Benchmarking Methodologies for Multi-Site Operations Networks: A Review of Advances in Regression-Based Performance Analysis

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Abstract
Organizations operating many comparable sites, including retail chains, bank branch networks, diagnostic laboratory systems, hospital groups, distribution centers, and regulated utility networks, face a recurring problem: separating performance differences that reflect managerial effort from those reflecting operating environment, scale, asset condition, and chance. Regression-based benchmarking is the dominant quantitative response. This review synthesizes methodological developments from the foundational frontier literature of the late 1970s through the state of practice in 2023, and integrates that canon with applied work on performance analytics in distributed operating environments. Seven method families are examined alongside five areas of recent methodological advance, and the synthesis is organized into a framework arranging benchmarking into five sequentially dependent layers with a feedback path from decision back to measurement, from which six propositions are derived. Three findings emerge. Benchmark validity is bounded above by the credibility of the comparison set, so returns to estimator sophistication diminish once common support fails. The two-stage practice of regressing efficiency scores on environmental variables persists despite sustained evidence that it yields invalid inference. And methods designed for measurement are routinely repurposed for target-setting, a role in which they degrade once measured units can anticipate the model. Theoretical, managerial, and policy implications are set out, the limitations of a narrative synthesis are stated, and an agenda is proposed centred on decision-relevant uncertainty, strategic robustness, and empirical testing of the framework.

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1. Introduction

A grocery chain with 900 stores, a bank with 1,400 branches, a diagnostic laboratory network spanning dozens of collection points, and a health system with 60 hospitals share a structural feature. Each consists of many units performing broadly the same transformation of inputs into outputs, under conditions differing across units in ways partly observable and partly not. This creates an opportunity and a trap. The opportunity is that units serve as comparators for one another, so performance can be assessed without an external standard. The trap is that comparison is meaningful only once systematic differences have been accounted for, and the accounting is never complete. Akin-Oluyomi and Akhigbe (2023a) frame this as improving multi-site operational efficiency through data-driven performance frameworks: data-driven because intuition cannot hold dozens of confounders in mind, a framework rather than a metric because no single ratio survives contact with heterogeneity.

Raw ratios such as sales per square meter or cost per case are almost always misleading, since they attribute to management the effects of catchment demographics, case mix, asset vintage, wage levels, competitive density, and scale. Regression-based benchmarking instead models expected performance conditional on the observable environment and treats the deviation as signal. This distinction between raw and conditional indicators is the pivot on which the field turns, recurring in cross-functional indicator frameworks (Seyi-Lande *et al*., 2022), accountability metrics for large commercial organizations (Sakyi *et al*., 2022b), and lifecycle performance models for infrastructure programs (Adelanwa *et al*., 2023a).

The methodological literature originates in two developments. Aigner *et al*. (1977) and Meeusen and van den Broeck (1977) introduced the composed-error stochastic frontier, splitting the residual into symmetric noise and a one-sided inefficiency term. Charnes *et al*. (1978) introduced data envelopment analysis, constructing a piecewise-linear frontier without imposing functional form, later extended to variable returns to scale by Banker *et al*. (1984). This review concentrates on the regression-based tradition.

Its scope is the multi-site operations network: units under common ownership or regulation, with substantial input and output commonality, observed repeatedly, managed by a center intending to act on the results. This differs from the cross-industry productivity studies that motivated the frontier literature in four ways. Sites are numerous but individually small, so asymptotics relying on large per-unit information may not hold. The center controls the data-generating process and can change it in response to the analysis. The purpose is intervention rather than description, raising the evidential bar toward causation. And sites are not independent, sharing supply chains, labor markets, information systems, and governance, a dependence explicit in supply chain governance models for retail networks (Akin-Oluyomi & Akhigbe, 2022) and program management models for coordinated expansion (Aminu-Ibrahim *et al*., 2021). The applied literature, meanwhile, has developed performance frameworks for distributed operations without the econometrics that would give them identification, producing indicator systems informative about what organizations measure but silent on how those numbers should be adjusted for context (Sanni & Atima, 2021).

2. Methodology

This is a narrative review structured around methodological families rather than a systematic review with a reproducible protocol. The relevant work spans econometrics, operations research, operations management, health services research, regulatory economics, and information systems, with inconsistent terminology, so a keyword protocol calibrated to one literature misses the others, a difficulty also present in cross-disciplinary reviews of machine learning in financial fraud detection and of anomaly detection in financial time series (Atakpa & Abetoh, 2022; Atakpa & Fobellah, 2023). The synthesis is therefore configurative rather than aggregative, organizing heterogeneous work into a coherent structure rather than pooling effect sizes across studies whose outcome definitions and units of analysis differ too widely for pooling to be interpretable.

The corpus was assembled in four passes: foundational contributions defining each method family, from the standard reference works (Bogetoft & Otto, 2011; Coelli *et al*., 2005; Fried *et al*., 2008); forward citations into applied multi-site work; econometric and machine learning methods imported into benchmarking practice; and applied work on operations analytics, procurement performance, distributed workforce management, and sector-specific frameworks. Sources were included where they developed or evaluated an estimator applicable to conditional performance comparison, described measurement infrastructure or data governance on which such comparison depends, or reported an applied analysis in a setting with multiple comparable units. Purely qualitative benchmarking was excluded, though process documentation work such as standard operating procedures as strategic assets sits at that boundary (Eyetsemitan *et al*., 2022). The data envelopment analysis literature is excluded except where it bears on regression-based practice, since Emrouznejad and Yang (2018) document a corpus exceeding ten thousand articles warranting separate treatment, and Lean Six Sigma work enters only where it supplies operational variables that benchmarking models consume (Ambali *et al*., 2021).

Each retained source was coded on four dimensions: unit of analysis, treatment of environmental heterogeneity, whether uncertainty was reported at unit level, and whether causal or merely associational claims were made. That coding produced the taxonomy in Section 3.2, identified the advances in Section 3.3, and generated the propositions in Section 4.2. Because the review is narrative, the coding is interpretive rather than independently replicated, a limitation returned to in Section 5.4.

3. Literature Synthesis

3.1. Conceptual Foundations of Conditional Performance Comparison

Every benchmarking exercise rests on a counterfactual: that had site *i* faced the conditions of the reference set, it would have achieved a specified level of performance. Credibility depends on whether that reference set is a plausible source of information about site *i*, a question prior to estimator choice. Comparability fails in three ways.

Technological heterogeneity arises when sites operate different production technologies, as when a network mixes service formats or one region has automated a process others have not. Pooling across technologies produces a frontier no site can attain and rankings reflecting format rather than management, a problem acute where facility generations differ in design standard (Ogbete *et al*., 2022, 2023). Environmental heterogeneity arises when sites face different exogenous conditions: catchment income, competitive density, regulatory regime, supplier reliability. This is what regression adjustment addresses, tractable to the extent conditions are measured. Geospatial location analysis and geomarketing analytics make environmental determinants measurable (Seyi-Lande *et al*., 2020; Tonoyan *et al*., 2022a), comparative procurement cost analyses show how much of an apparent gap reflects market conditions rather than buyer capability (Akokodaripon *et al*., 2023). Support failure arises when a site's covariate profile lies outside the region populated by others, so its expected performance is an extrapolation; the urban flagship among suburban units has no comparators, and any score assigned describes the functional form rather than the site, a point portfolio valuation frameworks make visible since the most distinctive units have the weakest comparison sets (Tonoyan *et al*., 2023).

Comparison-set construction therefore deserves as much attention as estimation: peer-group stratification, coarsened exact matching on dominant covariates, and common-support diagnostics following Rosenbaum and Rubin (1983). Reporting each site's effective comparison set alongside its score remains uncommon, though supply chain leadership models implicitly require it, since a target imposed without a visible comparison basis will not be accepted by the site expected to meet it (Akin-Oluyomi & Akhigbe, 2023b).

Greene (2005) drew the distinction structuring the subsequent panel literature: between heterogeneity belonging in the inefficiency term and heterogeneity belonging in the technology. A site persistently costly because it is badly run exhibits inefficiency to be measured; one persistently costly because it serves difficult terrain exhibits technology to be conditioned away. Data alone cannot resolve this, since the two are observationally equivalent within a site over a short panel; identification comes from assumptions, and estimator choice is in practice a choice among them. Kumbhakar *et al*. (2014) formalized the four-way decomposition into site effects, persistent inefficiency, transient inefficiency, and noise, making those assumptions explicit. Workforce composition is the most consequential confounder, since staffing is simultaneously an input, an environmental constraint, and a proxy for management quality: capability is built at network level and deployed unevenly at site level, staffing volatility during demand shifts produces transient inefficiency a poorly specified model records as persistent, and retention systems tied to productivity metrics feed measured performance back into the input mix (Falemi *et al*., 2020, 2023a, 2023b). Performance attributed to a site may also belong to a contracting arrangement it did not choose. Safety maturity models, team composition studies, project governance research, and work on human error causation and the recurrence of unsafe behavior reinforce that this boundary is drawn by the analyst rather than discovered in the data, and that identical outcomes can arise from individual, supervisory, or systemic causes a site-level indicator cannot separate (Amayo *et al*., 2023a, 2023c; Arumosoye & Obriki, 2021; Obogo *et al*., 2022; Obriki & Arumosoye, 2022).

A site-level score is therefore a conditional statement about a residual, not a measure of managerial quality or an estimate of achievable savings. Jondrow *et al*. (1982) showed it to be a conditional expectation of an unobservable carrying substantial uncertainty even when parameters are precisely estimated, and that uncertainty does not shrink as the network grows, because each score rests on a single residual, so rankings built from such scores are unstable. Yet dashboards and continuous performance visualization deliver point estimates at high frequency and rarely carry uncertainty (Ogbole *et al*., 2021; Sanni & Atima, 2021), and models measuring the strategic impact of financial analysis face the same difficulty (Oduleye & Medon, 2023b). Marketing measurement has confronted this more directly, in work on marketing return on investment and on attribution methods resolving bias in multi-touch journeys (Sanni *et al*., 2022); attribution and benchmarking are formally similar, since both allocate an aggregate outcome across contributing units under partial observability and both are sensitive to the assumed allocation model in ways point estimates conceal.

3.2. Regression-Based Method Families

Ordinary and corrected least squares: The baseline regresses performance on environmental controls and treats the residual as signal; corrected least squares shifts the intercept until all residuals are non-positive, yielding a deterministic frontier. Data-driven cost management models operate on this logic (Oduleye & Medon, 2021). The weaknesses are severe: all deviation counts as performance, the frontier is set by the single most extreme observation, and persistent and transient shortfall cannot be distinguished. Least squares is best treated as a diagnostic first step revealing which covariates carry weight, with residuals inspected for outliers and support failures beforehand. Profitability decomposition in retail procurement and data visualization in procurement decisions both show the value lying in the decomposition rather than the composite score (Babatope *et al*., 2023).

Stochastic frontier analysis: This family decomposes the error into symmetric noise and a one-sided inefficiency component, identified through the asymmetry of the composed error and dependent on distributional assumptions (Belotti *et al*., 2013). Three points matter. The distributional assumption affects individual scores more than aggregate efficiency, so sensitivity analysis should be routine. The skewness on which identification rests can fail in finite samples, collapsing estimated inefficiency variance to zero, and this occurs disproportionately in well-managed networks where dispersion is small. And the Battese and Coelli (1995) formulation, parameterizing the inefficiency mean as a function of environmental variables and estimating jointly, resolves in one stage what the two-stage practice handles badly; Simar and Wilson (2007, 2011) showed that regressing estimated scores on covariates produces invalid inference, since the scores are serially correlated by construction. Predictive budgeting models implicitly make the same separation of forecastable from unforecastable components (Adesuyi *et al*., 2022), while risk evaluation models for financial institutions in emerging markets face the problem in sharper form, since environmental variation across institutions is large relative to the managerial variation to be isolated (Akomolafe & Agu, 2019).

Panel data estimators: Repeated observation is the defining data advantage of multi-site networks and the one applied work most often wastes. Panel structure allows time-invariant unobservables to be differenced out and persistent inefficiency to be separated from transient (Kumbhakar *et al*., 2014), which is the separation managers want. Fixed effects applied naively absorbs persistent inefficiency into the site effect, so a consistently poor site can appear efficient; random effects gains efficiency by assuming the site effect is uncorrelated with regressors, implausible wherever placement was itself a management decision responsive to local conditions. The panel view aligns with lifecycle thinking in asset-intensive networks, since the object of interest is how a facility performs relative to its cohort over time (Adelanwa *et al*., 2023a; Ogbete *et al*., 2023). Chronically poor maintenance produces a stable rather than fluctuating shortfall, so the contrast between reactive and predictive regimes is one between transient and persistent profiles, and condition monitoring supplies the observations making separation estimable (Adaramola *et al*., 2018).

Quantile and expectile regression: Quantile regression (Koenker & Bassett, 1978) estimates conditional quantiles rather than the mean, requiring no distributional assumption, tolerating outliers in the response, and answering the question benchmarking actually asks, which is not what an average site achieves but what a good site achieves. The gain is a benchmark that is attainable rather than ideal; the cost is that the quantile level is chosen rather than estimated, making stringency a policy decision that should be documented. Tail-focused estimation connects benchmarking to anomaly detection and to anti-money-laundering analytics, where exposure-adjusted tail behavior is the object of interest (Atakpa, 2021; Atakpa & Fobellah, 2023). Behavioral explanations of enterprise performance add motivation, since the mechanisms producing exceptional performance are frequently not the mirror image of those producing poor performance (Lawal & Oduleye, 2023).

Semiparametric and shape-constrained approaches: Translog and Cobb-Douglas specifications can be badly wrong regarding scale effects at the extremes of the size distribution, where the largest and smallest sites sit. Kuosmanen and Kortelainen (2012) introduced stochastic nonsmooth envelopment of data, imposing only monotonicity and concavity while recovering a composed-error decomposition, which removes the functional form objection operating managers legitimately raise. Adoption has been limited by computational demands and absent implementations in the environments analytics teams use, a diffusion problem rather than a methodological one. Simulation offers a partial substitute, encoding returns-to-scale structure through process logic rather than a constraint set (Efobi *et al*., 2022; Ezeugwa *et al*., 2023a; Tonoyan *et al*., 2022b, 2022c).

Spatial econometric extensions: Sites compete for the same customers, share labor markets, transfer practices, and face correlated shocks, so standard errors computed under independence are understated. Methods developed by Anselin (1988) and treated comprehensively by LeSage and Pace (2009) extend naturally once the weight matrix is redefined on catchment overlap, common district management, or shared supply routes, and Glass *et al*. (2016) developed a spatial autoregressive stochastic frontier with asymmetric efficiency spillovers. Supporting infrastructure has improved: geographic information systems in utility asset management supply the spatial attributes weight matrices require, integrated aerial and LiDAR frameworks extend this to previously unmeasured corridor assets, and embedding drone operations in enterprise systems makes the data operational rather than episodic (Dagodzo & Ahiaeke Patrick, 2021a, 2021b, 2023). In procurement, spatially enabled frameworks place location inside the transaction system, and geospatial vendor evaluation shows supplier performance to have a spatial component a non-spatial model attributes to the buyer (Ahiaeke Patrick *et al*., 2021), while access-oriented network design makes placement and outcome jointly determined (Aminu-Ibrahim *et al*., 2020). Weight matrix specification has substantial influence with little data-driven guidance, and cannibalization is a spatial effect management controls, so it warrants separate modeling.

Machine learning augmented regression: Flexible learners predict conditional means better than linear specifications when relationships are nonlinear and interactions numerous. The naive application, in which a learner predicts site performance and the residual is called inefficiency, fails because a sufficiently flexible model of site performance predicts inefficiency away. Productive integrations embed learners within an inferential framework: double machine learning estimates nuisance functions flexibly while preserving valid inference through orthogonalization and cross-fitting (Chernozhukov *et al*., 2018), and generalized random forests and the causal forest estimate heterogeneous effects, answering which sites would benefit most from an intervention rather than which are furthest from the frontier (Athey *et al*., 2019; Wager & Athey, 2018). Athey and Imbens (2019) survey the broader toolkit, Hastie *et al*. (2009) remain the standard reference for the learners, and Shapley additive explanations support diagnostic use with the caveat that attribution of a prediction is not attribution of a cause (Lundberg & Lee, 2017). Applied work has moved quickly on prediction, in demand forecasting, inventory error reduction, asset-level predictive maintenance, and capacity scaling (Ahmed *et al*., 2020; Mayo *et al*., 2021; Tonoyan *et al*., 2021a). Interpretability is the recurring constraint: interpretable early failure prediction shows a benchmark must be explicable to the operator expected to act on it, while hybrid deep learning for wind power and renewable yield forecasting show both the accuracy gains and interpretive costs of flexible models (Ezeugwa *et al*., 2023b; Komi & Adamolekun, 2021). Acquisition, retention, and churn models show predicted lifetime value becoming the outcome variable in downstream benchmarking (Ogundairo & Ayivi-Donkor, 2023), and human-in-the-loop research matters because much operational training data is labeled by staff whose behavior varies across sites (Ladapo *et al*., 2022a).

3.3. Recent Methodological Advances

Endogeneity in frontier models: Treating regressors as exogenous is untenable where input levels respond to conditions the analyst does not observe: a store anticipating weak demand cuts labor hours, so labor input and the unobserved shock are correlated and the coefficient is biased. Amsler *et al*. (2016) distinguish endogeneity in the frontier equation from endogeneity in the inefficiency equation; Griffiths and Hajargasht (2016) developed Bayesian estimators and Kutlu (2010) an instrumental variables treatment of the Battese-Coelli specification. Instruments are scarce, since the center's allocation decisions are informed by exactly the variables the analyst wishes to instrument away; where administrative rules create discontinuities, as when staffing formulas depend on thresholds in floor area or registered patients, those rules are the most promising and least exploited source of identification. The production function literature, from Olley and Pakes (1996) through Levinsohn and Petrin (2003) to Ackerberg *et al*. (2015), addresses the same simultaneity using proxies for unobserved productivity, and transfer of these methods into benchmarking remains partial. Evidence that accurate forecasts are not automatically equitable shows a well-fitting conditional model can still misallocate when conditioning variables are themselves endogenous to policy (Komi, 2023), while scenario-based modeling acknowledges rather than resolves the problem (Filani *et al*., 2023).

Causal inference tools in benchmarking practice: Rankings generate interventions whose evaluation is causal. Goodman-Bacon (2021) showed that two-way fixed effects applied to staggered rollouts can return an effect of the wrong sign under heterogeneous treatment effects; de Chaisemartin and D'Haultfoeuille (2020) established the point generally and Callaway and Sant'Anna (2021) developed group-time estimators that avoid it. This matters directly, because staggered rollout is how networks deploy layouts, systems, staffing models, and training, and almost every internal evaluation uses two-way fixed effects. The safety literature makes causal claims routinely from such data: frameworks linking management walkthrough frequency and coverage to outcomes propose the dose-response relationship these designs identify, while risk control in large energy operations, near-miss and hazard observation reporting, internal audit systems, continuous hazard monitoring, behavioral safety programs, and the institutionalization of life-preserving practices supply the leading indicators whose relationship to lagging outcomes is the object of estimation (Obogo *et al*., 2021; Obriki & Arumosoye, 2019, 2021, 2023; Obriki *et al*., 2023a, 2023b). Healthcare infrastructure research raises the question in investment framing, asking how spending translates into measurable outcomes (Aminu-Ibrahim & Ogbete, 2023).

Hierarchical and Bayesian pooling: With many sites and few periods, site-level estimates are noisy while the network-level estimate is precise. Hierarchical models partially pool site estimates toward group means, yielding lower mean squared error than either the fully pooled or fully separate alternative (Gelman & Hill, 2007; Raudenbush & Bryk, 2002). Extreme scores shrink in proportion to how little information supports them, so a small site with one anomalous quarter is not ranked last, and the estimated variance components are themselves informative, since a network whose variance sits mostly at district level has a different problem from one whose variance sits at site level. Program management models and design frameworks for scalable networks make the hierarchy explicit in the operating model rather than only the statistical one, the condition under which variance decomposition becomes actionable (Aminu-Ibrahim *et al*., 2021; Ogbete *et al*., 2022). In clinical settings, multidisciplinary collaboration research locates variation at the interface between units rather than within them, and analytics-driven performance management confronts the same nesting (Nnaji & Akinlolu, 2023; Ohunyon *et al*., 2023).

High-frequency telemetry and the reporting cycle: Classical benchmarking assumes an annual or quarterly panel drawn from financial reporting, but operational data now arrive continuously. High-frequency within-site variation is informative about transient inefficiency while low-frequency variation identifies persistent inefficiency, so the two together support a decomposition short panels cannot deliver. Real-time health informatics shows the value of high-frequency data lying in shortening the feedback loop rather than improving the point estimate, an argument visible in logistics through real-time supply chain risk dashboards (Nnaji & Akinlolu, 2022). Condition monitoring supplies the clearest template through sensor-based fault detection and vibration monitoring of rotating machinery (Omoegun *et al*., 2023; Sunday & Omoegun, 2022), while maintenance-free wireless infrastructure determines whether telemetry arrives complete and comparable across sites (Asiedu & Quainoo, 2023), and predictive capacity planning applies the same logic to the technology estate (Edivri & Oteri, 2022).

Model governance as a design constraint: A benchmarking model deployed inside an organization is a decision system facing governance requirements that constrain design. Algorithmic accountability and model risk management establish documentation, validation, and challenge requirements applying directly to performance evaluation models, and harmonization of data protection obligations defines what such a model may use as input (Ominyi & Anichukwueze, 2022, 2023). Frameworks for artificial intelligence enabled general controls address the control environment, risk-based business intelligence architecture addresses the same at design stage, and security audit and assurance frameworks supply the vocabulary in which validation is expressed (Fadayomi *et al*., 2019; Mbonu *et al*., 2022b). These requirements bear on validity, not merely compliance: a model that cannot be reconstructed cannot be challenged by the sites it evaluates. Data integrity failures illustrate the consequences when the record cannot be relied upon, corrective and preventive action research shows the value of a finding depends on evidence traceability, and regulatory readiness maturity models describe how that traceability is built (Aneke *et al*., 2022, 2023; Eze *et al*., 2022).

3.4. Measurement and Information Infrastructure

Output definition: Aggregation by revenue embeds prices in the output measure and confounds efficiency with pricing power. Revenue assurance work treats revenue leakage as a failure mode distinct from operational inefficiency, and customer service analytics shows quality and revenue interacting in ways a single aggregated measure cannot represent (Sakyi *et al*., 2022a, 2023).

Quality: Cost efficiency achieved by degrading service is not efficiency. Where quality measures are absent, the cost frontier should carry an explicit statement that quality is unmeasured rather than a silent assumption that it is constant; workforce behavior models linked to real-time operational data offer one route to measurement at the required frequency (Akhigbe *et al*., 2023).

Capital: Book values reflect acquisition timing and accounting policy rather than service potential, so physical measures are cruder but more comparable across asset vintages. Asset lifecycle and inventory visibility frameworks supply what accounting systems do not, and materials readiness models connect asset state to operational outcome (Okonkwo *et al*., 2021a, 2023).

Environmental variables: The control set determines what is treated as beyond management's influence, and the boundary is a judgment rather than a fact. Controlling for everything measurable maximizes fit and minimizes the measured performance signal, the opposite of what benchmarking is for. Inventory availability models illustrate the difficulty, since supplier lead time is exogenous to the site but endogenous to the network (Okonkwo *et al*., 2018).

Sample size and dimensionality: Frontier methods degrade as covariates rise relative to sites, because each comparison set thins. Networks of fifty to two hundred sites cannot support the covariate sets appearing in studies of thousands of units.

Data architecture and integrity: Data backbone governance describes what is required for site-level data to be comparable at all, and end-to-end visibility establishes the traceability making cross-site comparison defensible (Ilodigwe & Adesemoye, 2021; Nnabueze *et al*., 2021). Reconciliation control determines whether financial figures for two sites mean the same thing, budget compliance research documents how far nominally identical regimes drift, and automated consolidation addresses the comparability of figures on which any multi-entity benchmark depends (Bola-Sadipe *et al*., 2023; Dogbatsey &

Ebhojie, 2018; Dogbatsey *et al*., 2019), while agile transformation of the supply chain record and blockchain-based audit trails describe how traceability survives system change (Oshoba *et al*., 2020). A benchmark also inherits the security posture of the record: continuous cloud misconfiguration monitoring, identity and access governance, data protection impact assessment in multi-cloud financial infrastructure, and securing operational technology networks in electric utilities all bear on whether site figures can be trusted and traced (Adegbite *et al*., 2020; Aliliele *et al*., 2023a; Mbonu *et al*., 2022a).

Platform effects: Where operations are mediated by shared platforms, the platform itself generates measured variation. Multi-tenant performance evaluation shows a site's apparent responsiveness may reflect platform load rather than local practice, and service management research documents how service desk structures shape the incident data benchmarks consume (Ladapo *et al*., 2023). Architecture and resource allocation choices propagate into measured responsiveness (Ladapo *et al*., 2022b; Odejobi *et al*., 2019), at a scale high-throughput digital collections platforms illustrate (Osuji *et al*., 2021).

3.5. Sectoral Applications

Retail and consumer networks: Store networks provide large samples and rich covariates, so the difficulty shifts to specifying catchment and competition variables, which geomarketing analytics and predictive location selection supply before a site exists (Seyi-Lande *et al*., 2020; Tonoyan *et al*., 2022a). Machine learning demand forecasting provides the conditional expectation against which realized revenue is judged, and predictive cash flow modeling extends the logic to working capital, often a larger source of cross-site variation than revenue (Tonoyan *et al*., 2021a, 2021b). Cost-side benchmarking draws on simulation-based and predictive cost optimization, while portfolio valuation addresses what a site is worth as distinct from how well it is run (Tonoyan *et al*., 2022b, 2022c, 2023). Profitability decomposition connects store-level and category-level views, predictive approaches to e-commerce procurement forecasting show physical and online channels sharing a substrate (Akin-Oluyomi *et al*., 2023c), and customer service analytics demonstrates that quality drives revenue rather than constituting a cost to minimize (Sakyi *et al*., 2022a). Predictive audience segmentation and brand positioning frameworks supply further conditioning variables (Atima *et al*., 2022), while telecommunications retail adds churn dynamics (Rukh *et al*., 2023).

Banking and financial services: The branch network literature is the oldest and largest application (Berger & Humphrey, 1997). Recurring issues include the production versus intermediation choice in output definition, branches loss-making by design, and migration of volume to digital channels, which invalidates historical comparisons (Okafor *et al*., 2021; Osuji *et al*., 2021). Risk and control functions are now a major locus of measurement: technology-enabled risk assessment establishes the framework for evaluating branch-level control performance, integrated data management addresses forecasting accuracy, compliance risk models apply conditional reasoning where raw incident counts are confounded by exposure, predictive models extend the logic to financial risk detection, and data-driven tax compliance extends it to statutory obligations (Adelanwa *et al*., 2023b; Agu *et al*., 2023; Akomolafe & Agu, 2018; Akomolafe *et al*., 2023; Bola-Sadipe *et al*., 2022). On the planning side, executive decision systems, capital allocation models, analytics-driven enterprise models, planning aligned with corporate strategy, sustainable profitability planning, working capital optimization, and data-led cost governance describe the dependent variables against which units are judged, so benchmark errors propagate into allocation (Adesuyi *et al*., 2023a; Lawal & Oduleye, 2021; Medon & Oduleye, 2023; Oduleye & Medon, 2023a). Treasury work adds the multi-entity dimension through cash flow consolidation, relationship-based forecasting for multichannel lenders, and joint-venture strategic finance (Dada *et al*., 2021a, 2021b; Isiekwu *et al*., 2021), while compliance training and tamper-proof recordkeeping are interventions whose evaluation raises the design questions of Section 3.3 (Anichukwueze *et al*., 2020, 2021). Cross-border payments are an instructive special case, since the operating units are corridors rather than branches (Adesuyi *et al*., 2023b; Akomolafe *et al*., 2022; Olaogun *et al*., 2023).

Healthcare and diagnostic networks: Hospital benchmarking is dominated by case-mix adjustment, and the interaction between measured efficiency and unmeasured quality is more consequential here than in any other sector (Hollingsworth, 2008). Diagnostic laboratory networks are a particularly clean setting, since the process is standardized and outputs countable: sustainable infrastructure models, capital project delivery for high-risk facilities, high-performance laboratory design, spatial planning affecting diagnostic accuracy, and access expansion across underserved regions collectively define the strata within which laboratories are comparable (Aminu-Ibrahim *et al*., 2019, 2020, 2022). Clinical service research supplies the quality measures whose omission distorts cost benchmarking, in care coordination for readmission reduction, multidisciplinary collaboration, infection prevention, and nurse-to-patient ratio governance (Ohunyon *et al*., 2023; Omaghomi *et al*., 2023). At population scale, surveillance systems, risk stratification, real-time disease dashboards, mobile health scaling, public health governance models, and business intelligence for behavioral health allocation illustrate measurement whose units are regions rather than facilities (Anioke & Atima, 2023a, 2023b; Ogunboye *et al*., 2023; Oparah *et al*., 2023; Owoade *et al*., 2022).

Energy, utilities, and infrastructure: Distribution benchmarking is the setting where benchmarks carry direct financial consequence through revenue allowances, and it has the most developed practice on robustness, appeal, and estimator triangulation (Jamasb & Pollitt, 2001); internal corporate benchmarking has more to learn from it than the limited cross-citation suggests. Automation research documents the changes that make historical benchmarks obsolete, and sustainable business model work addresses the transition strategically (Nnabueze *et al*., 2023a, 2023b). The energy transition adds conditioning variables conventional benchmarking does not carry: smart grid architectures for high renewable penetration, hierarchical versus decentralized control, tiered digital twins for resource-constrained settings, storage behavior in hot and weak-grid regions, and edge intelligence for microgrid resilience all alter what a distribution unit can be expected to achieve (Komi & Adeniji, 2023; Komi & Ganiu, 2022, 2023). Digital twin modeling and reliability engineering in complex electronic systems generate the condition signals the measurement layer consumes (Gideon *et al*., 2019; Shittu *et al*., 2023). Procurement supplies a further set of comparisons, in risk management for engineering and construction projects, resilience frameworks for critical infrastructure, strategic optimization in oil and gas, and regulatory-compliant procurement in high-risk environments (Ogunwole *et al*., 2021; Okonkwo *et al*., 2021b).

Manufacturing, logistics, and warehousing: Benchmarking identifies where to look and process methods determine what to change: Lean Six Sigma models formalize the improvement side, lean supply chain research documents the effects a benchmark should detect, and data-driven lean optimization connects the two (Efobi *et al*., 2022; Ezeugwa *et al*., 2023a). Procurement performance is measured across buying units much as operational performance is measured across sites, through negotiation optimization, process automation, and business intelligence applications (Akinleye *et al*., 2023), while supplier relationship management explains why the same supplier performs differently for different buying units (Akinleye & Adeyoyin, 2022). Predictive demand forecasting reduces the inventory variance that otherwise dominates cross-site comparison, resilience indices raise the weighting problems of any aggregate benchmark, and humanitarian logistics frameworks address measurement where the environment changes faster than the model (Anene & Clement, 2022; Efobi *et al*., 2023).

Public sector, regulated oversight, and sustainability reporting: Public sector networks differ in objective function, since output is not revenue, and budget compliance research documents the reporting variation complicating cross-entity comparison (Dogbatsey & Ebhojie, 2018). Regulatory bodies benchmark the entities they supervise, inverting the usual principal-agent structure: aerodrome certification benchmarking is an explicit case of cross-site regulatory comparison, and predictive compliance monitoring applies the logic at system level (Adeyelu, 2018; Adeyelu & Dagodzo, 2022). Sustainability reporting introduces a parallel demand, since evaluating environmental, social, and governance adoption faces the familiar problem of comparing entities with different exposures; supplier screening, automated reporting in energy projects, green procurement, supplier risk assessment in international procurement, sustainability metrics, artificial intelligence integrated environmental metrics, and emissions monitoring all define outcomes sitting alongside cost and throughput (Abioye *et al*., 2023; Akinleye, 2023; Akin-Oluyomi *et al*., 2023a, 2023b, 2023d; Okojie *et al*., 2023a, 2023b).

Education, agriculture, and the built environment: Educational institutions confront outputs jointly produced with student characteristics, and progress-data personalization, fidelity monitoring of individualized plans, and predictive analytics for retention illustrate measurement where the outcome is co-produced with the person served, the hardest version of the comparability problem in Section 3.1 (Aliliele *et al*., 2023c; Yeboah & Oloto, 2023). Small business research addresses networks of very small units where per-unit information is minimal (Eyetsemitan *et al*., 2023; Oyeleye *et al*., 2022). In agriculture, data-driven policy models apply frontier-style reasoning at farm level, quantitative models extend it to the system level, and work on crop resilience, digital tools, extension services, and platform integration describes the input and information conditions separating otherwise comparable production units (Michael & Ogunsola, 2023a, 2023b, 2023c). The built environment supplies units whose performance depends heavily on design vintage and local conditions (Uduokhai *et al*., 2022, 2023a, 2023b).

4. Conceptual Framework

4.1. Structure

Applied benchmarking is a sequence of dependent decisions in which an error at one stage cannot be repaired at a later one, yet the literature treats those stages as separable specialisms. Arranging them into five layers, each with a characteristic failure mode, makes the dependency explicit.

Layer 1, measurement foundation: Operational telemetry, financial panels, environmental covariates, and quality indicators. Its defining property is frequency mismatch, since telemetry arrives continuously while financial panels close periodically. Comparability of the record is established here or not at all, which is why data backbone architecture, end-to-end visibility, and reconciliation control are prerequisites rather than refinements (Dogbatsey *et al*., 2019; Ilodigwe & Adesemoye, 2021; Nnabueze *et al*., 2021).

Layer 2, comparability construction: Deciding which sites may legitimately serve as comparators for which others: partitioning into technology strata, stratifying peer groups, and testing common support (Ogbete *et al*., 2022; Rosenbaum & Rubin, 1983). Support failure propagates upward invisibly, because an estimator returns a score for a site with no comparators without signaling that the score is an extrapolation.

Layer 3, estimation: Method-family selection and functional form are settled here, and no family dominates. The appropriate disposition is triangulation across structurally different estimators rather than optimization within one, which the infrastructure described in Section 3.4 makes inexpensive (Ogbole *et al*., 2021).

Layer 4, inference and uncertainty: Site-level scores carry irreducible uncertainty (Jondrow *et al*., 1982). This layer converts point estimates into intervals, applies hierarchical shrinkage so thinly evidenced sites are not ranked as though precisely measured (Gelman & Hill, 2007; Raudenbush & Bryk, 2002), and validates intervention claims with estimators robust to staggered adoption (Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021). Its characteristic failure is uncertainty suppression: the interval is computed and then discarded before the number reaches a decision maker (Sanni & Atima, 2021).

Layer 5, decision and governance: The benchmark becomes consequential only when converted into diagnosis, targets, and intervention, and is increasingly constrained by documentation, validation, and challenge requirements that bear on validity rather than merely compliance, since a model that cannot be reconstructed cannot be contested by the sites it evaluates (Ominyi & Anichukwueze, 2023).

The feedback path: A return edge runs from Layer 5 to Layer 1: once measurement carries consequence, measured units adapt what they report, so the data-generating process becomes endogenous to decisions taken above it. This edge distinguishes internal benchmarking from observational productivity research and is the structural reason estimator quality alone cannot guarantee benchmark quality.

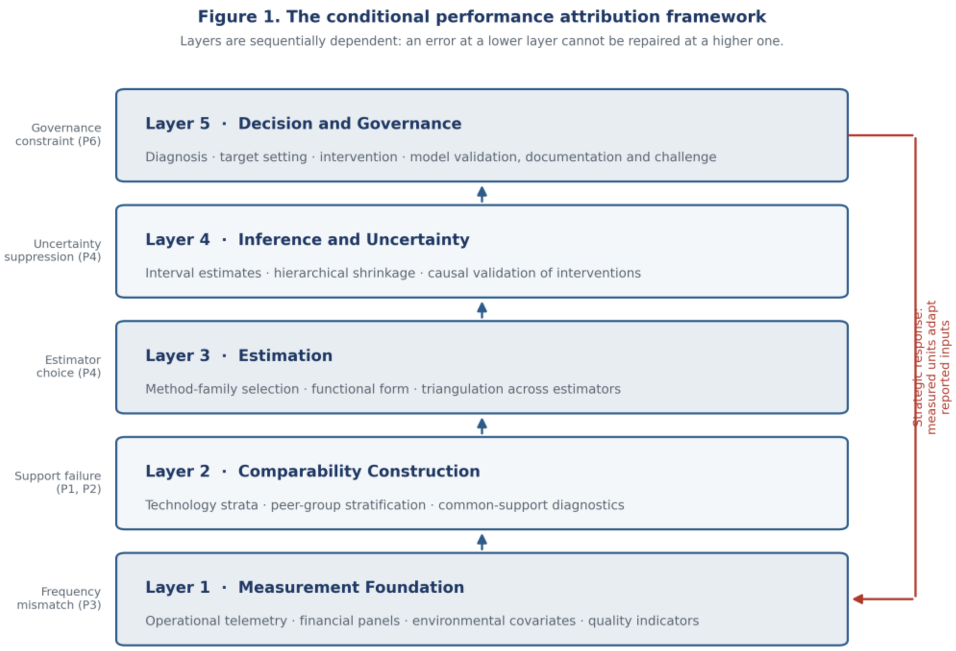

Fig 1: The Conditional Performance Attribution Framework

4.2. Propositions

P1 (comparability dominance): Benchmark validity is bounded above by the credibility of the comparison set, so returns to estimator sophistication diminish sharply once common support fails. Where a site's covariate profile lies outside the region populated by its peers, differences between method families are second-order relative to the extrapolation error common to all of them.

P2 (boundary endogeneity): Measured inefficiency varies monotonically with the size of the environmental control set, and the environment-management boundary is a governance choice rather than an empirical finding (Greene, 2005; Kumbhakar *et al.*, 2014). Two analysts applying identical estimators to identical data will report materially different inefficiency if they draw that boundary differently.

P3 (frequency complementarity): Joint use of high-frequency operational and low-frequency financial data identifies the persistent and transient components of inefficiency that neither identifies alone, so networks holding continuous telemetry alongside periodic accounts already possess the information required for the four-way decomposition (Adaramola *et al.*, 2018; Nnaji & Akinlolu, 2022; Sunday & Omoegun, 2022).

P4 (triangulation as diagnosis): Instability of a site's rank across structurally different estimators is diagnostic of comparability failure rather than of estimation noise. Rank dispersion is therefore informative output to be reported, not variance to be eliminated by model selection.

P5 (strategic degradation): The informativeness of a benchmark declines as the consequence attached to it rises, unless input auditing, rolling reference periods, and multiple estimators are combined. Regulated practice developed these safeguards under financial consequence (Jamasb & Pollitt, 2001); internal benchmarking generally has not, despite attaching consequence to individuals rather than firms.

P6 (auditability constraint): Sustained influence on decisions requires reconstructibility. Methods that cannot be documented, validated, and challenged within a governance framework will not be acted upon regardless of statistical merit, narrowing the effective design space to a subset of the estimators reviewed in Section 3.2 (Mbonu *et al.*, 2022b).

5. Discussion

5.1. Comparative Assessment of Method Families

Table 1

Method family	Noise handled	Functional form	Panel required	Site-level uncertainty	Main risk in practice
OLS / COLS	No (COLS)	Parametric	No	Poor	Outlier defines the frontier
Stochastic frontier	Yes	Parametric	No	Moderate	Distributional sensitivity; wrong skew
Panel frontier (true FE/RE, four-way)	Yes	Parametric	Yes	Good	Persistent inefficiency absorbed into fixed effects
Quantile regression	Implicitly	Semiparametric	No	Good	Quantile choice is a policy decision
StoNED / shape-constrained	Yes	Nonparametric with shape constraints	No	Moderate	Computation and software availability
Spatial frontier	Yes	Parametric	Usually	Moderate	Weight matrix specification
ML-augmented (DML, causal forests)	Partially	Nonparametric	Depends	Good with cross-fitting	Flexibility absorbs the signal if applied naively

No family dominates, and the choice should follow from the question rather than methodological preference. For aggregate savings potential, a parametric frontier with sensitivity analysis is adequate. For deciding which sites to intervene on, hierarchical shrinkage and interval estimates matter more than frontier sophistication. For whether a rollout worked, the relevant literature is difference-in-differences rather than frontier estimation. For target-setting, the answer should come from an attainable quantile of realized peer performance, since targets derived from estimated ideals are unachievable by construction. Frameworks linking measurement to accountability recognize this by tying indicators to levels at which action is possible, and cross-functional indicator frameworks make metric-decision alignment the central design question (Sakyi *et al*., 2022b; Seyi-Lande *et al*., 2022).

5.2. The Gap Between Methodological Capability and Applied Practice

Three manifestations recur. First, the two-stage practice persists long after Simar and Wilson (2007, 2011) demonstrated it yields invalid inference and despite the single-stage alternative from Battese and Coelli (1995); its persistence appears communicative rather than technical, since a two-step procedure is easier to narrate than a jointly estimated one. Second, uncertainty is computed and discarded: the applied corpus is rich in dashboards and monitoring systems and almost none carries intervals to the point of decision, a presentation failure with substantive consequences, since a ranking without intervals invites the reading that adjacent positions differ meaningfully when typically they do not (Ogbole *et al*., 2021; Sanni & Atima, 2021). Third, causal language attaches to associational evidence, because staggered rollout is the standard deployment pattern and two-way fixed effects the standard estimator applied to it, now known to be unreliable under heterogeneous effects (de Chaisemartin & D'Haultfoeuille, 2020; Goodman-Bacon, 2021).

The two literatures have complementary deficiencies. The methodological literature has resolved identification problems the applied literature does not recognize it faces, particularly endogeneity of input choice and separation of persistent from transient inefficiency (Amsler *et al*., 2016; Griffiths & Hajargasht, 2016; Kumbhakar *et al*., 2014). The applied literature has built measurement infrastructure, indicator systems, and organizational routines the methodological literature assumes into existence, in procurement, healthcare infrastructure, and distributed workforce management (Aminu-Ibrahim *et al*., 2021; Falemi *et al*., 2020; Okonkwo *et al*., 2023). Neither completes the other's work, and the framework of Section 4 arranges both into explicit positions.

5.3. Implications

Theoretical: Treating benchmarking as a layered attribution problem rather than an estimation problem has three consequences. It relocates the primary source of error from the estimator to the comparison set, implying that theoretical work on peer-group formation deserves the attention now directed at frontier specification. It makes the environment-management boundary an object of theory rather than a modeling convenience, since P2 holds that the boundary determines the quantity being measured. And by formalizing the feedback path it positions multi-site benchmarking within mechanism design rather than observational econometrics. Management practice research that measures practice directly rather than inferring it from a residual is the natural complement (Bloom & Van Reenen, 2007; Bloom *et al*., 2019).

Managerial: Report the effective comparison set alongside every score, a precondition for the ranking being accepted and acted upon (Akin-Oluyomi & Akhigbe, 2023b). Compute more than one benchmark and publish the spread, treating rank instability as a signal about comparability under P4. Derive targets from attainable peer quantiles rather than estimated frontiers. Separate the diagnostic question from the evaluative one, since identifying which sites underperform does not identify what they are doing differently, and the handoff to process comparison is where benchmarking programs most often fail (Akin-Oluyomi & Akhigbe, 2023c). Invest in the measurement foundation before the estimator, since Layer 1 defects cannot be repaired at Layer 3 (Nnabueze *et al*., 2021).

Policy and regulatory: Regulated benchmarking has developed safeguards internal practice lacks: estimator triangulation, rolling reference periods, audited inputs, and formal appeal (Jamasb & Pollitt, 2001). Transferring them is the clearest policy-relevant recommendation here, and P5 states the reason. Because benchmarking allocates capital, attention, and consequence, evidence that accurate forecasts are not automatically equitable applies directly to the choice of conditioning variables (Komi, 2023). And as governance regimes formalize documentation and challenge requirements, model risk functions will effectively select among the method families reviewed here, favouring transparency over marginal statistical performance (Ominyi & Anichukwueze, 2023).

5.4. Limitations

This is a narrative, configurative review rather than a systematic one. There is no pre-registered protocol, no reproducible search string, and no independent second coder, so selection and interpretation reflect the authors' judgment, and a different reviewer could assemble a materially different corpus. No meta-analysis is attempted: because primary studies differ in outcome definition, unit of analysis, and estimator, no pooled effect size is reported, so the review cannot state how large efficiency differences typically are, only how they should be estimated and interpreted.

A substantial share of the applied corpus consists of conceptual frameworks and model proposals rather than empirical estimations on primary data, which supports claims about how the field frames its problems and weaker claims about how well the proposed methods perform. Sector coverage is uneven, with retail, healthcare infrastructure, procurement, and financial services more densely represented than transport or hospitality, and coverage is restricted to English-language sources. The framework in Section 4 is derived from the synthesis rather than tested against it; P1 and P4 in particular would require a dataset in which one network is benchmarked under several estimators with comparison sets varied deliberately, which no study in the corpus provides. Finally, the review reflects practice through 2023.

5.5. Future research directions

Decision-relevant uncertainty: Research on presenting rank uncertainty in a form that supports operational decisions, and on how decision quality changes when it is presented, would have a larger practical effect than further estimator refinement.

Strategic robustness: Sites can influence scores through channels that do not improve performance: reclassifying activity, shifting the timing of recorded costs, adjusting recorded environmental variables, and investing effort selectively in measured dimensions. Formal analysis of estimator performance under strategic reporting, drawing on mechanism design, is largely absent, and workforce optimization frameworks are a natural venue because they already recognize the behavioral response to measurement (Falemi *et al*., 2023b).

High-frequency identification: Methods using within-site high-frequency variation to identify transient inefficiency, reserving low-frequency variation for persistent inefficiency, would operationalize P3 with data networks already hold, and capacity planning research shows what is possible when measurement infrastructure is already continuous (Edivri & Oteri, 2022).

Quantitative and qualitative integration: A regression identifies which sites underperform but not what they are doing differently, and the handoff to diagnostic process comparison is almost entirely unstudied; change management research describes conditions under which such translation succeeds (Eyetsemitan *et al*., 2023).

Network effects and empirical testing: In networks with shared fulfillment, cross-site inventory, and transferable staff, the network objective is not the sum of site objectives, and a site can be locally inefficient while serving a network-optimal role, which would require abandoning the independent-unit framework all current methods assume. A single network benchmarked under several estimators, with comparison sets constructed under alternative stratification rules and the control set deliberately varied, would provide evidence on P1, P2, and P4 simultaneously, while audit trail and configuration management research supports the parallel test of P6 (Oshoba *et al*., 2020).

6. Conclusion

Regression-based benchmarking for multi-site operations networks rests on a methodological base that is substantially complete. The estimators available in 2023 handle noise, heterogeneity, functional form flexibility, spatial dependence, and endogeneity to a standard exceeding what most applied settings can support with their data. The binding constraints lie elsewhere: in constructing credible comparison sets, in treating honestly the boundary between environment and management, in communicating uncertainty to decision makers, and in designing processes that convert a ranking into a diagnosis.

The applied corpus reinforces that conclusion from the other direction. Practitioner-researchers across retail, banking, healthcare, energy, logistics, procurement, and safety management have built substantial data infrastructure and standardized indicator frameworks, but generally not the inferential layer that would allow those indicators to support the causal claims made of them. The gap is one of translation between two literatures that cite each other rarely, and closing it requires no new mathematics. Arranging the work into five dependent layers, each with a named failure mode, makes explicit that benchmark quality is determined jointly rather than at the point of estimation, and that measured units respond to the regime that measures them; multi-site efficiency frameworks provide the organizational vehicle for operating such a structure (Akin-Oluyomi & Akhigbe, 2023a). The most consequential near-term development, however, is not within the frontier literature at all. It is the migration of robust difference-in-differences estimators into internal evaluation practice, which requires no data networks do not already hold, and which safety research linking management activity frequency to outcome shows is easily got wrong when the estimator assumes homogeneous effects (Obriki & Arumosoye, 2019).

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