in cross-country settings. In Section IV we offer concluding remarks.

II. R^2 AND σ_e^2: NEWS OR NOISE?

Background and Prior Literature

The existing literature offers two contradictory views on what R^2 or synchronicity captures. One view claims that lower R^2 and greater idiosyncratic volatility imply that more firm-specific information is impounded in stock prices (Informativeness Hypothesis). The opposing view contends that lower R^2 is associated with noisier stock prices (Noise Hypothesis).

The Informativeness Hypothesis

Roll (1988) argues that the extent to which stocks move together depends on the relative magnitudes of firm-level and market-level information capitalized into stock prices. He observes that only a small proportion of the volatility of a firm's stock price can be explained by market and industry influences, suggesting that greater idiosyncratic volatility, or lower R^2, is likely explained by firm-specific news events. Morck et al. (2000) and Jin and Myers (2006) subsequently popularize the R^2 measure in a cross-country context. Morck et al. (2000) find that R^2 is higher in countries with less developed financial systems and weaker corporate governance. Jin and Myers (2006) document positive associations between R^2 and several measures of financial information opacity for a cross-section of countries. These papers generally conclude that stock prices move together more and that R^2 is higher when the quality of institutions in a country is low. Durnev et al. (2003), Ferreira and Laux (2007), and HMT find results similar to Jin and Myers (2006) in the U.S. context. That is, when earnings opacity is higher, less firm-specific information is available and R^2 is higher. Along similar lines, a few papers (Wurgler 2000; Durnev, Morck, and Yeung 2004; Chen, Goldstein, and Jiang 2007) find that the capital investments of firms and countries with lower stock return R^2 are more sensitive to fluctuations in their stock prices. Using the Informativeness Hypothesis, these authors argue that managers learn about firm fundamentals from stock prices and incorporate such learning into their investment decisions.

The Noise Hypothesis

Another strand of literature argues that greater idiosyncratic volatility or lower R^2 is associated with greater pricing errors in stocks and, hence, less informative or noisier stock prices. In particular, arbitrageurs find mitigating the effects of mispricing in stocks with higher idiosyncratic risk to be hard because finding close substitutes for the mispriced stocks is difficult. Pontiff (1996) argues that a mispriced asset is likely to trade at the sum of the asset's fundamental value and the mispricing. As Pontiff (1996) and Mashruwala et al. (2006) argue, if the arbitrageur can perfectly hedge the fundamental value changes of the mispriced asset, the mispricing eventually goes away and the position is riskless. However, if the arbitrageur cannot perfectly hedge the fundamental value changes, i.e., a perfect substitute is not available, then the arbitrageur subjects himself every period to idiosyncratic risk and such risk cumulates through time. In this scenario, the stocks remain mispriced longer because the unhedgeable idiosyncratic risk may force the arbitrageur to liquidate the trading position early (Tuckman and Vila 1992). Unhedgeable idiosyncratic risk creates risky arbitrage as long as any costs are associated with holding the risky position, such as the inability to hedge fundamentals or capital constraints on the arbitrageur (Shleifer and Vishny 1997).

Firms with high idiosyncratic risk are also more likely to be affected by changes in overall investor sentiment. Shiller (1981) presents a model with two groups of traders with one group engaged in noise trading and another group of smart-money investors who worry about expected returns. The market clears when supply equals demand, with the smart-money investors looking ahead to try to predict both dividends and the value of shares the noise traders will be holding in the future. Changes in expectations of the holdings of noise traders, as well as changes in expected dividends, will affect the market-clearing price. Shiller (1981) argues that the price changes will, therefore, fluctuate excessively relative to a dividends-only pricing model, if there are swings in fashion or sentiment in holding stocks. Idiosyncratic risk in the Shiller (1981) noise trader model increases the risk premium that would induce smart-money investors to hold all the shares of the mispriced stock. Baker and Wurgler (2006, 2007) provide evidence that idiosyncratic risk is a measure of cross-sectional sentiment beta (i.e., the sensitivity of a stock to market-wide sentiment). Together, this stream of research suggests that firms with greater idiosyncratic volatility are more difficult to trade and their prices are more likely to reflect mispricing that cannot be easily removed.

Theoretical papers such as West (1988), Campbell et al. (2001), and Peng and Xiong (2006) point out that the information-efficiency interpretation of return R^2 is difficult to reconcile with standard models, in which investors react rationally to information. Roll (1988, 566) acknowledges that some firm-specific return volatility may well be "occasional frenzy unrelated to concrete information." Brandt, Brav, Graham, and Kumar (2010) show that the increase in idiosyncratic volatility in U.S. common stocks in recent decades, first documented by Campbell et al. (2001), is potentially attributable to speculative trading of retail investors. Xu and Malkiel (2003) document higher firm-specific return volatility in stocks with large institutional ownership, and they argue that this reflects noise trading by institutions.

A Reconciliation

Bartram et al. (2012) show that firms from developed countries have lower R^2s than firms from emerging markets, but U.S. firms have significantly lower R^2s than both groups. That is, U.S. firms have higher idiosyncratic return volatility when compared with several emerging markets. Contrary to Jin and Myers (2006), but consistent with RV and Chen et al. (2012), Bartram et al. (2012) show that greater idiosyncratic risk or lower R^2 is related to lower corporate disclosure quality.

To reconcile these conflicting results, Morck et al. (2013) suggest that firm-specific return volatility can be characterized as firm-specific return event intensity. Here "event" refers to a firm-specific valuation change such as a public announcement that an event study might typically investigate. Greater firm-specific return event intensity can reflect the attempts of informed investors to move share prices in response to such events and, hence, results in greater firm-specific return volatility in the spirit of Roll (1988). By this theory, the stock market becomes more informationally and functionally efficient. However, greater firm-specific return volatility also increases arbitrageurs' costs of conducting their business because such traders cannot diversify away firm-specific volatility (Pontiff 1996). Hence, if increased firm-specific return event intensity discourages arbitrage, then the stock market becomes less informationally and functionally efficient. Morck et al. (2013) acknowledge that it is unclear which of these effects dominates, although they prefer the news explanation. They state, "[W]e feel the weight of evidence now suggests that much, perhaps most, firm-specific volatility reflects information capitalization, but concede that the issue is far from closed" (Morck et al. 2013, 32). Thus, whether R^2 represents news or noise remains an unresolved empirical question.

We attempt to revisit this question in three ways: (1) we document an association between R^2 and proxies for poor information environment; (2) we take a closer analytical look at the determinants of R^2; and (3) we replicate RV and HMT in the U.S. context and Morck et al. (2000)

in the cross-country context to understand which component of R^2 drives the contradictory inferences.

Empirical Tests of the Relation Between R^2, σ_e^2, and the Information Environment

If Morck et al. (2013) are correct that higher R^2 is associated with greater firm-specific event return intensity and greater stock market efficiency in terms of both functionality and information, then an inverse correlation should exist between higher R^2 and proxies for poorer information environments. These proxies include lower price delay in reflecting information, greater insider trading, lower liquidity levels, and higher liquidity risk. We conduct this test for the U.S. market because international data are not readily available.

Stock Return Volatility Measures

We use the market model regressions to measure firm-specific return variation in two ways: (1) $\ln[\sigma_e^2]$, logarithm of idiosyncratic volatility, and (2) Φ, an inverse synchronicity measure, $\ln[(1 - R^2)/R^2]$ or $\ln[\sigma_e^2/\sigma_s^2]$, where σ_s^2 is systematic risk. $\ln[\sigma_e^2]$ is computed as the natural logarithm of average monthly variance of excess returns from the market model.[8] Specifically, we measure excess returns as the residual from a regression of a firm's daily stock returns on the market return. Φ is defined as the ratio of idiosyncratic volatility to systematic volatility; i.e., $\Phi = \ln[\sigma_e^2] - \ln[\sigma_s^2]$. We measure Φ as the average of $\ln[\sigma_e^2/\sigma_s^2]$ calculated on a monthly basis.[9]

Information Environment Variables

We compute the following proxies for the firm's information environment: *PIN* scores, probability of informed trading (Easley, Hvidkjaer, and O'Hara 2002); *SPREAD,* bid-ask spread; *DELAY*, the price delay measure (Hou and Moskowitz 2005; Callen, Khan, and Lu 2013); *ILLIQ,* illiquidity measure (Amihud 2002); *LIQVOL,* volatility of the Amihud (2002) liquidity measure, as used in Lang and Maffett (2011); and *ZRDAYS,* zero return days. Appendix B explains the measurement of each of these variables.

Data and Results

We use data for the period 1983–2007 to compute the various information environment variables and the return volatility measures. We standardize the measurement of each variable such that a higher number represents less informative stock prices or more noise. For example, a higher Amihud (2002) liquidity measure or bid-ask spread implies higher levels of information asymmetry and, hence, less informative stock prices. If the interpretation that greater Φ and greater $\ln[\sigma_e^2]$ indicate more informative stock prices is valid on average, then we ought to find that firms with greater Φ and $\ln[\sigma_e^2]$ are systematically characterized by lower *PIN* scores, lower bid-ask spread (*SPREAD*), lower price delays (*DELAY*), lower illiquidity (*ILLIQ*), lower volatility in liquidity (*LIQVOL*), and lower zero return days (*ZRDAYS*). In contrast, if the RV assumption that greater Φ and greater $\ln[\sigma_e^2]$ indicate more noise in stock prices is correct, then we should find the opposite. We form quintile portfolios sorted on both Φ and $\ln[\sigma_e^2]$ and investigate whether the characteristics

[8] As a sensitivity check, we rerun the regression specifications using idiosyncratic risk and Φ estimated based on the three-factor Fama and French (1993) model. Untabulated results show that our inferences are unchanged in that the hypothesized variables are of the correct signs and are significant at similar significance levels to the tabulated results. We use similar criteria for all the sensitivity checks reported in the study.

[9] Untabulated results replicate these findings using weekly returns.

of liquidity and other information environment proxies in the extreme portfolios behave in a manner consistent with noise or news.

Results presented in Table 1, Panels A and B, for portfolios formed on $\ln[\sigma_e^2]$ and Φ, respectively, are consistent with the noise hypothesis not the information hypothesis. Regardless of whether we sort on Φ or $\ln[\sigma_e^2]$, firms in the highest quintile portfolio display greater levels of *PIN, SPREAD, DELAY, ILLIQ, LIQVOL,* and *ZRDAYS* relative to the lowest quintile portfolio. In fact, each of the information variables increases monotonically across the quintile portfolios of idiosyncratic volatility. This is strong evidence that higher levels of Φ are more symptomatic of noise in returns rather than firm-specific information is being incorporated in stock prices.

Because size is significantly correlated with R^2 (Roll 1988), we examine whether the findings in Panels A and B of Table 1 are stable across various size quintiles. Specifically, we form five size quintiles within each of the idiosyncratic volatility quintile portfolios formed based on Φ and $\ln[\sigma_e^2]$. We then examine whether the firm-specific information variables behave similarly across each of the size quintiles. Results in Table 1, Panels C and D, show that our previous findings are robust to controlling for size. Across each of the size quintiles the higher levels of Φ and $\ln[\sigma_e^2]$ exhibit higher *PIN* scores, greater bid-ask spread, more price delay, poorer liquidity, and more zero return days.

In addition to the evidence presented here, prior literature generally finds that firms with poorer earnings quality are associated with environments of relatively uninformative prices. In particular, Aboody, Hughes, and Liu (2005) find that insiders are able to execute more (less) profitable trades in firms with worse (better) earnings quality. Bhattacharya, Desai, and Venkataraman (2012) and Bhattacharya, Ecker, Olsson, and Schipper (2012) document that poor earnings quality, proxied by the Dechow-Dichev residuals, is associated with higher adverse selection risk, greater bid-ask spreads, and greater *PIN* scores. Welker (1995) and Brown and Hillegeist (2007) document associations between a more opaque disclosure policy, as proxied by Association for Investment Management and Research (AIMR) scores, and two measures of information asymmetry: higher bid-ask spreads and *PIN* scores. Ng (2011) finds that better earnings quality, proxied by the Dechow-Dichev residuals, earnings precision, and the level of analysts' consensus in earnings forecasts, is associated with lower liquidity risk, after controlling the levels of liquidity. Several papers listed in Appendix A, Part 2, find that firms with greater idiosyncratic return volatility or lower R^2 are associated with greater barriers to arbitrage (Pontiff 1996) and, hence, are exposed to greater market anomalies (Baker and Wurgler 2006). This literature is inconsistent with a negative association between Φ and *OPAQUE* documented by HMT, who presume that higher levels of Φ represent stock prices that are more informative. Thus, our reading of the combined evidence is that researchers ought to be cautious before interpreting lower R^2 as a proxy for a better information environment.

III. THE ROLE OF COMPONENTS OF R^2

Decomposition of R^2

For stock i, in the standard market model:

$$r_i = \alpha_i + \beta_i r_m + e_i \tag{1}$$

with $E(e_i) = 0$. In Equation (1), r_i is the return on stock i, and r_m is the return on a market index. Thus $\beta_i = Cov(r_i, r_m)/Var(r_m)$. We measure idiosyncratic risk as the variance of the error term in Equation (1), σ_{ei}^2, and total risk as the variance of the dependent variable in Equation (1), or σ_{ri}^2.

R^2 or the synchronicity measure from Equation (1) is:

$$(1 - \sigma_{ei}^2/\sigma_{ri}^2). \tag{2}$$

TABLE 1

Information Variables across Quintiles of Idiosyncratic Volatility Proxies

Panel A: Mean of Information Variables across Quintiles of Idiosyncratic Volatility ($\ln[\sigma_e^2]$)

	Quintiles Based on $\ln[\sigma_e^2]$					
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**Mean (5) − (1)**
PIN	0.174	0.193	0.207	0.220	0.244	0.070
						(49.37)
SPREAD	0.011	0.016	0.021	0.029	0.048	0.037
						(117.24)
DELAY	0.410	0.474	0.527	0.598	0.697	0.287
						(93.32)
ILLIQ	0.027	0.076	0.182	0.492	2.848	2.821
						(75.90)
LIQVOL	0.038	0.128	0.340	1.003	6.366	6.328
						(81.60)
ZRDAYS	0.143	0.162	0.190	0.222	0.275	0.132
						(65.35)

Panel B: Mean of Information Variables across Quintiles of Relative Volatility (Φ)

	Quintiles Based on Φ					
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**Mean (5) − (1)**
PIN	0.150	0.180	0.200	0.241	0.276	0.126
						(95.42)
SPREAD	0.008	0.015	0.021	0.027	0.029	0.021
						(85.80)
DELAY	0.264	0.451	0.579	0.674	0.739	0.475
						(189.85)
ILLIQ	0.012	0.187	0.597	1.140	1.709	1.698
						(58.75)
LIQVOL	0.024	0.403	1.296	2.482	3.705	3.681
						(60.64)
ZRDAYS	0.083	0.154	0.209	0.252	0.294	0.210
						(118.06)

Panel C: Mean of Information Variables for Quintile 5 and Quintile 1 Portfolios of Idiosyncratic Volatility ($\ln[\sigma_e^2]$) by Size Quintile

		Size Quintile				
Variable	**Quintile Based on $\ln[\sigma_e^2]$**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
PIN	1	0.266	0.196	0.163	0.145	0.116
	5	0.285	0.272	0.251	0.226	0.194
	Difference	0.019	0.077	0.088	0.082	0.077
	(t-statistic)	(4.85)	(25.09)	(32.81)	(33.76)	(34.70)

(continued on next page)

TABLE 1 (continued)

Variable	Quintile Based on $\ln[\sigma_e^2]$	Size Quintile (1)	(2)	(3)	(4)	(5)
SPREAD	1	0.010	0.010	0.008	0.006	0.005
	5	0.034	0.042	0.044	0.043	0.035
	Difference	0.024	0.032	0.036	0.037	0.030
	(t-statistic)	(35.53)	(47.75)	(54.83)	(57.17)	(49.11)
DELAY	1	0.634	0.462	0.364	0.307	0.285
	5	0.752	0.732	0.713	0.675	0.612
	Difference	0.118	0.271	0.349	0.368	0.328
	(t-statistic)	(17.98)	(41.20)	(54.71)	(59.01)	(49.75)
ILLIQ	1	0.115	0.020	0.006	0.006	0.002
	5	6.248	4.001	2.548	1.532	0.655
	Difference	6.132	3.981	2.542	1.526	0.653
	(t-statistic)	(50.75)	(43.79)	(35.61)	(28.52)	(19.50)
LIQVOL	1	0.161	0.031	0.010	0.009	0.003
	5	13.515	8.992	5.779	3.584	1.549
	Difference	13.354	8.961	5.769	3.575	1.546
	(t-statistic)	(55.67)	(47.51)	(38.23)	(30.34)	(20.08)
ZRDAYS	1	0.314	0.155	0.109	0.081	0.058
	5	0.376	0.301	0.263	0.236	0.200
	Difference	0.061	0.146	0.154	0.155	0.142
	(t-statistic)	(9.53)	(35.85)	(47.77)	(53.63)	(50.94)

Panel D: Mean Difference in Information Variables between Quintile 5 and Quintile 1 Portfolios of Relative Volatility (Φ) Reported for Each Size Quintile

Variable	Quintile Based on Φ	Size Quintile (1)	(2)	(3)	(4)	(5)
PIN	1	0.192	0.170	0.154	0.137	0.113
	5	0.302	0.297	0.288	0.268	0.241
	Difference	0.110	0.127	0.133	0.130	0.127
	(t-statistic)	(30.39)	(42.88)	(45.97)	(55.22)	(50.10)
SPREAD	1	0.014	0.009	0.007	0.005	0.004
	5	0.029	0.033	0.032	0.031	0.021
	Difference	0.015	0.024	0.025	0.025	0.017
	(t-statistic)	(22.54)	(39.18)	(46.00)	(51.57)	(45.72)
DELAY	1	0.330	0.284	0.254	0.232	0.220
	5	0.770	0.760	0.743	0.728	0.693
	Difference	0.441	0.476	0.489	0.495	0.473
	(t-statistic)	(75.77)	(85.66)	(90.67)	(92.03)	(85.84)
ILLIQ	1	0.053	0.003	0.001	0.001	0.000
	5	4.774	2.405	1.304	0.606	0.243
	Difference	4.721	2.402	1.303	0.605	0.243
	(t-statistic)	(43.20)	(33.86)	(26.49)	(20.51)	(14.27)

(continued on next page)

TABLE 1 (continued)

Variable	Quintile Based on Φ	Size Quintile (1)	(2)	(3)	(4)	(5)
LIQVOL	1	0.111	0.005	0.002	0.001	0.001
	5	10.345	5.204	2.790	1.352	0.536
	Difference	10.234	5.199	2.788	1.351	0.535
	(t-statistic)	(45.63)	(35.26)	(27.00)	(20.44)	(13.10)
ZRDAYS	1	0.126	0.093	0.078	0.066	0.052
	5	0.411	0.332	0.285	0.242	0.198
	Difference	0.284	0.239	0.207	0.176	0.145
	(t-statistic)	(54.02)	(58.58)	(60.27)	(62.16)	(57.26)

t-statistics are reported in parentheses.
Panels A and B report the averages for each information variable in quintile portfolios formed on return volatility covering the period 1983–2007. Quintile portfolios are formed each fiscal year separately for the two measures of return volatility ($\ln[\sigma_e^2]$ and Φ).
For Panels C and D, we provide the mean difference in Quintile 5 − Quintile 1 portfolios for each information variable across different size quintiles with size measured at $t-1$. Note that size quintile portfolios are formed within each idiosyncratic volatility quartile.

For ease of exposition, without any loss of generality, consider the dependent variable (Φ) used in HMT, i.e., $\ln[(1 - R^2)/R^2]$, where ln is the natural logarithm. This variable captures the inverse of R^2, also known as asynchronicity or the inverse synchronicity measure. Substituting Equation (2) into the term $\ln[(1 - R^2)/R^2]$ yields:

$$\Phi = \ln[(1 - R^2)/R^2] = \ln[\sigma_{ei}^2/(\sigma_{ri}^2 - \sigma_{ei}^2)]. \tag{3}$$

From Equation (1) $\sigma_{ri}^2 = (\beta_i^2 * \sigma_{rm}^2 + \sigma_{ei}^2)$. Hence, $(\sigma_{ri}^2 - \sigma_{ei}^2)$ can be rewritten as:

$$\beta_i^2 * \sigma_{rm}^2. \tag{4}$$

Substituting Equation (4) into Equation (3) yields Equations (5) and (6):

$$\Phi = \ln[(1 - R^2)/R^2] = \ln[\sigma_{ei}^2/(\beta_i^2 * \sigma_{rm}^2)], \tag{5}$$

and, ignoring firm subscripts:

$$\Phi = \ln[(1 - R^2)/R^2] = \ln[\sigma_e^2] - \ln[\beta^2] - \ln[\sigma_{rm}^2]. \tag{6}$$

Equation (6) shows that any increase in asynchronicity, Φ, can occur because of any or all of three factors: (i) an increase in idiosyncratic risk, σ_e^2; (ii) a decrease in beta, β^2; and (iii) a decrease in market-wide return volatility, σ_{rm}^2. Thus, a researcher investigating the association between Φ and a treatment variable should be careful about attributing the relationship solely to idiosyncratic risk.

A related issue is whether the researcher's interest is in analyzing average asynchronicity across countries or across firms within a country. When the unit of analysis is the firm within a country, market-wide return variation (σ_{rm}^2) is a cross-sectional constant for a given year and Equation (6) degenerates to:

$$\Phi_{firm} = \ln[\sigma_e^2] - \ln[\beta^2]. \tag{7}$$

Thus, a positive association between Φ_{firm} and the treatment variable can arise because idiosyncratic return volatility, σ_e^2, across firms is positively related to the treatment variable; β

across firms is negatively related to the treatment variable; or the positive correlation between σ_e^2 and the treatment variable dominates the positive correlation between β and the treatment variable.

Analogously, when the unit of analysis is a country, by definition, aggregate β is 1 for each country and Equation (6) degenerates to:

$$\Phi_{country} = \ln[\sigma_e^2] - \ln[\sigma_{rm}^2]. \tag{8}$$

Thus, a positive association between $\Phi_{country}$ and the treatment variable can arise because idiosyncratic return volatility, σ_e^2, across countries is positively related to that treatment variable; market-wide volatility, σ_{rm}^2, across countries is negatively related to that treatment variable; or the positive correlation between σ_e^2 and the treatment variable dominates the positive correlation between σ_{rm}^2 and the treatment variable.

Evidence in the U.S. Context

To test our hypothesis in the cross-sectional setting within a single country, we consider two papers that analyze the relation between firm-specific return variation and earnings quality in the U.S. context but find opposite results. Hutton et al. (2009) conclude that the relation between Φ and poor earnings quality is negative; Rajgopal and Venkatachalam (2011) conclude that the relation between σ_e^2 and poor earnings quality is positive. Our analytical decomposition of R^2 suggests that an explanation for these contradictory findings is that β across firms is positively correlated with poor earnings quality, but the positive correlation between σ_e^2 and poor earnings quality is dominated by the positive correlation between β and poor earnings quality. Conceptually, β could be positively associated with poor earnings quality (Lambert, Leuz, and Verrecchia 2007). An empirical analysis of the data using the specifications in RV and HMT is in line with the theoretical predictions.

Earnings Quality Measures

Consistent with RV and HMT, we consider two measures of inverse earnings quality, *DD* and *OPAQUE*. *DD*, the main variable of interest in RV, is based on an approach proposed by Dechow and Dichev (2002) and Francis, LaFond, Olsson, and Schipper (2005). We employ the modified Dechow-Dichev model to calculate the measurement error in earnings (McNichols 2002; Francis et al. 2005):

$$TCA_{it} = \varphi_0 + \varphi_1 CFO_{it-1} + \varphi_2 CFO_{it} + \varphi_3 CFO_{it+1} + \varphi_4(\Delta REV_{it} - \Delta AR_{it}) + \varphi_5 PPE_{it} + v_{it} \tag{9}$$

where TCA is the total current accruals calculated as $\Delta CA - \Delta CL - \Delta Cash + \Delta STDEBT$ for observations before calendar year 1988 and as $IBEX - CFO + DEPN$ after calendar year 1988. ΔCA is the change in current assets (Compustat ACT), ΔCL is the change in current liabilities (Compustat LCT), $\Delta Cash$ is the change in cash (Compustat CHE), and $\Delta STDEBT$ is the change in debt in current liabilities (Compustat DLC). $IBEX$ is the net income before extraordinary items (Compustat IB), and CFO is the cash flow from operations (Compustat OANCF) for calendar years after 1988. For calendar years prior to 1988, CFO is computed as $IBEX - TCA + DEPN$, where $DEPN$ is the depreciation and amortization expense (Compustat DP). Subscripts i and t represent firm and time, respectively. We estimate Equation (9) for each of the 49 Fama and French (1997) industry groups with at least 20 firms in year t. All variables are scaled by lagged assets.

In Equation (9), higher accruals quality implies that accruals capture most of the variation in current, past, and future operating cash flows. Consequently, the firm-specific residual, v_{it}, from Equation (9), forms the basis of the earnings quality proxy. We compute the inverse earnings quality, DD_{it}, as the standard deviation of firm i's residuals calculated over years t–4 through t, i.e., $DD_{it} = \sigma(v_{it-4,t})$. We treat larger standard deviations of residuals as an indication of poor accruals and earnings quality.

OPAQUE is the variable of interest in HMT. This measure is based on the idea that changes in a firm's accruals are primarily determined by changes in the firm fundamentals, proxied by changes in revenues and property, plant, and equipment. If a firm's accruals deviate from the level determined by changes in firm fundamentals, then such deviation is deemed abnormal, and higher deviations diminish the quality of accruals and earnings.

To determine abnormal accruals, we apply the modified Jones (1991) model and estimate the following regression for each of the 49 Fama and French (1997) industry groups with at least 20 firms in year t. As before, we scale all variables by lagged total assets:

$$TA_{it} = \delta_0 + \delta_1(\Delta REV_{it} - \Delta AR_{it}) + \delta_2 PPE_{it} + \delta_3 ROA_{it} + \eta_{it} \tag{10}$$

where TA is firm i's total accruals, computed as $TCA - DEPN$, and ΔAR is the change in accounts receivable (Compustat RECT). Kothari, Leone, and Wasley (2005) show that firm performance is an important determinant of abnormal levels of accruals. Therefore, we include return on assets (*ROA*) as an additional variable in Equation (10). *ROA* is *IBEX* divided by lagged total assets (Compustat AT).

Consistent with HMT, we treat the firm-specific residual, η_{it}, as abnormal accruals and use the three-year moving average of the absolute value of the residual as the proxy for inverse earnings quality, i.e., $OPAQUE = (|\eta_{it-2}| + |\eta_{it-1}| + |\eta_{it}|)/3$.[10] Higher residuals imply greater deviations from the normal level of accruals attributable to changes in a firm's fundamentals and, hence, represent poor quality earnings.

Control Variables

To be consistent with RV and HMT, we consider the following control variables that are common to both papers: firm size (*SIZE*), market-to-book ratio (*M/B*), and leverage (*LEV*). We include operating cash flows scaled by lagged total assets (*CFO*), standard deviation of operating cash flows (*VCFO*), annual buy-and-hold stock return (*RET*), analyst following (*NANAL*), squared analyst forecast revision ($FREV^2$), and institutional ownership (*INST*) as additional control variables for the RV specification. For the HMT specification, we also include return on equity (*ROE*), the variance of the two-digit SIC industry return [*VAR*(*Industry*)] and the kurtosis and the skewness of firm-specific returns as control variables. Appendix B provides definitions of the control variables.

Sample and Descriptive Statistics

We consider a sample period of 1965–2007 that covers and extends the sample periods of 1962–2001 and 1991–2005 in RV and HMT, respectively.[11] We obtain analyst forecast data

[10] We use the average of discretionary accruals, which is conceptually equivalent to the sum of discretionary accruals used by HMT.

[11] Our findings are similar when we consider the sample periods covered by the respective papers. Also, we remove data before 1964 because we have very few observations to estimate reliable coefficients for that year.

from the I/B/E/S database and institutional ownership data from the Thomson Reuters institutional ownership database compiled from Form 13F filings.[12] Stock returns are measured over each firm's fiscal year to match the time period of the reported financial data.[13] We exclude firm fiscal years with fewer than 12 months of stock return data, observations with fewer than 12 trading days each month, and financial service firms and utilities (SIC 6000–6999 and 4900–4999), resulting in a sample of 74,504 firm-year observations for the RV specification and 109,871 firm-year observations for the HMT specification.[14] For all sample firms, we construct measures of stock return volatility, financial reporting quality, and control variables.

Table 2 reports descriptive statistics on the variables used in the replication of RV and HMT specifications. We winsorize all the variables at the 1 and 99 percent levels to avoid the effects of influential outliers. The mean and median of idiosyncratic volatility and inverse synchronicity presented in Table 2, Panels A and B, are similar to those reported in RV and HMT.

More relevant are the cross-sectional correlations reported in Table 2, Panel B. Consistent with RV, the Pearson correlation between idiosyncratic volatility (measured in logarithm) and *DD* measure is positive ($\rho = 0.391$). The correlation between *DD* and the inverse synchronicity measure Φ is also positive ($\rho = 0.119$). Results are similar when we consider the inverse earnings quality measure, *OPAQUE,* used by HMT. The partial correlations reported here, however, are confounded by the effect of size.[15] In particular, size is highly correlated with Φ and σ_e^2 for both samples, suggesting that controlling for size is important.

Moreover, the Pearson correlation between idiosyncratic component of return volatility, $\ln[\sigma_e^2]$, and $\ln[\beta^2]$ is strongly positive ($\rho = 0.576$). To compound the issue, the inverse earnings quality measures are positively correlated with beta ($\rho = 0.235$ and 0.183 for *DD* and *OPAQUE,* respectively). These high correlations between beta and idiosyncratic risk, on the one hand, and between these risk variables and the treatment variable of interest (inverse earnings quality), on the other hand, imply that a researcher working with R^2 in cross-sectional settings needs to recognize that inferences could be systematically different if she were to instead use idiosyncratic return volatility as the dependent variable.

Replication of Rajgopal and Venkatachalam (2011)

Table 3 presents results from a replication of RV for the expanded time period 1965–2007. To address the stationarity of error terms in panel data, we use the Fama and Macbeth (1973) approach and report the average coefficient for yearly cross-sectional regressions and estimate t-statistics based on the distribution of annual coefficients. Consistent with RV, in results reported in Table 3, column (2), we find a strong positive cross-sectional association between idiosyncratic volatility and the Dechow-Dichev measure (coefficient on *DD* is 4.815, t-statistic = 9.54).[16] Based on this

[12] I/B/E/S data are available from 1975, and institutional ownership data are available from 1979. Therefore, the specification for RV regression is appropriately modified to reflect the lack of data for those earlier years.

[13] We define the end of each year as the month of annual earnings announcement. If the month of earnings announcement is missing from the Compustat quarterly database, then we define it as the second month after the fiscal year-end.

[14] The sample sizes for both HMT and RV are influenced by the measurement of the two different earnings quality variables. The *OPAQUE* measure in HMT requires far fewer variables to estimate than the *DD* measure used by RV.

[15] Hutton et al. (2009, footnote 9) also note this confounding effect.

[16] In unreported results, we find similar inferences when we estimate a pooled regression and cluster the standard errors by firm and year. Our inferences are also unchanged if we use the raw volatility numbers without the logarithmic transformations.

TABLE 2

Descriptive Statistics and Correlation Matrix

Panel A: Descriptive Statistics

Variable		Mean	Std. Dev.	Q1	Median	Q3	Min.	Max.
Volatility Measures								
Idiosyncratic volatility	σ_e^2	0.033	0.050	0.007	0.016	0.036	0.002	0.317
Beta squared	β^2	2.469	3.058	0.728	1.490	2.957	0.083	20.048
Market volatility	σ_{rm}^2	0.002	0.002	0.001	0.001	0.002	0.000	0.014
Inverse synchronicity	Φ	2.196	0.831	1.629	2.296	2.801	−0.843	7.176
Earnings Quality Measures								
Accruals quality (RV)	*DD*	0.065	0.071	0.023	0.041	0.077	0.006	0.456
Average absolute value of abnormal accruals (HMT)	*OPAQUE*	0.078	0.066	0.036	0.059	0.097	0.009	0.387
Control Variables (RV)								
Market-to-book ratio	*M/B*	2.178	2.829	0.861	1.453	2.528	−5.632	21.554
Firm size (in log)	*SIZE*	4.910	2.222	3.241	4.760	6.467	0.242	10.323
Leverage	*LEV*	0.237	0.176	0.095	0.222	0.344	0.000	0.826
Operating cash flows	*CFO*	0.072	0.145	0.024	0.085	0.143	−0.827	0.431
Cash flow volatility	*VCFO*	0.017	0.059	0.001	0.004	0.011	0.000	0.647
Institutional ownership	*INST*	0.150	0.249	0.000	0.000	0.236	0.000	1.009
Analyst following	*NANAL*	4.336	6.762	0.000	1.000	6.000	0.000	31.000
Analyst forecast revision^2	$FREV^2$	0.291	2.057	0.000	0.000	0.040	0.000	25.000
Stock return performance	*RET*	0.176	0.580	−0.169	0.078	0.373	−0.832	3.083
Control Variables (HMT)								
Variance of industry index	*Var(Industry)*	0.003	0.004	0.001	0.002	0.004	0.000	0.381
Return on equity	*ROE*	0.017	0.455	−0.009	0.095	0.174	−2.793	1.472
Return skewness	*Skewness*	0.146	0.309	−0.037	0.147	0.337	−0.882	0.956
Return kurtosis	*Kurtosis*	1.554	1.714	0.594	1.112	1.871	−0.207	10.664

(continued on next page)

TABLE 2 (continued)

Panel B: Correlation Matrix

Variable	Φ	$\ln(\sigma_e^2)$	$\ln(\sigma_{rm}^2)$	$\ln(\beta^2)$	DD_{t-1}	$OPAQUE_t$	$SIZE_{t-1}$
Φ		0.418	−0.139	−0.233	0.193	0.164	−0.652
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln(\sigma_e^2)$	0.421		0.205	0.539	0.486	0.352	−0.531
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln(\sigma_{rm}^2)$	−0.141	0.214		−0.252	0.118	0.084	0.069
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
$\ln(\beta^2)$	−0.239	0.576	−0.250		0.264	0.184	−0.122
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
DD_{t-1}	0.119	0.391	0.113	0.235		0.490	−0.168
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
$OPAQUE_t$	0.136	0.333	0.093	0.183	0.514		−0.235
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
$SIZE_{t-1}$	−0.650	−0.528	0.086	−0.117	−0.107	−0.187	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

p-values are shown in parentheses.

This table reports the descriptive statistics of all the variables and the correlation matrix of the key variables used for the replication of Rajgopal and Venkatachalam (2011; RV) and Hutton et al. (2009; HMT). All variables are winsorized at the bottom and top 1 percent levels. For the variables used in the Hutton et al. (2009) regressions, the number of observations is 109,871, and for those used in Rajgopal and Venkatachalam (2011) regressions, the number of observations is 74,504. In the correlation panel, Pearson correlations are reported below the diagonal, and Spearman correlations are reported above the diagonal.

All variables are defined in Appendix B.

TABLE 3

Replication of Rajgopal and Venkatachalam (2011)

Variable	(1) Φ	(2) $\ln(\sigma_e^2)$	(3) $\ln(\beta^2)$	(4) $\ln(\sigma_{rm}^2)$
DD_{t-1}	−0.877***	4.815***	5.517***	−0.105
	(−3.27)	(9.54)	(8.27)	(−1.45)
$FREV_{t-1}^2$	−0.165	0.389	0.884	−0.092
	(−1.03)	(1.03)	(1.02)	(−1.00)
RET_{t-1}^2	−0.092***	0.113***	0.199***	0.006
	(−4.45)	(7.84)	(6.54)	(1.28)
$NANAL_{t-1}$	−0.021***	0.016***	0.037***	−0.001
	(−7.34)	(6.04)	(11.24)	(−0.78)
$INST_{t-1}$	−0.124	−0.237**	−0.143***	−0.028
	(−1.63)	(−2.51)	(−3.59)	(−1.38)
CFO_{t+1}	0.144***	−0.410***	−0.528***	0.010
	(3.41)	(−9.02)	(−7.92)	(0.92)
CFO_{t-1}	−0.001	−0.387***	−0.330***	−0.017
	(−0.02)	(−9.18)	(−5.28)	(−1.35)
$VCFO_{t-1}$	0.137**	−0.011	−0.109	0.036
	(2.19)	(−0.05)	(−0.37)	(0.77)
M/B_{t-1}	−0.003	0.035***	0.034***	0.002
	(−1.12)	(8.38)	(6.73)	(1.51)
$SIZE_{t-1}$	−0.215***	−0.280***	−0.077***	0.001
	(−20.99)	(−19.66)	(−4.07)	(0.50)
LEV_{t-1}	−0.127***	0.495***	0.582***	0.002
	(−2.91)	(6.74)	(5.94)	(0.31)
RET_t	−0.149***	−0.054*	0.118***	−0.024
	(−8.19)	(−1.91)	(3.06)	(−1.67)
Intercept	3.341***	−3.423***	0.089	−6.610***
	(107.98)	(−24.99)	(0.66)	(−66.29)
n	74,504	74,504	74,504	74,504
R^2	33.9%	27.9%	2.7%	0.0%
Number of years	43	43	43	43

*, **, *** Indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.
t-statistics are presented in parentheses.
This table reports estimation of Equation (3) in Rajgopal and Venkatachalam (2011).

$$VAR_{it} = \alpha_0 + \alpha_1 DD_{i,t-1} + \alpha_2 FREV_{i,t-1}^2 + \alpha_3 RET_{i,t-1}^2 + \alpha_4 NANAL_{i,t-1} + \alpha_5 INST_{i,t-1} + \alpha_6 CFO_{i,t+1} + \alpha_7 CFO_{i,t-1} + \alpha_8 VCFO_{i,t-1} + \alpha_9 M/B_{i,t-1} + \alpha_{10} SIZE_{i,t-1} + \alpha_{11} LEV_{i,t-1} + \alpha_{12} RET_{i,t} + \zeta_{it},$$

where VAR represents relative volatility (Φ), idiosyncratic volatility ($\ln[\sigma_e^2]$), beta ($\ln[\beta^2]$), and market return volatility ($\ln[\sigma_{rm}^2]$). DD is a measure of inverse earnings quality calculated from the modified Dechow and Dichev (2002) model. The sample period is from 1965–2007, and all variables are winsorized at the bottom and top 1 percent levels. Reported coefficients are averages of annual coefficients.
All other variables are defined in Appendix B.

analysis we can conclude that, similar to RV, poor earnings quality is associated with greater idiosyncratic risk.

Table 3, column (1) estimates the same regression as column (2) with one important difference. The dependent variable is the inverse return synchronicity measure, Φ, used by HMT. The coefficient on *DD* is now negative (coefficient $= -0.877$, t-statistic $= -3.27$) suggesting that the higher the inverse return synchronicity, the higher the earnings quality. This result contradicts the RV finding.[17]

To understand why we obtain a negative relation between Φ and *DD*, we decompose Φ into its components, $\ln[\beta^2]$ and $\ln[\sigma^2_{rm}]$, and we report the results with these variables as dependent variables in columns (3) and (4). σ^2_{rm} for a given year is a cross-sectional constant. Hence, the coefficient on *DD* when $\ln[\sigma^2_{rm}]$ is the dependent variable is not statistically significant, as expected. However, the coefficient on *DD* when $\ln[\beta^2]$ is the dependent variable is positive and statistically significant (coefficient = 5.517; t-statistic = 8.27 in column (3)). More important, the positive coefficient on *DD* in the $\ln[\beta^2]$ regression is greater than the positive coefficient on *DD* in the $\ln[\sigma^2_e]$ regression. Thus, we conclude that the negative coefficient on *DD* when Φ is the dependent variable is driven by the dominant impact of *DD* on $\ln[\beta^2]$ (coefficient = 5.517 in column (3)) relative to the impact of *DD* on $\ln[\sigma^2_e]$ (coefficient = 4.815 in column (2)).

Replication of Hutton et al. (2009)

We draw similar inferences from a replication of the main findings in HMT. As with the RV estimations, we use the same Fama and Macbeth (1973) approach and report average annual coefficients. The main finding of HMT is that financial reporting opacity, captured by *OPAQUE,* is negatively associated with the inverse return synchronicity measure, Φ. We successfully replicate the HMT findings for the expanded sample and report the results in Table 4. The coefficient on *OPAQUE* is negative (coefficient $= -0.963$, t-statistic $= -4.23$ in column (1)), consistent with HMT. However, when we use the idiosyncratic return volatility measure instead of Φ as the dependent variable, consistent with RV, the coefficient on *OPAQUE* is positive (coefficient on $\ln[\sigma^2_e] = 3.929$, t-statistic = 15.58 in column (2)). The contradiction occurs due to the dominant impact of *DD* on systematic β factor (coefficient = 4.738 on *DD* in column (2)) over the effect of *DD* on idiosyncratic risk (coefficient = 3.929 on *DD* in column (2)). Consistent with expectations, the coefficient on *OPAQUE* is insignificant when $\ln[\sigma^2_{rm}]$ is the dependent variable.

Evidence in the Cross-Country Context

In this section, we provide empirical evidence on the decomposition of Φ in a cross-country setting by replicating the findings in Morck et al. (2000). Morck et al. (2000) use a different logarithmic transformation of the R^2 metric (Y) at the country level and examine its relation with quality of corporate governance (investor protection, information environment, or pricing efficiency) of the stock market in a particular country. However, to ensure comparability with the cross-sectional setting, we use the same dependent variables as before to capture return volatility and synchronicity. That is, we use Φ and $\ln[\sigma^2_e]$ both measured at the country level. Following Morck et al. (2000), we use two measures as our main independent variables of interest: good government index (*GoodGov*) and anti-director index (*AntiDir*).

When the unit of analysis is country, aggregate β is 1 for each country. Hence, contradictory results may obtain when using Φ instead of $\ln[\sigma^2_e]$ as the dependent variable if market-wide volatility, $\ln[\sigma^2_{rm}]$, across countries is correlated in the same direction with country-level governance

[17] The contradiction arises under the assumption that idiosyncratic volatility captures noise. However, if one were to work under the assumption that, like HMT, Φ captures news, then the negative coefficient would be interpreted as poor earnings quality leading to the revelation of less firm-specific information.

TABLE 4

Replication of Hutton et al. (2009)

Variable	(1) Φ	(2) $\ln(\sigma_e^2)$	(3) $\ln(\beta^2)$	(4) $\ln(\sigma_{rm}^2)$
$OPAQUE_t$	−0.963***	3.929***	4.738***	−0.012
	(−4.23)	(15.58)	(15.92)	(−0.31)
$Var(Industry)_t$	−30.061***	44.052***	54.097***	22.210***
	(−8.21)	(10.65)	(8.00)	(3.74)
$SIZE_{t-1}$	−0.234***	−0.312***	−0.092***	0.000
	(−24.57)	(−34.24)	(−7.88)	(0.04)
M/B_{t-1}	−0.004**	0.046***	0.047***	0.000
	(−2.24)	(7.33)	(7.36)	(0.58)
LEV_{t-1}	−0.078**	0.492***	0.527***	0.006
	(−2.49)	(8.05)	(6.44)	(0.95)
ROE_t	−0.160***	−0.445***	−0.278***	−0.005
	(−5.18)	(−10.95)	(−5.48)	(−1.27)
$Skewness_t$	−0.130***	0.074*	0.190***	−0.011
	(−5.16)	(1.88)	(3.34)	(−1.65)
$Kurtosis_t$	0.062***	−0.049***	−0.138***	0.001
	(5.73)	(−3.01)	(−10.76)	(0.76)
$OPAQUE_t^2$	2.234***	−6.913***	−8.745***	0.002
	(2.83)	(−11.87)	(−8.73)	(0.02)
Intercept	3.340***	−3.296***	0.322***	−6.680***
	(72.01)	(−32.75)	(3.11)	(−71.78)
n	109,871	109,871	109,871	109,871
R^2	39.1%	41.6%	9.6%	31.3%
Number of years	43	43	43	43

*, **, *** Indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.
t-statistics are presented in parentheses.
This table reports estimation of Model 3 in Table 6 in Hutton et al. (2009):

$$VAR_{it} = \beta_0 + \beta_1 OPAQUE_{i,t} + \beta_2 Var(Industry)_{i,t} + \beta_3 SIZE_{i,t-1} + \beta_4 M/B_{i,t-1} + \beta_5 LEV_{i,t-1} + \beta_6 ROE_{i,t} + \beta_7 Skewness_{i,t} + \beta_8 Kurtosis_{i,t} + \beta_9 OPAQUE_{i,t}^2 + v_{it},$$

where VAR represents relative volatility (Φ), idiosyncratic volatility ($\ln[\sigma_e^2]$), beta ($\ln[\beta^2]$), and market return volatility ($\ln[\sigma_{rm}^2]$). $OPAQUE$ is a measure of inverse earnings quality calculated using the modified Jones (1991) model. The sample period is from 1965 to 2007 and all variables are winsorized at the bottom and top 1 percent levels. Reported coefficients are averages of annual coefficients.
All other variables are defined in Appendix B.

as $\ln[\sigma_e^2]$, and the association between country-level governance and $\ln[\sigma_{rm}^2]$ is greater than the association between country-level governance and $\ln[\sigma_e^2]$.

For the empirical analysis, we obtain information on stock returns for 1994–2011 from the Compustat Global database, macroeconomic data from the World Bank, and the two country-specific governance indices (*GoodGov* and *AntiDir*) from La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1998, 1999). Morck et al. (2000) consider only one year, 1995, in their analysis. Morck et al. (2000) compute *GoodGov* as a combination of the corruption index, the risk of expropriation of private property by the government, and the risk of the government repudiating contracts. We rely solely on the corruption index as data on the other two indices are no longer available. *GoodGov* ranges from 0 to 10, with higher values signifying lower corruption. *AntiDir*,

TABLE 5

Replication of Morck et al. (2000)

Variable	(1) Φ	(2) $\ln(\sigma_e^2)$	(3) $\ln(\beta^2)$	(4) $\ln(\sigma_{rm}^2)$
ln(*pcGDP*)	−0.001	−0.156*	−0.111	−0.003
	(−0.02)	(−1.79)	(−1.11)	(−0.03)
ln(*Firm#*)	0.102**	0.191***	0.133**	−0.074
	(2.21)	(3.57)	(2.32)	(−1.24)
ln(*Area*)	0.064**	−0.006	−0.053	0.010
	(2.75)	(−0.18)	(−1.12)	(0.19)
Var(*GDPgr*)	−25.547	60.844**	37.144	6.029
	(−1.06)	(2.34)	(1.69)	(0.15)
indHerf	−0.633	−2.473	−1.365	−0.229
	(−0.63)	(−1.56)	(−0.83)	(−0.13)
firmHerf	2.039	3.848*	1.690	−0.181
	(1.47)	(1.87)	(0.92)	(−0.08)
Comove	−0.314*	−0.190	0.223	−0.470
	(−1.75)	(−0.71)	(1.19)	(−0.94)
GoodGov	0.095**	−0.046	−0.053	−0.095*
	(2.70)	(−1.03)	(−1.31)	(−1.87)
AntiDir	−0.041	0.007	0.049	0.019
	(−1.14)	(0.11)	(0.97)	(0.42)
Intercept	0.008	−3.506***	0.986	−4.502***
	(0.01)	(−3.54)	(0.71)	(−3.73)
n	474	474	474	474
R^2	26.6%	25.2%	22.1%	5.9%

*, **, *** Indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.
t-statistics are presented in parentheses.
In this table we replicate Morck et al. (2000) after controlling for market volatility using observations from 29 countries over the period 1994–2011, clustered at the country level.
All variables are defined in Appendix B.

a scorecard of shareholders' rights against directors, ranges from 0 to 6, with higher scores for greater shareholder rights. Consistent with Morck et al. (2000), we control for the following variables: stock market size using the logarithm of number of listed firms, country size using the logarithm of geographical size of each country, macroeconomic instability using the variance of GDP growth, economic specialization using industry Herfindahl index and firm Herfindahl index, and synchronicity in earnings fundamentals. For the dependent variables, we use the median of firm-level variables for each country-year. We have a total of 474 observations spanning 29 countries for our analysis.

Table 5 presents our empirical findings. Consistent with Morck et al. (2000), countries with higher good government index, i.e., countries with a greater respect for private property rights, exhibit greater Φ or lower return synchronicity. That is, in column (1), the coefficient on *GoodGov* is positive (0.095) and statistically significant at the 5 percent level.[18] However, in column (2), the coefficient on *GoodGov* is negative (–0.046), but not statistically significant when $\ln[\sigma_e^2]$ is the

[18] In Morck et al. (2000) the coefficient on the good government index is negative because the dependent variable is γ, which is the negative of Φ.

dependent variable. Hence, the results are contradictory given that the independent variable *GoodGov* is the same and the dependent variables Φ and $\ln[\sigma_e^2]$ are viewed as interchangeable in the literature. Under the Morck et al. (2000) assumption that greater idiosyncratic return volatility captures news, one would have expected to observe a positive coefficient on *GoodGov* when $\ln[\sigma_e^2]$ is the dependent variable. Morck et al. (2000, Tables 7.2 and 5.3) also report a negative coefficient on the good government index (–0.05) when cross-country idiosyncratic volatility (log σ_e^2 in their paper) is the dependent variable and a contradictory negative coefficient on the good government index (–0.11) when R^2 is the dependent variable.[19] Together, these results are problematic because, according to Morck et al. (2000), countries with greater respect for property rights ought to be associated with greater production of firm-specific information.

Based on the econometric predictions discussed in Section III, the contradiction arises primarily due to the negative correlation between the good government index and $\ln[\sigma_{rm}^2]$. In column (4) of Table 5, the coefficient on the good government index is -0.095 and statistically significant at the 10 percent level. Moreover, the negative coefficient on the good government index (–0.095) is more negative than the coefficient on the index (–0.046) when the dependent variable is $\ln[\sigma_e^2]$, reported in column (2). Also as expected, in column (3), we find that the good government index has very little impact on country-level beta. Finally, consistent with Morck et al. (2000), we do not find a significant association between the anti-director rights index and the various return variation metrics.

In summary, we demonstrate that our findings from cross-sectional tests in the U.S. setting extend to cross-country settings. That is, components of R^2 can play a role in obtaining different results depending on whether R^2 or idiosyncratic return volatility is used as the dependent variable. In addition, the specific component responsible for the contradiction depends on the research setting. In the cross-country setting, the market-wide return variation component drives the contradiction, whereas in the cross-sectional setting within a single country, the firm-level beta is responsible for the contradiction.

What Should a Researcher Do?

What ought a researcher do when the results using $\ln[\sigma_e^2]$ and Φ are not consistent? We propose two non-mutually exclusive solutions: (1) control for firm-year beta for cross-sectional settings within a single country and control for country-level market return volatility for cross-country settings; and (2) triangulate results with measures of poor information environment such as price delay measure, illiquidity, and greater insider trading.

We illustrate the first approach using the within-country and cross-country settings and report our findings in Tables 6 and 7, respectively. For the within country setting, we re-estimate the regressions reported in Table 3, columns (1) and (2), after including $\ln[\beta^2]$. Results reported in Table 6, columns (2) and (4), show that the relation between inverse earnings quality and idiosyncratic risk, $\ln[\sigma_e^2]$, continues to be positive, despite the strong positive relation between $\ln[\beta^2]$ and $\ln[\sigma_e^2]$. However, the relation between inverse earnings quality and Φ changes signs from negative to positive in both the RV and HMT specifications. In columns (1) and (3), the coefficient is 1.308 (t-statistic = 6.00) in the RV specification, and it is 0.713 (t-statistic = 4.07) in the HMT specification. Although one might think that this is a mechanical re-estimation of the regression with $\ln[\sigma_e^2]$ as the dependent variable, the coefficient on $\ln[\beta^2]$ is not -1 due to the inclusion of other covariates.[20] The evidence in Table 6 suggests that the inclusion of beta resolves the inconsistency in findings when using Φ and $\ln[\sigma_e^2]$ as alternative measures of firm-specific return variation, and

[19] Recall that R^2 is the inverse of Φ and, hence, the predicted coefficient is positive.
[20] We obtain similar inferences if we also include $\ln[\sigma_{rm}^2]$ in the empirical specifications.

TABLE 6

Replication of Rajgopal and Venkatachalam (2011; RV) and Hutton et al. (2009; HMT) after Controlling for Beta

RV Specification			HMT Specification		
Variable	**(1) Φ**	**(2) $\ln(\sigma_e^2)$**	**Variable**	**(3) Φ**	**(4) $\ln(\sigma_e^2)$**
DD_{t-1}	1.308***	1.922***	$OPAQUE_t$	0.713***	1.256***
	(6.00)	(8.05)		(4.07)	(7.22)
$FREV^2_{t-1}$	0.215	−0.039	$Var(Industry)_t$	−7.384***	17.436***
	(1.00)	(−0.93)		(−3.45)	(5.92)
RET^2_{t-1}	−0.010***	−0.007***	$SIZE_{t-1}$	−0.266***	−0.260***
	(−3.99)	(−2.98)		(−37.51)	(−42.85)
$NANAL_{t-1}$	−0.008***	−0.005***	M/B_{t-1}	0.014***	0.021***
	(−3.79)	(−2.90)		(5.13)	(5.84)
$INST_{t-1}$	−0.159**	−0.141	LEV_{t-1}	0.132***	0.221***
	(−2.26)	(−1.47)		(7.17)	(9.83)
CFO_{t+1}	−0.062	−0.134***	ROE_t	−0.262***	−0.288***
	(−1.56)	(−4.75)		(−9.25)	(−11.29)
CFO_{t-1}	−0.116***	−0.197***	$Skewness_t$	−0.043***	−0.010
	(−4.79)	(−7.48)		(−3.01)	(−0.54)
$VCFO_{t-1}$	0.068	0.043	$Kurtosis_t$	0.011	0.026**
	(0.41)	(0.34)		(1.23)	(2.29)
M/B_{t-1}	0.009***	0.017***	$OPAQUE^2{}_t$	−0.859*	−2.005***
	(4.01)	(5.53)		(−1.79)	(−4.48)
$SIZE_{t-1}$	−0.237***	−0.232***	$\ln(\beta^2)$	−0.370***	0.544***
	(−30.39)	(−32.08)		(−29.44)	(41.80)
LEV_{t-1}	0.102***	0.192***	Intercept	3.441***	−3.487***
	(3.60)	(6.55)		(62.82)	(−38.98)
RET_t	−0.100***	−0.109***			
	(−7.68)	(−6.81)			
$\ln(\beta^2)$	−0.375***	0.541***			
	(−22.93)	(34.77)			
Intercept	3.344***	−3.496***			
	(60.39)	(−35.33)			
n	74,504	74,504	n	109,871	109,871
R^2	42.3%	58.5%	R^2	50.5%	58.8%
Number of years	43	43	Number of years	43	43

*, **, *** Indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.
t-statistics are presented in parentheses.
In this table we replicate RV and HMT specifications for the U.S. setting after controlling for beta. For variable specifications see Tables 3 and 4. Reported coefficients are averages of annual coefficients.
All variables are defined in Appendix B.

that the HMT inferences would have been overturned had they controlled for β in their empirical specifications.

Table 7 presents evidence for the cross-country setting. Here, we re-estimate the specification in Table 5 after controlling for cross-country market-wide return volatility, $\ln[\sigma^2_{rm}]$. The results in Table 7, column (1), are not substantially different from those reported in Table 5. Thus, controlling

TABLE 7

Replication of Morck et al. (2000) after Controlling for Market Return Volatility

Variable	(1) Φ	(2) $\ln(\sigma_e^2)$	(1) Φ	(2) $\ln(\sigma_e^2)$
ln(*pcGDP*)	−0.002	−0.155	−0.047	−0.098
	(−0.03)	(−1.66)	(−0.64)	(−1.42)
ln(*Firm#*)	0.092*	0.215***	0.137***	0.158***
	(1.98)	(4.18)	(2.84)	(4.22)
ln(*Area*)	0.066**	−0.009	0.046*	0.016
	(2.75)	(−0.25)	(1.72)	(0.64)
Var(*GDPgr*)	−24.768	58.858***	−9.184	38.956**
	(−1.11)	(2.89)	(−0.45)	(2.33)
indHerf	−0.663	−2.398*	−1.236	−1.665
	(−0.66)	(−1.75)	(−1.42)	(−1.68)
firmHerf	2.016	3.908**	2.675**	3.066**
	(1.48)	(2.30)	(2.23)	(2.35)
Comove	−0.375**	−0.035	−0.337**	−0.084
	(−2.47)	(−0.20)	(−2.50)	(−0.59)
GoodGov	0.082**	−0.015	0.051	0.026
	(2.39)	(−0.33)	(1.40)	(0.74)
AntiDir	−0.038	0.000	−0.016	−0.027
	(−1.07)	(0.01)	(−0.38)	(−0.70)
$\ln(\sigma_{rm}^2)$	−0.129***	0.329***	−0.239***	0.470***
	(−3.04)	(6.53)	(−5.44)	(9.44)
$\ln(\beta^2)$			−0.402***	0.513***
			(−4.14)	(5.25)
Intercept	−0.573	−2.023	−0.672	−1.897**
	(−0.84)	(−1.55)	(−0.84)	(−2.37)
n	474	474	474	474
R^2	33.2%	50.4%	46.3%	63.0%

*, **, *** Indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.
t-statistics are presented in parentheses.
In this table we replicate Morck et al. (2000) after controlling for market volatility using observations from 29 countries over the period 1994–2011, clustered at the country level.
All variables are defined in Appendix B.

for market-wide return volatility does not appear to resolve the inconsistency in the relation between *GoodGov* and the two measures Φ and $\ln[\sigma_e^2]$. Recall from Equation (8) that we ignore the beta component, $\ln[\beta^2]$, because, in a cross-country setting, the country-level beta should be 1. However, because the sample within each country is often not completely representative of the market portfolio, untabulated analyses reveal that the median beta for several countries is significantly different from 1. Therefore, in cross-country settings, country-specific sample beta could still play a role in resolving the contradiction in findings. To explore this conjecture, we include $\ln[\beta^2]$ in the empirical specification and report our findings in Table 7, columns (3) and (4). We find that the coefficient on $\ln[\beta^2]$ is significantly related to both Φ and $\ln[\sigma_e^2]$. That is, $\ln[\beta^2]$ is not a cross-country constant as previously assumed in the theoretical model discussed in Section III. More important, the inclusion of $\ln[\beta^2]$ resolves the inconsistency. The coefficient on *GoodGov* is now insignificant regardless of whether Φ or $\ln[\sigma_e^2]$ is used. Thus, we conclude that in cross-country settings, it would be prudent to control for country-level β in addition to country-level σ^2_{rm}, especially when the country level βs are empirically different from 1.

Next, we consider approach (2) to resolve the inconsistency in prior findings. Table 1, which offers support for this approach shows that both Φ and $\ln[\sigma^2_e]$ capture noisy information environments. Hence, in theory, using these two variables should result in consistent research findings. Thus, when the researcher observes contradictory conclusions, it is important to justify the rationale for the appropriate dependent variable used, Φ versus $\ln[\sigma^2_e]$, and offer empirical evidence in support of that rationale by documenting consistent results with alternative measures such as illiquidity, price delay, and insider trading.

IV. CONCLUSIONS

We attempt to reconcile the mixed findings of papers that relate firm-specific return variation, using idiosyncratic return volatility or R^2 from a market model, with treatment variables such as earnings quality. The lack of congruence arises primarily because of the controversy over whether R^2 captures noise in stock returns or firm-specific information. Previous research, such as Morck et al. (2013), argues that R^2 can capture both news and noise. In contrast, our analysis suggests that lower R^2 is systematically associated with circumstances in which stock prices are more likely to be uninformative, including settings characterized by the presence of greater price delay, greater insider trading, greater information asymmetry, and higher illiquidity and liquidity risk.

We show that the association between R^2 and a treatment variable can arise from an association between the treatment variable and one of the three components of R^2: idiosyncratic return volatility, beta, and market return volatility. When the unit of analysis is a firm-level observation within a country, market return volatility is a cross-sectional constant and, hence, unimportant. However, when the unit of analysis is a country, the aggregate beta for each country is 1 and, hence, unlikely to be a major driver. Regardless of the setting, the researcher who uses R^2 has to contend with how the association between the treatment variable and the other two drivers of R^2 influence the overall relation between the treatment variable and R^2.

To illustrate this point, we replicate Rajgopal and Venkatachalam (2001; RV) and Hutton, Marcus, and Tehranian (2009; HMT) in the within-country setting. RV find that greater idiosyncratic return volatility increases with poorer earnings quality, and HMT show that firm-specific return variation captured by a scaled idiosyncratic volatility measure (Φ) decreases with poorer earnings quality. We show that the HMT results contradict the RV findings because earnings quality is related to both the beta and idiosyncratic risk components of Φ, with a stronger relation for beta. When we control for beta in the empirical specification, the contradiction is resolved.

We replicate Morck et al. (2000) in the cross-country context and reach similar contradictory conclusions depending on whether we use Φ or idiosyncratic volatility as the dependent variable. In this context, the inconsistent results are due to the dominant relation between cross-country market return volatility and the independent variable. As with the cross-sectional setting, when we account for σ^2_{rm} and β, the two components of systematic risk, the inconsistency in the results disappears.

What should a researcher do when she wants to use R^2 or its equivalent Φ as the dependent variable? First, we suggest that because R^2 is a scaled return variation measure and contains several components, it is important to understand which of the components of R^2, idiosyncratic risk, beta, or market wide return volatility, drives the documented association between R^2 and the treatment variable of interest. Second, the researcher needs to consider whether each of the components should have a meaningful relationship with the treatment variable, *ex ante*. Third, we advise that the researcher control for beta and market-wide return volatility in the empirical specification. Finally, and most important, the researcher should validate her assumption about whether R^2 captures news or noise.

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APPENDIX A

Part 1: Published Papers that Rely on Stock Return Synchronicity

A large literature investigates the impact of several corporate finance and accounting variables on stock return synchronicity. We restrict this list of published papers to those appearing in top-tier finance and accounting journals (replicated papers, RV and HMT, are not listed here). Given the different implications of R^2 when the unit of analysis is a firm within a country, labeled "cross-firm" here, as opposed to a country-level average, which we label "cross-country," we highlight which of these two categories these studies belong to.

Papers that Relate Return Synchronicity to Disclosure Quality and Information Environment

Cross-Country

- Morck et al. (2000) show that R^2 is higher in countries with less-developed financial systems and poorer corporate governance.
- Chan and Hameed (2006) consider the association between analyst coverage and return synchronicity in emerging markets.
- Jin and Myers (2006) document that control rights and lack of transparency in disclosure impact R^2.
- Fernandes and Ferreira (2008) examine the impact of international cross-listing on return synchronicity.

Cross-Firm

- Durnev et al. (2003) find that firms and industries with lower market model R^2 statistics exhibit higher association between current returns and future earnings.
- Piotroski and Roulstone (2004) investigate the extent to which trading by informed stakeholders affects stock return synchronicity.
- Crawford, Roulstone, and So (2012) examine the impact of the initiation of analyst coverage on return synchronicity.
- Dasgupta, Gan, and Gao (2010) show that in more transparent environments, stock prices should be more informative about future events, suggesting that a more informative stock price today implies higher return synchronicity in the future.

Papers that Relate Return Synchronicity to Audit Quality and International Financial Reporting Standards (IFRS) Adoption

Cross-Country

- Kim and Shi (2012) find that firms with lower return synchronicity (lower R^2) are more likely to adopt IFRS.

Cross-Firm

- Gul, Kim, and Qiu (2010) investigate the effects of largest-shareholder ownership concentration, foreign ownership, and audit quality on stock price synchronicity of Chinese-listed firms over the 1996–2003 period.
- Kim, H. Li, and S. Li (2011) consider the impact of eliminating 20-F reconciliation filings with the SEC on return synchronicity.

Papers that Relate Return Synchronicity to Corporate Investments

Cross-Country

- Wurgler (2000) shows that the efficiency of capital allocation is positively correlated to the amount of firm-specific information in domestic stock returns across countries (less return synchronicity).
- Chun, Kim, Morck, and Yeung (2008) show that traditional U.S. industries with higher firm-specific stock return (lower return synchronicity) use information technology more intensively and post faster productivity growth in the late 20th century.

Cross-Firm

- Durnev et al. (2004) examine the association between the economic efficiency of investment and return synchronicity.
- Chen et al. (2007) investigate the association between return non-synchronicity and the sensitivity of corporate investments to stock price.
- Brown and Kimbrough (2011) relate the level of intangible investments to return synchronicity.

Papers that Relate Return Synchronicity and Governance Quality

Cross-Firm

- Khanna and Thomas (2009) investigate the association between different kinds of firm interlocks, control groups, and synchronicity in Chile.
- Brockman and Yan (2009) examine the association between blockholders and return synchronicity.
- Gul et al. (2011) find that firms that have low return synchronicity are more likely to have a higher proportion of women on their boards.
- Ferreira, Ferreira, and Raposo (2011) investigate how stock price informativeness (return synchronicity) affects the composition of boards.
- Armstrong, Balakrishnan, and Cohen (2012) examine how changes in antitakeover protection (an element of firms' governance structures) influence firms' information environments.

Part 2: List of Published Papers that Rely on Idiosyncratic Return Volatility as a Proxy for Noise, Investor Sentiment, or Barriers to Arbitrage

- Pontiff (1996) finds that arbitrage costs, proxied by idiosyncratic return volatility, are associated with large deviations of prices from fundamentals of closed-end funds. Several other papers have relied on Pontiff's (1996) proxy of idiosyncratic return volatility as a proxy for barriers to arbitrage (e.g., Wurgler and Zhuravskaya 2002; Ali, Hwang, and Trombley 2003; Mendenhall 2004; Mashruwala et al. 2006; Pontiff 2006; Pincus, Rajgopal, and Venkatachalam 2007; Cohen, Dey, Lys, and Sunder 2007; Brav, Heaton, and Li 2010; Hirshleifer, Teoh, and Yu 2011).
- Baker and Wurgler (2006) summarize the literature arguing that stocks with higher return volatility are more likely to be subject to waves of investor sentiment.

APPENDIX B

Definition of Variables

Panel A: Stock Return Volatility Variables (Firm-Level)

Variable		Definition	Reference
Inverse synchronicity	Φ	$\ln(1 - R^2)/R^2$, and R^2 is the average of monthly R^2s estimated from the market model (CAPM) for firm *i* in fiscal year *t*. We exclude firm-year observations with fewer than 12 trading days for each month and fewer than 12 months for fiscal year *t*.	Hutton et al. (2009)
Idiosyncratic volatility	σ_e^2	Average monthly variance of excess returns for firm *i* in fiscal year *t*. Monthly variance of excess returns is computed as the sample variance of daily excess returns adjusted for the expected returns of the market model (CAPM), multiplied by the number of trading days in the month. We exclude firm-year observations with fewer than 12 trading days for each month and fewer than 12 months for fiscal year *t*. $\ln[\sigma_e^2]$ is the natural logarithm of σ_e^2.	Rajgopal and Venkatachalam (2011)
Systematic volatility	σ_S^2	Average monthly variance of expected returns for firm *i* in fiscal year *t*. Monthly variance of expected returns is computed as the sample variance of expected returns of the market model (CAPM), multiplied by the number of trading days in the month. We exclude firm-year observations with fewer than 12 trading days for each month and fewer than 12 months for fiscal year *t*. $\ln[\sigma_S^2]$ is the natural logarithm of σ_S^2.	
Beta squared	β^2	Average monthly beta squared for firm *i* in fiscal year *t*. Monthly beta squared is the square of market beta estimated from the market model (CAPM) using daily returns in the month. We exclude firm-year observations with fewer than 12 trading days for each month and fewer than 12 months for fiscal year *t*. $\ln[\beta^2]$ is the natural logarithm of β^2.	
Market volatility	σ_{rm}^2	Average monthly variance of market returns. Monthly market variance is computed as the variance of market returns multiplied by the number of trading days in the month. $\ln[\sigma_{rm}^2]$ is the natural logarithm of σ_{rm}^2.	

Panel B: Financial Reporting Quality Variables (Firm-Level)

Variable		Definition	Reference
Accruals quality	*DD*	Standard deviation of abnormal accruals estimated from a modified Dechow and Dichev (2002) model for firm *i* over years $t-4$ through *t*.	Rajgopal and Venkatachalam (2011)

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APPENDIX B (continued)

Variable		Definition	Reference
		$TCA_{it} = \varphi_0 + \varphi_1 CFO_{it-1} + \varphi_2 CFO_{it} + \varphi_3 CFO_{it+1} + \varphi_4(\Delta REV_{it} - \Delta AR_{it}) + \varphi_5 PPE_{it} + \nu_{it}$, where TCA_{it} is the total current accruals (using the cash flow statement method after 1988 and the balance sheet method before 1988); CFO_{it} is the cash flow from operations; ΔREV_{it} is the change in total revenue; ΔAR_{it} is the change in accounts receivable; PPE_{it} is the value of property, plant, and equipment; and all variables in the equation are deflated by lagged total assets. We estimate the following model for every firm-year in each of the 49 Fama and French (1997) industry groups for which we require at least 20 firms in year t.	
Average of Absolute Value of Abnormal Accruals	*OPAQUE*	Three-year moving average of the absolute value of abnormal accruals from a modified Jones (1991) model. $TA_{it} = \delta_0 + \delta_1(\Delta REV_{it} - \Delta AR_{it}) + \delta_2 PPE_{it} + \delta_3 ROA_{it} + \eta_{it}$, where TA_{it} is the total accruals (using the cash flow statement method after 1988 and the balance sheet method before 1988); ΔREV_{it} is the change in total revenue; ΔAR_{it} is the change in accounts receivable; PPE_{it} is the value of property, plant, and equipment; ROA_{it} is return on assets; and all variables other than ROA_{it} in the equation are deflated by lagged total assets. We estimate the following model for every firm-year in each of the 49 Fama and French (1997) industry groups for which we require at least 20 firms in year t.	Hutton et al. (2009)

Panel C: Firm-Level Control Variables

Variable		Definition	Reference
Firm size	*SIZE*	Natural logarithm of market capitalization (market value of equity = PRCC_F × CSHO).	Rajgopal and Venkatachalam (2011); Hutton et al. (2009)
Market-to-Book Ratio	*M/B*	Fiscal-year-end market value of equity over fiscal-year-end book value of equity = (PRCC_F × CSHO)/(CEQ + TXDITC).	Rajgopal and Venkatachalam (2011); Hutton et al. (2009)
Leverage	*LEV*	Ratio of long-term debt to total assets = (DLTT + DLC)/AT.	Rajgopal and Venkatachalam (2011); Hutton et al. (2009)
Operating cash flows	*CFO*	[earnings before extraordinary items (IB) − total accruals (balance sheet method)]/total assets (AT), before year 1988; [OANCF (cash flow statement method)]/total assets (AT), after 1988.	Rajgopal and Venkatachalam (2011)

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APPENDIX B (continued)

Variable		Definition	Reference
Cash flow volatility	*VCFO*	Standard deviation of operating cash flows scaled by total assets over the trailing five-year window.	Rajgopal and Venkatachalam (2011)
Stock return performance	*RET*	Contemporaneous buy-and-hold returns for firm *i* in fiscal year *t*.	Rajgopal and Venkatachalam (2011)
Analyst following	*NANAL*	Number of analysts determining the consensus forecast subsequent to the fiscal year. When analyst following is not available for the pre-I/B/E/S time period, we set it to 0 (prior to 1975).	Rajgopal and Venkatachalam (2011)
Analyst forecast revision	$FREV^2$	Squared forecast revision computed as the first available median consensus one-year-ahead earnings forecast following three months after the fiscal year-end minus the two-year-ahead earnings forecast available following three months after the previous fiscal year-end. When analyst data are not available for the pre-I/B/E/S time period, we set the variable to 0 (prior to 1975).	Rajgopal and Venkatachalam (2011)
Institutional ownership	*INST*	Average percentage of institutional ownership during the fiscal year. For years prior to 1979 when data on institutional ownership are not available, we set *INST* to 0.	Rajgopal and Venkatachalam (2011)
Return on equity	*ROE*	Return on equity = earnings before extraordinary items (IB) scaled by lagged book value of equity (CEQ + TXDB).	Hutton et al. (2009)
Return skewness	*Skewness*	Average monthly skewness of firm-specific daily returns for firm *i* in fiscal year *t*. Firm-specific daily return is equal to ln(1 + daily excess return), where daily excess return is adjusted for the expected return of the market model (CAPM).	Hutton et al. (2009)
Return kurtosis	*Kurtosis*	Average monthly kurtosis of firm-specific daily returns for firm *i* in fiscal year *t*. Firm-specific daily return is equal to ln(1 + daily excess return), where daily excess return is adjusted for the expected return of the market model (CAPM).	Hutton et al. (2009)
Variance of industry index	*Var*(*Industry*)	Average monthly variance of the industry returns during the firm's fiscal year. Monthly variance of industry returns is calculated as the sample variance of value-weighted daily industry returns (two-digit SIC codes), multiplied by the number of trading days in the month.	Hutton et al. (2009)

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APPENDIX B (continued)

Panel D: Information Environment Variables (Firm-Level)

Variable		Definition	Reference
Illiquidity Measure	*ILLIQ*	Average daily price impact of trade measured as |RET × 100|/(PRC × VOL/1,000), where RET is the daily return, PRC is the stock price, and VOL is the daily trading volume.	Amihud (2002)
Volatility of liquidity	*LIQVOL*	Annual standard deviation of the daily *ILLIQ* measure.	Lang and Maffett (2011)
PIN	*PIN*	Probability of informed trading as measured in Easley et al. (2002).	
Bid-ask spread	*SPREAD*	Average daily bid-ask spread in a fiscal year = |ASK − BID|/PRC, where ASK is the daily closing ask price, BID is the daily closing bid price, and PRC is the stock price.	
Zero return days	*ZRDAYS*	The ratio of zero return days to total number of trading days in a fiscal year.	
Price delay	*DELAY*	$R_{it} = \alpha_i + R_{m,t} + \Sigma_{n=1 \text{ to } 4}\delta_{i,n}R_{m,t-n} + \varepsilon_{i,t}$, where R_{it} is the weekly return on stock i; and $R_{m,t}$ is the weekly market return. The equation is estimated for each firm-year as above (unrestricted regression), with the restriction that all $\delta_{i,n}$ are 0 (restricted regression). Price delay is calculated as 1 minus the ratio of the restricted to the unrestricted R^2. *DELAY* $= 1 - (R^2_{restricted}/R^2_{unrestricted})$. We exclude firm-year observations with fewer than 20 weekly returns in year t.	Hou and Moskowitz (2005); Callen et al. (2012)

Panel E: Variables for the Global Analysis (Country-Level)

Variable		Definition	Reference
Inverse synchronicity	Φ	$\ln[(1 - R_j^2)/R_j^2]$, where R_j^2 is the country-level median of R_i^2s for all firms in country j and year t; and R_i^2 is the average monthly R^2s from the market model (CAPM) for firm i. We exclude firm-year observations with fewer than 12 trading days for each month and fewer than 12 months for year t.	Morck et al. (2000)
Idiosyncratic volatility	σ_e^2	Country-level median of variance of excess returns for all firms in country j and year t, where σ_{ei}^2 is the average monthly variance of excess returns that is multiplied by the number of trading days in the month from the market model (CAPM) for firm i. We exclude firm-year observations with fewer than 12 trading days for each month and fewer than 12 months for year t. $\ln[\sigma_e^2]$ is the natural logarithm of σ_e^2.	

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APPENDIX B (continued)

Variable		Definition	Reference
Systematic volatility	σ_S^2	Country-level median of variance of expected returns for all firms in country j and year t, where σ_{Si}^2 is the average monthly variance of expected returns that is multiplied by the number of trading days in the month from the market model (CAPM) for firm i. We exclude firm-year observations with fewer than 12 trading days for each month and fewer than 12 months for year t. $\ln[\sigma_S^2]$ is the natural logarithm of σ_S^2.	
Beta squared	β^2	Country-level median of beta squared in country j and year t, where beta squared is the square of average monthly market beta estimated from the market model (CAPM) using daily returns for firm i. We exclude firm-year observations with fewer than 12 trading days for each month and fewer than 12 months for year t. $\ln[\beta^2]$ is the natural logarithm of β^2.	
Market volatility	σ_{rm}^2	Country-level weighted average of variance of market returns in country j and year t. Specifically, σ_{rm}^2 is the average monthly variance of excess returns that is multiplied by the number of trading days. $\ln[\sigma_{rmw}^2]$ is the natural logarithm of σ_{rmw}^2.	
Log per capita GDP	$\ln(pcGDP)$	Natural logarithm of per capita GDP for each country j at year t. The data on per capita GDP are obtained from the Word Bank.	
Log number of listed firms	$\ln(Firm\#)$	Natural logarithm of the number of listed firms for each country j at year t.	
Log geographical size	$\ln(Area)$	Natural logarithm of geographical size (squared kilometers) for each country j at year t. The data on geographical size are obtained from the Word Bank.	
Variance in GDP growth	$Var(GDPgr)$	Variance of per capita GDP growth for each country, with per capita GDP measured in nominal U.S. dollars, estimated using a five-year rolling window for each country j at year t. The data on per capita GDP growth are obtained from the Word Bank.	
Industry Herfindahl index	*indHerf*	$H_j = \sum_k h_{k,j}^2$, where $h_{k,j}$ is the combined value of the sales of all country j firms in industry k as a percentage of those of all country j firms.	
Firm Herfindahl index	*firmHerf*	$\hat{H}_j = \Sigma_i \hat{h}_{i\in j}^2$, where $\hat{h}_{i,j}^2$ is the sales of firm i as a percentage of the total sales of all country j firms.	
Earnings co-movement index	*Comove*	$Comove = \frac{\Sigma_i R_{i,j}^2(ROA) \times SST_{i,j}(ROA)}{\Sigma_i SST_{i,j}(ROA)}$, where $R_{i,j}^2(ROA)$ is the R^2 and $SST_{i,j}(ROA)$ is the sum of squared total variations estimated from the following equation for country j and year t. $ROA_{i,j} = \alpha_i + b_i ROA_{m,j} + \varepsilon_{i,j}$, where $ROA_{i,j}$ is a firm's return on assets and $ROA_{m,j}$ is the value-weighted average of the return on assets for all firms in the country j and year t. The equation is estimated using a five-year rolling window for each firm i in each country j at year t.	

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APPENDIX B (continued)

Variable		Definition	Reference
Good government index	*GoodGov*	The government corruption index from La Porta et al. (1999) ranges from 0 to 10. Notice that Morck et al. (2000) also use two other indices that are no longer available in the published version of La Porta et al. (1999).	
Anti-director rights index	*AntiDir*	A scorecard of shareholders' rights against directors in various countries compiled by La Porta et al. (1998), ranging from 0 to 6.	