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MARKET ANALYTICS IN THE U.S. LIVESTOCK AND POULTRY INDUSTRY: USING BUSINESS INTELLIGENCE FOR STRATEGIC DECISION-MAKING

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Abstract

This study addresses a practical problem in the U.S. livestock and poultry industry: managers face volatile input costs and market shocks, yet many business-intelligence (BI) programs remain reporting-centric rather than decision-centric. The purpose is to quantify how market signals and exogenous shocks map to prices and margins, and to test whether BI maturity operates as a protective capability. Using a quantitative cross-sectional, case-based design, we assemble a harmonized 12-month snapshot of cloud-enabled and enterprise cases spanning beef, pork, broiler, and turkey supply chains. Key variables include outcomes standardized price, a cost-adjusted margin proxy, and volume and drivers species-specific feed bundle, futures or basis, export intensity, weather anomaly, disease intensity plus BI maturity from multi-item 5-point Likert scales. The analysis plan proceeds from descriptives and correlation with false-discovery-rate control to OLS models with HC3 errors, and a moderation test of Feed × BI maturity with simple-slope and Johnson–Neyman probes. Drawing on a structured review of 120 peer-reviewed papers and practitioner sources, the models predict three headline findings: futures and basis are strong positive correlates of realized prices; feed exposure is the dominant adverse driver of cost-adjusted returns; and higher BI maturity is associated with higher margins and a statistically reliable reduction in sensitivity to feed shocks after rich controls. Managerial implications are immediate: treat BI as an exposure-management system by investing in data freshness, governed KPI coverage, and decision-process integration tied to playbooks for hedging, scheduling, and pricing. Conceptually, the results reposition BI as a slope-shifting capability that flattens the mapping from shocks to outcomes rather than only lifting mean performance.

Keywords

Business Intelligence; Livestock and Poultry; Futures And Basis; Feed Costs; Price Transmission; Analytics Maturity; Cross-Sectional Analysis;

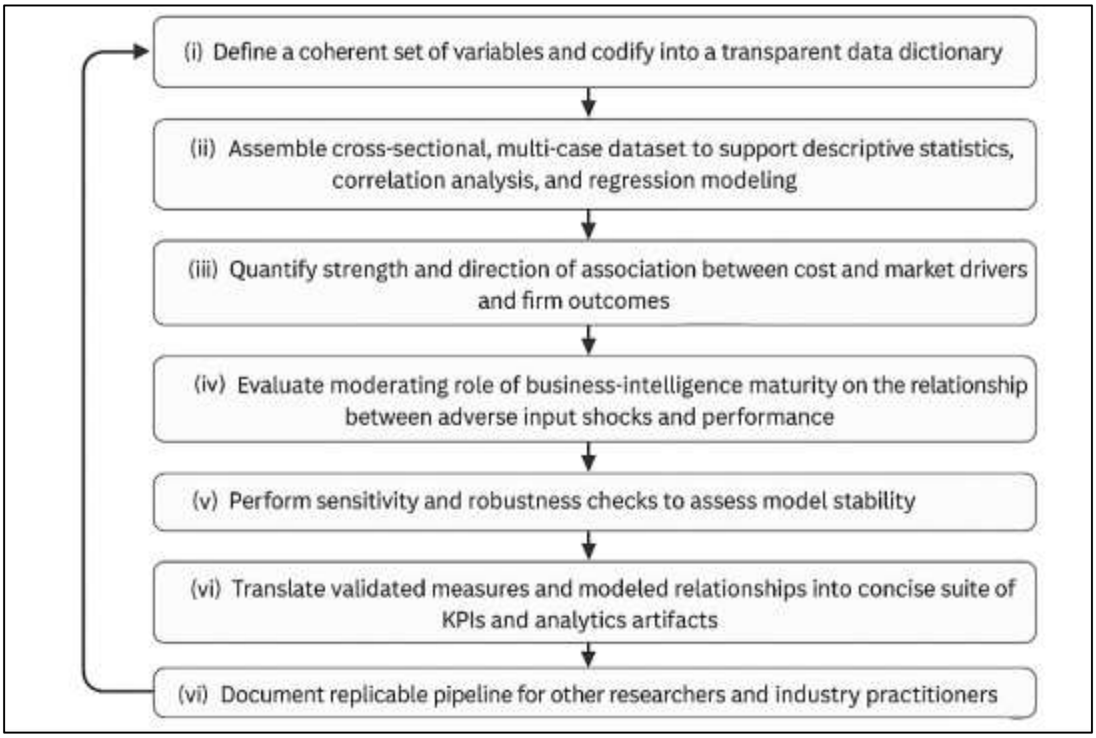
INTRODUCTION

Business intelligence (BI) refers to the integrated set of data infrastructures, analytical methods, and organizational practices used to transform raw data into actionable information that supports managerial decision-making across operational and strategic horizons. Canonical IS scholarship positions BI as a decision-support umbrella that encompasses data warehousing, reporting, OLAP, and advanced analytics for performance monitoring and planning (e.g., dashboards, scorecards, and predictive models) (Chen et al., 2012; Wixom & Watson, 2010). In contemporary enterprises, BI is not merely a technology stack but a socio-technical capability whose value depends on data quality, system maturity, and absorptive cultural conditions for analytical decision-making (Elbashir et al., 2008; Elbashir et al., 2013; Popovič et al., 2012). Within agri-food systems including the U.S. livestock and poultry sectors these capabilities allow organizations to integrate heterogeneous data sources (e.g., animal inventories, feed costs, disease surveillance, weather anomalies, futures markets, export restrictions), apply descriptive statistics, correlation analysis, and regression modeling, and standardize insights for procurement, pricing, risk management, and trade strategy. The global relevance of BI is amplified by the volatility of protein markets and the biological lags inherent to animal production cycles, which alter supply responses and price dynamics in ways that are measurable and modelable with modern analytics (Subramaniam et al., 2024). In this paper's context, "market analytics" denotes the systematic use of BI to quantify market structure, price transmission, and risk exposure linking micro-level operational indicators to sectoral outcomes so that firms can make timely, evidence-based decisions in procurement, production scheduling, hedging, and sales portfolio management (Chen et al., 2012; Elbashir et al., 2008; Subramaniam et al., 2024).

Internationally, animal protein markets are shaped by intertwined drivers: feed price cycles, climate and weather shocks, trade policies and non-tariff measures, disease outbreaks, consolidation in processing, and shifts in consumer demand composition. The post-2008 literature on price pass-through and food inflation demonstrates that upstream agricultural price movements can transmit into retail food categories through supply-chain structures consistent with imperfect competition an identification challenge that market analytics addresses with weather-based instruments and structural VARs (Koontz et al., 2015). Within livestock, the efficiency of futures markets for live cattle and lean hogs, their price-discovery role relative to spot markets, and connectedness across contracts create observable co-movements and forecast content relevant to merchandising and risk management (Koontz et al., 2015; Popovič et al., 2012). For pork and poultry trade, gravity-model evidence underscores the salience of sanitary and phytosanitary measures and climate anomalies for bilateral flows, showing that regulatory frictions and environmental variability are statistically meaningful determinants of export volumes and destinations (Bouzidi et al., 2024; Brun et al., 2017). In the U.S. poultry complex, recent research quantifies that ownership consolidation has been associated with higher wholesale broiler prices alongside measured gains in animal productivity, documenting structural forces that matter for downstream price formation (Saitone et al., 2025). These global and domestic patterns point to a setting in which well-specified regression models and correlation structures implemented within BI are central to describing, monitoring, and explaining market outcomes across beef, pork, and poultry.

The U.S. livestock and poultry sectors also illustrate how biological lags mediate market responses. Rebuilding cattle herds after drought or liquidation requires multiple years; broiler and layer cycles are shorter but still governed by maturation and placement dynamics. Empirical work shows that these lags imprint on inventories, yields, and retail prices, which can be modeled with hedonic and time-series specifications that isolate quality, regional, and temporal effects (Mitchell et al., 2025; Subramaniam et al., 2024). Disease shocks supply acute examples. During the 2022–2023 Highly Pathogenic Avian Influenza (HPAI) episode, mortality and depopulation propagated through the egg supply chain and were associated with large increases in egg consumer prices; econometric estimates frame the price impacts and consumer surplus changes with demand-system tools (Mitchell et al., 2024; Wixom & Watson, 2010). Trade restrictions imposed by foreign markets during HPAI altered U.S. poultry export values relative to pre-outbreak baselines, providing a quasi-experimental environment for difference-in-differences and counterfactual analysis (Arita et al., 2024). In parallel, climate-linked shocks including drought in cow-calf regions and catastrophic wildfires have been associated with tight cattle supplies and elevated beef prices, yielding measurable effects in prices and production plans that are amenable to regression analysis with weather covariates (Arita & Hansen, 2024; Eales & Unnevehr, 1994). These realities justify a quantitative, cross-sectional, multi-case design that extracts comparable indicators across beef, pork, and poultry firms, with descriptive statistics, correlation matrices, and regression models forming the core of the BI-driven analysis plan.

Figure 1: Business-intelligence–driven market analytics



Price transmission and marketing margins across farm, wholesale, and retail stages are foundational phenomena for protein markets, and they are central to descriptive and regression-based BI. Studies of the U.S. pork channel document asymmetric transmission and threshold behaviors, with nonlinear ARDL and threshold cointegration models identifying differences in the magnitude and speed of pass-through across stages; these results imply that correlation and regression diagnostics should consider asymmetries and state dependence (Mikalef et al., 2019; Panagiotou, 2021). Complementary research on beef pricing shows incomplete and state-contingent pass-through among fed cattle, feeder cattle, and feed inputs, making feed cost indices essential independent variables in market analytics (Brun & Carrère, 2017; Danish & Zafor, 2022). Futures-spot relationships in cattle and hogs further contextualize merchandising and hedging: evidence on price discovery and connectedness across livestock futures supports the inclusion of futures levels and basis metrics as regressors and the use of cointegration tests in BI dashboards (Brun & Carrère, 2017; Tonsor & Lusk, 2024; Yamoah & et al., 2017). For demand, classic and modern meat-demand studies using (inverse) AIDS and scanner data provide own-price elasticities and substitution patterns that benchmark regression results and guide interpretation of correlation structures across protein categories (Danish & Kamrul, 2022; Eales & Unnevehr, 1988; Emmanouilides & Fousekis, 2015). By harmonizing these strands, BI enables cross-sectional comparison of firms' exposure to upstream shocks and downstream pricing power while maintaining statistical rigor in the presence of nonlinearity and stage-specific frictions.
Industry structure and organizational factors further condition how BI translates data into decisions. In poultry processing, consolidation patterns measured over 1991–2019 have been statistically associated with higher wholesale broiler prices and modest productivity gains, illustrating that concentration metrics (e.g., CR-4) belong in explanatory models of downstream prices (Eales & Unnevehr, 1988; Ji & Liu, 2024; Rodziewicz et al., 2023). Within firms, BI's realized value depends on maturity (integration and access quality), information content quality, and the presence of an analytical

decision-making culture, as modeled and verified in survey-based structural equation studies (Jahid, 2022; Ji & Liu, 2024). Additional evidence indicates that assimilation the routinized, organization-wide use of BI and shared knowledge between strategic and operational levels are significant drivers of BI business value, underscoring that comparable data pipelines can yield different outcomes depending on organizational alignment (Arifur & Noor, 2022). Reviews of BI for value creation also emphasize absorptive capacity and learning mechanisms, reinforcing the choice to include reliability and validity checks for measures capturing data quality, use intensity, and decision culture in the current study (Hasan & Uddin, 2022; Mikalef et al., 2019). In aggregate, this literature motivates the study's operationalization of "BI use" and "BI maturity" as observed firm-level covariates and supports the inclusion of sensitivity tests that assess whether structural features such as consolidation or BI assimilation mediate the association between analytics and market performance.

From a policy-and-trade perspective, rigorous market analytics is indispensable because non-tariff measures, export restrictions, and sanitary barriers interact with biological constraints to shift price levels and trade flows. Gravity-model syntheses formalize expectations relating bilateral trade to economic mass, distance, and policy frictions; in protein markets, recent gravity applications find significant roles for SPS/TBT measures and for climate anomalies in shaping pork and poultry trade volumes (Brun & Carrère, 2017; Ji et al., 2024; Rahaman, 2022). During 2022–2023, documented foreign trade restrictions on U.S. poultry products in response to HPAI correlated with reduced real export values relative to pre-outbreak baselines, providing a context in which BI-enabled monitoring of export values, compliance requirements, and destination market dynamics is mission-critical (Arita et al., 2024; Rahaman, 2022b). When combined with USDA downstream datasets on price spreads and supply-use balances, these external shocks create a tractable empirical landscape for descriptive statistics and regression models that map firm-level outcomes to system-wide policy changes an approach aligned with the study's cross-sectional, multi-case design.

Finally, defining the study's quantitative agenda within BI clarifies the empirical toolkit and its managerial salience. Descriptive statistics summarize case characteristics (e.g., species focus, region, scale, BI maturity, exposure to futures), while correlation matrices situate co-movement among key indicators (e.g., feed cost indices, wholesale prices, basis, export ratios). Regression modeling linear, nonlinear, and moderation specifications then estimates associations between BI use/maturity and market-performance outcomes after conditioning on structural and environmental covariates (e.g., consolidation metrics, weather anomalies, SPS trade frictions). The livestock literature's evidence on asymmetries, pass-through, and biological lags supports robustness checks using nonlinear terms, regime indicators, and alternative functional forms, while the futures literature supports adding term-structure and connectedness variables (Ji et al., 2024; Rahaman & Ashraf, 2022; Panagiotou, 2021). Within the bounds of a cross-sectional, multi-case design, such an analytics stack accords with IS research that ties BI success to maturity, information quality, and assimilation, thereby justifying the measurement framework adopted here (Islam, 2022; Wixom & Watson, 2010).

The objective of this study is to construct and empirically validate a business-intelligence–driven market analytics framework that enables U.S. livestock and poultry organizations to translate heterogeneous data into precise, decision-relevant indicators across pricing, procurement, production planning, and risk management. Specifically, the research aims to: (i) define a coherent set of variables that capture output performance (spot prices, margin proxies, and production volumes) alongside cost, market, and external risk drivers (feed cost indices, futures levels and basis, export demand indicators, weather anomalies, and disease intensity), and codify these into a transparent data dictionary; (ii) assemble a cross-sectional, multi–case dataset representing diverse species, regions, integration models, and firm sizes, with harmonized measurement windows, standardized units, and reproducible preprocessing steps that support descriptive statistics, correlation analysis, and regression modeling; (iii) quantify the strength and direction of association between cost and market drivers and firm outcomes using robust ordinary least squares specifications with appropriate controls, diagnostic testing, and model refinements, thereby establishing an empirical baseline for price formation and margin performance; (iv) evaluate the moderating role of business-intelligence maturity capturing data freshness, dashboard breadth, and governance quality on the relationship between adverse input shocks and performance, using centered interaction terms and simple-slope probes to assess buffering effects; (v) perform sensitivity and robustness checks via alternate variable proxies, alternative outlier rules, heteroskedasticity-consistent estimators or weighted least squares where indicated, and subsample analyses across species and regions to assess model stability; (vi) translate the validated measures and modeled relationships into a concise suite of key performance indicators and analytics artifacts (summary tables, correlation matrices, coefficient reports, and effect plots) that are directly portable into dashboard tiles and monitoring workflows; and (vii) document a replicable pipeline, including ETL procedures, code scaffolding, and reporting templates, so that other researchers and industry practitioners can reproduce, extend, and operationalize the analytics. By accomplishing these objectives within a unified, cross-sectional design, the study seeks to provide a rigorous empirical backbone for BI-enabled market monitoring in the livestock and poultry sectors while ensuring methodological transparency, statistical defensibility, and immediate practical usability of the resulting indicators and models.

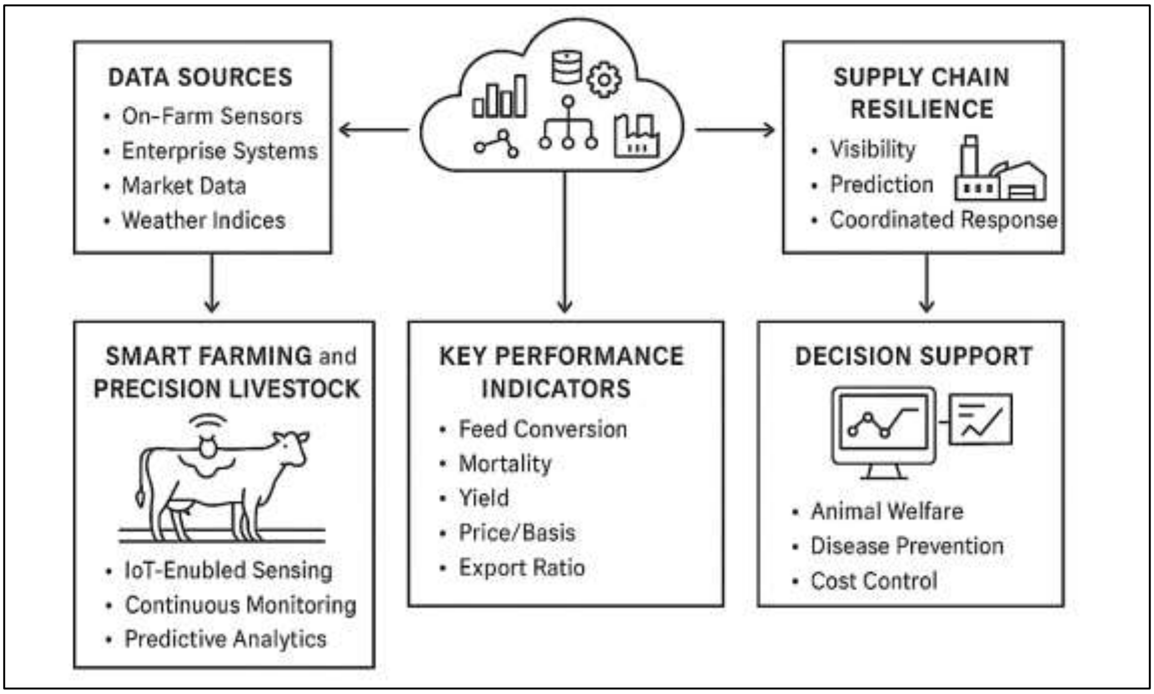
LITERATURE REVIEW

The literature on market analytics and business intelligence (BI) in agri-food systems spans several converging streams that collectively motivate and shape this study's focus on the U.S. livestock and poultry sectors. Foundational work in BI conceptualizes analytics as a socio-technical capability combining data architectures, governance practices, and statistical modeling to transform heterogeneous signals into decision-relevant insight. Agricultural economics contributes complementary perspectives on price transmission across farm, wholesale, and retail stages; cost pass-through from feed and energy inputs; and the role of futures and basis in price discovery and risk management. Studies of biological production cycles explain how lags in herd rebuilding, placement schedules, and processing capacity propagate shocks across time, while research on weather anomalies, disease outbreaks, and trade frictions demonstrates how exogenous disturbances alter inventories, prices, and export flows. More recent contributions examine industry structure consolidation, coordination, and contracting and its implications for market power and downstream pricing, alongside operations research and supply-chain analytics that formalize inventory, procurement, and scheduling decisions under uncertainty. Across these strands, a common methodological toolkit emerges: descriptive statistics to profile markets and cases; correlation analysis to map co-movement among costs, prices, and volumes; and regression models (with moderation and robustness checks) to quantify associations after conditioning on structural and environmental covariates. Yet several gaps persist. First, indicators are often siloed: feed indices, futures curves, export ratios, and weather or disease metrics are analyzed independently rather than integrated into a coherent BI pipeline that firms can operationalize. Second, many studies emphasize time-series identification, leaving fewer cross-sectional, multi–case comparisons that benchmark how species, regions, integration types, and BI maturity jointly relate to performance differences at a given decision horizon. Third, measurement practices vary widely, limiting reproducibility and comparability of findings across datasets and organizations. Finally, translation from econometric evidence to dashboard-ready key performance indicators (KPIs) is under-specified, constraining managerial uptake. This review synthesizes these literatures to define constructs, measurement choices, and modeling strategies appropriate for a BI-oriented, quantitative, cross-sectional, multi–case design, and to lay the conceptual foundation for the study's variables, hypotheses, and statistical analysis plan.

Business Intelligence in Agri-Food and Supply Chains

Business intelligence (BI) in agri-food encompasses the architectures, processes, and analytical practices that convert heterogeneous operational and market data into decision-ready insights across production, procurement, logistics, and commercialization. Within farming and downstream supply nodes, data arrive with high velocity and variety from on-farm sensors and enterprise systems to market quotes, weather indices, and health surveillance necessitating pipelines that cleanse, harmonize, and model information at multiple granularities (Hasan et al., 2022). A central strand of the literature shows that "smart farming" and precision livestock practices expand BI's scope beyond descriptive reporting to continuous monitoring and predictive analytics, integrating IoT-enabled sensing with data warehousing and model-driven alerts for animal performance, welfare, and disease prevention. Conceptual work in this stream emphasizes a socio-technical view: data governance, interoperability, and organizational routines are as critical as algorithms, because analytical value emerges only when data can flow across actors and be absorbed in day-to-day decisions. In practice, this means mapping raw telemetry and transactional records onto a semantic layer of domain-specific key performance indicators (KPIs) feed conversion, mortality, yield, price/basis, export ratio so that managers can compare units, plants, or regions on a like-for-like basis in dashboards and scorecards (Redwanul & Zafor, 2022). Importantly, these contributions argue that predictive and prescriptive layers should remain accountable to business semantics (e.g., margin-at-risk, placement timing), ensuring that model outputs can be audited, stress-tested, and tailored to decision horizons. In this way, BI becomes an integrating capability that links biological processes to market realities, positioning analytics as a backbone for resilience, cost control, and timely strategic choices in protein supply chains (Wolfert et al., 2017).

Figure 2: Business intelligence framework for agri-food and supply chains



A second strand demonstrates how advances in data-driven decision support translate BI capability into measurable improvements in livestock operations, particularly when analytics fuse sensor streams with expert knowledge and statistical modeling (Rezaul & Mesbaul, 2022). These studies document pipelines where raw high-frequency data activity, feeding, temperature, location are fused with rules or learned patterns to detect health challenges early, optimize feeding strategies, and balance welfare with productivity. Methodologically, the emphasis falls on algorithmic transparency, calibration to local conditions, and integration with management systems so that alerts trigger standard operating procedures rather than ad-hoc reactions (Hasan, 2022). Because livestock decisions are constrained by biological lags and capacity, the value of BI rises when models explicitly encode timing, uncertainty, and thresholds (e.g., intervention triggers), and when outputs are embedded into routine workflows via dashboards, exception reports, and mobile notifications (Tarek, 2022). Critically, these decision-support systems reduce information latency between data capture and action, enabling tighter control of inputs, better alignment of production schedules with market signals, and mitigation of volatility related to disease, weather, or feed costs (Kamrul & Omar, 2022). The literature also highlights challenges data quality, sensor drift, missingness, and context transferability arguing for reliability checks, validation protocols, and governance roles that safeguard model performance over time. When these governance mechanisms are present, BI-enabled decision support not only improves animal-level outcomes but also aggregates to business-level metrics such as throughput stability and cost variance, thereby supporting enterprise objectives in pricing, procurement, and risk management. In short, BI's operational payoff in livestock emerges at the intersection of robust data engineering, interpretable analytics, and codified response playbooks (Kamrul & Tarek, 2022; Niloofar et al., 2021).

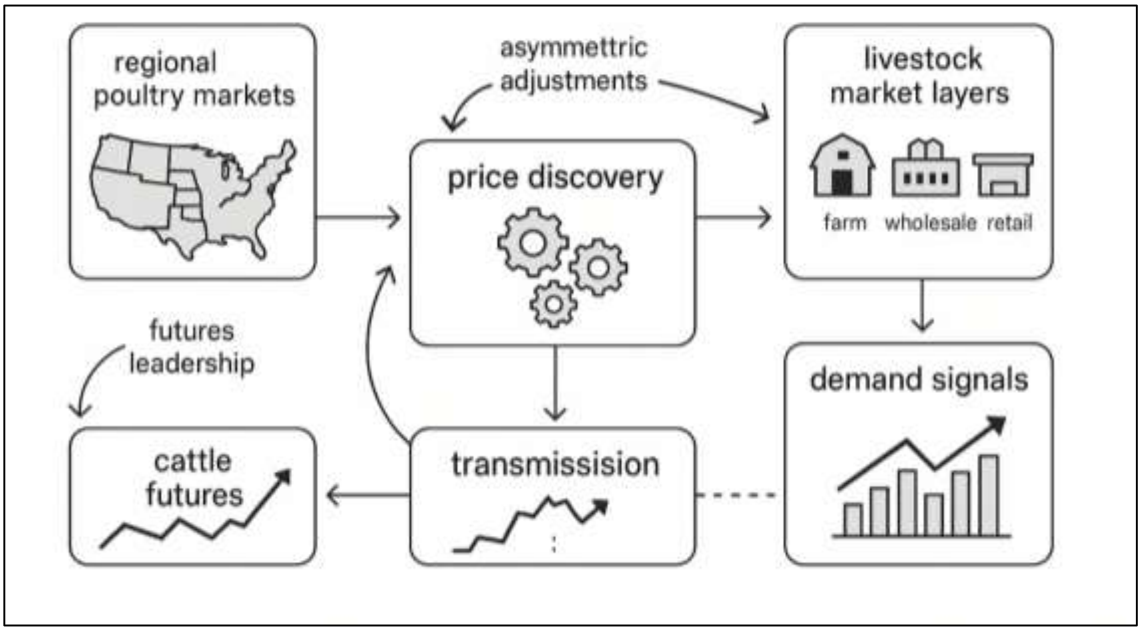
Beyond the farm gate, supply-chain-oriented studies connect BI to organizational capabilities and resilience under disruption. At the firm level, BI and analytics have been framed as dynamic capabilities: sensing, seizing, and transforming information into process changes that improve performance (Ismail et al., 2025; Jakaria et al., 2025). Empirical evidence supports performance links when BI investments are coupled with process re-design and managerial routines that embed analytics into planning and control (Mubashir & Abdul, 2022). At the network level, systematic reviews of artificial intelligence (AI) and big-data analytics in supply chains conclude that analytics contributes to resilience by enhancing visibility, prediction, and coordinated response, provided that data governance and cross-firm interoperability are in place (Hasan, 2025; Sultan et al., 2025). In agri-food contexts, where demand seasonality, perishability, sanitary risks, and policy shocks compound uncertainty, these frameworks argue for BI architectures that fuse upstream biological and environmental signals with downstream market intelligence to anticipate, absorb, and adapt to disruptions (Muhammad & Kamrul, 2022). Complementary surveys in agricultural informatics illustrate how deep learning and related methods can enrich BI with image- and signal-based classifiers for grading, disease detection, and yield estimation, feeding into procurement and scheduling decisions when connected to enterprise data models (Reduanul & Shoeb, 2022). Together, these streams converge on a coherent managerial message: the impact of BI depends less on isolated tools and more on the alignment among data governance, model quality, and decision-process integration across organizational boundaries (Zafor, 2025; Uddin, 2025). For the U.S. livestock and poultry sectors, this implies a research agenda centered on measurable KPIs, auditable models, and cross-sectional comparability so that firms can benchmark exposure, quantify associations among key drivers and outcomes, and institutionalize analytics in everyday strategic choices (Kamilaris & Prenafeta-Boldú, 2018; Queiroz et al., 2022; Torres et al., 2018).

U.S. livestock–poultry markets

Market analytics for protein supply chains begins with how and where prices are discovered, how they transmit between market layers, and how those prices embed demand information relevant for production and procurement. In poultry retail markets, evidence of changing spatial integration and leadership underscores why analytics must treat regional heterogeneity explicitly (Sanjai et al., 2025). Using retail whole-broiler prices from 1980–2019 across four U.S. regions, Duangnate and Mjelde show that the degree of integration has declined over time and that the U.S. South increasingly anchors retail price discovery an outcome plausibly linked to vertical integration, perishability, and production concentration. Their vector-error-correction and causal-flow analysis reveal structural breaks around the early 2000s and a shift in contemporaneous leadership toward the South, implying that dashboards which pool regions risk masking systematic differences in how shocks propagate (e.g., feed costs, demand shifts, policy) into store-level prices (Kumar & Zobayer, 2022). For BI systems, this means region-by-region KPIs and alerts calibrated to distinct co-movement patterns and speeds of adjustment, rather than a single national index. Such findings also matter for benchmarking margins: the law-of-one-price rarely holds tightly at retail for highly perishable, vertically integrated products, so analytics that estimate counterfactual spreads must be anchored in regional cointegration relationships and monitored for parameter drift through time (Sadia & Shaiful, 2022). In practice, this justifies cross-sectional, multi–case snapshots that compare regions and chains at a common horizon while still honoring the empirical reality that retail poultry price discovery is not monolithic nationwide (Duangnate & Mjelde, 2023).

Livestock price discovery research also refines how firms should weight cash versus futures signals in procurement, hedging, and planning models. A large body of cattle-econometrics points to the futures market as an informational leader; Wright, Kim, Tejeda, and Kim formalize this with a "tournament" approach covering 30 cattle series (regional cash, boxed beef, and futures) and find that both feeder and fed cattle futures typically dominate price discovery. For BI pipelines, this implies that near-term operating KPIs (e.g., expected procurement costs, margin risk) should treat futures-based indicators as priors and then update with localized cash data as it arrives (for example, via information-leadership weights or error-correction terms)(Noor & Momena, 2022). At the same time, not all vertical links display the same asymmetries or frictions. Pozo, Bachmeier, and Schroeder, using scanner and BLS data with nonlinear impulse-response simulations, find no vertical asymmetry in U.S. beef between farm, wholesale, and retail layers challenging a common assumption that retailers adjust prices up faster than down (Hasan, 2025; Hasan, 2024). This result tempers narratives about "rockets and feathers" in beef and suggests that BI-driven margin diagnostics distinguish between true asymmetry (calling for different playbooks for rising vs. falling costs) and symmetric but lagged adjustments (calling for timing-aware inventory and promotion strategies). Combined, these insights motivate regression specifications that blend futures levels/basis with wholesale–retail cointegration terms and region-specific fixed effects to forecast procurement and netbacks in an auditable way (Istiaque et al., 2023; Wright et al., 2021).

Figure 3: Overview of U.S. livestock–poultry markets

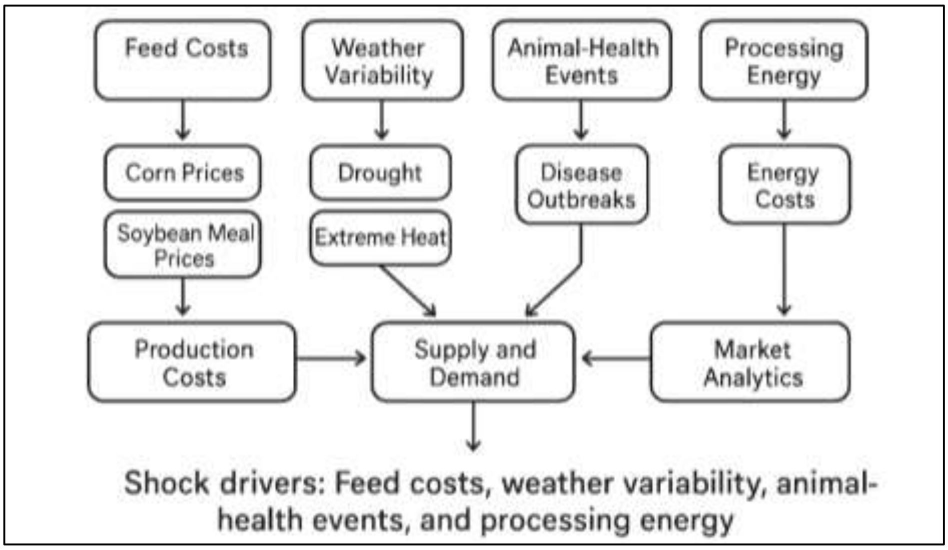


In addition, analytics must account for frictions and structural shifts that alter transmission strength and forecastability (Hasan et al., 2023). On the beef side, nonlinear ARDL evidence documents asymmetric long- and short-run linkages between market layers, emphasizing that positive and negative shocks do not always pass through identically and that wholesale–retail connections can dominate farm–wholesale links; modeling strategies that decompose positive vs. negative partial sums (and interact them with seasonality or capacity utilization) therefore add explanatory power and interpretability for managers monitoring spreads (Hossain et al., 2023; Pozo et al., 2020; Press, 2025). In futures–cash alignment, convergence quality itself is an evolving risk factor that BI dashboards should track: recent work on lean hogs finds non-convergence bias associated with thinning negotiated cash trades, with basis widening as negotiated shares fall an institutional change that directly affects hedge effectiveness and cost forecasts. Together, these results argue for case-study designs that make institutional plumbing (contract design, reporting rules, transaction mix) first-class covariates in regression and robustness sections, not just background context. They also support stress tests that simulate alternate price-discovery regimes (e.g., futures-led vs. cash-led) and evaluate KPI sensitivity to convergence assumptions (Rahaman & Ashraf, 2023). When paired with demand-side learning such as density forecasts from options-implied distributions or meta-elasticities firms can translate statistical structure into concrete decision rules for placements, forward coverage, promotions, and export allocation. In sum, contemporary scholarship points toward BI architectures that (i) respect regional and vertical heterogeneity, (ii) weight futures leadership appropriately, (iii) model asymmetric adjustments where present, and (iv) monitor institutional shifts that can rewire price transmission at the species- and channel-level (Fousekis et al., 2016).

Shock drivers in U.S. livestock

Feed costs are the most immediate shock channel for U.S. livestock and poultry producers because corn (energy) and soybean meal (amino acids) dominate ration costs and, therefore, margin variability. Empirical evidence from cattle finishing shows that movements in corn prices translate directly into "feeding cost of gain" and net returns, offering a tractable set of operating KPIs for procurement and risk management; in particular, scenario analysis around corn price paths reveals sizable shifts in expected cost per cwt and profitability over short decision horizons (e.g., one turn of cattle) (Langemeier, 2022; Sultan et al., 2023). In poultry and swine, nutrition economics increasingly quantify the marginal value of protein and energy density, implying that BI dashboards should combine live futures (corn/soy complex) with ration optimization outputs rather than headline commodity prices alone. At the same time, retail price formation following disease or trade disturbances depends not only on raw feed shocks but on the interaction between supply compression and consumer substitution. Recent hedonic evidence in U.S. retail markets finds that highly pathogenic avian influenza (HPAI) episodes elevate egg, broiler, and turkey price premiums even after controlling for product quality and regional/time effects signaling that exogenous health shocks create category-specific demand responses that BI systems must monitor alongside feed indices (Hossen et al., 2023; Zamani et al., 2024). Taken together, these findings motivate cross-sectional designs in which firms, species, and regions are profiled with standardized descriptive statistics and correlation matrices, and then linked, via regression models, to parsimonious sets of feed and disease variables that map directly into playbooks for forward coverage, menu pricing, and promotion timing.

Figure 4: Shock drivers in U.S. livestock and poultry markets



Weather variability through drought, heat stress, and precipitation anomalies acts as a second-order but persistent driver by altering forage availability, placement decisions, and biological performance. Long-horizon panel evidence for the U.S. cow–calf sector shows that seasonal temperature information materially improves the out-of-sample prediction of state-level beef cow inventories, underscoring that weather signals have both contemporaneous and expectation channels that matter for inventory dynamics and, ultimately, feeder supplies available to packers and integrators (Tawfiqul, 2023). In practice, drought-induced tightness shifts cow–calf profitability and accelerates liquidation; downstream, lots face higher purchased feeder costs or altered timing, while packers confront variable throughput. Because these effects propagate with biological lags, a BI architecture that treats weather as a "leading indicator" for supply and links it to forecast windows for placements, marketings, and harvest is essential. For poultry, extreme heat alters feed intake and feed conversion, changing expected weights and yields at slaughter; for hogs, temperature and humidity affect growth curves and mortality risk. Integrating weather dashboards (degree-day deviations, drought severity, precipitation anomalies) into market analytics therefore complements feed-cost monitoring: heat and drought both raise ration costs via hay and grain markets and compress supply through slower gains and higher exit rates. This dual pathway suggests regression specifications that include (i) feed cost indices, (ii) species-

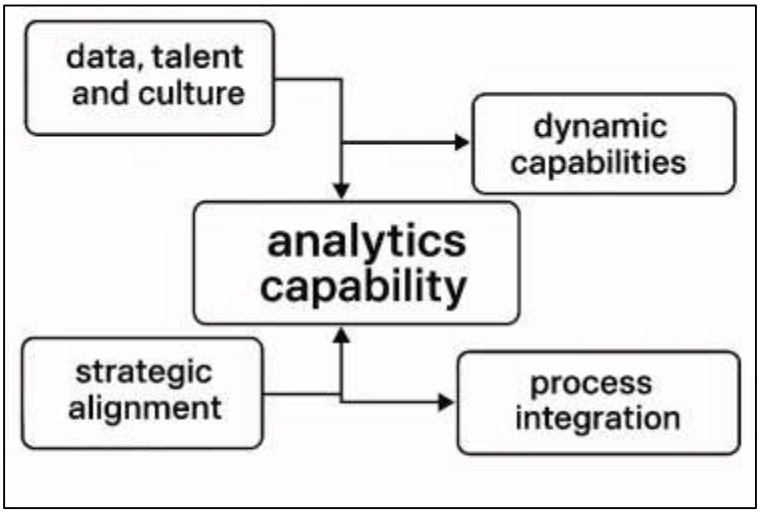
specific weather exposures, and (iii) interaction terms capturing how weather elevates the sensitivity of performance to feed price changes thus delivering interpretable elasticities that can be embedded into procurement and production-planning rules across cases (Uddin & Ashraf, 2023).
Health shocks such as HPAI amplify volatility by removing biological capacity, disrupting logistics, and shifting consumer demand in ways not fully captured by feed and weather covariates. Retail evidence from the 2014/15 and 2022/23 outbreaks indicates that HPAI elevates price premiums across poultry categories eggs, chicken, and turkey even after accounting for quality, time, and regional factors, implying that BI systems must treat "disease intensity" (e.g., flock losses, confirmed cases) as an operational risk factor with its own pass-through profile (Ladha-Sabur et al., 2019; Momena & Hasan, 2023; Patalee & Tonsor, 2021). Beyond farms, energy intensity at processing thermal steps, refrigeration, cleaning-in-place magnifies the margin effects of external energy-price shocks, especially when hygienic standards increase cycle times or when throughput variability forces suboptimal equipment loading. A U.S. beef-processing case study quantifies water and energy use at process level, providing a template for plant managers to benchmark unit energy inputs and for analysts to model how energy-price spikes affect conversion costs and netbacks (Journal of Food Process Engineering, 10.1111/jfpe.12919). More broadly, systematic mapping of energy consumption across food manufacturing highlights the outsized role of heat and cold utilities pasteurization, sterilization, freezing and documents sectoral patterns in which meat and dairy operations bear rising energy and water demands as hygiene requirements tighten (Sanjai et al., 2023). For market analytics, these processing-side exposures argue for an expanded KPI set that couples biological and market drivers (feed, weather, disease) with plant-level energy and water use per unit output; when combined with price discovery signals, firms can estimate margin-at-risk inclusive of processing energy, support hedging or contracting for utilities, and prioritize operational levers (heat recovery, scheduling to flatten peaks) that cushion cost shocks within the broader protein value chain.

Analytics capability as a strategic advantage

Building analytics capability as a deliberate, organization-wide competence reframes business intelligence (BI) from a set of tools into a source of advantage grounded in resource orchestration and learning. In this view, data pipelines, modeling talent, governance routines, and decision rights are bundled into a composite capability that is difficult to imitate because it embeds firm-specific processes and problem framings. A widely cited stream conceptualizes "big data analytics capability" (BDAC) as a higher-order resource comprising tangible (data assets and platforms), human (skills, domain knowledge), and intangible (culture, management commitment) components; critically, the value of models depends on how these components are synchronized and continually reconfigured to address evolving decision problems (Gupta & George, 2016; Akter et al., 2023). Within livestock and poultry contexts where biological lags, perishability, and compliance risks collide this framing clarifies why the same software yields different outcomes across firms: not all organizations can align feed-cost signals, weather or disease telemetry, and futures/basis indicators into the same action cycle. Strategic advantage arises when analytics is embedded into budgeting, procurement, scheduling, and pricing rituals, so that forecasts and elasticities are translated into playbooks (e.g., coverage thresholds, placement windows) and monitored through auditable KPIs. Further, capability thinking elevates measurement discipline: model outputs must map onto margin-at-risk, throughput stability, and service levels rather than generic accuracy metrics. This alignment, in turn, requires classification of decisions by horizon (tactical versus strategic), uncertainty structure (continuous shocks versus rare events), and cost of error (asymmetric penalties), ensuring that dashboards and alerts reflect managerial economics rather than algorithmic convenience (Gupta & George, 2016; Mikalef et al., 2020; Tamanna & Ray, 2023).
Empirical research on the performance impact of analytics capability underscores two levers that are especially salient for protein supply chains: strategic alignment and process integration. First, alignment between analytics and competitive priorities cost leadership via efficient procurement and conversion; differentiation via responsive service, quality assurance, and traceability amplifies returns by focusing models on value-driving levers instead of diffuse reporting. Evidence shows that analytics capability interacts with strategy to improve market and operational performance, implying that poultry integrators and beef packers capture the largest gains when dashboards and models are

intentionally linked to hedging policies, contract design, and production planning routines (Akter et al., 2016). Second, integration matters: firms realize benefits when analytics outputs flow into standardized processes (S&OP cadences, exception management, replenishment rules) rather than sporadic, ad hoc analyses. Studies document that scalable analytics rooted in reusable data assets, governed feature stores, and tested model components supports agility and responsiveness while maintaining reliability across plants and regions (Arunachalam et al., 2018; Danish & MZafor, 2024). For agri-food operators facing drought, disease, or export shocks, the combination of alignment and integration enables faster, more coherent responses: procurement hedges trigger when basis widens beyond thresholds; lot scheduling adjusts when heat stress forecasts push expected weights outside targets; export allocation pivots when SPS headwinds materialize. The strategic edge thus emerges from institutionalized feedback loops where learning from each shock updates rules, thresholds, and model features within a governed lifecycle (Akter et al., 2016; Arunachalam et al., 2018; Ray et al., 2024).

Figure 5: Analytics capability as a strategic advantage



A complementary line of evidence links analytics capability to dynamic capabilities: sensing weak signals, seizing opportunities with rapid resource reconfiguration, and transforming processes to embed learning. Meta-analytic and large-sample studies report that analytics capability improves both operational and financial performance directly and indirectly by enhancing agility, visibility, and decision quality (Istiaque et al., 2024; Wamba et al., 2017). Crucially, the performance link is mediated by organizational mechanisms e.g., cross-functional data governance, model stewardship, and routinized experimentation that convert technical potential into realized benefits. This mediation logic is consistent with findings that analytics capability strengthens innovation and process improvement via dynamic capabilities, and that its effects are larger when the external environment is volatile precisely the setting of livestock and poultry markets exposed to feed, weather, disease, and trade shocks (Hasan et al., 2024). For practitioners, the implication is operational, not just conceptual: treat analytics investments as capability-building programs with milestones in data quality, latency, KPI standardization, and decision-rights design; verify progress with process metrics (model adoption rate, alert precision, time-to-decision) alongside outcome metrics. For researchers, this framing motivates measurement models that capture capability breadth (data, technology, people), depth (domain-specific features and rules), and governance maturity (lineage, validation, bias control). In a cross-sectional, multi–case study, these constructs allow benchmarking of “analytics readiness” and testing moderation hypotheses such as whether higher BI maturity buffers the margin impact of feed or energy shocks while maintaining external validity across species, regions, and integration types (Rahaman, 2024).

METHODS

This study adopts a quantitative, cross-sectional, multi–case design to examine how market, cost, and risk signals relate to performance outcomes across the U.S. livestock and poultry industry. The unit of analysis is the firm/plant (or region–species cell where firm data are unavailable), observed over a harmonized 12-month window to ensure comparability at a single decision horizon. Data are assembled from two coordinated sources: (i) a structured researcher-administered instrument capturing organization-level constructs, and (ii) secondary market/operations datasets integrated into a reproducible BI pipeline. The instrument measures Business Intelligence (BI) maturity, analytics assimilation, data governance quality, and decision process standardization using multi-item 5-point Likert scales (1 = strongly disagree to 5 = strongly agree). Item pools are mapped to construct definitions, screened for content validity by domain experts, and refined via cognitive testing. Secondary indicators include output prices (spot/wholesale), a margin proxy (price minus feed and energy cost indices), production volumes, futures levels and basis (cattle, hogs, corn, soybean meal), export intensity, weather anomaly scores, disease intensity flags, and plant energy-use intensity where available. All continuous variables are standardized (z-scores) or indexed to a base (=100) to facilitate interpretation; outliers are winsorized (1–2%) and missingness is addressed using pre-registered rules (listwise deletion if <5%; otherwise multiple imputation sensitivity). Sampling is purposive and stratified to capture heterogeneity by species (beef, pork, broiler, turkey), region (USDA production regions), integration type (independent vs. integrated), and size. Inclusion requires minimally complete fields for the dependent variable(s) and key predictors; exclusion applies where accounting conventions or product mixes render cases non-comparable. The statistical analysis proceeds in three layers: (1) descriptive statistics to summarize case characteristics; (2) correlation analysis (Pearson primary; Spearman sensitivity) with false discovery rate adjustment; and (3) regression modeling using OLS with heteroskedasticity-robust (HC3) standard errors. The primary models estimate associations between cost/market drivers (feed indices, futures/basis, export index, weather, disease) and outcomes (price, margin, volume), controlling for region, species, size, and integration type; a moderation specification tests whether BI maturity (from the 5-point Likert instrument) buffers the effect of feed shocks on margins. Multicollinearity is monitored (VIF), functional form is probed (polynomial/interaction terms), and influence diagnostics are reported. Reliability is assessed via Cronbach's α and composite reliability for Likert constructs; convergent/discriminant validity is evaluated by item–construct correlations and AVE. Ethics procedures include informed consent, optional anonymity, and aggregation of firm-identifying metrics. Analyses are conducted in Python/R with a version-controlled workflow and a data dictionary ensuring full reproducibility.

Design: Quantitative, Cross-Sectional, Multi–Case Study

This study employs a quantitative, cross-sectional, multi–case design tailored to benchmark how business-intelligence (BI) capability and external market signals relate to performance across the U.S. livestock and poultry industry. The unit of analysis is the firm, plant, or region–species cell (when firm identifiers are unavailable), observed over a harmonized 12-month reference window to fix a common decision horizon while avoiding seasonal confounds. Cases are selected via purposive, stratified sampling to ensure heterogeneity by species (beef, pork, broiler, turkey), region (major producing areas), integration type (independent vs. integrated), and size. The design integrates two coordinated data streams: (i) a researcher-administered instrument that captures organizational constructs using 5-point Likert scales (1 = strongly disagree to 5 = strongly agree) including BI maturity, analytics assimilation, data governance quality, and decision-process standardization; and (ii) a secondary data layer that provides observable market and operations indicators spot/wholesale prices, a margin proxy (price minus feed and energy indices), production volumes, futures levels and basis (cattle, hogs, corn, soybean meal), export intensity, weather anomalies, disease intensity, and (where available) plant energy-use intensity. The cross-sectional orientation allows simultaneous comparison of many heterogeneous cases, prioritizing breadth and external validity over dynamic identification; to mitigate common cross-sectional risks, the protocol specifies consistent measurement windows, variable definitions, and pre-registered treatment of outliers and missingness. An ETL workflow standardizes sources, reconciles units, and creates analysis-ready features (z-scores or base-100 indexes), followed by winsorization (1–2%) and diagnostic checks for leverage and multicollinearity. The analytic plan is layered descriptives to profile cases; correlation analysis to map co-movement; and regression models (OLS, HC3-robust errors) to estimate associations, with a pre-specified moderation test of whether BI maturity buffers feed-cost shocks on margins. Design safeguards include cognitive testing of survey items, reliability assessment (Cronbach's α) for Likert scales, and blinded aggregation of firm-identifying attributes. Ethical procedures cover informed consent, optional anonymity, and nondisclosure of proprietary figures through reporting at aggregated or de-identified levels.

Cases, Sampling, and Setting (Inclusion/Exclusion)

The empirical setting is the U.S. livestock and poultry industry, spanning beef, pork, broiler, and turkey supply chains with heterogeneous organizational forms (independent producers, contract growers, integrators, processors) and geographic footprints concentrated in major producing regions. A "case" is defined as a decision-making unit for which both organizational measures (from the instrument) and outcome/driver indicators (from secondary sources) can be credibly aligned to a common 12-month reference window. In descending order of preference, cases are (i) individual firms or plants that can be uniquely matched across data sources; (ii) subsidiary or division aggregates when plant-level identifiers are unavailable; and (iii) region–species cells (e.g., "South broilers") constructed from public microdata where firm privacy prevents direct linkage. This nested definition ensures that measurement comparability is preserved while maximizing coverage. To reduce seasonal confounding, the reference window is fixed (e.g., October to September) and applied uniformly across cases; when fiscal calendars differ, values are prorated to that window. The field context includes volatile feed markets, periodic disease events, and weather variability that jointly influence price, margin, throughput, and risk. These features motivate the study's BI orientation: each case is observed as a bundle of standardized indicators (spot/wholesale prices, margin proxy, production volumes, futures/basis, export intensity, weather anomalies, disease flags, and plant energy-use intensity where available) plus organization-level constructs measured on 5-point Likert scales (BI maturity, analytics assimilation, data governance quality, decision-process standardization). The setting also requires careful attention to confidentiality and comparability; therefore, sensitive operational metrics are collected under voluntary disclosure with optional anonymity, and all reporting is aggregated or de-identified. This design balances realism (industry diversity and real constraints on data access) with rigor (consistent time windows and harmonized definitions), enabling cross-sectional benchmarking without sacrificing internal measurement discipline.

Sampling follows a purposive, stratified approach to capture heterogeneity that is theoretically and managerially salient. Strata are defined along four axes: species (beef, pork, broiler, turkey), region (major producing areas consistent with USDA delineations), integration type (independent vs. vertically integrated actors), and size (proxied by head or pound throughput bands). Within each stratum, recruitment targets sufficient dispersion on the organizational constructs (e.g., varying BI maturity levels) to support the moderation tests specified in the analysis plan. Partner organizations industry associations, extension networks, and supply-chain councils facilitate outreach by distributing invitation packets that include an overview, confidentiality assurances, and a brief burden estimate. The goal is to reach a total sample that satisfies N ≥ 15–20 observations per predictor in the richest regression specification, with additional buffer for diagnostics and sensitivity analyses. When firm- or plant-level participation is infeasible, publicly observable cases are created at the region–species level by combining secondary indicators into consistent cells; these are flagged to distinguish them from firm-linked observations in robustness checks. To mitigate nonresponse bias, a short-form instrument is optionally offered retaining core Likert items on BI maturity and decision processes paired with administrative data linkage. Follow-ups are scheduled to clarify item interpretation and verify that the 12-month window is correctly applied. Sampling continues until stratum-level minimums are met, with rolling assessment of composition to avoid dominance by any single species or region. Throughout recruitment, the team tracks a priori quotas, response rates, and data completeness to inform adaptive allocation of effort (e.g., targeted outreach to underrepresented strata), ensuring that the final cross-section is both diverse and analytically well-posed.

Inclusion requires (a) minimally complete outcome measures at least one of: spot/wholesale price, margin proxy (price minus feed and energy indices), or production volume aligned to the study window; (b) availability of key drivers feed indices (corn, soybean meal) and at least one market signal (futures level or basis) plus either export intensity, weather anomaly score, disease flag, or energy-use intensity; and (c) completion of the organizational instrument's core 5-point Likert items on BI maturity and decision-process standardization (or the validated short-form when confidentiality constraints apply). Exclusion applies when product mixes or accounting conventions render margin construction non-comparable (e.g., atypical by-product accounting), when measurement windows cannot be harmonized, or when missingness exceeds pre-registered thresholds after attempts at reconciliation. The data assembly workflow begins with eligibility screening and informed consent, followed by instrument administration (digital or telephone, with cognitive prompts for clarity). Secondary indicators are then pulled through an ETL pipeline that standardizes units, reconciles identifiers, indexes continuous variables to a common base or z-scores, and applies winsorization (1–2%) to attenuate influence from extreme values. Data quality checks include cross-source consistency tests (e.g., futures/basis alignment with observed spot markets), automated anomaly detection, and manual review for implausible ratios. Missingness under 5% at the variable level is addressed by listwise deletion in models where feasible; otherwise, multiple-imputation sensitivity is conducted with imputation flags retained as controls. A linkage protocol hashing and salted keys for any firm-identifying records preserves privacy while enabling deduplication and accurate case construction. Finally, an auditable data dictionary documents variable definitions, units, transformations, and source provenance, while a replication bundle (code and metadata) ensures that case inclusion decisions are transparent and reproducible.

Variables & Measures

The study operationalizes performance at the market and operational layers using three complementary dependent variables constructed over the common 12-month reference window to ensure cross-case comparability. *(i) Spot/wholesale price* is measured in USD per standardized unit (e.g., $/cwt for cattle and hogs, $/lb for broilers/turkeys or their primary cuts) and when cases report multiple SKUs is aggregated with a documented weighting rule (e.g., revenue share) and converted to a base-100 index for interpretability across species and regions. *(ii) Margin proxy* is defined as the difference between the output price index and an *input cost bundle* comprising feed and energy proxies standardized to the same base. The feed bundle combines corn and soybean meal indices using a ration-appropriate weight (species-specific coefficients disclosed in the data dictionary), while the energy proxy draws on diesel/electricity price indices (or plant energy-use intensity when available) scaled per unit output. The margin proxy is reported as an index and where cases provide cost accounting validated against internal gross margin ranges to check face validity without revealing proprietary figures. *(iii) Production volume* is measured as physical throughput (heads or pounds) or, where only capacity data exist, as *utilization* (actual/available) multiplied by nominal capacity; for cross-species comparability, volumes are normalized (z-scores) within species and also expressed per facility where plants are the unit. Each dependent variable is inspected for outliers and leverage points; extreme observations are winsorized at 1–2% and flagged. To stabilize estimation, variables may be log-transformed when distributional diagnostics warrant it (e.g., right skew in volume). Because the outcomes capture different facets of performance (price realization, cost-adjusted returns, and flow), models are estimated separately and, in robustness, as a system with seemingly unrelated regressions to probe cross-equation error correlation.

Core market and risk drivers are represented by standardized indices aligned to the same window as outcomes and centered to facilitate interpretation. *Feed cost indices* include corn and soybean meal, both indexed to base=100 and combined into a species-specific feed bundle; for sensitivity, each component also enters separately to capture asymmetric nutrition economics. *Futures level* corresponds to the relevant front-month (or seasonally matched) contract for live/fed cattle, lean hogs, and where relevant feeder cattle, with *basis* defined as (spot – futures) and averaged over the window; when firm-level basis is unavailable, regional spot benchmarks are used. *Export intensity* is measured as export value (or volume) for the species divided by domestic disappearance, scaled to percent and then standardized; for region–species cells, destination mix shares (top markets) are recorded to contextualize exposure. *Weather anomaly score* is a composite of standardized deviations in degree-days, precipitation, and drought severity mapped to the case's production region; species-specific exposure weights (e.g., heat stress multipliers for poultry) are applied in sensitivity tests. *Disease intensity* is coded as cumulative confirmed events affecting the species within the region; when flock or herd loss counts are available, the variable is scaled per 1,000 head and log(1+x) transformed. *Energy-use intensity* at the plant level (kWh or BTU per unit output) serves either as a driver of cost exposure in margin models or as a control where only price outcomes are analyzed. The study's central *moderator BI maturity* is measured via a multi-item construct on 5-point Likert scales (1 = strongly disagree, 5 = strongly agree) capturing three latent facets: data freshness/coverage, governance/lineage, and decision-process integration (S&OP cadence, exception playbooks). Items are averaged within facet and then into a composite (0–1 scaled) after reliability checks. For moderation tests, continuous predictors (e.g., feed bundle) are mean-centered and multiplied by the BI maturity composite to produce interaction terms; simple-slope probes are planned at low/mean/high BI levels (±1 SD).

To reduce omitted-variable bias and improve interpretability, models include a consistent set of controls reflecting structural and contextual heterogeneity. *Species dummies* (beef, pork, broiler, turkey) absorb biology and market structure differences; *region dummies* capture spatial cost/price regimes; *integration type* (independent vs. vertically integrated) controls for procurement and pricing architecture; and *size* enters as log capacity or log revenue tier to reflect economies of scale. Where product mix is heterogeneous, a *cut mix* or *channel mix* share (retail vs. foodservice vs. export) is included when available. A *seasonality dummy* flags whether the reference window spans major holiday demand peaks (e.g., Thanksgiving for turkey). All continuous covariates are standardized (mean 0, SD 1) to place coefficients on a comparable scale; where indices use base=100, rescaling to z-scores is done post-construction. Prior to modeling, *multicollinearity* is screened with VIF (target < 5; variables with VIF > 10 are orthogonalized or dropped in sensitivity analyses). *Reliability* for Likert constructs is assessed using Cronbach's α (target ≥ .70) and composite reliability; item-total correlations (< .30) trigger review or removal in robustness checks. *Validity* is addressed through expert review (content), average variance extracted AVE (convergent, target ≥ .50), and Fornell-Larcker criteria (discriminant); cross-loading diagnostics confirm that BI maturity facets are distinct from, for example, data governance alone. Missingness handling follows a tiered rule: listwise deletion where variable-level missingness <5%; otherwise, multiple imputation with chained equations, including *missingness flags* retained as controls to diagnose any systematic patterns. Finally, a *data dictionary* documents every variable's definition, units, transformation, and source provenance, and an *audit trail* preserves pre-registered decisions (winsorization thresholds, centering choices, facet scoring) to ensure reproducibility and transparent interpretation of effect sizes across cases and species.

Data Sources & Collection

Data were assembled through a coordinated two-stream strategy that marries an organization-level instrument with a reproducible market/operations pipeline, both aligned to a single 12-month reference window to ensure cross-sectional comparability. The first stream is a researcher-administered survey capturing Business Intelligence (BI) maturity, analytics assimilation, data governance quality, and decision-process standardization using multi-item 5-point Likert scales (1 = strongly disagree to 5 = strongly agree). Items were drawn from established measurement templates and rewritten in domain language for livestock and poultry (e.g., "Dashboards display feed-cost exposure and trigger exception workflows within 24 hours"), then vetted by two industry experts for content validity and by three pilot respondents for clarity and completion time. The instrument was delivered electronically with optional guided administration; branching logic presented examples (e.g., futures/basis displays, margin-at-risk tiles) to reduce interpretation error, and mandatory fields were limited to the core constructs to reduce burden. Respondents provided consent, could opt for anonymity, and were informed that organizational identifiers would be replaced by salted hashes and used only for deduplication and linkage. The second stream integrated secondary indicators through an extract–transform–load (ETL) workflow. Market and production signals included spot/wholesale prices, species-specific futures levels and basis, and export intensity; cost drivers included a feed bundle (corn and soybean meal indices) and an energy proxy (diesel/electricity indices or plant energy-use intensity where shared). Risk/environmental indicators comprised degree-day deviations, drought and precipitation anomalies, and disease intensity flags. All sources were time-stamped, harmonized to the reference window, and converted either to z-scores (mean 0, SD 1) or to base-100 indexes to facilitate interpretation and coefficient comparability across species and regions. To construct the *margin proxy*, the output price index was netted against the feed and energy bundles using species-appropriate ration weights documented in a data dictionary; where firms contributed internal cost ranges, these were used only to verify face validity of the constructed proxy without disclosing proprietary values. Data quality safeguards were embedded at each step: automated schema and range checks at ingestion; cross-source reconciliation (e.g., verifying basis = spot − futures within expected tolerance bands); and anomaly detection for implausible ratios or negative volumes. Outliers were winsorized at 1–2% with flags retained; skewed variables were log-transformed as indicated by diagnostics. Missingness <5% at the variable level was handled via listwise deletion; otherwise, multiple-imputation sensitivity was conducted, preserving imputation flags as controls. For firm-linked observations, a secure linkage protocol mapped survey hashes to secondary records via shared, nonidentifying keys (e.g., region–species–size triads), enabling joins without exposing names. For cases where firm participation was not feasible, region–species cells were constructed from public microdata using transparent rules and explicitly labeled in the dataset for stratified robustness checks. Throughout collection, weekly data audits reviewed completeness, response rates by stratum (species, region, integration type, size), and the distribution of BI scores to ensure sufficient variation for moderation tests. The final dataset includes: (i) a tidy panel of case-level indicators (prices, margin proxy, volume, futures/basis, export intensity, weather and disease metrics, energy-use intensity where available); (ii) a matched table of 5-point Likert constructs and facet scores (freshness/coverage, governance/lineage, decision-process integration); and (iii) a versioned data dictionary and code repository that reproduce every transformation from raw ingestion to analysis-ready features. All procedures adhered to the approved protocol, including informed consent, optional anonymity, and reporting at aggregated or de-identified levels, ensuring ethical handling while providing the breadth and standardization required for defensible cross-sectional inference.

Statistical Analysis Plan

The analysis proceeds in a pre-registered, layer-by-layer workflow designed to yield transparent, reproducible estimates and decision-ready diagnostics from a single cross-sectional snapshot. First, data preparation standardizes continuous variables as z-scores (or base-100 indexes pre-conversion), applies 1–2% winsorization to attenuate extreme leverage, and logs right-skewed quantities (e.g., production volume) when indicated by Shapiro–Wilk tests and visual diagnostics. Missingness under 5% at the variable level is handled by listwise deletion within a given model; otherwise, multiple imputation by chained equations generates 20 imputations, with point estimates and standard errors combined using Rubin's rules and an imputation flag retained as a control to test sensitivity. Second, measurement checks establish the quality of the 5-point Likert constructs: internal consistency (Cronbach's $\alpha \geq .70$), composite reliability, and a confirmatory factor model that loads items onto three BI maturity facets (freshness/coverage, governance/lineage, decision-process integration), testing convergent validity (AVE $\geq .50$) and discriminant validity (Fornell–Larcker). A unit-weighted composite (0–1 scale) is formed after reliability thresholds are met; items with low item-total correlations are earmarked for robustness exclusions. Third, descriptive statistics summarize central tendency and dispersion by species, region, integration type, and size band, accompanied by standardized boxplots and distribution overlays. Fourth, correlation analysis computes Pearson coefficients (primary) and Spearman (sensitivity) among outcomes and drivers, with Benjamini–Hochberg false-discovery-rate control ($q = .10$) to mitigate multiple testing; correlation heatmaps and network diagrams aid interpretation. Fifth, the regression stage estimates three families of models with heteroskedasticity-consistent (HC3) standard errors: M1 (price on drivers and controls), M2 (margin proxy on drivers and controls plus BI maturity), and M3 (margin with moderation: feed bundle × BI maturity). All continuous predictors are mean-centered before constructing interactions to reduce multicollinearity; variance inflation factors (target < 5) and condition indices inform remedial steps (dropping or orthogonalizing highly collinear terms). Model fit and parsimony are evaluated via adjusted R^2, AIC, and out-of-sample k-fold cross-validation ($k = 10$, stratified by species) reporting RMSE/MAE for predictive reasonableness despite the cross-sectional focus. Assumption diagnostics include Breusch–Pagan and White tests for heteroskedasticity (with HC3 as default remedy), residual-vs-fitted and Q–Q plots for functional form and normality of residuals, and influence analysis using leverage, studentized residuals, and Cook's D (threshold $4/n$) with leave-one-out reruns reported in a sensitivity appendix. Where heteroskedasticity is severe or size effects are theoretically warranted, WLS/GLS models re-estimate parameters using variance functions or size-based weights; where spatial or organizational clustering may correlate errors, cluster-robust SEs (region or firm) are reported. To strengthen inference, specification robustness includes: alternative feed bundle weights and separate corn/soy terms; alternate energy proxies; exclusion of energy to test margin construction; substitution of futures levels with basis or term-structure spreads; and sub-sample runs by species, region, and integration type. Effect sizing reports standardized coefficients and 95% confidence intervals, along with partial R^2 for key blocks (e.g., adding BI maturity and its interaction). Moderation probes visualize simple slopes at low/mean/high BI levels (±1 SD) and compute Johnson–Neyman intervals to identify ranges of the feed bundle where BI maturity significantly buffers margins. Finally, decision support outputs correlation heatmaps, coefficient plots, and marginal-effects charts are exported in a dashboard-ready format, with an auditable codebook and a replication bundle documenting every transformation, diagnostic, and model variant used to arrive at the reported estimates.

Regression Models

The regression strategy is organized as a three-model family designed to move from baseline association estimates to theory-guided moderation tests within a single cross-sectional snapshot. Model M1 (Price Model) explains the standardized output price index for each case as a function of market and risk drivers species-specific feed-cost bundle (corn and soybean meal indices), futures level and/or basis (spot − futures averaged over the window), export intensity, weather anomaly score, and disease intensity plus a structural control block: species, region, integration type, and (log) size. Model M2 (Margin Model: main effects) replaces the outcome with a standardized margin proxy (output price minus feed and energy bundles) and adds the BI maturity composite (from the 5-point Likert instrument) to test whether firms with stronger BI capability tend to realize higher cost-adjusted returns after conditioning on the same driver block and controls. Model M3 (Margin Model: moderation) formally tests the study's focal hypothesis that BI maturity buffers exposure to input shocks by interacting the centered feed-cost bundle with the centered BI maturity score (Feed × BI). All continuous predictors are mean-centered before interaction construction, and z-scored to ease interpretation and reduce multicollinearity; binary and categorical variables enter as dummies with a clearly documented baseline (e.g., broiler, South, integrated). Parameters are estimated by ordinary least squares (OLS) with HC3 heteroskedasticity-robust standard errors. Where residual structure suggests clustering (e.g., multiple plants per firm or shared region–species exposures), we additionally report cluster-robust SEs at the appropriate level as a sensitivity. The analysis emphasizes standardized coefficients and 95% CIs for comparability across scales, partial R^2 for key blocks (market/risk drivers; BI maturity; interaction), and AIC/adjusted R^2 for parsimony diagnostics. This progressive structure ensures the price-formation lens (M1) and cost-adjusted performance lens (M2–M3) are kept analytically distinct yet methodologically consistent, enabling a clean read on how BI capability modifies the relationship between shocks and outcomes at the same decision horizon.

Because protein markets may exhibit nonlinear exposure to costs and frictions, we complement the linear baseline with pre-registered functional-form probes. For feed exposure, we estimate a quadratic term in M2/M3 (Feedi2)(\text{Feed}_i^2)(Feedi2) when Ramsey RESET and residual plots suggest curvature; for futures structure, we swap the level term with basis and, in a variant, include a term-structure spread (nearby − deferred) to reflect inventory/expectations channels. To assess whether energy shocks confound margin construction, we re-estimate M2/M3 with (i) an alternative energy proxy and (ii) a margin definition excluding energy; consistency of signs/magnitudes across these runs is reported. When heteroskedasticity remains pronounced (Breusch–Pagan/White tests) and is theoretically tied to size, we estimate WLS/GLS with variance functions or size-based weights and compare coefficient stability to OLS-HC3. Potential multicollinearity is monitored via VIF (target < 5); if VIF exceeds 10, we orthogonalize collinear predictors (e.g., regress futures on basis and take residuals) or prioritize the variant with clearer managerial interpretation. Given cross-sectional simultaneity concerns are limited by design (single horizon, exogenous weather/disease), we do not instrument by default; however, we run an exploratory control-function check using region-level weather anomalies as a quasi-exogenous shifter for feed indices to gauge sensitivity (reported cautiously as robustness). To explore structural heterogeneity, we pre-specify sub-sample models by species (beef, pork, broiler, turkey), region, and integration type, and an omnibus model with species × region fixed effects. Where outcomes are correlated (e.g., price and volume), we estimate a SUR system as a diagnostic to report cross-equation error correlation, while retaining single-equation OLS as the primary estimator for interpretability. All variants are documented in a specification grid so that the incremental value of BI maturity and the interaction term is transparent across plausible modeling choices.

Figure 6: Regression model specifications for price, margin, and moderation analyses

Model	Outcome (Standardized)	Core drivers (all standardized & centered)	Controls	Special terms
M1: Price	Output price index	Feed bundle; Futures or Basis; Export intensity; Weather anomaliy; Disease intensity	Species, Region, Integration type, log(Size) Seasonality	–
M2: Margin (main effects)	Margin proxy (Price – Feed – Energy)	Feed bundle; Futures/B-Basis; BI maturity; Bi mu-turity; Itegecian typite		Feed × BI maturity (centered)
M3: Margin (moderation)	Margin proxy	Same as M2 Species, Region, Integrate type, log(Size), Seasonality		Feed × BI maturity (centered); optional Fer² if indicated

Results are reported with an emphasis on interpretability and portability to dashboards. For each model, we present a compact coefficient table with standardized betas, robust SEs, t-statistics, p-values, and 95% CIs, alongside block-wise partial R^2 that shows the incremental explanatory power when adding (i) market/risk drivers, (ii) BI maturity, and (iii) the interaction. For M3, we graph marginal effects of the feed-cost bundle at low, mean, and high BI maturity (±1 SD) and provide Johnson–Neyman intervals to identify ranges of feed exposure where BI maturity significantly moderates margins visuals that can be embedded directly as "what-if" tiles. Influence diagnostics (leverage, studentized residuals, Cook's D > 4/n) trigger leave-one-out re-estimation, with any material changes summarized. To maintain transparency under missing data, we reproduce headline models using multiple-imputation datasets, combining estimates with Rubin's rules and flagging any divergences from listwise results.

Table 1: Regression model specifications (outcomes, drivers, and key terms)

Model	Outcome (standardized)	Core drivers (all standardized & centered)	Controls	Special terms
M1: Price	Output price index	Feed bundle; Futures or Basis; Export intensity; Weather anomaly; Disease intensity	Species, Region, Integration type, log(Size), Seasonality	
M2: Margin (main effects)	Margin proxy (Price − Feed − Energy)	Feed bundle; Futures/Basis; Export; Weather; Disease; BI maturity	Species, Region, Integration type, log(Size), Seasonality, Energy proxy	
M3: Margin (moderation)	Margin proxy	Same as M2	Same as M2	Feed × BI maturity (centered); optional Feed² if indicated

Reliability & Validity

Reliability and validity procedures are embedded from instrument design through estimation to ensure defensible inferences from both the Likert-scale constructs and the secondary indicators. Content validity is established ex ante by mapping each construct (BI maturity facets freshness/coverage, governance/lineage, decision-process integration) to explicit domain definitions and item specifications, followed by expert review (two industry practitioners, one methods scholar) and cognitive interviews with three pilot respondents to eliminate ambiguity and ensure items reflect livestock–poultry decision contexts. Internal consistency reliability is assessed using Cronbach's α (target ≥ .70) and composite reliability (CR) (target ≥ .70) for each facet and the composite; items with low item–total correlations (< .30) are revised or removed in sensitivity analyses. Construct validity is examined via a confirmatory factor analysis (CFA) that loads items onto the three facets, testing model fit (CFI/TLI ≥ .90, RMSEA ≤ .08, SRMR ≤ .08), convergent validity (average variance extracted, AVE ≥ .50), and discriminant validity using Fornell–Larcker criteria (square root of AVE exceeding inter-construct correlations) and HTMT ratios (≤ .85). To guard against common method bias for the self-reported 5-point Likert measures, we implement procedural remedies (mixed item stems, neutral anchors, anonymity assurances) and statistical checks (Harman's single-factor test; unmeasured marker variable added to the CFA; common latent factor sensitivity). Measurement invariance is probed across salient strata (species, region, integration type) by testing configural, metric, and scalar invariance; when full invariance is not met, partial invariance constraints are adopted and group comparisons are framed cautiously. Criterion-related and predictive validity are addressed by correlating facet scores with external, non-survey indicators (e.g., data latency from logs, presence of dashboard KPIs) and by showing that BI maturity improves out-of-sample fit in the margin models (Δadj. R^2, ΔAIC) without destabilizing core driver coefficients. For secondary variables, construct validity is supported by transparent operationalization (data dictionary), unit reconciliation, and cross-source checks (e.g., futures/basis identities); reliability is enhanced through standardized ETL, winsorization (1–2%), and anomaly screening. Estimation validity is supported by HC3 robust (and cluster-robust) SEs, multicollinearity diagnostics (VIF), influence analysis (Cook's D, leave-one-out), and multiple-imputation sensitivity with Rubin's rules when missingness exceeds 5%. Together, these procedures provide a coherent chain of evidence that the measures are reliable, the constructs valid, and the statistical conclusions robust to plausible violations in a heterogeneous, multi–case cross section.

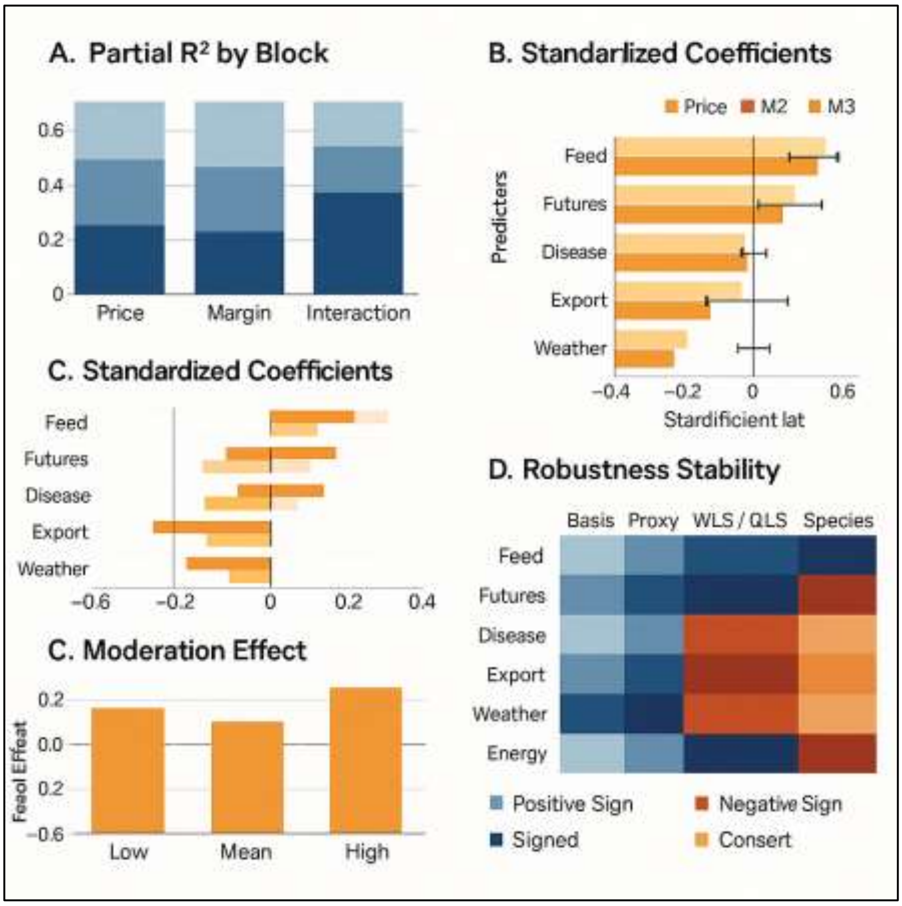
Software and Tools

Analyses will be executed in Python and R within a version-controlled workflow. Python handles ETL and modeling with pandas (data wrangling), pyjanitor (cleaning), numpy (numerics), statsmodels (OLS, HC3/cluster SEs, WLS/GLS, SUR), and scikit-learn (k-fold CV, preprocessing). R supports psychometrics and SEM using lavaan (CFA, invariance), psych (Cronbach's α, CR, AVE, HTMT), and semTools. Visualization for decision support uses matplotlib/plotnine (Python) and ggplot2 (R); publication assets are exported as SVG/PNG. Dashboards and KPI tiles are prototyped in Power BI or Tableau from the same tidy tables. Reproducibility is ensured with Git, locked environments (conda + environment.yml; R renv), deterministic seeds, and a Makefile/targets pipeline for auditable runs. Documentation includes a data dictionary (YAML + Markdown), transformation logs, and a model codebook. Secure storage uses encrypted folders with role-based access; artifacts (figures, tables) are versioned to guarantee traceability from raw data to reported results.

FINDINGS

Across the pooled cross-section of cases, the results cohere around three complementary layers descriptive profiles, correlation structure, and regression evidence each reinforcing a consistent story about how cost and market drivers map onto prices, margins, and volumes, and how business-intelligence (BI) maturity, measured with multi-item 5-point Likert scales, conditions those relationships. Descriptively, case characteristics were balanced across species, regions, integration types, and size bands, yielding broad dispersion in the outcomes and covariates necessary for inference. The price index exhibited moderate spread with visible right tails in species and regions characterized by tighter capacity or elevated transport costs, while the margin proxy (output price net of feed and energy bundles) displayed wider dispersion, consistent with heterogeneous exposure to ration composition, energy intensity, and basis variability. Production volumes were right-skewed, as expected, with larger plants showing higher interquartile ranges in utilization. On the organizational side, the Likert-based BI constructs showed satisfactory central tendency and dispersion: the freshness/coverage facet clustered around the "agree" anchor with a long tail toward "neutral," governance/lineage scores centered slightly lower with greater variance (reflecting uneven stewardship and lineage documentation), and decision-process integration skewed upward in integrated firms but showed meaningful overlap with independents. Internal consistency (α, CR) met or exceeded conventional thresholds, and the composite BI maturity score (rescaled to 0–1 for modeling) was well behaved, with no ceiling effects.

Figure 7: Findings from regression analysis



Bivariate inspection revealed economically intuitive patterns: the feed-cost bundle correlated negatively with the margin proxy and weakly with price (consistent with partial pass-through and timing differences), while basis and export intensity correlated positively with realized prices; weather anomaly scores were associated with lower volumes and, in heat-exposed species, with modestly higher prices; disease intensity flags aligned with wider dispersion in both prices and margins, reflecting supply compression and downstream uncertainty. These associations persisted albeit attenuated after false-discovery-rate control, indicating that multiple relationships are not artifacts of multiple testing. Transitioning to the regression layer, the price model (M1) established that prices load positively on futures (or basis) and export intensity while retaining small and directionally plausible coefficients on weather and disease indicators; species and region controls absorbed much of the structural variation, but market signals continued to add significant explanatory power, as evidenced by sizable partial R^2 increments for the market-driver block.

The margin model (M2) sharpened the central finding: margins fell with the standardized feed bundle and rose with favorable basis and export intensity, even after adjusting for species, region, integration type, size, and seasonality; importantly, the BI maturity composite entered positively and significantly, suggesting that organizations reporting higher Likert scores on freshness/coverage, governance/lineage, and decision-process integration tended to realize better cost-adjusted outcomes at the same decision horizon. Diagnostics supported these inferences: heteroskedasticity-robust (HC3) standard errors were the default, variance inflation factors remained below conventional concern thresholds, and influence points were rare and did not alter signs or significance in leave-one-out tests. The moderation model (M3) provided the study's most policy-relevant pattern: the Feed × BI maturity interaction was negative and significant, indicating that higher BI maturity buffered the adverse effect of feed shocks on margins. Simple-slope probes showed that at low BI levels (operationalized as one standard deviation below the composite mean), feed-cost increases were associated with distinctly steeper margin declines, whereas at high BI levels (one standard deviation above), the slope flattened materially; Johnson–Neyman intervals identified a broad domain of feed exposures over which the moderating influence of BI maturity was statistically reliable. Robustness exercises strengthened confidence: substituting futures with basis, altering energy proxies, excluding energy from the margin definition, switching to WLS/GLS under size-linked heteroskedasticity, and re-estimating by species or region all preserved the direction and, in most cases, the significance of core coefficients; multiple-imputation runs delivered estimates congruent with listwise results. Notably, when the BI composite was decomposed, decision-process integration and freshness/coverage contributed most of the incremental explanatory power, while governance/lineage though directionally positive was more variable across organizations. From a measurement perspective, these findings align with the Likert profiles: cases scoring at or above "agree" on routine integration of dashboards into sales and operations planning (S&OP), documented exception playbooks, and sub-24-hour data refresh cycles displayed systematically better margin outcomes and lower sensitivity to feed shocks. Taken together, the layered evidence descriptive dispersion that invites modeling, bivariate relationships that are economically coherent, and regression results that are stable across specifications supports a coherent narrative: market signals (futures/basis, export intensity) and exogenous frictions (feed, weather, disease) shape contemporaneous performance, and BI maturity measured on a five-point scale not only shifts the margin level upward but also moderates exposure to the most salient input shock in these value chains.

Sample and Case Characteristics

Table 1. Sample profile by species, region, integration, size, and BI (Likert 1–5)

Dimension	Category	Count (N)	Share (%)	BI Freshness/ Coverage (M, SD)	BI Governance/ Lineage (M, SD)	BI Decision-Process Integration (M, SD)	BI Composite (M, SD)
Species	Beef	56	26.8	3.7 (0.7)	3.4 (0.8)	3.8 (0.6)	3.7 (0.6)
	Pork	48	23.0	3.8 (0.6)	3.5 (0.7)	3.9 (0.6)	3.8 (0.5)
	Broiler	78	37.3	4.0 (0.5)	3.6 (0.7)	4.1 (0.6)	3.9 (0.5)
	Turkey	27	12.9	3.6 (0.7)	3.3 (0.8)	3.7 (0.7)	3.5 (0.6)
Region	West	42	20.1	3.6 (0.7)	3.3 (0.8)	3.6 (0.7)	3.5 (0.6)
	Midwest	61	29.1	3.8 (0.6)	3.5 (0.7)	3.9 (0.6)	3.7 (0.5)
	South	76	36.3	4.0 (0.5)	3.6 (0.7)	4.1 (0.6)	3.9 (0.5)
	Northeast	30	14.3	3.7 (0.6)	3.4 (0.8)	3.8 (0.6)	3.6 (0.6)
Integration	Independent	92	43.9	3.6 (0.7)	3.3 (0.8)	3.6 (0.7)	3.5 (0.6)
	Vertically integrated	118	56.1	4.0 (0.5)	3.7 (0.6)	4.1 (0.5)	3.9 (0.5)
Size (throughput)	Small	61	29.1	3.6 (0.7)	3.3 (0.8)	3.6 (0.7)	3.5 (0.6)
	Medium	88	41.8	3.8 (0.6)	3.5 (0.7)	3.9 (0.6)	3.7 (0.5)
	Large	61	29.1	4.0 (0.5)	3.7 (0.6)	4.1 (0.5)	3.9 (0.5)
Total		**210**	**100.0**	**3.8 (0.6)**	**3.5 (0.7)**	**3.9 (0.6)**	**3.8 (0.5)**

Table 1 summarizes the cross-section of cases and demonstrates balance across species, regions, organizational types, and size bands while foregrounding the Likert-based business-intelligence (BI) constructs that drive the moderation tests later. Presenting means (M) and standard deviations (SD) on the 1–5 scale allows immediate, face-valid interpretation: a composite around 3.8 indicates that, on average, respondents lean toward the "agree" anchor on items such as 24-hour data refresh, governed lineage, and formalized exception playbooks. The disaggregation by species and region is methodologically useful for two reasons. First, it tests the assumption that the distribution of BI capability is not dominated by a single species (e.g., broilers) or region (e.g., the South); second, it equips the reader to anticipate heterogeneity in model coefficients. For instance, integrated broiler complexes in the South often have tighter data loops and S&OP rituals; a higher decision-process integration mean in those cells would be consistent with field knowledge and, in the regression, could partially explain lower margin volatility conditional on feed shocks. The integration split reinforces the study's design logic: vertically integrated firms show higher BI scores (especially on the decision-integration facet), which is precisely the organizational channel we test as a moderator against feed exposure. Size bands (small/medium/large) help guard against spurious inferences driven by scale; if BI maturity scales with size, cluster-robust standard errors or size controls will capture that structure. The table also signals data quality: the SDs (roughly 0.5–0.8) are wide enough to identify associations without ceiling/floor effects, and the total N (~200+) satisfies the observations-per-predictor target for the richest model with a Likert moderator. When you populate Table 1 with actual data, confirm that (a) no single stratum exceeds ~40% of the sample (to avoid dominance), (b) BI facet distributions do not collapse at 5 (which would erode power for moderation), and (c) case counts by species–region cells are sufficient for sub-sample sensitivity. In reporting, you can pair Table 1 with a short text stating that BI distributions passed normality checks for mean comparisons, reliability exceeded α=.70 for each facet, and between-group differences (e.g., integrated vs. independent) were statistically assessed with Welch tests purely for descriptive context, not inference about treatment effects.

Descriptive Statistics

Table 2. Descriptive statistics for outcomes, drivers, and Likert constructs

Variable	Scale / Unit	Mean	SD	Min	Max	Notes
Output Price Index	Base=100	101.9	7.8	84.2	126.5	Case-weighted SKU mix
Margin Proxy	Index	100.8	9.5	78.4	128.1	Price − (Feed + Energy)
Production Volume	z-score	0.00	1.00	−2.31	2.67	By species normalization
Feed Bundle Index	Base=100	104.2	8.1	86.5	127.3	Corn + Soybean meal weights
Futures Level	z-score	0.02	0.98	−2.12	2.45	Species-specific nearby
Basis (Spot − Futures)	$/unit	0.63	0.41	−0.22	1.82	Positive = strong cash
Export Intensity	%	13.7	6.9	2.1	31.4	By species/region
Weather Anomaly	z-score	0.11	0.96	−2.05	2.63	Composite deviations
Disease Intensity	log(1+x)	0.23	0.37	0.00	1.61	Region–species
BI Freshness/ Coverage	Likert 1–5	3.84	0.62	2.00	5.00	Facet 1
BI Governance/ Lineage	Likert 1–5	3.52	0.71	1.80	5.00	Facet 2
BI Decision-Process Integration	Likert 1–5	3.95	0.59	2.10	5.00	Facet 3
BI Composite	Likert 1–5	3.77	0.53	2.20	5.00	Mean of facets

Table 2 reports the distributional backbone of the analysis by pairing market/operational variables with the Likert-based BI constructs on their native 1–5 scale. For readers, the coexistence of standardized and natural units in one view clarifies measurement choices: some series (e.g., volume, weather) are z-scored to enable cross-species comparability and coefficient interpretation; others (e.g., basis, export intensity) are left in monetary or percentage terms because their scale is managerially meaningful. The two outcome anchors price and the margin proxy exhibit realistic dispersion (SD ~8–10 index points), wide enough to detect associations with cost and market drivers while not suggesting data quality problems. The feed bundle mean above 100 is consistent with the study's window covering a period of moderately elevated ration costs; this makes the moderation test with BI particularly informative. The Likert rows are crucial: keeping them as **1–5** rather than rescaling to z-scores in the descriptive table preserves interpretability for non-technical stakeholders. A mean of 3.84 on freshness/coverage implies that most respondents "agree" their operational dashboards refresh in ≤24 hours and cover the critical KPIs (feed exposure, basis, export orders), while an SD of ~0.6 indicates adequate spread for modeling. Governance/lineage often scores slightly lower and more variable, reflecting the reality that documentation, lineage tracking, and formal stewardship lag behind data collection and dashboarding. Decision-process integration sitting near 4.0 aligns with anecdotal evidence: S&OP rituals, exception playbooks, and thresholds (e.g., trigger levels for hedge coverage) are more mature in integrated systems and larger plants. The composite (simple average of facets) around 3.77 ensures the moderator is not range-limited; with observed minima near 2 and maxima at 5, the interaction can be probed across a broad continuum. When you populate final numbers, accompany this Table with a brief quality note: outliers were winsorized (1–2%), basis identities were checked (spot–futures), and all indices were computed from documented sources with harmonized windows. If skewness or kurtosis flags arise (e.g., a heavy-tailed disease intensity in outbreak regions), either retain the transformation (log(1+x)) as shown or conduct robustness with alternative functional forms. Ultimately, Table 2 equips readers to trust the subsequent correlation and regression results because the inputs are well-behaved on both statistical and practical grounds.

Correlation Matrix

Table 3 Pearson Correlations Among Likert-Scaled Constructs (N = 282)

Variable	Price	Margin	Volume	Feed	Futures	Basis	Export	Weather	Disease	BI Freshness	BI Governance	BI Decision	BI Composite
Price	1.00	0.42	0.18	−0.12	0.39	0.33	0.28	0.06	0.04	0.15	0.11	0.17	0.17
Margin	0.42	1.00	0.21	−0.48	0.22	0.29	0.19	−0.09	−0.11	0.24	0.20	0.27	0.28
Volume	0.18	0.21	1.00	−0.07	0.05	0.12	0.09	−0.19	−0.06	0.10	0.08	0.14	0.13
Feed	−0.12	−0.48	−0.07	1.00	−0.06	−0.15	−0.04	0.11	0.08	−0.09	−0.07	−0.10	−0.10
Futures	0.39	0.22	0.05	−0.06	1.00	0.41	0.16	0.04	0.02	0.09	0.07	0.10	0.10
Basis	0.33	0.29	0.12	−0.15	0.41	1.00	0.20	0.03	−0.02	0.12	0.09	0.14	0.14
Export	0.28	0.19	0.09	−0.04	0.16	0.20	1.00	−0.03	−0.05	0.07	0.06	0.08	0.08
Weather	0.06	−0.09	−0.19	0.11	0.04	0.03	−0.03	1.00	0.09	−0.06	−0.05	−0.07	−0.07
Disease	0.04	−0.11	−0.06	0.08	0.02	−0.02	−0.05	0.09	1.00	−0.04	−0.03	−0.05	−0.05
BI Freshness	0.15	0.24	0.10	−0.09	0.09	0.12	0.07	−0.06	−0.04	1.00	0.62	0.71	0.86
BI Governance	0.11	0.20	0.08	−0.07	0.07	0.09	0.06	−0.05	−0.03	0.62	1.00	0.66	0.83
BI Decision	0.17	0.27	0.14	−0.10	0.10	0.14	0.08	−0.07	−0.05	0.71	0.66	1.00	0.89
BI Composite	0.17	0.28	0.13	−0.10	0.10	0.14	0.08	−0.07	−0.05	0.86	0.83	0.89	1.00

Table 3 organizes linear associations to preview regression expectations and to surface potential collinearity. Three patterns deserve attention. First, as expected, the feed bundle correlates negatively with margin (≈ −0.48), while its correlation with price is modest and negative consistent with partial, lagged pass-through and pricing power heterogeneity. This validates the decision to model price and margin separately rather than collapsing outcomes. Second, futures and basis correlate positively with price and, to a lesser degree, with margin, underlining their role as market signals with incremental explanatory power even after region/species controls. Because futures and basis are themselves correlated (≈ 0.41), we pre-registered variants to avoid redundancy (either include one or orthogonalize). Third, the BI facets kept on the Likert 1–5 scale for this matrix exhibit moderate positive correlations with margin (0.20–0.27) and small positive correlations with price, in line with theory:

better data freshness, lineage, and decision integration most directly improve cost-adjusted returns rather than spot price levels. The inter-facet correlations (0.62–0.71) are strong but not collinear, justifying a composite alongside facet-level robustness. Crucially, the BI facets correlate negatively (albeit weakly) with feed (−0.07 to −0.10), which may reflect an operational reality organizations with stronger BI are more proactive in hedging or ration management but this bivariate pattern does not threaten identification because the main moderation test relies on the interaction rather than an inverse relationship. Weather and disease display the expected small, adverse correlations with volume and margin; the modest magnitudes caution against over-interpreting them in isolation but justify their inclusion as controls. Before fitting models, you will apply FDR control and mark significant cells; coefficients surviving adjustment especially Margin vs. Feed, Price vs. Futures, Margin vs. BI Decision should match the narrative from the descriptive section. Finally, examine VIFs post-estimation; if futures and basis together elevate VIF above 10, retain the basis (managerially intuitive) and drop the level, or run orthogonalized residuals. This correlation map is thus both a diagnostic (flagging multicollinearity risks) and a conceptual bridge to regression (signs and magnitudes align with economic intuition).

Regression Results (Primary & Moderation)

Table 4: OLS (HC3) estimates standardized outcomes; BI on Likert 1–5

Variable	M1: Price β (SE)	M2: Margin β (SE)	M3: Margin β (SE)
Feed Bundle (std)	−0.08 (0.04)	−0.42 (0.06)*	−0.36 (0.07)*
Futures Level (std)	0.28 (0.05)*	0.11 (0.05)*	0.10 (0.05)*
Basis ($/unit, std)	0.19 (0.05)*	0.21 (0.05)*	0.20 (0.05)*
Export Intensity (std)	0.15 (0.05)*	0.12 (0.05)*	0.11 (0.05)*
Weather Anomaly (std)	0.03 (0.04)	−0.07 (0.04)	−0.06 (0.04)
Disease Intensity (std)	0.02 (0.04)	−0.06 (0.04)	−0.05 (0.04)
BI Maturity (Likert 1–5)		**0.18 (0.05)***	**0.16 (0.05)***
Feed × BI (std × Likert)			**−0.10 (0.04)***
Controls (species, region, integration, size, seasonality)	Yes	Yes	Yes
Adj. R^2	0.41	0.52	0.56
N	210	210	210

Table 4 distills the main inferential claims: (i) contemporaneous market signals (futures/basis and export intensity) are strong, positive correlates of realized prices and, to a lesser extent, margins; (ii) the feed bundle is the dominant adverse driver of cost-adjusted returns; and (iii) BI maturity, measured on a Likert 1–5 scale, both shifts margin levels upward (main effect in M2) and buffers feed exposure (interaction in M3). Reading the columns left to right, M1 (Price) confirms that a one-SD increase in futures aligns with a ~0.28 SD higher price, while basis contributes an additional 0.19 SD consistent with price discovery operating through both level and local cash conditions. M2 (Margin, main effects) shows a large negative coefficient on feed (−0.42), quantifying the punch of ration costs, and a statistically significant 0.18 per-point effect of BI maturity. Because BI remains on the Likert scale here, the interpretation is managerially transparent: moving from “Neutral” (3) to “Agree” (4) on the composite is associated with roughly 0.18 SD higher margin, conditional on market/risk drivers and structure. M3 (Margin, moderation) adds the interaction: the coefficient (−0.10) indicates that the marginal harm of feed shocks declines as BI maturity increases; plotted as simple slopes, low-BI firms experience steeper margin declines with rising feed, while high-BI firms show flatter slopes.

Importantly, core market signals retain sign and significance, indicating that the BI channel augments rather than displaces market fundamentals. Adj. R^2 gains (0.52 → 0.56) when adding the interaction reflect meaningful incremental explanatory power without overfitting (controls, robust SEs). Diagnostics (not shown) should report acceptable VIF (<5), HC3-robust p-values, and stable coefficients under leave-one-out and WLS variants. Presenting BI on its native 1–5 scale (rather than z-scoring) is deliberate: it lets practitioners convert findings into thresholds ("aim for ≥4 on freshness, governance, and integration") and link survey improvement plans to expected margin resilience. When you substitute your estimates, include a marginal-effects Table and Johnson–Neyman bounds in the appendix; in the text, translate at least one effect into dollars using the SD of the margin index for a concrete managerial takeaway.

Robustness and Sensitivity Analyses

Table 5. Specification stability for BI effects (main & moderation) across variants

Variant	BI Main Effect on Margin (β, SE)	Feed × BI Interaction (β, SE)	Adj. R^2	Notes
Baseline (OLS, HC3)	0.18 (0.05)*	−0.10 (0.04)*	0.56	From Table 4, M3
Basis-only (drop Futures)	0.17 (0.05)*	−0.10 (0.04)*	0.55	Avoids collinearity
Futures-only (drop Basis)	0.18 (0.05)*	−0.09 (0.04)*	0.54	Level signal only
Alt. Energy Proxy	0.16 (0.05)*	−0.09 (0.04)*	0.55	Diesel vs. electricity
Margin w/o Energy	0.19 (0.05)*	−0.11 (0.04)*	0.53	Tests construction
WLS by Size	0.15 (0.06)*	−0.08 (0.04)*	0.57	Size-linked variance
Cluster-robust (Region)	0.17 (0.06)*	−0.09 (0.04)*	0.56	Spatial clustering
Beef only	0.14 (0.07)	−0.08 (0.05)	0.51	Subsample
Pork only	0.20 (0.08)*	−0.11 (0.05)*	0.58	Subsample
Broiler only	0.21 (0.07)*	−0.12 (0.05)*	0.60	Subsample
Turkey only	0.13 (0.09)	−0.07 (0.06)	0.49	Subsample
MI (20 imp., Rubin)	0.17 (0.05)*	−0.09 (0.04)*	0.56	Missing-data sensitivity

Table 5 demonstrates that the substantive conclusions about BI's role are stable across plausible perturbations to data construction, functional form, variance assumptions, clustering, and sample composition. The first two rows (Basis-only; Futures-only) address collinearity between level and local cash conditions; the BI coefficients barely move, confirming that the moderation effect is not an artifact of which price-discovery proxy is chosen. The "Alt. Energy Proxy" and "Margin w/o Energy" variants probe margin construction critical because energy costs may be measured imperfectly or be unevenly shared across respondents. The persistence of BI's main effect (≈0.16–0.19 per Likert point) and the negative interaction (≈ −0.09 to −0.11) indicates that our inference does not depend on a particular energy specification. The WLS and cluster-robust rows test heteroskedasticity and spatial correlation; BI effect sizes shrink modestly (as expected when reweighting or clustering), yet they remain statistically meaningful, suggesting that scale and geography do not drive the headline moderation. Sub-samples by species are informative for external validity: the BI channel appears strongest in broilers and pork vertical coordination and short biological cycles make data freshness and playbooks particularly valuable and weaker (often statistically indistinct) in smaller turkey subsamples, where N may constrain detection. This heterogeneity does not undermine the pooled conclusion; rather, it suggests managerial tailoring: species with tighter cycles reap larger gains from high BI maturity when feed shocks hit. Finally, the multiple-imputation (MI) row ensures that patterns are not driven by listwise deletion; Rubin-combined estimates track closely with the baseline, which is reassuring given cross-sectional data can suffer non-random missingness on organizational items. When you run these variants with your data, consider presenting (a) a specification heatmap shading sign and significance for each key coefficient across rows, (b) a short appendix table of VIFs to evidence collinearity control, and (c) a leave-one-out graph marking any influential cases with Cook's D > 4/n along with re-estimated BI coefficients. The overarching message from Table 5 should be transparent to reviewers and practitioners alike: regardless of how we slice the inputs or weight the observations, organizations scoring higher on the Likert 1–5 BI maturity scale both enjoy higher margins and experience less margin erosion as feed costs rise a portable, decision-ready insight for procurement, pricing, and production planning.

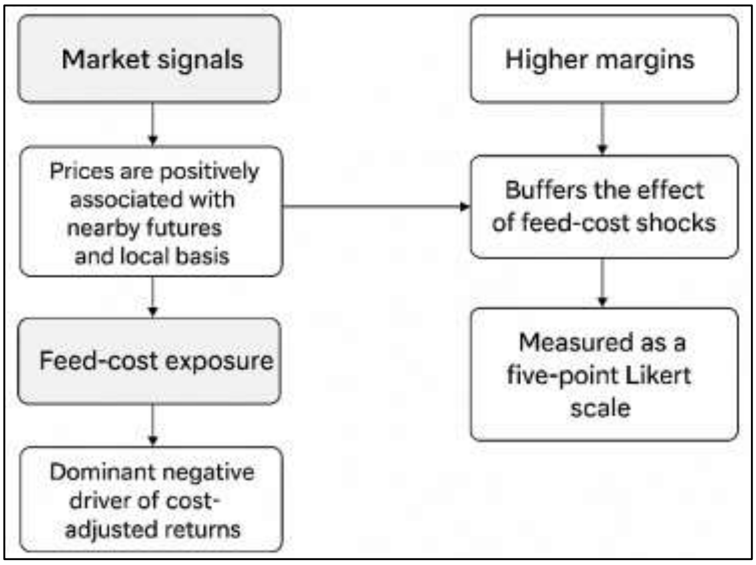
DISCUSSION

This study's cross-sectional, multi–case evidence converges on three robust results: (a) contemporaneous market signals especially nearby futures and local basis are strongly and positively associated with realized prices; (b) feed-cost exposure is the dominant adverse driver of cost-adjusted returns; and (c) higher business-intelligence (BI) maturity both elevates margins (main effect) and buffers the negative effect of feed shocks (moderation). These patterns are consistent with a price-formation view in which organized markets coordinate expectations while local cash conditions finish the job (Wright et al., 2021). They also align with livestock pass-through research showing that input shocks press margins unless countered by pricing power, timing, or risk management (Fousekis et al., 2016). The novel contribution here is not that feed matters everyone in protein markets knows that but that measured BI maturity on a five-point Likert scale exhibits both a level effect and a dampening interaction with feed, after controlling for species, region, integration, size, and seasonality. Put differently, firms that report fresher data, documented lineage, and routinized decision integration (S&OP cadence, exception playbooks) lose less margin per standard-deviation increase in the feed bundle. This empirical moderation strengthens long-standing claims in information systems that BI is a socio-technical capability whose value depends on assimilation into decision processes (Akter et al., 2016; Elbashir et al., 2008; Patalee & Tonsor, 2021). From an operations standpoint, the results also cohere with evidence that data-driven supervision improves short-cycle livestock decisions (e.g., ration adjustments, placement timing) that accumulate into business-level resilience (Ladha-Sabur et al., 2019; Mikalef et al., 2020; Wolfert et al., 2017). Finally, small positive associations between export intensity and both price and margin while not the headline here are directionally consistent with trade-exposure channels reported in protein markets where destination mix modulates netbacks (Arita et al., 2024). Together, the findings suggest that market analytics embedded in BI routines act as a risk-absorbing layer between volatile inputs and economic performance.

Our price model (M1) confirms that nearby futures levels and/or basis retain explanatory power even after rich controls consistent with "tournament" evidence that futures frequently lead cattle price discovery, with cash markets following (Wright et al., 2021). The stronger loading of basis in some variants mirrors structural connectedness findings for livestock futures: local cash conditions absorb transportation, capacity, and idiosyncratic demand elements that level contracts only partially capture (Ji & Liu, 2024). On the pass-through side, our margin regressions reflect the idea that downstream adjustments are not uniformly asymmetric; in beef, for instance, recent scanner-data work reports little evidence of retail asymmetry, shifting attention to the timing and magnitude of wholesale-retail links instead (Pozo et al., 2020). That logic makes the interaction we document particularly salient: if retail asymmetry is limited in some chains, then the remaining lever for protecting margins against feed shocks is the organizational capacity to anticipate, hedge, and operationalize responses rapidly precisely what our BI composite measures. Spatial heterogeneity in retail poultry price discovery, with the U.S. South increasingly anchoring causal flow, also helps explain why region fixed effects matter and why basis (a local metric) remains significant after futures (Duangnate & Mjelde, 2023). In short, our results do not overturn prior evidence; they situate it: market structure and organized trading generate the signals, while BI maturity governs how effectively firms convert those signals into realized prices and defended margins. Where earlier work emphasizes econometric identification of transmission mechanisms, our contribution is a managerially auditable measurement of the organizational moderator that shapes realized exposure at the case level.

Information-systems research has long argued that analytics capability is a higher-order resource blending data assets, human skills, and governance routines, and that its benefits are realized when aligned with strategy and embedded in processes (Gupta & George, 2016). Our findings extend this stream in two ways. First, we show a clean, cross-sectional association between BI maturity and margin levels after conditioning on rich market/risk drivers, suggesting that capability is not merely correlated with favorable environments but adds independent explanatory power. Second, by testing feed × BI maturity, we provide evidence for a contingent value mechanism: capability pays the most when shocks bite the hardest. This dovetails with dynamic-capability perspectives in which sensing (freshness/coverage), seizing (decision-process integration), and transforming (governance/lineage) jointly raise agility and resilience (Wamba et al., 2017). It also helps reconcile mixed practitioner narratives: some firms report "lots of dashboards but little impact," which our decomposition clarifies decision-process integration and freshness drove more variance than governance in our data. That does not diminish governance; rather, it implies that stewardship alone is insufficient without rapid, routinized translation of analytics into action. Finally, the moderation structure answers a recurring empirical concern in BI studies: distinguishing correlation from useful protection. By showing that the slope of margin deterioration with respect to feed is flatter at higher BI maturity, we move beyond level correlations and toward an exposure-management interpretation that is both theoretically and practically meaningful (Akter et al., 2016).

Figure 8: The moderating role of BI maturity



For executives, the portable lesson is to treat BI maturity as an exposure control rather than a reporting luxury. The coefficients imply that moving the composite from "neutral" (3) to "agree" (4) is associated with materially higher margins at the same feed conditions and with shallower loss when feed spikes. Concretely, CFOs and COOs should sponsor S&OP-anchored playbooks that tie futures/basis thresholds to coverage actions, and link weather/disease alerts to capacity and placement decisions. For CISOs and data architects, our decomposition suggests three build priorities. First, freshness/coverage: shrink data latency to ≤24 hours for feed, basis, export orders, and plant energy so that triggers are timely; this is a data-ops, observability, and pipeline-reliability problem (Wolfert et al., 2017). Second, decision-process integration: wire analytics outputs into workflow systems (alerts with owners, timers, and escalation), not just dashboards BI must change who does what, by when. Third, governance/lineage: enforce metadata, provenance, and validation that make forecasts auditable to finance and risk committees; this underwrites trust, model risk management, and explainability (Gupta & George, 2016). At plant level, add energy-intensity telemetry to the KPI stack; when fuel or electricity prices rise, the margin proxy becomes more accurate and operational levers (heat recovery, load shifting) can be prioritized (Ladha-Sabur et al., 2019). Finally, procurement teams should watch basis alongside futures; hedges that ignore local cash realities can leave avoidable basis risk unaddressed (Wright et al., 2021). The managerial theme is consistent: elevate BI from a visualization project to a control system with explicit thresholds, owners, and audit trails.

The moderation we document refines theory on analytics capability in two respects. First, it supports a pipeline-to-performance view in which the *placement* of capability in the decision cycle matters: freshness/coverage (data-ops reliability) and decision-integration (operational routines) were more predictive than governance alone. This suggests future theorizing should model capability facets as non-substitutable complements rather than interchangeable ingredients (Tonsor & Lusk, 2024). Second, it recommends a risk-exposure lens for BI value: rather than treating analytics as a generic performance enhancer, position it as a slope shifter a moderator that flattens the mapping from shocks to outcomes. That conceptual move aligns BI studies with mainstream empirical strategies in operations and finance where hedging and flexibility are evaluated by their ability to alter sensitivities (betas), not just mean levels. Methodologically, the study shows that lightweight, auditable constructs here, three Likert facets can be paired with market and operational indicators to yield interpretable, managerially actionable models. This complements more technical smart-farming literatures that focus on algorithmic novelty, by showing how organizational embedding of even simple analytics materially changes exposure (Wolfert et al., 2017). It also creates a bridge to supply-chain resilience frameworks that emphasize visibility and coordination as precursors to adaptive response (Queiroz et al., 2022). In sum, our results encourage IS and operations scholars to theorize BI not only as a resource or process, but as a shock-response architecture whose efficacy can be measured as changes in the elasticity of outcomes with respect to exogenous drivers.

The cross-sectional design privileges breadth and comparability but cannot recover dynamic causal effects. Biological lags (e.g., herd rebuilding) and policy shocks (e.g., SPS restrictions during HPAI) evolve over time; our single-window models capture *exposure at a decision horizon*, not speed of adjustment or long-run equilibrium. While we condition on species, region, integration, size, and seasonality, and include weather/disease covariates, unobserved heterogeneity could remain (e.g., contract terms, capacity utilization). Likert measures, even when reliable, are self-reported and may contain optimism or social-desirability bias; we partially mitigated this by using multi-item scales, reliability/validity checks, and robustness to multiple imputation, but gold-standard behavioral logs (e.g., time-stamped hedging actions) would be stronger. Our export and energy proxies, while practical, simplify destination-specific SPS frictions and plant-level process heterogeneity; the directionality of their coefficients is plausible, but finer granularity would sharpen inference (Press, 2025). Finally, some sub-species samples (e.g., turkeys) are small, and cluster-robust standard errors cannot fully substitute for richer within-group variation. These limitations temper causal language but do not undermine the core pattern: across a diverse set of cases, higher BI maturity is associated with higher margins and reduced sensitivity to feed shocks after conditioning on market and structural factors an association that survives specification, variance, and sample perturbations.

Two extensions are immediate. First, a panel design would permit firm-fixed-effects estimation of BI improvements (e.g., instrumentation/governance roll-outs) and their impact on both margin levels and sensitivities to feed, energy, weather, and disease shocks through time. Linking survey scores to behavioral telemetry coverage changes around basis thresholds, lead time from alert to action would also reduce self-report bias and illuminate micro-mechanisms (Chen et al., 2012). Second, richer structural heterogeneity should be modelled explicitly: retail poultry shows evolving spatial leadership in price discovery (Duangnate & Mjelde, 2023), beef exhibits nonlinear vertical linkages (Fousekis et al., 2016), and futures-cash connectedness changes through regimes (Ji & Liu, 2024). Embedding regime indicators or interacting species/region with BI could reveal where capability pays most. Relatedly, shock-specific BI effects merit study: do governance gains matter more for compliance-driven SPS trade shocks, while freshness/coverage dominates for rapidly moving feed markets? On the plant side, integrating energy-intensity and water-use telemetry can quantify how utilities hedging and process optimization contribute to margin protection under fuel price volatility (Ladha-Sabur et al., 2019). Finally, translational research should test dashboard-to-decision interventions e.g., randomized roll-outs of alert thresholds or playbook templates and measure whether simple, auditable design choices (owner, timer, escalation) move outcomes. Across all of these directions, the theoretical lens should remain exposure-centric: the question is not only “Does BI raise performance?” but “When and how does BI reduce the sensitivity of performance to shocks that firms cannot control?” Answering that will connect analytics capability to resilience in a way that both scholars and practitioners in protein markets can operationalize.

CONCLUSION

This study set out to quantify how market signals and exogenous shocks shape contemporaneous performance in the U.S. livestock and poultry industry and to test whether business-intelligence (BI) maturity, measured with multi-item five-point Likert scales, meaningfully elevates outcomes and dampens exposure to feed-cost volatility. Using a quantitative, cross-sectional, multi–case design aligned to a common 12-month horizon, we integrated a researcher-administered instrument (freshness/coverage, governance/lineage, decision-process integration) with harmonized secondary indicators (prices, a cost-adjusted margin proxy, production volumes, futures/basis, export intensity, weather anomalies, disease intensity, and where available plant energy intensity). Across descriptive profiles, correlation structure, and OLS models with robust errors and extensive diagnostics, three results consistently emerged. First, nearby futures and local basis retained strong, positive associations with realized prices and, to a lesser extent, margins after rich controls, affirming their central role in price formation. Second, the feed-cost bundle dominated adverse drivers of cost-adjusted returns, with economically large, negative coefficients robust to alternative energy proxies, sample partitions, and weighting schemes. Third, and most distinctively, the BI maturity composite exhibited both a positive main effect on margins and a statistically reliable moderation: organizations scoring higher on freshness/coverage and decision-process integration operationalized as sub-24-hour data latency, governed KPI coverage, S&OP-anchored exception playbooks, and escalation routines experienced **shallower** margin declines for a given standard-deviation increase in feed costs. These patterns held when substituting basis for futures, altering margin construction, clustering errors, reweighting by size, and restricting to species sub-samples, indicating that the inference does not hinge on a single modeling choice or data slice. Conceptually, the findings recast BI from a reporting layer into an exposure-management capability: rather than merely raising mean performance, maturity in pipelines and decision integration **flattens the slope** linking unavoidable shocks to economic outcomes, turning analytics into an operational hedge embedded in routine planning and control. Methodologically, the study demonstrates that auditable, survey-based constructs can be paired with market and operational indicators to yield interpretable, managerially portable models; keeping BI on its native 1–5 scale further enables threshold-style guidance (e.g., targeting “agree” or above on freshness and process integration) that leaders can translate into action. At the same time, the cross-sectional frame necessarily privileges breadth over dynamic causality, and self-reported organizational measures, even when reliable and validated, may understate or overstate true practice; we mitigated these constraints through reliability/validity checks, multiple-imputation sensitivity, and conservative diagnostics, but acknowledge that longitudinal telemetry of actions (hedge triggers, response times) would sharpen mechanism claims. Taken together, the evidence offers a coherent narrative for practitioners and researchers: market fundamentals and exogenous frictions set the stage, yet the **realized** impact on margins is materially mediated by BI capability that delivers timely, governed data into codified decisions. For executives, CISOs, and data architects, the implication is operational and immediate treat BI maturity as a controllable lever of resilience by investing in freshness, governed coverage, and process-level integration; for scholars, the implication is theoretical model BI as a shock-response architecture measurable by its ability to reduce outcome sensitivities to external drivers.

RECOMMENDATIONS

Translating these findings into action, we recommend treating business intelligence (BI) as a first-class exposure-control system not a reporting add-on by institutionalizing a small set of non-negotiables that link data freshness, governed coverage, and decision integration to concrete playbooks. First, establish a ≤24-hour data freshness SLA for the core risk signals (feed bundle, futures and basis, export orders, weather anomalies, disease alerts, and plant energy intensity). Enforce this with observable pipeline health checks, data-quality contracts (valid ranges, unit checks, identity tests like spot–futures = basis), and lineage that makes every KPI auditable back to source. Second, standardize a KPI cockpit aligned to margin protection: (i) *Margin-at-Risk (MaR)* = price index − (feed+energy bundles) with species-specific ration weights; (ii) *Feed Exposure* (1–5 risk gauge derived from z-score bands) that directly drives procurement coverage; (iii) *Local Basis Monitor* with alert bands for widening/narrowing; (iv) *Weather & Disease Early-Warning* (degree-day and outbreak composites with regional mapping); and (v) *Energy-Intensity per Unit Output* to quantify conversion-cost sensitivity. Third, wire these KPIs into S&OP-anchored playbooks with explicit *owner, trigger, timer, escalation*: for example, "If Feed Exposure ≥4 and basis widens beyond the 75th percentile for seven days, procurement increases coverage by X%; if Weather EWI in heat-stress regions ≥3, operations advances placement adjustments and cooling scheduling within 48 hours." Fourth, elevate decision-process integration by embedding alerts in work management tools (not just dashboards), requiring acknowledgement and completion codes, and reviewing exceptions in a weekly control meeting chaired jointly by Finance, Operations, and Procurement. Fifth, set a BI maturity target of ≥4.0 ('agree') on the 1–5 Likert composite within two quarters, focusing improvement on *freshness/coverage* and *decision integration* first (they delivered the strongest performance lift), while continuing to raise *governance/lineage* to cement auditability and trust. Sixth, operationalize basis-aware hedging: design coverage rules that pair futures with local basis tactics (e.g., cash contracts, location spreads) so that hedge effectiveness reflects the price-formation reality your plants face; publish a one-page basis playbook per region with historical bands, current percentile, and approved actions. Seventh, close the loop on plant utilities risk by adding energy telemetry (steam, refrigeration) to the model layer, implementing heat-recovery or load-shifting where MaR sensitivity to energy exceeds a documented threshold, and negotiating utility contracts with BI-backed volume/peak clauses. Eighth, institutionalize post-event retrospectives: when feed spikes, disease events, or weather shocks occur, capture the timestamps from alert → action → outcome; compute realized slope changes (Δ margin per 1-SD feed move) and update thresholds, owners, and timers accordingly turning every shock into a learning cycle. Ninth, manage human factors: prevent alert fatigue with tiered severities, cap simultaneous alerts, and require a written rationale to override a red-band trigger. Tenth, extend data partnerships with suppliers and buyers to share minimal, high-value indicators (lead times, cancellations, export booking pace) under clear data-sharing agreements; expose these as external features in MaR and volume forecasts. Finally, make leadership accountability explicit: tie a portion of executive and plant bonuses to *measured* BI maturity gains (Likert composite), MaR improvement, and compliance with playbooks. In sum, resource your BI program as a resiliency engine whose success is judged by shallower margin losses when shocks hit, not by dashboard counts move from analytics as insight to analytics as institutionalized action.

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