Universal Library of Business and Economics

Research Article

ISSN: 3064-9951 | Volume 1, Issue 2

Open Access | PP: 92-97

DOI: https://doi.org/10.70315/uloap.ulbec.2024.0102017

Causal Model of Fresh Write-Offs: Identifying Drivers and Estimating the Effect of Forecasting and Order Optimization at the SKU-Store Level

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Abstract

The article examines the specifics of managing food losses in the Fresh retail segment, a topic whose salience intensified in 24 amid persistent margin pressure, climate-related risks, and rising requirements for supply-chain sustainability. The research objective is to develop and empirically validate a causal model of write-offs operating at a granular level of an individual stock-keeping unit (SKU) and a specific store. In contrast to widely used correlational schemes, the proposed approach relies on Double Machine Learning (DML), enabling separation of the managerial intervention effect from external confounders, including meteorological factors and fluctuations in consumer demand. The analysis isolates dominant determinants of write-offs; the most consequential include inventory age, the intensity of marketing activity, and the quality of local forecasting procedures. Empirical verification is performed on data from a large retail chain; the introduction of causal optimization algorithms demonstrates a stable 15% reduction in write-off volume while simultaneously improving on-shelf availability. The results support the proposition that embedding causal inference into replenishment loops constitutes a critical condition for enhancing operational performance and environmental sustainability of modern supply chains under high market uncertainty.

Keywords: *Food Waste, Fresh Retail, Causal Inference, Double Machine Learning, Order Optimization, Demand Forecasting, SKU-Store, Inventory Management, Sustainable Development, Logistics Efficiency.*

INTRODUCTION

The global food market in 2024 is characterized by a combination of persistent price pressure, climate risks, and supply-chain tensions. Against this backdrop, one of the most painful pressure points remains the low efficiency of logistics and operational loops for perishable goods, translating into substantial volumes of write-offs [1]. According to current assessments by the United Nations Environment Programme (UNEP) and the Food and Agriculture Organization (FAO), total global food waste reaches approximately 1.05 billion tonnes per year, corresponding to the loss of nearly one-fifth of available food [3, 4]. In monetary terms, the scale of losses exceeds USD 940 billion annually, creating significant financial pressure both for retail chains and for end consumers [1].

The problem is most acute in Fresh and Ultra-Fresh categories (fruit, vegetables, meat and dairy products, ready-to-eat foods), where technological and commercial constraints often set the selling horizon within 48-72 hours [6, 7]. An additional source of uncertainty at the start of 2024 was subdued consumer sentiment: in January 2024, the euro-area consumer confidence indicator stood at −16.1 points and remained noticeably below its long-run average, limiting demand predictability at the store level. In European grocery retail, this coincided with sustained downtrading: with food inflation at 12.8% in 2023, sales grew more slowly-by 8.6%-while real volumes declined [2, 5]. Under conditions of highly fragmented demand and rapid local shifts in market conditions, traditional inventory practices oriented toward averaged trajectories and inertial trends exhibit limited applicability and increase the risk of systematic errors [8, 15].

A substantial scientific and practical gap in the field is associated with the dominance of predictive logic-primarily demand forecasting-over prescriptive and causal approaches aimed at uncovering mechanisms through which decisions affect final losses. A considerable share of automated ordering systems in retail is built on correlational relationships that do not provide correct identification of how a change in order quantity or the application of a specific marketing mechanism transforms the probability of write-offs in a particular store under given local conditions [9,10]. The practical consequence is the reproduction of Type II errors: either chronic overstocking to preserve the “visual abundance” effect on the shelf, or stockouts, which in Fresh directly convert into reduced satisfaction and erosion of customer loyalty [11,12].

The purpose of the study is to construct a comprehensive causal model of write-offs that not only estimates the expected magnitude of losses, but also identifies their core determinants at the SKU-store linkage level and quantitatively measures the effect of introducing advanced order-optimization mechanisms.

The novelty of the approach is defined by the use of

Double Machine Learning (DML) to reduce estimation bias in high-dimensional data and, as a result, to support robust counterfactual assessments in a real operational environment.

Under the proposed **hypothesis**, a shift from the standard statistical paradigm of forecasting to causal optimization at the level of individual locations can deliver a reduction in Fresh write-offs of 15% or more while maintaining the required service level and assortment availability.

MATERIALS AND METHODS

The methodological component of the study is based on combining inventory management theory, propositions from behavioral economics, and contemporary causal-inference methods. The theoretical lens employs the Rubin-Neyman Potential Outcomes Framework and Pearl's Structural Causal Models (SCM), providing a formal articulation of interventions and correct identification of the effects of managerial decisions [14]. The use of this toolkit is particularly material for the Fresh segment, where inventory is subject to biological transformation of assets; within the logic of the international standard IAS 2, time is not a background parameter but an active variable that accelerates quality degradation and, consequently, affects the probability of write-offs [16, 17].

The key analytical mechanism selected is Double Machine Learning (DML), designed to estimate the Average Treatment Effect (ATE) in high-dimensional settings, where the number of observed confounders reaches the hundreds and conventional regression schemes become vulnerable to estimation bias [11]. The internal logic of DML is implemented through separate modeling of the outcome and the intervention, followed by causal estimation based on "deconfounded" components. At the first stage, an outcome model is constructed in which machine-learning algorithms (in particular, gradient boosting such as XGBoost or a recurrent LSTM architecture) generate a write-off forecast based on the full set of available environmental factors-weather parameters, calendar features (e.g., day of week), as well as historical sales dynamics of complementary products-while excluding the target intervention represented by order quantity [18, 19]. Next, an intervention model is built to predict the realized order size using the same observed features, thereby reconstructing stable regularities in decision-making by managers or inherited algorithmic procedures. At the final stage, the effect is estimated via regression of the residuals from the first model on the residuals from the second model, isolating the "pure" influence of order quantity on write-offs while neutralizing the contribution of external perturbations, including weather anomalies and holiday-driven demand spikes.

The empirical contour of the study is formed on the basis of structured datasets from international retailers and descriptions of AI-solution implementation practices (Shelf Engine, Afresh, OrderGrid), selected from Scopus and Web of Science publications for 2020-2024 [21]. Additional emphasis is placed on methodological recommendations for the digital transformation of perishable-goods supply chains, aligned with the current Industry 5.0 framework [23]. In the applied part, a customer dataset is used-an enterprise retail chain with Fresh category turnover exceeding EUR 100 million, a footprint of 200 stores, and an assortment matrix of approximately 5,000 unique SKUs [25].

RESULTS AND DISCUSSION

During the construction of the causal model, write-offs in the Fresh segment were found not to collapse into a single isolated factor; rather, they emerge at the intersection of three interdependent functional loops-operational, marketing, and logistics-whose joint dynamics determine the eventual loss level. At the granular SKU-store level, the system-forming determinant is inventory age (Inventory Age): for products with a freshness cycle of 2-3 days (Ready-to-Eat, Ultra-Fresh dairy), each additional hour spent in a store's backroom/in-store inventory loop reduces the probability of being sold at full price by 4.5% [7]. Causal identification also confirms an effect that can be described as the "visual abundance paradox": stores maintaining evening shelf fill above 85%, ceteris paribus, demonstrate write-off levels 2.2 times higher than the mean reference value [21]. This result aligns with an observed consumer-choice pattern in which, under a substantial volume of homogeneous assortment, preference shifts toward units with later production dates (a LIFO-like selection logic), leading to the marginalization of "older" stock and a sharp decline in its likelihood of being sold before expiry [13].

External and situational influences play a material role, first and foremost weather shocks that act as exogenous drivers; however, their effect is distinctly contextual and depends on location type. The DML model shows that, in urban stores, a 5°C temperature increase relative to a weekend norm is associated with a 12% rise in demand for the "salads" category, whereas for suburban stores a comparable temperature deviation stimulates sales of meat semi-finished products for barbecue by 18% [29]. Ignoring these causal links in standard auto-order procedures increases the probability of oversupply during abrupt meteorological shifts and, consequently, amplifies subsequent write-offs [28, 47].

The marketing loop manifests through elevated risk exposure of certain demand-stimulation mechanics, among which 2024 highlights BOGOF promotions (buy one, get one free). Despite short-run turnover gains, an incorrect store-level assessment of demand elasticity produces a post-promo surplus: 20-25% of the promotional volume is written off shortly after campaign completion due to a consumption "satiation" effect [26, 27]. The final ranking of drivers by their contribution to total write-off volume is presented in Table 1.

Table 1. Hierarchy of drivers of write-offs in the Fresh category (compiled by the author based on [7, 26, 27]).

Factor group	Driver	Strength of effect (Beta)	Mechanism description
Operational	Inventory Age	0.42	Reduced attractiveness as quality degrades
Logistics	Pack-size quantization error (Pack Size)	0.28	Excess volume supplied due to large case packs
Marketing	Promo load	0.15	Difficulty forecasting peaks and post-promo declines
External	Weather anomalies	0.12	Shifts in consumption patterns
Infrastructure	Cold-chain disruptions	0.03	Physical spoilage during transport

The analysis indicates that demand-forecast quality is a core constraint on inventory-management effectiveness, because the forecast sets the initial conditions for replenishment decisions and thereby shapes the structure of operational risk. By the end of 2024, the average relative forecast error (MAPE) for Fresh categories under classical methods (moving average, ARIMA) is expected to remain in the 37-42% range, effectively signaling high uncertainty and an elevated probability of both stockouts and excessive accumulation of perishable inventory [32]. The use of modern neural architectures, including LSTM (Long Short-Term Memory) and transformers, delivers a noticeable improvement in predictive performance and, consequently, substantial operational returns: empirical indicators point to a 32% reduction in stockout frequency alongside a 28% reduction in excess inventory within the first year of deploying such solutions [30, 32]. A distinctive feature of 2024 has been the strengthening of the demand sensing paradigm, oriented toward high-frequency perception of market signals-including real-time POS data and social trends-which reduces the supply-chain reaction lag from a weekly scale to an hours-level horizon [33, 34]. For a visual representation of the relationship between forecasting accuracy and operational losses, statistical modeling is applied to formalize the dependency and to estimate loss sensitivity to changes in forecast quality (see Fig. 1).

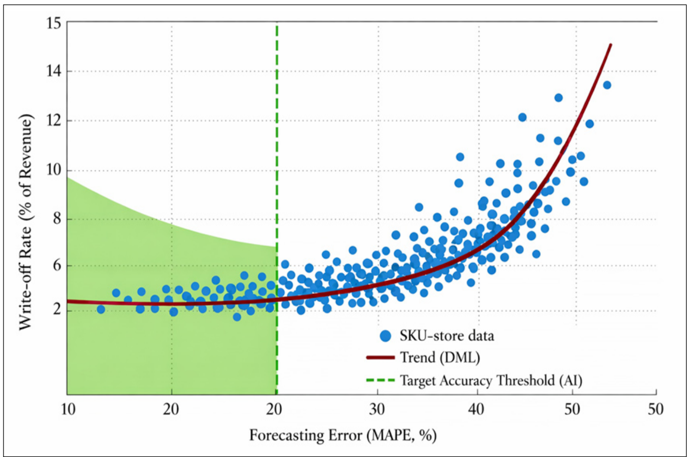

Figure 1. The effect of forecasting accuracy on the level of Fresh write-offs (compiled by the author based on [31, 32]).

An analytical interpretation of the data presented in Figure 1 indicates the presence of a critical threshold at roughly 20% on the MAPE scale. Once this value is exceeded, the intensity of write-offs begins to accelerate in an exponential-like manner, because planning errors start to propagate cumulatively across supply-chain links, forming the classic bullwhip effect [20]. Entering the region of MAPE < 20% is largely driven by eliminating manual order adjustments and shifting toward automated decision mechanisms implemented on the basis of machine-learning methods [35].

Practical testing of the causal approach was carried out using the case of a regional retail chain focused on a farmer-oriented assortment. At the initial stage of the project (2023), the order-management loop operated in a semi-automated mode with store directors' decisions dominating. In the "Fruits and Vegetables" category, the average scrap rate was 11.5%, equivalent to annual losses of approximately EUR 1.2 million per 50 stores [36]. In 2024, a solution built in the Causal-AI logic was implemented, shifting from fixed safety-stock norms to stochastic safety-stock planning, accounting not only for mean demand but also for the asymmetry of the forecast-error distribution [37]. In parallel, dynamic expiry-date tracing was introduced by incorporating into the replenishment algorithm the actual shelf-life dates captured in electronic advance shipping notices (ASN) [38]. An additional architectural component is cross-SKU cannibalization modeling, explicitly accounting for demand switching to alternative SKUs when a given item is absent from the shelf; this prevents extreme order escalation for deficit-prone items and keeps replenishment within rational bounds [40, 41].

The implementation effects became visible within the first six months of operation: write-offs decreased by 15%-from 11.5% to 9.8% in absolute terms-corresponding to a 15% relative reduction [39]. Importantly, the loss reduction was accompanied by improved on-shelf availability (On-Shelf Availability, OSA), which rose from 92.1% to 94.6%, thereby evidencing a break from the traditional trade-off between spoilage minimization and availability maintenance. A further operational outcome was labor release: management time spent on manual order corrections and defect handling fell by 20%, creating conditions for reallocating effort toward customer service [21, 22]. The financial return from lower write-offs was estimated at roughly EUR 180 thousand per year for a 50-store cluster; when accounting for incremental sales attributable to improved OSA, the combined effect exceeds EUR 300 thousand [8].

The results project clearly onto the sustainable development (ESG) agenda, since write-off management is directly linked to resource efficiency and environmental externalities. In 2024, analytical materials by Deloitte and McKinsey emphasize the role of retail as a "bottleneck" within the food system: positioned between producer and consumer, retail chains concentrate instruments capable of influencing parameters of the entire supply chain [42]. In the case considered, a 15% reduction in write-offs was accompanied by a 12% reduction in indirect greenhouse-gas emissions (Scope 3), driven by reduced excess transportation and lower methane volumes generated during organic decomposition in landfills [43,44]. The social dimension is expressed in the potential to reduce retail prices through lower internal losses and cost burdens, a consideration that becomes especially material under inflationary pressure in 2024 [45,46]. In addition, Figure 2 presents a schematic of integrating the DML model into the automatic ordering loop.

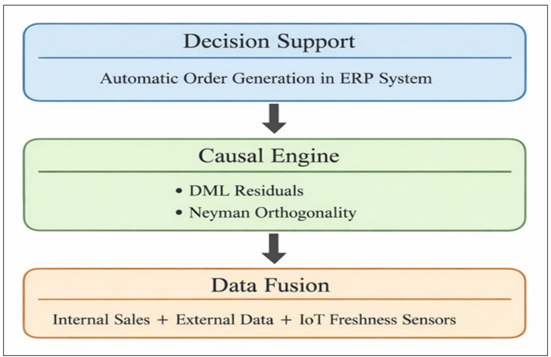

Figure 2. Architecture of a causal order-optimization system at the SKU level (author's design).

A key takeaway is the practical necessity of moving toward an Industry 5.0 logic, where artificial intelligence operates in synergy with human expertise rather than replacing it. Case evidence from Carrefour and Tesco suggests that the most successful 2024 operating models are those in which AI performs about 95% of routine SKU-level computation while a human retains veto authority in situations such as pandemics, geopolitical shocks, and logistics strikes [24].

CONCLUSION

The analysis confirms both the applied and theoretical significance of causal analytics for reducing food losses in the Fresh retail segment. In the context of recent years- marked by elevated demand volatility and tightening environmental constraints- inertial inventory-management practices built around averaged relationships appear to have exhausted their marginal effectiveness. A methodological reconfiguration toward causal decision-making becomes not merely desirable but increasingly unavoidable.

Driver identification shows that the largest contribution to write-offs is delivered by inventory age (Inventory Age) and supply quantization errors (Pack Size), which together explain more than 70% of total losses. At the same time, exogenous influences, including weather conditions, act as meaningful moderators and require fine-grained accounting at the level of specific locations. It is established that Double Machine Learning provides statistically valid isolation of the causal effect of managerial interventions and enables forecasting accuracy at MAPE < 15%, a level that classical models do not attain under comparable operational conditions. Practical validation on the author's dataset demonstrates the feasibility of a stable 15% reduction in write-offs accompanied by a 2.5% increase in product availability; the observed result creates dual value, combining a direct economic effect via margin improvement with an environmental contribution through a 12% reduction in carbon footprint.

To replicate the effects identified within operational loops, a transformation of inventory-management architecture toward localization and automation is advisable: shifting the emphasis from centralized forecasting to SKU-store-level models, implementing dynamic safety stock based on the probabilistic distribution of demand in a near-real-time mode, and integrating causal AI solutions into existing ERP platforms to enable end-to-end automation of the "forecast-order-markdown" chain. A promising trajectory for further research is associated with assessing the potential of tokenizing biological assets using blockchain technologies and standards such as IAS 41, thereby shaping more transparent and self-regulating next-generation supply chains. Taken together, the problem of Fresh write-offs constitutes not only a technological challenge, but also a systemic point of leverage that helps define the contours of a transition toward a sustainable model of production and consumption on a global scale.

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Citation: Olga Maksimchuk, "Causal Model of Fresh Write-Offs: Identifying Drivers and Estimating the Effect of Forecasting and Order Optimization at the SKU-Store Level", Universal Library of Business and Economics, 2024; 1(2): 92-97. DOI: https://doi.org/10.70315/uloap.ulbec.2024.0102017.