Exploration of Information Transparency on Beef Supply Chain Dynamics Using System Dynamics

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Abstract

The beef industry faces growing demands for transparency and traceability due to consumer awareness of supply chain impacts. Lack of transparency and misinformation challenge brand trust and supply chain efficiency. Technologies like blockchain are being explored to address this issue. This study examines the potential of information technologies to enhance traceability and shift the beef supply chain structure toward coordination. We employed System Dynamics (SD) to model the U.S. beef supply chain from 2013 to 2022, capturing complexities and feedback loops to assess structural changes. The model was evaluated and simulated to evaluate the transparent beef introduction dynamics relative to the conventional beef.

Introducing transparent beef shifted consumer demand from conventional due to prices and ordering decisions. Major packers consolidated in the conventional market, while smaller packers found niches in the transparent market. Increased coordination and consumer premiums were necessary to sustain transparent production. The simulation highlighted the supply chain's adaptability but underscored the need for effective strategies for sustainable development. This research bridges a gap in beef supply chain coordination studies and provides insights for stakeholders on integrating technology for transparency. The findings suggest policies supporting technological integration could bolster consumer confidence and supply resilience.

Keywords: Beef Supply Chain, Information Asymmetry, Market Power, Blockchain, System Dynamics

1. Introduction

Global beef supply chains are complex networks of stakeholders experiencing increasing pressure for transparency as consumers demand greater clarity on food choices and their impact on the environment and society (Insight, 2016; Singh & Sharma, 2022). The call for transparency within the agricultural production and distribution system is not only a matter of consumer preference but also a foundational element for building trust amongst all stakeholders. Advances in information technology, such as RFID and blockchain, have emerged as key transparency enablers. Blockchain, for instance, facilitates tracking food product flow from farm to consumer. Major food producers and large scale retailers such as Nestlé, Tyson Foods, Kroger, Unilever, and Walmart emphasize their commitment to consumer trust and food safety, for example, Walmart's implementation of full supply chain traceability of leafy greens (Collart & Canales, 2022.)

However, blockchain adoption within the beef supply chain introduces distinct challenges, largely due to its complex structure and the need for greater coordination among firms. Characterized by long production cycles and horizontally oriented segments involving diverse stakeholders in different geographical locations, the beef supply chain faces potential traceability challenges (Silvestre *et al.,* 2018). These complexities are further amplified by specialization in production stages, industry consolidation, varying international standards, and the environmental implications associated with beef production. Blockchain implementation in the beef supply chain thus requires adaptations to its unique geographic dispersion and disaggregated production and distribution processes. It also raises questions about potential changes to the existing supply chain's structure and the need for greater collaboration among firms. Despite these challenges, blockchain technology has the potential to reduce costs and increase efficiency by reducing participants transaction costs, including information searching, bargaining and monitoring costs (Bischoff & Seuring, 2021; Chen *et al.*, 2022; Sun *et al.,* 2020). Several studies on food supply chains have shown the importance of trust among and between firms in enhancing supply chain performance via more effective coordination and data sharing (Cao *et al.,* 2022; Capaldo & Giannoccaro, 2015; Ferdousi *et al.,* 2020; Ghosh & Fedorowicz, 2008). Blockchain technology, by ensuring traceability and transparency, has received attention for its potential to fortify trust and efficiency within complex supply chains, including the halal food market (Ali *et al.,* 2021; Surjandari *et al.,* 2021; Tan *et al.,* 2022).

Given these challenges, a methodology that captures the dynamic interdependencies within the beef supply chain is required. The system dynamics method is particularly useful for analyzing dynamic problems that involve significant response delays and multidimensional variables connected by feedback processes (Ford, 1999; Sterman, 2000). Because of the power of SD to identify the causal relationships, and connect the physical and information components, it provides a means of modeling and simulating those dynamics. Previous research has investigated beef supply chain traceability using various methods and numerous studies have modeled commodity supply chains using the system dynamics (SD) approach (Feng, 2012; Georgiadis *et al.,* 2005; Herrera & Orjuela-Castro, 2021; Stave & Kopainsky, 2015; Tama *et al.,* 2018). Existing research within food supply chains has primarily examined how information technology can be used to meet transparency demands without fully exploring their dynamic impact on supply chain structures (Bischoff & Seuring, 2021; Chen *et al.,* 2022; Sun *et al.,* 2020). A literature review revealed that the theoretical benefits of blockchain in reducing information asymmetry and transaction costs are widely discussed (Clarkson *et al.,* 2007; Schmidt & Wagner, 2019). Specifically, in the beef industry, a variety of studies have examined environmental or management issues across the supply chain (reviewed below). To our knowledge, no study has specifically focused on transparency adoption implications such as Blockchain in an industrialized beef supply chain, illustrating a gap in empirical and simulation-based research work to understand their implications within the context of beef production.

To address this gap in existing research, we employed SD modeling to investigate the dynamic effects of blockchain implementation on the market dynamics of the beef supply chain, which has thus far been missing from previous beef supply chain modeling efforts (Table 1). For example, Menendez *et al.* (2023) employed SD to refine the assessment of the beef water footprint, resulting in an integrated model from calf production to meat harvest that included market-driven feedbacks which alter supply flow (timing and volume) through the supply chain. Blignaut *et al.* (2022) estimated the carbon footprint of a cow and eight generations of her offspring, emphasizing the importance of full lifecycle analysis and improved land use practices for mitigating greenhouse gas emissions but again excluding market-driven feedbacks on production decisions. Mahbubi & Uchiyama (2020) used SD to model the Indonesian halal meat market but focused on government policies (rather than market supply and demand feedbacks) to counteract meat deficits. In Nigeria, Odoemena *et al.* (2020) explored policies to reverse the trend of declining beef consumption, recommending a multifaceted approach involving carcass yield, slaughter rates, and feed quality. Adl & Parvizian (2009) analyzed the drought impact on Iran's livestock sector using SD, showing increased sheep slaughter due to drought led to temporary short-term increases in meat supply and decreased prices, necessitating feed imports to sustain production long-term.

Table 1. Overview of System Dynamics Applications in Beef Supply Chain: Studies and Findings.

Authors	**Findings**
Menendez *et al.* (2023)	Provides a significant advancement in the methodology for assessing and managing the water footprint in beef production that could lead to more sustainable practices and policies in the livestock sector
Blignaut *et al.* (2022)	Evaluates the carbon footprint across their life cycles using SD, considering scenarios for methane's impact and manure-based carbon sequestration. showed that net emissions can significantly vary, influenced by methane accounting and soil health
Mahbubi & Uchiyama (2020)	Identify the best policy scenario to respond to halal meat deficits
Simões *et al.* (2020)	Find the impact of production technology adoption on profitability and prices
Odoemena *et al.* (2020)	Suggest having combinations of carcass yield, slaughter rate and feed improvement policies as the most efficient solution to the problem of declining per capita consumption of beef
Tinsley *et al.* (2019)	Suggest focusing on heifer retention rate as the more impactful variable than other options
Susanty *et al.* (2019)	Examine different policies to find the best to increase the performance of the supply chain

Authors	Findings
Lie *et al.* (2018)	Reveal that improving the feeding system through improved pastures, increased use of concentrates, or investment and training in pasture management can increase milk productivity, but also have different effects on producer profits and require different time horizons
Turner *et al.* (2013)	Explore financial strategies within the beef supply chain, revealing that targeted adjustments in cow sales can significantly affect ranch profitability. Their model underscores the potential of strategic cow culling to improve Net Income and Return on Investment, while also indicating the flexibility of heifer retention strategies
Adl & Parvizian (2009)	Drought led to increased sheep slaughter, resulting in higher meat supply and reduced prices. Suggested implementing appropriate policies, such as importing animal feed, could help preserve the country's production capacity

Many other works have focused on specific segments of beef supply chains. For example, Simões *et al.* (2020) examined how technological advances in production affect market prices and profitability in Brazil's dairy sector by focusing on strategic decisions at the farm level. Turner *et al.* (2013), Tinsley *et al.* (2019) and Susanty *et al.* (2019) identified how herd management variables such as heifer retention rates, cow culling rates, or policy reforms on the farm sector can significantly enhance the operational and financial performance of ranches and dairy supply chains, respectively. Lie *et al.* (2018) noted that enhancements in feed systems could boost milk productivity but might have varied effects on profitability and operational timelines. These reviews highlight the unique capability of SD to understanding and modeling the complex dynamics of the beef supply chain and production situations.

This research aims to fill the identified knowledge gap by exploring the dynamic impacts of increased transparency demand on the beef supply chain's structure by using SD. To address this main objective, we develop a dynamic model of the beef supply chain as a foundational tool for our analysis to assess how changes in transparency demand impact the beef supply chain structure. Then, we simulate various scenarios of blockchain adoption across the supply chain to examine its potential in meeting transparency demands, and evaluate different beef production and supply decision components in response to the transparency demand on the beef supply chain structure. The resulting SD model helps to identify how different market segments (feeder, packer, and retailer) respond to varying consumer demands, shedding light on potential opportunities and vulnerabilities in beef supply chains from changing consumer preferences, and finally allow supply chain professionals to design and evaluate management policies for each stage of the beef supply chain.

This paper is organized into sections as follows: Section 2 outlines the SD approach, including the steps taken to formulate the dynamic hypothesis, and development and evaluation of the SD model. Section 3, the results, and discussion section, delivers the model’s evaluation results, including the simulation results, and an analysis of the implemented policies and scenarios on the beef supply chain, focusing on their implications. Finally, the conclusion section summarizes the key findings of the study in section 4.

2. Materials and Methods

The beef supply chain is characterized by uncertainties at various stages, often with long lead times. These uncertainties force the stakeholders to continually reassess and revise their strategies as new information becomes available. The dynamic interactions among the stakeholders, coupled with the essential role of feedback, underscore the inherent dynamism of the supply chain (Hwarng & Xie, 2008). Given these complexities, the SD methodology, which is designed to handle complex systems and capture the interplay among system variables, is ideally suited to model the intricate structures of supply chains. By utilizing stocks, flows, internal feedback loops, table functions, and time delays, it captures the system's complexity and uncertainty, revealing emergent properties and behavior patterns (Forrester, 1997).

2.1. Conceptualization and Model Overview

The conceptualization process began with a comprehensive literature review to identify key variables influencing blockchain adoption and coordination decisions in the beef supply chain. We articulated a problem statement reflecting the beef industry's transparency challenges, the dynamic nature of these challenges as they evolve over time —including specific delays, rate changes, and accumulation effects— and interact with factors like market power and transaction costs, and the potential for blockchain in response to transparency demand.

Our analysis emphasizes the consumer-driven shift towards food transparency and examines enhanced supply chain integration and coordination via technology like blockchain. We reviewed literature from agricultural economics and supply chain management focusing on information transparency demand, transaction costs, market power, and the agribusiness firms' responses to these factors (Table 2) to develop the dynamic hypothesis.

Table 2. Key Conceptual Insights from Literature on Technology Adoption and Information Transparency in Beef Supply Chain Management.

Conceptual Insights	Source
Consumers are showing a willingness to pay for beef products that offer transparency	Abidoye *et al.,* 2011; Checketts, 2006; Dickinson & Bailey, 2002; Lim *et al.,* 2018; Loureiro & Umberger, 2003a, 2003b; Umberger *et al.,* 2009
Blockchain adoption can reduce transaction costs and increase supply chain efficiency	Chen *et al.,* 2022; Sun *et al.,* 2020; Bischoff and Seuring 2021
To meet demand, firms are adopting information sharing technology such as blockchain	Dutta *et al.,* 2020; Dalton *et al.,* 2018; Sarker *et al.,* 2019
The potential adoption of blockchain could enhance supply chain profitability through an increased share of transparent beef production and a reduction in transaction costs	Chen *et al.,* 2022; Sun *et al.,* 2020; Bischoff and Seuring 2021
Decrease chain information asymmetry due to information availability and sharing information	Francisco and Swanson, 2018
An increase in transparency and traceability and more motivation for blockchain adoption	Schmidt & Wagner, 2019

Then, we visualized the system's structure as a causal loop diagram (CLD; Figure 1), to represent the interactions within the beef supply chain from a feedback perspective. The CLD shows the cause-and-effect relationships —including time delays and rate effects— between various elements, facilitating the formulation of dynamic hypotheses. A positive sign (+) on the arrows indicates that an increase or decrease in the "cause" variable will correspondingly increase or decrease the affected variable. Conversely, a negative sign (-) implies that an increase or decrease in the "cause" variable will inversely affect the variable in question. The combination of positive and negative causes (arrows) generates loops in the system. If the loop creates positive feedback, it is termed a reinforcing loop, while negative feedback generates a balancing loop. Our dynamic hypothesis was stated as follows:

> As consumers show a willingness to pay for transparency, the supply chain is motivated to adopt blockchain technology. This adoption, however, does not occur instantaneously but follows a temporal buildup as firms address implementation delays. Once adopted, blockchain could be a critical driver for reducing transaction costs and improving efficiency, profitability, and coordination captured as the 'Transparency-Driven Profit and Coordination Cycle' (Reinforcing Loop 1). Over time, the adoption of blockchain is anticipated to create a virtuous cycle of reduced costs and increased efficiency, further encouraging its use, termed 'Blockchain Facilitates Coordination' (Reinforcing Loop R2). As blockchain reinforces transparency, it consequently heightens market power and consolidates profits, detailed in 'Blockchain Reinforces Transparency' (Reinforcing Loop R3). On the other hand, increasing information asymmetry can have immediate disruptive effects that gradually dampen supply chain profits and market power, leading to less coordination efforts among firms in effort to maintain market power position and profitability captured in 'Coordination-Driven Efficiency' and 'Entrenchment Slows Coordination effort' (Balancing Loop B1 and B2). 'Asymmetry Mitigation via Integration Loop' (Balancing Loop 3) reflect the time-dependent dynamic interplay between information asymmetry and the efficiency of the supply chain, particularly when considering transaction costs and the efforts toward supply chain coordination. 'Coordination Regulates Efficiency' (Balancing Loop B4) highlights the mutual effect of vertical integration and supply chain efficiency. As information asymmetry increases, transaction cost will rise and chain efficiency will decline, leading to a reduction in coordination efforts, as shown in 'Asymmetry and Power Calibration' (Balancing Loop 5). Each balancing loop serves as a critical check within the system and embodies the complexities and perspectives of various segments stakeholders given existing asymmetric information flows and market power positions.

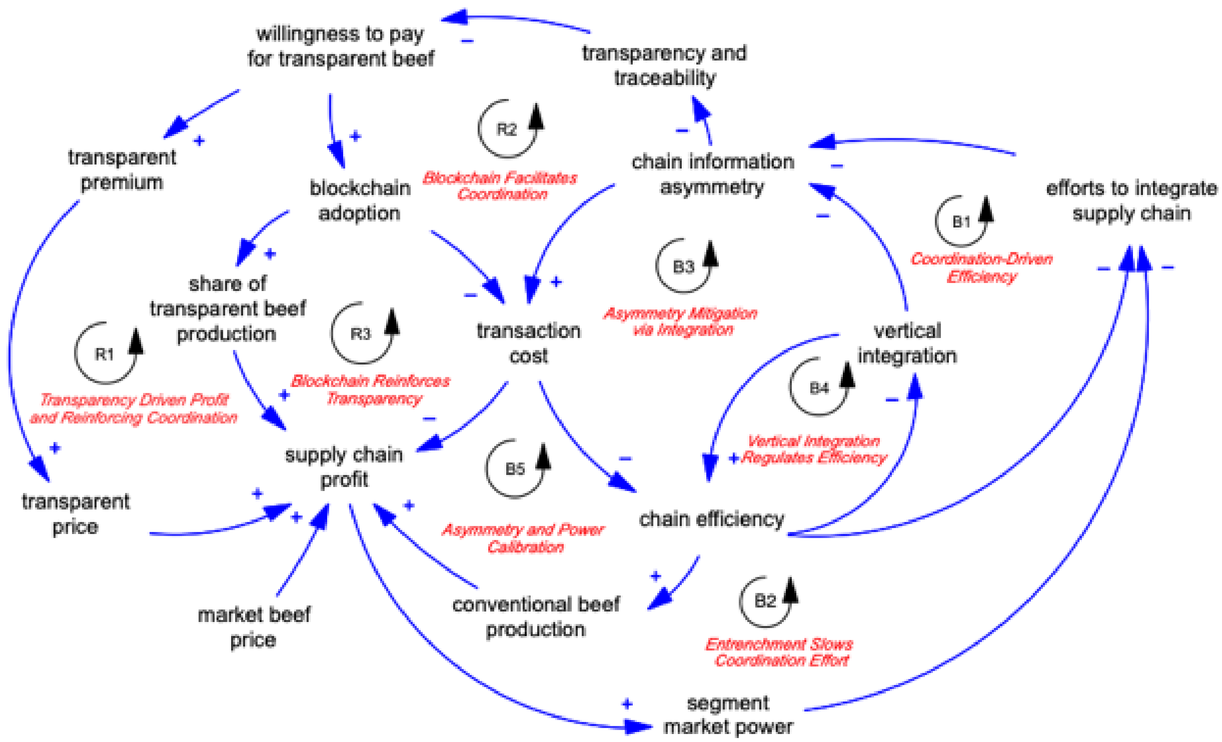

Figure 1 The dynamic hypothesis of transparency demand in the beef supply chain, along with associated costs and integration efforts (i.e., Causal Loop Diagram). Where, the variables in italics are loop names. Loops are either balancing (B) or reinforcing (R) based on their polarity. Polarity is denoted by a plus (+) for same direction or a minus (-) opposite direction relative to the preceding variable.

2.2. *Quantitative Model Description*

We develop our model based on the generic commodity market model proposed by Sterman (2000) that is a generalization of the seminal model of hog cycles published by Meadows (1971). The initial phase of our methodology involves precisely defining the problem space, the system's boundaries, key stocks (e.g., feedlot inventory), flows (e.g., feeder input and finished to harvest flow), and auxiliary variables (e.g., packer order), outlining interactions between key variables, and establishing a reference mode to depict behavioral dynamics over time. For model construction, we employ the DSS version of Vensim software (Ventana System, Inc.). At each simulation time step the model retrieves the current values for each variable from the previous time step's simulation results and uses them as the starting point for the current iteration. This process follows equations to update the stock, flow and auxiliary variables over time. This protocol, executed iteratively within the simulation, ensures that the dynamic feedback and timing of adjustments are consistently applied.

The simulation is conducted with a time step of 0.0125 months, and the model's development, calibration, and evaluation extend over a 120-month period from January 2013 to December 2022. Initial values, serving as reference inputs for the model, are derived from USDA historical data (Livestock & Meat Domestic Data: All Meat Statistics. 2023).

The model is segmented into three distinct, yet highly integrated and feedback-rich subsystems. These three interrelated subsystems are Inventory and Production, Demand, and Price. Building on this foundation, the model replicates historical behaviors over a decade, focusing on the path from feedlot to consumer, with a detailed emphasis on inventory management across different stages of the supply chain. This aspect of the model is important in understanding how production and inventory decisions impact supply chain dynamics, pricing strategies, and the overall system.

2.2.1. Inventory and Production Sub Model

The sub model presented in this section captures the production and inventory aspects of the beef supply chain (Figure 2, Inventory and Production panel). This subsystem traces the path of cattle from entering the feedlot through to consumer beef sales.

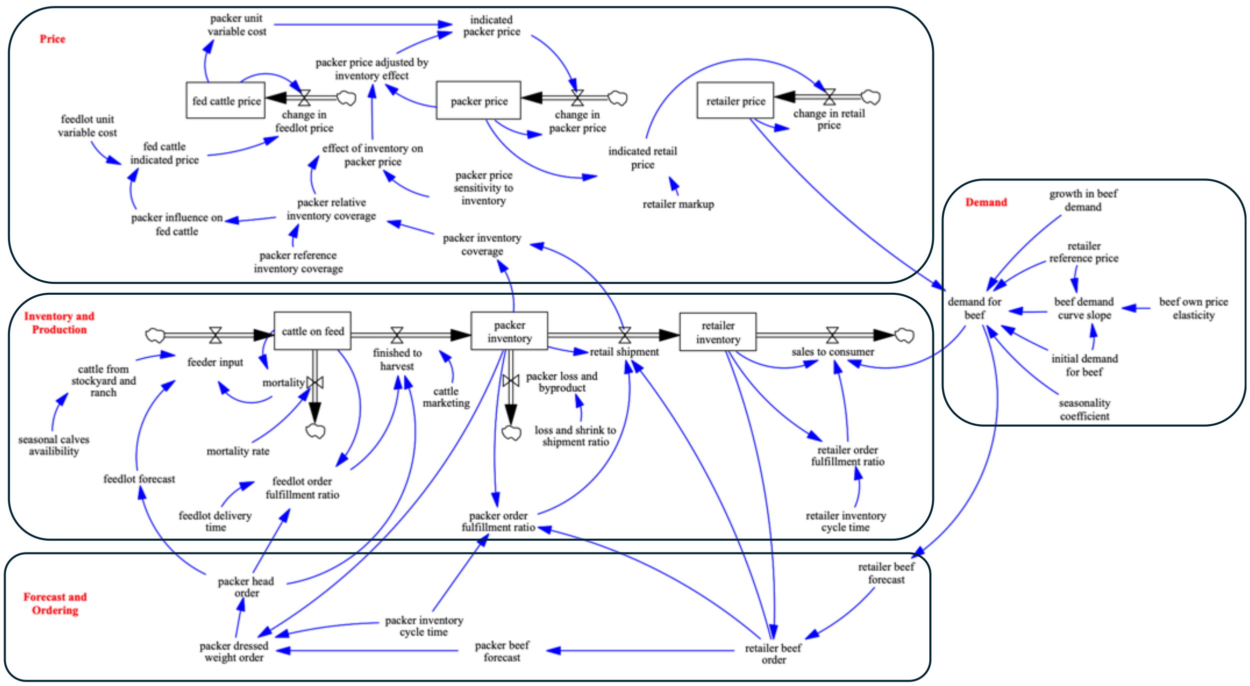

Figure 2 Beef supply chain stock and flow diagram illustrating the linkage between price, inventory and production, forecast and ordering and demand subsystems in the beef supply chain, along with the associated feedback loops. Rectangles represent stock variables, while inflows and outflows are shown as pipes pointing into or out of the stock. Clouds represent the sources and sinks of flows within the system.

Feedlot inventory is replenished through feeder input, calculated based on feedlot forecasts and the arrival of cattle from ranches and stockyards, adjusted for monthly mortality rates.

Parameterization also requires industry knowledge from outside the feeder-packer-consumer model boundary, such as the observed increase in dressed weight by 127 grams per head per month from 2013 to 2022; likely due to advancements in genetics and breeding practices in the cow-calf sector (Coyne *et al.,* 2019; Haley & Jones, 2017).

From feedlot inventory, cattle are moved monthly via a flow known as finished to harvest, F_f (Equation 1), where C_f denotes cattle marketing, H_p is packer head order, and r_f is feedlot fulfillment ratio:

$$F_f = \min(C_f, \min(H_p, r_f * H_p)) \qquad (1)$$

This outflow is determined by the lowest value among the packer's orders, the feedlot's fulfillment capacity, and cattle marketing readiness. The fraction of packer orders filled, called feedlot fulfillment ratio (r_f) is derived by the ratio of the normal shipment rate to the desired rate. The normal rate is the current inventory's permissible rate under normal circumstances. Low inventory availability reduces shipments (Sterman, 2000). The cattle marketing variable, C_f is a supply function showing the total feedlot's supply of cattle that is available for marketing based on the current market conditions. We estimate the cattle supply curve based on historical data and used the fed cattle supply elasticity, which also was calibrated, consistent with the real-world data from USDA and literature (Jeong, 2019). This supply variable can be adjusted according to the actual demand and capacity of the packers via finished to harvest outflow. The packer head order, H_p, is based on the packer's order (kg) converted to the number of head, establishing a mechanism for balancing demand with current inventory.

The dressed weight a beef packer requires to fulfill consumer demand was based on its existing inventory and a consumer demand forecast (Equation 2):

$$W_p = \max\left(0, \begin{cases} M_p + \alpha * \left(\frac{M_p * \gamma \cdot T_p}{\gamma \cdot T_p}\right) & \text{if } M_p \cdot \gamma \cdot T_p > I_p \\ M_p + \beta * \left(P_b - \frac{I_p}{\gamma \cdot T_p}\right) & \text{otherwise} \end{cases}\right) \qquad (2)$$

Where, W_p is packer dressed weight order, M_p is packer beef forecast, T_p is packer inventory cycle time, I_p is packer inventory, α and β coefficients for adjustment based on inventory levels relative to forecast and cycle time, and γ is an adjustment factor for packer inventory cycle time. This function represents packers ordering decisions designed to balance packers own supply constraints with existing beef demand. Depending on the forecasted demand relative to their current inventory, packers adjust W_p, which helps to smooth out any imbalances in inflows from feeders and order outflows to retailers (as shown in Figure 2, Forecast and Ordering panel).

2.2.2. Demand Sub Model

The demand sub-model determines the quantity of a product that consumers are willing to buy at various price points (Figure 2, Demand panel). This demand function follows Sterman's (2000) demand function for commodities, modified using beef industry parameters, adjusted in each time step in response to retail prices (the price that consumer pays at retail store) for conventional beef.

The consumer demand for conventional beef, D_b, (Equation 3) estimates the demand for conventional beef by using a combination of factors: the retailer's conventional price set by the retailer, P_r , the initial demand in the market, D_0, the demand curve slope, m, and the seasonality coefficient, ω. The demand variable interacts with the price sub-model using retail price to determine quantity demanded of D_b, using a classic demand curve. At each simulation time step the model update the relevant variables (e.g., $R(t), D_0, P_r, P_{rrf}$), and calculates D_b by computing the inner adjustment factor (ensuring it is non-negative) and then applying the outer max function to maintain a minimum demand threshold.

$$D_b = \max\left(45000, \omega * \left((R(t) + D_0) * \max\left(0{,}1 + m * \frac{P_r - P_{rrf}}{D_0}\right)\right)\right) \quad (3)$$

Where D_b signifies demand for conventional beef, D_0 is initial demand, m is the Demand curve slope, P_r is the retailer price, P_{rrf} is the reference retailer price, ω is the seasonality coefficient, and $R(t)$ is the RAMP function of growth in beef demand from an initial to final time.

To find the demand curve slope (m), we use historical data from United States Department of Agricultural (USDA) and Livestock Marketing Information Center (LMIC) and calculate it using Equation 4, where P_{rrf} is reference retailer price and ε is the own price elasticity, with ε values derived from literature (Brester *et al.,* 2004; Lusk & Anderson, 2004; Okrent & Alston, 2012), and calibrated to match the historical data trends observed within the model's time frame.

$$m = -\varepsilon * \frac{D_0}{P_{rrf}} \quad (4)$$

Equation 4 uses inputs to create a robust model for estimating the demand for conventional beef, adjusting for both static (initial demand) and dynamic (retailer price) factors, thereby providing a comprehensive representation of how different elements interact to shape the market demand for conventional beef.

2.2.3. Price Sub Model

The price subsystem captures the complex interplay of prices at different levels of the supply chain, from feedlot to the retailer. Price directly influences demand, supply decisions, and ultimately system behavior. This subsystem includes beef price at different levels of the supply chain, structured such that the current price is built by adjusting the previous price based on how price changes across the supply chain (Figure 2, price panel). The initial value assigned to these prices in the reference mode is obtained from USDA historical beef price data.

The most significant stock in this structure is the packer price, which influences both the retailer price and the fed cattle price. The packer price, P_p in the model refers to the price that a retailer pays to purchase boxed beef from a packer, adjusted by inventory effects ($P_{p(inv)}$) as presented in Equation 5. Here, η represents the inventory effect on price, modifying the packer price P_p, based on current inventory conditions relative to desired levels.

$$P_{p(inv)} = P_p * \eta \quad (5)$$

In the beef and similar perishable commodity markets, inventory management is a critical concern. The packer price adjusts according to its inventory levels. As such, a lower than its reference (normal) inventory coverage, triggers a price increase to help balance the inventory. Thus, the variable packer price adjusted by inventory effect, $P_{p(inv)}$, represents the adjusted packer price, reflecting inventory-related price modifications, effectively capturing market dynamics adjusting for the effects of inventory (Equation 5).

Moreover, the model considers the sensitivity of packer price to its inventory, Equation 6, using a power function:

$$\eta = (\frac{I_{pc}}{I_{prc}})^{\zeta} \qquad (6)$$

Here, ζ represents the sensitivity of packer price to packer inventory, I_{pc} is packer inventory coverage and I_{prc} is packer reference inventory coverage.

Thus far, these interconnected sub-sections accurately reflect the economic structures of real-world beef supply chains. For example, the retailer price, P_r, from the price sub-section is used to calculate the demand, D_b, which in turn forecasts retailer order and determines the quantity of sales to consumer flow. The depletion of packer inventory in fulfilment of retailer orders then pulls inventory from the feedlot segment, the flow rate being influenced by the relative inventories and prices in each segment.

2.3. Model Calibration and Evaluation

Leading system dynamics modelers have developed various tests to identify model flaws and guide improvement in model structure, behavior, and policy testing effectiveness (Barlas, 1996; Senge & Forrester, 1980; Sterman, 2000). We follow SD best management practices by conducting a range of tests, including structure and parameter tests to assess the appropriateness of our model's configuration and values. Integration error tests are carried out to check for inconsistencies under various numerical integration methods, and dimensional consistency tests ensure unit consistency. Additionally, we perform sensitivity analyses to measure the impact of parameter value changes on model output, extreme conditions tests to examine the model behavior under extreme input values, and boundary adequacy tests to evaluate the appropriateness of the model scope and boundaries.

Beyond these tests model confidence is also supported by calibration to real world data. We source data from literature and official databases, such as USDA and LMIC from 2000 to 2022, with 2013-2022 data used for calibration and verification. For price calibration, we compare the model generated to real-world data of feeder and fed cattle, packer prices, by-products, and retail prices, tracing the product's journey from feedlot to consumer. Inventory calibration include data on feedlot inventories, cattle placement and marketing, and slaughter statistics.

This comparison with historical data ensures that the model captures price-quantity relationships, seasonal supply and demand effects, and consumption patterns relative to population growth.

Both manual and automated calibration via Vensim software align the model with historical data from USDA and LMIC. Calibration statistics include Mean Bias and Root Mean Square Error Percentage (RMSEP) to measure both accuracy and precision in model generated behavior compared to observed values (Tedeschi, 2006). To find the source of error in addition to its magnitude (Oliva, 1995, 2003), we employ the Theil inequality statistic (Theil, 1971) that decomposes the error into biases of unequal mean, unequal variance, and unequal covariance.

2.4. Exploratory Simulation Experiment

Upon completion of the calibration and evaluation phase, we craft a model experiment to test the impact of transparency adoption in the supply chain to meet a new customer demand for transparent beef. To achieve this, we define two products with identical supply chain structural functions (e.g. feeder and packer inventory, price structures and consumer demand) but vary in the type of beef: conventional beef (the market status quo) and transparent beef; the new product. To realistically assess the capacity and willingness of supply chain segments to respond to consumer demand, we used the subscript function of Vensim DSS software, and define two multi-agent segments: 10 heterogeneous packers and 100 heterogonous feedlots, each varying in their maximum capacity in existing industry and firm structure (Lowe & Gereffi, 2009).

A key distinguishing feature of this model, compared to other SD commodity models, lies in our inclusion of packer market power, reflecting the impact of transactional dynamics among actors. We also introduce an initial market share variable, calibrated to represent real-world market shares of packers (or feedlots) in the market. A study by Lowe & Gereffi (2009) found percentages for beef market share for four major packers, which we use as the initial market share for the first four big packers, with the total market share of the remaining six packers accounting for 25% of the market. To find the initial market share for the feedlots, we use Lowe & Gereffi (2009) along with USDA data to calculate the firms' initial market shares based on various parameters such as the number of marketed head in each category and their one-time capacity (Table 3).

Table 3. Feedlot and Packer Market Share.

Feedlot Group	**Capacity Range (Head)**	**Initial Market Share (%)**
Feedlot 1-6	≥32,000	52%
Feedlot 7-13	16,000–31,999	19%
Feedlot 14-20	8,000–15,999	11%
Feedlot 21-37	4,000–7,999	8%
Feedlot 38-62	2,000–3,999	6%
Feedlot 63-100	1,000–1,999	4%

Packer Group	**Capacity Range (Head/Day)**	**Initial Market Share (%)**
Packer 1-4	≥ 2,500	75%
Packer 5-7	1,000-2,499	17%
Packer 8-10	<1,000	9%

To accurately model the adoption of transparent beef and reflect real-world conditions, we adopt an S-shaped growth function. Various Country of Origin Labeling (COOL) studies have predicted that approximately 30% of the market will ultimately choose transparent products if they are available (Gao *et al.,* 2010; Lubben, 2005). Therefore, the demand for transparent beef initiates with a minor share and gradually increases until it reaches a saturation point (≈30%). The parameters for conventional and transparent beef are designed to respond dynamically to market demand. As the demand for transparent beef increases, conventional demand decreases, and vice versa, reflecting the substitute nature of these two products.

In relevant literature 'Willingness to pay' values vary widely, ranging from 21% to 50% of the base price (Abidoye *et al.,* 2011; Bailey *et al.,* 2005; Dickinson *et al.,* 2003; Loureiro & Umberger, 2003a, 2003b, 2007; Umberger *et al.,* 2009). Following a review of the literature and relevant data, we adopt 48% of the base price for this parameter. Additionally, we assume that the production cost for transparent beef remains similar to conventional beef. However, the total cost of transparent beef differs due to added costs associated with blockchain adoption, changes in transaction costs, and variations in transparent cattle price (Chen *et al.,* 2022; Ferdousi *et al.,* 2020; Sun *et al.,* 2020).

We also introduce the 'transparent demand switch' variable to the model. This switch functions as an on/off control, set to zero for conventional beef production only, despite the existence of blockchain adoption and other variables related to transparent beef, all producers/firms only produce conventional beef. Conversely, activating the switch (on mode) triggers a demand for transparent beef, thereby signaling a portion of the total beef demand to be allocated to consumers willing to pay a premium over the conventional price, incentivizing the supply chain to respond to this new demand.

In our model, the adoption of blockchain technology significantly alters the cost structure of firms within the beef supply chain. Initially, the adoption of blockchain requires an upfront cost. However, it is expected to decrease direct transaction costs—information search, negotiation, and monitoring costs—due to the enhanced transparency and streamlined processes. Specifically, the reduction in information asymmetry and improved data accessibility through blockchain allows firms to efficiently manage these costs. Furthermore, as firms continue to utilize blockchain technology, we observe a compounded effect on transaction costs over time. This ongoing reduction is modeled to reflect both the immediate efficiencies from initial blockchain adoption, and the longer-term benefits derived from learning and adapting to the technology.

Subsequently, each firm calculates its benefit in terms of revenue and cost, and both packers and feedlots jointly decide on the volume of transparent beef to produce. This decision considers each agent's benefit in each segment and the current transparent beef demand.

3. Results and Discussion

3.1. Model Calibration and Evaluation Results

We calibrated the model using statistical tools to align outputs with real-world data (2013-2022). Key parameters were determined through data analysis and literature review. For example, demand own price elasticity was calibrated from an initial 0.71 to 0.74, consistent with USDA data and literature ranges.

Statistical validation confirmed model accuracy: Mean Bias results showed reliable predictions with all variable biases under 1%, RMSEP values close to 0, and C_b values near 1, indicating unbiased predictions. Theil inequality statistics revealed that unequal covariance dominated Mean Square Error Percentage, confirming the model captured observed patterns effectively.

We conducted a sensitivity analysis to understand how changes in parameters and assumptions influence the model's behavior or numerical values. In the model, we chose 'sensitivity of prices to packer inventory' and 'cycle times' parameters for testing. Sensitivity analysis using Monte Carlo simulation (200 iterations, ±25% parameter range) demonstrated model stability with minimal deviation in key variables. Extreme condition tests using mortality rate increases validated the model's performance under unexpected events.

3.2. Exploratory Simulation Experiment Results

Following calibration, we examined transparent beef introduction effects on market dynamics. As shown in Figure 3, splitting total demand (~700M kg/month) into conventional and transparent segments reallocated purchases without growing the overall consumer base, consistent with consumer choice theory and empirical studies (Abidoye *et al.,* 2011; Boncinelli *et al.,* 2021; Checketts, 2006; Dickinson & Bailey, 2002; Lim *et al.,* 2018; Umberger *et al.,* 2009).

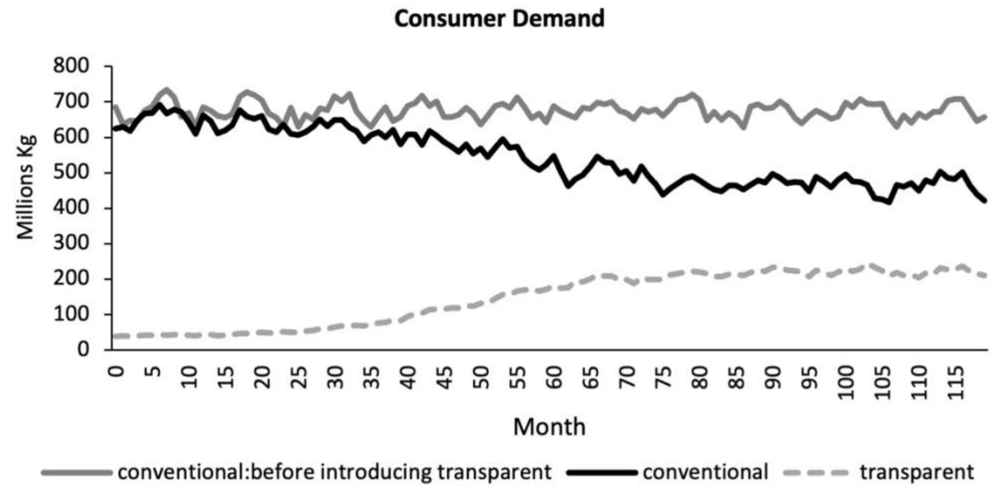

Figure 3 Changes in beef supply chain consumer demand due to introducing transparent beef (2013-2022)

Retailer and packer prices for conventional beef initially declined slightly, then increased moderately due to supply-demand adjustments and resource reallocation. Transparent beef entered at premium pricing levels. Fed cattle prices remained stable due to longer production cycle.

Larger packers (1-4) consolidated conventional market share (75% to 89% market share), while smaller packers (8-10) captured niches in transparent beef (50% market share) but lost conventional market position. This reflects resource-based competitive advantages and strategic market positioning. On the feedlot side, the largest yards increased conventional share (from 52% to 68%); smaller feedlots (1,000–1,999 head) accounted for about 23% of transparent beef by the end period.

In summary, this simulation shows the immediate and complex effects of introducing new products in the beef market on consumer demand and pricing. It reveals the beef supply chain's resilience and adaptability to a new type of product contingent to technological availability, such as transparent beef. It also showed the market price sensitivity to introduction of new product and indicates the existence of robust feedback mechanism to maintain market efficiency.

3.3. Comparison with Other Commodity Models

In comparing this SD model with extant commodity models within the literature, we highlight its unique contributions to the domain of agricultural supply chains, particularly within the beef industry. Prominent research utilizing SD for analyzing various supply chains includes Meadow (1971) and Sterman (2000), who used SD to model livestock sector supply chain.

Upon reviewing past studies and literature on the food and agriculture supply chain, we identified dynamic aspects specifically related to the U.S beef and cattle market. Our model aims to depict the interaction within the supply chain to find solutions for improving information symmetry. However, to the best of our knowledge, no existing SD model of the beef supply chain addresses the asymmetry of information or implements interventions to rectify this.

We have expanded Sterman's model to include multiple actors such as feedlot, packer, retailer, and consumers in the supply chain. As such, it endogenously captures price and quantity dynamics at different stages of the beef supply chain and their feedback loops.

In parallel, we drew inspiration from Meadows' hog production model, particularly in its depiction of cyclical behaviors due to delayed responses to price signals and subsequent correction mechanism. Unlike Meadows livestock production model, which emphasizes breeding decisions and their impact on supply cycles, our model focuses on the relation between consumer demand, supply response, and changes in quantity and price.

Furthermore, our model also incorporate market power dynamics and market share distributions, important features of the U.S. beef market. It enables us to explore scenarios that include strategic interactions between firms with varying degrees of market power and to assess their impact on the supply chain.

These enhancements have allowed us to model a more comprehensive simulation of the beef supply chain and market. It enables the simulation of different demand and supply scenarios under varying product characteristics within the same supply chain. By considering specific characteristics and the unique market power structure of the beef industry, we provide a robust platform for analyzing modern beef supply chains like those in the U.S. and the EU.

Unlike most SD models focused on the livestock supply chain that primarily consider production side and supply-side interventions, we specifically address the information asymmetry inherent in the beef supply chain by integrating traceability demand and information, which has not yet been explored in existing models.

3.4. Discussion, Limitation and Implications For Agricultural Systems Policymaking

In this study, we explored the roles of information, transparency and market power in the beef supply chain using system dynamics. However, the absence of data on supply chain integration, acquisition, and merger costs across beef supply chain , and obtaining information for various variables, especially transaction costs throughout different beef supply chain segments hindered our ability to fully analyze integration and comparing with it current coordination decisions in the market.

This model reproduces observed dynamics with low bias, passes calibration and validation tests, and shows that transparency reallocates demand and reshapes shares without destabilizing upstream cattle prices.

The results of this model offers a pathway to deeper insight into the structure, management, and behavior of beef supply chains. It helps to understand the resilience of the supply chain while introducing new products in presence of new information technology platforms. The model provides insights for developing decision support tools and examining policy impacts on market structure and coordination under varying consumer demand conditions.

4. Conclusions

This study developed a comprehensive system dynamics model of the beef supply chain that incorporated various industry-specific parameters and agent behaviors, such as cattle production biological delays, packer concentration, supply chain coordination and market power, as well as trends in efficiency and production improvements. The model was rigorously calibrated, using data from 2013 to 2022, to offer a significantly more accurate representation of the real-world, especially within the U.S market, surpassing generic supply chain models and other SD beef models. The model's unique treatment of price mechanisms and endogenous coordination significantly enhances its capability, offering a superior representation of the beef supply chain.

Through this analysis we demonstrated a resilient beef supply chain that can adapt to changing consumer preferences for transparency (via blockchain or similar technologies) by forecasting industry supply between larger packers that focus on economies of scale to produce conventional commodity beef where smaller packers focus on the smaller emerging markets for transparent beef where price premium products justify the additional investment needed for transparency.

In line with the objectives presented in the introduction, our findings demonstrate that the introduction of transparent beef can alter market structures, pricing, and coordination among supply chain participants. Specifically, larger firms, both feedlots and packers, tend to consolidate their share in the conventional beef market, while smaller firms capture a niche in the transparent beef segment, showing a strategic response to emerging consumer preferences. This result underscores the importance of adopting relevant technologies to facilitate transparent beef production and manage the additional coordination requirements that transparency involves.

Moreover, our results highlight how shifting consumer demand can force retailers, packers, and feedlots to adjust production strategies, reinforcing the model's ability as a decision support tool for analyzing market decisions and optimizing operational strategies in an increasingly information-driven environment.

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