Accounting Classification Entropy*

Nan Li
University of Minnesota

Pierre Jinghong Liang
Carnegie Mellon University

Jane Jae Yeon Pyo
Carnegie Mellon University

Gaoqing Zhang
Carnegie Mellon University

November 2025

Abstract

We theoretically develop and empirically apply a new information measure that quantifies the structural dimension of financial statements. Building on the entropy concept from Shannon's (1948) information theory, our approach captures firm fundamentals directly embedded in accounting numbers and formally measures the information conveyed by their classification structure. The measure is transparent, easy to implement, and adaptable across various classification-based settings. Using balance sheet data for U.S. public firms, we construct firm-quarter entropy-based measures and examine their relationship with market-based proxies that indirectly capture information content. In the first extension, we further demonstrate the measure's empirical usefulness by applying it to explain financial analysts' attention allocation decisions. In the second extension, we illustrate the framework's flexibility by incorporating richer accounting structures using the concept of mutual information and exploring additional empirical applications. Overall, our study offers a theory-based yet practical measure of financial statement classification that complements existing approaches to quantifying accounting information.

*We are grateful for the helpful comments from William Baber, Jeremy Bertomeu, Jung Ho Choi, Zhaoyang Gu, Mario Milone, Suresh Radhakrishnan, Stefan Reichelstein, Shyam Sunder, Ming Yang, Dave Ziebart and the participants at the 2024 CMU Accounting Research Mini Conference, the Third HKU Accounting Theory Conference, the 2025 Accounting Economics Society Conference, the 2025 Accounting Junior Theory Conference, the Accounting Design Project (ADP) webinar, the Chinese University of Hong Kong Seminar, Tsinghua University, UT-Dallas, UC-San Diego, Pennsylvania State University and University of Minnesota. All errors are our own.
Email: Nan Li (nanli@umn.edu), Pierre Jinghong Liang (liangj@andrew.cmu.edu), Jane Jae Yeon Pyo (jaeyeonp@andrew.cmu.edu), and Gaoqing Zhang (gaoqingz@andrew.cmu.edu).

Accounting Classification Entropy

November 2025

Abstract

We theoretically develop and empirically apply a new information measure that quantifies the structural dimension of financial statements. Building on the entropy concept from Shannon's (1948) information theory, our approach captures firm fundamentals directly embedded in accounting numbers and formally measures the information conveyed by their classification structure. The measure is transparent, easy to implement, and adaptable across various classification-based settings. Using balance sheet data for U.S. public firms, we construct firm-quarter entropy-based measures and examine their relationship with market-based proxies that indirectly capture information content. In the first extension, we further demonstrate the measure's empirical usefulness by applying it to explain financial analysts' attention allocation decisions. In the second extension, we illustrate the framework's flexibility by incorporating richer accounting structures using the concept of mutual information and exploring additional empirical applications. Overall, our study offers a theory-based yet practical measure of financial statement classification that complements existing approaches to quantifying accounting information.

1 Introduction

We propose a novel theory-based framework that quantifies the classification structure of financial statement numbers. Evaluating the informational role of financial statements lies at the core of accounting research. A central challenge in this endeavor is that researchers often cannot directly observe abstract economic constructs, such as information content, and often rely on proxies derived from observable data, such as financial statements. This challenge has become increasingly relevant as recent research underscores that systematic analysis of information processing requires rigorous measurement (Blankespoor, deHaan, and Marinovic, 2020). A theoretical foundation is therefore important for developing empirical measures that faithfully capture the economic constructs of interest.

Consider financial accounting research: ever since the tight link between two central economic constructs of value and income was rigorously formalized by Hicks (1946)'s classical and foundational work, researchers interested in corporate value creation have been interested in accounting income and owners' equity, two key financial statement summary measures, as empirical proxies of value creation. These measures are considered as informative about corporate value creation, and the information conveyed by these financial statement numbers is useful for valuation tasks.

In this paper, we dive deeper into financial statement numbers beyond traditional summaries and propose a measure that quantifies the classification structure of financial statements. Our core idea is to apply entropy from information theory to quantify innovation in the common-sized financial statements between two different periods. The resulting distance measure is analogous to the notion of earnings surprise commonly used in capital markets research, but incorporates the *structure* of multiple financial statement items rather than a single-dimensional earnings number. We call this framework Accounting Classification Entropy and, in this study, develop its theoretical foundation and present empirical applications to showcase its potential.

The motivation of our approach is that the classification structure within a financial statement contains fundamental knowledge about the internal resource structure of the firm that accompanies its income flow and capital scale in the process of value creation. The development of microeconomic theory has emphasized the importance of internal asset deployment structure in value creation. As early as the 1940s, Cooper (1949, 1951) suggested revisions to the then-standard firm theory that ignores considerations internal to the firm, such as the importance of cash position, liquidity, and different levels of control, and offered a rich outlook for microeconomics of the firm to progress. A full-blown development of the theory of corporate finance, corporate investment, and corporate operations has underlined the role of the internal structure of resource deployment in value creation. Accordingly, classified financial statements provide granular line items describing firm fundamentals beyond summary measures such as net income or owners' equity figures and are thus specifically designed to reflect corporate choices of financial, investing, and operational decisions. Our proposed empirical measure provides a quantification for such structural dimension of value creation, to accompany proxies for overall income and value. While information economics does not offer explicit empirical guidelines on how internal resource structure should be quantified, our empirical quantification leans on the formal Information Theory of Shannon (1948) and on Theil (1969)'s pioneering work on financial statements.

Specifically, we build on Theil (1969)'s intuition of applying information theory concepts to financial statements by theoretically generalizing the entropy concept to settings of any positive vectors (beyond just probability distribution). Accordingly, when financial statement line items are represented as positive vectors, the entropy and the Kullback-Leibler (K-L) divergence from one period to the next naturally lead to "expected information" contained in the current release of the financial statements (as compared to the previous release). Building on this foundation, we develop a framework consisting of two core measures: Accounting Classification Entropy (ACE), based on Shannon (1948)'s entropy, and ACE-Relative (ACER), based on Kullback and Leibler (1951)'s relative entropy. While ACE serves as a baseline construct, ACER captures the new information in successive financial statements, a feature that makes it especially useful for many empirical applications.

As observed by Theil (1969), the empirical quantification we propose applies to any set of financial statement numbers that obey aggregation properties (or the adding-up relation). We first theoretically prove that our entropy measures (ACE and ACER) are the only measures that satisfy a grouping property that is natural and desirable for classificational datasets with hierarchical aggregation structure (such as financial statements like balance sheets). Second, we apply our quantification approach to a large dataset of firm-quarters and develop a few use-cases to explore the usefulness of the ACE and ACER measures in standard empirical research tasks such as analyst forecast behavior.

Our proposed framework offers several desirable properties. First, it is formally grounded in the well-established information theory, which has been widely recognized and applied in fields such as engineering, computer science, and economics. We accomplish this by theoretically generalizing the entropy concept of Shannon (1948) to settings of any positive vectors. Second, it is transparent and easy to implement without requiring opaque algorithms or model-specific constructs. Importantly, our measures capture firm fundamentals directly embedded in financial statement numbers rather than inferred from the reactions of external decision makers. We refer to this property as "internal," which is particularly useful for analyzing information processing questions where researchers need to separate information itself from users' reactions. Third, the approach is versatile and can be applied across a broad range of research questions and empirical settings involving classification-based data. When the classification expands or contracts to more or fewer line items along the classification or aggregation hierarchy, the corresponding entropy measures also obey precise mathematical relations, giving our quantification a consistent mathematical structure.

After developing the information-theoretic foundation, we next take the measures to empirical settings. Specifically, we construct a prototype ACER from the asset accounts of the balance sheet. In the first step, we decompose total assets in each quarter into eight standardized accounts and express each account as a fraction of the total. Next, we use these fractions to calculate the relative entropy from the quarter $q-4$ to q, following the approach commonly used in the literature that compares accounting numbers for the same quarter in the previous year. Intuitively, this asset-based ACER quantifies the information updates in how firms allocate economic resources. After constructing the measure, we empirically examine whether it captures relevant information for capital market participants. We find that our entropy measure is significantly associated with the unsigned stock returns and the trading volumes surrounding the publication of the financial statements. These relationships persist after controlling for various firm characteristics such as size, unexpected earnings, and investment intensity. Furthermore, the results are robust to the inclusion of firm fixed effects and year fixed effects. These results collectively provide two key takeaways: (1) the ACER can meaningfully quantify information in financial statements; (2) the information captured by the ACER is not fully explained by existing firm characteristics or fixed effects commonly used in accounting research.

Next, we explore an empirical application centered on the allocation of information processing capacity. Specifically, we examine whether and how processing capacity allocation adjusts to the amount of information in financial statements. The key features of ACER make it well-suited for this research question, which requires a measure that summarizes complex accounting information independently of processing outcomes or the processing itself. Using analyst forecasts as a setting to measure processing capacity allocation, we find a positive relationship between a firm's ACER and analysts' processing resources dedicated to the firm. Results show that, as a firm's ACER increases, analysts allocate more processing capacity to that firm by providing forecasts for more periods and making more frequent revisions. These findings provide new evidence on the relationship between accounting information and the allocation of processing capacities.

In the final part of our analysis, we provide a standalone extension to the ACE framework that incorporates a richer representation of accounting structure. Employing the concept of Mutual Information, we theoretically develop an approach to quantify the information conveyed by the structures of financial statements beyond simple classifications. Specifically, we quantify the information embedded in the balance sheet structure described by Penman (2013) and Nissim (2022) by applying the Mutual Information concept. Our descriptive results show that accounting structure itself conveys a significant amount of information, and that this source of information varies systematically with firm characteristics and broader economic trends discussed in the literature (Core et al., 2003; Barth et al., 2023).

First, our paper contributes to the growing literature on information processing cost and capacity in accounting research, where quantifying information plays a central role (Blankespoor et al., 2020). This literature is often grounded in the rational inattention framework, which formally represents both information and processing cost using entropy-based constructs (Sims, 2003). Our approach aligns with this information-theoretic foundation and demonstrates how entropy-based constructs can be empirically operationalized within financial statements and similar classification data. Furthermore, a key insight from this literature is the importance of distinguishing between information to be processed and information that has been processed, both conceptually and empirically. By deriving entropy measures directly from financial statements, we quantify the information embedded in accounting representations themselves independent of user behavior or market reactions. We believe this approach can help advance the study of information processing by providing a direct and scalable way to measure the information available for processing in the structural dimension of financial statements.

Second, our study complements the empirical evaluation of financial statement numbers by bringing the financial statement classification into the quantification exercise in a theory-consistent way. A key distinctive feature of our approach is that ACE and ACER do not rely on observing users' decisions or assuming unobserved causal links between information and decisions. While user-decision-based quantification exercises such as Ball and Brown (1968) have achieved wide acceptance, their limitations are also well-known. Observed decisions are equilibrium objects, and the role of complex, structural financial information is hard to isolate from observed decisions. Although user decisions remain a high standard for evaluating accounting information, the internal, self-contained framework we propose offers a useful and practical alternative in a wide range of empirical settings, including but not limited to cases where decision-based measures are more difficult to observe or implement. Furthermore, market-based information proxies directly capture decisions and reactions (rather than the information itself), which can give rise to endogeneity or reverse-causality concerns when used as explanatory variables. Our entropy-based measure mitigates these concerns by quantifying information directly from financial statements, which can be particularly useful when examining how disclosure choices or other firm policies respond to information shocks.

Third, our paper contributes to the long-standing accounting theory literature that, starting from the late 1960s and early 1970s, links accounting numbers to the information economics framework (Beaver and Demski, 1979). Since then, accounting theorists have broadly adopted the "decision-making" approach that assesses the information content of accounting numbers in their usefulness for decision-making under uncertainty.[1] Despite the wide success of the decision-making approach, some observers allege that, in the extreme of merging accounting with decision-centric information economics, accounting numbers are represented as reduced-form statistical signals about some underlying states, in which the rich structures of accounting numbers are either obfuscated or even lost (Mattessich, 2006). To complement the decision-making approach, we draw on the classical measurement tradition in accounting theory (Ijiri, 1975) and apply information-theoretical tools to quantify the information embedded in accounting classifications, thereby linking the measurement and decision traditions in accounting theory.

[1]Notice this was a clear departure from the earlier measurement approach to accounting theory. Since the early 20th century, accounting theorists pioneered the measurement approach, positing that "accounting numbers are the outcome of the accounting measurement process of classifying and quantifying economic resources controlled by an entity resulting from recognized exchanges between resources" (Ijiri, 1975). During the decades before the 1970s, the major theoretical project of evaluating accounting income measurement against the ideal economic income concepts dominated accounting scholarship. See the anthology with a celebrated introduction by Parker and Harcourt (1969).

2 Literature Review

Our study is an accounting application of the entropy concept pioneered by Shannon (1948) and specifically, the Kullback–Leibler divergence (Kullback and Leibler, 1951). These information-theoretic concepts have been widely applied in science and engineering, and Cover and Thomas (2006) offer a comprehensive discussion. Closely related to our paper, in the late 1960s, the entropy concept was first applied by Theil (1969) to analyze the information content of financial statements, followed by Lee and Bedford (1969), and Lev (1968, 1970). Our paper is built on this early stream of studies and revisits the application of entropy to quantify the amount of information produced from accounting classification. Furthermore, we augment the previous work by developing more thoroughly the theoretical foundation behind applying the entropy concept, constructing an entropy-based summary measure of accounting classification information based on balance sheet data for a large sample of publicly traded firms in the US, and demonstrating the usefulness of the measure in applications of interest to accounting researchers.[2]

More broadly, the entropy concept serves as the building block for the economics literature on rational inattention pioneered by Sims (2003), where entropy is used as a measure to model agents' limited information processing capacities. In that vein, entropy has been extensively used in information economics models and their applications to accounting problems, e.g., Myatt and Wallace (2012), Jiang and Yang (2017), Angeletos and Sastry (2019), and Bonham and Riggs-Cragun (2022). Our paper abstracts from such strategic incentives in information processing and focuses on the measurement exercise to quantify information production in accounting classification.[3] The concept of entropy also plays a key role in many areas

[2]The early studies either were purely theoretical or only analyzed the financial statements of a small sample. For instance, the seminal paper by Theil (1969) studied the annual reports of Ford Motor Company in 1964 and 1965.

[3]In applied statistics, a common method that involves the concept of entropy is entropy balancing (Hainmueller, 2012). McMullin and Schonberger (2020) introduce entropy-balanced accruals, a specific application of entropy balancing. Entropy balancing is a sample-weighting technique designed to balance the covariates between the treated and control units by assigning new weights to the control units. The method applies entropy to the sample weights, rather than to the covariates, with the aim of minimizing the

of machine learning and artificial intelligence, where it is used to quantify information and evaluate models (Bishop, 2006). In a recent study, Costello, Levy, and Nikolaev (2025) utilize entropy when applying algorithmic methods to process and summarize corporate disclosures.

Under the modern information economics paradigm, quantifying information content is either impossible in general (Demski, 1973) or directly tied to decision-making by users. As a result, research on internal summary measures of financial statements has been limited and has generally relied on heuristic approaches. For example, Brown et al. (2023) represent a firm-year's 147 financial statement items as a vector and use cosine similarity between vectors of two firms to capture cross-sectional similarity. With advances in natural language processing, other work has focused on the information content of financial statement text. Brown and Tucker (2011), for instance, introduce a modification score to quantify changes in the qualitative MD&A disclosure from one year to the next. Similarly, Cohen et al. (2020) proposed four quantification approaches, directly taken from the literature in linguistics, textual similarity, and NLP, to capture quarter-on-quarter similarities between 10-Q and 10-K filings : (i) cosine similarity, (ii) Jaccard similarity, (iii) minimum edit distance, and (iv) simple similarity.

Our approach departs from heuristic methods in both conceptual underpinnings and application. Information theory offers a rigorous basis for defining accounting classification information within a consistent mathematical structure. Under this structure, incremental changes of the entropy-based information measure obey precise mathematical relations when the classification expands or contracts to more or fewer line items along the classification hierarchy. In contrast, the heuristic measures generally do not define what constitutes "information." The theoretical foundation makes our approach a natural fit for quantifying the information content of accounting classifications, yielding a measure that can be interpreted as information. For this reason, the measure is particularly well-suited for addressing questions in economics-based accounting research. Moreover, as we illustrate in Section 6,

divergence between the new sample weights and the original ones. In contrast, our study focuses on directly applying entropy to financial statements to measure the classification information in these statements.

the richness of the information theory makes the entropy framework a flexible platform for developing new applications. Specifically, we demonstrate how the concept of mutual information can be applied to quantify the information embedded in the accounting structure itself, such as the balance sheet's joint structure of assets and funding sources. While accounting information is inherently structured through the systematic linkages embedded in accounting systems, the quantification of this structured information has remained conceptually abstract. Our application addresses this challenge by providing a numerical summary measure for the information embedded in accounting systems.

3 An Information-Theoretic Framework of Accounting Classification

3.1 Problem Definition

The theoretical challenge we confront is to define accounting classification information. To facilitate the deployment of the measure to empirical analysis, we seek to construct a summary (single-dimensional) measure that convey to users fundamental knowledge about the internal resource allocation in the firm. Specifically, we build a measure that is

1. built internally based on classified accounting statements such as balance sheets;
2. free from having to specify how users would use the accounting figures in their decisions (which is often context-specific and hard to measure);
3. flexible to accommodate classification changes or data structures, e.g., when the classifications are expanded or reduced via disaggregating or aggregating line items.

We appeal to the Information Theory, built upon the fundamental entropy ideas pioneered by Shannon (1948), in search of such a summary measure of accounting classification. While Shannon's original idea is ushered in a broader and deeper Information Theory, we focus on two basic measures as the foundation to construct our internal summary measure of accounting information: Entropy and Relative Entropy (Kullback and Leibler, 1951).[4] In the remainder of this section, we will first review the information-theoretic concepts and then apply them to develop a summary measure that quantifies the accounting classificational structure while respecting the three properties listed above.

3.2 Information Theory Concepts: Entropy and Relative Entropy

Shannon's Entropy

Definition 1 (Entropy) *Let X be a discrete random variable with alphabet $\mathcal{X}$ and probability mass function $p(x) = Pr\{X = x\}, x \in \mathcal{X}$. The entropy $H(X)$ of X is*

$$H(X) = -\sum_{x \in \mathcal{X}} p(x) \log_b \ p(x),$$

where b is the base of the logarithm.

Note that Entropy is a property of a distribution $p(x)$ (x need not be a real number), but entropy itself is the expectation of a real random variable:

$$H(X) = \sum_{x \in \mathcal{X}} p(x) log_b \frac{1}{p(X)} = E_p \log_b \frac{1}{p(X)}.$$

If the log is to the base 2 (or e, or 10), entropy is expressed in bits (or nats or bans). If the set of signals x's consists of n potential messages that have equal probabilities $p_x = 1/n$, the Entropy of the information source is $H(X) = -n(1/n)\log(1/n) = \log(n)$, which is increasing in parameter n. Intuitively, one can interpret that the larger the n, the more the underlying uncertainty. Equivalently, the larger the n, the more precise the signal serves as an information instrument (Marshak, 1959). From an operational perspective, the larger

[4] Mutual information, a special case of K-L divergence and widely used in theory and practice, will be introduced and discussed in the standalone Section 6, including an financial statement analysis use-case.

the n, the more resources it takes to transmit the signal X in expectation. For example, Entropy provides the minimum expected number of bits to encode the message to be shared with a decoder (Shannon, 1948).

Based on this idea, joint entropy and conditional entropy are similarly defined for joint and conditional probability distributions, with the desirable properties such as additivity and the chain rule.[5]

Relative Entropy: Kullback-Leibler Divergence

Definition 2 (Relative Entropy) *Let $p(x)$ and $q(x)$ be two probability functions of random variable X with alphabet $\mathcal{X}$, the Relative Entropy, or Kullback-Leibler (K-L) Divergence, from probability function $q(x)$ to $p(x)$ is defined as*

$$D(q||p) = \sum_{X \in \mathcal{X}} q(x) \log \frac{q(x)}{p(x)} = E_q \log \frac{q(X)}{p(X)}.$$

Relative Entropy, or K-L divergence, is always non-negative but is not a true "distance" measure (it violates symmetry and triangle inequality). It offers a measure of the inefficiency of assuming distribution q when distribution p is true. Under the true distribution p, $H(p)$ is the average description length of variable X, but if one instead uses q by error, $H(p)+D(p||q)$ is the average length instead. When applying the K-L divergence to quantify the movement from prior probability distribution to the posterior, the K-L divergence captures the new

[5]Let random variables (X, Y) has a joint distribution $p(x, y)$, define the *joint* entropy $H(X, Y)$ and the *conditional* entropy as

$$H(X,Y) = -\sum_{y \in \mathcal{Y}} \sum_{x \in \mathcal{X}} p(x,y) \log \ p(x,y),$$

and

$$H(Y|X) = -\sum_{X \in \mathcal{X}} p(x) \sum_{y \in \mathcal{Y}} p(y|x) \log \ p(y|x) = \sum_{X \in \mathcal{X}} p(x) H(y|X=x).$$

It can be easily shown that

$$H(X,Y) = H(X) + H(Y|X) \ \text{ and } \ H(X,Y) = H(Y) + H(X|Y),$$

and $H(X, Y) = H(X) + H(Y)$ if X and Y are independent and $H(X, Y) = H(X) = H(Y)$ if X and Y are perfectly dependent.

information content contained in the posterior as compared to the prior distribution.[6]

3.3 Accounting Classification Entropy (ACE)

Now we adapt the aforementioned information theory concepts into measures more suitable for quantifying the information content of financial statement line items, not immediately considered probability distribution. Here we follow and extend the pioneering work by Theil (1969) who was the first to apply Shannon's entropy concept and the relative entropy measure to classified financial statements such as balance sheets and income statements. While mostly descriptive and exploratory, the key idea Theil (1969) introduced was that these two concepts can be used as "useful descriptive devices for the changes ... as well as analysis of the difference between companies" (page 459).

We extend the Theil (1969) analysis along several dimensions. First, we theoretically derive a generalized version of entropy measure, termed Accounting Classification Entropy (ACE), for a generic vector of positive elements, such as the balances of classified financial statement accounts (instead of a probability distribution that can be viewed as a vector of positive elements adding up to one). In this Section, we consider a simple application of the ACE measure to a single classification, such as the asset classification on the balance sheet. In Section 6, we extend the application of the ACE measure to dual classifications (or potentially multi-classification) such that the asset-and-funding-source (i.e., liabilities and stockholders' equities) classification on the two sides of the balance sheet. We will show that because accounting structure specifies a connection between the classifications, the structure

[6] In modern machine learning, K-L divergence has become a critical theoretical and empirical measure of difference between two information representations (such as model-prediction versus ground-truth). Consider a simple procedure to train a single neuron as a binary classifier: let a finite (training) *input* data-set: $X = \{x_1, x_2, ..., x_N\}$ with binary labels $\{t^1, t^2, ..., t^N\}$ and $t \in \{0, 1\}$. Consider a single neuron $y(x; w)$ parameterized by w generating output bounded between 0 and 1. The *error function* is

$$G(w) = -\sum_i \left[t^i \ln y(x^i; w) + (1 - t^i) \ln(1 - y(x^i, w))\right] = KL(q : p),$$

where $q = \{t^1, t^2, ..., t^N\}$ is the empirical distribution; and $p = \{y(x^1; w), y(x^2; w), ..., y(x^N; w)\}$ is the distribution implied by the single neuron $(y, 1 - y)$. The objective function is bounded away from zero below and attains zero only if $y(x^i, w) = t^i$ for all i, a perfect fit.

contains information besides the information conveyed in the classifications themselves. We also demonstrate that the concept of mutual information can be used to measure the amount of information built into accounting structure.

In many empirical settings, researchers are interested in the new information conveyed by accounting classifications relative to what was known before the update. As explained by Theil (1969), relative entropy—an extension of Shannon's entropy—is well suited for quantifying such informational updates. We apply the relative entropy concept to fine-tune the ACE measure and construct a measure, termed Accounting Classification Entropy-Relative (ACER), capturing the new information content from one positive vector of classified financial account balances into another. We propose the set of measures {ACE, ACER} as candidates for internal, summary measures of accounting classification. We report the derivation and interpretation below. Second, we apply the theoretical internal measure to a large sample panel dataset of US publicly traded firms for an empirical exercise of measure analysis and applications to the economic setting of analysts' attention allocation, and compensation contracts (included in the Appendix).

Generalized Entropy Measure to Financial Accounts Classifications Consider a firm's financial statement (e.g., the asset section of the balance sheet) of period t that includes n accounts (e.g., current assets, noncurrent assets, etc.), each of which has a balance of X_i. The information of the financial statement is thus represented in the vector of signals $\boldsymbol{X} = [X_1, X_2, ...X_n]'$. Without loss of generality, this information can be decomposed into (1) information about the total balance of the financial statement $K \equiv \sum_{i=1}^{n} X_i$, and (2) information about the classification of the total balance K into n accounts. The latter is captured by the accounts' fractions of the total, $\boldsymbol{x} = [x_1, x_2, ...x_n]'$, where $x_i = X_i/K$. In our primary empirical application to assets, the total balance K contains fundamental knowledge about the firm's aggregate holdings of economic resources, whereas the classificational data $\boldsymbol{x}$ captures the firm's internal resource allocation in value creation. Our focus is on generalizing the entropy measure to capture the information in accounting classification $\boldsymbol{x}$.

Toward this end, denote $J_n(\boldsymbol{x})$ as any scalar measure (summary) of the information in financial accounts classification, $\boldsymbol{x} = [x_1, x_2, ...x_n]'$. The following proposition establishes that, in the set of summary measures $J_n(\boldsymbol{x})$ that satisfy three properties, the only one that exists is the entropy of the probability distribution represented by the vector $\boldsymbol{x}$.

Proposition 1 (Cover and Thomas (2006)) *Consider a $n \times 1$ vector $\boldsymbol{x} = [x_1, x_2, ...x_n]'$ representing the classification of financial accounts, where $0 < x_i < 1$, $\sum_{i=1}^{n} x_i = 1$, and $n \in \{2, 3, 4, ...\} \subset \mathbb{N}$. Now consider a sequence of symmetric functions $J_n(\boldsymbol{x})$ indexed by n, satisfying the following three properties:*

1. *Normalization: $J_2(\frac{1}{2}, \frac{1}{2}) = 1$.*

2. *Continuity: $J_2(x, 1-x)$ is continuous in $x \in (0, 1)$.*

3. *Grouping:*

$$J_n(x_1, x_2, x_3, x_4...x_n) = J_{n-1}(x_1 + x_2, x_3, x_4...x_n) + (x_1 + x_2)J_2\left(\frac{x_1}{x_1 + x_2}, \frac{x_2}{x_1 + x_2}\right).$$

Then J_m must be in the form of:

$$J_n(x_1, x_2, x_3, x_4...x_m) = -\sum_{i=1}^{n} x_i \log(x_i) = H_n(\boldsymbol{x}),$$

where $H_n(\boldsymbol{x})$ is Shannon's entropy of the probability distribution represented by the vector $\boldsymbol{x}$.

The first two properties of the summary measure (Normalization and Continuity) are relatively weak technical requirements; we thus focus on interpreting the last property (Grouping). To illustrate, consider the following classification of a firm's asset accounts. Suppose that the firm first classifies its assets into current and noncurrent assets, where the fractions of the two accounts are equally given by $[\frac{1}{2}, \frac{1}{2}]'$. The summary measure of this classification is thus $J_2(\frac{1}{2}, \frac{1}{2})$. Next, the firm improves the accounting classification by separating the current assets into two sub-accounts, cash and non-cash. Suppose that one-third of current assets are classified into cash, and two-thirds of them are classified into non-cash. The fractions of the resulting three accounts' balances are thus given by $[\frac{1}{6}, \frac{1}{3}, \frac{1}{2}]'$, and the corresponding summary measure is $J_3(\frac{1}{6}, \frac{1}{3}, \frac{1}{2})$. Intuitively, the information of the three-account classification should be higher than that of the two-account classification, i.e., $J_3(\frac{1}{6}, \frac{1}{3}, \frac{1}{2}) > J_2(\frac{1}{2}, \frac{1}{2})$. Furthermore, the amount of the incremental information should be proportional to both the information from classifying current assets into cash and non-cash, $J_2(\frac{1}{3}, \frac{2}{3})$, and the relative size of the current assets, $\frac{1}{2}$. Writing out this intuitive requirement on the summary information measure yields the Grouping property:

$$J_3\left(\frac{1}{6}, \frac{1}{3}, \frac{1}{2}\right) = J_2\left(\frac{1}{2}, \frac{1}{2}\right) + \frac{1}{2} J_2\left(\frac{1}{3}, \frac{2}{3}\right).$$

More generally, the Grouping property requires that any information improvement from finer accounting classification is proportional to the amount of information gained from the additional classification; and the additional classification contributes more information when a larger account balance is classified into sub-accounts.[7]

Relative Entropy as Measure of Information Arrival The ACE measure serves as one measure of the *total* amount of information in financial accounts classification. In many empirical applications, one may be more interested in measuring the *net* increase in information when a new financial statement arrives, conditional on some past information or expectation. In the spirit of Theil (1969), we apply Relative Entropy (the K-L divergence)

[7]Specifically, the Grouping property in Proposition 1 can be interpreted as follows. Consider a firm's classification of its financial statement with $n-1$ accounts. The fractions of the accounts are $[x_1+x_2, x_3, x_4 ... x_n]'$. The firm now classifies the first account into two accounts, and the fractions of the resulting n accounts are $[x_1, x_2, x_3, x_4 ... x_n]'$. The incremental information from the finer classification

$$J_n(x_1, x_2, x_3, x_4 ... x_n) - J_{n-1}(x_1 + x_2, x_3, x_4 ... x_n) = (x_1 + x_2) J_2\left(\frac{x_1}{x_1 + x_2}, \frac{x_2}{x_1 + x_2}\right),$$

which is the product of the size of the first account, $x_1 + x_2$, and the information gained from separating the first account into two, $J_2\left(\frac{x_1}{x_1+x_2}, \frac{x_2}{x_1+x_2}\right)$.

to the ACE measure to construct a measure that captures the incremental information from the arrival of a new financial statement.

Specifically, denote $\boldsymbol{p} = [p_1, p_2, ..., p_n]'$ as the prior information/expectation about the fractions of the total balance classified into n accounts. Now suppose the new financial statement arrives with the fractions of the n accounts denoted by $\boldsymbol{q} = [q_1, q_2, ..., q_n]'$. Recall that under ACE, the information of classifying q_i fraction of the total balance into account i is represented by the function $\log(q_i)$, and the information in the set of classification $\boldsymbol{q} = [q_1, q_2, ...q_n]'$ is an average of each classification's information, $\log(q_i)$, weighted by the relative balance of each account q_i. If we continue to use the log function to measure the information of classifying q_i into account i, the incremental information from the prior classification of p_i to the new classification of q_i is given by the difference:

$$\log(q_i) - \log(p_i) = \log\left(\frac{q_i}{p_i}\right).$$

The new information in the set of new classification $\boldsymbol{q}$ thus equals the information increase in the classification of each account i, weighted by its relative balance q_i:

$$ACER = \sum_{i=1}^{n} q_i \log \frac{q_i}{p_i}.$$

We formally define our construct of the measure for information arrival, Accounting Classification Entropy-Relative (ACER), below.

Definition 3 ***Accounting Classification Entropy-Relative (ACER)*** *Let* $\mathbf{p} = [p_1, p_2, ..., p_n]'$ *and* $\boldsymbol{q} = [q_1, q_2, ..., q_n]'$ *be the prior expectation and the current report of classification in* n *financial accounts, respectively. The* <u>*ACER*</u> *measure that captures the new information from the arrival of the new classification is defined as*

$$ACER = \sum_{i=1}^{n} q_i \log \frac{q_i}{p_i}. \tag{1}$$

Our discussion above extends the use of the K-L divergence to measure the information from the arrival of a new accounting classification, when the reported classification is not (necessarily) generated from probability distributions.[8]

Empirical Construction Returning to the problem definition, we seek to derive an internal summary (one-dimensional) measure of information content of classified accounting numbers. Based on the derivation and discussion in this section, we propose ACE and its variant $ACER$ as a solution to the problem we posed. Suppose we are interested in measuring the new information in period t relative to $t-1$, we can calculate $ACER_t$ according to Equation (1) in Definition 3 using the following steps:[9]

1. For a given firm, extract the dollar amount of a financial statement line item.

2. Transform the dollar balance as a fraction of the total.

3. Let $X\%_{i,t}$ denote account i's fraction of period t, calculate the entropy divergence for account i from $t-1$ to t:

$$IX\%_{i,t} = X\%_{i,t} \times \log\left(\frac{X\%_{i,t}}{X\%_{i,t-1}}\right),$$

where X_i represents each financial statement line-item.

[8] Interestingly, Theil (1969) also offers a probabilistic interpretation of adapting the entropy measures to a financial statement setting naturally. For example, balance sheet fractions are probabilities when we ask the following question: "If one takes a random dollar of the company's assets at the end of 1964, what is the chance that this dollar falls under current assets (say)?" (page. 462). By extension, Theil's *Expected Information* measure, equivalent to the K-L divergence between the current balance sheet fractions and previous fractions, tells "how far we have to travel" from the fractions of the first year to those of the second. (page. 463).

[9] In this formulation, t denotes a general time period, such as a quarter or year, and $t-1$ represents a previous period. The period $t-1$ does not necessarily have to be the preceding quarter or year, but can vary depending on the specific measurement context. Our baseline application in Section 4 uses quarterly balance sheet and seasonal divergence (i.e., from $q-4$ to q).

4. Summing $IX\%_{i,t}$ over all i's gives rise to $ACER$ for period t (from $t-1$):

$$ACER_t = \sum_{i=1}^{n} IX_i\%_{i,t}.$$

Discussions Before we move to the empirical part of our paper, we summarize the properties of our proposed measures of ACE and $ACER$ as theoretically appealing because it is grounded in formal Information Theory, and are a uni-dimensional summary measure of multi-dimensional classificational objects such as financial statements. While its literal meaning is the expected number of extra bits needed to encode the message of period t if using the stale information of period $t-1$, its expanded meaning is a lower bound of total new information that has arrived in period t since $t-1$. Finally, it serves as the solution to the problem we seek to solve: an internal measure of information, independent of potential uses, focusing on the immediate output from accounting information production. Accordingly, it is a departure from the notion of information in the standard decision-usefulness-based information economics framework of State-Act-Outcome, with information represented as partitions of decision-specific states.

A limitation of general summary measures is that they do not specify the exact sources of variation across different observations. Nevertheless, high-level summary metrics such as stock return, volatility, trading volume, and the size and aggregation level of disclosure have been widely adopted as general information proxies in accounting research (Basu, 1997; Ball, Kothari, and Robin, 2000; Leuz and Verrecchia, 2000; Chen, Miao, and Shevlin, 2015; Hail, Wang, and Zhang, 2024). Similarly, while the entropy-based measures do not, on their own, retain the full information about the specific causes of their variation, their construct flexibility allows users to tailor the measurement scope to capture only the relevant variations for specific research questions.

In addition to the three properties of the information measure we seek in our problem statement, the Entropy-based measures possess a fourth property of interpretability. Generally, the mechanical process of calculating the measures is a convex transformation of the line-item vectors. In fact, the measures are some particular convex transformations (negative of a log function of scaled individual line-items), among many other potential convex transformations. What makes this particular transformation, thus our measures, unique and useful is indeed its information-theoretical foundation. That is, we can interpret our measures as information in a scientific way. This direct information interpretation makes the entropy-based measures especially useful in rigorously investigating theories and hypotheses founded on information economics. In addition, properties of the entropy-based measures developed in information theory apply as we extend our empirical application beyond just assets on the balance sheet. For example, when incorporating the liabilities and shareholders' equity line-items, the entropy concept on the joint distribution (with or without independence), as well as the mutual information measure, can be easily applied and interpretable with theoretical and empirical ease, as shown in Section 6.

4 Empirical Evidence

4.1 Data and Methods

Our first empirical analysis examines the relationship between ACER and market-based proxies that indirectly capture information. Because ACER measures the amount of new information embedded in accounting classification during a given quarter, we expect it to be positively associated with indicators of stronger market reactions around the release of financial statements, such as larger absolute stock returns and higher trading volume.

We construct a prototype empirical measure of ACER based on the quarterly balance sheets of U.S. public companies. Our sample starts from the intersection of Compustat and CRSP. We obtain the 10-K and 10-Q filing dates from the SEC Analytics Suite (coverage beginning in 1993) to conduct the market reaction analysis. Our baseline sample contains 281,928 firm-quarter observations in 1993–2022. For the analyses involving financial analysts in Section 5, we further require I/B/E/S data coverage.

To apply the entropy framework to financial statement data, we first define the set of accounts that form the basis for measuring information content. Our baseline measure focuses on the asset section of the balance sheet. We decompose total assets into eight standardized categories: four current asset accounts (cash and short-term investments, receivables, inventory, and other current assets) and four non-current asset accounts (property, plant, and equipment, intangible assets, long-term investments, and other non-current assets).

It is worth noting that the theoretical construct of ACE and ACER is versatile and not confined to a specific set of accounts. In practical applications, researchers have the flexibility to devise their own empirical entropy measures that best fit their research questions and data structures. Our application in this section focuses on an asset-based measure for two reasons. First, asset accounts represent economic resources of a firm and are directly informative of business fundamentals. Second, empirical research often uses total assets as a proxy of size-based information, motivating our choice to use assets to measure classification information.

Next, we calculate the entropy measure for each firm-quarter observation following several steps. First, we transform the dollar balance of each account as a fraction of the total book asset. Second, for each account, we calculate the divergence from quarter $q-4$ to q. To illustrate the calculation, let $Cash\%_q$ denote the dollar amount of the total assets of quarter q scaled by the total book asset of quarter q; let $Cash\%_{q-4}$ denote the total revenue of quarter $q-4$ scaled by the total book asset of quarter $q-4$. The divergence associated with total revenue from $q-4$ to q is define as $ICASH = Cash\%_q \times \log(Cash\%_q / Cash\%_{q-4})$.[10] After calculating the information content measure for each account, we sum them up across the eight standardized accounts to obtain the total Accounting Classification Entropy-Relative,

[10] In this calculation, $ICash_q$ is undefined if $Cash\%_q$ or $Cash\%_{q-4}$ equals zero. In our application, if the balance of an account is zero in both q and $q-4$, we set the information content for that specific account to zero. This assumption is appropriate because having a zero balance in two consecutive quarters implies having no information update from that account during the measuring period. The entropy measure is not directly applicable if a balance changes from zero to a non-zero value, or vice versa. Essentially, the standard entropy measure is not well-suited to handle variables that often switch between zeros and nonzero values intertemporally. To mitigate this limitation, a simple solution is to aggregate these accounts with others that are rarely zero and share similar economic interpretations, thereby reducing the data sparsity.

which we label as $ACER$ for the result of the paper. To facilitate interpretation and mitigate outliers, we convert $ACER$ into decile ranks, which we denote as $ACER\_Rank$.

A common challenge in quantifying the information content of accounting numbers using stock returns is that stock prices gradually integrate the information in financial statements (for example, Ball and Brown (1968) shows that earnings information can be gradually integrated into the stock price before and after earnings announcements). For a given set of financial statement information, researchers often cannot precisely observe the beginning and end of the integration process. In our context, we cannot directly observe when stock prices start to incorporate the information in a balance sheet or when the information becomes fully incorporated. For this reason, our analysis focuses on examining the direction of correlation between $ACER$ and the short-window stock returns surrounding the release 10-K and 10-Q reports. Although this approach may underestimate the total association between $ACER$ and the absolute market reaction, the results can still provide qualitative evidence for $ACER$ as an information measure. We estimate the following OLS regression model.

$$ACAR_{i,q} = \beta_1 ACER\_Rank_{i,q} + \Gamma Controls_{i,q} + \epsilon_{i,q}, \tag{2}$$

where $ACAR_{i,q}$ stands for firm i's absolute cumulative abnormal return in the $[0, +3]$ window surrounding the release date of the 10-K or 10-Q report of quarter q.[11] Since ACER is an unsigned measure of the quantity of information (that is, it does not directly distinguish positive and negative news from the perspective of shareholders), we use the absolute value of stock returns as an unsigned measure of new information integrated into stock price. To calculate abnormal returns, we estimate daily expected returns by applying the five-factor model of Fama and French (2015). Following Loughran and McDonald (2014), for each 10-K or 10-Q report, we estimate the pricing model using trading days $[-252, -6]$ prior to the

[11]The time subscript q denotes the fiscal quarter covered by the accounting reports. Typically, these reports are filed and released in the subsequent quarter. Therefore, the measurement window $ACAR_{i,q}$ generally falls in fiscal quarter $q + 1$.

report release date. This rolling window approach allows factor loadings to vary over time within each firm. $ACER\_Rank_{i,q}$ is the decile rank of $AE_{i,q}$.

In the baseline specification, we first estimate a simple model without controlling for additional firm characteristics or fixed effects. The simple model allows us to observe the total association between $ACAR_{i,q}$ and $ACER\_Rank_{i,q}$. Next, we include a set of control variables to further investigate whether the entropy measure captures information beyond the common firm characteristics documented in the literature. These control variables include the absolute value of seasonally differenced earnings[12], the natural logarithm of total book assets, book-to-market ratio, leverage ratio, sales growth rate, research and development expense, capital expenditure, and the historical stock return and its volatility measured prior to the release of 10-K or 10-Q. In the baseline specification, we do not include fixed effects and explore the pooled variation of $ACER\_Rank_{i,q}$. In additional specifications, we include year fixed effects and firm fixed effects to further explore within-group variations. In all specifications, we apply two-way clustered standard errors by quarter and firm.

4.2 Market Reaction Analysis

Table 2 reports the results of estimating equation (1) using four specifications. In column (1), we estimate a simple regression model without control variables or fixed effects to establish the baseline relationship between ACER and short-window market reaction. The result shows that a one-decile-rank increase in $ACER\_Rank$ is associated with an increase of approximately 0.27% in $ACAR$. The coefficient is significant at 1% with a t-statistic of 30.04. The positive association suggests that as the amount of information in the financial statements increases, the stock price reflects this by updating more intensively.

In column (2), we control for the decile rank of seasonally differenced earnings and a battery of other firm characteristics. Note that the information content of the ACER can overlap with the information captured by these control variables, such as capital expendi-

[12]Similar to $ACER\_Rank$, we use the decile rank of unsigned seasonally differenced earnings to facilitate interpretation and mitigate the influences of outliers and skewness.

ture ($CapEx$), unsigned historical return ($AbsRet$), and return volatility ($StdRet$). The estimated coefficient of $ACER\_Rank$ is 0.076, smaller than the coefficient in column (1) and still statistically significant at 1%. The result suggests that the commonly used financial statement variables and market indicators do not fully explain the association between $ACER\_Rank$ and $ACAR$. The next two columns report the results after incorporating fixed effects. In column (3), we include quarter fixed effects (i.e., an indicator variable for each year-quarter combination); in column (4), we further include firm fixed effects. The coefficient of $ACER\_Rank$ remains positive and statistically significant in both specifications, indicating that the within-quarter and within-firm variations in ACER are also meaningfully associated with the intensity of the market reaction.

Next, we examine event-window trading volume, another market indicator frequently used to assess investors' response to accounting information (e.g., Beaver, 1968; Landsman and Maydew, 2002). Our primary trading volume variable is $Volume$, the average daily trading volume scaled by the number of outstanding shares (expressed as a percentage) for the $[0, +3]$ window surrounding the release of 10-K or 10-Q reports.

Table 3 reports the results of estimating equation (2) using $Volume$ as the dependent variable, using the same four specifications in Table 2. Across the four specifications, $ACER\_Rank$ is positively and significantly associated with $Volume$, indicating a higher level of trading activities when the ACER is higher. Interestingly, the coefficient of $ACER\_Rank$ in column (1) is similar in magnitude to columns (2), suggesting that common firm characteristics have limited power in explaining the relationship between ACER and trading volume. In column (3) and (4), this association remains statistically significant after the inclusion of quarter fixed effects and firm fixed effects.

Taken together, the evidence from Tables 2 and 3 suggests that ACER captures information used by market participants in valuation and trading decisions. This finding highlights the economic relevance of accounting classification and demonstrates that our framework provides a useful and tractable measure of such information. Importantly, the market reaction variables in our analysis are not intended as benchmarks for validating ACER. Our objective is to examine the information in accounting classification, whereas stock prices and trading volumes reflect many forces beyond accounting classification. For this reason, market-based proxies cannot serve as benchmarks for ACER from a measurement perspective. Rather, the analysis supports the notion that the information content summarized by ACER is economically relevant.

5 Extension 1: The Allocation of Processing Resources

In this section, we demonstrate how the entropy measure can be useful in investigating empirical questions. Specifically, we use ACER to examine how financial analysts allocation information processing resources in response to accounting information. We first provide the conceptual background and then discuss the analysis and results.

5.1 Conceptual Underpinnings

In a recent review, Blankespoor, deHaan, and Marinovic (2020) identify the cost of processing information as a key friction in capital markets, highlighting the importance of understanding to what extent processing resources are efficiently allocated. A natural question is how this resource allocation responds to the amount of information in financial statements. Theories of limited attention posit that rational information users should prioritize the allocation of processing capacity to information with the lowest opportunity costs (Peng, 2005). Assuming the marginal benefit of processing is increasing in the amount of unprocessed information, disclosure with higher total amount of information should receive more processing resources. Similarly, regulators may prefer disclosures with a greater amount of raw information to receive more processing, so that the processed information is useful to end users. On the other hand, certain market frictions can prevent the processing capacity from responding to the amount of information to be processed, such as adjustment costs and various agency conflicts in information intermediaries (e.g., Groysberg, Healy, and Maber, 2011).

Empirically examining this relationship requires a method for quantifying the amount of information in financial statements to be processed, as well as a setting that allows researchers to observe the allocation of processing capacity. ACER is well-suited for this application because it directly quantifies a key aspect of financial statement information. In particular, ACER is an internal measure, meaning that it is not influenced by the extent to which the information has been processed or integrated into stock prices. This feature allows the entropy approach to avoid potential reverse causality concerns associated with using proxies involving stock price or other market indicators. For demonstration purposes, we continue to use *ACER_Rank* described in Section 4.2 as the main independent variable.

To capture the allocation of processing resources, we use the coverage of sell-side analysts as the empirical setting. This setting aligns well with our purpose for several reasons. First, analysts are influential information intermediaries that are often regarded as sophisticated users of accounting information (Kothari, So, and Verdi, 2016). Second, previous studies find that coverage and forecast decisions involve trade-offs associated with allocating processing resources (e.g., Harford, Jiang, Wang, and Xie, 2019; Lee and So, 2017). Third, whether and how analysts respond to variations in the amount of accounting information is ex ante unclear and ultimately an empirical question. While the classic framework without agency conflicts predicts a positive association between the amount of information and processing capacity, analysts' personal incentives may induce countervailing forces.

5.2 Empirical Results

Our summary measure of analyst processing capacity is based on variations in earnings forecast coverage and frequency. We start from the firm-level total coverage in Lee and So (2017), defined as the number of unique combinations of analyst and earnings forecasting period ("FP") in a 90-day window. In addition, we incorporate the number of forecast revisions for each analyst-FP pair, as the frequency of revision is also an economically meaningful dimension of processing capacity (Harford et al., 2019). We define APC (Analyst Processing Capacity) as the natural logarithm of unique combinations of analyst, FP, and forecast revisions. For each firm-quarter, we measure APC for a 90-day window around the release date of the corresponding 10-K or 10-Q.[13] In further analysis, we break down APC into its three key components: the number of unique analysts (ANA), the average number of FP per analyst (PER), and the average number of forecast revisions per analyst-FP pair (REV, which captures variations in revision frequency). Similar to the construct of APC, we apply the natural logarithm to these three variables.

We estimate the following regression model

$$AnalystVar_{i,q} = \beta_1 ACER\_Rank_{i,q} + \Gamma Controls_{i,q} + \mu_i + \delta_q + \epsilon_{i,q}, \tag{3}$$

where $AnalystVar_{i,q}$ is one of the four analyst variables described above. Other variables are defined in the same way as in equation (2). In estimating equation (3), we include the full set of control variables to account for observed firm characteristics that may explain the coverage and frequency of analyst forecasts. In addition, we use both firm fixed effects (μ_i) and quarter fixed effects (δ_q) to mitigate potential confounding effects from unobserved time-invariant firm characteristics and aggregate shocks. Standard errors are clustered by firm and quarter.

Table 4 reports the results of estimating equation (3). Column (1) shows that APC, the summary measure of analyst processing capacity, is positively associated with $ACER\_Rank$. This result is consistent with the notion that analysts allocate more processing resources as the amount of information in the financial statement increases. To further investigate which dimension(s) of the analyst processing capacity respond to information changes, we decom-

[13] We measure APC using 90-day windows, in line with the typical length of a fiscal quarter. This approach aligns with prior research (e.g., Lee and So, 2017), which employed similar time frames to construct analyst coverage. The window is centered on the release dates of accounting reports to account for the gradual arrival and processing of the information contained in the reports before and after their releases.

pose APC into its three components described above: ANA, PER, and REV. Column (2) shows that the number of unique analysts following the firm is positively associated with $ACER\_Rank$, but the association is only marginally significant. In columns (3) and (4), we find that both the average number of forecast periods and the average frequency of revisions respond positively and significantly to $ACER\_Rank$.

Overall, the results suggest that financial analyst allocate their processing capacities in a way consistent with economic intuitions. While the amount of information to be processed does not substantially alter which firms analysts choose to cover, it does influence how analysts allocate processing capacities within their coverage. As a firm's ACER increases, analysts devote more attention to that firm by extending their forecasting horizons and issuing more frequent revisions. Consequently, the total analyst processing capacity is positively associated with the amount of accounting information captured by ACER.

6 Extension 2: ACE within Accounting Structure

In our analysis so far, we apply the concept of relative entropy to quantify information updates in financial statements. Our findings suggest that ACER is associated with capital market reactions to financial statement releases and helps explain how analysts allocate their processing capacity. In this section, we present a separate, standalone extension of the ACE framework introduced in Section 3 to incorporate a richer accounting structure with dual classifications (e.g., balance sheet with a side of assets and a side of funding sources, including liabilities and stockholders' equities).

Specifically, we employ Mutual Information, a key construct from information theory, to quantify the information embedded in the balance sheet structure. A main takeaway from our analysis is that, because accounting structure imposes a connection between different classifications, the structure itself contains information beyond the information conveyed in the classifications. We then explore an empirical application—standalone from the analyses in Sections 4 and 5—that quantifies the information conveyed by accounting structure. Our descriptive evidence shows that the information in the accounting structure varies meaningfully with firm characteristics and economic trends discussed in the literature.

6.1 An Information-Theoretic Framework of Dual-Classification Accounting Structure

Mutual Information

Definition 4 (Mutual Information) *Consider two random variables $\{X, Y\}$ with a joint distribution $p(x, y)$ and marginal probability mass functions $p(x)$ and $p(y)$. The mutual information $I(X; Y)$ is the relative entropy between the joint distribution and the product distribution $p(x)p(y)$:*

$$I(X; Y) = D(p(x, y)||p(x)p(y)) = \sum_{X \in \mathcal{X}} \sum_{y \in \mathcal{Y}} p(x, y) \log \frac{p(x, y)}{p(x)p(y)}.$$

Shannon (1948) shows that the mutual information $I(X; Y)$ measures the reduction in the uncertainty of X due to the knowledge of Y, and vice versa:

$$I(X; Y) = H(X) - H(X|Y) = H(Y) - H(Y|X) \geq 0,$$

with the inequality strict if and only if X and Y are independent. Intuitively, the distance (in the sense of K-L divergence) between the joint distribution $p(x, y)$ and the product distribution $p(x)p(y)$ is 0 if X and Y are independent, whereas this distance is bigger when X and Y are more dependent of each other. In addition, using $H(X, Y) = H(X) + H(Y|X)$ (see Footnote 5), we note the following relationship between Entropy and Mutual Information, which will play an instrumental role in characterizing the information of accounting structure:

$$I(X; Y) \ = \ H(X) \ + \ H(Y) \ - \ H(X, Y). \tag{4}$$

We also illustrate this relationship in the following Venn diagram in Figure 1a. The Venn diagram shows well that the mutual information $I(X;Y)$ represents the *intersection* of the information in X with the information in Y (Cover and Thomas, 2006).

Balance Sheet Accounting Structure What accounting structure is embedded in financial statements? Financial statements provide more information than a one-dimensional list of balances. For instance, consider a firm's balance sheet with an asset side and a funding source (liabilities and stockholders' equity) side. Motivated by Feltham and Ohlson (1995), Penman (2013) and Nissim (2022) (hereinafter referred to as the "PN classification") propose one way to reformulate balance sheet classification, which decomposes the balance sheet by economic function (operating vs. financing). Published balance sheets are usually classified into horizon (current and long-term) categories, which is useful for credit analysis. In contrast, the function-based classification provides information about assets and liabilities used in the business of selling to customers or financing the business. The operating assets are preferentially funded by operating liabilities (net operating assets), and financing assets are preferentially funded by financing liabilities (net financing assets, or net debt). The cross-classification yields four asset types, short-term operating assets (STOA), long-term operating assets (LTOA), short-term financing assets (STFA), and long-term financing assets (LTFA), and five funding sources, short-term operating liabilities (STOL), long-term operating liabilities (LTOL), short-term financing liabilities (STFL), long-term financing liabilities (LTFL), and equity (Eq). Table A.1 Panel A is an illustrative example of the marginal distribution of Nvidia's balance sheet for the fiscal year ended January 29, 2023, using the combination of PN classification (by economic function) and horizon classification.

Mutual Information as Measure of Accounting Structure Information Our main analysis in Proposition 1 lends some support to generalizing the notion of entropy to measure the information in financial account classification, thereby yielding the measure of Accounting Classification Entropy (ACE). To illustrate, a firm classifies the assets into n line-items, where the fractions of the assets' balances are represented by the vector $\boldsymbol{A} = [A_1, A_2, ...A_n]'$ with $\sum_{i=1}^{n} A_i = 1$. The firm also classifies the funding sources into m line-items, where the fractions of the items' balances are represented by the vector $\boldsymbol{F} = [F_1, F_2, ...F_m]'$ with $\sum_{j=1}^{m} F_j = 1$.

Under the classification $\{\boldsymbol{A}, \boldsymbol{F}\}$ of both the assets and funding sources, one may propose the summary measure of accounting classification information as $H_n(\boldsymbol{A}) + H_m(\boldsymbol{F})$ using the additive property of entropy. Nonetheless, the sum $H_n(\boldsymbol{A}) + H_m(\boldsymbol{F})$ generally overstates the amount of information in the classification of assets and funding sources. The reason is that the structure of accounting systems connects the firm's asset classification $\boldsymbol{A}$ to its funding source classification $\boldsymbol{F}$; hence the two classifications are not independent. To appreciate the "joint distribution" of the two sides of the balance sheet, consider again the example of the function-horizon dual classification. The first connection between the classifications stems from the basic accounting identity that, at the aggregate level, the assets must be supported by the funding sources:

$$STOA + LTOA + STFA + LTFA = STOL + LTOL + STFL + LTFL + Eq.$$

Second, along the two dimensions of classification, each category of assets should be supported by the corresponding category of funding sources in a priority sequence, reflecting both the accounting identity and real-world financing logic. Operating (financing) assets are first funded by operating (financing) liabilities, and then equity. In addition, the firm should turn to less liquid sources to fund short-term assets only when they are insufficiently funded by short-term liabilities.

Specifically, using the ACE measure, we compute the information in the dual classifications of assets and funding sources $\{\boldsymbol{A}, \boldsymbol{F}\}$ as follows:

$$H(\boldsymbol{A}, \boldsymbol{F}) = -\sum_{i=1}^{n}\sum_{j=1}^{m} A_i Q_{ij} \log(A_i Q_{ij}).$$

The vector $\boldsymbol{Q_i} = [Q_{i1}, Q_{i2}, ...Q_{im}]'$ represents the fractions of asset i that are supported by the set of funding sources $j \in \{1, 2, ...m\}$, where $\sum_{j=1}^{m} Q_{ij} \equiv 1$ for any $i \in \{1, 2, ...n\}$. Utilizing the relationship between mutual information and entropy specified in Equation (4) yields:

$$I(\boldsymbol{A}; \boldsymbol{F}) = H_n(\boldsymbol{A}) + H_m(\boldsymbol{F}) - H(\boldsymbol{A,F}) \geq 0. \tag{5}$$

That is, recognizing the connection between the assets and the funding sources under accounting structure, an observer learns less information $H(\boldsymbol{A,F})$ from the dual classifications of assets and funding sources than the sum of the information in the classifications of assets and in the funding sources, $H_n(\boldsymbol{A}) + H_m(\boldsymbol{F})$. Equation (5) shows that the difference between the two represents the information that is already embedded in the accounting structure, which is measured by the mutual information $I(\boldsymbol{A}; \boldsymbol{F})$. We illustrate Equation (5) graphically in the Venn diagram in Figure 1b.

To appreciate the mutual-information measure of accounting structure information, suppose that accounting structure implies no connection on the classification of financial accounts such that each asset i is funded by the funding sources in proportion to the funding sources' sizes, i.e., $Q_{ij} \equiv F_j$ for any pair of $\{i, j\}$. It is straightforward to obtain that:

$$H(\boldsymbol{A,F}) \ = \ H_n(\boldsymbol{A}) \ + \ H_m(\boldsymbol{F}) \quad \Longrightarrow \quad I(\boldsymbol{A}; \boldsymbol{F}) \ = \ 0.$$

Since there is no relationship between assets and funding sources, the information in observing the two classifications jointly is simply the sum of the information in observing the two separately.

In contrast, accounting structure specifies a link between assets and funding sources. Recall that in the example of the function-horizon dual classification, an asset i is more likely to be funded by a funding source with a similar horizon and function (e.g., short-term operating assets are first funded by short-term operating liabilities). Accordingly, $Q_{ij} \neq F_j$ for at least some $\{i, j\}$. Leveraging their knowledge of accounting structure, observers of the asset classification $\boldsymbol{A}$ are able to infer some information about the funding source classification $\boldsymbol{F}$, even before observing the latter. For instance, upon learning that the firm holds a significant amount of short-term operating liabilities, an observer infers that the firm should hold a corresponding amount of short-term operating assets in order to avoid liquidity concerns. Equation (5) suggests that the mutual information measure quantifies the amount of information in the accounting structure.

Structured Balance Sheet Example Refer back to Nvidia's example of its marginal distribution of the balance sheet in Table A.1 Panel A. Although each side sums to 100%, these separate distributions alone do not reveal the accounting structure embedded in balance sheets–namely, how a particular combination of liabilities or equity funds any specific asset. Once asset and liability/equity categories are identified, we apply a structured allocation rule that combines the function-horizon classification. Specifically, we use an "inventory-clearing" algorithm to allocate funding sources to asset uses in a priority sequence: operating assets are first funded by operating liabilities (short-term first, then long-term), then equity. Financing assets are funded by financing liabilities (short-term first, then long-term), then equity. Economically, the firm has to turn to less liquid sources to fund short-term assets if it is not sufficiently funded by short-term liabilities. Figure 1c is a graphical representation of this process.

This approach generates a 4×5 joint balance sheet assuming the accounting structure, which can be normalized by total assets. Nvidia's reformulated balance sheet using accounting structure, presented in raw amounts and proportions normalized by total assets in Panels B and C of Table A.1, respectively.

Benchmark: Unstructured Balance Sheet A natural way to benchmark the effect of accounting structure is to construct a naive balance sheet assuming independence: each asset category is funded by liabilities/equity in proportion to its overall shares. Formally, this implies

$$P^{\text{indep}}(A_i, F_j) = P(A_i) \cdot P(F_j)$$

where $P(A_i)$ is the fraction of total assets in category A_i, and $P(F_j)$ is the fraction of total liabilities and equity in category F_j. Under this assumption, there is no consideration for accounting structure or economically meaningful dependence between asset categories and funding categories. Instead, this unstructured balance sheet can serve as a null hypothesis of purely random allocation, where each asset is equally likely to be funded by any liability or equity source. Table A.1 Panel D is Nvidia's balance sheet under the independence assumption, which is the outer product of the marginal distributions in Panel A.

By construction, the mutual information in Equation (5) is zero:

$$I(\boldsymbol{A}; \boldsymbol{F}) = H_n(\boldsymbol{A}) + H_m(\boldsymbol{F}) - H(\boldsymbol{A}, \boldsymbol{F}) = 0,$$

since the joint entropy $H(\boldsymbol{A}, \boldsymbol{F})$ attains its maximum when the marginals are independent, where $I(\boldsymbol{A}; \boldsymbol{F}) = 0$ due to the lack of dependence between assets and funding sources.

Consequently, any observed deviation from this benchmark ($I(\boldsymbol{A}; \boldsymbol{F}) \geq 0$)can be interpreted as evidence of information restrictions imposed by the accounting classification system. For instance, the accounting knowledge that operating assets are more likely to be funded by operating liabilities than any other funding sources introduces systematic dependence that reduces joint entropy and generates positive mutual information.

6.2 Empirical Analysis of Accounting Structure Information

In this section, we apply the PN classification to construct joint balance sheets for firms in the Compustat database. For each balance sheet, we compute the ACE of both the unstructured balance sheet (assuming independence between assets and funding sources) and the balance sheet assuming accounting structure, and use their difference (Mutual Information) to quantify the information embedded in the accounting structure. We also present descriptive evidence on how this structural information varies with firm characteristics.

Figure 2 presents the distributions of firm-quarter ACE measures under two different assumptions: (i) accounting structure in the joint balance sheet (*structured entropy*), and (ii) independence between assets and liabilities/equity (*unstructured entropy*). The distributions are displayed as histograms at the firm-quarter level. When comparing the distributions of Panel B (unstructured entropy) to Panel A (structured entropy), the distribution for Panel B is shifted visibly further to the right, implying greater uncertainty when assets and liabilities/equity are assumed independent. Because no systematic link is imposed using the accounting structure, the joint distribution is more diffuse, increasing entropy.

Panel C shows the mutual information, calculated by the difference between the unstructured entropy and structured entropy at the firm-quarter level as shown in Equation (5). This distribution is greater than or equal to zero, highlighting that the accounting structure indeed restricts uncertainty. Panel D shows a relative comparison by calculating the ratio of structured entropy divided by unstructured entropy. Most values lie between 0.3 and 0.8, suggesting that a substantial fraction of uncertainty is eliminated by imposing the structural connections between accounting classifications.

Taken together, Figure 2 shows that the accounting structure lowers entropy compared to an unstructured, independence-based approach. On average, mutual information is significantly positive, corroborating the idea that knowing the asset category restricts information about how it is funded (and vice versa).

A key question in accounting research is how the role of accounting information evolves over time, particularly as the nature of business undergoes significant transformation (Core et al., 2003; Barth et al., 2023). We illustrate how our approach can contribute to this question by quantifying the information embedded in accounting structures across three dimensions: firm size, firm age, and an indicator for whether a firm belongs to the "new economy." This analysis provides insight into how the informational role of existing accounting structure varies with firm characteristics and broader economic shifts.

Table 5 provides descriptive statistics of the same entropy measures, partitioned by total assets, firm age, and economy type (new vs. old). For firm age, we use the IPO date as the first date of the firm's birth. Following Core et al. (2003) and Barth et al. (2023), we use the industry classification by Francis and Schipper (1999). For each subgroup, we report the mean, median, and standard deviation of the structured entropy, unstructured entropy, and their difference, which is mutual information.

In Panels A and B, we find that the larger and older firms show a significantly higher value of the accounting structure, measured by mutual information. Intuitively, mutual information would be greater for larger and older firms, as these firms are more likely to have diverse funding from different sources of assets and liabilities, thus more likely to benefit from the use of accounting structure to reduce uncertainty. In contrast, younger and smaller firms have simpler funding structures, resulting in a smaller gap between structured assumptions and independence.

In panel C, we show that "Old Economy" firms exhibit significantly larger reduction in entropy than "New Economy" firms. This aligns with the intuition that traditional industries with tangible assets and standardized capital structures fit better within the classic function/horizon classification scheme, whereas "New Economy" firms' balance sheets may not align as neatly with traditional accounting classifications.

Collectively, these results confirm the central hypothesis that accounting structure meaningfully constrains the asset-liability pairing, thereby reducing joint entropy. The degree of mutual information varies systematically with firm characteristics: larger, older, and more traditional firms tend to exhibit greater mutual information when leveraging accounting classifications in the balance sheet. In contrast, smaller, younger, or less traditional firms show a less pronounced pattern, suggesting that conventional accounting structures may embed less information in these settings. One interpretation is that younger, smaller, or new economy firms tend to operate with less conventional business models and more intangible assets, which may not map cleanly onto traditional accounting classification frameworks. Another possibility is that these firms use more flexible or unstructured financing arrangements, which may lead to a weaker relationship between assets and funding sources.

These findings highlight that the information relevance of accounting structure is not uniform across firms. The observed heterogeneity has implications for regulators and practitioners concerned with how effectively existing financial statement structures capture the underlying economic substance across different firms and industries. While standard-setters recognize the need to account for the varying informativeness of accounting structure across different types of firms, such as economic shifts toward knowledge-intensive business models, such considerations have been difficult to quantify systematically. Our entropy-based framework offers a potential solution by translating these abstract concerns about structural informativeness into measurable summary statistics.

7 Conclusions

We develop an entropy-based framework to quantify the structural dimension of financial statements. Inspired by Shannon (1948)'s information theory and Theil (1969)'s application insight, we formalize how accounting classifications convey information and derive a suite of two internal summary measures, ACE and ACER. These measures provide a mathematically consistent representation of the information embedded in the classification structure of financial statement numbers. Using balance sheet data, we find that ACER is significantly associated with market based proxies such as stock returns and trading volume, suggesting that it captures economically relevant information contained in accounting classifications. Our first extension further demonstrates that ACER helps explain how information processing capacity is allocated across firms, suggesting that the measure can serve as a useful input for answering empirical questions on information processing. In the second extension, we incorporate dual classification structure of the balance sheet and apply the concept of mutual information to measure the information conveyed by balance sheet structure itself.

The results indicate that conventional balance sheet structures convey greater informational content for established firms than for younger or new-economy firms.

Taken together, our study shows that information theory offers a rigorous yet practical foundation for quantifying the structural dimension of accounting information. Our framework complements existing empirical approaches and provides a new perspective for analyzing how financial statements represent and convey information about the firm.

References

Angeletos, George-Marios, and Karthik Sastry, 2019, Inattentive economies, Technical report, National Bureau of Economic Research.

Ball, Ray, and Philip Brown, 1968, An empirical evaluation of accounting information numbers, *Journal of Accounting Research* 6, 159–178.

Ball, Ray, SP Kothari, and Ashok Robin, 2000, The effect of international institutional factors on properties of accounting earnings, *Journal of Accounting and Economics* 29, 1–51.

Barth, Mary E., Ken Li, and Charles G. McClure, 2023, Evolution in value relevance of accounting information 98, 1–28.

Basu, Sudipta, 1997, The conservatism principle and the asymmetric timeliness of earnings1, *Journal of Accounting and Economics* 24, 3–37.

Beaver, William H, 1968, The information content of annual earnings announcements, *Journal of Accounting Research* 6, 67–92.

Beaver, William H, and Joel S Demski, 1979, The nature of income measurement, *The Accounting Review* 38–46.

Bishop, Christopher M, 2006, *Pattern recognition and machine learning* (Springer).

Blankespoor, Elizabeth, Ed deHaan, and Ivan Marinovic, 2020, Disclosure processing costs, investors' information choice, and equity market outcomes: A review, *Journal of Accounting and Economics* 70, 101344.

Bonham, Jonathan, and Amoray Riggs-Cragun, 2022, Contracting on value, *SSRN Electronic Journal* .

Brown, Stephen V, Guang Ma, and Jennifer Wu Tucker, 2023, Financial statement similarity, *Contemporary Accounting Research* 40, 2577–2615.

Brown, Stephen V, and Jennifer Wu Tucker, 2011, Large-sample evidence on firms' year-over-year MD&A modifications, *Journal of Accounting Research* 49, 309–346.

Chen, Shuping, Bin Miao, and Terry Shevlin, 2015, A new measure of disclosure quality: The level of disaggregation of accounting data in annual reports, *Journal of Accounting Research* 53, 1017–1054.

Cohen, Lauren, Christopher Malloy, and Quoc Nguyen, 2020, Lazy prices, *The Journal of Finance* 75, 1371–1415.

Cooper, William W, 1949, Theory of the firm: Some suggestions for revision, *The American Economic Review* 39, 1204–1222.

Cooper, William W, 1951, A proposal for extending the theory of the firm, *The Quarterly Journal of Economics* 65, 87–109.

Core, John E., Wayne R. Guay, and Andrew Van Buskirk, 2003, Market valuations in the new economy: an investigation of what has changed 34, 43–67.

Costello, Anna, Bradford Levy, and Valeri Nikolaev, 2025, Uncovering information: Can ai tell us here to look?, *Working Paper* .

Cover, Thomas M, and Joy A Thomas, 2006, *Elements of information theory* (Wiley-Interscience).

Demski, Joel S, 1973, The general impossibility of normative accounting standards, *The Accounting Review* 48, 718–723.

Denis, Diane K, Torsten Jochem, and Anjana Rajamani, 2020, Shareholder governance and CEO compensation: The peer effects of say on pay, *The Review of Financial Studies* 33, 3130–3173.

Edmans, Alex, Xavier Gabaix, and Dirk Jenter, 2017, Executive compensation: A survey of theory and evidence, *The Handbook of the Economics of Corporate Governance* 1, 383–539.

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Feltham, Gerald A., and James A. Ohlson, 1995, Valuation and clean surplus accounting for operating and financial activities, *Contemporary Accounting Research* 11, 689–731.

Francis, Jennifer, and Katherine Schipper, 1999, Have financial statements lost their relevance?, *Journal of Accounting Research* 37, 319–352.

Groysberg, Boris, Paul M Healy, and David A Maber, 2011, What drives sell-side analyst compensation at high-status investment banks?, *Journal of Accounting Research* 49, 969–1000.

Hail, Luzi, Clare Wang, and Rachel Xi Zhang, 2024, Investor uncertainty and voluntary disclosure, *Working Paper* .

Hainmueller, Jens, 2012, Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies, *Political Analysis* 20, 25–46.

Harford, Jarrad, Feng Jiang, Rong Wang, and Fei Xie, 2019, Analyst career concerns, effort allocation, and firms' information environment, *The Review of Financial Studies* 32, 2179–2224.

Hicks, John Richard, 1946, *Value and capital: An inquiry into some fundamental principles of economic theory* (Oxford University Press).

Ijiri, Yuji, 1975, Theory of accounting measurement, *Studies in Accounting Research No. 10, American Accounting Association* .

Jiang, Xu, and Ming Yang, 2017, Properties of optimal accounting rules in a signaling game, *Journal of Accounting and Economics* 63, 499–512.

Kothari, Sagar P, Eric So, and Rodrigo Verdi, 2016, Analysts' forecasts and asset pricing: A survey, *Annual Review of Financial Economics* 8, 197–219.

Kullback, Solomon, and Richard A Leibler, 1951, On information and sufficiency, *The Annals of Mathematical Dtatistics* 22, 79–86.

Landsman, Wayne R, and Edward L Maydew, 2002, Has the information content of quarterly earnings announcements declined in the past three decades?, *Journal of Accounting Research* 40, 797–808.

Lee, Charles MC, and Eric C So, 2017, Uncovering expected returns: Information in analyst coverage proxies, *Journal of Financial Economics* 124, 331–348.

Lee, Lucy C, and Norton M Bedford, 1969, An information theory analysis of the accounting process, *The Accounting Review* 44, 256–275.

Leuz, Christian, and Robert E Verrecchia, 2000, The economic consequences of increased disclosure, *Journal of Accounting Research* 91–124.

Lev, Baruch, 1968, The aggregation problem in financial statements: An informational approach, *Journal of Accounting Research* 247–261.

Lev, Baruch, 1970, The informational approach to aggregation in financial statements: Extensions, *Journal of Accounting Research* 78–94.

Loughran, Tim, and Bill McDonald, 2014, Measuring readability in financial disclosures, *The Journal of Finance* 69, 1643–1671.

Marshak, Jacob, 1959, Remarks on the economics of information (1959), in *Economic Information, Decision, and Prediction: Selected Essays: Volume II*, 91–117 (Springer).

Mattessich, Richard, 2006, The information economic perspective of accounting: Its coming of age, *Canadian Accounting Perspectives* 5, 209–236.

McMullin, Jeff L, and Bryce Schonberger, 2020, Entropy-balanced accruals, *Review of Accounting Studies* 25, 84–119.

Myatt, David P, and Chris Wallace, 2012, Endogenous information acquisition in coordination games, *The Review of Economic Studies* 79, 340–374.

Nissim, Doron, 2022, Reformulated financial statements, `https://doi.org/10.2139/ssrn.4064722`, Working Paper.

Parker, Robert Henry, and Geoffrey Colin Harcourt, 1969, *Readings in the Concept and Measurement of Income* (Cambridge University Press Cambridge).

Peng, Lin, 2005, Learning with information capacity constraints, *Journal of Financial and Quantitative Analysis* 40, 307–329.

Penman, Stephen H., 2013, *Financial Statement Analysis and Security Valuation*, fifth edition (McGraw Hill, New York).

Shannon, Claude Elwood, 1948, A mathematical theory of communication, *The Bell System Technical Journal* 27, 379–423.

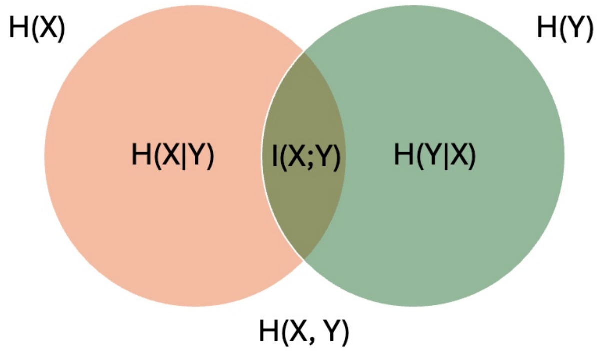
Sims, Christopher A, 2003, Implications of rational inattention, *Journal of Monetary Economics* 50, 665–690.

Theil, Henri, 1969, On the use of information theory concepts in the analysis of financial statements, *Management Science* 15, 459–480.

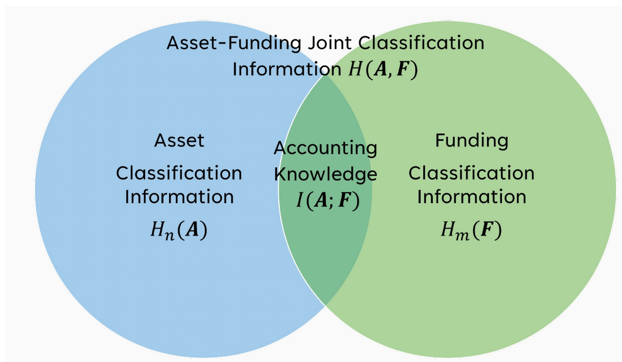
Variable Definition

Variable	Definition
ACER	The relative entropy of the standardized asset account classification from quarter $q-4$ to q.
ACER_Rank	The decile rank of $ACER$.
ACAR	The absolute value of the cumulative abnormal return in the $[0,+3]$ window surrounding the filing of 10-K or 10-Q. Daily abnormal returns are calculated based on the Fama-French five factor model. A value of 1 represents 1%.
AMR(k)	The absolute value of the monthly abnormal return in the k^{th} month after the filing of 10-K or 10-Q. Monthly abnormal returns are calculated based on the Fama-French five factor model. A value of 1 represents 1%.
Volume	The average daily trading volume scaled by the number of shares outstanding in the $[0,+3]$ window surrounding the filing of 10-K or 10-Q. A value of 1 represents 1%.
ASDE	The absolute value of seasonally differenced earnings, defined as the income before extraordinary Items of quarter q minus that of quarter $q-4$, scaled by the market value of equity at the beginning of quarter q.
ASDE_Rank	The decile rank of $ASDE$.
Size	The natural logarithm of total book assets.
BM	The ratio of the book value of equity to its market value.
Lev	The ratio of total debts to total book assets.
SG	The seasonal percentage change in quarterly revenue.
RD	The quarterly research and development expense.
CapEx	The quarterly capital expenditure.
StdRet	The standard deviation of daily return in trading days [-252, -6] prior the the filing of 10-K or 10-Q.
AbsRet	The absolute value of average daily return in trading days [-252, -6] prior the the filing of 10-K or 10-Q.

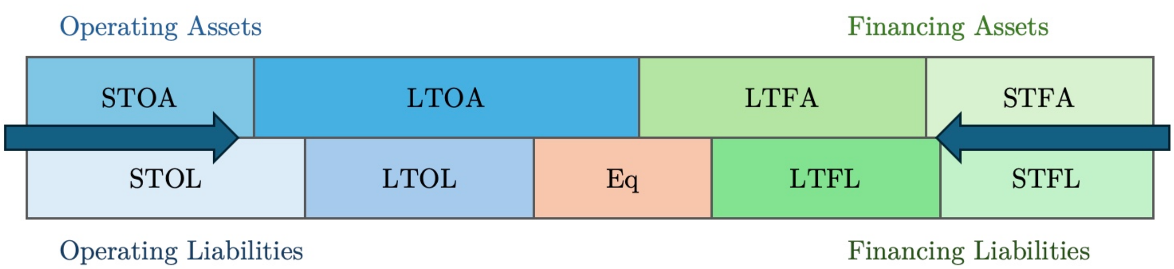
Variable	Definition
APC	The summary measure of analyst processing capacity, define as the natural logarithm of the number of unique analyst-FP-forecast combinations for firm i measured in the [-45, +45] window centered on the filing of 10-K or 10-Q.
ANA	The natural logarithm of the number of unique analysts making at least one forecast for firm i in the [-45, +45] window centered on the filing of 10-K or 10-Q.
PER	The natural logarithm of the average number of forecasting periods of the analysts making at least one forecast for firm i in the [-45, +45] window centered on the filing of 10-K or 10-Q. For example, if an analyst made EPS forecast for firm i's next two quarters and next fiscal year, her number of forecasting periods for firm i is 3.
REV	The natural logarithm of the average number of forecasts for each analyst-FP combination of firm i in the [-45, +45] window centered on the filing of 10-K or 10-Q.



(a) The Relationship between Mutual Information and Entropy



(b) Accounting Structure Information and Dual Asset-Funding Classifications



(c) Inventory-clearing Algorithm for Asset Funding Relationship

Figure 1: **Venn Diagram: Mutual Information and Entropy Relationship in Accounting Structure**
Figure 1a illustrates the relationship between mutual information $I(X;Y)$ and entropy $H(X)$ and $H(Y)$. Graphically, the intersection of the information in X with the information Y represents the mutual information $I(X;Y)$, and this intersection increases as X and Y are more dependent on each other. Figure 1b applies this to the accounting structure embedded in the funding relationship within balance sheets (assets A and funding sources F). The accounting structure creates dependence between assets and funding sources classification; therefore, the mutual information $I(A;F)$ quantifies the amount of information in the accounting structure. Figure 1c is a graphical representation of the "inventory-clearing" algorithm to allocate funding sources to asset uses in priority sequence: operating/financing assets are first funded by operating/financing liabilities (short-term first, then long-term), then equity.

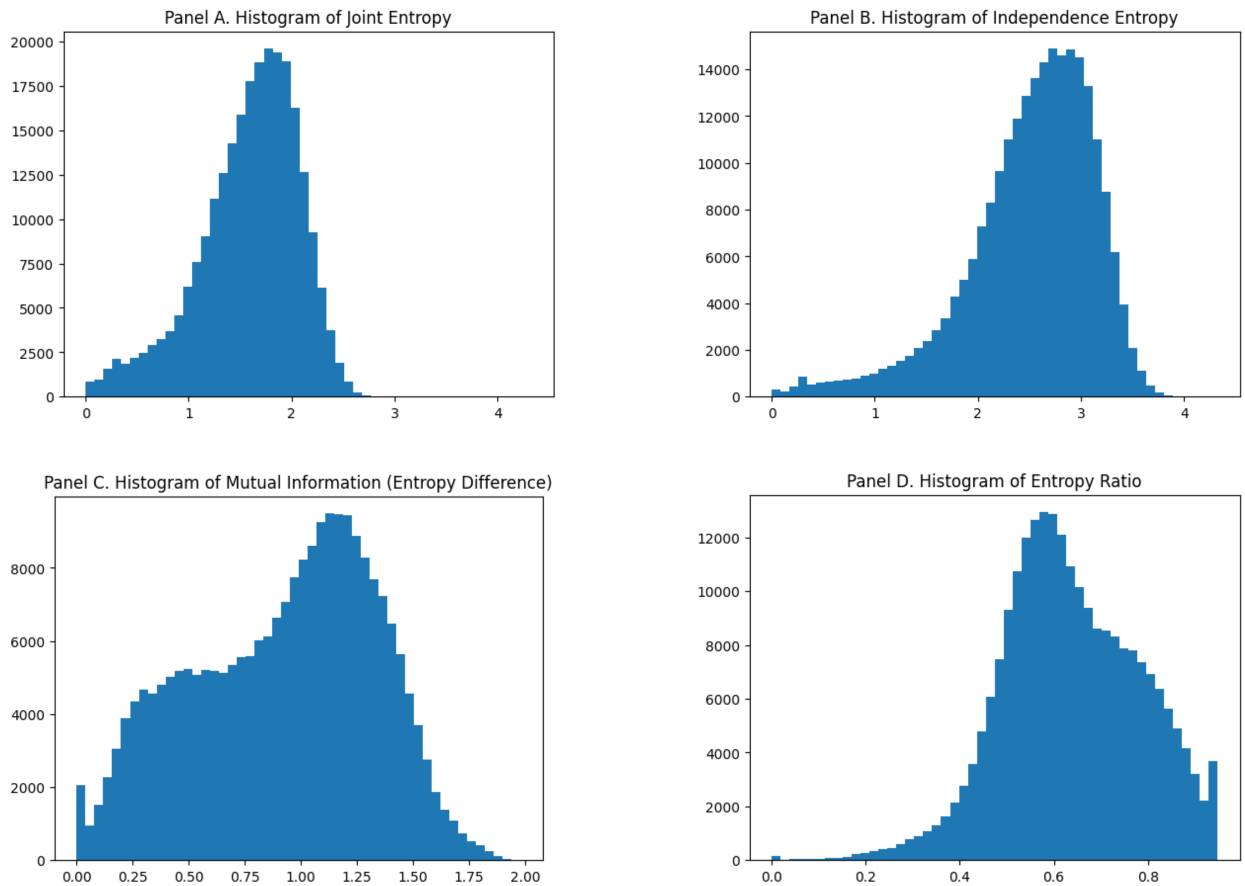


Figure 2: **Distribution of Joint Entropy, Mutual Information, and Entropy Ratio** Panels A and B show the histogram of firm-quarter joint balance sheets' joint entropy assuming accounting structure and assuming independence, respectively. Panel C shows the mutual information, as defined as the difference between the firm-quarter's independent and accounting-structure-based balance sheets' joint entropy. Panel D shows the ratio of the joint entropy of joint balance sheets assuming accounting structure, divided by the joint entropy of joint balance sheets assuming independence.

Table 1: **Summary Statistics**

This table reports the summary statistics and correlation matrices of the variables in the analysis. Panel A reports the number of observations and distribution properties of key dependent and independent variables. Panels B, C, and D report correlation matrices for market indicators, firm characteristics, and analyst coverage variables, respectively.

Panel A: Summary Statistics

Variables	N	Mean	S.D.	25%	Median	75%
ACER	246,481	0.072	0.133	0.009	0.024	0.069
ACER_Rank	246,481	5.500	2.872	3	5	8
ACAR	246,481	4.604	5.425	1.113	2.710	5.918
AMR1	243,966	10.593	11.344	3.020	6.921	13.894
AMR2	240,855	11.165	11.869	3.231	7.391	14.683
Volume	246,454	0.971	1.291	0.215	0.544	1.175
ASDE	233,713	0.028	0.058	0.003	0.008	0.023
ASDE_Rank	233,713	5.426	2.861	3	5	8
Size	233,713	6.116	1.982	4.622	6.013	7.482
BM	233,713	0.612	0.546	0.269	0.468	0.761
Lev	233,713	0.216	0.189	0.028	0.193	0.350
SG	233,713	0.151	0.459	-0.035	0.074	0.221
RD	233,713	0.013	0.025	0	0	0.016
CapEx	233,713	0.014	0.017	0.004	0.008	0.017
StdRet	233,713	3.114	1.949	1.735	2.586	3.930
AbsRet	233,713	0.165	0.160	0.055	0.118	0.220
APC	188,674	3.470	1.193	2.639	3.555	4.344
ANA	188,674	1.869	0.757	1.386	1.792	2.398
PER	188,674	1.603	0.351	1.386	1.674	1.856
REV	188,674	0.933	0.156	0.823	0.908	1.021

Panel B: Correlation with Market Variables

	ACER_Rank	ACAR	AMR1	AMR2	Volume
ACER_Rank	1.000				
ACAR	0.142	1.000			
AMR1	0.174	0.210	1.000		
AMR2	0.167	0.188	0.290	1.000	
Volume	0.106	0.351	0.071	0.064	1.000

Panel C: Correlation with Firm Characteristics

	ACER_Rank	ASDE_Rank	Size	BM	Lev	SG	RD	CapEx	StdRet	AbsRet
ACER_Rank	1.000									
ASDE_Rank	0.198	1.000								
Size	-0.265	-0.251	1.000							
BM	-0.015	0.363	-0.134	1.000						
Lev	-0.134	0.086	0.340	0.043	1.000					
SG	0.164	-0.034	-0.041	-0.153	-0.013	1.000				
RD	0.178	0.086	-0.281	-0.193	-0.268	0.101	1.000			
CapEx	0.026	-0.042	0.025	-0.086	0.054	0.111	-0.100	1.000		
StdRet	0.289	0.418	-0.588	0.290	-0.066	0.038	0.244	-0.037	1.000	
AbsRet	0.190	0.234	-0.247	0.035	-0.039	0.128	0.148	0.006	0.512	1.000

Panel D: Correlation with Analyst Variables

	ACER_Rank	APC	ANA	PER	REV
ACER_Rank	1.000				
APC	-0.083	1.000			
ANA	-0.120	0.900	1.000		
PER	0.018	0.607	0.249	1.000	
REV	0.000	0.534	0.293	0.340	1.000

Table 2: **Accounting Entropy and Event-window Return**
This table reports the results from the OLS regression relating the Accounting Entropy and short-window unsigned stock return around the filing of 10-K and 10-Q. $ACAR$ is the absolute value of the cumulative abnormal return in the $[0, +3]$ window surrounding the filing of 10-K or 10-Q. $ACER\_Rank$ is the decile rank of Accounting Entropy based on the standardized asset accounts from quarter $q-4$ to q. Standard errors are clustered by firm and quarter. T-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) ACAR	(2) ACAR	(3) ACAR	(4) ACAR
ACER_Rank	0.270***	0.076***	0.055***	0.022***
	(30.04)	(10.30)	(13.75)	(5.07)
ASDE_Rank		0.097***	0.088***	0.066***
		(11.63)	(14.03)	(10.79)
Size		-0.064***	-0.192***	-0.190***
		(-2.63)	(-14.19)	(-4.99)
BM		0.303***	0.283***	0.540***
		(4.99)	(7.06)	(8.86)
Lev		1.063***	0.896***	1.469***
		(6.15)	(9.46)	(8.81)
SG		0.131***	0.171***	0.088**
		(2.96)	(4.97)	(2.28)
RD		4.535***	0.955	1.907
		(4.57)	(1.46)	(1.52)
CapEx		-5.001***	1.825**	2.710***
		(-3.43)	(2.45)	(2.70)
StdRet		0.693***	0.747***	0.539***
		(22.33)	(38.33)	(22.52)
AbsRet		1.738***	1.761***	1.687***
		(6.44)	(8.30)	(8.96)
Observations	246,481	233,713	233,713	233,164
Adjusted R-squared	0.020	0.126	0.164	0.218
Firm FE	No	No	No	Yes
Quarter FE	No	No	Yes	Yes
Two-way Clustering	Yes	Yes	Yes	Yes

Table 3: **Accounting Entropy and Trading Volume**
This table reports the results from the OLS regression relating the Accounting Entropy and short-window Volume around the filing of 10-K and 10-Q. $Volume$ is the average daily trading volume scaled by the number of shares outstanding in the $[0, +3]$ window surrounding the filing of 10-K or 10-Q. $ACER\_Rank$ is the decile rank of Accounting Entropy based on the standardized asset accounts from quarter $q-4$ to q. Standard errors are clustered by firm and quarter. T-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) Volume	(2) Volume	(3) Volume	(4) Volume
ACER_Rank	0.047***	0.042***	0.034***	0.013***
	(12.62)	(15.22)	(16.29)	(10.94)
ASDE_Rank		0.021***	0.012***	0.007***
		(7.59)	(5.28)	(4.54)
Size		0.213***	0.179***	0.236***
		(20.73)	(18.20)	(14.66)
BM		-0.204***	-0.193***	-0.183***
		(-10.27)	(-11.47)	(-9.54)
Lev		-0.399***	-0.368***	-0.024
		(-6.08)	(-7.26)	(-0.40)
SG		0.120***	0.159***	0.094***
		(8.72)	(14.43)	(9.92)
RD		3.267***	2.082***	-0.223
		(7.70)	(5.70)	(-0.61)
CapEx		1.285**	4.056***	2.230***
		(2.27)	(8.72)	(6.90)
StdRet		0.075***	0.128***	0.124***
		(5.19)	(10.60)	(11.04)
AbsRet		1.294***	1.228***	0.947***
		(18.21)	(20.00)	(22.21)
Observations	246,454	233,689	233,689	233,140
Adjusted R-squared	0.011	0.117	0.186	0.418
Firm FE	No	No	No	Yes
Quarter FE	No	No	Yes	Yes
Two-way Clustering	Yes	Yes	Yes	Yes

Table 4: **Accounting Entropy and Analyst Processing Capacity**
This table reports the results from the OLS regression relating the Accounting Entropy and measures of analyst coverage. APC is the summary measure of analyst coverage, defined as the natural logarithm of the number of unique analyst-FP-forecast combinations for a given firm measured in the [-45, +45] window centered on the filing of 10-K or 10-Q. ANA is the natural logarithm of the number of unique analysts; PER is the natural logarithm of the average number of forecasting periods of the covering analysts; REV is the natural logarithm of the average number of forecasts for each analyst-FP combination. $ACER\_Rank$ is the decile rank of Accounting Entropy based on the standardized asset accounts from quarter $q-4$ to q. Standard errors are clustered by firm and quarter. T-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) APC	(2) ANA	(3) PER	(4) REV
ACER_Rank	0.007***	0.001*	0.003***	0.001***
	(6.73)	(1.72)	(6.76)	(8.10)
ASDE_Rank	-0.006***	-0.009***	0.003***	0.001***
	(-5.84)	(-16.08)	(7.44)	(6.20)
Size	0.506***	0.360***	0.030***	0.029***
	(37.91)	(43.18)	(8.30)	(17.26)
BM	-0.437***	-0.249***	-0.074***	-0.026***
	(-24.39)	(-22.37)	(-14.38)	(-11.48)
Lev	-0.437***	-0.271***	-0.075***	-0.018***
	(-9.67)	(-9.25)	(-5.86)	(-3.32)
SG	0.044***	0.007	0.023***	0.004***
	(5.56)	(1.51)	(9.09)	(3.43)
RD	1.711***	0.657***	0.643***	0.118***
	(6.78)	(4.24)	(6.49)	(3.31)
CapEx	3.674***	1.547***	0.874***	0.437***
	(13.80)	(9.62)	(9.80)	(10.09)
StdRet	0.007	-0.006	0.006***	0.006***
	(1.27)	(-1.63)	(3.48)	(5.85)
AbsRet	0.058*	-0.053***	0.061***	0.025***
	(1.74)	(-2.75)	(6.64)	(4.40)
Observations	181,406	181,406	181,406	181,406
Adjusted R-squared	0.723	0.813	0.439	0.304
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Two-way Clustering	Yes	Yes	Yes	Yes

Table 5: **Information Contained in the Balance Sheet Structure**
This table reports descriptive statistics of the structured entropy, unstructured entropy, and mutual information for different subgroups of firms. Structured entropy is the balance sheet entropy computed under the accounting structure, where assets are allocated to funding sources following a priority sequence based on function (operating vs. financing) and horizon (short-term vs. long-term). Unstructured entropy is the balance sheet entropy assuming no accounting structure, where each asset classification is funded proportionally by all funding sources. Mutual information is the difference between unstructured entropy and structured entropy, measuring the information gain attributable to the balance sheet structure. Panel A partitions the sample by total asset quintiles, Panel B by age quintiles using each firm's IPO Date as the age start date, and Panel C by economy type. For each subgroup, we present the mean, median, and standard deviation of these three entropy measures. The rows labeled "Largest – Smallest", "Oldest – Youngest" and "Old – New" report the differences in mean and corresponding t-statistics comparing the respective groups. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Structured Entropy		Unstructured Entropy		Mutual Information	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Panel A: Size Quintile						
1 (Smallest)	1.508	0.569	2.188	0.719	0.677	0.396
2	1.584	0.520	2.326	0.673	0.738	0.399
3	1.637	0.451	2.561	0.550	0.922	0.388
4	1.612	0.445	2.695	0.495	1.087	0.325
5 (Largest)	1.588	0.419	2.753	0.463	1.167	0.291
Largest- Smallest					0.490*** (215.814)	
Panel B: Age Quintile						
1 (Youngest)	1.381	0.623	2.096	0.853	0.724	0.419
2	1.519	0.540	2.392	0.641	0.876	0.394
3	1.602	0.481	2.504	0.579	0.902	0.389
4	1.671	0.434	2.576	0.519	0.902	0.396
5 (Oldest)	1.710	0.389	2.655	0.458	0.943	0.400
Oldest - Youngest					0.219*** (61.531)	
Panel C: Economy Type						
New Economy	1.599	0.545	2.381	0.702	0.775	0.392
Old Economy	1.649	0.347	2.838	0.425	1.190	0.267
Other	1.577	0.456	2.563	0.575	0.987	0.399
Old - New					0.415*** (69.701)	

Appendix A: Illustrative Example Using Nvidia's Balance Sheet

Table A.1: **Nvidia Balance Sheet: Marginal and Joint Distributions**
This table presents Nvidia's balance sheet for the fiscal year ended January 29, 2023, using the Penman-Nissim (PN) classification combining economic function (operating vs. financing) and horizon (short-term vs. long-term). Panel A shows the marginal distributions of assets and liabilities plus equity. Panel B presents the structured balance sheet in dollar amounts using an inventory-clearing algorithm that allocates funding sources to assets based on matching function and horizon priorities. Panel C shows the same structured allocation as percentages of total assets. Panel D presents the unstructured balance sheet, assuming each asset is funded proportionally to the overall distribution of funding sources, serving as a benchmark for comparison.

Panel A: Marginal Balance Sheets

Assets	USD m	Prob(%)	Liab	USD m	Prob(%)
STOA	9,777	23.7%	STOL	5,313	12.9%
STFA	13,296	32.3%	STFL	1,250	3.0%
LTOA	18,109	44.0%	LTOL	1,913	4.6%
LTFA	-	0.0%	LTFL	10,605	25.8%
			Eq	22,101	53.7%
Total	41,182	100.0%	Total	41,182	100.0%

Panel B: Structured BS - Amount (USD m)

	Liabilities + Equity					
Assets	STOL	STFL	LTOL	LTFL	Eq	Sum
STOA	5,313	-	1,913	-	2,551	9,777
STFA	-	1,250	-	10,605	1,441	13,296
LTOA	-	-	-	-	18,109	18,109
LTFA	-	-	-	-	-	-
Sum	5,313	1,250	1,913	10,605	22,101	41,182

Table A.1: **Nvidia Balance Sheet: Marginal and Joint Distributions** (continued)

Panel C: Structured BS - Asset Weighted (%)

	Liabilities + Equity					
Assets	STOL	STFL	LTOL	LTFL	Eq	Sum
STOA	12.9%	0.0%	4.6%	0.0%	6.2%	23.7%
STFA	0.0%	3.0%	0.0%	25.8%	3.5%	32.3%
LTOA	0.0%	0.0%	0.0%	0.0%	44.0%	44.0%
LTFA	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Sum	12.9%	3.0%	4.6%	25.8%	53.7%	100.0%

Panel D: Unstructured BS (%)

	Liabilities + Equity					
Assets	STOL	STFL	LTOL	LTFL	Eq	Sum
STOA	3.06%	0.72%	1.10%	6.11%	12.74%	23.73%
STFA	4.17%	0.98%	1.50%	8.31%	17.33%	32.29%
LTOA	5.67%	1.33%	2.04%	11.32%	23.60%	43.96%
LTFA	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Sum	12.90%	3.03%	4.64%	25.74%	53.67%	100.0%

Appendix B: Additional Application – Structural Change in Executive Compensation

In this appendix, we illustrate how the concept of relative entropy can be applied to construct summary measures in other settings. Specifically, we propose compensation structure divergence (CSD) as a measure for the change in the composition of executive pay packages. We then use CSD to investigate the relationship between Say-on-Pay (SOP) votes and future changes in compensation structure.

The executive pay literature often investigates two aspects of compensation policies: pay level and pay structure (Edmans et al., 2017). Studies examining the influence of SOP votes on compensation practices typically focus on pay level, likely for two reasons. First, the pay level, being a scalar variable, is relatively easy to measure. Second, there is a natural prediction regarding how SOP votes affect pay level: assuming shareholders are concerned with excessive pay, firms tend to reduce pay levels if they respond to high SOP dissent. In contrast, investigating the influence of SOP votes on pay structure is more complex, as firms' existing pay structures may deviate from shareholders' preferences in various ways. As a result, predictions about how dissenting votes affect individual components of pay *on average* can be ambiguous. Analyzing individual pay components in standard regression models may fail to capture changes in the overall composition, even if such changes exist. To circumvent this challenge, we propose compensation structure divergence (CSD) as a summary metric to measure a firm's year-to-year change in the composition of executive pay packages. If firms respond to SOP votes by adjusting the pay structure, we expect a positive association between the level of dissent in year t and CSD measured from t to $t + 1$.

To implement this approach, we collect shareholder voting data from Institutional Shareholder Services (ISS) and executive compensation data from ExecuComp. Our sample includes firm-year observations from 2011 to 2021 that (1) have a recorded SOP vote and (2) have the necessary voting variables, compensation variables, and other relevant firm characteristics. We first decompose the total pay of the top five executives of the firms into five categories following the approach of Edmans et al. (2017): salary, bonus, option, restricted stock, and others. In this exercise, we focus on a parsimonious application with five categories commonly used in the literature. However, our method can be extended to a more granular set of categories, such as by incorporating detailed information on vesting conditions. We next represent the value of each pay component as a fraction of the total pay, representing the compensation structure with a vector of five elements that sum up to 1. Lastly, we apply the KL divergence to the vectors in fiscal year t and $t+1$ and label the resulting metric $CSD_{i,t+1}$.

In our regression analysis, the main dependent variable is $CSDRank_{i,t+1}$, which represents the decile rank of the raw $CSD_{i,t+1}$. The key independent variable of interest is $Dissent_{i,t}$, which captures the overall level of dissent in the SOP vote for firm i in year t. We control for a similar set of firm characteristics as in Table 2 with a few adjustments. Specifically, we replace the decile rank of seasonal differenced earnings (ASDE_Rank) with signed seasonal differenced earnings (SDE) to better account for firm performance. Similarly, we substitute unsigned stock returns ($AbsRet$) with signed stock returns (Ret). Finally, we include $TotalPay$, the natural logarithm of the total pay of the top five executives, to account for the pay level. Control variables are measured with a one-year lag following the Denis et al. (2020).

Table A.2 presents the results. Column (1) reports a positive and statistically significant relationship between $Dissent$ and $CSDRank$, suggesting that firms receiving more negative SOP votes are more likely to adjust their pay structure in the following year. Column (2) shows that this association remains significant after incorporating firm fixed effects, indicating that the relationship is not merely influenced by time-invariant firm characteristics. One potential alternative explanation for this finding is that the observed change in pay structure might simply reflect firms' attempts to adjust pay levels. To address this concern, we examine whether our results hold after excluding firms with large changes in pay level.

Specifically, in column (3), we exclude observations where the year-over-year change in pay level exceeds 20% or falls below -20%. The results remain robust and the magnitude of the point estimate increases, suggesting that the association between $Dissent$ and $CSDRank$ is unlikely to be fully explained by firms with substantial changes in pay levels.

In columns (3) through (6), we examine our results using the natural logarithm transformation to mitigate the skewness of the raw CSD as an alternative to using decile ranks. The results remain robust. Overall, the finding suggests that firms are more likely to adjust their compensation structure in response to higher dissent in SOP votes, adding to the literature on the economic consequences of SOP votes. Furthermore, this application demonstrates that the concepts of entropy and KL divergence can also serve as versatile measurement tools in research settings outside financial statement analysis.

Table A.2: **SOP Votes and Compensation Structural Change**
This table reports the results from the OLS regression relating SOP votes and the change in future compensation structure. CSD is the KL divergence from year t to $t+1$ based on the following pay components (scaled by total pay) of the top five executives: salary, bonus, option, restricted stock, and others. $CSDRank$ is the decile rank of CSD. $CSDLn$ is the natural logarithm of CSD. $Dissent$ is the number of dissenting votes divided by the total number of votes cast in the SOP vote in year t. Columns (1), (2), (4), and (5) use the full sample, while columns (3) and (6) focus on a subset of firms with a percentage change in total pay between -20% and +20%. Standard errors are clustered by firm and year. T-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full	Full	Stable Pay Level	Full	Full	Stable Pay Level
Variables	CSDRank	CSDRank	CSDRank	CSDLn	CSDLn	CSDLn
Dissent	1.690***	0.848**	2.324***	0.969***	0.469*	1.450***
	(4.81)	(2.42)	(3.96)	(4.00)	(2.04)	(4.13)
Size	-0.234***	0.144	0.179	-0.167***	0.040	0.019
	(-4.79)	(0.68)	(0.72)	(-5.07)	(0.31)	(0.11)
BM	-0.151	-0.090	0.341	-0.057	-0.020	0.342
	(-0.92)	(-0.31)	(0.76)	(-0.54)	(-0.11)	(1.23)
Lev	-0.230	0.496	-0.201	-0.146	0.299	-0.106
	(-0.81)	(0.75)	(-0.30)	(-0.71)	(0.70)	(-0.23)
SG	0.145	-0.260	-0.003	0.108	-0.145	-0.025
	(1.03)	(-1.27)	(-0.01)	(1.13)	(-1.07)	(-0.12)
RD	-3.723	25.345	32.888*	-1.512	11.030	15.096
	(-0.95)	(1.70)	(1.87)	(-0.59)	(1.17)	(1.26)
CapEx	-3.758	3.944	3.818	-1.267	3.484	4.289
	(-0.91)	(0.78)	(0.50)	(-0.44)	(0.89)	(0.72)
StdRet	0.651***	0.128	0.087	0.416***	0.061	0.019
	(8.61)	(1.26)	(0.52)	(7.78)	(0.94)	(0.18)
Ret	-1.649***	-1.290**	-0.384	-1.066***	-0.852***	-0.170
	(-3.57)	(-3.05)	(-0.68)	(-3.70)	(-3.38)	(-0.50)
SDE	-2.254**	-1.446	-1.154	-1.449**	-0.925	-0.639
	(-3.01)	(-1.62)	(-0.98)	(-2.91)	(-1.45)	(-0.87)
TotalPay	0.232**	0.034	0.491	0.198**	0.040	0.486**
	(2.36)	(0.14)	(1.75)	(2.69)	(0.24)	(2.88)
Observations	5,796	5,717	3,466	5,796	5,717	3,466
Adjusted R-squared	0.065	0.234	0.234	0.061	0.234	0.227
Firm FE	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Two-way Clustering	Yes	Yes	Yes	Yes	Yes	Yes