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Consistency as a Means to Comparability: Theory and Evidence

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Abstract. This paper studies financial statement consistency — the purported means to comparability — from an information perspective. We model consistency as firms' required propensity to apply common accounting methods to individual transactions and show that consistency creates information spillover through correlated measurements ("spillover channel") while potentially reducing the informativeness of one's own report ("standalone channel"). The model generates two central predictions. First, optimal consistency decreases with a transaction's fundamental correlation as high correlation diminishes information gains via the spillover channel. Second, optimal consistency decreases with a transaction's fundamental volatility as high volatility exacerbates information losses via the standalone channel. Empirical evidence supports both predictions. Overall, this paper contributes a framework for studying comparability and draws useful policy implications.

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1. Introduction

Across the globe, accounting regulators, educators, and practitioners repeatedly stress the role of comparability in enhancing the usefulness of financial statements because comparable reporting supposedly provides more information and facilitates decision making (e.g., Statement of Financial Accounting Concepts (SFAC) No. 8, 2010). Despite its perceived importance, comparability remains an elusive concept. Sunder (2010) explains that comparability is intrinsically difficult to conceptualize because identifying like/different things is tricky given the multifaceted nature of business transactions. To help reporting entities grasp the concept of comparability, the Financial Accounting Standards Board (FASB) points to "consistency" as a definitive means to achieve comparability, with consistency defined as the use of the same accounting methods across entities and time periods (SFAC No. 8 Q22 and Q25, 2010, p.19).[1] This paper aims to lay out the theoretical underpinnings of comparability via consistency, the purported means to comparability. In taking this important first step, the paper seeks to address the following questions: How should we model consistency? What are the information benefits and costs of consistent reporting? When does consistent reporting improve the informativeness of financial statements?

We start by building a one-period, multitransaction model of consistency, which focuses on its cross-sectional property (i.e., the propensity to require the same methods across entities in a single period).[2] The model features a standard setter and two firms that may each engage in multiple transactions. The standard setter (e.g., the FASB in the United States) establishes accounting policies at the transaction level to maximize the aggregate informativeness of two firms' reports (or to minimize the conditional variance of the transaction's economic fundamentals). In setting the policy for each transaction, the standard setter prescribes a common accounting method for both firms but also allows them to use an idiosyncratic method. He or she then chooses the extent to which the two firms are required to adopt the common method. The standard setter's propensity to require firms' adoption of the common method (as opposed to an idiosyncratic method) represents our key theoretical construct of interest, financial statement consistency (or consistency for brevity). Alternatively, one may view this construct as the extent of consistency required in the application of a single permissible accounting method for a given transaction. We further discuss this point in Section 2.1.

The model illustrates two effects of consistency on informativeness. When firms adopt a common method to account for a type of transaction, one firm's report of its earnings from the transaction becomes more informative about another firm's fundamental cash flows from the transaction through correlated accounting measurements. For this reason, consistency can indeed increase informativeness of firms' reports. We refer to this effect of consistency as the "spillover channel." However, a high level of consistency also requires a firm to use a common method even when an idiosyncratic method is more informative about the firm's own cash flows. As a result, consistency potentially decreases the informativeness of the firms' own report. We refer to this effect of consistency as the "standalone channel." At the optimal level of consistency, the two effects offset each other, and informativeness is maximized.[3]

We draw two predictions from the model. First, for each type of transaction, the level of optimal consistency should decrease as firms' fundamental cash flows from the transaction become more correlated. Although the information spillover that we focus on is through firms' correlated accounting measurements (which are affected by consistency), firms' reports are also informative about one another's cash flows through correlated fundamentals themselves. As the correlation between firms' cash flows increases, financial statement users can rely more on this correlation and less on the correlation between firms' accounting measurements, thus reducing the information gains from increasing consistency via the spillover channel. As such, the prediction also speaks to the accrual versus cash accounting debate, as accrual accounting can be more informative about firm fundamentals when firms' cash flows are less correlated (e.g., due to some firms permitting credit sales and others not).

Second, the level of optimal consistency should decrease as firms' fundamental cash flows from a transaction become more volatile. If a firm has volatile cash flows, financial statement users have a very imprecise prior and need to rely more on the firm's individual report to infer fundamentals. This increases the benefits of firms using idiosyncratic accounting methods that are potentially more informative, and thus the costs of consistency via the standalone channel. As suggestive evidence in favor of this prediction, Black et al. (2020) showed that firms are more likely to deviate from sector norms in their non-GAAP reporting when they tend to incur nonrecurring items that drastically change between years and that these deviations are primarily for informative reasons.

In testing these predictions, we focus on two broad sets of transactions: those related to sales and those related to cost of sales. To parallel the model, we adapt the De Franco et al. (2011) (hereafter DKV) measure to capture transaction level consistency. In our model, firms' earnings reports contain information about cash flows from transactions, but the realizations of these cash flows are unknown at the time of the reports. We thus reconstruct the DKV measure to evaluate firms' similarity in their mapping between sales revenue-to-asset ratio of a given quarter and cash collected from customers-to-asset ratio of the same quarter next year and firms' similarity in their mapping between cost of sales-to-asset ratio of a given quarter and their cash paid to suppliers-to-asset ratio of same quarter next year, both over the past 12 quarters. We denote the two resulting measures revenue recognition consistency and cost recognition consistency, respectively. We prove that both measures strictly increase with firms' required propensity to adopt common accounting methods within our analytical framework. Because these measures build on the idea that consistency is a path to comparability, we refer to them as measures of consistency or consistency-based comparability interchangeably throughout the paper.

The first prediction concerns how optimal consistency varies with a transaction's fundamental correlation. For revenue-related transactions, we measure fundamental correlation as the average correlation coefficient between the cash collected from customers-to-asset ratio of the firm and those of the same industry peers used in the calculation of revenue recognition consistency. For cost-related transactions, we measure fundamental correlation as the average correlation coefficient between the cash paid to suppliers-to-asset ratio of the firm and those of the same industry peers used in the calculation of cost recognition consistency. We calculate both measures over the past 20 quarters for each firm-year using cash flows from the same quarter next year.

Using a sample of U.S. firms from 1996 to 2016, we observe a negative association between consistency and fundamental correlation for both revenue- and cost-related transactions. This association is robust to controlling for firm characteristics, industry, and year fixed effects as well as firm fixed effects. In the specifications that include firm and year fixed effects, a one-standard deviation increase in fundamental correlation of revenue-related transactions is associated with a 3.4% decrease in revenue recognition consistency, and a one-standard deviation increase in fundamental correlation of cost-related transactions is associated with a 2.3% decrease in cost recognition consistency relative to consistency's standard deviation. The magnitude of this association is sizable, as it is comparable to the magnitude of the association between consistency and book to market, an important firm characteristic. This result supports the first model prediction that the optimal level of consistency decreases with fundamental correlation, because the information benefits of consistency-based comparability dissipate when firms' fundamental cash flows from a transaction are highly correlated.

The second prediction concerns how optimal consistency varies with a transaction's fundamental volatility. We measure each firm-year's fundamental volatility as the variance of the firm's cash collected from customers-to-asset ratio for revenue-related transactions and the variance of the firm's cash paid to suppliers-to-asset ratio for cost-related transactions over the past 20 quarters.[4] We observe a negative association between consistency and fundamental volatility. A one-standard deviation increase in fundamental volatility of revenue-related transactions is associated with a 17.6% decrease in revenue recognition consistency, and a one-standard deviation increase in fundamental volatility of cost-related transactions is associated with a 25.3% decrease in cost recognition consistency, relative to consistency's standard deviation in the sample. This association is even more economically impactful, as its magnitude is nearly comparable to the magnitude of the association between consistency and firm size, arguably the most defining firm characteristic. This result supports the second model prediction that the optimal level of consistency decreases with fundamental volatility, because the information costs of consistency-based comparability increase when firms' fundamental cash flows from a transaction are more volatile.

Finally, we study the relation between informativeness of accounting reports and consistency. We rely on the implied volatility from standardized option prices immediately following an earnings announcement as a measure of firm information uncertainty (the inverse of informativeness) and link it to consistency. We form four subsamples based on two-way sorting of firms' fundamental correlation and volatility. We find a strong negative association between implied volatility and consistency in the subsample with both fundamental correlation and volatility below the sample median. In this subsample, a one-standard deviation increase in firm level consistency is associated with a 9.8% decrease in implied volatility relative to its standard deviation. The association weakens in other subsamples. In fact, it becomes insignificant in the subsample with both fundamental correlation and volatility above the sample median. Combined, these results support our model predictions and point to a nonlinear relation between implied volatility and consistency, which is consistent with the existence of two offsetting information channels.

This study makes three contributions to the literature. First, we provide one analytical view of financial statement comparability. Comparability is listed among the most desirable characteristics of financial reporting but is generally overlooked in the theoretical literature. This is partly because comparability is theoretically ambiguous, and its common notion (i.e., a reporting characteristic that enables like things to look alike and different things to look different) is difficult to conceptualize and operationalize (Sunder 2010). Practically, standard setters frequently employ consistency as a means to achieve comparability both within the United States (see, e.g., Jiang, Wang, and Wangerin 2018) and outside the United States (e.g., the adoption of International Financial Reporting Standards in the European Union). Thus, theorizing about and examining consistency — the closest concept to comparability — is a necessary first step to developing a better understanding of comparability.

Our approach is related to but distinct from that in Wang (2015). We define consistency-based comparability as firms' required propensity to apply common accounting methods, whereas Wang (2015) defined comparability as the correlation between firms' measurement errors. Our model further differs from Wang's (2015) in two important aspects. First, we examine a simultaneous reporting model, whereas Wang (2015) examines a model in which firms report sequentially. Second, players are fully rational in our model; they use all firms' earnings reports in estimating terminal cash flows. In contrast, Wang (2015) made two behavioral assumptions that investors use only a firm's own report in pricing and that investors care about short-term prices rather than terminal cash flows. Our definition of consistency is also distinct from the notion of uniformity that prior theories have studied (see, e.g., Dye and Verrecchia 1995, Dye and Sridhar 2008, and Chen et al. 2017). Although both concepts involve firms' use of accounting methods, consistency emphasizes the propensity required of firms to adopt common methods, whereas uniformity refers to the rigidity of the range of admissible methods.[5]

Second, our model serves as a bridge linking various measures developed in the burgeoning empirical literature that examines the determinants and economic consequences of comparability. Whereas earlier studies in this literature mostly used input-based measures (see, e.g., Ashbaugh and Pincus 2001, Young and Guenther 2003, Bradshaw et al. 2004, Bae et al. 2008, and Bradshaw and Miller 2008), recent studies turn to output-based measures (see, e.g., DKV 2011, Barth et al. 2012, and Fang et al. 2015). Both sets of measures have pros and cons. Although output-based measures are easier to construct (DKV), they are more difficult to interpret (Klein 2018). Our model lays a brick in the foundational walls of this literature by reconciling input- and output-based measures. It shows that an adapted DKV measure at the transaction level can indeed capture the degree of consistency in firms' use of accounting methods. It also shows that using the DKV measure at the firm level requires more stringent assumptions, which we discuss in Section 3.1. These insights are useful in assisting future researchers in choosing the appropriate measures to capture comparability.

Finally, our model allows us to evaluate whether increasing comparability via consistency indeed serves the FASB's stated objective of general purpose financial reporting, which is to provide decision useful information to financial statement users. The model formally identifies one information benefit of consistency-based comparability, that is, spillover through correlated accounting measurements, which is often intuitively described in prior studies.[6] However, the model also highlights one information cost of consistency-based comparability; that is, it potentially impairs the informativeness of firms' own reports. The two information effects offset each other and give rise to an optimal level of consistency. We demonstrate that this level decreases with fundamental correlation and fundamental volatility of economic transactions both analytically and empirically.

2. A Model of Consistency

2.1. Model Setup and the Definition of Consistency

We set up a one-period reporting game that features an accounting standard setter and two firms (indexed by $i \in \{1,2\}$). Both firms conduct multiple transactions. The standard setter sets policies that regulate firms' accounting measurements for individual transactions. We structure the model this way to mirror the typical standard setting process, as most accounting rules are written at the transaction level.[7]

Firms' terminal cash flows are determined by their transactions. There are N types of transactions (indexed by $j \in \{1,2,\ldots,N\}$). We denote the amount of cash flows contributed by one unit of transaction j to firm i's terminal cash flows as v_i^j and the units of transaction j that firm i conducts as x_i^j, where $x_i^j \geq 0$. The total cash flows for firm i are thus

$$V_i = \sum_{j=1}^{N} x_i^j v_i^j. \tag{1}$$

We assume that firms' per-unit cash flows from transaction j, v_1^j and v_2^j, are drawn from a normal distribution with mean $\bar{v}^j$ and variance $(\sigma_v^j)^2$. We also assume that v_1^j and v_2^j are correlated with coefficient $\rho_v^j \in [-1,1]$. Thus, transaction j can be characterized by the set of parameters $\{\bar{v}^j, \rho_v^j, (\sigma_v^j)^2\}$. For simplicity, we further assume that cash flows from different transactions are uncorrelated, that is, $cov(v_i^j, v_{i'}^{j'}) = 0$ for $j \neq j'$.

Firm i discloses an earnings report $r_i^j = v_i^j + \varepsilon_i^j$ about the amount of cash flows that it generates from each unit of transaction j. The term ε_i^j represents measurement noise in the firm's reporting system. It depends on the accounting methods that firm i uses, which are regulated by the standard setter. For simplicity, we assume that for each type of transaction, there are two available accounting methods. *Method A* is consistent across firms and generates a common measurement noise δ^j for both firms, and *method B* is firm specific and generates an idiosyncratic measurement noise η_i^j. Both δ^j and η_i^j are normally distributed, with mean zero and variance $(\sigma_\delta^j)^2$ and $(\sigma_\eta^j)^2$, respectively. We assume that noises are independent of each other and also independent of all v_i^j.

For each transaction j, the standard setter sets a rule that governs the portion of the transaction that the firms must account for using *method A*; we denote this portion m^j. Given the standard setter's choice of m^j, we write the total measurement noise of firm i's report about transaction j as[8]

$$\varepsilon_i^j = m^j \delta^j + (1 - m^j)\eta_i^j, m^j \in [0,1]. \tag{2}$$

The variable m^j, which reflects the standard setter's propensity to require firms' adoption of the common method (as opposed to an idiosyncratic method), represents our key theoretical construct of interest, consistency, or consistency-based comparability. In practice, some transactions can only be accounted for using a single method. For such transactions, one may interpret m^j as a measure of consistency in firms' application of the permissible method.[9]

We assume that in setting consistency, $\{m^j\}_{j=1}^N$, the standard setter maximizes reporting precision or the aggregate informativeness of firms' reports, $\{r_1^j, r_2^j\}_{j=1}^N$. This is equivalent to minimizing the aggregate conditional variance of firms' cash flows, V_i:

$$\{m^{j*}\}_{j=1}^N = \arg\min_{\{m^j\}_{j=1}^N} \sum_{i=1}^{2} var\left(V_i \middle| \left\{r_1^j, r_2^j, m^j\right\}_{j=1}^N\right). \tag{3}$$

This function assumes that the standard setter seeks to maximize reporting precision. It reflects the information perspective that we take in analyzing consistency and the objective of general purpose financial reporting, which is to "provide financial information about the reporting entity that is useful to existing and potential investors, lenders, and other creditors in making decisions about providing resources to the entity." (SFAC No. 8, 2010, p.1). We further discuss the microfoundation for this function in the online appendix.

2.2. Discussion of Model Assumptions

In building the model, we borrow a key assumption from the aggregation literature that a firm's accounting report is an aggregate of the measurements that result from the firm's application of all accounting methods. The aggregation literature recognizes that financial reporting is a process of collecting accounting inputs within each category and then summing up these inputs. A main insight from this literature is that although aggregation leads to some information loss, it can also generate information benefits, such as permitting measurement errors to offset each other (see, e.g., Arya et al. 2006, Caskey and Hughes 2011, Fan and Zhang 2012, Beyer 2013, and Bertomeu and Marinovic 2016). Building on this insight, we model the information outcomes of aggregating accounting measurements from a mix of common and idiosyncratic methods.

Several other model assumptions also warrant discussion. First, we assume that cash flows are uncorrelated across different transactions. One can potentially relax this assumption by allowing cash flows to be correlated across different transactions of the same firm, given that these transactions are all impacted by the firm's management and overall business environment. In this extension, requiring a higher level of consistency, m^j, likely brings additional information benefits because accounting reports about one of a firm's transactions generate information not only about cash flows from the same transaction of other firms but also about cash flows from different transactions of other firms through the cross-transaction correlation within the same firm.

Second, we assume that measurement noises that result from the application of the common and idiosyncratic methods, δ^j and η_i^j, are independent of each other as well as cash flows v_i^j. As in prior theories (see, e.g., Dye and Sridhar 2008 and Chen et al. 2017), we make these assumptions to simplify our analysis, but the implications that we draw on the determinants of consistency are likely to be valid if we relax the assumptions.[10]

Third, although we assume that δ^j, measurement noise from applying the common method, is the same for both firms, we verify that our model predictions hold qualitatively even if measurement noise from this method differs across firms (i.e., $\delta_1^j \neq \delta_2^j$) as long as δ_1^j and δ_2^j are positively correlated.[11]

Fourth, we also assume that measurement noise from applying the idiosyncratic method, η_i^j, is independent across firms. This assumption is made for simplicity, and we verify that our model predictions hold qualitatively even if measurement noises from the idiosyncratic methods are correlated as long as the correlation between η_i^j is not perfect. Detailed proofs are in Proposition 4 of Appendix A.

Finally, we note that the optimal consistency, m^{j*}, solved in our model represents a local optimum. This optimum balances two specific information channels that we explain below. As such, it does not condition on other potential benefits and costs of accounting methods and/or other qualitative characteristics of financial reporting. For example, our model abstracts away from an important characteristic of financial reporting, bias. Introducing a constant bias into firms' reports (as in Stein 1989) does not alter our inferences below because such bias is unraveled and has no effect on reporting precision. Introducing a random bias (see, e.g., Dye and Sridhar 2004) does allow the bias to influence reporting precision. To the extent that the effect of consistency on bias is at least partly orthogonal to the effects of consistency on reporting precision that we model, our inferences remain valid.

2.3. Model Analysis and Empirical Implications

To solve the model, we first simplify the standard setter's objective function in Equation (3). Plugging in the expression that $V_i = \sum_{j=1}^{N} x_i^j v_i^j$, we obtain

$$var\left(V_i \middle| \left\{r_1^j, r_2^j, m^j\right\}_{j=1}^N\right) = var\left(\sum_{j=1}^{N} x_i^j v_i^j \middle| \left\{r_1^j, r_2^j, m^j\right\}_{j=1}^N\right) = \sum_{j=1}^{N}\left(x_i^j\right)^2 var\left(v_i^j \middle| \left\{r_1^j, r_2^j, m^j\right\}_{j=1}^N\right). \quad (4)$$

The second step uses the assumption that v_i^j are uncorrelated with each other. As such, only the reports that measure transaction j's cash flows, $\{r_1^j, r_2^j\}$, contain information about v_i^j, and only the accounting rule that governs the measurement of transaction j, m^j, matters for $var(v_i^j|\{r_1^j, r_2^j\}_{j=1}^N)$. We thus obtain

$$var\left(v_i^j \middle| \left\{r_1^j, r_2^j, m^j\right\}_{j=1}^N\right) = var\left(v_i^j \middle| r_1^j, r_2^j, m^j\right). \quad (5)$$

For the standard setter to minimize the aggregate conditional variance, it is equivalent for him or her to individually choose m^j for each of the N transactions that minimizes conditional variance $var(v_i^j|r_1^j, r_2^j, m^j)$. Because v_1^j and v_2^j are symmetric, it is without loss of generality to assume that the standard setter minimizes the conditional variance of a single v_i^j. That is,

$$m^{j*} = \arg\min_{m^j} var(v_i^j|r_1^j, r_2^j, m^j). \quad (6)$$

With the analysis above, we now solve for the optimal $m^{j*}(\rho_v^j, (\sigma_v^j)^2)$ for a representative single transaction. Taking the derivative of $var(v_i^j|r_1^j, r_2^j, m^j)$ with respect to m^j gives the first order condition (F.O.C.):

$$\frac{dvar(v_i^j|r_1^j, r_2^j, m^j)}{dm^j} = \frac{\partial var(v_i^j|r_1^j, r_2^j, m^j)}{\partial \sigma_{\varepsilon_1\varepsilon_2}^j}\frac{\partial \sigma_{\varepsilon_1\varepsilon_2}^j}{\partial m^j} + \frac{\partial var(v_i^j|r_1^j, r_2^j, m^j)}{\partial\left(\sigma_\varepsilon^j\right)^2}\frac{\partial\left(\sigma_\varepsilon^j\right)^2}{\partial m^j} = 0. \quad (7)$$

The F.O.C. depicts two channels through which consistency affects the conditional variance of firm i's report about transaction j. The first term of the solution to $\frac{dvar(v_i^j|r_1^j, r_2^j, m^j)}{dm^j}$ shows that an increase in m^j affects

$var(v_i^j|r_1^j, r_2^j, m^j)$ through $\sigma^j_{\varepsilon_1\varepsilon_2}$, the covariance between two measurement noises. The second term shows that such an increase affects $var(v_i^j|r_1^j, r_2^j, m^j)$ through $(\sigma^j_\varepsilon)^2$, which is negatively related to firms' own reporting precision of transaction *j*. We label the two effects of consistency on reporting precision, the spillover channel and the standalone channel, respectively. Proposition 1 of Appendix A proves that there exists a unique m^{j*} that solves the F.O.C. Given m^{j*}, the two effects of consistency exactly offset each other, and reporting precision of transaction *j* is maximized.

To better understand the intuition behind the two effects, first consider the case in which ρ^j_ε, the correlation coefficient of measurement noises, exceeds ρ^j_v, the correlation coefficient of fundamental cash flows. With $\rho^j_\varepsilon > \rho^j_v$, $var(v_i^j|r_1^j, r_2^j, m^j)$ decreases with ρ^j_ε (i.e., $\frac{\partial var(v_i^j|r_1^j, r_2^j, m^j)}{\partial \sigma^j_{\varepsilon_1\varepsilon_2}} < 0$) because a higher ρ^j_ε allows one to better infer v_i^j through more correlated noises. Because ρ^j_ε strictly increases with m^j (i.e., $\frac{\partial \sigma^j_{\varepsilon_1\varepsilon_2}}{\partial m^j} > 0$), the first term of the solution to $\frac{dvar(v_i^j|r_1^j, r_2^j, m^j)}{dm^j}$ is negative. The first term thus points to a beneficial role of consistency. It potentially enhances the usefulness of financial reporting by making firms' earnings reports more informative about one another's fundamentals.

However, increasing consistency is not costless. If we mute the spillover effect, there exists an optimal level of m^j that minimizes individual firms' reporting precision of transaction *j*. Intuitively, using a mix of common and idiosyncratic methods improves reporting precision, which is essentially a diversification benefit that underlies a portfolio approach. Under the assumption that δ^j and η^j_i are independent of each other, this diversification benefit arises regardless of how their variances compare with each other.[12]

With the spillover effect considered, the optimal level of m^j that minimizes the conditional variance is beyond the level that minimizes individual firms' reporting precision of transaction *j*. As a result, $(\sigma^j_\varepsilon)^2$ increases with m^j, or $\frac{\partial (\sigma^j_\varepsilon)^2}{\partial m^j} > 0$. Because $var(v_i^j|r_1^j, r_2^j, m^j)$ strictly increases with $(\sigma^j_\varepsilon)^2$ (i.e., $\frac{\partial var(v_i^j|r_1^j, r_2^j, m^j)}{\partial (\sigma^j_\varepsilon)^2} > 0$), the second term of the solution to $\frac{dvar(v_i^j|r_1^j, r_2^j, m^j)}{dm^j}$ is positive. Thus, this term highlights a potential cost of consistency. This cost arises because a higher m^j, while increasing the precision of firms' earnings reports through the spillover channel, limits the use of firm-specific accounting measurements that potentially increase the precision of individual firms' own reports of transaction *j*. Detailed proofs are in Proposition 2 of Appendix A.

When the spillover effect and standalone effect exactly offset each other, consistency reaches its optimal level. We draw two predictions on how the optimal level of consistency, m^{j*}, varies with two key transaction level characteristics, ρ^j_v and $(\sigma^j_v)^2$. First, m^{j*} decreases with ρ^j_v; that is the correlation between firms' fundamental cash flows from transaction *j*. That is, $\frac{\partial m^{j*}}{\partial \rho^j_v} < 0$. To see this, firms' earnings reports of transaction *j* are informative about one another's cash flows from the transaction not only through ρ^j_ε, the correlation between their measurement noises (which we refer to as the spillover channel), but also through ρ^j_v, the correlation between their fundamental cash flows. When ρ^j_v is low, the information gains from increasing consistency are high because financial statement users rely mainly on correlated measurement noises to infer fundamentals through the spillover channel. However, as ρ^j_v increases, this channel becomes less valuable because one can gradually rely more on correlated fundamentals and less on correlated noises to infer fundamentals. As the information benefits of consistency become smaller, the standard setter chooses a lower m^{j*}.

Second, m^{j*} decreases with $(\sigma^j_v)^2$; that is, the volatility of firms' fundamental cash flows from transaction *j*. That is, $\frac{\partial m^{j*}}{\partial (\sigma^j_v)^2} < 0$. Although $(\sigma^j_v)^2$ does not affect the information benefits of consistency via the spillover channel, it does increase the costs of consistency via the standalone channel. This is because when $(\sigma^j_v)^2$ is high, one has a very imprecise prior about v^j_i and relies heavily on the information he or she can learn from the firm's own earnings report of transaction *j*. As discussed earlier, increasing consistency potentially reduces the precision of the firm's own report. Such information losses, if any, are heightened for transactions with higher $(\sigma^j_v)^2$, which points to a lower m^{j*}. Detailed proofs of the two predictions are in Proposition 3 of Appendix A. Building on these predictions, we also prove that, at the equilibrium level of m^{j*}, ρ^j_v and $(\sigma^j_v)^2$ negatively affect consistency's net information benefits, that is, $\frac{\partial}{\partial \rho^j_v}\frac{dvar(v_i^j|r_1^j, r_2^j, m^j)}{dm^j}\big|_{m_j = m_j^*} > 0$ and $\frac{\partial}{\partial (\sigma^j_v)^2}\frac{dvar(v_i^j|r_1^j, r_2^j, m^j)}{dm^j}\big|_{m_j = m_j^*} > 0$.

We note that our empirical analyses are joint tests of the predictions and the underlying assumption of $\rho^j_\varepsilon(m^{j*}) > \rho^j_v$; in particular, the proofs show that $\rho^j_\varepsilon(m^{j*}) > \rho^j_v$ is a sufficient and necessary condition for $\frac{\partial m^{j*}}{\partial (\sigma^j_v)^2} < 0$ (the comparative static underlying our second prediction). The assumption of $\rho^j_\varepsilon > \rho^j_v$ seems reasonable because ρ_ε^j is positive by construction, and the true level is likely high because the FASB routinely mandates accounting rules to increase consistency (Jiang et al. 2018), whereas ρ_v^j can be negative. We provide empirical support for the assumption in Section 3.2 below.

It is also noteworthy that although the level of consistency chosen by the standard setter entails information costs, leaving the choice to firms themselves does not necessarily result in the socially optimal outcome. This is because the two channels contain both an informational effect on an individual firm itself and an externality on the other firm. First, consider the spillover channel. When firm 1 increases its use of the common method to increase $\sigma^j_{\varepsilon_1\varepsilon_2}$, this reduces not only the conditional variance of its own report about transaction j but also the conditional variance of firm 2's report about the transaction (a positive externality). Second, consider the standalone channel. When firm 1 decreases its own reporting precision of transaction j, it increases not only its own conditional variance but also the conditional variance of firm 2 (a negative externality). Because firms cannot internalize the externalities that fall upon others, their private choices of consistency that maximize their own reporting precision will not coincide with the socially optimal choices made by the standard setter.

3. Variable Measurement, Data, and Sample

3.1. Measuring Consistency-Based Comparability

Our model defines consistency or consistency-based comparability as m^j, the firm's required propensity to adopt a common accounting method as opposed to an idiosyncratic method. Ideally, we would employ an input-based measure that reflects firms' application of accounting methods to capture m^j. However, as DKV (2011, p. 898) note, "Using these input-based measures can be challenging because researchers must decide which accounting choices to use, how to weight them, how to account for variation in their implementation, etc. In addition, it is often difficult (or costly) to collect data on a broad set of accounting choices for a large sample of firms." Hence, they proposed an output-based measure.[13]

The DKV measure builds on the idea that an accounting system maps economic transactions to financial statement items, and thus two firms' reporting practices are comparable if their accounting systems produce similar accounting figures given the same set of economic transactions. We adapt the DKV measure to the transaction level to gauge its economic foundation. Fitting the DKV measure into our model for transaction j, we obtain

$$r_1^j = f_1\left(v_1^j\right) = v_1^j + \varepsilon_1^j, \tag{8}$$

$$r_2^j = f_2\left(v_2^j\right) = v_2^j + \varepsilon_2^j. \tag{9}$$

Substituting v_1^j, firm 1's economic fundamentals of transaction j, into firm 2's accounting system gives

$$r_1^{\prime j} = f_2\left(v_1^j\right) = v_1^j + \varepsilon_2^j. \tag{10}$$

Then, based on the construction of the DKV measure, we can write it as

$$CB\_COMP_1^j = -E(r_1^{\prime j} - r_1^j)^2 = 2\sigma^j_{\varepsilon_1\varepsilon_2} - \left(\sigma^j_{\varepsilon_1}\right)^2 - \left(\sigma^j_{\varepsilon_2}\right)^2. \tag{11}$$

It is easy to see that $CB\_COMP_1^j$ and $CB\_COMP_2^j$ are symmetric. Thus, Equation (11) gives a mathematical expression of the DKV measure for both firms at the transaction level, which we denote CB_COMP^j.

Our particular interest is in how the DKV measure varies with m^j. Substituting the optimal level of consistency $m^j = m^{j*}$, into Equation (11), we simplify CB_COMP^j as

$$\begin{aligned} CB\_COMP^j &= -E\left(r_1^{\prime j} - r_1^j\right)^2 \\ &= 2(m^{j*})^2\left(\sigma_\delta^j\right)^2 - 2\left[(m^{j*})^2\left(\sigma_\delta^j\right)^2 + (1-m^{j*})^2\left(\sigma_\eta^j\right)^2\right] \\ &= -2(1-m^{j*})^2\left(\sigma_\eta^j\right)^2. \end{aligned} \tag{12}$$

Equation (12) shows that CB_COMP^j fits the notion of consistency-based comparability, as it strictly increases with m^{j*} because $m^{j*} \in [0,1]$. This reasoning justifies the use of a DKV-style measure as an empirical proxy for m^{j*}, at least at the transaction level. We discuss the firm-level DKV measure and how it compares to our transaction level measures in Section 4.2 and the online appendix.

The DKV measure uses stock returns to proxy for firm level economic fundamentals, which are not available at the transaction level. We use future reported cash flows to proxy for transaction level economic fundamentals, v_i^j. In our model, firms' earnings reports, r_i^j, contain information about v_i^j, but the realizations of v_i^j are not known when the reports are released. Future reported cash flows are suitable candidates to proxy for v_i^j because current earnings are informative about future cash flows (see, e.g. Dechow 1994 and Dechow et al. 1998), and the realizations of future cash flows are revealed only at a later time. Based on prior evidence that there exists a strong correlation between the cash flows from quarter q and quarter $q + 4$ (see, e.g., Lorek et al. 1993, Lorek and Willinger 1996, and Lorek and Willinger 2011), we measure v_i^j using cash flows from quarter $q + 4$.[14]

A further challenge is that we observe only aggregated financial statements as opposed to reports of individual transactions. We thus focus our tests on two broad sets of transactions — those related to sales and those related to cost of sales — to move closer to a transaction-level analysis. In doing so, we essentially compute each firm's revenue (cost) recognition consistency or consistency-based comparability measure by aggregating m^j across all types of revenue (cost) transactions weighted by x_i^j, the number of units that the firm engages in each type of transaction j.[15] Even though m^j for transaction j is set by the standard setter to be the same for all firms, our measure varies across firms because each firm i has a different set of x_i^j.

We first adapt the DKV measure to evaluate firms' similarity in their mapping between sales revenue in quarter q and cash collected from customers in quarter $q + 4$. For each firm 1 in year t (and for firm 2 within the same two-digit SIC group as firm 1 in year t), we estimate the rolling-window time-series regressions below:[16]

$$REV_{1,q} = \alpha_1 + \beta_1 CFC_{1,q+4} + \varepsilon_{1,q}, \quad (13)$$

$$REV_{2,q} = \alpha_2 + \beta_2 CFC_{2,q+4} + \varepsilon_{2,q}. \quad (14)$$

The first subscript indexes firm, and the second subscript indexes quarter. The regressions are estimated using each firm's past 12 quarters of data from $q - 11$ to q, with quarter q being Q4 of year t. We require a minimum of 10 quarters of nonmissing data. REV_q is a firm's sales revenue-to-asset ratio in quarter q, which proxies for the quarter's revenue-related earnings, r_i^j, in our model. CFC_{q+4} is the firm's cash collected from customers-to-asset ratio in quarter $q + 4$, which proxies for the quarter's cash flows, v_i^j, from revenue-related transactions in quarter q, as discussed earlier. Specifically, we calculate CFC as sales revenue minus changes in accounts receivable plus changes in unearned revenues, scaled by total assets. The mapping between REV in quarter q and CFC in quarter $q + 4$ takes into account the seasonality in firms' cash flows. Firm financials are from the Compustat quarterly files.

Similar to DKV, we use the estimated coefficients from Equations (13) and (14), $\{\hat{\alpha}_1$ and $\hat{\beta}_1\}$ and $\{\hat{\alpha}_2$ and $\hat{\beta}_2\}$, to proxy for the accounting function that firm 1 and firm 2 apply to revenue-related transactions, respectively. Applying both accounting functions to firm 1's v_i^j from revenue-related transactions, we obtain its fitted revenues in quarter q as

$$RE\hat{V}_{1,1,q} = \hat{\alpha}_1 + \hat{\beta}_1 CFC_{1,q+4}, \quad (15)$$

$$RE\hat{V}_{1,2,q} = \hat{\alpha}_2 + \hat{\beta}_2 CFC_{1,q+4}. \quad (16)$$

The first subscript indexes firm, the middle subscript (if any) indexes accounting function, and the last subscript indexes quarter. Based on the fitted revenues computed above, we define revenue recognition consistency for each pair of firm 1 and firm 2 in year t, $CB\_REVCOMP_{1,2,t}$, as the negative of the average absolute difference between $RE\hat{V}_{1,1,q}$ and $RE\hat{V}_{1,2,q}$ over the 12 quarters from $q - 11$ to q:

$$CB\_REVCOMP_{1,2,t} = -\frac{1}{12}\sum_{q-11}^{q} \mid RE\hat{V}_{1,1,q} - RE\hat{V}_{1,2,q} \mid. \quad (17)$$

Finally, for each firm 1-year t, we calculate the mean of the four largest values of $CB\_REVCOMP_{1,2,t}$. We denote the resulting measure $CB\_REVCOMP$. By construction, larger values of $CB\_REVCOMP$ indicate greater revenue recognition consistency.

We also adapt the DKV measure to evaluate firms' similarity in their mapping between cost of sales in quarter q and cash paid to suppliers in quarter $q + 4$. For each firm 1 and firm 2 in year t, we estimate the following rolling-window time series regressions over the past 12 quarters (requiring a minimum of 10 quarters of nonmissing data):

$$COST_{1,q} = \alpha_1 + \beta_1 CTS_{1,q+4} + \varepsilon_{1,q}, \quad (18)$$

$$COST_{2,q} = \alpha_2 + \beta_2 CTS_{2,q+4} + \varepsilon_{2,q}. \quad (19)$$

Subscripts are as in Equation (13) and Equation (14). $COST_q$ is a firm's cost of sales-to-asset ratio in quarter q, and CTS_{q+4} is the firm's cash paid to suppliers-to-asset ratio in quarter $q + 4$. We calculate $COST$ as cost of goods sold plus changes in inventory and minus changes in accounts payable, scaled by total assets.

Applying the accounting functions estimated from Equations (18) and (19) to firm 1's v_i^j from cost-related transactions, we obtain its fitted cost of sales in quarter q as

$$COS\hat{T}_{1,1,q} = \hat{\alpha}_1 + \hat{\beta}_i CTS_{1,q+4}, \quad (20)$$

$$COS\hat{T}_{1,2,q} = \hat{\alpha}_2 + \hat{\beta}_2 CTS_{1,q+4}. \quad (21)$$

Subscripts are as in Equation (15) and (16). We define cost recognition consistency for each pair of firm 1 and firm 2 in year t, $CB\_COSTCOMP_{1,2,t}$, as the negative of the average absolute difference between $COS\hat{T}_{1,1,q}$ and $COS\hat{T}_{1,2,q}$ over the 12 quarters from q – 11 to q:

$$CB\_COSTCOMP_{1,2,t} = -\frac{1}{12}\sum_{q-11}^{q} |COS\hat{T}_{1,1,q} - COS\hat{T}_{1,2,q}|. \quad (22)$$

Finally, we calculate the mean of the four largest values of $CB\_COSTCOMP_{1,2,t}$ for each firm 1-year t. We denote the resulting measure $CB\_COSTCOMP$. Like $CB\_REVCOMP$, it is positively related to consistency-based comparability by construction. We calculate both measures at the annual level to be consistent with DKV, which assumes that the variation in consistency-based comparability is likely to occur between years.

3.2. Measuring Fundamental Correlation and Fundamental Volatility

Section 2.3 yields two main predictions regarding how the optimal level of consistency varies with the correlation between firms' fundamental cash flows from a transaction and the volatility of firms' fundamental cash flows from a transaction. To measure fundamental correlation, ρ_v^j, we first calculate the correlation coefficient between a given firm's *CFC* and *CFCs* of the same four firms used in the calculation of *CB_REVCOMP* for revenue-related transactions. We then calculate the correlation coefficient between the firm's *CTS* and *CTSs* of the same four firms used in the calculation of *CB_COSTCOMP* for cost-related transactions. We denote the two resulting measures, *REVRHO* and *COSTRHO*, respectively. We use a longer measurement window, 20 quarters, to estimate these two variables because correlation coefficients estimated using small samples may present a bias (Fisher 1915). Fisher (1915) proved that this bias decreases quickly with sample size, and it becomes negligible for a sample size greater than 20.[17]

We similarly estimate measurement noise correlation, ρ_ε^j, by taking the correlation coefficient of the residuals from Equations (13) and (14) for revenue-related transactions and the residuals from Equations (18) and (19) for cost-related transactions between each firm and the same four firms used in the calculation of ρ_v^j. The mean value of estimated ρ_ε^j for revenue-related transactions is 0.302, which is significantly larger than the mean value of *REVRHO*, 0.105. The mean value of estimated ρ_ε^j for cost-related transactions is 0.294, which is also significantly larger than the mean value of *COSTRHO*, 0.06. These estimates provide empirical support for our model assumption of $\rho_\varepsilon^j > \rho_v^j$ discussed in Section 2.3.

To measure fundamental volatility, $(\sigma_v^j)^2$, we calculate the variance of the firm's *CFCs* for revenue-related transactions and the variance of the firm's *CTSs* for cost-related transactions, also over the past 20 quarters. We denote the two resulting measures *REVVAR* and *COSTVAR*, respectively.

3.3. Control Variables

We include a number of firm characteristics as controls. They are the natural logarithm of the book value of total assets (*SIZE*), the ratio of the book value of equity to the market value of equity (*BTM*), the ratio of total liabilities to total assets (*LEV*), and the natural logarithm of one plus the number of analysts that issue at least one earnings forecast for the firm during a quarter (*ANALYSTS*), all calculated at the end of year *t*. Finally, we include *TURNOVER*, which is the average daily turnover during quarter *q* of year *t*, measured as trading volume in shares divided by shares outstanding. Firm financials are from the Compustat quarterly files, trading volume and shares outstanding are from the CRSP quarterly files, and analyst coverage is from I/B/E/S. Detailed variable definitions are in Appendix B.

3.4. Sample Selection and Descriptive Statistics

We merge measures of consistency-based comparability, measures of fundamental correlation and volatility, and controls for each firm *i*-year *t*. We exclude firms in the financial services (SIC 6000–6999) and utilities (SIC 4900–4949) industries because revenue and/or cost generating processes are significantly different for these firms, and so the consistency measures may not apply. The final sample, which includes variables available for all analyses, contains 31,904 firm-years between 1996 and 2016. Tables 1 and 2 report sample descriptive statistics. As shown, the average firm has a book value of assets (in natural logarithm) of 6, a book-to-market ratio of 2.1, a leverage ratio of 0.5, and a share turnover of 1%.

Tables 3 and 4 present the Pearson (Spearman) correlation coefficients below (above) the diagonal for all variables. For revenue-related transactions, of particular interest are the correlation coefficient between *CB_REVCOMP* and *REVRHO* and that between *CB_REVCOMP* and *REVVAR*. For cost-related transactions, of particular interest are the correlation coefficient between *CB_COSTCOMP* and *COSTRHO* and that between *CB_COSTCOMP* and *COSTVAR*. All are

Table 1. Descriptive Statistics for the Sample Linking Consistency-Based Comparability to Properties of Firms' Cash Flows

Variable	Mean	SD	P10	Median	P90
CB_REVCOMP	−1.245	1.265	−2.690	−0.810	−0.300
CB_COSTCOMP	−1.046	1.208	−2.390	−0.610	−0.190
REVRHO	0.106	0.224	−0.168	0.090	0.406
COSTRHO	0.060	0.193	−0.177	0.050	0.310
REVVAR	0.467	0.769	0.034	0.201	1.131
COSTVAR	0.321	0.496	0.014	0.132	0.830
SIZE	6.035	2.106	3.304	5.941	8.855
BTM	2.080	4.540	0.317	0.976	3.553
LEV	0.471	0.237	0.170	0.462	0.770
ANALYSTS	1.278	1.017	0.000	1.386	2.708
TURNOVER	0.008	0.008	0.001	0.005	0.017

Notes. Descriptive statistics for all variables used in the analysis linking consistency-based comparability to properties of firms' cash flows, including the mean, standard deviation (SD), 10th percentile (P10), median, and 90th percentile (P90) for all variables. Statistics for the sample linking consistency-based comparability to properties of firms' cash flows (used in Tables 5–7). Detailed variable definitions are reported in Appendix B. All continuous variables are winsorized at the 1st and the 99th percentile. The sample period is between 1996 and 2016.

Table 2. Descriptive Statistics for the Sample Linking Implied Volatility to Consistency-Based Comparability

Variable	Mean	SD	P10	Median	P90
IMPVOL	0.419	0.195	0.219	0.374	0.687
CB_COMP	−0.375	0.633	−0.830	−0.170	−0.050
SIZE	7.722	1.583	5.732	7.670	9.904
BTM	0.451	0.320	0.129	0.381	0.844
LEV	0.504	0.208	0.214	0.514	0.771
ANALYSTS	2.237	0.591	1.386	2.197	3.045
TURNOVER	0.011	0.007	0.004	0.008	0.020
| RET|	0.059	0.055	0.007	0.042	0.134
| ESURP|	0.003	0.007	0	0.001	0.008
NEG_ESURP	0.322	0.467	0	0	1
LOSS	0.174	0.379	0	0	1
VIX	0.207	0.084	0.124	0.191	0.310

Notes. Descriptive statistics for all variables used in the analysis linking implied volatility to consistency-based comparability, including the mean, standard deviation (SD), 10th percentile (P10), median, and 90th percentile (P90) for all variables. Statistics for the sample linking implied volatility to consistency-based comparability (used in Table 8). Detailed variable definitions are reported in Appendix B. All continuous variables are winsorized at the 1st and the 99th percentile. The sample period is between 1996 and 2016.

negative and significant at the 5% level or lower, based on both Pearson and Spearman correlation coefficients. This result provides preliminary evidence that consistency-based comparability, on average, decreases with transaction level fundamental correlation and fundamental volatility.

4. Empirical Analyses

4.1. Determinants of Consistency-Based Comparability: Main Analyses

To test the two main model predictions, we estimate the following ordinary least squares (OLS) models:

$$CB\_REVCOMP_{i,t} = \beta_0 + \beta_1 REVRHO_{i,t}(REVVAR_{i,t}) + \beta_c CONTROL_{i,t} + FE + \varepsilon_{i,t}, \tag{23}$$

$$CB\_COSTCOMP_{i,t} = \beta_0 + \beta_1 COSTRHO_{i,t}(COSTVAR_{i,t}) + \beta_c CONTROL_{i,t} + FE + \varepsilon_{i,t}, \tag{24}$$

where subscript i indexes firm and t indexes year. *CB_REVCOMP* and *CB_COSTCOMP* measure consistency or consistency-based comparability, *REVRHO* and *COSTRHO* measure fundamental correlation, *REVVAR* and *COSTVAR* measure fundamental volatility, and *CONTROL* are controls, all defined in Section 3. *FE* includes either year fixed effects and industry fixed effects (defined at the two-digit SIC level) or year fixed effects and firm fixed effects. We cluster standard errors by firm and year in our main analyses. Our model predicts that $\beta_1 < 0$ in both specifications.

We first study the relation between revenue recognition consistency and fundamental correlation of revenue-related transactions. Table 5 reports the results of estimating Equation (23) with *REVRHO* as the key regressor. In Column (1), with year and industry fixed effects included, the coefficient estimate on *REVRHO* is negative and significant at the 5% level, which suggests that consistency decreases with the correlation between firms' cash flows from revenue-related transactions. When industry fixed effects are included, we study how consistency varies in response to changes in fundamental correlation of revenue-related transactions within industries over time.

Column (2) of Table 5 repeats the analysis replacing industry fixed effects with firm fixed effects, which studies how consistency varies in response to changes in fundamental correlation within firms over time while controlling for time-invariant factors that might account for firm-level variation in consistency. The coefficient estimate on *REVRHO* becomes more significant after the inclusion of firm fixed effects both statistically and economically. Based on this coefficient

Table 3. Univariate Correlations for the Sample Linking Consistency-Based Comparability to Properties of Firms' Cash Flows

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	CB_REVCOMP		**0.750**	**−0.041**	**−0.028**	**−0.453**	**−0.465**	**0.170**	**−0.127**	**−0.153**	**0.170**	**0.124**
(2)	CB_COSTCOMP	**0.775**		**−0.038**	**−0.049**	**−0.383**	**−0.569**	**0.101**	**−0.211**	**−0.202**	**0.140**	**0.134**
(3)	REVRHO	**−0.054**	**−0.053**		**0.223**	**−0.049**	**−0.021**	**0.131**	**0.045**	**0.025**	**0.106**	**0.047**
(4)	COSTRHO	**−0.057**	**−0.070**	**0.258**		−0.010	**0.013**	**0.111**	**0.038**	**0.036**	**0.094**	**0.054**
(5)	REVVAR	**−0.360**	**−0.300**	**−0.016**	**0.014**		**0.697**	**−0.434**	**−0.026**	0.004	**−0.301**	**−0.071**
(6)	COSTVAR	**−0.387**	**−0.451**	−0.006	**0.034**	**0.632**		**−0.370**	**0.103**	**0.083**	**−0.299**	**−0.129**
(7)	SIZE	**0.118**	**0.063**	**0.129**	**0.118**	**−0.274**	**−0.269**		**0.143**	**0.342**	**0.723**	**0.374**
(8)	BTM	**−0.015**	**−0.047**	**0.015**	**0.017**	**−0.027**	0.006	**0.168**		**0.399**	**−0.167**	**−0.219**
(9)	LEV	**−0.116**	**−0.159**	**0.014**	**0.033**	**0.037**	**0.099**	**0.292**	**0.222**		**0.149**	0.005
(10)	ANALYSTS	**0.124**	**0.102**	**0.111**	**0.104**	**−0.183**	**−0.206**	**0.716**	**−0.125**	**0.118**		**0.519**
(11)	TURNOVER	**0.056**	**0.070**	**0.045**	**0.050**	−0.008	**−0.020**	**0.227**	**0.030**	−0.006	**0.376**	

Notes. Pearson (Spearman) correlation coefficients below (above) the diagonal for all variables used in the analysis linking consistency-based comparability to properties of firms' cash flows. Statistics for the sample linking consistency-based comparability to properties of firms' cash flows (used in Tables 5–7). Detailed variable definitions are reported in Appendix B. Correlation coefficients in bold are significantly different from zero at the 0.05 level or lower using two-tailed tests.

Table 4. Univariate Correlations for the Sample Linking Implied Volatility to Consistency-Based Comparability

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	IMPVOL		**−0.202**	**−0.490**	**0.195**	**−0.152**	**−0.237**	**0.324**	**0.316**	**0.340**	**0.103**	**0.359**	**0.425**
(2)	CB_COMP	**−0.112**		**0.085**	**−0.275**	**−0.209**	**0.144**	**−0.127**	**−0.058**	**−0.328**	**−0.073**	**−0.213**	**0.106**
(3)	SIZE	**−0.450**	**0.061**		0.018	**0.410**	**0.630**	**−0.105**	**−0.188**	**−0.190**	**−0.050**	**−0.200**	**0.004**
(4)	BTM	**0.256**	**−0.131**	0.013		**−0.139**	**−0.092**	**0.058**	**0.049**	**0.347**	**0.087**	**0.120**	**0.066**
(5)	LEV	**−0.116**	**−0.188**	**0.381**	**−0.125**		**0.130**	**−0.123**	**−0.080**	**0.050**	**0.026**	**0.052**	**0.044**
(6)	ANALYSTS	**−0.214**	**0.124**	**0.627**	**−0.071**	**0.120**		**0.146**	**−0.141**	**−0.142**	−0.009	**−0.119**	**0.038**
(7)	TURNOVER	**0.333**	**−0.133**	**−0.111**	**0.076**	**−0.110**	**0.146**		**0.213**	**0.142**	0.005	**0.130**	0.010
(8)	| RET|	**0.352**	**−0.032**	**−0.208**	**0.102**	**−0.072**	**−0.128**	**0.217**		**0.195**	0.003	**0.105**	**0.091**
(9)	| ESURP|	**0.351**	**−0.187**	**−0.145**	**0.309**	**0.092**	**−0.197**	**0.188**	**0.190**		**0.086**	**0.319**	**0.026**
(10)	NEG_ESURP	**0.109**	**−0.049**	**−0.053**	**0.106**	**0.027**	−0.009	−0.011	0.005	**0.146**		**0.115**	0.001
(11)	LOSS	**0.371**	**−0.149**	**−0.212**	**0.177**	**0.059**	**−0.122**	**0.134**	**0.128**	**0.334**	**0.115**		**0.026**
(12)	VIX	**0.439**	**0.102**	−0.006	**0.133**	**0.024**	**0.034**	**0.073**	**0.128**	**0.096**	0.017	**0.023**	

Notes. Pearson (Spearman) correlation coefficients below (above) the diagonal for all variables used in the analysis linking implied volatility to consistency-based comparability. Statistics for the sample linking implied volatility to consistency-based comparability (used in Table 8). Detailed variable definitions are reported in Appendix B. Correlation coefficients in bold are significantly different from zero at the 0.05 level or lower using two-tailed tests.

estimate, a one-standard deviation increase in *REVRHO* is associated with a 3.4% decrease in *CB_REVCOMP* relative to its standard deviation in the sample.[18]

We then study the relation between cost recognition consistency and fundamental correlation of cost-related transactions. Columns (3) and (4) of Table 5 report the results of estimating (24) with *COSTRHO* as the key regressor. The coefficient estimate on *COSTRHO* is negative and significant at the 1% level in both columns, with either industry or firm fixed effects included. This result suggests that consistency decreases with the correlation between firms' cash flows from cost-related transactions. Based on the coefficient estimate on *COSTRHO* from Column (4), a one standard deviation increase in *COSTRHO* is associated with a 2.3% decrease in *CB_COSTCOMP* relative to its standard deviation in the sample.

The associations between consistency and fundamental correlation are economically meaningful when

Table 5. Consistency-Based Comparability and Fundamental Correlation

Dependent variable =	(1) CB_REVCOMP	(2) CB_REVCOMP	(3) CB_COSTCOMP	(4) CB_COSTCOMP
REVRHO	−0.110**	−0.192***		
	(0.050)	(0.038)		
COSTRHO			−0.216***	−0.150***
			(0.047)	(0.033)
SIZE	0.139***	0.198***	0.101***	0.183***
	(0.008)	(0.019)	(0.009)	(0.017)
BTM	0.009***	0.013***	0.006**	0.007**
	(0.002)	(0.002)	(0.002)	(0.003)
LEV	−0.467***	−0.169*	−0.556***	−0.261***
	(0.046)	(0.084)	(0.052)	(0.063)
ANALYSTS	0.019	−0.016	0.042**	−0.003
	(0.016)	(0.011)	(0.016)	(0.011)
TURNOVER	−8.917***	−7.892***	−4.721***	−5.119***
	(1.244)	(1.256)	(1.256)	(1.002)
Observations	31,904	31,904	31,904	31,904
Adj R-Squared	0.387	0.650	0.382	0.697
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes

Notes. Results of ordinary least squares (OLS) regressions that assess the relation between consistency-based comparability and the correlation between firms' cash flows from transactions. Columns (1) and (2) define consistency-based comparability and fundamental correlation using revenue-related transactions. Columns (3) and (4) define consistency-based comparability and fundamental correlation using cost-related transactions. Detailed variable definitions are reported in Appendix B. All standard errors are clustered by firm and year and are presented in parentheses below coefficient estimates.

*0.10; **0.05; ***0.01; statistical significance for two-tailed tests.

benchmarked against the associations between consistency and book to market, an important firm characteristic. Based on the coefficient estimates on *BTM* from Column (2) (Column (4)), a one-standard deviation increase in *BTM* is associated with a 4.7% (2.6%) increase in *CB_REVCOMP* (*CB_COSTCOMP*) relative to its standard deviation in the sample. Results in Table 5 provide support for the first model prediction, which arises because the information benefits of consistency-based comparability dissipate when firms' fundamental cash flows from a transaction are highly correlated.

Turning to the relation between consistency and fundamental volatility, Table 6 reports the results of estimating (23) and (24) with *REVVAR* or *COSTVAR* as the key regressor. The coefficient estimate on *REVVAR* is negative and significant at the 1% level in both Column (1) when industry fixed effects are included and in Column (2) when firm fixed effects are included. These results suggest that revenue recognition consistency decreases with the volatility of firms' cash flows from revenue-related transactions. In Column (2), a one-standard deviation increase in *REVVAR* is associated with a 17.6% decrease in *CB_REVCOMP* relative to its standard deviation in the sample. We similarly observe a negative association between cost recognition consistency and fundamental volatility of cost-related transactions in Columns (3) and (4) of Table 6, as evidenced by a significantly negative coefficient estimate on *COSTVAR*. In Column (4), a one-standard deviation increase in *COSTVAR* is associated with a 25.3% decrease in *CB_COSTCOMP* relative to its standard deviation in the sample.

The associations between fundamental volatility and consistency are even more economically impactful, as they are of magnitude similar to the associations between consistency and firm size, arguably the most defining firm characteristic. Based on the coefficient estimates on *SIZE* from Column (2) (Column (4)), a one-standard deviation in *SIZE* is associated with a 28.3% (22.3%) increase in *CB_REVCOMP* (*CB_COSTCOMP*) relative to its standard deviation in the sample. Results in Table 6 support the second model prediction, which arises because the information costs of consistency-based comparability increase when firms' fundamental cash flows from the transaction are highly volatile.

Table 7 reports the results of estimating a specification that includes measures of both fundamental correlation and fundamental volatility. Column (1) relates *CB_REVCOMP* to *REVRHO* and *REVVAR* for revenue-related transactions, including year and industry fixed effects. The coefficient estimates on both *REVRHO* and *REVVAR* remain significantly negative. Column (2) replaces industry fixed effects with firm fixed effects and finds consistent results. Columns (3) and (4) repeat these analyses, relating *CB_COSTCOMP*

Table 6. Consistency-Based Comparability and Fundamental Volatility

Dependent variable =	(1) CB_REVCOMP	(2) CB_REVCOMP	(3) CB_COSTCOMP	(4) CB_COSTCOMP
REVVAR	−0.473***	−0.276***		
	(0.026)	(0.026)		
COSTVAR			−0.930***	−0.615***
			(0.041)	(0.035)
SIZE	0.079***	0.170***	0.024***	0.128***
	(0.008)	(0.018)	(0.007)	(0.015)
BTM	0.009***	0.011***	0.006***	0.006**
	(0.002)	(0.002)	(0.002)	(0.003)
LEV	−0.277***	−0.136	−0.203***	−0.136**
	(0.039)	(0.081)	(0.040)	(0.057)
ANALYSTS	0.032*	−0.013	0.040**	0.001
	(0.015)	(0.011)	(0.015)	(0.011)
TURNOVER	−5.336***	−6.935***	0.083	−3.207***
	(1.029)	(1.218)	(1.141)	(0.930)
Observations	31,904	31,904	31,904	31,904
Adj R^2	0.458	0.659	0.500	0.716
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes

Notes. Results of OLS regressions that assess the relation between consistency-based comparability and the volatility of firms' cash flows from transactions. Columns (1) and (2) define consistency-based comparability and fundamental volatility using revenue-related transactions. Columns (3) and (4) define consistency-based comparability and fundamental volatility using cost-related transactions. Detailed variable definitions are reported in Appendix B. All standard errors are clustered by firm and year and are presented in parentheses below coefficient estimates.

*0.10; **0.05; ***0.01; statistical significance for two-tailed tests.

Table 7. Consistency-Based Comparability, Fundamental Correlation, and Fundamental Volatility

Dependent variable =	(1) CB_REVCOMP	(2) CB_REVCOMP	(3) CB_COSTCOMP	(4) CB_COSTCOMP
REVRHO	−0.083*	−0.176***		
	(0.043)	(0.038)		
COSTRHO			−0.105**	−0.090***
			(0.042)	(0.031)
REVVAR	−0.473***	−0.274***		
	(0.027)	(0.026)		
COSTVAR			−0.928***	−0.611***
			(0.041)	(0.036)
SIZE	0.080***	0.170***	0.025***	0.128***
	(0.008)	(0.018)	(0.007)	(0.015)
BTM	0.009***	0.011***	0.006***	0.006**
	(0.002)	(0.002)	(0.002)	(0.003)
LEV	−0.280***	−0.143*	−0.204***	−0.138**
	(0.039)	(0.081)	(0.040)	(0.057)
ANALYSTS	0.033**	−0.012	0.041**	0.002
	(0.015)	(0.011)	(0.015)	(0.011)
TURNOVER	−5.310***	−6.815***	0.119	−3.162***
	(1.031)	(1.208)	(1.141)	(0.927)
Observations	31,904	31,904	31,904	31,904
Adj R^2	0.458	0.660	0.500	0.716
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes

Notes. Results of OLS regressions that assess the relation between consistency-based comparability and the correlation between firms' cash flows from transactions as well as the volatility of firms' cash flows from transactions. Columns (1) and (2) define consistency-based comparability, fundamental correlation, and fundamental volatility using revenue-related transactions. Columns (3) and (4) define consistency-based comparability, fundamental correlation, and fundamental volatility using cost-related transactions. Detailed variable definitions are reported in Appendix B. All standard errors are clustered by firm and year and are presented in parentheses below coefficient estimates.

*0.10; **0.05; ***0.01; statistical significance for two-tailed tests.

to *COSTRHO* and *COSTVAR* for cost-related transactions. The coefficient estimates on both *COSTRHO* and *COSTVAR* are also significantly negative. Overall, the results in Table 7 provide evidence that the two proxies for fundamental correlation and volatility do not subsume each other but rather capture two separate mechanisms through which consistency-based comparability's net information benefits might decrease; that is, a high correlation reduces its information gains, whereas a high volatility increases its information losses.

Yet fundamental volatility (which speaks to the "standalone channel") likely matters more than fundamental correlation (which speaks to the "spillover channel") in determining consistency-based comparability. The *P* values from pairwise *t*-tests of *REVVAR* < *REVRHO* in Columns (1) and (2) are <0.01 and 0.05, respectively, and the *P* values from *t*-tests of *COSTVAR* < *COSTRHO* in Columns (3) and (4) are both < 0.01. This result indicates that the potential benefit from information spillover is likely secondary to the potential cost of reducing the informativeness of a firm's own report. This evidence supports the consensus view held by prior literature on information transfer that a mere switch to a common set of accounting standards is not sufficient to change the properties of accounting numbers at individual firms (see, e.g., Ball et al. 2000, Ball et al. 2003, and Wang 2014).

We next assess the sensitivity of the results to two specific design choices. First, in our main analyses, we cluster standard errors by firm and year to help ensure that they are not underestimated (Thompson 2011). In robustness checks, we bootstrap standard errors. We also acknowledge that one-way clustering may yield higher — not lower — standard errors in some applications and thus also try clustering by just firm or just year. The results remain robust to bootstrapping and to alternative ways of clustering.

Second, in our main analyses, we use four-quarter ahead cash flows to proxy for economic fundamentals in the current quarter, which builds on prior evidence that quarterly cash flows tend to be seasonally autocorrelated. In robustness checks, we use an alternative window to measure future cash flows. Specifically, we divide the firm's average accounts receivable by its total sales and multiply the resulting number by 365 days to estimate a firm's average receivables collection period, *CP*. We then convert *CP* into number of quarters (i.e., one quarter for $CP \leq 90$ days, two quarters for $90 < CP \leq 180$ days, three quarters for $180 < CP$

≤ 270 days, and four quarters for $CP > 270$ days). We estimate transaction-level revenue recognition consistency by evaluating firms' similarity in their mapping between sales revenue in quarter q and cash collected from customers in quarter $q + CP$ (in quarters). In this analysis, we also use the same cash collected from customers in quarter $q + CP$ to calculate fundamental correlation and fundamental volatility. The results, reported in Table OA1 of the online appendix, are qualitatively similar to those reported in Tables 5–7 for revenue-related transactions.[19]

4.2. Consistency-Based Comparability and Informativeness

Results thus far support the two main predictions from our model. Recall that the first prediction works via the spillover channel as high fundamental correlation diminishes the information gains of consistency-based comparability, whereas the second prediction works via the standalone channel as high fundamental volatility exacerbates the information losses of consistency-based comparability. These intuitions imply that fundamental correlation and volatility negatively affect the net information benefits of consistency-based comparability, when consistency is set at the equilibrium level (see Section 2.4 for a detailed discussion and proofs). In this section, we directly link consistency to informativeness.

We start by measuring informativeness. In our model, the standard setter seeks to minimize the expected variance of firms' fundamentals conditional on their earnings reports. To operationalize conditional variance, we extract the implied volatility from equity option prices. Implied volatility fits well with the theoretical construct of conditional variance because option prices reflect market participants' expectations about future changes in stock price conditional on all available information (Black and Scholes 1973). Although traded options generally mature on the third Friday of the contract month, firms make their earnings announcements at various times during a month. To alleviate concerns about nonconstant maturity, we use the implied volatility from 30-day standardized option prices provided by OptionMetrics. Specifically, we take the average of 30-day call-implied volatility and the 30-day put-implied volatility, both calculated two days after the annual earnings announcement, to capture the market's uncertainty about firm fundamentals after receiving the earnings reports. We denote the variable *IMPVOL*.

Because *IMPVOL* is not available at the transaction level, we calculate a firm-level comparability measure for this test. Specifically, we calculate *CB_COMP* by first regressing each firm's current earnings on four-quarter ahead operating cash flows (with both scaled by total assets) in a DKV-style rolling-window time series model and then calculating the negative of the absolute differences between fitted earnings for a given firm i and each of its industry peer firms j. Finally, we take the average of the four largest values. It is important to lay out the analytical conditions under which this firm-level measure reflects consistency. In the online appendix, we derive the firm-level DKV measure, discuss these conditions, and analyze its correlations with firm-level fundamental correlation and fundamental volatility. An important takeaway is that the use of the firm-level DKV measure requires more stringent assumptions and is most appropriate when the firms involved in the pairwise calculation of the measure exhibit similar distributions of transactions and similar transaction characteristics.[20]

We link consistency to implied volatility by estimating the following OLS model:

$$IMPVOL_{i,t} = \beta_0 + \beta_1 CB\_COMP_{i,t} + \beta_c CONTROL2_{i,t} + FE + \varepsilon_{i,t}, \qquad (25)$$

where *IMPVOL* is firm i's average implied volatility two days after annual earnings announcement of year t, *CB_COMP* is the firm's consistency-based comparability measure of year t, and *CONTROL*2 is a vector of controls all measured for year t. We predominantly take these controls from Rogers et al. (2009). In addition to controls already defined, *CONTROL*2 further includes the absolute value of the cumulative return over the three-day period centered on the earnings announcement date ($|RET|$), the absolute value of earnings surprise calculated as the difference between the actual earnings per share (EPS) and the latest mean analyst consensus EPS forecast scaled by the stock price two days before the earnings announcement ($|ESURP|$), an indicator variable to denote negative earnings surprise (*NEG_ESURP*), an indicator variable to denote loss (*LOSS*), and the 30-day standardized implied volatility of the S&P 500 index (*VIX*) two days after the earnings announcement. We measure all controls at the end of a given firm's fiscal year unless otherwise specified. We include industry and year fixed effects and continue to cluster standard errors by firm and year.

We first estimate Equation (25) using the full sample. Results, reported in Column (1) of Table 8, suggest that *CB_COMP* is on average negatively related to *IMPVOL*. Next, we calculate firm level *RHO* as the firm-year average of *REVRHO* and *COSTRHO* and firm level *VAR* as the firm-year average of *REVVAR* and *COSTVAR*. Based on median values of firm level *RHO* and *VAR*, we divide the full sample into four subsamples. Results estimating Equation (25) separately for these four subsamples are reported in Columns (2) –(5) of Table 8. The negative association between *CB_COMP* and *IMPVOL* is strongest in the

Table 8. Information Uncertainty and Consistency-Based Comparability

Subsample (RHO, VAR)	(1) All Obs	(2) (Low,Low)	(3) (High,Low)	(4) (Low,High)	(5) (High,High)
			Dependent variable = IMPVOL		
CB_COMP	−0.0168***	−0.0411***	−0.0331***	−0.0118***	−0.0072
	(0.0036)	(0.0109)	(0.0095)	(0.0039)	(0.0043)
SIZE	−0.0458***	−0.0380***	−0.0313***	−0.0533***	−0.0501***
	(0.0028)	(0.0030)	(0.0028)	(0.0051)	(0.0041)
BTM	0.0737***	0.0792***	0.0814***	0.0501***	0.0816***
	(0.0155)	(0.0176)	(0.0186)	(0.0170)	(0.0176)
LEV	0.0328	0.0167	−0.0015	0.0221	0.0421
	(0.0202)	(0.0190)	(0.0251)	(0.0267)	(0.0296)
ANALYSTS	0.0073*	0.0145**	−0.0003	0.0095	−0.0049
	(0.0042)	(0.0053)	(0.0078)	(0.0065)	(0.0071)
TURNOVER	5.5730***	4.8355***	5.2001***	4.9085***	6.2398***
	(0.7334)	(0.7679)	(0.7839)	(0.8488)	(0.7662)
| RET|	0.4302***	0.4236***	0.4575***	0.4398***	0.3875***
	(0.0548)	(0.0637)	(0.0624)	(0.0847)	(0.0738)
| ESURP|	2.7794***	4.1273***	4.0809***	1.7017***	2.5585***
	(0.4170)	(0.7682)	(1.2256)	(0.5140)	(0.7649)
NEG_ESURP	0.0138***	0.0114**	0.0132**	0.0159***	0.0136***
	(0.0028)	(0.0047)	(0.0060)	(0.0055)	(0.0045)
LOSS	0.0853***	0.0684***	0.0600***	0.1120***	0.0759***
	(0.0077)	(0.0111)	(0.0087)	(0.0103)	(0.0114)
VIX	0.7498***	0.7952***	0.8268***	0.7121***	0.6240***
	(0.1079)	(0.1145)	(0.1241)	(0.1244)	(0.1120)
p-value of difference			0.465	0.030	0.008
Observations	8,076	2,057	2,001	1,959	2,059
Adj R^2	0.6561	0.6848	0.6804	0.6480	0.6146
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Notes. Results of OLS regressions that assess the relation between implied volatility two days after an annual earnings announcement and firm-level consistency-based comparability for the year. Column (1) presents results for the full sample. Columns (2)–(5) present results for the four subsamples based on median cuts of firm-level fundamental correlation and firm-level fundamental volatility. Detailed variable definitions are reported in Appendix B. The row labeled "*p*-value of difference" reports the *p* value from an *F*-test comparing the coefficient estimate on firm-level comparability measure in a given column and that in Column (2). All standard errors are clustered by firm and year and are presented in parentheses below coefficient estimates.

*0.10; **0.05; ***0.01; statistical significance for two-tailed tests.

subsample with both fundamental correlation and volatility below the sample median (Column (2)). In this subsample, a one-standard deviation increase in *CB_COMP* is associated with a 9.8% decrease in *IMPVOL* relative to its standard deviation. However, this association weakens in other subsamples and becomes insignificant in the subsample with both fundamental correlation and volatility above the sample median (Column (5)). These results are consistent with our model predictions and suggest that a consistency-based approach is most effective at reducing information uncertainty when fundamental correlation and volatility are low. More important, these results point to a nonlinear relation between implied volatility and consistency-based comparability, which is consistent with the spillover channel and standalone channel offsetting each other and them varying with properties of firms' fundamental cash flows.

Interestingly, the results in Table 8 again suggest that fundamental volatility likely matters more than fundamental correlation in determining consistency-based comparability. To see this, note that the difference in the coefficient on *CB_COMP* between Column (2) using the subsample of {*Low RHO*, *Low VAR*} and Column (4) using the subsample of {*Low RHO*, *High VAR*} is much larger than the difference in the coefficient on *CB_COMP* between Column (2) using the subsample of {*Low RHO*, *Low VAR*} and Column (3) using the subsample of {*High RHO*, *Low VAR*}; the *P* values of the difference are 0.03 (significant) and 0.465 (insignificant), respectively. Similarly, the difference in the coefficient on *CB_COMP* between Column (3) using the subsample of {*High RHO*, *Low VAR*} and Column (5) using the subsample of {*High RHO*, *High VAR*}is much larger than the difference in the coefficient on *CB_COMP* between Column (4) using the subsample of {*Low RHO*, *High VAR*} and Column (5) using the subsample of {*High RHO*, *High VAR*}; the *P* values of the difference are 0.013 (significant) versus 0.257 (insignificant), respectively.

5. Conclusion

Financial statement comparability is often embraced as one of the most desirable qualitative characteristics of external financial reporting. With the aim of boosting comparability, accounting standard setters often mandate standards and rules that require consistent use of accounting methods (see, e.g., Jiang et al. (2018)). This paper studies the determinants of comparability from an information perspective. We first build a theoretical framework to define consistency-based comparability. Within this framework, we analyze its information benefits and costs. Our analysis shows that consistency yields information benefits via the spillover channel but at the same time entails information costs via the standalone channel. The two effects exactly offset each other at the optimal level of consistency, and the informativeness of firms' reports is maximized.

We draw two predictions from the model. First, for each type of transaction, the level of optimal consistency should decrease as firms' fundamental cash flows from the transaction become more correlated. This prediction works via the spillover channel as a high fundamental correlation diminishes the information gains of consistency-based comparability. Second, the level of optimal consistency should decrease as firms' fundamental cash flows from the transaction become more volatile. This prediction works via the standalone channel as a high fundamental volatility exacerbates the information losses of consistency-based comparability. Empirical evidence provides strong support for these predictions. Specifically, the evidence suggests that consistency decreases with fundamental correlation as well as fundamental volatility both for revenue- and cost-related transactions. In an additional test, we find that there exists a nonlinear relation between consistency and implied volatility. The negative relation between the two is strongest when fundamental correlation and volatility are low and becomes insignificant when fundamental correlation and volatility are high. This last result provides further support for our model predictions.

These results shed light on the determinants of consistency-based comparability in the standard setting process. In particular, our model predicts that if a firm has volatile cash flows (e.g., due to the firm adopting a unique business model, being in the early stages of its life cycle, operating in a volatile economic environment, or experiencing macro and/or technological shocks), financial statement users need to heavily rely on the firm's individual report to infer fundamentals. As such, the firm benefits from deviating from industry norms and adopting more informative idiosyncratic accounting methods. Without the ability to do so within the confines of GAAP, management may opt for non-GAAP disclosure. As previously noted, Black et al. (2020) found evidence consistent with this prediction when studying firms' non-GAAP reporting. More importantly, the number of firms conducting non-GAAP reporting has increased dramatically in recent years (Blacket al. (2018)), coinciding with a continued push for comparability of GAAP reporting. Although non-GAAP reporting may arise out of the necessity to supplement GAAP reporting with useful information (should GAAP reporting become too rigid), the two are not perfect substitutes, because non-GAAP reporting is a form of voluntary disclosure and thus leaves room for opportunistic behavior.[21] If standard setters are concerned about the prevalence and quality of non-GAAP reporting, they may consider relaxing the requirement of the highest level of comparability in prescribing accounting policies for transactions that are concentrated in firms with unique business models, early-stage firms, or in the face of macro and/or technological shocks.

These results carry policy implications. The spillover channel that we formalize and analyze makes clear why a standard setter is necessary to shape financial reporting such that its attributes maximize the aggregate informativeness of financial statements. In our model, this channel increases the aggregate information benefits, but these benefits can only be achieved by mandating the use of similar accounting rules. More generally, firms' financial reporting generates information externalities, but each firm can internalize only the externalities that fall on itself but not those that fall on other firms. As such, leaving accounting rules to firms' own devices is unlikely to result in socially optimal financial reporting. That said, our analysis also demonstrates a separate channel through which consistency can decrease informativeness, namely the standalone channel. The offsetting effects of consistency-based comparability present a trade-off. Because increasing consistency is not costless, there should be limits to the pursuit of comparability.

Our paper opens up several prospects for future research. First, one possible extension of our analysis is to consider the interaction effects between consistency and other qualitative characteristics of financial reporting, which remain unexplored.[22] Second, whereas we adopt a consistency-based approach to model comparability, future studies could explore alternative approaches to expand our narrow definition of comparability to a more general one. Third, our model takes an information perspective and focuses on two specific information channels. It might be interesting to build on our model to investigate consistency's other information effects or its potential benefits and costs aside from information.

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Appendix A. Proofs

In Section 2.3, we prove that it is without loss of generality to analyze a simplified case in which the standard setter minimizes the conditional variance $var(v_i^j|r_1^j, r_2^j, m^j)$ for a representative single transaction j. In the proofs below, we omit the transaction superscript j to economize on notations. We also use a shorter notation $var(v_i|r_1, r_2)$ for the conditional variance, although it continues to be a function of both r_i and m.

Proposition 1. *There exists a unique solution in which m^* solves the following first-order condition*:

$$\frac{dvar(v_i|r_1,r_2)}{dm}=\frac{\partial var(v_i|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}}\frac{\partial\sigma_{\varepsilon_1\varepsilon_2}}{\partial m}+\frac{\partial var(v_i|r_1,r_2)}{\partial\sigma_\varepsilon^2}\frac{\partial\sigma_\varepsilon^2}{\partial m}=0. \quad (26)$$

Proof. For conciseness, we focus on discussing the minimization of $var(v_1|r_1, r_2)$ (as the minimization of $var(v_2|r_1, r_2)$ is identical), which is given by

$$\begin{aligned} &var(v_1|r_1,r_2)\\ &=\sigma_v^2-\frac{cov(v_1,r_1)var(r_2)-cov(v_1,r_2)cov(r_1,r_2)}{var(r_1)var(r_2)-[cov(r_1,r_2)]^2}cov(v_1,r_1)\\ &\quad-\frac{cov(v_1,r_2)var(r_1)-cov(v_1,r_1)cov(r_1,r_2)}{var(r_1)var(r_2)-[cov(r_1,r_2)]^2}cov(v_1,r_2), \end{aligned} \quad (27)$$

where

$$cov(v_1, r_1) = var(v_1) = \sigma_v^2, \quad (28)$$

$$cov(v_1, r_2) = cov(v_1, v_2) = \rho_v\sigma_v^2, \quad (29)$$

$$cov(r_1, r_2) = cov(v_1, v_2) + \sigma_{\varepsilon_1\varepsilon_2} = \rho_v\sigma_v^2 + m^2\sigma_\delta^2, \quad (30)$$

$$var(r_1) = var(r_2) = \sigma_v^2 + \sigma_\varepsilon^2 = \sigma_v^2 + m^2\sigma_\delta^2 + (1-m)^2\sigma_\eta^2. \quad (31)$$

The conditional variance can be simplified into

$$var(v_1|r_1,r_2) = \sigma_v^2\left[\frac{1-\sigma_v^2(\sigma_v^2+\sigma_\varepsilon^2)(1+\rho_v^2)-2\rho_v(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})}{(\sigma_v^2+\sigma_\varepsilon^2)^2-(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})^2}\right]. \quad (32)$$

Taking the derivative of $var(v_1|r_1, r_2)$ with respect to m gives

$$\frac{dvar(v_1|r_1,r_2)}{dm}=\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}}\frac{\partial\sigma_{\varepsilon_1\varepsilon_2}}{\partial m}+\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_\varepsilon^2}\frac{\partial\sigma_\varepsilon^2}{\partial m}=0. \quad (33)$$

At $m = 0$, the derivative is $-\frac{2\sigma_v^4\sigma_\eta^2\left[(\sigma_v^2+\sigma_\eta^2)^2+\rho_v^2(\sigma_\eta^4-2\sigma_\eta^2\sigma_v^2-2\sigma_v^4)+\rho_v^4\sigma_v^4\right]}{\left[(\sigma_v^2+\sigma_\eta^2)^2-\rho_v^2\sigma_v^4\right]^2}<0$, whereas at $m = 1$, the derivative is $\frac{2\sigma_v^4\sigma_\delta^2(1-\rho_v^2)^2}{(1-\rho_v)^2(\sigma_v^2+2\sigma_\delta^2+\rho_v\sigma_v^2)^2}>0$. Hence, by the intermediate value theorem, the equilibrium is always interior. There can be multiple solutions (local minima) to the first order condition; however, the standard setter's equilibrium choice is unique because the standard setter always chooses the one local minimum at which $var(v_1|r_1, r_2)$ is the smallest. We denote the unique equilibrium choice as m^*. □

Proposition 2. *Evaluated at $m_1 = m_2 = m^*$, for $\rho_\varepsilon > \rho_v$ (with ρ_ε being the correlation coefficient between ε_1 and ε_2 and ρ_v being the correlation coefficient between v_1 and v_2), $\frac{\partial var(v_i|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}}<0$, $\frac{\partial\sigma_{\varepsilon_1\varepsilon_2}}{\partial m}>0$, $\frac{\partial var(v_i|r_1,r_2)}{\partial\sigma_\varepsilon^2}>0$, and $\frac{\partial\sigma_\varepsilon^2}{\partial m}>0$. For $\rho_\varepsilon < \rho_v$, $\frac{\partial var(v_i|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}}>0$, $\frac{\partial\sigma_{\varepsilon_1\varepsilon_2}}{\partial m}>0$, $\frac{\partial var(v_i|r_1,r_2)}{\partial\sigma_\varepsilon^2}>0$, and $\frac{\partial\sigma_\varepsilon^2}{\partial m}<0$.*

Proof. We derive the signs of the four terms in the first order condition evaluated at $m = m^*$, respectively.

The first term $\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}}$ represents the effect of $\sigma_{\varepsilon_1\varepsilon_2}$ on $var(v_1|r_1, r_2)$ and is given by

$$\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}}=-\sigma_v^4\frac{2\sigma_\varepsilon^2[(\sigma_v^2+\sigma_\varepsilon^2)-\rho_v(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})]\left[\frac{\sigma_{\varepsilon_1\varepsilon_2}}{\sigma_\varepsilon^2}-\rho_v\right]}{\left[(\sigma_v^2+\sigma_\varepsilon^2)^2-(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})^2\right]^2}. \quad (34)$$

One can verify that at $m = m^*$,

$$\begin{aligned} &(\sigma_v^2+\sigma_\varepsilon^2)-\rho_v(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})\\ &\quad=(1-\rho_v^2)\sigma_v^2+(1-\rho_v)(m^*)^2\sigma_\delta^2+(1-m^*)^2\sigma_\eta^2>0, \end{aligned} \quad (35)$$

and

$$\frac{\sigma_{\varepsilon_1\varepsilon_2}}{\sigma_\varepsilon^2}-\rho_v=\rho_\varepsilon-\rho_v, \quad (36)$$

where ρ_ε is given by

$$\rho_\varepsilon=\frac{(m^*)^2\sigma_\delta^2}{(m^*)^2\sigma_\delta^2+(1-m^*)^2\sigma_\eta^2}>0. \quad (37)$$

Therefore, the sign of $\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}}$ is solely determined by the sign of $\rho_\varepsilon - \rho_v$. The term is thus negative (positive) if $\rho_\varepsilon > (<)\rho_v$.

The second term $\frac{\partial\sigma_{\varepsilon_1\varepsilon_2}}{\partial m}$ represents the effect of consistency m on $\sigma_{\varepsilon_1\varepsilon_2}$. Because $\frac{\partial\sigma_{\varepsilon_1\varepsilon_2}}{\partial m}=2m^*\sigma_\delta^2$, it is strictly positive. Therefore, the product of the first and the second terms, $\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}}\frac{\partial\sigma_{\varepsilon_1\varepsilon_2}}{\partial m}$, is negative (positive) if and only if $\rho_\varepsilon > (<)\rho_v$, which points to a benefit (cost) of consistency in decreasing (increasing) the conditional variance through increasing the covariance of ε_1 and ε_2.

The third term $\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_\varepsilon^2}$ represents the effect of σ_ε^2 on $var(v_1|r_1,r_2)$ and is given by

$$\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_\varepsilon^2} \tag{38}$$
$$=\sigma_v^4\frac{(1+\rho_v^2)\left[(\sigma_v^2+\sigma_\varepsilon^2)-(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})\right]^2+2(1-\rho_v)^2(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})(\sigma_v^2+\sigma_\varepsilon^2)}{\left[(\sigma_v^2+\sigma_\varepsilon^2)^2-(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})^2\right]^2}$$
$$>0.$$

That is, increasing the variance of the measurement noise σ_ε^2 always increases the conditional variance.

The fourth term $\frac{\partial\sigma_\varepsilon^2}{\partial m}$ represents the effect of consistency m on σ_ε^2 and is given by $\frac{\partial\sigma_\varepsilon^2}{\partial m}=2[m^*(\sigma_\delta^2+\delta_\eta^2)-\sigma_\eta^2]$. It is easy to see that this term is positive (negative) for $m^*>(<)\frac{\sigma_\eta^2}{\sigma_\delta^2+\delta_\eta^2}$. Therefore, the product of the third and the fourth terms, $\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_\varepsilon^2}\frac{\partial\sigma_\varepsilon^2}{\partial m}$, is positive (negative) if and only if $m^*>(<)\frac{\sigma_\eta^2}{\sigma_\delta^2+\delta_\eta^2}$, which points to a cost (benefit) of consistency in increasing (decreasing) the conditional variance through increasing (decreasing) the variance σ_ε^2. As we prove above, given $\rho_\varepsilon>(<)\rho_v$, the product of the first and the second terms is negative (positive) in the first-order condition, and this means that the product of the third and the fourth terms must be positive (negative) to make the condition equal zero. In other words, we must have either $\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_\varepsilon^2}\frac{\partial\sigma_\varepsilon^2}{\partial m}>0$ and $m^*>\frac{\sigma_\eta^2}{\sigma_\delta^2+\delta_\eta^2}$ when $\rho_\varepsilon>\rho_v$ or $\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_\varepsilon^2}\frac{\partial\sigma_\varepsilon^2}{\partial m}<0$ and $m^*<\frac{\sigma_\eta^2}{\sigma_\delta^2+\delta_\eta^2}$ when $\rho_\varepsilon<\rho_v$. □

Proposition 3. *For $\rho_\varepsilon>\rho_v$, the optimal consistency m^* decreases with ρ_v and σ_v^2,that is, $\frac{\partial m^*}{\partial\rho_v}<0$ and $\frac{\partial m^*}{\partial\sigma_v^2}<0$.*

Proof. By the implicit function theorem, $\frac{\partial m^*}{\partial t}=-\frac{\frac{\partial}{\partial t}\frac{dvar(v_1|r_1,r_2)}{dm}}{\frac{d^2var(v_1|r_1,r_2)}{dm^2}}$, where $t\in\{\rho_v,\sigma_v^2\}$. We first derive the sign of $\frac{\partial m^*}{\partial\sigma_v^2}$. Because m^* minimizes $var(v_1|r_1,r_2)$, $\frac{d^2var(v_1|r_1,r_2)}{dm^2}>0$, with the aid of *Mathematica*, we verify that at $m=m^*$,

$$\frac{\partial}{\partial\sigma_v^2}\frac{dvar(v_1|r_1,r_2)}{dm}\propto m^*(\sigma_\delta^2+\delta_\eta^2)-\sigma_\eta^2, \tag{39}$$

where "∝" means "having the same sign." Given $\rho_\varepsilon>\rho_v$, from Proposition 2, $m^*>\frac{\sigma_\eta^2}{\sigma_\delta^2+\delta_\eta^2}$. As a result, $\frac{\partial}{\partial\sigma_v^2}\frac{dvar(v_1|r_1,r_2)}{dm}>0$ and $\frac{\partial m^*}{\partial\sigma_v^2}=-\frac{\frac{\partial}{\partial\sigma_v^2}\frac{dvar(v_1|r_1,r_2)}{dm}}{\frac{d^2var(v_1|r_1,r_2)}{dm^2}}<0$. For $\rho_\varepsilon<\rho_v$, $m^*<\frac{\sigma_\eta^2}{\sigma_\delta^2+\delta_\eta^2}$, $\frac{\partial}{\partial\sigma_v^2}\frac{dvar(v_1|r_1,r_2)}{dm}<0$ and $\frac{\partial m^*}{\partial\sigma_v^2}>0$. That is, $\rho_\varepsilon>\rho_v$ is a sufficient and necessary condition for $\frac{\partial}{\partial\sigma_v^2}\frac{dvar(v_1|r_1,r_2)}{dm}>0$.

For the sign of $\frac{\partial m^*}{\partial\rho_v}$, with the aid of *Mathematica*, we verify that $\frac{\partial}{\partial\rho_v}\frac{dvar(v_1|r_1,r_2)}{dm}>0$. Combined with $\frac{d^2var(v_1|r_1,r_2)}{dm^2}>0$, we have $\frac{\partial m^*}{\partial\rho_v}=-\frac{\frac{\partial}{\partial\rho_v}\frac{dvar(v_1|r_1,r_2)}{dm}}{\frac{d^2var(v_1|r_1,r_2)}{dm^2}}<0$. □

Proposition 4. *Consider an extension of our main model in which η_i is positively correlated across firms. In this extension, for $m^*>\frac{\sigma_\eta^2}{\sigma_\delta^2+\delta_\eta^2}$ and $\rho_\varepsilon>\rho_v$, the optimal consistency m^* decreases with ρ_v and σ_v^2.*

Proof. Denote the correlation between η_i as $\rho_\eta\in(0,1)$. From Equation (32) in the proof of Proposition 1, the conditional variance is given by

$$var(v_1|r_1,r_2)=\sigma_v^2\left[1-\sigma_v^2\frac{(\sigma_v^2+\sigma_\varepsilon^2)(1+\rho_v^2)-2\rho_v(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})}{(\sigma_v^2+\sigma_\varepsilon^2)^2-(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})^2}\right], \tag{40}$$

where

$$\sigma_\varepsilon^2=m^2\sigma_\delta^2+(1-m)^2\sigma_\eta^2, \tag{41}$$

$$\sigma_{\varepsilon_1\varepsilon_2}=m^2\sigma_\delta^2+(1-m)^2\rho_\eta\sigma_\eta^2. \tag{42}$$

Note that the expressions in this extension are the same as those in the main model except for the expression of $\sigma_{\varepsilon_1\varepsilon_2}$. Thus, from Equations (34) and (38) in the proof of Proposition 2,

$$\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}}=-\sigma_v^4\frac{2\sigma_\varepsilon^2\left[(\sigma_v^2+\sigma_\varepsilon^2)-\rho_v(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})\right]\left[\frac{\sigma_{\varepsilon_1\varepsilon_2}}{\sigma_\varepsilon^2}-\rho_v\right]}{\left[(\sigma_v^2+\sigma_\varepsilon^2)^2-(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})^2\right]^2}, \tag{43}$$

$$\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_\varepsilon^2}=\sigma_v^4\frac{(1+\rho_v^2)\left[(\sigma_v^2+\sigma_\varepsilon^2)-(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})\right]^2}{\left[(\sigma_v^2+\sigma_\varepsilon^2)^2-(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})^2\right]^2} \tag{44}$$
$$+\sigma_v^4\frac{2(1-\rho_v)^2(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})(\sigma_v^2+\sigma_\varepsilon^2)}{\left[(\sigma_v^2+\sigma_\varepsilon^2)^2-(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})^2\right]^2},$$

$$\frac{\partial\sigma_\varepsilon^2}{\partial m}=2\left[m^*(\sigma_\delta^2+\delta_\eta^2)-\sigma_\eta^2\right]. \tag{45}$$

Finally, at $m=m^*$,

$$\frac{\partial\sigma_{\varepsilon_1\varepsilon_2}}{\partial m}=2\left[(\sigma_\delta^2+\rho_\eta\sigma_\eta^2)m^*-\rho_\eta\sigma_\eta^2\right]. \tag{46}$$

Note that if $m^*>\frac{\sigma_\eta^2}{\sigma_\delta^2+\delta_\eta^2}$,

$$\frac{\partial\sigma_{\varepsilon_1\varepsilon_2}}{\partial m}>2\frac{\sigma_\delta^2\sigma_\eta^2(1-\rho_\eta)}{\sigma_\delta^2+\delta_\eta^2}>0. \tag{47}$$

Recall from Proposition 2 that $\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_\varepsilon^2}>0$, and $\frac{\partial\sigma_\varepsilon^2}{\partial m}>0$ for $m^*>\frac{\sigma_\eta^2}{\sigma_\delta^2+\delta_\eta^2}$. To make the first-order condition equal zero at $m=m^*$, it must be the case that $\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}}<0$. Furthermore, Proposition 2 shows that $\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}}<0$ if and only if $\rho_\varepsilon>\rho_v$. This proves that $m^*>\frac{\sigma_\eta^2}{\sigma_\delta^2+\delta_\eta^2}$ leads to $\rho_\varepsilon>\rho_v$.

Plugging the expressions of $\left\{\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}},\frac{\partial\sigma_{\varepsilon_1\varepsilon_2}}{\partial m},\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_\varepsilon^2},\frac{\partial\sigma_\varepsilon^2}{\partial m}\right\}$ into $\frac{dvar(v_1|r_1,r_2)}{dm}$, we obtain the following first-order condition regarding m^*:

$$\frac{dvar(v_1|r_1,r_2)}{dm}$$
$$=\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_{\varepsilon_1\varepsilon_2}}\frac{\partial\sigma_{\varepsilon_1\varepsilon_2}}{\partial m}+\frac{\partial var(v_1|r_1,r_2)}{\partial\sigma_\varepsilon^2}\frac{\partial\sigma_\varepsilon^2}{\partial m}$$
$$=-\sigma_v^4\frac{2\sigma_\varepsilon^2\left[(\sigma_v^2+\sigma_\varepsilon^2)-\rho_v(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})\right]\left[\frac{\sigma_{\varepsilon_1\varepsilon_2}}{\sigma_\varepsilon^2}-\rho_v\right]}{\left[(\sigma_v^2+\sigma_\varepsilon^2)^2-(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})^2\right]^2}2\left[(\sigma_\delta^2+\rho_\eta\sigma_\eta^2)m^*-\rho_\eta\sigma_\eta^2\right] \tag{48}$$
$$+\sigma_v^4\frac{(1+\rho_v^2)\left[(\sigma_v^2+\sigma_\varepsilon^2)-(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})\right]^2+2(1-\rho_v)^2(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})(\sigma_v^2+\sigma_\varepsilon^2)}{\left[(\sigma_v^2+\sigma_\varepsilon^2)^2-(\rho_v\sigma_v^2+\sigma_{\varepsilon_1\varepsilon_2})^2\right]^2}$$
$$\times 2\left[m^*(\sigma_\delta^2+\delta_\eta^2)-\sigma_\eta^2\right]=0.$$

We now derive the signs of $\frac{\partial m^*}{\partial \sigma_v^2}$ and $\frac{\partial m^*}{\partial \rho_v}$. By the implicit function theorem, $\frac{\partial m^*}{\partial t} = -\frac{\frac{\partial}{\partial t}\frac{dvar(v_1|r_1,r_2)}{dm}}{\frac{d^2var(v_1|r_1,r_2)}{dm^2}}$, where $t \in \{\rho_v, \sigma_v^2\}$. With the aid of *Mathematica*, we verify that at $m = m^*$, if $m^* > \frac{\sigma_\eta^2}{\sigma_\delta^2+\delta_\eta^2}$, $\frac{\partial}{\partial \sigma_v^2}\frac{dvar(v_1|r_1,r_2)}{dm} > 0$ and $\frac{\partial}{\partial \rho_v}\frac{dvar(v_1|r_1,r_2)}{dm} > 0$. Combined with $\frac{d^2var(v_1|r_1,r_2)}{dm^2} > 0$ proved in Proposition 3, we have $\frac{\partial m^*}{\partial \sigma_v^2} = -\frac{\frac{\partial}{\partial \sigma_v^2}\frac{dvar(v_1|r_1,r_2)}{dm}}{\frac{d^2var(v_1|r_1,r_2)}{dm^2}} < 0$ and $\frac{\partial m^*}{\partial \rho_v} = -\frac{\frac{\partial}{\partial \rho_v}\frac{dvar(v_1|r_1,r_2)}{dm}}{\frac{d^2var(v_1|r_1,r_2)}{dm^2}} < 0$. □

Appendix B. Variable Definitions

Variable	Definition
CB_REVCOMP	Measure of consistency-based comparability for revenue-related transactions, calculated in four steps. 1) We estimate a firm's accounting function for revenue-related transactions in year *t* by regressing its quarterly sales revenue-to-asset ratio on its four-quarter ahead cash collected from customers-to-asset ratio over the past 12 quarters. Cash collected from customers is sales revenue minus changes in accounts receivable plus changes in unearned revenue. 2) For each firm 1-year *t*, we calculate the fitted sales revenue of the firm in a quarter based on its own accounting function and the accounting functions of all other firms (firms 2) within the same two-digit SIC group of firm 1 (given firm 1's four-quarter ahead cash collected from customers-to-asset ratio). 3) We calculate the absolute differences between the fitted sales revenue for firm 1 in a quarter for each pair of firm 1 and firm 2, multiply the differences by -1, and average them over the past 12 quarters. 4) We take the average of the four largest values from step three.
CB_COSTCOMP	Measure of consistency-based comparability for cost-related transactions, calculated in four steps. 1) We estimate a firm's accounting function for cost-related transactions in year *t* by regressing its quarterly cost of sales-to-asset ratio on its four-quarter ahead cash paid to suppliers-to-asset ratio over the past 12 quarters. Cash paid to suppliers is the cost of sales plus changes in inventory minus changes in accounts payable. 2) For each firm 1-year *t*, we calculate the fitted cost of sales of the firm in a quarter based on its own accounting function and the accounting functions of all other firms (firms 2) within the same two-digit SIC group of firm 1 (given firm 1's four-quarter ahead cash paid to suppliers-to-asset ratio). 3) We calculate the absolute differences between the fitted cost of sales for firm 1 in a quarter for each pair of firm 1 and firm 2, multiply the differences by −1, and average them over the past 12 quarters. 4) We take the average of the four largest values from step three.
REVRHO	Measure of fundamental correlation for revenue-related transactions. For each firm *i*-year *t*, we calculate the correlation coefficient between the firm's cash collected from customers-to-asset ratio and the cash collected from customers-to-asset ratio for each of the four firms used to calculate *CB_REVCOMP* over the past 20 quarters and then take the average. The inputs for cash collected from customers are consistent with *CB_REVCOMP*.
COSTRHO	Measure of fundamental correlation for cost-related transactions. For each firm *i*-year *t*, we calculate the correlation coefficient between the firm's cash paid to suppliers-to-asset ratio and the cash paid to suppliers-to-asset ratio for each of the four firms used to calculate *CB_COSTCOMP* over the past 20 quarters and then take the average. The inputs for cash flows paid to suppliers are consistent with *CB_COSTCOMP*.
REVVAR	Measure of fundamental volatility for revenue-related transactions. For each firm *i*-year *t*, we calculate the variance of the firm's cash collected from customers-to-asset ratios over the past 20 quarters. The inputs for cash collected from customers are consistent with *CB_REVCOMP*.
COSTVAR	Measure of fundamental volatility for cost-related transactions. For each firm *i*-year *t*, we calculate the variance of the firm's cash paid to suppliers-to-asset ratios over the past 20 quarters. The inputs for cash paid to suppliers are consistent with *CB_COSTCOMP*.
SIZE	Book value of total assets in log, measured for firm *i* at the end of year *t*.
BTM	The book value of common equity divided by the market value of common equity, measured for firm *i* at the end of year *t*.
LEV	Total liabilities divided by total assets, measured for firm *i* at the end of year *t*.
ANALYSTS	The natural logarithm of one plus the number of unique analysts who issue at least one earnings forecast for firm *i* during Q4 of year *t*.
TURNOVER	Average daily turnover (calculated as trading volume in shares divided by the number of shares outstanding), measured for firm *i* during Q4 of year *t*.
CB_COMP	The firm level measure of consistency-based comparability. Similar to *CB_REVCOMP* and *CB_COSTCOMP*, we calculate the measure in four steps. 1) We estimate a firm's accounting function in year *t* by regressing its quarterly earnings-to-asset ratio on its four-quarter ahead operating cash flow-to-asset ratio over the past 12 quarters. 2) For each firm 1-year *t*, we calculate the fitted earnings of the firm in a quarter based on its own accounting function and the accounting funct*CB_COMP* ions of all other firms (firm 2) within the same two-digit SIC group of firm 1 (given firm 1's four-quarter ahead operating cash flow-to-asset ratio). 3) We calculate the absolute differences between the fitted earnings for firm 1 in a quarter for each pair of firm 1 and firm 2, multiply the differences by -1, and average them over the past 12 quarters. 4) We take the average of the four largest values from step three.
RHO	The average of *REVRHO* and *COSTRHO* for firm *i*-year *t*.
VAR	The average of *REVVAR* and *COSTVAR* for firm *i*-year *t*.
|*RET*|	The absolute value of the cumulative stock return over the three-day period centered on the earnings announcement date of firm *i*-year *t*.

Appendix B. (Continued)

Variable	Definition
|ESURP|	The absolute value of the earnings surprise at the earnings announcement of firm *i*-year *t*. Earnings surprise is calculated as actual EPS minus the latest mean analyst consensus EPS forecast, scaled by the stock price two days before the earnings announcement date.
NEG_ESURP	An indicator variable that equals one if the earnings surprise at the earnings announcement of firm *i*-year *t* is negative, and zero otherwise.
LOSS	An indicator variable that equals one if firm *i* 's earnings before extraordinary items in year *t* are negative and zero otherwise.
VIX	The 30-day implied volatility of the S&P 500 index measured two trading days after the earnings announcement date of firm *i*-year *t*.
IMPVOL	The average of the 30-day call and put option implied volatility, with both measured two trading days after the earnings announcement of firm *i*-year *t*.

Endnotes

[1] Specifically, the FASB states that "Consistency refers to the use of the same methods for the same items, either from period to period within a reporting entity or in a single period across entities. Comparability is the goal; consistency helps to achieve that goal" (SFAC No. 8 Q22, 2010, p.19) and that "Although a single economic phenomenon can be faithfully represented in multiple ways, permitting alternative accounting methods for the same economic phenomenon diminishes comparability" (SFAC No. 8 Q25; FASB 2010, p.20). In practice, the one recipe that regulators universally prescribe to improve comparability is to require the adoption of common accounting methods and limit allowable alternatives (for example, see Jiang et al. (2018) for a study of the U.S. accounting standards issued over the past four decades).

[2] We focus on the cross-sectional property of consistency because accounting standards constantly evolve. When new standards and rules are introduced, firms are required to comply with them going forward rather than being internally consistent over time. For example, it is important that all firms apply the purchase method to account for business combinations after 2001, when the FASB discontinued the usage of pooling-of-interest method, regardless of which method they were using before.

[3] The FASB has long recognized that the pursuit of useful financial reporting (or informativeness) must carefully weigh both benefits and costs. In the now superseded SFAC No. 2 (FASB 1980, p.30), the FASB states that "The better choice is the one that, subject to considerations of cost, produces from among the available alternatives information that is most useful for decision making." The cost considerations continue to be a part of the FASB's calculus. In SFAC No. 8 (QC35-QC39; FASB 2010, pp. 21–22), the FASB reemphasizes the cost constraints on useful financial reporting and the need to balance them with desired benefits.

[4] We report results using measures of fundamental correlation and volatility computed over the past 20 quarters because a longer measurement window helps mitigate the small sample bias in the estimation of correlation coefficients (Fisher 1915). The results are similar throughout if we instead compute these measures over the past 12 quarters to be consistent with the consistency measures. Separately, we show that the results for revenue-related transactions are also robust if we first estimate each firm's average receivable collection period during the year and then evaluate the mapping between the firm's sales revenue in the current quarter and its future cash collected from customers based on this estimated period.

[5] Dye and Verrecchia (1995, p.393) define uniformity as "the ranges of … procedures allowed under GAAP, as well as whether the manager opportunistically exploits any freedom in his reporting choice." To see the difference between uniformity and consistency, consider a change by the IFRS to disallow the use of last-in, first-out (LIFO) inventory cost method. As long as the propensity required of firms to adopt the common method (i.e., first-in, first-out (FIFO) method) is held constant, permitting firms to use only one idiosyncratic method (weighted-cost average cost method, WAC) instead of two (WAC and LIFO) increases the level of uniformity as Dye and Verrecchia (1995) define, but the level of consistency as we model remains unchanged.

[6] Prior studies identified several benefits of comparability via the spillover effect. They found that comparability improves analyst forecasts (Ashbaugh and Pincus (2001), DKV), increases foreign investment (DeFond et al. 2011), facilitates transnational information transfer and capital mobility (Young and Guenther 2003, Wang 2014), promotes efficient acquisition decisions (Chen et al. 2018), raises liquidity and institutional ownership (Lang and Stice-Lawrence 2015), lowers borrowing costs (Fang, et al. 2016), and lowers stock price crash risk (Kim et al. 2016).

[7] For example, FAS (Financial Accounting Standards) 133 governs accounting for derivative and hedging transactions, and FAS 13 governs accounting for leasing transactions.

[8] Alternatively, one can assume that the firm discloses a report $r_i^j = x_i^j v_i^j + \varepsilon_i^j$ about the total cash flows that it generates from transaction j, $x_i^j v_i^j$. Given m^j, the measurement noise becomes $\varepsilon_i^j = x_i^j m^j \delta^j + x_i^j(1 - m^j)\eta_i^j$, and the report becomes $r_i^j = x_i^j v_i^j + x_i^j m^j \delta^j + x_i^j(1 - m^j)\eta_i^j$. We can now write the per-unit report as $\frac{r_i^j}{x_i^j} = v_i^j + m^j \delta^j + (1 - m^j)\eta_i^j$, which is the same as the report that we currently have in the model.

[9] Under this interpretation, $m = 1$ (i.e. the common method) represents the case where firms apply the accounting method with complete consistency, which results in perfectly correlated measurement noises; $m = 0$ (i.e. the idiosyncratic method) represents the case where firms apply the method with very little consistency, which results in independent measurement noises, and $0 < m < 1$ represents a case of intermediate consistency in application, which results in less than perfectly correlated measurement noises. As an example, although all investment securities are measured with fair value accounting, Level 1 assets are valued using specific asset prices for identical assets (similar to the standard setter setting m close to one); Level 2 assets are valued using observable prices for similar assets (similar to the standard setter setting m between zero and one); Level 3 assets are valued using unobservable inputs (similar to the standard setter setting m closer to zero).

[10] One way to relax this assumption would be to allow measurement noises to be positively correlated between the two methods, given that they likely share some similarities. In this extension, it may be less desirable to allow a mixture of accounting methods as opposed to mandating a single one. This is because, when measurement noises from the common and the idiosyncratic methods are highly correlated anyway, allowing the usage of both is less likely to diversify away their measurement noises.

[11] It is possible that δ_1^j and δ_2^j are independent of firm fundamentals but positively correlated with each other. To see this, consider a firm that makes toothbrushes and another one that makes mouse pads. Assume that both firms use the FIFO inventory cost method. In periods of inflation, the application of FIFO likely underestimates cost of goods sold (COGS) for both firms. As a result, the two firms' use of FIFO as the common method results in a positive correlation between the measurement noises in their estimation of COGS because both noises are affected by the inflation rate, even though the two firms' inflation-adjusted fundamentals may be minimally correlated.

[12] To better see this diversification benefit, consider a two-asset portfolio. Given any two assets, one can always find a set of weights such that the overall portfolio variance is lower than each asset's individual variance as long as the two assets are not perfectly correlated; the risk is hence diversified. Because our model assumes no correlation between the measurement noises from the common and idiosyncratic methods, we can simply write the total measurement noise as $\varepsilon_i^j = m^j\delta^j + (1-m^j)\eta_i^j$, so $(\sigma_\varepsilon^j)^2 = (m^j)^2(\sigma_\delta^j)^2 + (1-m^j)^2(\sigma_\eta^j)^2$. Taking the F.O.C. gives $\frac{\partial(\sigma_\varepsilon^j)^2}{\partial m^j} = 2m^j(\sigma_\delta^j)^2 - 2(1-m^j)(\sigma_\eta^j)^2 = 0$, and we can solve $m^{j*} = \frac{(\sigma_\eta^j)^2}{(\sigma_\eta^j)^2+(\sigma_\delta^j)^2}$ such that $(\sigma_\varepsilon^j)^2$ is minimized and lower than either $(\sigma_\delta^j)^2$ or $(\sigma_\eta^j)^2$.

[13] As DKV (2011) further pointed out, quantifying variation in the implementation of accounting choices is difficult because even if a common method is required for an economic transaction, it is still difficult to observe the degree of similarity in its application. This issue is heightened in settings where accounting standards promote highly uniform measurements to begin with, such as in the United States. For this reason, prior studies that employ input-based measures focus on capturing similarity/dissimilarity across international accounting standards (see, e.g., Ashbaugh and Pincus 2001, Young and Guenther 2003, Bradshaw et al. 2004, Bae et al. 2008, and Bradshaw and Miller 2008).

[14] For example, Lorek and Willinger (2011, Table 4) demonstrated the seasonal autoregressive behavior in the undifferenced quarterly cash flow from operations (CFO) series, as values from the sample autocorrelation functions (SACFs) decline markedly at lags 4, 8, and 12, and values from partial autocorrelation functions (PACFs) cut off after the first lag, which is consistent with a seasonal autoregressive parameter. In contrast, other lags exhibit autocorrelation consistent with a white-noise series.

[15] The assumption underlying this approach is that if the predictions from the model hold with respect to each individual m^j, they should reasonably extend to the empirically measured consistency-based comparability measure, $\sum_{j=1}^N x_i^j m^j$, at least for a limited N of similar transactions. Admittedly, this empirical proxy for m^j is less than ideal due to the lack of transaction-level reports. Our inferences likely remain valid to the extent that measurement noise, if any, does not introduce systematic bias.

[16] We follow DKV (2011) and limit sample firms to those whose fiscal years end in March, June, September, or December. We also exclude from the calculation holding firms, American Depository Receipts (ADRs), limited partnerships, and firms with highly similar names. All are defined as in DKV (2011).

[17] Fisher (1915) further showed that this bias is more conservative in normal data and thus proposes a way to transform the correlation coefficient z (i.e., the Fisher transformation), where $z = \frac{1}{2}\ln\left(\frac{1+r}{1-r}\right) = \arctan h(r)$. The z variable is approximately normal and has a variance that is stable over different values of the underlying true correlation. In untabulated analyses, we perform the Fisher transformation on *REVRHO* and *COSTRHO* and find similar results.

[18] We calculate this economic significance as the coefficient estimate of −0.192 multiplied by the standard deviation of *REVRHO*, 0.224, and then divided by the standard deviation of *CB_REVCOMP*, 1.265. Other quoted economic significances are analogously calculated.

[19] Unlike revenue-related transactions for which cash is collected in the future relative to the time of credit sales (and *CP* measures the length of this lead period), cash is often paid for inventory to suppliers before the inventory is sold, and it is difficult to estimate a lead period from the recognition of cost of sales to related cash payments. Thus, we do not attempt to conduct a similar robustness check for cost-related transactions.

[20] Specifically, we derive the firm level DKV measure as $CB\_COMP = -\sum_{j=1}^N\left\{(x_2^j - x_1^j)^2(\sigma_\delta^j)^2(m^{j*})^2 + \left[x_2^{j2} + x_1^{j2}\right](\sigma_\eta^j)^2(1-m^{j*})^2\right\}$. We prove that, when x_1^j and x_2^j are sufficiently close to each other, firm level *CB_COMP* is positively related to the optimal level of consistency m^{j*}. Interestingly, since DKV (2011) calculate *CB_COMP* within industries, it helps ensure that this condition is reasonably met. The model, however, has no clear predictions for the correlations between *CB_COMP* and firm-level fundamental correlation and volatility because the direction of these correlations depends on not only transaction-specific characteristics but also intertransaction characteristics (i.e., how x_1^j compares with x_2^j).

[21] Prior literature shows that the quality of non-GAAP metrics improves when firms are under scrutiny by regulators, creditors, or short-sellers (see Black et al. 2018 for a summary).

[22] The FASB recognizes possible interaction effects between the desired characteristics of financial reporting. For example, SFAC No. 8 (QC34, 2010, p.21) writes that "Sometimes, one enhancing qualitative characteristic may have to be diminished to maximize another qualitative characteristic. For example, a temporary reduction in comparability as a result of prospectively applying a new financial reporting standard may be worthwhile to improve relevance or faithful representation in the longer term. Appropriate disclosures may partially compensate for noncomparability."

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