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Candidate SCOR-Linked Financial Proxies: Exploratory Evidence from a 12-Firm Panel Using SCOR_E Ratio Analysis of Supply Chain Efficiency

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Abstract

Background: Many SCOR performance measures rely on internal operational data, which limits empirical work using public information. *Methods:* This study evaluates a small set of publicly auditable, SCOR-linked ratios (SCOR_E) in a panel of 12 publicly traded firms across four sectors from 2000 to 2022. Using firm- and year-fixed-effects panel models, the paper examines whether these candidate proxies show pre-specified directional associations within firms and whether the same ratios are associated with operating margin in parallel models. Instrumental-variable (IV) specifications are reported only as sensitivity analyses, and nearly all are weak by the paper's reported first-stage diagnostics. *Results:* Accordingly, most findings are interpreted as associative rather than causal. After false-discovery-rate adjustment and weak-instrument-robust inference, only four firm–proxy pairs meet the paper's detection criterion; all remaining estimates are treated as non-robust. *Conclusions:* The contribution is therefore narrow: this is a constrained exploratory screening exercise showing which candidate mappings survive the paper's inferential filters in this sample and which do not. The results do not establish a validated cross-industry scorecard, a scalable benchmarking framework, or a basis for policy claims.

Keywords: SCOR; supply chain efficiency; financial ratios; observability; panel data; weak instruments

1. Introduction

The Supply Chain Operations Reference (SCOR) model is commonly used to organize supply-chain processes and to describe performance attributes such as reliability, responsiveness, flexibility, cost, and asset-management efficiency [1,2]. A recurring empirical difficulty, however, is that many SCOR measures depend on internal operational data that are not publicly disclosed. This limits the use of SCOR constructs in studies that rely on audited public information and constrains comparison when only financial statements are available [1,2].

This paper addresses a narrower question than whether SCOR can be converted into a general external scorecard. Recent studies have linked individual SCOR-related constructs to financial ratios derived from audited statements in specific sectoral settings, including airlines [3], internet retail [4], integrated oil and gas [5], and entertainment [6]. A related SCOR-based financial modeling effort also points toward this interface [7]. More broadly, financial-ratio analysis and productive-efficiency research have long used public accounting data when direct process measures are unavailable [8–10]. A related stream of operations–finance research examines how operational choices such as working capital management,

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asset utilization, and cost discipline are reflected in accounting outcomes, which makes that literature relevant to the present proxy question [11–15]. What remains less developed is a cautious attribute-level mapping that asks whether a small set of publicly auditable ratios can serve as candidate indicators of selected SCOR Level 1 attributes within firms and within comparable sectoral settings, while remaining distinct from the latent operational capabilities they are intended to approximate.

The paper uses the label SCOR_E for these candidate public-data ratios and uses Financial Observability of SCOR Capabilities (FOSC) as an organizing term for this measurement question. In this manuscript, neither term implies that public accounting ratios fully recover operational capabilities, that the proposed mappings are broadly validated, or that the resulting measures support cross-industry benchmarking. Because accounting aggregates can reflect multiple mechanisms and raise endogeneity concerns [11], the empirical objective is limited to examining whether pre-specified directional proxy patterns appear in a small sample once firm heterogeneity, time effects, and identification limits are taken seriously.

Three research questions follow from that limited objective. First, which candidate SCOR-linked ratios display pre-specified within-firm directional patterns in longitudinal panel models? Second, do those same ratios show parallel associations with operating margin in comparable specifications? Third, in which sectoral settings do those mappings survive the paper's screening rules, appear unstable, or prove non-informative? The study answers these questions using firm- and year-fixed-effects models and reports instrumental-variable specifications only as sensitivity analyses. Because weak-instrument diagnostics are pervasive in this setting, most estimates are interpreted as associative rather than causal.

Empirically, the analysis uses a panel of 12 large, publicly traded firms observed between 2000 and 2022 across four supply-chain-intensive sectors: mainline airlines, integrated oil and gas, internet retail, and entertainment studios. The firms are included because the relevant GAAP/IFRS line items are continuously available and because each sector has material supply-chain exposure. The design is deliberately limited. With 12 firms, the study cannot support strong claims about scalability, representative sector effects, moderator estimation, or broad cross-industry benchmarking. The evidence should therefore be read as exploratory and sample-bound.

Within those limits, the paper makes a constrained measurement contribution. It assembles a transparent set of SCOR-linked ratio constructions that can be replicated from audited filings, states in advance the directional patterns that would count for or against observability in context, and reports exploratory evidence on which candidate mappings survive the paper's screening rules in this sample, and which fail. The contribution is therefore to document, in this sample, which candidate mappings survive the paper's screening rules under public-data constraints, and which do not, not to establish a field-defining framework or a validated diagnostic instrument.

The remainder of the paper proceeds as follows. Section 2 reviews SCOR studies alongside adjacent work on financial proxies, efficiency analysis, and operations–finance linkages, and narrows the measurement question addressed here. Section 3 sets out the observability logic and hypotheses. Section 4 describes the sample, proxy construction, models, diagnostics, and inference policy. Section 5 reports the exploratory results, and Sections 6 and 7 discuss the findings, limitations, and implications in a deliberately bounded manner.

2. Literature Review

This review situates SCOR_E between two established empirical traditions. SCOR research provides structured vocabulary for describing supply-chain attributes, but most applications operationalize those attributes with internal process measures. Studies using

public accounting data, by contrast, offer externally auditable measures of performance and efficiency, yet they rarely map those measures back to the SCOR attribute taxonomy. The issue addressed here lies at that intersection: whether a limited set of audited ratios can be treated as candidate indicators of selected SCOR Level 1 attributes without assuming that financial statements fully reveal the underlying capabilities.

2.1. SCOR Research and the Limits of Public Measurement

SCOR has been adapted across manufacturing, logistics, humanitarian, service, sustainability, and digitally enabled supply chains [1,2,13–34]. These studies show the model's usefulness as an organizing vocabulary, but their empirical implementations are usually local and internally measured. Researchers extend SCOR with multi-criteria tools, simulation, fuzzy logic, machine learning, digital metrics, and sector-specific KPI systems [1,2,16–33]. That flexibility supports managerial diagnosis, yet it also makes external replication difficult because many of the underlying measures are not disclosed in audited public filings.

At the attribute level, reliability, responsiveness, flexibility, cost, and asset-management efficiency are substantively rich concepts, but publicly replicable measures remain unsettled [7–9,29,35–78]. Reliability often requires failure or disruption data; responsiveness depends on integration, visibility, and decision speed; flexibility can entail slack-cost trade-offs; and cost and asset measures are frequently sector- or model-specific. The literature, therefore, clarifies what these constructs mean more readily than it shows how they can be inferred from audited public data.

2.2. Public Accounting Proxies, Efficiency Analysis, and Operations–Finance Links

Financial-ratio analysis, productive-efficiency research, and transaction-cost or operations-efficiency studies approach the problem from the opposite direction by using public accounting data when direct process data are unavailable [8–12]. These traditions are useful because they rely on auditable information, foreground measurement, and endogeneity issues, but they usually analyze profitability, productivity, or efficiency rather than SCOR attributes as such.

The closest antecedents to the present study are sector-specific papers that relate individual SCOR-linked constructs to public financial ratios in airlines, internet retail, integrated oil and gas, and entertainment [3–6], together with prior SCOR-based financial modeling [7]. Those studies show that finance-facing proxies have been proposed in narrow sectoral settings, but they do not establish general proxy validity. At the same time, their industry specificity leaves open whether a given ratio is capturing an attribute-specific signal, a context-bound association, or a broader construct that does not map cleanly to SCOR.

2.3. Precise Research Gap and Constrained Role of SCOR_E

The gap addressed here is therefore narrow. It is not a field-defining deficiency in OSCM, and this manuscript does not claim to solve SCOR measurement generally. The narrower problem is whether a small set of publicly auditable ratios can be organized as candidate proxies for selected SCOR Level 1 attributes and evaluated against transparent empirical criteria in a public-firm panel. SCOR_E is introduced as an exploratory mapping device for that purpose only. It is not presented as a validated cross-industry framework, a general benchmarking tool, or a substitute for internal operational dashboards.

A further implication of this literature is that publicly observed accounting ratios should be treated as candidate proxies rather than direct measures of latent supply-chain capabilities. Because accounting aggregates can combine multiple operational and non-operational influences, construct validity cannot be assumed from face correspondence alone. The empirical question is therefore narrower: whether a given ratio exhibits the pre-

specified directional pattern that would make it a plausible indicator of a SCOR attribute in a given context. When signs are unstable, null, or reversed under those conditions, that counts against using the ratio as a proxy in that setting.

2.4. Boundary Conditions as Interpretive Scope Conditions

Prior research also implies that any accounting-based proxy is conditional on context. Asset intensity, production-cycle length, demand clock speed, shock exposure, and accounting conventions can all change what a ratio reflects [7–9,62,73,76–80]. In this manuscript, these conditions are treated as interpretive scope conditions rather than as tested moderators. The 12-firm panel does not support high-dimensional interaction modeling, so the empirical analysis uses sector-stratified estimation, fixed effects, and robustness checks as contextual controls, not moderator tests. This distinction is important for falsification: within the stated scope conditions, unstable or reversed signs count against observability for that proxy in that setting rather than being retained through post hoc explanation.

3. Theory and Hypotheses

SCOR attributes are treated here as latent operational capabilities rather than directly observed accounting outcomes. The theoretical question is therefore limited: under what conditions can an audited financial ratio function as a candidate indicator of a SCOR attribute within firms? The claim is directional and measurement-oriented, not causal. If a proposed ratio is a plausible indicator, a stronger expression of the underlying capability should be accompanied by movement in a pre-specified direction; if that pattern does not appear, the mapping is not supported in that context.

This logic draws on resource-based, dynamic capability, transaction cost, and contingency perspectives without assuming that every attribute has a universally monotonic accounting signature. Reliability and asset-management efficiency are expected to coincide with more stable and more productive use of resources, while responsiveness and cost efficiency are expected to coincide with faster cash recovery and leaner operating burdens. Flexibility is the most contestable mapping because liquidity slack can reflect either adaptive capacity or precautionary finance. In this study, that ambiguity does not rescue the proxy: if the predicted sign does not appear, the result counts first against observability via the proposed ratio.

Accordingly, the theory can be wrong in identifiable ways. For a given proxy in a given setting, repeated nulls, unstable signs across comparable specifications, or systematic sign reversals indicate poor proxy fit, construct invalidity in context, or failure of the assumed scope conditions. Contextual explanations remain possible, but they are secondary interpretations and do not preserve the observability claim in the absence of a stable predicted sign.

3.1. Hypothesis Development

Each hypothesis is stated as a directional association between a sign-standardized SCOR_E ratio and the study's efficiency signal. In observability models, coefficients with the predicted sign count as evidence consistent with observability; opposite-signed or unstable coefficients count against it. Parallel associations with operating margin are examined only as ancillary evidence and do not by themselves validate a proxy.

H1. Higher SCRe (reliability) is positively associated with efficiency (β_SCRe > 0). If SCRe is a plausible reliability proxy, more reliable source-make-deliver routines should coincide with lower disruption-related margin instability. Persistent null or negative SCRe coefficients, therefore, count against using SCRe as a reliability indicator in that setting.

H2. Higher −SCRs (faster responsiveness) are positively associated with efficiency (β_−SCRs > 0). If shorter cash-cycle recovery reflects greater operational responsiveness in the sampled setting, −SCRs should move with the efficiency signal in the predicted direction. Null or negative estimates indicate that the proposed responsiveness proxy is not informative in that context.

H3. Higher SCF (flexibility) is positively associated with efficiency (β_SCF > 0). SCF is measured as liquid slack relative to operating expense, so the hypothesis is deliberately demanding: for this ratio to proxy flexibility here, greater slack must coincide with the efficiency signal rather than merely reflecting idle cash or financing choices. Null or negative coefficients, therefore, count against SCF as a flexibility proxy in that setting.

H4. Higher −SCC (leaner cost structures) is positively associated with efficiency (β_−SCC > 0). If reduced working capital and operating cost burden reflect more efficient coordination and lower transactional frictions, −SCC should exhibit the predicted sign. Opposite-signed or unstable coefficients count against observability via this cost proxy.

H5. Higher SCAME (asset-management efficiency) is positively associated with efficiency (β_SCAME > 0). If supply-chain assets are being converted more productively into revenue and cash flow, SCAME should be positively associated with the efficiency signal. Null, unstable, or negative SCAME coefficients indicate poor proxy fit or boundary failure in that setting.

3.2. Financial Observability of SCOR Capabilities

We define financial observability as the ability of a proposed audited ratio to provide a directional indicator of a latent SCOR capability within a stated context. FOSC is used here as a falsifiable measurement logic, not as a validated framework. Four conditions are required. (N1) Auditability: the ratio must be reproducible from consistently disclosed GAAP/IFRS line items. (N2) Within-firm informativeness: the ratio must vary enough over time to identify change. (N3) Directional monotonicity: the expected sign must be specified in advance. (N4) Conditional separability: once broad scope conditions are held approximately constant, the ratio must predominantly reflect the intended attribute rather than unrelated accounting or financing mechanisms.

In this study, evidence counts against FOSC for a given proxy in a given context when one or more of the following occurs: the estimated coefficient takes the opposite sign to the pre-specified hypothesis; the sign is not stable across comparable pairwise and joint specifications; the proxy has too little within-firm variation to be informative; or any apparent support disappears once multiple-testing adjustments and weak-instrument-robust inference are applied.

Such patterns are interpreted first as non-observability of that proxy in that setting. Attenuation, buffering, or sector-specific factors are secondary possibilities only and do not preserve the observability claim in the absence of stable predicted signs.

On that basis, SCOR_E is treated as a set of candidate proxies whose usefulness must be earned empirically. The econometric strategy below evaluates whether each proposed mapping survives these criteria.

Table 1 presents the proposed mapping of SCOR Level 1 performance attributes to the SCOR_E financial proxies.

Table 1. Mapping of SCOR Level 1 performance attributes to the proposed SCOR_E financial proxies.

SCOR Attribute	SCOR_E Ratio	Formula	Financial Account
Reliability	SCRe	$1 - \lvert\Delta$ Gross Margin%$\rvert$	Revenue, COGS
Responsiveness	SCRs	Cash conversion cycle/365	AR, Inventory, AP, COGS, Sales
Flexibility	SCF	(Cash + STI)/OpEx	Cash, short-term investments, OpEx
Cost	SCC	Working-capital burden/cost burden	PP&E, WC items, OpEx, CapEx
Asset efficiency	SCAME	Turnover composite/asset productivity	AR, Inventory, Assets, Intangibles, AP

Note: The mapping is based on SCOR attribute definitions and prior SCOR performance measurement studies [1,2,15].

SCOR_E Ratios and Sign Convention

We compute five firm-year ratios corresponding to SCOR Level 1 attributes. Ratios for which lower raw values imply better performance are multiplied by -1, yielding $-$SCRs and $-$SCC. All hypotheses are therefore stated so that $\beta > 0$ denotes evidence consistent with the proposed mapping; $\beta \leq 0$ does not.

Table 2 summarizes variable construction. Sign standardization aids directional comparison but does not itself establish construct validity. Because accounting classifications and business models differ across industries, inference focuses on within-firm variation, sign stability, diagnostics, and the distinction between associative and causal interpretation.

Table 2. Variable definitions, constructions, and roles in the empirical models.

Variable	Description	Construction (GAAP/IFRS Line Items)	Role in Analysis
SCRe	Reliability proxy (sign-standardized)	$1 - \lvert\Delta$ Gross Margin%$\rvert$	SCOR_E proxy; DV in observability models; regressor in OMR models
$-$SCRs	Responsiveness proxy (sign-standardized)	$-$(Cash Conversion Cycle ÷ 365)	SCOR_E proxy; DV in observability models; regressor in OMR models
SCF	Flexibility proxy (liquidity slack)	(Cash + Short-Term Investments) ÷ Operating Expenses	SCOR_E proxy; DV in observability models; regressor in OMR models
$-$SCC	Cost proxy (sign-standardized)	Sign-standardized cost/working-capital burden ratio (see Table 1; full construction in Table S26)	SCOR_E proxy; DV in observability models; regressor in OMR models
SCAME	Asset-efficiency proxy (sign-standardized)	Turnover composite scaled by asset productivity (see Table 1; full construction in Table S26)	SCOR_E proxy; DV in observability models; regressor in OMR models
gm_vol	Gross-margin volatility	Volatility of gross margin percentage over time (see Table S26)	Endogenous efficiency signal in observability models
OMR	Operating margin ratio	Operating income ÷ net sales/revenue	Parallel outcome in validation models
ln(Assets)	Firm size control	Natural log of total assets	Control in all models
CAPEX intensity	Investment control	Capital expenditures ÷ total assets (or net sales; see Table S26)	Control in all models

Note: Full ratio constructions, shock controls, and equation specifications are provided in the Supplementary Materials (Tables S14–S26).

Ratios are computed at the firm-year level. When constructions combine stock and flow components, stock variables are annual-averaged to align timing and reduce mechanical endogeneity. Full firm-year series, the composite summary used in sector notes, and equation details are reported in Tables S1, S11 and S26.

4. Method

4.1. Sample and Panel

The empirical setting is a firm-year panel of 12 publicly traded companies observed over fiscal years 2000–2022 (n = 254 firm years after accounting for listing dates and filing availability). We focus on publicly listed firms because audited GAAP/IFRS statements

provide consistent, replicable inputs for constructing SCOR_E ratios. Firms were selected within each sector based on continuous disclosure of the required line items, large scale within the sector, and substantive supply-chain exposure in their operating model.

The panel spans four sectors chosen to provide variation in boundary conditions that plausibly affect financial observability: mainline airlines (high regulation and disruption sensitivity), integrated oil and gas (capital intensity and commodity-cycle shocks), internet retail (high clock-speed demand and working-capital intensity), and entertainment studios (intangible intensity and platform-driven demand dynamics). This design permits limited within-sector comparison and shows where the SCOR_E mappings appear more or less stable in this sample.

Because the sample is small (three firms per sector) and not randomly drawn, results should not be interpreted as population estimates for each industry. The objective is analytical: to evaluate whether the proposed proxies behave in theoretically consistent directions and to document where identification and measurement limitations constrain inference.

4.2. Model Families

We estimate two complementary model families. Observability models relate each SCOR_E proxy to gross-margin volatility (gm_vol) in firm- and year-fixed-effects panels; in IV sensitivity analyses, gm_vol is replaced by its first-stage fitted value. gm_vol is treated as potentially endogenous because profitability volatility and accounting-based ratios may be jointly determined and may share accounting components [11]. The IV setup is therefore an attempted identification strategy, not a design that by itself resolves endogeneity.

Parallel OMR models regress operating margin (OMR) on the SCOR_E ratios using comparable controls and fixed effects. These models are interpreted associatively and are used only to assess whether the candidate proxies co-move with operating margin in comparable specifications.

Inference is deliberately restrictive. When first-stage diagnostics indicate weak instruments, conventional 2SLS Wald statistics are treated as descriptive rather than causal evidence; weak-IV-robust LIML estimates and Anderson–Rubin (AR) confidence intervals are used only to assess whether any more-than-associative interpretation remains arguable. We also apply Benjamini–Hochberg false discovery rate (BH-FDR) adjustments and report q-values alongside *p*-values, with * ($q \leq 0.10$), ** ($q \leq 0.05$), and *** ($q \leq 0.01$).

4.3. Instrument Construction

In the observability models, the endogenous efficiency signal is gross-margin volatility (gm_vol). The baseline excluded instrument is the one-period lag of operating margin (Lag_OMR_{t−1}). The intended logic is limited: lagged profitability may proxy persistent operating conditions that predict later profitability volatility, and the lag weakens purely contemporaneous simultaneity with current-year SCOR_E construction. This is a relevance argument only.

The exclusion restriction is more contestable. Past profitability is plausibly entangled with investment, liquidity, working capital policy, and asset allocation, and those channels may also be reflected in the SCOR_E ratios—especially SCF, −SCC, and SCAME. Fixed effects, year effects, and observed shock controls do not eliminate that conceptual vulnerability. Accordingly, the IV strategy is used as a cautious sensitivity-based attempt at identification rather than a definitive solution to endogeneity.

Structural (second stage):

$$Y_{it}^{(k)} = \beta_k \hat{gm_vol}_{it} + \gamma_k' X_{it} + \alpha_i + \tau_t + \varepsilon_{it}$$

First stage:

$$gm_vol_\{it\} = \pi' Z_\{it\}\hat{}\{(s)\} + \delta' X_\{it\} + \alpha_i + \tau_t + u_\{it\}$$

In these equations, $Y_\{it\}\hat{}\{(k)\}$ is a SCOR_E ratio for firm i in year t; $gm_vol_\{it\}$ is the potentially endogenous gross-margin volatility term; $X_\{it\}$ includes log(Assets) and CAPEX intensity; α_i and τ_t are firm and year fixed effects; and $Z_\{it\}\hat{}\{(s)\}$ denotes the excluded instrument(s), which vary by sector.

All models include log(Assets) and CAPEX intensity. KP-F statistics use HC1 covariance matrices; coefficient inference uses HC3 errors, supplemented by Driscoll–Kraay standard errors, R^2, and Newey–West corrections (lag = 1). Most firm-ratio equations are exactly identified. The overidentified oil and gas SCAME specification adds ASC 842, so a Hansen J test can be reported, but non-rejection is not taken as proof of exogeneity.

A further limitation deserves emphasis. Weak first stages are prevalent in this setting (Supplementary Table S17), so the IV specifications rarely support more than provisional interpretation. When instruments are weak, even LIML/AR results are used only to narrow the set of potentially defensible claims; coefficients that do not remain supported are treated as associative only.

4.4. Diagnostic and Robustness Checks

First, auditability and replicability are addressed by constructing all variables from GAAP/IFRS line items in audited annual reports and SEC/EDGAR filings and by reporting full ratio definitions and equation specifications in the Supplementary Materials (Table S26).

Second, we probe endogeneity and simultaneity rather than claim to eliminate them. Fixed effects and IV sensitivity analyses are used to reduce obvious sources of confounding while retaining an associative interpretation when the identifying assumptions are not persuasive [11]. Firm size is controlled using ln(Assets), consistent with standard corporate-finance practice [12].

Third, we examine construct separability using triangulation: correlations among ratios and related accounting quantities, rotated factor structures (Table S11), multicollinearity diagnostics (Table S23), and influential-observation checks (Table S7). These checks inform proxy distinctness but do not validate the IV exclusion restriction. Direct validation against SCOR Level 1 KPIs was infeasible because comparable public KPI data are unavailable for this sample.

Fourth, we report robustness checks for distributional sensitivity and observed shocks, including winsorization (Table S14), firm-cluster and Newey–West covariance estimators (Table S18), cluster bootstrapping (Table S15), and sector-shock and accounting-regime controls such as Brent prices, COVID-19 stringency, and ASC 842 timing (Tables S19–S22). These checks do not resolve the instrument's conceptual vulnerability.

Instrument strength is reported via Kleibergen–Paap rk F-statistics with Stock–Yogo benchmarks (Table S17). Because weak instruments are prevalent, the paper prioritizes weak-IV-robust inference (LIML and AR tests) and treats non-robust coefficients as associative. Hansen J is available only for the oil and gas SCAME model with the additional ASC 842 instrument (Table S9) and is interpreted narrowly as a check on the overidentifying restrictions, not as confirmation of exogeneity.

4.5. Diagnostics and Inference Policy

Reported diagnostics include Kleibergen–Paap rk F-statistics (KP-F), Shea partial R^2, and robust standard errors (HC3, firm-cluster, and Newey–West), with Hansen J reported where overidentification is available. Shea's partial R^2 is descriptive and not a substitute for strong instruments. A result is classified as detected only if it (i) matches the pre-

specified sign restriction, (ii) survives Benjamini–Hochberg FDR adjustment ($q \leq 0.10$), and (iii) remains supported by weak-instrument-robust inference when first-stage strength is inadequate. All other coefficients are interpreted as associative exploratory patterns. The IV analysis, therefore, functions only as a bounded sensitivity exercise under severe identification limits, not as a demonstration that endogeneity has been solved.

5. Results

5.1. Overview

Across the 60 firm-level observability equations, the evidence is heterogeneous and should be read in a strict hierarchy. Descriptive within-firm patterns and conventional 2SLS estimates are reported for completeness, but they are not sufficient evidence of observability on their own. Under the study's inference rule, a result is emphasized only if it matches the pre-specified sign restriction, survives BH-FDR adjustment, and remains supported by weak-instrument-robust inference when the first stages are weak.

Conventional IV estimates are more numerous than the final retained set. They are therefore treated as provisional. Nominal significance at the 2SLS stage merely marks specifications that warrant no more than provisional attention; it does not by itself justify a substantive interpretation.

Weak instrument limitations substantially narrow the evidence. Supplementary Table S17 classifies all firms except Disney as weak-IV under the reported Stock–Yogo benchmarks. As a result, most conventional IV coefficients remain vulnerable to weak-instrument distortion, and parallel OMR associations are used only as descriptive patterns rather than as confirmation that upgrade non-robust observability results.

After the full screening rule is applied—including BH-FDR and weak-instrument-robust LIML/AR checks—only four firm-proxy pairs remain: Chevron with −SCC, Exxon with −SCC, Amazon with SCRe, and Disney with SCRe. Table S2 reports the corresponding conventional 2SLS slopes as −3.783, −2.388, −1.000, and −1.000, respectively. These magnitudes are reported descriptively, not as stand-alone causal effects. Disney–SCRe is the only surviving pair without a weak-IV flag in Table S17; the other three remain in the retained set only because weak-IV-robust inference did not eliminate them, and they should still be read cautiously. Several non-surviving specifications also show unexpected or reversed signs, which count against rather than for the observability argument in those proxy-firm contexts.

5.2. Sector Summaries

The sector discussion, therefore, stays tightly tied to the surviving firm-proxy pairs. Non-robust coefficients, directionally suggestive OMR patterns, and nominal 2SLS significance are not used to make broader sector claims.

5.3. SCOR_E Index: Oil and Gas

In oil and gas, the only surviving relationships are Chevron with −SCC and Exxon with −SCC. These are the only oil-and-gas pairings that remain consistent with the pre-specified cost mapping after full screening. No broader oil-and-gas conclusion is drawn for the remaining proxies, and Shell contributes no surviving pair.

5.4. SCOR_E Index: Internet Retail

In internet retail, only Amazon with SCRe survives the full screening rule. This leaves, at most, a firm-specific Amazon result for SCRe. Results for Mercado Libre and Alibaba remain non-robust or unstable, so the evidence does not support a broader sector claim.

5.5. SCOR_E Index: Airline-Mainline Passenger

No airline firm-proxy pair survives weak-instrument-robust inference. The airline results are therefore descriptive only. Where signs are unstable or contrary to the pre-specified pattern, they count against rather than for the observability argument in this sector.

5.6. SCOR_E Index: Entertainment

In entertainment, only Disney with SCRe survives the full screening rule. No sector-wide claim is drawn from this single result. The remaining entertainment coefficients stay provisional, and sign instability or reversals count against the proposed mappings in that sector.

6. Discussion

The discussion is intentionally narrow. Under the paper's inference policy, most estimates remain descriptive or associative because weak-instrument concerns are widespread and only four firm–proxy pairs survive both BH-FDR adjustment and weak-IV-robust screening.

Those four retained pairs—Chevron with −SCC, Exxon with −SCC, Amazon with SCRe, and Disney with SCRe—are the only results that merit focused emphasis. Even here, the evidence is firm-specific and sample-bound rather than sector-wide, and it does not justify broader claims about the same proxies in other firms or industries.

The remaining coefficients are not upgraded by nominal IV significance, parallel OMR associations, or contextual storytelling. Null, unstable, or reversed signs are treated as evidence that the proposed mapping is uninformative or unsupported in those settings. Contextual explanations remain possible, but the present design does not identify them and therefore does not preserve the observability claim.

6.1. Interpreting FOSC Under the Observed Limits

The paper's conceptual contribution is correspondingly limited. FOSC is not validated here as a general measurement framework. Rather, it is used as a falsifiable screening logic: a candidate public-data ratio must show the pre-specified directional pattern under the paper's inference rules, or the mapping is not supported in that context. Under that standard, support is sparse.

6.2. What the SCOR_E Ratios Can Support

Because many SCOR metrics rely on internal and sector-specific data [1,2], SCOR_E should be understood as a set of candidates, finance-facing ratios rather than as direct measures of supply-chain capabilities. In this sample, the only retained findings concern −SCC in Chevron and Exxon and SCRe in Amazon and Disney, and even those results remain conditional on the sample, specification, and identification limits described earlier.

No comparable claim is supported for the remaining proxy-firm combinations. In particular, responsiveness, flexibility, and asset-management efficiency do not show a stable public-data mapping across this sample, and several coefficients take unexpected signs. Those departures count against the proposed observability argument in those contexts rather than being explained away.

The practical implication is limited to measurement triage. At most, the retained firm–proxy pairings remain candidates for retesting in closely matched settings; the present evidence does not support treating them as a transferable scorecard, a cross-industry benchmark, or a stand-alone representation of SCOR capabilities.

6.3. Cautious Managerial Interpretation

Managerial implications are modest. Any managerial use would be purely exploratory: a firm in a closely comparable setting could treat movements in these ratios as prompts for internal review alongside proprietary operational KPIs, not as direct evidence that a specific capability improved or deteriorated. The results do not support using SCOR_E for target setting, incentive design, vendor evaluation, or cross-firm performance ranking.

6.4. Policy and Disclosure Implications

Policy implications are narrower still. The evidence does not support recommendations for standardized external disclosure, required reporting, or a sector-neutral reporting template. At most, future validation work may retest the small, retained subset in closely matched sectoral settings before any disclosure application could even be considered.

6.5. Limitations and Future Research

The main limitations remain the small non-random sample, the likely construct heterogeneity of accounting ratios across firms and industries, the prevalence of weak instruments, and the absence of direct validation against internal SCOR KPI systems. These limits mean that most results remain associative and that non-robust or contrary findings cannot be converted into support through secondary interpretation.

Future research should first replicate the same screening exercise in larger sector-specific samples and, where possible, compare the candidate ratios directly with proprietary operational measures. Stronger identification strategies may be informative, but only if they address the exclusion and weak-instrument problems more convincingly than the present design. Extensions to new proxy families or disclosure applications would be premature before narrower validation work is done.

7. Conclusions

This study contributes a transparent, falsifiable public-data screening approach for evaluating whether candidate financial ratios can serve as indicators of selected SCOR Level 1 attributes. Rather than assuming that audited financial statements can recover supply-chain capabilities directly, the paper specifies ex ante sign expectations, applies multiple-testing controls, and treats weak identification as a binding limit on inference. The result is a disciplined measurement test that distinguishes candidate mappings deserving further scrutiny from those that do not survive the paper's criteria.

In the 12-firm panel examined here, the evidence is narrow. Weak instruments are widespread, most estimates remain associative, and many proposed mappings are unstable, null, or sign-reversing under the study's inference rules. After Benjamini–Hochberg adjustment and weak-instrument-robust screening, only four firm-specific pairings remain: Chevron with −SCC, Exxon with −SCC, Amazon with SCRe, and Disney with SCRe.

This pattern still yields a substantive contribution. It shows that the main issue in public-data SCOR measurement is not merely whether a ratio appears conceptually related to a SCOR attribute, but whether that ratio survives a demanding falsification-oriented test within a defined context. In that sense, the study contributes both positive and negative evidence: it identifies a small, retained subset for retesting, and it shows that many seemingly plausible finance-facing mappings should not be treated as supported on the basis of this evidence.

SCOR_E ratios should therefore be interpreted as a constrained measurement device, not as a validated cross-industry benchmarking framework, similar to early interpretations of traditional financial ratio analysis before validation and eventual widespread implementation. The retained pairings are sample-bound candidates for follow-on val-

idation in closely matched settings, not a basis for managerial ranking, disclosure standardization, or broad policy prescription. More generally, the study suggests that public financial statements may illuminate selected supply-chain attributes only in limited, context-dependent ways.

The clearest takeaway is that this manuscript advances the field less by claiming broad observability than by sharpening the evidentiary standard for it. It offers a replicable way to test candidate SCOR-linked financial proxies under public-data constraints, shows that support is sparse once weak-identification and multiple-testing limits are taken seriously, and sets a clearer agenda for future work in larger, sector-matched samples with direct validation against internal operational measures.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/logistics10040070/s1, Table S1: SCOR_E Values by Firm and Year (2000–2022)—Full Listing; Table S2: Two-Stage Least Squares (2SLS) firm-level regressions: SCOR_E ratios on gm_vol; Table S3: Ordinary Least Squares (OLS) firm-level regressions with HC3 standard errors; Table S4: Limited Information Maximum Likelihood (LIML) firm-level regressions; Table S5: Benjamini–Hochberg False Discovery Rate (FDR) adjustments; Table S6: Anderson–Rubin test and confidence intervals; Table S7: Cook's Distance by firm year (2000–2022); Table S8: Pooled OLS of SCOR_E ratios on gm_vol with Driscoll–Kraay standard errors; Table S9: Overidentification (Hansen J) for the Oil and Gas SCAME equation (the manuscript's only overidentified baseline equation); Table S10: Power analysis: Ex ante, post hoc, and Monte Carlo; Table S11: Exploratory factor analysis (Varimax rotation): Factor loadings; Table S12: Variance inflation factors (VIF) by firm and regressor; Table S13: Wooldridge test for AR(1) serial correlation; Table S14: Winsorization (1st/99th percentiles) summary; Table S15: Bias-corrected and accelerated (BCa) cluster bootstrap (1,000 replications); Table S16: Heteroskedasticity tests: White and Breusch–Pagan; Table S17: Kleibergen–Paap rk F statistic with Stock–Yogo critical values; Table S18: Robust covariance estimates: HC3, cluster-robust (HC1), and Newey–West (lag = 1); Table S19: Concentration metrics by industry in the SCOR_E study; Table S20: OxCGRT government stringency scores (country day panel → firm-year variable); Table S21: Brent spot prices (EIA series RBRTE, daily → firm-year average); Table S22: ASC 842 Lease Accounting Dummy; Table S23: Variance-Inflation Factors (VIFs) for the Second-Stage 2SLS Regressors (pooled panel, n = 254 firm-years); Table S24: Summary of β-coefficients and stability test; Table S25: Supply Chain Operations Reference (SCOR) metrics—Full Mapping; Table S26: SCOR_E Design matrix for two-stage least squares estimations—Full Mapping; Figure S1: Cook's Distance for the Baseline SCAME Equation; Figure S2: Econometric workflow for the two-stage least squares (2SLS) procedure.

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