Informativeness of Flexibility in Cash Flow Classification Standards

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August 2022

Acknowledgements: I thank my dissertation committee members Tom Linsmeier (chair), Dan Wangerin, Terry Warfield, and Jack Porter for their valuable guidance. I also thank Seung Kyo Ahn, Julia Ariel-Rohr, In Gyun Baek, Amanda Carlson, Matt Cedergren, Willie Choi, Derek Christensen, Abbie Daly, Vicki Dickinson, Ivy Feng, Zach King, Dan Lynch, Venky Nagar, Nate Nguyen (discussant), Ben Osswald, Clay Partridge, and Erika Wheeler. The manuscript also benefited from workshop participants at the University of Wisconsin – Madison, Menlo College, Western Illinois University, University of Wisconsin - Whitewater, Radford University, participants at 2021 AAA Spark Meeting of the Regions, 2021 Dairyland Accounting Research Symposium, and 2021 AAA Annual Meeting. I gratefully acknowledge financial support from the Wisconsin School of Business at University of Wisconsin - Madison.

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Abstract: I examine the effect of flexibility in cash flow classification standards on cash flow informativeness. In the context of cash flow classification, informativeness means users can infer similarities (differences) in transactions from similar (different) classification of items across firms, i.e., comparable cash flows. Current cash flow classification guidance is a collection of uniform and flexible standards with differences in standard setting approaches sometimes used for the same items. I exploit variation in flexibility permitted under U.S. GAAP and IFRS in classifying cash interest paid, and cash interest and dividends received, and find that flexibility (IFRS) produces more informative cash flows than uniformity (U.S. GAAP) when firms have a more heterogeneous interest and dividend generating process than peers. Additionally, classification opportunism undermines informativeness more under flexible than uniform standards. This is the first study to directly examine flexibility in cash flow classifications on comparability, which is arguably the most relevant quality metric for reported cash flows. It also provides timely evidence for IASB's effort to improve cash flow statement comparability via changes in classification guidance.

Keywords: cash flow classification informativeness, cash flow quality, cash flow comparability, heterogeneity in cash flow nature, reporting opportunism.

JEL Classification: G18, M41.

I. INTRODUCTION

Although the topic of cash flow classification taught in accounting classrooms seems straightforward, cash flow classification in practice is challenging, especially for transactions that have characteristics that can be associated with more than one cash flow statement activity (i.e., operating, investing, or financing).[1] As a result, such transactions could be classified as different activities across firms, and many of which result in financial restatements due to cash flow classification errors (Audit Analytics 2020).

Current cash flow reporting guidance, both U.S. and international, is a collection of uniform and flexible classification standards. In some instances, standard setters mandate classification for activities and create classification uniformity. In other instances, standard setters permit the use of managerial judgment to classify activities by either (a) explicitly providing a choice between different classification categories, or (b) requiring that preparers apply the predominance principle to classify activities for which there is no explicit guidance. Both cases create classification flexibility.[2] To make classification even more puzzling, U.S. GAAP and IFRS sometimes take different approaches in classifying the *same* activities.

Given users' significant reliance on reported cash flows, particularly operating cash flows, for valuation and contracting purposes,[3] it is imperative to understand effects of different

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[1] For example, prior to 2016, some firms classify cash payments for debt prepayment or extinguishment costs as cash outflows for financing activities, while others classify them as operating outflows. Debt prepayment/extinguishment costs is one of seven items for which Accounting Standards Update 2016-15 clarified classification guidance in hopes to promote cash flow comparability (FASB 2016). These seven items are examples of challenging cash flows that have characteristics of more than one category, and were brought to FASB's attention because of observed classification diversity in the absence of explicit guidance.

[2] The predominance principle states that in the absence of specific guidance, firms will classify cash flows that have aspects of more than one class based on the nature of the predominant source or use of cash flows (FASB 2016).

[3] DCF-based valuation models calculate free cash flows which typically take the difference between operating cash flows and capital expenditures (Adame, Koski, and McVay 2020). Operating cash flows are also inputs to executive compensation contracts (Gong, Li and Shin 2011), debt covenants (Bharath, Sunder and Sunder 2008) and bankruptcy predictions (Casey and Bartczak 1985).

classification standards on the quality of reported cash flows. In light of ongoing FASB and IASB efforts to improve cash flow classification guidance (IASB 2019; FASB 2022), the objective of this study is to understand whether and how flexibility in classification standards produces high quality, informative cash flows. In the context of cash flow classification, informative cash flows enable users to infer similarities (differences) in transactions from similar (different) classification of items across firms. Comparability, by definition, allows users to discern and understand similarities in, and differences among, items (FASB Concept Statement 8, QC20). In other words, cash flow comparability is the most conceptually relevant benchmark to assess cash flow quality in the context of classification.[4] Throughout this study, I consider cash flow information comparable between firms if similar cash flows are classified similarly. Cash flow information lacks comparability if similar (different) cash flows are classified differently (similarly).

Neither flexibility nor uniformity in cash flow classification standards necessarily creates informative cash flows. The FASB ASU 2016-15 mandates uniform classifications for seven additional items not explicitly addressed in SFAS 95, citing comparability improvements as a result of the mandate (FASB 2016).[5] This ASU is a response to observed diversity in practice from firms inconsistently applying the predominance principle, and reflects FASB's belief that flexibility in classification impairs comparability. On the other hand, U.S. GAAP takes a uniform approach and classifies cash interest paid, cash interest received, and dividends received all as operating activities, while IFRS allows these same items to be classified as either operating, investing or financing activities. This is an example where standard setters disagree in uniform classification creating comparability.

[4] Informativeness and comparability are used interchangeably in the context of cash flow classification.

[5] Three of the seven items addressed in ASU 2016-15 relate to the classification of interest and dividends. Hence, in the pre-ASU 2016-15 period, there is some inherent flexibility under U.S. GAAP in classifying certain cash interest paid and cash dividends received.

Prior theoretical literature on flexibility in accounting standards suggests that relative to flexible standards, uniform standards are less subject to opportunistic manipulation but suppress the ability to inform on heterogeneity in underlying economics (Dye and Sridhar 2008, hereafter, DS 2008). I leverage DS (2008) and directly study the effect of classification flexibility on cash flow comparability and whether this effect varies based on: (1) the degree of heterogeneity in underlying cash flow nature, and (2) the extent of opportunistic classification incentives.

I exploit the classification setting for cash interest paid, cash interest received, and dividends received (i.e., interest and dividend cash flows) because I can separately identify the two aforementioned conditions under a uniform and a flexible classification environment. There is varying extent of flexibility permitted in classifying these cash flows under IFRS (more flexible) and U.S. GAAP (less flexible), as well as within U.S. GAAP in the pre- (more flexible) and post-ASU 2016-15 period (less flexible). This quasi-experimental setting allows me to examine the usefulness of different cash flow classifications for the same (rather than different) activities, strengthening my research design. Additionally, interest and dividend cash flows are pervasive and material in magnitude for firms across many industries.[6] The classifications of interest and dividends are often used to justify classifications for activities that have interest and dividends components, e.g., derivative instruments or leases (FASB 2016; BDO IFR Advisory Limited 2020). That is, the classification for interest and dividend cash flows creates an important and unique setting well suited to study cash flow quality implications of flexibility in classification standards.

[6] Cash interest paid on average represents 14% of total revenue in my sample. This statistic only captures interest outflows related to debt financing activities, not including operating- or investing-natured interest paid. Cash interest received and dividends received also are *unknown* as firms do not usually disclose these items. Such nondisclosure makes it practically infeasible for investors to know how different types of interest and dividend cash flows are classified, let alone undo the effect of noncomparability due to classification.

Second, heterogeneity in cash flow nature arises when interest and dividend cash flows stem from activities of a different nature across different firms. The primary differentiating characteristic of interest and dividend cash flows that could cause them to be classified differently is whether they are financial or non-financial in nature (FAS 95-10, FASB 2010; IASB 2007). The fact that interest and dividend cash flows can be of either nature makes them difficult to classify even within the same industry, which if done poorly can lead to noncomparability.

For example, Ford Motor Company has an automobile manufacturing segment and a financial segment called Ford Credit that conducts customer-financing and leasing services. Ford pays cash interest on debt borrowed by its automobile segment, as well as cash interest on customer-financing and leasing activities at Ford Credit (Ford Motor Company 10-K, 2019). The cash interest on debt arises from Ford's financing activity, while cash interest on customer-leasing arises from Ford's operating activity (as a part of Ford Credit regular operations). In contrast, Tesla Incorporated does not have a financial segment; it pays interest on debt borrowing only (Tesla 10-K, 2019). If standards require all cash interest be classified as operating activities (i.e., uniformity), Ford would classify operating-natured interest similar to Tesla's financing-natured interest. The reported net operating and financing cash flows between the two firms would lack comparability, as *differently* natured interests are classified *similarly*. Flexible standards, on the other hand, would allow separate classifications of Ford's financing- and operating-natured interest, which in theory promotes comparability with Tesla's financing-natured interest.

This example illustrates two attributes about heterogeneity in cash flow nature. First, it is a relative concept in that a firm's heterogeneity is assessed relative to a comparison group. In this study, a firm's heterogeneity is defined as its similarity to *industry peers* in activity mix (financial or non-financial) that generates interest and dividend cash flows. Second, heterogeneity in cash flow nature affects how flexibility affects cash flow comparability. I hypothesize that, all else equal, when underlying cash flows are homogeneous across industry peers, uniform classification standards better enhance cash flow comparability than flexible standards. As firms' cash flows increase in heterogeneity, flexible standards better promote comparability than uniform standards.

My second hypothesis relates to opportunistic reporting incentives. Lee (2012) and Gordon et al. (2017) show that firms are more likely to inflate operating cash flows via classification flexibility when firms are in financial distress, highly leveraged, or performing poorly. If flexible standards are more susceptible to opportunistic classification incentives, I expect increasing opportunistic incentives to reduce cash flow comparability under flexible classification standards.

To test these hypotheses, I collect annual financial statement and monthly returns data for non-financial firms filing under U.S. GAAP or IFRS for 2005-2018. My final sample includes 68,574 firm-year observations for 13,485 firms. To capture the construct of flexibility in classification standards, I exploit varying degrees of flexibility permitted in classifying interest and dividend cash flows between IFRS and U.S. GAAP, and between IFRS and adjusted U.S. GAAP (for flexibility in the pre-ASU 2016-15 period). I measure cash flow informativeness via cash flow comparability, which is modified from the De Franco, Kothari, and Verdi (2011) model (DKV hereafter). Given a set of economic events, the more similar (closer) two firms are in their associations between reported firms' cash flows and economic events, the more comparable are their cash flow systems. I measure firm-level heterogeneity in interest and dividend cash flow nature by assessing how different a firm's activity mix (financial or non-financial) is relative to its industry peers (i.e., a firm with non-financial natured core operations and a financial-natured segment would have high heterogeneity if few of the firm's industry peers had a financial-natured segment). Lastly, I capture firms' opportunistic classification incentives with financial distress, low profitability, and high leverage, as firms with these characteristics are more prone to inflate operating cash flows via classification flexibility (Gordon et al. 2017).

Holding constant opportunistic classification incentives, I find cash flow comparability to be higher (lower) under flexible than under uniform standards when cash flows are heterogeneous (homogeneous). Second, controlling for heterogeneity in cash flow nature, I document that increasing opportunistic classification incentives reduces comparability under flexible classification standards. These findings are consistent with my predictions.[7]

This study makes several contributions. With respect to cash flow reporting, this is the first study to directly test cash flow quality implications of flexibility in classification standards. Standard setting discussions on cash flow classification most commonly cite comparability as the ultimate benchmark for usefulness (e.g., FASB 2016, IASB 2020), yet no research has provided empirical evidence on the influence of flexible classification guidance on comparability. Gordon et al. (2017, 869) infer that flexibility in classification creates noncomparability that is "absent under the more rigid requirements of U.S. GAAP."[8] I show that noncomparability also exists under U.S. GAAP when cash flows are heterogeneous, and when managerial opportunism is high.

Second, I contribute to the "uniformity-vs.-flexibility" debate by directly testing two determining factors of usefulness of flexibility in standards: economic heterogeneity, and

[7] As falsification tests, I test my hypotheses using a sample of financial firms for two reasons. First, the non-financial segments of financial firms typically provide auxiliary support services which do not incur interest and dividends in amounts that would introduce heterogeneity in the overall mix of interest and dividends cash flows. Second, while non-financial firms incur an overall net outflow of cash related to interest and dividends, financial firms experience an overall net inflow of these cash flows (most financial institutions have net positive interest margins). To the extent that flexibility in classification incentivizes firms to inflate operating cash flows, financial firms maintain their operating classification for interest and dividends regardless of opportunism level. As expected, I find no results in the financial firm sample.

[8] This study differs from flexibility consequences in Gordon et al. (2017) related to market pricing of the persistence of cash flows, and models of predicting operating cash flows. I directly test the cash flow quality implications of classification flexibility via cash flow comparability, which has been the primary motivation for recent cash flow classification standard changes.

managerial opportunism. I provide another perspective to capture economic heterogeneity through firm-vs.-segment structure, alternative to traditional risk-factor based models. My findings suggest that flexibility in classifying heterogeneous cash flows, on average, improves comparability and informativeness of cash flows. This is consistent with studies such as Hann, Lu, Subramanyam (2007) in documenting a net benefit of flexibility in standards.

Third, this study provides timely evidence relevant to current FASB and IASB discussions on improving cash flow classifications. My results suggest that the IASB Exposure Draft (2019) proposal to classify interest and dividend cash flows based on the nature of their activities—financial or non-financial—could improve comparability by requiring classification based on the key characteristic that differentiates the nature of these cash flows, while also reducing reporting opportunism. My findings on U.S. GAAP shed light on the long-standing debate regarding the appropriateness of the mandated operating classification of interest and dividends for non-financial firms, as it seems to misalign the nature of interests and dividends with the underlying financing/investing activities (e.g., Nurnberg and Largay 1998; FASB 2010 para 88-90).

Overall, the takeaway for cash flow classification is that neither uniform nor flexible classification standards consistently enhances comparability—their effects hinge on the nature of the cash flows and incentives for managerial opportunism. Thus, it would not be surprising to find that standard setters will continue to employ both approaches going forward.

II. HYPOTHESES DEVELOPMENT

DS (2008) presents a positive theory of flexibility in accounting standards, which introduces a framework to understand effects of discretion (i.e., flexibility) in standards. In this reduced-form model, DS describes a setting where firms produce transactions that are valued by the capital market. Firms are willing to adjust their investment in production based on how the marketplace values those transactions. The financial reports firms prepare influence the market's perception of transaction values. A firm's objective is to choose the accounting standard (uniform or flexible) that maximizes its market value.

The firm value inferred from information on financial reports depends on the economic value of the transaction, the accounting standards applied, and firms' ability to influence how transactions are represented under accounting standards. Financial reporting informativeness refers to the extent to which firms' investments in productive activities are faithfully represented in the reported financials under uniform or flexible standards. DS argue that the accounting standard that maximizes firm value is also the standard that produces the most informative financial reports. This is because firms benefit from having reports that are maximally informative; firm owners' incentives to invest increase as accounting reports under a standard (uniform or flexible) better reflect a firm's productive investments.

DS's model suggests two conditions under which uniform and flexible standards predictably differ in producing informative reports. The first is the degree to which reporting under the standard reflects heterogeneity in underlying economics. The second is the degree to which reporting under the standard is subject to opportunistic reporting. DS argue that uniform standards are desirable at curbing opportunistic reporting but suppress variation in reported transactions. Thus, uniform standards work best when the underlying transactions are cross-sectionally homogeneous. Flexible standards can reflect transaction heterogeneity but also are subject to opportunistic manipulation.

I leverage insights from DS and test both conditions in the cash flow classification setting. First, with respect to cash flow classification, heterogeneity in underlying economics describes the extent to which a firm's underlying interest and dividend generating activities are different in nature *compared to peer firms*. Interest and dividend generating activities can differ in nature across firms even within the same industry as illustrated by the Ford and Tesla example in the introduction. Heterogeneity in this study describes not pairwise comparisons between two firms, rather, comparisons of each firm with the rest of the industry. It is a relative concept in the sense that if majority of firms in an industry has a structure akin to Ford, Tesla (Ford) is perceived to have heterogeneous (homogeneous) natured interest generating activities relative to peers.

If accounting standards require firms to uniformly classify, e.g., cash interest in one category without regard to cross-sectional differences in cash flow heterogeneity, I expect that cash flows will lack comparability because differently natured interest cash flows are forced to be classified similarly across firms. In this case, applying flexible standards would enhance cash flow comparability because it allows different interest to be classified differently. In contrast, if all peer firms either have or do not have a financial segment, then the nature of cash interest generating activities among them is homogeneous. Applying uniform standards will better produce informative cash flows by ensuring similar cash flows are classified similarly. Thus, I predict that,

> ***H1a:*** *All else equal, when underlying cash flows are homogeneous in nature, cash flow informativeness, i.e., comparability, is lower under flexible classification standards relative to uniform standards.*
>
> ***H1b:*** *All else equal, increasing heterogeneity in the nature of cash flows enhances cash flow informativeness, i.e., comparability, under flexible classification standards relative to uniform standards.*

Second, opportunistic classification incentives refer to firm characteristics that incentivize managers to exploit flexibility in classification to inflate operating cash flows. Lee (2012) and Gordon et al. (2017) find that firms that are in financial distress, less profitable and more leveraged are more likely to report higher operating cash flows via classification. As such, I predict that all else equal, opportunistic classification incentives weaken the ability of flexible standards to faithfully represent underlying economics, and in turn, reduce cash flow comparability.

H2: All else equal, increasing opportunistic classification incentives decreases cash flow informativeness, i.e., comparability, under flexible classification standards.

By definition, there is no ability to opportunistically manipulate classification under uniform standards (DS 2008). That is, if uniformity in cash flow classification standards is perfectly observable, opportunistic classification incentives should have no effect on cash flow comparability. In practice, accounting standards, U.S. GAAP, IFRS, local GAAP, etc., inherently allow for some degree of managerial discretion, and cash flow classification standards are no exception. U.S. GAAP is not comprehensive enough to preclude the use of managerial discretion in classifying business activities without explicit guidance. In this case, increasing opportunistic classification incentives could decrease cash flow comparability relating to classification decisions other than interest and dividends even in the presence of relatively uniform classification standards for interest and dividends under U.S. GAAP.[9]

III. RESEARCH DESIGN AND VARIABLE CONSTRUCTION

H1: Heterogeneity in the Nature of Underlying Cash Flows

H1a and H1b test the effect of heterogeneity in cash flow nature on the relation between classification standards (uniform vs. flexible) and cash flow informativeness. All variables are at the firm-year level. I omit subscripts "i" for firm and "t" for year for brevity. Appendix 1 describes variable definitions. I estimate the following OLS model to test H1a and H1b:

$$CompCF = b_0 + b_1 FLEXvar + b_2 Hetero + b_3 FLEXvar * Hetero + b_4 SRZscore + b_5 SRRoa + b_6 SRLev + \sum b_n Controls + \gamma_k + \lambda_t + e \qquad (1)$$

[9] For example, Lee (2012) shows that prior to EITF 00-15 (which eliminated the choice to classify the cash inflow associated with the tax benefit received upon exercise of a nonqualified employee stock option as either operating or financing), U.S. GAAP filers classified the inflow as an operating rather than a financing activity when incentives are greater to inflate operating cash flows (FASB 2000).

$CompCF$ measures cash flow comparability. $FLEXvar$ is one of two measures, $FLEX$ and $FLEX2$, both of which are indicator variables capturing the degree of flexibility permitted in standards to classify interest and dividend cash flows. $Hetero$ measures the extent to which a firm's interest and dividend generating activities are heterogeneous in nature relative to its peers. $Hetero$ is one of two measures: $HeteroLevel$ and $Hetero4$. $SRZscore$, $SRRoa$ and $SRLev$ are the scaled decile rank of firm i's Altman's Z score, return on assets, and total debt ratio. $Controls$ includes $Size$, BTM, $Predictability$, $Loss$ and $Accruals$ which are factors DKV (2011) show to be related to comparability. γ_k and λ_t are country and year fixed effects, respectively.

The coefficients b_0, b_1, b_2, and b_3 are interpreted incremental to the other three. The intercept, b_0, is the base comparability level under uniform standards when cash flows are homogeneous to peers. When cash flows are homogeneous (i.e., $Hetero$ = 0 and hence no effect on comparability through b_2 and b_3), b_1 represents the incremental comparability effect of flexible standards relative to that of uniform standards. H1a predicts that $b_1 < 0$. The coefficient b_2 captures the comparability effect from a one unit increase in cash flow heterogeneity under uniform standards, and b_3 captures the incremental comparability effect of increasing heterogeneity under flexible standards. H1b predicts that increasing cash flow heterogeneity enhances cash flow comparability under flexible standards relative to uniform standards, or $b_3 > 0$.

I control for opportunistic classification incentives using $SRZscore$, $SRRoa$, and $SRLev$. $Controls$ include $Size$, BTM, $Predictability$, $Loss$, and $Accruals$ as DKV (2011) suggest that firms that are smaller, have lower book-to-market ratios, have lower earnings predictability, and report a loss contribute to skewness in the comparability measure, and comparability predictably varies with accruals. I add country fixed effects to account for any time-invariant unobservable country-level factors that could affect cash flow comparability. Year fixed effects capture the average effect of unobservable time-variant economic characteristics in cash flow comparability. I cluster standard errors at the firm and year level (Gow, Ormazabal, and Taylor 2010). I identify and drop influential observations whose absolute values of studentized residuals are greater than two or whose Cook's D values are greater than 4/n (Leone, Minutti-Meza, and Wasley 2019).

H2: Opportunistic Classification Incentives

H2 tests the effect of opportunistic classification incentives on the relation between the discretion in standards and cash flow comparability. I estimate the following OLS model:

$$CompCF = c_0 + c_1 FLEXvar + c_2 Incentive + c_3 FLEXvar * Incentive$$
$$+c_4 HeteroLevel + \sum c_n Controls + \gamma_k + \lambda_t + e \qquad (2)$$

$Incentive$ captures the extent to which firm i has characteristics that make it more likely to exploit classification flexibility. It is one of four incentive variables: $AggIncentive$, $SRZscore$, $SRRoa$, or $SRLev$. $AggIncentive$ is the main variable of interest, which is the average of $SRZscore$, $SRRoa$, or $SRLev$.

Similar to model (1), the coefficients c_0, c_1 , c_2, and c_3 in model (2) are all interpreted incremental to the other three coefficients. H2 tests that all else equal, increasing opportunistic classification incentives weakens comparability under flexible classification standards, or $c_3 < 0$. Within uniform standards (i.e., $FLEXvar$ is zero), there is no comparability effect of c_1 or c_3 (i.e., c_1 and c_3 are zero). The coefficient c_2 captures the comparability effect of increasing incentives incremental to the base level comparability, c_0. In theory, increasing opportunistic classification incentives does not affect comparability under uniform standards, i.e., c_2 should equal zero. As discussed previously and shown in Lee (2012), to the extent there is inherent flexibility in cash flow classification for items unrelated to interest and dividends that firms could exploit to inflate operating cash flows in relatively uniform standards, c_2 could be negative empirically. I control for cash flow heterogeneity, $HeteroLevel$, along with other controls similar to those in model (1).

Dependent Variable Construction

Cash flows are informative if users can infer similarities (differences) in transactions from similar (different) classification of items across firms, making cash flow comparability the most relevant characteristic to assess the quality of cash flow information in this context. Financial statement comparability stems from the notion that the accounting system is a mapping from economic events to financial statements (DKV 2011). Given a set of economic events, two firms produce similar financial statements if they have comparable accounting systems. In this study, cash flow comparability is the "closeness" in the mapping of economic events into cash flows. Given a set of economic events, the closer the firms' reported cash flows, the more comparable their cash flow systems are.

Since cash flow comparability refers to similarity in the *aggregate cash flow accounting system*, I modify DKV's earnings comparability approach to account for unique characteristics of my setting. I explain the construction of cash flow comparability measure below and highlight key modifications from DKV when needed. I define peer firms as firms in the same two-digit SIC industry classification in the same year, so that firms being compared are, to a large extent, similar in economic activities. Following DKV (2011), I require at least 11 firms in every industry-year so that each firm has at least ten peers.

First, for each firm-year, I estimate the firm-specific accounting mapping from economic events to cash flow information using 16 quarters of data:

$$CFO_{it} = a_{i0} + a_{i1}Return_{it} + e \tag{3.1}$$

$$CFI_{it} = b_{i0} + b_{i1}Return_{it} + e \tag{3.2}$$

$$CFF_{it} = c_{i0} + c_{i1}Return_{it} + e \quad (3.3)$$

$Return_{it}$ is the stock price return during the quarter. CFO_{it}, CFI_{it}, and CFF_{it} are the ratios of quarterly net cash from operating, investing, and financing activities to the beginning-of-period market value of equity, respectively. In these models, $\widehat{a_i}$, $\widehat{b_i}$, and $\widehat{c_i}$ proxy for the cash flow function of firm i, and $\widehat{a_j}$, $\widehat{b_j}$, and $\widehat{c_j}$ proxy for the cash flow function of firm j.

Different from DKV's approach where returns are mapped to aggregate earnings, I estimate the firm-specific cash flow system by mapping firm returns to operating, investing and financing cash flows, respectively. This is because returns capture economic activities related to all types of activities, not exclusively operating or financing. Additionally, the return-cash flow relation could vary based on the nature of the activity, i.e., a_{i1}, b_{i1}, and c_{i1} may vary within-firm. In fact, the mean a_{i1}, b_{i1}, and c_{i1} (return relations with operating, investing and financing cash flows) are 0.011, -0.009 and 0.008, respectively, and statistically different from one another.[10] Separately estimating the return-cash flow relations for each type of activity most accurately captures the cash flow mapping system for each firm.

Next, I predict firm i's operating, investing, and financing cash flows using both firm i and j's cash flow functions. Holding constant firm i's set of economic events, I calculate the "would-be" cash flow amounts reported under firm i and j's cash flow systems. I hold constant the underlying economic events using $Return_{it}$ in both predictions. Given firm i's return in period t, $E(CFO_{iit}\ or\ CFI_{iit}\ or\ CFF_{iit})$ is the predicted cash flows using firm i's cash flow function, and $E(CFO_{ijt}\ or\ CFI_{ijt}\ or\ CFF_{ijt})$ is the predicted cash flows using firm j's function.

[10] Pairwise tests for differences in means of return-cash flow relation coefficient estimates show that they are all statistically different from one another (untabulated). Appendix 2 Panel A presents these mean coefficients by economic partitions such as industry, size and BTM, which suggest that they are different even within industry, within same size or BTM quintile. Such descriptive statistics suggest there is substantial variation across activity type with returns that justify separately estimating each to best capture firm-specific cash flow accounting system.

$$E(CFO_{iit}\ or\ CFI_{iit}\ or\ CFF_{iit}) = \hat{a}_{0i}, \hat{b}_{0i}, or\ \hat{c}_{0i} + \hat{a}_{1i}, \hat{b}_{1i}, or\ \hat{c}_{1i} * Return_{it} \quad (3.4)$$

$$E(CFO_{ijt}\ or\ CFI_{ijt}\ or\ CFF_{ijt}) = \hat{a}_{0j}, \hat{b}_{0j}, or\ \hat{c}_{0j} + \hat{a}_{1j}, \hat{b}_{1j}, or\ \hat{c}_{1j} * Return_{it} \quad (3.5)$$

Third, I calculate pairwise cash flow comparability as the negative value of the average absolute difference between predicted cash flows using firm i and j's functions. Greater values of $CompCFO_{ijt}$, $CompCFI_{ijt}$, $CompCFF_{ijt}$ (i.e., less negative) mean greater pairwise cash flow comparability between firm i and firm j in period t.

$$CompCFO_{ijt} = -\frac{1}{16} * \sum_{t-15}^{t} |E(CFO_{iit}) - E(CFO_{ijt})| \quad (3.6)$$

$$CompCFI_{ijt} = -\frac{1}{16} * \sum_{t-15}^{t} |E(CFI_{iit}) - E(CFI_{ijt})| \quad (3.7)$$

$$CompCFF_{ijt} = -\frac{1}{16} * \sum_{t-15}^{t} |E(CFF_{iit}) - E(CFF_{ijt})| \quad (3.8)$$

Fourth, I produce a firm-year measure of cash flow comparability by aggregating $CompCFO_{ijt}$, $CompCFI_{ijt}$, and $CompCFF_{ijt}$ for a given firm i in the same year. For simplicity, I use operating cash flow comparability to illustrate the steps I take. Investing and financing counterparts are computed similarly. Upon obtaining the estimated $CompCFO_{ijt}$ for each firm i-j pair in year t, I rank all j values of $CompCFO_{ijt}$ for each firm i from the highest to lowest. I create $CompCFO4_{it}$ which is the average $CompCFO_{ijt}$ of the four firms j with the highest comparability to firm i during year t. Firms with high $CompCFO4_{it}$, $CompCFI4_{it}$, and $CompCFF4_{it}$ have accounting functions that are more similar to their peer firms.

$$CompCFO4_{it} = 100\% * \frac{1}{4} * \sum_{j=1}^{4} top\ 4\ CompCFO_{ijt} \quad (3.9)$$

$$CompCFI4_{it} = 100\% * \frac{1}{4} * \sum_{j=1}^{4} top\ 4\ CompCFI_{ijt} \quad (3.10)$$

$$CompCFF4_{it} = 100\% * \frac{1}{4} * \sum_{j=1}^{4} top\ 4\ CompCFF_{ijt} \quad (3.11)$$

Fifth, I aggregate component cash flow comparability variables to derive a comprehensive cash flow comparability variable, $CompCF_{it}$. This aggregate measure is my dependent variable, and it is the weighted average of $CompCFO4_{it}$, $CompCFI4_{it}$, and $CompCFF4_{it}$.[11] Formally,

$$CompCF_{it} = w_1 CompCFO4_{it} + w_2 CompCFI4_{it} + w_3 CompCFF4_{it} \quad (3.12)$$

where $w_{CFO,CFI,or\ CFF} = \frac{CompCFO,\ CompCFI,\ or\ CompCFF}{CompCFO+CompCFI+CompCFF}$.

This last step is another key adaptation to DKV. My research setting calls for aggregating the component cash flow comparability measures because similarity in the cash flow accounting system across firms depends on similarities in mapping all three types of cash flows. Additionally, interest and dividend cash flows could be classified as either operating, investing, or financing activities; measuring cash flow comparability using any individual component cash flow comparability measures would reveal only one side of the classification effect.

In Appendix 2, I perform a series of tests similar to those in DKV (2011) to gain comfort over the validity of $CompCF$. Descriptive statistics show that $CompCF$ varies predictably with economic partitions such as industry, size, and book-to-market. Further, I test whether higher values of $CompCF$ is associated with documented benefits of comparability using analyst forecast data. I find that $CompCF$ is significantly associated with greater cash flow forecast accuracy and lower cash flow forecast dispersion. These findings provide assurance over the construct validity of the cash flow comparability metric.

Independent Variable Constructions

I have three conceptual independent variables of interest. The first captures accounting standard flexibility in classifying interest and dividend cash flows, $FLEXvar$. I operationalize this

[11] An alternative weighting scheme is to weight the components of CompCF using the absolute magnitude of each cash flow. Inferences are unchanged if CompCF are constructed under this alternative weight scheme.

variable with $FLEX$ and $FLEX2$. $FLEX$ is one if a firm reports using IFRS, and zero if a firm reports using U.S. GAAP. In my context, U.S. GAAP requires all entities to classify cash interest paid, interest received, and dividends received as operating activities under SFAS 95, and IFRS permits classification as either operating or investing/financing activities for these same activities.

$FLEX2$ refines $FLEX$ as it accounts for flexibility within U.S. GAAP in classifying certain interest and dividend cash flows prior to ASU 2016-15 taking effect in 2018. This ASU describes diverse classifications for interest cash flows related to zero-coupon debt settlement, and for dividends received from equity method investments.[12] Considering my sample period is almost entirely prior to the effective date of ASU 2016-15, U.S. GAAP filers that have zero-coupon debt settlement and equity method investments had some degree of classification flexibility for such interest and dividends. Hence, $FLEX2$ is an indicator variable that equals one if any of the three conditions is met: an IFRS firm, a U.S. GAAP firm that experiences a decline in year-over-year zero-coupon debt, or a U.S. GAAP firm that has a non-zero year-end equity method investment balance; $FLEX2$ is zero otherwise.

The second independent variable is the cash flow nature heterogeneity variable, which captures the extent to which a firm's interest and dividend cash flow generating activities is different in nature (non-financial or financial) from peers. The concept of heterogeneity is relative and cannot be assessed on any standalone firm. Measuring firm-level heterogeneity involves pairing each firm with peer firms in the same industry.

[12] ASU 2016-05 describes diverse classifications for debt prepayment/extinguishment costs, which sometimes are viewed as interest payments and classified as operating, and other times viewed as payments of principal and classified as financing. I do not include this item in *FLEX*2 adjustment because no existing data identify firms with debt prepayments/extinguishments. I inspected note disclosures of firms related to adopting ASU 2016-15 in Calcbench for the first 281 non-financial firms whose notes contain the keyword "2016-15". Only 11 firms discuss that they change classification related to debt prepayment or extinguishment upon adopting this Update. The majority of these 11 firms do not disclose numerical amounts adjusted, suggesting those amounts were immaterial. This hand collection exercise suggests that the effect of debt prepayment/extinguishment is not material, and the true population of firms with debt prepayment/extinguishment cash flows is not believed to be systematically under-represented.

I define peers using industry because one cannot understand the effect of heterogeneity in interest and dividend cash flows on cash flow comparability, absent controlling for differences in core operations (non-financial or financial). Interest and dividend cash flows could be of the same nature as core operations of a bank, but of a different nature in automobile industry such as those illustrated in the Ford and Tesla example. Across-firm comparisons for heterogeneity in interest and dividend cash flows are meaningful only upon controlling for differences in underlying core operations, which is captured by industry classifications. As shown by the industry descriptive statistics for CompCF in Appendix 2, CompCF is higher for firm i if peer firm j is from the same industry, than if it is from a different industry. Thus, confining comparisons to within industry best isolates the effect of interest and dividend cash flow heterogeneity on comparability, strengthening my research design and bolstering construct validity.

I take four steps to construct the heterogeneity variable. The source of heterogeneity in classifying interest and dividends lies in varying types of firm structure among peer firms, i.e., non-financial firms with or without financial natured business segments. I consider a firm or segment "financial" if its two-digit SIC classification is between 60 and 67, and "non-financial" otherwise. In step one, I identify industry classifications for each firm and all of its segments. I label a firm "pure" when it is a non-financial firm with only non-financial segments, or "hybrid" when it is a non-financial firm with at least one financial segment.

Second, I create firm i-j pairs by pairing each firm with peers in the same industry. Consider an industry with N firms in year t, this step would create N×(N-1) firm i-j pairs for that year. When two firms in a pair are both pure or both hybrid, this pair is "homogeneous." When a pure firm is paired up with a hybrid firm, this pair is "heterogeneous."

Third, for each firm I calculate $HeteroLevel$, my first proxy variable for heterogeneity, as the ratio of heterogeneous firm pairs to the total number of firm pairs. In the same industry in year t, if firm A is a pure firm and has four peers, three of which are hybrid and one is pure, the number of heterogeneous firm pairs associated with firm A is three, and the total number of firm pairs is four. In this case, firm A's $HeteroLevel$ in year t is 0.75.

Fourth, I calculate my second variable of heterogeneity, $Hetero4$, similar to $HeteroLevel$, except that the peer firm group is restricted to firms that constitute each of $CompCFO4$, $CompCFI4$, and $CompCFF4$. $Hetero4$ is the ratio of the number of heterogeneous firm pairs to the total number of firm i-j pairs of firm i. $Hetero4$ has an advantage over $HeteroLevel$ as it uses the same set of firms on which I assess cash flow comparability.

The third independent variable is opportunistic classification incentives. Prior literature identifies financial distress, low profitability and high leverage as characteristics that incentivize firms to opportunistically inflate operating cash flows via classification (Gordon et al. 2017). I measure financial distress using Altman's Z-score (Altman 1968). I measure profitability with return on assets, which is the ratio of net income to total assets, and leverage with total debt ratio, which is the ratio of total liabilities to total assets. I decile rank each of the three incentive variables from zero to nine, then scale the deciles by nine so they range between zero (low opportunistic incentive) and one (high opportunistic incentive). Note that I reverse decile rank Z-score and return on assets so that higher ranks correspond to greater financial distress (i.e., lower Z-scores) and lower profitability (i.e., lower return on assets), respectively. High ranks of total debt ratio suggest higher leverage. The scale-ranked incentive proxy variables are denoted $SRZscore$, $SRRoa$, and $SRLev$. Lastly, $AggIncentive$ is the average of $SRZscore$, $SRRoa$, and $SRLev$, with higher values indicating greater opportunistic classification incentives; it is my main incentive variable because it captures all three aspects of incentives.

IV. DATA, SAMPLES AND DESCRIPTIVE STATISTICS

Data and Samples

I obtain annual financial statement data and segment data from FactSet Fundamentals Global (V3.6.1) database, and monthly returns data from FactSet Monthly Prices (V3) database for all available U.S. and non-U.S. firms from 2005 to 2018. I obtain zero-coupon debt and total equity method investment balances from Standard & Poor's Capital IQ.[13] My sample begins in 2005 because the majority of sample firms are in countries that adopted IFRS mandatorily in 2005 (e.g., the Europe Union member countries, Australia, and South Africa). My sample ends in 2018 due to data availability on quarterly returns in FactSet.

I keep observations that have non-missing firm and segment industry classification information. For firms that have different classes of securities issued, I keep the primary listed security, which most likely represents the firm's largest and broadest common shareholder base.[14] I require each industry-year cohort to have at least 11 firms to construct comparability variables and drop observations that do not meet this criterion. I also require firms to have non-missing and non-zero cash interest paid as a percentage of total sales. Despite not having data on cash interest

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[13] I use Capital IQ to supplement FactSet because FactSet does not have zero-coupon debt information.

[14] FactSet V3 provides information on securities (not entities) across the globe, i.e., one firm could be associated with multiple securities if it issues different classes of securities or is traded on multiple exchanges at a single point in time. I apply the following screening procedures to identify the primary listing and remove duplicate securities for reporting entities with multiple securities. First, I keep the security that is listed in the country where the reporting entity is incorporated. I assume the primary listing for the firm usually is in the firm's home country. If there are multiple listings in the home country, I remove securities that represent "preferred shares" or "depositary shares" to keep securities that represent common shares. Entities that still have multiple securities after the previous two screens have multiple classes of securities that represent common shares. In this case, I calculate the percentage of common shares with which each security is associated and keep the security with the highest percentage. Lastly, for firms where these three screens all fail, which total 132 entities, I manually inspect firms' annual reports and company websites to identify and keep the security with the highest average daily traded volume. I use trading volume as an indicator for the liquidity of the stock; the more liquid the stock, the more likely the security is the primary listing for the firm.

and dividends received, this screening procedure ensures that, to the extent possible, firms in my sample have meaningful amounts of interest cash flows. Lastly, I drop influential observations. The final sample has 70,852 observations, of which 68,574 observations form the primary analyses sample representing 13,485 non-financial firms. The remaining 2,278 constitute the falsification sample representing 564 financial firms. Table 1 summarizes the sample selection process.

I employ two samples of firms in my empirical tests—non-financial firms for primary analyses and financial firms for falsification tests. I use financial firms for falsification purposes because these firms lack key characteristics related to classifying interest and dividends pertinent to finding hypothesized effects. With respect to the test of heterogeneity (H1a and H1b), I expect to find hypothesized effects in non-financial firms only. The hybrid segment of a non-financial firm is financial in nature, and serves to significantly promote the primary, non-financial operations of the business, e.g., Ford Credit to Ford. These financial segments generate frequent and considerable amounts of interest and dividend cash flows that are of an operating nature to the firm. Peer firms without such financial segments, however, generate interest and dividend cash flows mainly from financing and investing activities, e.g., Tesla. As such, hybrid firm structures in non-financial industries introduce heterogeneity to interest and dividend generating activities among peer firms.

In contrast, the hybrid segment of a financial firm is non-financial and is usually auxiliary and peripheral to the main financing/investing business. Common non-financial segments of financial firms provide corporate services, software or information technology support, or administrative services. These segments are unlikely to generate material interest and dividend cash flows, if any at all, to induce heterogeneity in cash flow nature within and across firms. The interest and dividend cash flows are still operating activities to a financial firm with or without a non-financial segment. That is, hybrid firm structures do not change the nature of interest and dividend generating activities among financial firms.

I also do not expect to find support for H2 in financial firms. This is because increasing opportunism likely will not alter operating classifications for interest and dividend cash flows of financial firms. Financial firms tend to experience a net inflow of interest and dividends. To the extent that opportunism sways firms to inflate operating cash flows via classification, financial firms maintain the operating classification for such inflows. Non-financial firms, pure or hybrid alike, tend to incur a net outflow of cash related to interest and dividends (i.e., on average more interest paid than interest and dividends received). In this case, given classification flexibility, opportunistic non-financial firms may be inclined to classify such net outflows as investing or financing activities. These considerations together call for conducting my primary analyses in the non-financial sample and falsification tests in the financial firm sample.

Descriptive Statistics

Table 2 Panel A and B present descriptive statistics for both the non-financial and financial samples. In the non-financial sample, mean $FLEX$ is 0.545. IFRS observations represent slightly more than half of the sample. $FLEX2$ identifies not only IFRS firms, but also U.S. GAAP firms with flexibility in classifying certain interest and dividend cash flows.[15] The mean $FLEX2$ is 0.643 in the non-financial sample. The financial sample has more IFRS than U.S. GAAP observations; the mean $FLEX$ and $FLEX2$ are 0.743 and 0.817.

In the non-financial sample (Panel A), the mean $HeteroLevel$ and $Hetero4$ are both 0.112, and the 75th percentiles are 0.083, and 0.091, respectively. The distribution of hybrid vs. pure firms, 95% to 5%, explains this right-skewness in heterogeneity variables. Untabulated mean

[15] Following this procedure, there are 6690 (170) observations in the non-financial (financial) sample that are reclassified as having flexibility (i.e., FLEX is zero and FLEX2 is one).

$HeteroLevel$ varies greatly by industry ranging from 0 (a homogeneous industry) to 0.49 (about even split of pure and hybrid firms in the industry).[16] Common financial segments of non-financial firms take on the form of real estate investments, holding and investment offices, and non-depositary credit institutions.

In the financial sample (Panel B), the mean $HeteroLevel$ and $Hetero4$ is 0.503 and 0.496.[17] Common non-financial segments have segment labels such as "other", "diversified activities", "eliminations", "corporate". This contextual evidence suggests that hybrid segments of financial firms are conspicuously different in nature from those of non-financial firms. This distinction makes financial firms appropriate for falsification tests.

The scaled decile rank incentive variables $SRZscore$, $SRRoa$, and $SRLev$ derive from Z-score (ZSCORE), return on asset (Roa) and total debt ratio (Lev). In the non-financial sample, ZSCORE, Roa, and Lev are skewed and have very large standard deviations. The financial sample share similar properties in these variables. Large standard deviations justify transforming these variables into scaled decile ranks. Decile ranked $SRZscore$, $SRRoa$, and $SRLev$ preserve the original rank ordering of the base variables without subjecting the measures to undue influence from extreme values.

On average, cash flow comparability ($CompCF$) is -0.152 for non-financial firms. This indicates the average error in quarterly cash flow predictions among firm i's closest four peers is 0.152% of market value. $CompCF$ is highly left skewed with large negative values. In the financial sample, mean $CompCF$ is -0.150 and similarly left-skewed. Consistent with DKV (2011), the

[16] The top five most heterogeneous industries are building construction, food stores, agricultural services, forestry, general merchandise stores. The least heterogeneous industries are railroad transportation, measuring and analyzing instruments and coal mining.

[17] Holding and investment offices, insurance carriers, and non-depositary credit institutions are the most heterogeneous. Insurance agents, broker, and services is the least heterogeneous.

skewness is driven by firms that are smaller, have lower book-to-market ratios, have lower earnings predictability, and report a loss. I control for these factors in my main analyses.[18] Of the control variables, book-to-market, (BTM), has the largest standard deviation which could be due to data errors related to FactSet's market capitalization variable in the non-financial sample. I use an alternative measure of market capitalization by multiplying period end price by shares outstanding, which has a smaller standard deviation. Regression results and inferences remain unchanged if I use this alternative measure.

Table 3 presents the top 35 countries in the primary sample (Panel A) and breakdown of sample by Fama-French 12 industry (Panel B). Panel A shows there are 4,916 U.S. firms, representing 35% of the sample by firm count. These top 35 countries represent 95% of primary sample by firm count, and 96% by observation count. Panel B shows sample breakdown using Fama-French 12 industries. The top three industries in the primary sample are business equipment, other, and manufacturing.

I present Pearson and Spearman correlations for the non-financial sample in Table 4, Panel A and B, respectively. $CompCF$ is not strongly correlated with $FLEX$ or $FLEX2$ in magnitude, though this does not control for other variables that affect comparability. $CompCF$ is negatively correlated with both $HeteroLevel$ and $Hetero4$ (p < 0.05). Further, $CompCF$ is significantly negatively correlated with $SRZscore$, $SRRoa$, $SRLev$, as well as $AggIncentive$ in both Pearson and Spearman correlations. $FLEX$ and $FLEX2$ are positive and significantly correlated (Pearson r and Spearman ρ = 0.82, p < 0.05). Correlations between $HeteroLevel$ and $Hetero4$ are positive and significant (Pearson r = 0.95, p < 0.05; Spearman ρ = 0.61, p < 0.05), indicating strong correlations in both a linear and monotonic function. Among incentive proxy variables, $SRZscore$

[18] I re-estimate model (1) and (2) using a decile rank transformation of CompCF and inferences are unchanged.

is positively correlated with $SRRoa$ and $SRLev$. $AggIncentive$ is the average of $SRZscore$, $SRRoa$, $SRLev$, and is positively correlated with all three with the highest correlation with $SRZscore$, all significant at $p < 0.05$.

V. RESULTS

Heterogeneity in Nature of Underlying Cash Flows (Test of H1a and H1b)

Table 5 Panel A presents results from testing H1a and H1b in non-financial firms. Results are similar across four combinations of $FLEXvar$ and $Hetero$ variables. H1 tests whether cash flow heterogeneity differentially affects uniformity and flexibility on cash flow informativeness. For H1a, I find negative and significant coefficients on three of the four specifications (with the fourth being significant at $p < 0.101$), suggesting that when interest and dividend cash flow generating activities are homogeneous, cash flow comparability under flexible standards is lower than that under uniform standards. For H1b, I find positive interactions between $FLEXvar$ and $Hetero$ variables with magnitudes ranging from 0.071 to 0.142, all $p < 0.01$. These results suggest that increasing heterogeneity in cash flow nature enhances comparability under flexible standards relative to uniform standards. Overall, both H1a and H1b are supported.

The coefficients on $HeteroLevel$ and $Hetero4$ are consistently negative and significant, suggesting that greater heterogeneity is associated with lower cash flow comparability under uniform standards. Another interesting inference from Table 5 is that I can estimate the level of heterogeneity needed to observe greater comparability from applying flexible standards instead of uniform standards. The back-of-the-envelope calculation of the heterogeneity threshold ranges from 0.196 to 0.235 across specifications.[19] This is not a particularly high level to attain. I require

[19] The heterogeneity threshold is the value of Hetero at which $b_1 + b_3 * Hetero = 0$. The cutoff Hetero value is obtained by solving $-\frac{b_1}{b_3} = 0$ with Table 5 coefficient estimates.

each industry-year group to have at least 11 firms. Assume an industry has one hybrid firm and ten pure firms (i.e., 11 firms in total and a relatively homogeneous industry), a pure firm's $HeteroLevel$ is 0.1. If another pure firm takes on a hybrid structure (i.e., 2-vs-9 in hybrid-vs-pure ratio), a pure firm's $HeteroLevel$ increases to 0.2. This exercise suggests that it does not require much heterogeneity for flexibility to enhance comparability relative to uniformity.[20]

Variables $SRZscore$ and $SRLev$ are negative and significant, though $SRRoa$ is not significant in any specification. $Size$ and BTM are positive and significant, while $Predictability$ and $Loss$ are insignificant. These somewhat coincide with DKV's (2011) discussion that small and low growth firms tend to have less comparable information. $Accrual$ is negative and significant, suggesting increasing comparability in accrual quality (i.e., low levels of accruals).

Table 5 Panel B presents falsification tests using financial firms. Recall that I do not expect to find support in the financial sample because having hybrid segments in financial firms does not introduce the same heterogeneity to the nature of interest and dividend cash flows as observed in non-financial firms. Consistent with my expectations, neither $FLEXvar$ nor the interaction between $FLEXvar$ and $Hetero$ is significant across specifications. I find no support for H1a or H1b in financial firms. Among control variables, only $SRLev$ and $Size$ are significant: cash flow comparability seems to decline as financial firms increase in leverage and increase when firms grow larger in size.

Opportunistic Classification Incentives (Test of H2)

Table 6 Panel A presents tests of H2 using non-financial firms. Columns (1) through (4) use $FLEX$, and columns (5) through (8) use $FLEX2$ across four $Incentive$ variables. Among

[20] In the primary non-financial sample, 15 of the total 59 industries defined by two-digit SIC codes have average heterogeneity greater than this estimated threshold (i.e., HeteroLevel = 0.196). By observation count, 9% of the non-financial sample exceeds this threshold.

$Incentive$ variables, I focus my discussion on $AggIncentive$, while presenting results for all specifications, because $AggIncentive$ is a more comprehensive measure of incentives than $SRZscore$, $SRRoa$, or $SRLev$ individually. H2 predicts that increasing opportunistic classification incentives decreases cash flow comparability under flexible standards. Consistent with my prediction, I find that the interaction term is -0.088 ($p < 0.01$) in $FLEX$ and -0.085 ($p < 0.01$) in $FLEX2$ specifications with $AggIncentive$. Further, the interaction coefficient is statistically significant and negative across other incentive specifications. H2 is supported.

In theory, if U.S. GAAP and IFRS differ only in classifying interest and dividends cash flows, increasing opportunistic incentives is not expected to affect cash flow informativeness under a perfectly measured uniform regime (DS 2008). However, there is discretion within U.S. GAAP in classifying cash flows other than interest and dividends, which implies that empirically, increasing opportunistic incentives could reduce cash flow quality under U.S. GAAP. Table 6 Panel A shows that incentive variables indeed are all negative and statistically significant at $p < 0.01$. For instance, a one-decile increase in $AggIncentive$ leads to a decline in cash flow comparability by 0.154% of market value in the $FLEX$ model, or 0.147% in the $FLEX2$ model. This finding is attributable to the fact that the uniformity of U.S. GAAP in my study is confined to classifying interest and dividend cash flows. Cash flow classification within U.S. GAAP for other activities could introduce flexibility, and if exploited opportunistically, impairs comparability and informativeness of reported cash flows. An example of such flexibility is the application of the predominance principle for activities without uniform classification prescription.

Recall that the coefficient on $FLEXvar$ captures the comparability of flexible classification standards relative to uniform standards at low levels of opportunistic classification incentives. Panel A shows that c_1 is positive and significant when $AggIncentive$ is used to measure reporting incentives in both $FLEX$ ($p < 0.05$) and $FLEX2$ ($p < 0.01$) specifications. These results suggest that when incentives are measured in the aggregate, cash flow comparability could be higher under flexible rather than uniform standards at low levels of opportunistic classification incentives.[21] Similar to Table 5, I find on average, increasing heterogeneity in the nature of cash flows weakens cash flow comparability. The other control variables also behave similarly to those in Table 5 Panel A.[22]

Panel B provides falsification test using financial firms for H2. I do not expect to find support for H2 in financial firms because financial firms are more likely have a net inflow of cash related to interests and dividends. To the extent opportunism sways firms into boosting operating cash flows, financial firms would continue to classify interest- and dividends-related net inflows as operating. As expected, the interaction term, c_3, is not statistically negative in any specification. Opportunistic reporting incentives do not appear to affect cash flow comparability for financial firms under flexible standards, as incentives are unlikely to trigger a change in classification away from operating in the financial industry.

VI. ADDITIONAL ANALYSES

Cross Country Legal System and Enforcement Differences

With respect to testing effects of opportunistic classification incentives (i.e., H2), I operationalize uniformity and flexibility in cash flow classification using U.S. GAAP and IFRS, and IFRS filers in my sample are from multiple jurisdictions. One concern is that differences in institutional factors such as enforcement or legal systems across countries could contribute to observed differences in cash flow informativeness. For instance, prior literature suggests that

[21] Similar results are found in SRZscore but not SRRoa and SRLev specifications.
[22] I find similar results in H1 and H2 when the models include stock exchange fixed effects instead of country fixed effects as well as industry fixed effects. Results and inferences also remain unchanged if I winsorize variables and estimate the OLS model without dropping influential observations.

institutional factors such as legal origins or enforcement affect observable properties of accounting earnings and comparability of IFRS-based and U.S. GAAP-based accounting amounts (e.g., Ball, Kothari, Robin 2000; Barth, Landsman, Lang, and Williams 2012).

I take two approaches to alleviate the concern that my documented findings in H2 are attributable to differences in enforcement and legal systems. First, a country's legal system and enforcement intensity usually do not change over time. Prior literature that examines these factors usually capture legal origin or enforcement using country-level dummy variables that are constant during the sample period (Barth et al. 2012). In this case, country fixed effects included in my analyses should capture such time-invariant country-level heterogeneity.

Second, I directly examine the effects of legal system and enforcement in a subsample of firms where there is flexibility in classifying interest and dividend cash flows (i.e., where $FLEX2$ = 1). I expect that common law countries (as opposed to code law) and greater enforcement reduce the negative effect of opportunistic classification incentives on cash flow comparability (Barth et al. 2012). To test this expectation, I estimate the following model using OLS:

$$CompCF = d_0 + d_1 AggIncentive + d_2 EnforceVar + d_3 AggIncentive * EnforceVar$$

$$+ d_4 HeteroLevel + \sum d_n Controls + \gamma_k + \lambda_t + e \quad (4)$$

$EnforceVar$ is one of two measures: $CommLaw$ and WGI. $CommLaw$ is an indicator variable that is one for common law countries, and zero for code law countries. This variable does not change over time, so the coefficient on $CommLaw$, d_2, is omitted when country fixed effects are included. WGI is Worldwide Governance Index, a country-year variable that measures the strictness of countries' enforcement regimes. It has six dimensions of governance with higher values reflecting greater overall quality of governance and enforcement environment (Daske, Hail, Leuz and Verdi 2008; Kaufmann, Kraay, and Mas-truzzi 2010). Country average WGI ranges from -6.35 (Afghanistan) to 10.98 (Finland).

Table 7 presents tests of $CommLaw$ (column 1) and WGI (column 2) on the relation between opportunistic classification incentives and cash flow comparability. As expected, I find a positive and significant interaction between $EnforceVar$ and $AggIncentive$: 0.041 in $CommLaw$ (p < 0.10) and 0.010 in WGI specifications (p < 0.01). These results suggest that common law system and greater enforcement environments mitigate the negative effect of opportunistic classification incentives on cash flow comparability in a flexible reporting environment. These findings are consistent with predictions in DS (2008) with regard to the cost of report manipulation: informativeness of financial reports under flexible regimes increases in cost of report manipulation, i.e., common-law or stricter enforcement environments.

Note that within this flexibility subsample, $AggIncentive$ is still negative and significant, and significantly greater in magnitude than the positive interaction term in both specifications. This implies that the overall effect of $AggIncentive$ in common law countries is still negatively related to $CompCF$; the overall effect of $AggIncentive$ in even the highest WGI countries also is negatively related to $CompCF$. Together, I infer from these findings that given classification flexibility, common law systems and greater enforcement reduce, but do not fully mitigate the negative impact on cash flow comparability.

VII. CONCLUSION

I study conditions under which flexibility in cash flow classification standards enhances the informativeness of cash flow information. In the context of cash flow classification, informative cash flows enable users to identify similarities for those classified similarly and discern differences for those classified differently, i.e., comparable cash flows. Existing literature on cash flow classification has been silent on the comparability effect of flexibility in classification standards. I fill this void by directly testing conditions theorized in DS (2008) under which flexibility and uniformity are useful in creating informative financial reports.

I exploit variation in flexibility permitted in IFRS and U.S. GAAP, and within U.S. GAAP regarding classifications of interest and dividend cash flows to study this question. I predict and find that, holding constant opportunistic classification incentives, as a firm's underlying interest and dividend generating activities become more heterogeneous relative to peers in industry, flexible standards outperform uniform standards in promoting cash flow comparability. Second, all else equal, flexibility impairs cash flow comparability as firms experience heightened opportunistic classification incentives. Comparability under uniform standards in theory should not change with opportunistic incentives. The assumption is that the same cash flows are always classified uniformly without exception, and uniformity is perfectly measured. Empirically, I find that increasing opportunism still weakens cash flow comparability under U.S. GAAP, even upon refining the measurement of flexibility within U.S. GAAP regarding interests and dividends classification. This result is attributed to discretion inherent in U.S. GAAP for classifications beyond interest and dividend cash flows.

A caveat of this study is that I identify and attribute the source of heterogeneity in interest and dividend cash flows to firms having different mixtures of financial or non-financial natured activities that generate such cash flows. For classification considerations of other activities, the source of heterogeneity certainly could be different. I acknowledge a limitation in relying on industry affiliation to control for similarity in underlying economics between flexible and uniform reporting firms. To the extent I can, I follow prior literature, and show that my findings hold after controlling for factors that contribute to differences in underlying economics.

This study makes several contributions. It is the first study to my knowledge that directly examines cash flow quality implications of classification flexibility. While it is a widely held assumption that uniform classifications create comparability, e.g., standard setting discussions criticize observed diversity in classification as hurting comparability (see Basis for Conclusion in ASU 2016-15, FASB 2016), I show that classification flexibility can enhance cash flow comparability when underlying cash flows are heterogeneous in nature. My empirical findings also validate analytical predictions in DS (2008) regarding circumstances where flexibility in standards would improve information quality.

Second, my results are timely to current standard setting discussions. The IASB is contemplating removing the operating classification alternative for cash interest and dividends for non-financial firms (ED 2019/07), citing comparability improvements after the change (IASB 2020). I show that U.S. GAAP underperforms IFRS in cash flow comparability when non-financial firms have more heterogeneous interest and dividend cash flows relative to peers. With respect to classifying cash interest and dividends, the IASB proposal has potential to improve comparability while curbing reporting opportunism. This calls into question the appropriateness of imposing an operating classification for interest and dividends on all non-financial entities in SFAS 95 (Nurnberg and Largay 1998).

Interestingly, Gordon et al. (2017) find IFRS firms cross-listed in the U.S. are more likely to classify interest and dividend the same way as their U.S. peers, i.e., as operating activities. My findings caution that uniformity in classification does not necessarily provide comparable cash flows if the classification choice disregards the underlying differences in cash flow nature and the effects of incentives for managerial reporting opportunism. For other activities where standard setters must decide which approach—flexibility vs. uniformity—to use in classification, I provide evidence supporting continued use of both going forward, while carefully weighing the comparability implications of accommodating heterogeneity and managerial reporting incentives.

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Appendix 1. Variable Definitions for Main Tests

Dependent Variable	**Definition**
CompCF	Cash flow comparability for firm i in year t, calculated as the weighted average of comparability of operating (CompCFO4), investing (CompCFI4) and financing (CompCFF4) cash flows.
Independent Variables	
FLEX	Indicator variable that equals 1 if the firm reports under IFRS (FF_ACTG_STANDARD is 23), or 0 if the firm reports under U.S. GAAP (FF_ACTG_STANDARD is 03), in year t.
FLEX2	Indicator variable that equals 1 if a firm reports under IFRS (FF_ACTG_STANDARD is 23), or a U.S. GAAP firm (FF_ACTG_STANDARD is 03) when ZeroCoupon is one, or a U.S. GAAP firm when EquityMethod is one; the variable is zero otherwise. The zero-coupon debt variable, ZeroCoupon, is one if year-over-year change in zero-coupon debt (S&P Capital IQ data item [41589]) is negative, and zero otherwise. The equity method investment variable, EquityMethod, is one if total equity method investment balance (S&P Capital IQ data item [3063]) has a non-zero year-end balance, and zero otherwise.
HeteroLevel	The proportion of firm ij pairs that are pure-hybrid out of total ij pairs for firm i in year t, where firm j is defined as each peer firm in the same industry-year cohort.
Hetero4	The proportion of firm ij pairs that are pure-hybrid out of the total ij pairs of firm i in year t, where firm j is restricted to firms that make up CompCFO4, CompCFI4 and CompCFF4.
SRZscore	Decile rank of reverse-coded Zscore (FF_ZSCORE) from 0 (least distressed) to 1 (most distressed).
SRRoa	Decile rank of reverse-coded return on asset from 0 (most profitable) to 1 (least profitable), where return on asset is net income (FF_NET_INCOME) divided by total assets (FF_ASSETS) for firm i in year t.
SRLev	Decile rank of leverage from 0 (least leveraged) to 1 (most leveraged), where leverage is total liabilities (FF_LIABS) divided by total assets (FF_ASSETS) for firm i in year t.
AggIncentive	Aggregate opportunistic classification incentive variable which is the average of SRZscore, SRRoa, and SRLev.
CommLaw	Indicator variable that equals 1 if the legal system of firm's country of incorporation is of common law origin, and 0 otherwise.
WGI	Sum of six dimensions of governance from Worldwide Governance Indicators (WGI) project by Kaufmann, Kraay, and Mastruzzi (2010). The six dimensions include Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption for over 200 countries and territories since 1996. Each

	governance dimension is in standard normal units ranging from approximately -2.5 (weak) to 2.5 (strong) governance performance.
Controls	
Size	Natural log of market value of equity, FF_MKT_VAL, for firm i in year t.
BTM	Ratio of book value of equity, FF_ASSETS - FF_LIABS, to the market value of equity, FF_MKT_VAL, for firm i in year t.
Predictability	The R-squared of a firm-specific regression of earnings on prior-year earnings using the previous 16 quarters of data. Earnings before extraordinary items (FF_NET_INC_BASIC_BEFT_XORD) is scaled by beginning market value of equity which is month-end price (PRICE_M) multiplied by shares outstanding (FF_SHS_OUT). The variable is winsorized at 1st and 99th percentile by year.
Loss	Indicator variable that equals 1 if the current earnings before extraordinary items (FF_NET_INC_BASIC_BEFT_XORD) are less than zero, or 0 otherwise.
Accrual	Total accruals, calculated as income before extraordinary items (FF_NET_INC_BASIC_BEFT_XORD) minus net cash flows from operating activities (FF_OPER_CF), scaled by total assets (FF_ASSETS).
Country	Country fixed effects based on country of incorporation (FF_COUNTRY_INCORP).
Year	Year fixed effects.

Appendix 2. Validation Tests for CompCF

The DKV (2011) model maps total economic events, i.e., returns, into an accounting outcome, i.e., earnings. One concern with using the adapted DKV model for cash flow comparability is how well cash flows capture accounting outcomes of total economic events. To assess the validity of my cash flow comparability measure, I provide descriptive statistics on $CompCF$ in different economic partitions, and document benefits of high cash flow comparability for sell-side analysts.

Separately Estimate Return-Cash Flow Relations by Activity

The first step in creating $CompCF$ is to estimate the firm-specific cash flow system. I do so by mapping returns separately into operating, investing and financing activities, as it allows the return-cash flow relation to vary depending on the nature of the activity. Appendix 2 Table Panel A presents mean return-cash flow relations from regressing CFO, CFI and CFF on Returns for each firm, i.e., $\widehat{a_i}$, $\widehat{b_i}$, and $\widehat{c_i}$ from equations 3.1 to 3.3.

For industry partition, I randomly select a sample of firms from banking (two-digit SIC 60-67), manufacturing (two-digit SIC 20-39), and utilities (two-digit SIC 40-49) industries in 2010. Within each industry, the coefficients $\widehat{a_i}$, $\widehat{b_i}$, and $\widehat{c_i}$ differ across activity types. For size and book-to-market partitions, I use a sample of manufacturing firms in 2010, and create quintiles based on size and book-to-market. Within each size (or BTM) quintile, there is variation in return-cash flow relation by activity. Although $\widehat{a_i}$, $\widehat{b_i}$, and $\widehat{c_i}$ do not monotonically change in size or BTM across quintiles, these summary statistics suggest that the return-cash flow relations do vary across operating, investing and financing activities, justifying estimating each to best capture firm-specific cash flow accounting system.

Descriptive Statistics of CompCF by Economic Partitions

I take an exploratory approach similar to DKV (2011) to understand whether values of $CompCF$ are consistently higher for subsamples that are expected to be comparable than those that are expected to be *not* comparable. The economic characteristics I use are industry, size and BTM. I expect that firm fundamentals are more comparable within than across industry. Hence, for a given set of firms, $CompCF$ is expected to be higher when firms i are paired with firms j from the same industry than with firms j from different industries.

Appendix 2 Table Panel B presents mean $CompCF$ for different firm pairs. I find that mean $CompCF$ is -0.194 when firms i and j are both banks, greater than (i.e., less negative than) -1.956 and -1.035, when firm j is a manufacturing firm and a utility firm. The differences between mean $CompCF$ for each group are significant at 1% (two-sided). This finding supports the notion that cash flow comparability is greater for firms that belong to the same industry.

Next, for each factor (size and book-to-market), pairing firms up based on quintiles creates 25 mutually exclusive partitions. I compare values of $CompCF$ for firm pairs in the same extreme quintile (i.e., largest firms paired up with largest firms, or smallest firms paired up with smallest firms) to those for firm pairs in the opposite extreme quintiles (i.e., largest firms paired up with smallest firms, and vice-versa). I expect that firms in the same extreme quintile of size or book-to-market are more comparable than those in opposite extreme quintiles.

Mean $CompCF$ is -0.393 when firms i and j are from the same extreme size quintile, greater than -0.947 when firms i and j are from opposite extreme size quintiles. Partition by book-to-market shows similar results. All differences in means are statistically significant at 1%.

Sell-Side Analyst Tests

I test whether $CompCF$ varies predictably with analysts' cash flow forecast quality (DKV 2011). The notion is that higher information comparability lowers analysts' information acquisition and processing costs. If $CompCF$ reasonably captures cash flow comparability, greater values of $CompCF$ should be associated with more accurate and less dispersed cash flow forecasts. Since analysts' cash flow forecasts are most commonly forecasts of operating cash flows, I also assess $CompCFO4$ in addition to $CompCF$. I have the same directional predictions for both $CompCF$ and $CompCFO4$, though I expect the association to be stronger in $CompCFO4$ models because cash flow forecasts are more directly related to operating activities.

I obtain analyst forecasts of cash flows from I/B/E/S detail file to construct forecast quality measures. I then merge I/B/E/S data with FactSet sample using the CRSP link files from WRDS to construct other control variables (DKV 2011).[23] I test the association between cash flow comparability measures and analyst forecast quality with the following model:

$$Quality_{it} = a + \beta_1 Comparability_{it} + \gamma Controls_{it} + \varepsilon_{it} \qquad \text{(A5.1)}$$

$Quality_{it}$ is $Accuracy$ or $Dispersion$ of cash flow forecasts. $Accuracy$ is the absolute value of cash flow forecast error multiplied by -100, and scaled by stock price at the end of the prior fiscal year. $Dispersion$ is the standard deviation of individual analysts' annual cash flow forecasts, scaled by stock price at the end of the prior fiscal year. $Comparability$ is $CompCF$ or $CompCFO4$. Controls in equation (A5.1) include $Size$, $Loss$, $Predictability$, $SUOCF$, $NEGOCF$, $NEGSI$, $DAYS$, $Vol(Return)$, and $Vol(OCF)$. $SUOCF$ captures the unexpected portion of operating cash flows: it is the absolute value of the difference between actual and prior year operating cash flows, scaled by beginning period stock price. $NEGOCF$ is one if a firm's operating cash flows are below that of a year ago, zero otherwise. $NEGSI$ captures the extent to which there are special items: it is the absolute value of special items scaled by total assets if negative, and zero otherwise. $DAYS$ is the logarithm of the mean number of days between forecast date to firm's earnings announcement date. $Vol(Return)$ and $Vol(OCF)$ are standard deviations of 48 months of returns and 16 quarters of operating cash flows.

Similar to my main tests, I drop influential observations and cluster standard errors at firm and year. I include industry and year fixed effects. Appendix 2 Table Panel C presents analyst forecast quality test results. As expected, I find that comparability variables are positively associated with cash flow forecast accuracy ($CompCF$: 8.898, $p < 0.05$; $CompCFO4$: 9.265, $p < 0.01$), and negative associated with forecast dispersion ($CompCF$: -4.936, $p < 0.10$; $CompCFO4$: -5.824, $p < 0.05$). In sum, these tests show that $CompCF$ varies predictably with economic characteristics and analyst forecast quality. Results here provide comfort over the validity of the cash flow comparability measure that I use in main tests.

[23] I do not find other relatively reliable linking suites to match all firms from FactSet to IBES. Thus, the analyst coverage and forecast quality tests are conducted on a sample in which there is a common PERMNO in CRSP linking suites with FactSet and with IBES. Since CRSP covers NYSE, AMEX and NASDAQ stock markets, the final sample consists of primarily U.S. firms (93% of total matched observations), with the other 7% being international firms that are traded on these three exchanges.

Appendix 2 Table. Validating CompCF

Panel A. Descriptive Statistics of Returns-Cash Flow Relations by Economic Partition

	Return relation with		
By *Industry*	CFO (a_i)	CFI (b_i)	CFF(c_i)
Manufacturing	0.022	0.002	-0.010
Utility	0.028	-0.015	-0.016
Banking	-0.003	-0.022	0.004
By *Size* Quintile for Manufacturing Industry			
1 (Smallest)	0.022	0.002	-0.001
2	0.021	-0.002	-0.004
3	0.018	-0.021	0.005
4	0.034	-0.014	-0.021
5 (Largest)	0.029	0.004	-0.042
By *Book-to-Market* Quintile for Manufacturing Industry			
1 (Smallest)	0.027	-0.005	-0.006
2	0.026	-0.012	-0.002
3	0.025	-0.004	-0.008
4	0.025	-0.004	-0.028
5 (Largest)	0.022	-0.006	-0.019

Panel B. Descriptive Statistics of CompCF by Economic Partition

		CompCF (%)	
	N	Mean	Median
By *Industry*			
Firms i and j in banking industry	55,932	-0.194	-0.116
Firm i in banking while firm j in manufacturing industry	64,701	-1.956	-0.438
Firm i in banking while firm j in utility industry	57,354	-1.035	-0.259
By *Size* Quintile for Manufacturing Industry			
Firm i in the same extreme quintile as firm j	5,832	-0.393	-0.195
Firm i in the opposite extreme quintile from firm j	5,940	-0.947	-0.245
By *Book-to-Market* Quintile for Manufacturing Industry			
Firm i in the same extreme quintile as firm j	5,832	-0.602	-0.235
Firm i in the opposite extreme quintile from firm j	5,940	-0.772	-0.469

Panel C. Cash Flow Forecast Quality

		DV = Accuracy			DV = Dispersion	
		(1)	(2)		(3)	(4)
Variables	Pred.	CompCF	CompCFO4	Pred.	CompCF	CompCFO4
Comparability	+	8.898**	9.265***	-	-4.936*	-5.824**
		(3.196)	(2.500)		(2.535)	(2.219)
SUOCF	-	-0.138***	-0.141***	?	0.104***	0.105***
		(0.031)	(0.032)		(0.025)	(0.026)
NEGOCF	-	-1.483***	-1.385***	+	0.756	0.701
		(0.316)	(0.327)		(0.609)	(0.612)
LOSS	-	-1.362*	-1.417*	+	2.081*	2.118*
		(0.648)	(0.653)		(1.010)	(0.998)
NEGSI	-	-27.461	-25.619	+	209.272	208.511
		(33.107)	(32.320)		(140.337)	(139.891)
DAYS	-	-1.762***	-1.795***	+	4.680***	4.681***
		(0.415)	(0.427)		(1.355)	(1.344)
Size	+	2.101***	2.195***	-	-2.536***	-2.574***
		(0.273)	(0.279)		(0.585)	(0.567)
Predictability	+	-0.035	-0.026	-	-1.810	-1.817
		(1.297)	(1.236)		(1.778)	(1.746)
Vol(Return)	-	-0.180***	-0.197***	+	0.264**	0.271**
		(0.042)	(0.047)		(0.094)	(0.095)
Vol(OCF)	-	0.000	-0.000	+	0.003	0.003
		(0.001)	(0.001)		(0.002)	(0.002)
Constant		-6.854**	-7.458**		-7.062	-6.757
		(2.632)	(2.635)		(6.296)	(6.364)
Observations		6,697	6,697		7,103	7,103
Adj. R-squared		0.156	0.153		0.105	0.105
Fixed Effects		Industry, Year	Industry, Year		Industry, Year	Industry, Year
Cluster		Firm, Year	Firm, Year		Firm, Year	Firm, Year

Robust t-statistics in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%. *Accuracy* is the absolute value of the forecast error multiplied by −100, scaled by beginning stock price. Forecast error is IBES reported analysts' mean cash flow forecast less the actual cash flow per share reported by IBES. *Dispersion* is the cross-sectional standard deviation of individual analysts' annual cash flow forecasts, scaled by beginning period stock price. *DAYS* is the logarithm of the mean number of days from the cash flow forecast date to the earnings announcement date. *NEGOCF* is an indicator variable that equals one if firm i's operating cash flows are below the reported operating cash flows a year ago, zero otherwise. *NEGSI* is the absolute value of the special item deflated by total assets if negative, zero otherwise. *SUOCF* is the absolute value of unexpected operating cash flows, scaled by the stock price at the end of the prior year. Unexpected operating cash flows are actual operating cash flows minus reported operating cash flows from the prior year. *Vol(OCF)* is the standard deviation of 16 quarterly operating cash flows. *Vol(Return)* is the standard deviation of 48 months of stock returns.

Table 1. Sample Selection

	Observations	Firms
FactSet Universe from 2005-2018	803,696	67,001
Less: Observations missing firm or segment industry classification	(196,810)	(14,283)
Less: Observations with duplicate security issues	(168,743)	(5,243)
Less: Observations missing data to create key variables	(297,026)	(23,726)
Less: Observations with fewer than 11 firms in each industry-year cohort	(18,477)	(1,420)
Less: Observations with missing or zero cash interest paid	(32,394)	(4,877)
Less: Influential observations	(19,394)	(3,403)
Final Sample	**70,852**	**14,049**
Nonfinancial Sample (For Primary Analyses)	68,574	13,485
Financial sample (For Falsification Test)	2,278	564

Table 2. Descriptive Statistics

Panel A. Primary Analysis Sample - Non-Financial Firms

Variables	N	Mean	Std. Dev.	p25	Median	p75
CompCF	68574	-0.152	0.242	-0.163	-0.056	-0.022
FLEX	68574	0.545	0.498	0.000	1.000	1.000
FLEX2	68574	0.643	0.479	0.000	1.000	1.000
HeteroLevel	68574	0.112	0.209	0.029	0.048	0.083
Hetero4	68574	0.112	0.219	0.000	0.000	0.091
AggIncentive	68574	0.478	0.232	0.296	0.481	0.630
SRZscore	68574	0.485	0.281	0.222	0.444	0.667
SRRoa	68574	0.444	0.303	0.222	0.444	0.667
SRLev	68574	0.506	0.278	0.333	0.556	0.778
Size	68574	6.961	3.056	4.809	6.935	8.918
BTM	68574	256.221	36801.663	0.310	0.583	1.015
Predictability	68574	0.118	0.162	0.009	0.047	0.162
Loss	68574	0.351	0.477	0.000	0.000	1.000
Accrual	68574	-0.067	1.441	-0.047	-0.021	-0.002
ZSCORE	68574	-0.769	189.742	1.303	2.490	4.073
Roa	68574	-0.157	3.740	-0.021	0.030	0.069
Lev	68574	0.906	31.364	0.345	0.505	0.657
CompCFO4	68574	-0.114	0.212	-0.111	-0.039	-0.015
CompCFI4	68574	-0.096	0.196	-0.088	-0.030	-0.010
CompCFF4	68574	-0.108	0.212	-0.101	-0.034	-0.012
wCFO	68574	0.370	0.198	0.214	0.353	0.508
wCFI	68574	0.299	0.195	0.143	0.266	0.423
wCFF	68574	0.331	0.191	0.181	0.306	0.454
ZeroCoupon	68545	0.010	0.099	0.000	0.000	0.000
EquityMethod	68545	0.093	0.291	0.000	0.000	0.000

Note: variables from ZSCORE to EquityMethod are base variables used to construct the main proxy variables used in models (1) and (2), but they are not used in regression analyses. I present their descriptive statistics to provide more details about the sample.

Panel B. Falsification Test Sample - Financial Firms

Variables	N	Mean	Std. Dev.	p25	Median	p75
CompCF	2278	-0.150	0.233	-0.157	-0.062	-0.029
FLEX	2278	0.743	0.437	0.000	1.000	1.000
FLEX2	2278	0.817	0.386	1.000	1.000	1.000
HeteroLevel	2278	0.503	0.322	0.188	0.705	0.774
Hetero4	2278	0.496	0.332	0.167	0.545	0.818
AggIncentive	2278	0.528	0.231	0.370	0.519	0.704
SRZscore	2278	0.581	0.271	0.444	0.667	0.778
SRRoa	2278	0.493	0.292	0.222	0.556	0.667
SRLev	2278	0.511	0.294	0.222	0.556	0.778
Size	2278	5.992	3.087	3.867	5.595	7.927
BTM	2278	1.112	2.175	0.436	0.914	1.630
Predictability	2278	0.107	0.152	0.010	0.043	0.144
Loss	2278	0.414	0.493	0.000	0.000	1.000
Accrual	2278	-0.089	2.071	-0.042	-0.015	0.008
ZSCORE	2278	-3.335	107.691	0.751	1.744	2.987
Roa	2278	-0.294	8.152	-0.026	0.017	0.053
Lev	2278	1.184	15.630	0.335	0.508	0.685
CompCFO4	2278	-0.127	0.241	-0.116	-0.040	-0.016
CompCFI4	2278	-0.082	0.164	-0.077	-0.031	-0.014
CompCFF4	2278	-0.089	0.158	-0.088	-0.036	-0.018
wCFO	2278	0.376	0.227	0.188	0.348	0.530
wCFI	2278	0.298	0.197	0.131	0.274	0.436
wCFF	2278	0.326	0.191	0.177	0.305	0.454
ZeroCoupon	2277	0.013	0.114	0.000	0.000	0.000
EquityMethod	2277	0.064	0.245	0.000	0.000	0.000

Table 3. Sample Breakdown by Country and Industry

Panel A. Top 35 Countries for Primary Analyses Sample

Country	Observations	Firms	Cum % by Obs	Cum % by Firms
United States of America	29,306	4,916	43%	36%
South Korea	6,375	1,510	52%	48%
Taiwan	5,604	1,326	60%	57%
Canada	3,729	975	66%	65%
Malaysia	2,008	484	69%	68%
Poland	1,927	363	71%	71%
Sweden	1,876	331	74%	73%
Germany	2,181	310	77%	76%
Israel	1,095	228	79%	77%
Turkey	1,091	217	80%	79%
Greece	810	185	82%	80%
Pakistan	557	151	82%	82%
Sri Lanka	600	149	83%	83%
Brazil	494	137	84%	84%
Philippines	722	125	85%	85%
Chile	662	118	86%	85%
Finland	1,021	115	88%	86%
Norway	503	113	88%	87%
Italy	411	88	89%	88%
Japan	463	86	90%	88%
Mexico	420	85	90%	89%
Denmark	508	74	91%	90%
Bermuda	369	69	91%	90%
Kuwait	375	68	92%	91%
Peru	343	67	93%	91%
Cayman Islands	206	62	93%	92%
Oman	312	62	93%	92%
Netherlands	318	61	94%	93%
Bulgaria	203	57	94%	93%
Croatia	189	54	94%	93%
Bangladesh	163	53	95%	94%
United Kingdom	316	51	95%	94%
Jordan	161	49	95%	94%
Austria	306	47	96%	95%
Saudi Arabia	46	46	96%	95%

Panel B. Industry Breakdown by Fama-French 12 for Primary Analyses Sample

Fama-French 12 industries	**Observations**	**Firms**
Consumer NonDurables	5,601	1,140
Consumer Durables	2,616	521
Manufacturing	11,343	2,040
Oil, Gas, and Coal Extraction and Products	3,368	716
Chemicals and Allied Products	2,930	553
Business Equipment	14,050	2,845
Telephone and Television Transmission	2,397	434
Utilities	2,578	439
Wholesale, Retail, and Some Services (Laundries, Repair Shops)	6,036	1,159
Healthcare, Medical Equipment, and Drugs	6,459	1,306
Other -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment	11,196	2,332
Total	**68,574**	**13,485**

Note: For presentation purposes, industry breakdowns are organized using Fama-French 12 classifications. Industries are defined as two-digit SIC classifications consistently throughout analyses.

Table 4. Correlations for Primary Analysis Sample – Non-Financial Firms

Panel A. Pearson Correlation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) CompCF	1													
(2) FLEX	0.009*	1												
(3) FLEX2	0.008*	0.816*	1											
(4) HeteroLevel	-0.099*	0.146*	0.146*	1										
(5) Hetero4	-0.097*	0.143*	0.144*	0.952*	1									
(6) AggIncentive	-0.198*	-0.082*	-0.069*	-0.003	0	1								
(7) SRZscore	-0.184*	0.007	0.014*	0.027*	0.029*	0.893*	1							
(8) SRRoa	-0.120*	-0.065*	-0.093*	-0.034*	-0.032*	0.786*	0.606*	1						
(9) SRLev	-0.180*	-0.140*	-0.086*	0.004	0.005	0.742*	0.563*	0.263*	1					
(10) Size	0.141*	0.255*	0.301*	0.080*	0.078*	-0.297*	-0.276*	-0.346*	-0.086*	1				
(11) BTM	0.002	-0.008*	-0.001	-0.002	-0.003	0.004	0.009*	0.002	-0.001	-0.027*	1			
(12) Predictability	0.003	-0.029*	-0.035*	-0.035*	-0.035*	-0.021*	-0.037*	0.015*	-0.030*	-0.023*	-0.003	1		
(13) Loss	-0.088*	-0.039*	-0.067*	-0.038*	-0.037*	0.508*	0.391*	0.674*	0.142*	-0.272*	-0.005	0.032*	1	
(14) Accrual	0.001	0.022*	0.020*	0.010*	0.011*	-0.066*	-0.052*	-0.057*	-0.049*	0.047*	0.000	-0.002	-0.058*	1

Note: * indicates significance at 0.05 or less.

Panel B. Spearman Correlation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) CompCF	1													
(2) FLEX	0.008*	1												
(3) FLEX2	-0.001	0.816*	1											
(4) HeteroLevel	-0.208*	0.234*	0.230*	1										
(5) Hetero4	-0.182*	0.149*	0.150*	0.609*	1									
(6) AggIncentive	-0.239*	-0.063*	-0.046*	-0.003	0.006	1								
(7) SRZscore	-0.234*	0.017*	0.026*	0.003	0.016*	0.894*	1							
(8) SRRoa	-0.132*	-0.053*	-0.079*	-0.068*	-0.040*	0.778*	0.606*	1						
(9) SRLev	-0.212*	-0.134*	-0.079*	0.055*	0.032*	0.724*	0.551*	0.257*	1					
(10) Size	0.167*	0.240*	0.294*	0.122*	0.075*	-0.262*	-0.258*	-0.341*	-0.048*	1				
(11) BTM	-0.146*	0.318*	0.288*	0.147*	0.113*	0.032*	0.180*	0.133*	-0.309*	-0.035*	1			
(12) Predictability	0.015*	-0.008*	-0.017*	-0.042*	-0.034*	-0.043*	-0.048*	-0.010*	-0.043*	-0.011*	-0.044*	1		
(13) Loss	-0.092*	-0.039*	-0.067*	-0.080*	-0.052*	0.498*	0.388*	0.657*	0.136*	-0.283*	0.029*	0.011*	1	
(14) Accrual	0.023*	0.066*	0.074*	0.071*	0.052*	-0.189*	-0.105*	-0.243*	-0.120*	0.110*	0.099*	-0.021*	-0.341*	1

Note: * indicates significance at 0.05 or less.

Table 5. Regression Table for Hypothesis 1a and 1b

Panel A. Primary Analysis on Non-Financial Firms

		Hetero Variables			
		(1)	(2)	(3)	(4)
DV = CompCF	Pred.	HeteroLevel	Hetero4	HeteroLevel	Hetero4
Intercept (Uniform)	?	-0.133***	-0.134***	-0.128***	-0.131***
		(-13.674)	(-13.855)	(-14.547)	(-14.922)
FLEX	H1a: -	**-0.021***	-0.020		
		(-1.842)	(-1.763)		
FLEX2	H1a: -			**-0.028*****	**-0.026*****
				(-4.948)	(-4.691)
Hetero	-	-0.184***	-0.162***	-0.237***	-0.204***
		(-7.660)	(-7.702)	(-7.680)	(-7.772)
FLEX*Hetero	H1b: +	**0.087*****	**0.071*****		
		(3.263)	(3.131)		
FLEX2*Hetero	H1b: +			**0.142*****	**0.116*****
				(4.424)	(4.290)
SRZscore	-	-0.048***	-0.048***	-0.047**	-0.047**
		(-3.052)	(-3.058)	(-2.943)	(-2.939)
SRRoa	-	0.004	0.004	0.003	0.003
		(0.618)	(0.636)	(0.467)	(0.509)
SRLev	-	-0.128***	-0.129***	-0.128***	-0.129***
		(-9.262)	(-9.252)	(-9.264)	(-9.257)
Size	+	0.014***	0.014***	0.014***	0.014***
		(12.131)	(12.124)	(11.884)	(11.869)
BTM	+	0.000**	0.000**	0.000**	0.000**
		(2.567)	(2.564)	(2.733)	(2.760)
Predictability	+	-0.005	-0.004	-0.005	-0.005
		(-0.500)	(-0.486)	(-0.579)	(-0.558)
Loss	-	-0.004	-0.004	-0.004	-0.004
		(-1.370)	(-1.368)	(-1.369)	(-1.393)
Accrual	?	-0.002***	-0.002***	-0.002***	-0.002***
		(-3.916)	(-3.898)	(-3.946)	(-3.917)
Observations		68,571	68,571	68,571	68,571
Adj. R-squared		0.116	0.115	0.117	0.116
Fixed Effects		Country, Year	Country, Year	Country, Year	Country, Year
Cluster		Firm, Year	Firm, Year	Firm, Year	Firm, Year
Cutoff Estimate		0.235*	0.274	0.196***	0.224***

Robust t-statistics in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%.

Panel B. Falsification Tests on Financial Firms

		Hetero Variables			
		(1)	(2)	(3)	(4)
DV = CompCF	Pred.	HeteroLevel	Hetero4	HeteroLevel	Hetero4
Intercept (Uniform)	?	-0.289***	-0.264**	-0.291***	-0.247***
		(-3.130)	(-2.969)	(-3.748)	(-3.242)
FLEX	H1a: -	0.082	0.067		
		(0.743)	(0.627)		
FLEX2	H1a: -			0.074	0.038
				(1.031)	(0.524)
Hetero	-	0.058	0.017	0.110	0.047
		(0.775)	(0.246)	(1.199)	(0.530)
FLEX*Hetero	H1b: +	-0.005	0.032		
		(-0.067)	(0.422)		
FLEX2*Hetero	H1b: +			-0.065	-0.003
				(-0.706)	(-0.038)
SRZscore	-	-0.013	-0.013	-0.017	-0.014
		(-0.336)	(-0.327)	(-0.457)	(-0.378)
SRRoa	-	0.037	0.038	0.039	0.039
		(1.342)	(1.411)	(1.382)	(1.418)
SRLev	-	-0.080*	-0.082*	-0.072*	-0.078*
		(-2.086)	(-2.115)	(-2.045)	(-2.142)
Size	+	0.014***	0.013***	0.013***	0.012***
		(3.501)	(3.544)	(3.291)	(3.325)
BTM	+	0.000	-0.000	0.000	-0.000
		(0.015)	(-0.053)	(0.046)	(-0.066)
Predictability	+	-0.013	-0.010	-0.012	-0.009
		(-0.357)	(-0.250)	(-0.328)	(-0.231)
Loss	-	0.002	0.002	0.002	0.002
		(0.154)	(0.149)	(0.139)	(0.144)
Accrual	?	0.000	0.000	-0.000	0.000
		(0.023)	(0.162)	(-0.140)	(0.091)
Observations		2,274	2,274	2,274	2,274
Adj. R-squared		0.130	0.128	0.131	0.128
Fixed Effects		Country, Year	Country, Year	Country, Year	Country, Year
Cluster		Firm, Year	Firm, Year	Firm, Year	Firm, Year

Robust standard errors in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%.

Table 6. Regression Table for Hypothesis 2

Panel A. Primary Analysis on Non-Financial Firms

DV = CompCF		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Incentive =	Pred.	AggIncentive	SRZscore	SRRoa	SRLev	AggIncentive	SRZscore	SRRoa	SRLev
Intercept (Uniform)	?	-0.139***	-0.165***	-0.200***	-0.165***	-0.142***	-0.165***	-0.197***	-0.162***
		(-12.799)	(-15.859)	(-19.598)	(-14.206)	(-17.159)	(-20.038)	(-24.767)	(-17.650)
FLEX	?	**0.029****	**0.032****	0.008	0.011				
		(2.219)	(2.569)	(0.588)	(0.836)				
FLEX2	?					**0.024*****	**0.022*****	-0.004	-0.001
						(3.678)	(3.609)	(-0.677)	(-0.122)
Incentive	?/-	**-0.154*****	**-0.089*****	**-0.042*****	**-0.135*****	**-0.147*****	**-0.082*****	**-0.035*****	**-0.137*****
		(-15.383)	(-9.925)	(-5.839)	(-11.737)	(-15.045)	(-9.184)	(-4.567)	(-11.953)
FLEX*Incentive	H2: -	**-0.088*****	**-0.088*****	**-0.044*****	**-0.045*****				
		(-6.218)	**(-7.541)**	**(-4.991)**	**(-3.420)**				
FLEX2*Incentive	H2: -					**-0.085*****	**-0.083*****	**-0.049*****	**-0.032****
						(-7.248)	**(-8.568)**	**(-5.943)**	**(-2.690)**
HeteroLevel	-	-0.123***	-0.122***	-0.133***	-0.123***	-0.122***	-0.122***	-0.132***	-0.122***
		(-7.550)	(-7.197)	(-7.634)	(-8.035)	(-7.550)	(-7.200)	(-7.639)	(-8.003)
Size	+	0.011***	0.011***	0.012***	0.015***	0.011***	0.011***	0.013***	0.015***
		(10.954)	(10.697)	(12.288)	(14.862)	(11.113)	(10.706)	(12.415)	(14.925)
BTM	+	0.000**	0.000***	0.000**	0.000**	0.000**	0.000***	0.000***	0.000**
		(2.787)	(3.187)	(3.000)	(2.502)	(2.945)	(3.668)	(3.241)	(2.528)
Predictability	+	-0.004	-0.005	0.005	-0.002	-0.004	-0.005	0.005	-0.003
		(-0.404)	(-0.512)	(0.523)	(-0.244)	(-0.461)	(-0.564)	(0.468)	(-0.328)
Loss	-	0.019***	0.001	0.001	-0.008**	0.019***	0.001	0.001	-0.009**
		(6.608)	(0.342)	(0.381)	(-2.895)	(6.465)	(0.206)	(0.347)	(-2.919)
Accrual	?	-0.002***	-0.001**	-0.001*	-0.002***	-0.002***	-0.002**	-0.001*	-0.002***
		(-3.156)	(-2.666)	(-2.042)	(-3.770)	(-3.276)	(-2.789)	(-2.126)	(-3.871)
Observations		68,571	68,571	68,571	68,571	68,571	68,571	68,571	68,571
Adj. R-squared		0.110	0.104	0.088	0.114	0.110	0.104	0.089	0.114
Fixed Effects		Country, Year	Country, Year	Country, Year	Country, Year	Country, Year	Country, Year	Country, Year	Country, Year
Cluster		Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year

Robust t-statistics in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%.

Panel B. Falsification Tests on Financial Firms

DV = CompCF Incentive =	Pred.	(1) AggIncentive	(2) SRZscore	(3) SRRoa	(4) SRLev	(5) AggIncentive	(6) SRZscore	(7) SRRoa	(8) SRLev
Intercept (Uniform)	?	-0.281**	-0.287***	-0.329***	-0.265**	-0.234***	-0.253***	-0.317***	-0.197***
		(-3.007)	(-3.189)	(-3.701)	(-2.996)	(-3.385)	(-3.907)	(-4.751)	(-3.686)
FLEX	?	0.090	0.089	0.095	0.063				
		(0.767)	(0.771)	(0.845)	(0.536)				
FLEX2	?					0.025	0.042	0.073	-0.022
						(0.325)	(0.570)	(1.140)	(-0.348)
Incentive	?/-	-0.054	-0.034	0.032	-0.088	-0.083	-0.045	0.046	**-0.145***
		(-0.681)	(-0.543)	(0.678)	(-1.342)	(-0.988)	(-0.687)	(0.833)	(-2.078)
FLEX*Incentive	H2: -	-0.031	-0.026	-0.049	0.018				
		(-0.404)	(-0.428)	(-1.044)	(0.279)				
FLEX2*Incentive	H2: -					0.019	-0.005	-0.059	0.099
						(0.218)	(-0.077)	(-1.071)	(1.351)
HeteroLevel	-	0.056*	0.055*	0.058*	0.055*	0.060*	0.060*	0.062*	0.056*
		(1.867)	(1.795)	(1.907)	(1.919)	(2.031)	(1.968)	(2.077)	(2.054)
Size	+	0.011***	0.011***	0.013***	0.013***	0.010**	0.010**	0.012***	0.012***
		(3.375)	(3.455)	(3.533)	(3.746)	(2.883)	(2.986)	(3.158)	(3.262)
BTM	+	0.002	0.003	0.003	-0.000	0.001	0.002	0.002	-0.001
		(0.590)	(0.844)	(0.836)	(-0.004)	(0.448)	(0.748)	(0.805)	(-0.174)
Predictability	+	-0.017	-0.020	-0.019	-0.012	-0.015	-0.019	-0.019	-0.012
		(-0.440)	(-0.538)	(-0.534)	(-0.318)	(-0.397)	(-0.505)	(-0.505)	(-0.311)
Loss	-	0.019	0.013	0.006	0.012	0.018	0.013	0.007	0.012
		(1.229)	(0.912)	(0.457)	(0.884)	(1.190)	(0.910)	(0.467)	(0.918)
Accrual	?	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.000
		(0.160)	(0.174)	(0.262)	(0.016)	(0.012)	(0.078)	(0.234)	(-0.283)
Observations		2,274	2,274	2,274	2,274	2,274	2,274	2,274	2,274
Adj. R-squared		0.126	0.126	0.123	0.130	0.126	0.126	0.124	0.132
Fixed Effects		Country, Year	Country, Year	Country, Year	Country, Year	Country, Year	Country, Year	Country, Year	Country, Year
Cluster		Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year

Robust t-statistics in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%.

Table 7. Additional Analyses – Legal Systems and Enforcement

Variables	Predicted	(1) CompCF	(2) CompCF
AggIncentive	?	-0.246***	-0.284***
		(-17.492)	(-17.074)
CommLaw * AggIncentive	+	0.041*	
		(1.836)	
WGI * AggIncentive	+		0.010***
			(4.218)
HeteroLevel	-	-0.094***	-0.094***
		(-7.131)	(-7.166)
Size	+	0.011***	0.011***
		(8.429)	(8.540)
BTM	+	0.000***	0.000***
		(8.256)	(8.166)
Predictability	+	-0.008	-0.009
		(-0.765)	(-0.909)
Loss	-	0.015***	0.015***
		(3.945)	(3.851)
Accrual	?	-0.002***	-0.002***
		(-6.229)	(-6.133)
WGI	?		0.008**
			(2.226)
Constant	?	-0.119***	-0.164***
		(-12.818)	(-8.168)
Observations		44,080	43,984
Adjusted R-squared		0.129	0.130
Fixed Effects		Country, Year	Country, Year
Cluster		Firm, Year	Firm, Year

Robust t-statistics in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%. CommLaw is an indicator variable that equals one for common law countries, and zero for code law countries. WGI is the sum of six dimension of governance that capture an overall country's governance and enforcement environment. Country average WGI ranges from -6.35 (Afghanistan) to 10.98 (Finland).