Estimating the Global Cattle Meat Supply and Demand

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Abstract: This paper analyzes the global cattle beef sector with a structural time series model. We estimate the supply and demand for cattle meat by applying shocks in Structural Vector Autoregression (SVAR) model. We attempt to close the gap between econometric and epidemiological model by defining SVAR model such that the shocks could be disaggregated into mortality and morbidity shocks resulting from disease outbreaks. Our estimates suggest that producers and consumers reacts to disease related shocks more than the other regular market shocks. We find that the distribution of gains or losses across the beef supply chain differs due to market disruptions caused by mortality and morbidity shocks. Results suggests that the estimated global loss in the cattle beef sector is USD 1200 to 2000 billion, which is 1.2% to 1.9% of the global GDP.

JEL Classification: Q11, Q17, Q18, I18, C32

Keywords: Global beef market; Structural vector autoregression (SVAR); Disease shocks; Supply and demand estimation; Welfare impacts; Agricultural policy

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1. Introduction

Livestock is a cornerstone of the global economy, providing food, draft power, and by-products, while also reducing poverty and serving as a financial asset for millions worldwide (World Bank, 2021). Livestock diseases distort markets by reducing productivity, leading to food supply chain disruptions (Rushton et al., 2018, 2021; Hennessy and Marsh, 2021) and the redistribution of economic welfare across the globe (Hennessy and Marsh, 2021). The redistribution of economic welfare through impacts on firms and consumers is vital information for global planning, for stakeholder livelihoods, and for food security. Therefore, studies on the identification and estimation of global demand and supply of commodities are emphasized in the economic literature. For example, Kilian (2009) and Kilian and Murphy (2012) examine global demand and supply of oil. Roberts and Schlenker (2013) use instrumental variable (IV) method to estimate the global demand and supply of crops. Ghanem and Smith (2022) estimate the global demand and supply of crops with a time series approach.

National and regional studies on the demand and supply of the livestock sector across the value chain constitute a vast body of literature (Wohlgenant 1989; Bielik, P., & Šajbidorová, Z. 2009; Lusk and Tonsor, 2016; Delport et al., 2017). Elasticities estimated in these studies are often used to assess policy impacts or economic shocks, especially in ex-ante livestock disease outbreak studies (Pendell et al., 2007; Tozer and Marsh, 2012; Shakil et al., 2025). To fill out the gaps of the literature, oftentimes, researchers studying what if scenarios resulting from disease outbreaks, estimate regional and value chain elasticities pertaining to their studies (Cakir et al, 2018;

Thompson et al., 2019). However, studies on the global meat demand and supply are scarce in the existing literature.

There are two main approaches to study global models, each having its own pros and cons. One can estimate elasticities for each and every region or country, and then aggregate results to the global level. A major challenge with this approach is the substantial commitment of resources required to examine the vast number of models, a difficulty further compounded by severe data unavailability, particularly in underdeveloped and developing countries. Another approach is to estimate a single global model of demand and supply. Challenges in this approach is to account for the country level heterogeneity that exists in the livestock sector.

This paper develops a global econometric model of cattle beef demand and supply. With a global population of about 1.5 billion (FAOSTAT), Cattles are regarded as the most important species in the global livestock sector that provide food, income security, draft power and so on. Although global demand and supply output does not capture the heterogeneity that country level or finer disaggregation does, it provides global quantitative measures and global perspectives on the assessment of shocks. For instance, Kilian (2009) demonstrates how to disentangle global demand and supply shocks in the crude oil market. In this study, we model the global cattle beef sector by fitting a multivariate time series model, namely the structural vector autoregression (SVAR) model.

There are many advantages of using the SVAR models in this context. First, SVAR models are especially useful for the examination of the dynamic relationship between the key determinants of global demand and supply using impulse response functions (Ghanem and Smith, 2022). Second, when appropriately specified, these models generate structural estimates (Ghanem and Smith, 2022), such as elasticities from specific shocks, which can be aligned with welfare economics (Hennessy and Marsh, 2021) to evaluate the redistribution of wealth from shocks to specific impacts of livestock diseases or other exogenous impacts (Thurman and Wohlgenant, 1989; Hennessy and Marsh, 2021). Third, such multivariate time series models can take the epidemiological model outputs as input shocks to estimate counterfactuals from market outcomes (Barratt et al., 2019; Gilbert et al., 2024) including point estimates and confidence intervals.

Building on these advantages, this study applies the SVAR framework to the global beef sector and offers several key contributions to the existing literature. First, the elasticities of global beef demand and supply are estimated from the SVAR model. These elasticities could be directly used as model parameters for ex-ante economic studies (e.g., Pendell et al., 2007; Tozer and Marsh, 2012) and for welfare analysis (Thurman and Wohlgenant, 1989). Second, the production mechanism in the SVAR model is disaggregated to make the framework readily adaptable to detailed epidemiological inputs, such as mortality and morbidity shocks. This alignment with livestock disease economics also ensures that the econometric estimates can be directly applied in the disease impact models. Finally, we show that the distribution of gains and losses from market disruptions caused by mortality and morbidity shocks differs and measure the welfare changes in the global beef cattle sector resulting several disease disruptions. To our knowledge, no other studies have econometrically estimated the economic impact of livestock diseases at a global scale.

It is important to distinguish our study from the literature examining regime-dependent market behavior under disease disruptions, such as differences in demand and supply responses during outbreaks (Acosta et al., 2020) or variations in elasticity estimates between small and large disease shocks (Goodwin, 2024). Our focus is to estimate the overall market behavior resulting from sudden changes in demand and supply, which may include shocks of various nature caused by droughts or livestock diseases. These shocks are exogenous to regular market dynamics and can therefore be used to estimate market forces. Linking these exogenous shocks to disease outbreaks is an important contribution of this study, enabling us to use its results to draw inferences in the context of livestock disease economics.

The rest of the paper is organized as follows. Next, Section 2 introduces our methodological approach for modeling the global beef sector. The data and their sources are described in Section 3. In the following section (Section 4), outputs from the SVAR model along with the model diagnostics are provided. In Section 5, application of SVAR outputs in welfare measurement and the economic assessment disease outbreaks are discussed. Finally, Section 6 presents the concluding remarks of the study.

2. Methods

Let us start with outlining the SVAR framework. Let Y_t be a random vector of outcomes at time t for $t = 1, \ldots, T$.

$$A_0 Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_l Y_{t-l} + f(t) + \nu_t \tag{1}$$

Here A_0 is called the structural or contemporaneous matrix that structures the relationships between the endogenous variables, Y_t. A_i matrices structures the lagged vector Y_{t-i}. Several methods can be used to identify A_0 (Hamilton, 1994). For example, Kilian (2009) used sign restrictions on identifying demand and supply shocks of oil. Ghanem and Smith (2022) impose triangular restrictions to identify shocks in global crops model. Kilian and Murphy (2012) examines less restrictive triangular restrictions and alternative conditions on sign restrictions.

The vector function $f(t)$ are fixed functions of time, e.g., trend, cyclicity etc. The vector v_t is a matrix of innovations or shocks. These shocks are uncorrelated of other contemporaneous variables which allows for the OLS estimation (Appendix A). Impulse responses are identified using the recursive structure (Ghanem and Smith, 2022). The identified impulse responses are then used to calculate indirect cost (Barratt et al., 2019).

2.1. Global Cattle Beef Model

We specify a triangular SVAR model of the global cattle beef sector[1]. In this study, $Y_t \equiv (a_t, y_t, i_t, p_t)'$ where a_t is the cattle stock, y_t is the meat yield per cattle, i_t is the change in inventory and p_t is average price of beef in year t. Our four-equation system is as followed:

$$a_t = \rho_{11} Y_{t-1} + \cdots + f_{i(t)} + v_{at} \tag{2}$$

$$y_t = \beta_{21} a_t + \rho_{21} Y_{t-1} + \cdots + f_{y(t)} + v_{yt} \tag{3}$$

$$i_t = \beta_{31} a_t + \beta_{32} y_t + \rho_{31} Y_{t-1} + \cdots + f_{i(t)} + v_{it}$$

[1] Refer to Appendix A for a detailed discussion of the triangular SVAR identification with strict restrictions.

$$p_t = \beta_{41}\, a_t \; + \beta_{42}\, y_t \; + \beta_{43} i_t + \rho_{41}\, Y_{t-1} \; + \cdots \; + \; f_{p(t)} \; + \; v_{pt} \qquad (4)$$

Figure 1 shows the causal ordering of the four endogenous variables in equations (2), (3) and (4). Similar to Shakil et al., (2025), production is broken-down into two components: stock size (a_t) and per animal yield (y_t).

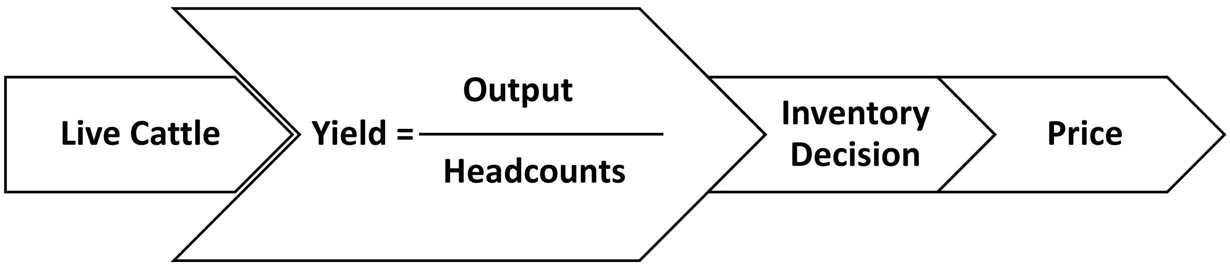

Figure 1: Causal Ordering of Global Beef Cattle SVAR Model

2.2. Identification of the Structural Matrix

Due to the biological nature of livestock production, at the beginning of a year t, the number of live cattle at the farm level is exogenous of the yield and price of that year t, but depends on the yield, inventory and prices of previous year. Yield is directly impacted by the live cattle stock in year t through the relationship described in figure1. Meat processors then make inventory decision based on the number of cattle to slaughter. The price of beef is determined by taking both the inventory size and yield in year t into consideration. This provides a recursive structure that gives a lower triangular shape of the contemporaneous matrix. We define the A_0 and A_i as:

$$A_0 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \beta_{21} & 1 & 0 & 0 \\ \beta_{31} & \beta_{32} & 1 & 0 \\ \beta_{41} & \beta_{42} & \beta_{43} & 1 \end{bmatrix} \text{ and } A_i = \begin{bmatrix} \alpha_{11}^i & \alpha_{12}^i & \alpha_{13}^i & \alpha_{14}^i \\ \alpha_{21}^i & \alpha_{22}^i & \alpha_{23}^i & \alpha_{24}^i \\ \alpha_{31}^i & \alpha_{32}^i & \alpha_{33}^i & \alpha_{34}^i \\ \alpha_{41}^i & \alpha_{42}^i & \alpha_{43}^i & \alpha_{44}^i \end{bmatrix} \text{ for } i = 1, 2, \dots, l$$

2.3. Estimating Elasticities from IRFs

Short, intermediate, and long run elasticities can be estimated using the IRFs. In a static system, elasticities are estimated directly from regression coefficients (e.g., Roberts and Schlenker, 2009). In a dynamic system such as the SVAR, IRF is used to trace out how each variable reacts to a structural shock over time. So, the natural way to recover an elasticity is to look at ratio of the IRFs that gives us the change in one variable relative to another when a shock hits the system.

In order to identify the beef demand elasticity, we need a shock that shifts beef supply. In our model, there are two components of production: live cattle stock and yield per cattle. A sudden shift in stock might be a result of mortality due to diseases. Similarly, disease induced morbidity might cause a shift in yield. Therefore, we refer the shock introduced through the live cattle and yield as mortality and morbidity shock, respectively.

Since, IRF is the partial derivative with respect to shocks, so short-run demand elasticates can be expressed as the following:

$$\frac{\partial q_t}{\partial p_t} = \frac{\partial q_t/\partial v_a}{\partial p_t/\partial v_a} = \frac{\frac{\partial a_t}{\partial v_a}+\frac{\partial y_t}{\partial v_a}-\frac{\partial i_t}{\partial v_a}}{\partial p_t/\partial v_a} = \frac{IRF(a_t,v_a)+IRF(y_t,v_a)-IRF(i_t,v_a)}{IRF(p_t,v_a)} \quad (5)$$

Here, the elasticity is estimated using the mortality shock, i.e., shock to the cattle inventory. Similarly, demand elasticity can also be estimated using the morbidity shock (v_y) and inventory shock (i_t). Medium and long-run elasticities can also be estimated by aggregating the IRFs over a period of time (Ghanem and Smith, 2021).

In this study, supply elasticity is identified with lagged shock. Disease induced shock changes the beef supply in the current period. Suppliers observe the change in beef prices and make the stock and inventory decision for the following period. In order to estimate the supply elasticity, responses of the suppliers in the next period is under consideration.

$$\frac{\partial q_{t+1}}{\partial p_t} = \frac{\partial q_{t+1}/\partial \nu_a}{\partial p_t/\partial \nu_a} = \frac{\partial a_{t+1}/\partial \nu_a + \partial y_{t+1}/\partial \nu_a}{\partial p_t/\partial \nu_a} = \frac{IRF(a_{t+1}, \nu_a) + IRF(y_{t+1}, \nu_a)}{IRF(p_t, \nu_a)} \tag{6}$$

Here, the short run supply elasticity is estimated using the mortality shock. Elasticities from morbidity shock and longer-run elasticities can also be estimated as described above.

3. Data

We collected time series data from different sources for the period 1961–2023 for use in this study. Stock data is collected from the Food and Agricultural Organization Statistics (FAOSTAT) database. The cattle stock is calculated at the beginning of the year in FAOSTAT and represents the live cattle inventory in our model. Yield data is reported in carcass weight (kg) per slaughtered animal in FAOSTAT. Hence, the product of stock and yield in the model represents the upper bound of global beef production. The difference between the stock and animal slaughtered data is used to approximate the change in inventory size, as inventory decision directly influence the number of cattle supplied to slaughterhouses. Since production in our model is measured in kilograms of beef, we use the price per kilogram as the corresponding price variable. We source the real annual price of beef data from the world bank commodity database (WBCMO). Descriptive statistics of the time series variables are provided in Table 1.

Table 1: Descriptive statistics of the time series variables from year 1961 to 2023

	Cattles Stock	**Yield (Kg/Head)**	**Inventory Change**	**Price (USD/Kg)**
Mean	1.03×10^9	201.31	7.77×10^8	3.75
Standard Deviation	1.21×10^9	18.15	8.92×10^7	1.02
Minimum	7.69×10^8	158.45	5.83×10^8	1.94
25th Percentile	9.57×10^8	190.88	7.24×10^8	3.06
50th Percentile	1.05×10^9	206.67	7.92×10^8	3.64
75th Percentile	1.12×10^9	215.35	8.33×10^8	4.49
Maximum	1.24×10^9	225.17	9.34×10^8	6.51

Table 1 illustrates that the variables are of different scales. We therefore transform all series into their natural logarithms to ensure comparability across variables and help achieve stationarity. Log transformation also facilitates the interpretation of impulse responses in percentage terms (Barratt et al., 2019), which is an important step for the welfare measurement of the current study.

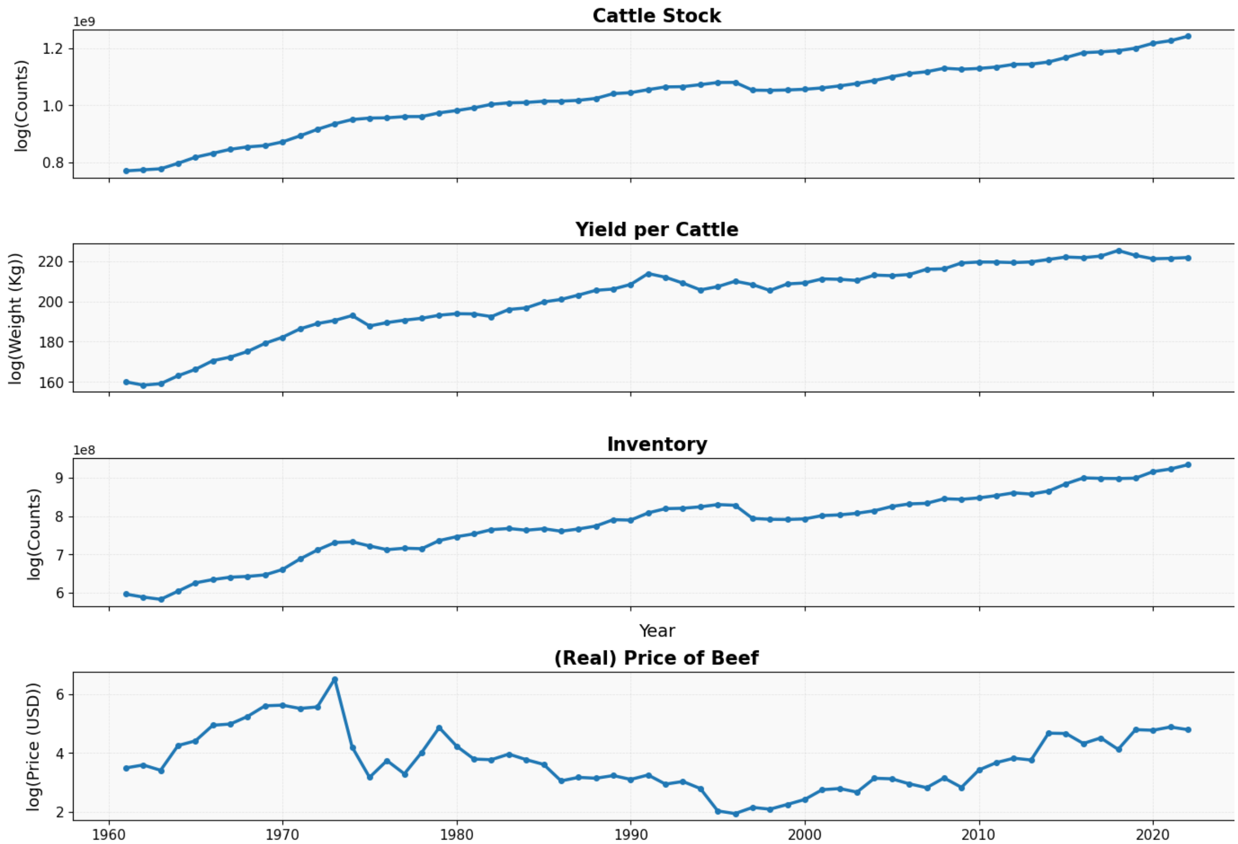

Figure 2: Log transformed global cattle stock, yield per cattle, inventory chnage and real price of beef from year 1961 to year 2023

4. Results

The results are presented in the following manner. First, the data are tested for unit roots. Second, tests are provided for lag-order selection. Third, IRFs are estimated and used in computing elasticities. Fourth, economic surplus for producers and consumers are provided.

4.1. Unit Root Test

Figure 2 illustrates that the log-transformed series exhibit non-stationary behavior. It is well documented in the literature that there is a 10–12 year biological and economic cycle in the cattle industry (AAA, 2022; USDA ERS, 2025). This long-term cycle reflects the lagged adjustments in herd size as producers respond to changes in prices and productivity. In order to tackle these non-stationarity in the time series, we take the first difference. We plot autocorrelation function (ACF) of the first differenced data in Figure 3. We describe the data cleaning and model diagnostic process in details in Appendix B. Figure 4 illustrates our time series data after correcting for stationarity.

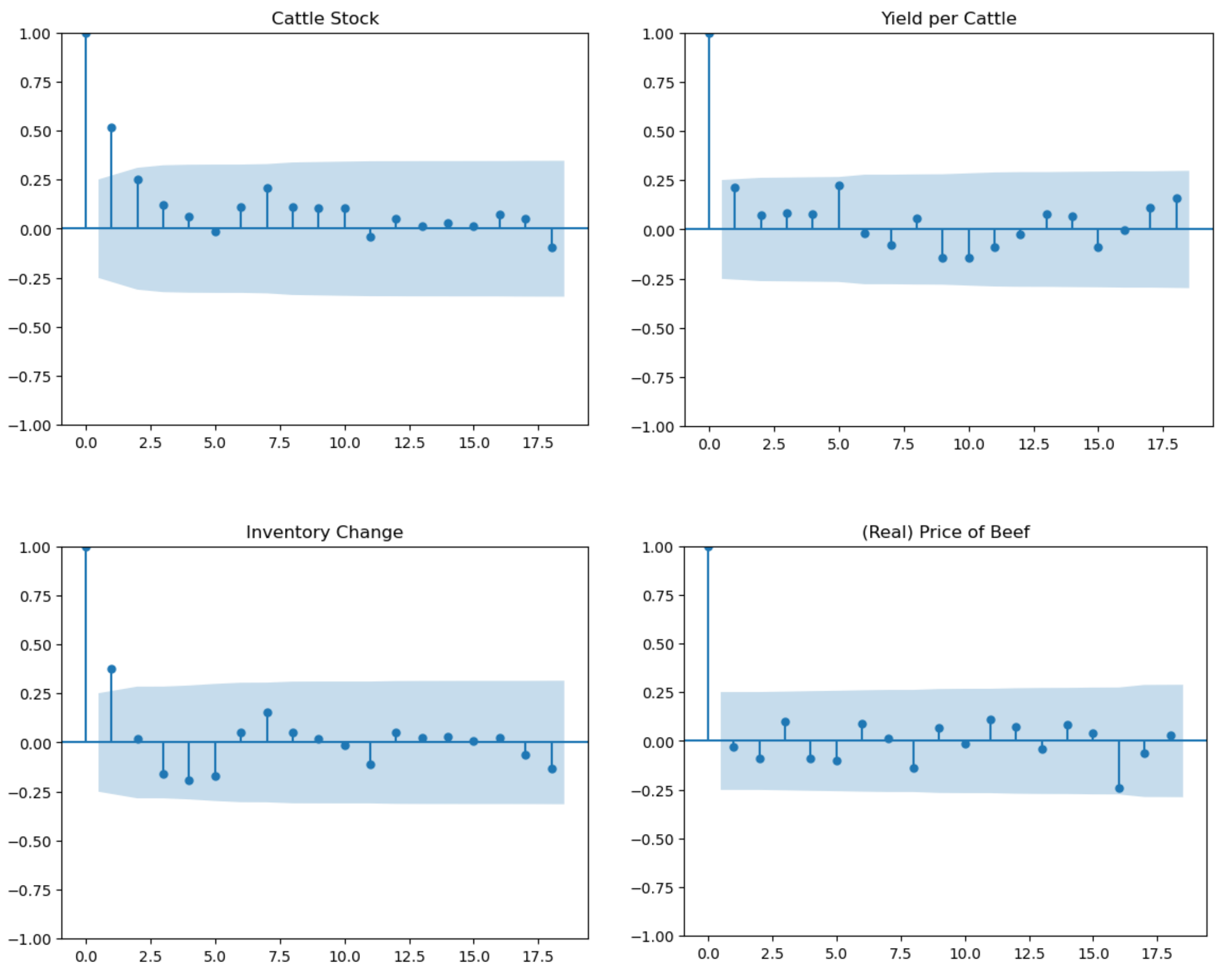

Figure 3: ACF plot of first differenced log transformed variables

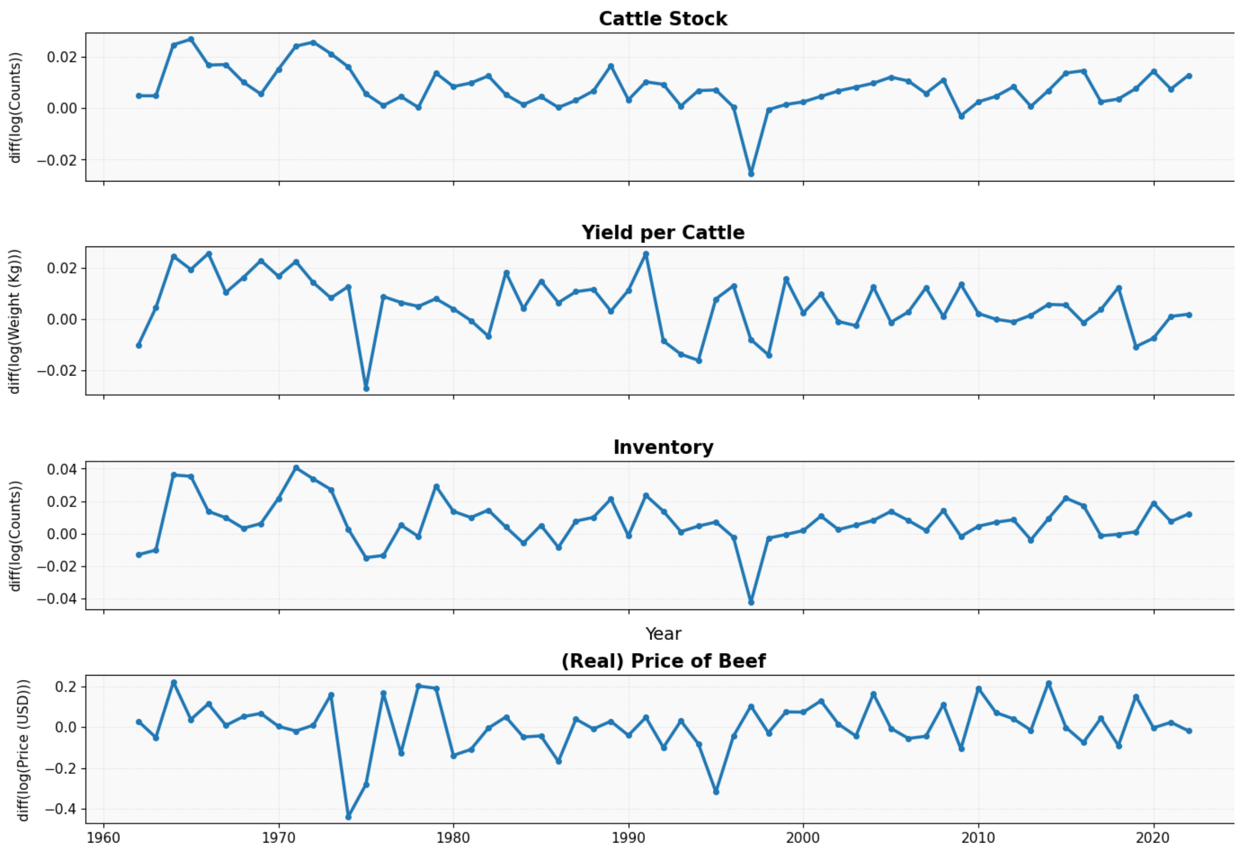

Figure 4: Log-transformed time series after removing non-stationary components

Augmented Dickey Fuller (ADF) test results are shown for the time series after decomposing non-stationarity in Table 2. From the right column of table, we can see that the null hypothesis of non-stationarity is rejected at the 1% level of significance for all three variables.

Table 1: ADF test results for variables detrended and decomposed to remove cyclical variation

Variable	ADF Test Statistic	p-Value
Stock	-4.28	5.79×10^{-4}

Yield	-6.23	5.09×10^{-8}
Inventory	-5.22	7.93×10^{-6}
Price	-7.84	5.76×10^{-12}

4.2. Lag Order Selection

The length of the lag-order is an important step in the identification of demand-supply models. Table 3 illustrates information criteria, such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Final Prediction Error (FPE) and Hannan–Quinn Information Criterion (HQIC), for different lag-orders. The lag order associated with the smallest value is chosen. We can observe from Table 2 that all the criteria, apart from the BIC, select the model with the first lag.

Table 2: Lag-order selection based on information criteria

Lag-order	AIC	BIC	FPE	HQIC
0	-33.74	-33.59*	2.22×10^{-15}	-33.68
1	-34.10*	-33.36	1.55×10^{-15}*	-33.82*
2	-33.85	-32.51	2.02×10^{-15}	-33.33
3	-33.91	-31.98	1.96×10^{-15}	-33.17
4	-33.71	-31.18	2.53×10^{-15}	-32.73
5	-33.77	-30.64	2.60×10^{-15}	-32.57
6	-33.56	-29.84	3.68×10^{-15}	-32.13
7	-33.57	-29.26	4.49×10^{-15}	-31.92
8	-33.84	-28.94	4.71×10^{-15}	-31.96

*Smallest value

The BIC, being the most conservative criterion, favors a lag length of zero, implying a static system. To account for the expected short-run dynamics, and in line with the other selection criteria, we choose one lag. Residual diagnostic of the selected model is provided in appendix B.

4.3. Impulse Response Functions

The impulse response functions (IRFs) are shown in Figure 5. The main purpose is to describe the evolution of a model's variables in reaction to a shock in one or more variables.

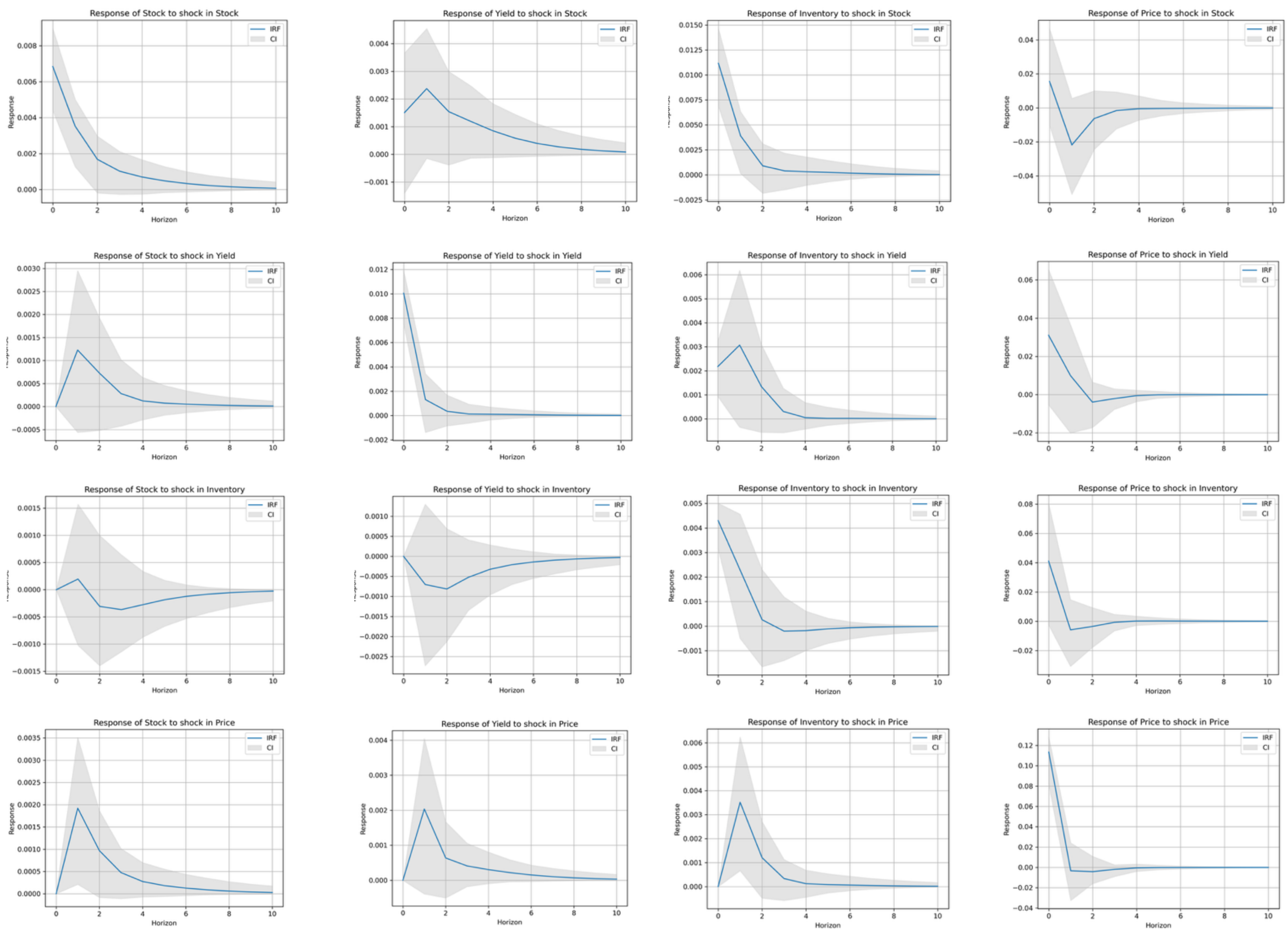

Figure 5: SVAR results of global cattle beef model: impulse response plot

From figure 5, we see that the shocks on the number of animals slaughtered, e.g., mortality shock, generates the strongest reaction on the other variables and remain statistically significant over a longer time horizon. This is consistent with the fact that, farmers would need more time to adjust to mortality losses compared to, let's say, losses due to less yield per cattle.

4.4. Estimated Elasticities

Elasticities are calculated from IRFs following the methodologies described in section 2.3. IRFs obtained from the SVAR model from current year to year 4 is reported in Table 3.

Table 3: Impulse responses from the global beef SVAR model

Impulse	Lag	Stock	Yield	Inventory	Price
Stock	0	0.0068	0.0015	0.0112	0.0156
	1	0.0035	0.0024	0.0039	-0.0218
	2	0.0017	0.0015	0.0009	-0.0063
	3	0.0010	0.0012	0.0004	-0.0015
	4	0.0007	0.0009	0.0003	-0.0005
Yield	0	0.0000	0.0101	0.0022	0.0310
	1	0.0012	0.0013	0.0031	0.0099
	2	0.0007	0.0004	0.0013	-0.0039
	3	0.0003	0.0001	0.0003	-0.0021
	4	0.0001	0.0001	0.0001	-0.0006
Inventory	0	0.0000	0.0000	0.0043	0.0411
	1	0.0002	-0.0007	0.0023	-0.0059
	2	-0.0003	-0.0008	0.0003	-0.0036
	3	-0.0004	-0.0005	-0.0002	-0.0007
	4	-0.0003	-0.0003	-0.0002	0.0002
Price	0	0.0000	0.0000	0.0000	0.1134
	1	0.0019	0.0020	0.0035	-0.0033
	2	0.0010	0.0006	0.0012	-0.0042

	3	0.0005	0.0004	0.0003	-0.0019
	4	0.0003	0.0003	0.0001	-0.0005

We estimate two supply elasticities: one from the shock in cattle stock and the other is from the shock in yield. We refer the former as mortality and the latter as morbidity shock. Equation (6) allows us to calculate the supply elasticity from mortality shock: $\frac{\partial q_{t+1}}{\partial p_t} = \frac{IRF(a_{t+1}, v_a)+IRF(y_{t+1}, v_a)}{IRF(p_t, v_a)} = \frac{0.0035+0.0024}{0.0156} = 0.38$. Similarly, using the IRF values form table 3, we can compute supply elasticity from the morbidity shock: $\frac{\partial q_{t+1}}{\partial p_t} = \frac{IRF(a_{t+1}, v_y)+IRF(y_{t+1}, v_y)}{IRF(p_t, v_y)} = \frac{0.0012+0.0013}{0.0311} = 0.08$.

We also estimate two demand elasticities by utilizing each of mortality and inventory shock. We calculate demand elasticity using mortality shock from equation (5): $\frac{\partial q_t}{\partial p_t} = \frac{IRF(a_t, v_a)+IRF(y_t, v_a)-IRF(i_t, v_a)}{IRF(p_t, v_a)} = \frac{0.0068+0.0015-0.0112}{0.0156} = -0.18$. We calculate another demand elasticity from the shock of processors supply decision, i.e., v_i. Demand elasticity using inventory shock is $\frac{\partial q_t}{\partial p_t} = \frac{IRF(a_t, v_i)+IRF(y_t, v_i)-IRF(i_t, v_i)}{IRF(p_t, v_i)} = \frac{0+0-0.0043}{0.0411} = -0.11$. Robustness check of the estimates is provided in Appendix C.

4.5. Redistribution of Economic Welfare

To calculate redistribution of economic welfare, we consider producer surplus (PS) and consumer surplus (CS).[2] We can calculate the PS and CS by the following equations (Lusk and Tensor, 2021):

$$\Delta PS_t = P_0 Q_0 \left[\left(\frac{\delta}{\eta} + EP_t \right) (1 + 0.5 \times EQ_t) \right] \tag{7}$$

$$\Delta CS = -P_0 Q_0 \times EP_t \, (1 + 0.5 \times EQ_t) \tag{8}$$

where the E operator indicates percentage change ($\approx dln(.)$), η is the supply (morbidity or mortality) elasticity and δ is the shock or shift size, which is 1% in IRF case[3]. Since the IRFs are calculated based on the log-transformed variables, they can be used directly into the surplus change equations (7) and (8) (Barratt et al., 2019). For instance, $EQ_t = \frac{Q_t - Q_0}{Q_0} \approx dln(Q_t) = dq_t = IRF(a_t, v_j) + IRF(y_t, v_j) - IRF(i_t, v_j); j = \{a, y\}$.

[2] Ghanem and Smith (2022) estimate a SVAR model of global demand and supply, calculate IRFs, and recommend following Thurman and Wohlgenant (1988) to estimate welfare impacts. Barrett et al. (2019) estimate a supply side VAR model, calculate IRFs, which is not necessarily causal in nature, and estimate indirect costs to shocks sourced from an epidemiological model. We follow the former.

[3] We have used SD change IRFs throughout this study; hence, we are examining responses due to 1% impulses. It is also worth mentioning that, when we say, e.g., 1% mortality shock, we mean a positive change in the live cattle stock. That is a decrease in mortality of cattle by 1%.

In order to calculate the producer and consumer surplus as in equation (7) and (8), we need baseline price and quantity, P_0 and Q_0, respectively. We get the price data from WBCMO and quantity from FAOSTAT. The nominal price of beef for the year 2023 is USD 4.90/Kg and quantity demanded for the year is USD 69.46 billion kilogram.

As evident by equation (7) and (8), supply elasticities (η) affects the magnitude of producer and consumer surplus. For calculating producer surpluses in case of a mortality shock, we used short run supply elasticity as estimated in section 4.4. One can also estimate long-run elasticities as discussed in Ghanem and Smith (2021). For example, long-run (T years) supply elasticity calculated from morbidity shock would be:

$$\eta_{LR} = \frac{\sum_{j=1}^{T} \partial q_{t+j}}{\partial p_t} = \frac{\sum_{j=1}^{T} IRF\left(a_{t+j}, \nu_y\right) + IRF\left(y_{t+j}, \nu_y\right)}{IRF\left(p_t, \nu_y\right)} \tag{9}$$

We use long-run supply elasticity estimated by equation (9) for calculating morbidity related surplus changes. Further justification of using short or long-run elasticities are discussed in the next section.

4.6. Case Study

In this section we aim to provide an analysis of the burden of cattle disease in the global beef market using equation (7) and (8). These equations take both economic and epidemiological inputs. For economic inputs, results from the SVAR model is used. In the absence of explicit epidemiological forecasts, we look into the literature for an approximation of the size of the disease related market distortion. Existing literature on the impact of diseases at national or regional level might give us some idea about the production losses associated with cattle diseases. Since impact of diseases vary across diseases and regions (Rasmussen et al., 2024), we attempt to find out an interval that might contain the true value of the mortality and morbidity effect for diseases. For example, Kelly and Janzen (1986) found that the mortality rates and disease occurrence in North American feedlot cattle was between 1%-5% in their meta-analysis. Another meta-analysis of calf morbidity and mortality studies in Ethiopia suggests that the pooled mortality rate is about 15% (Tora et al., 2021). We take these two results and evaluate the disease loss due to mortality for both 5% and 15% and assume that the actual figure can be anywhere in between.

It is more challenging to find out the morbidity loss from the literature as, unlike mortality, morbidity does not account for 100% production loss. Although we do not have morbidity related production loss for beef cattle, Rasmussen et al. (2024) provided comorbidity adjusted total yield loss for 12 major cattle diseases about 33% for global dairy cattle. We also take into consideration of the range provided by Kelly and Janzen (1986) for morbidity rates which is 15% to 45%. We assume that the production loss due to morbidity lies within the range of 33% and 45%.

Let us start with the surplus changes with positive mortality and morbidity shock of 1%. Figure 6 shows the present value of the producer and consumer surpluses for the following years.

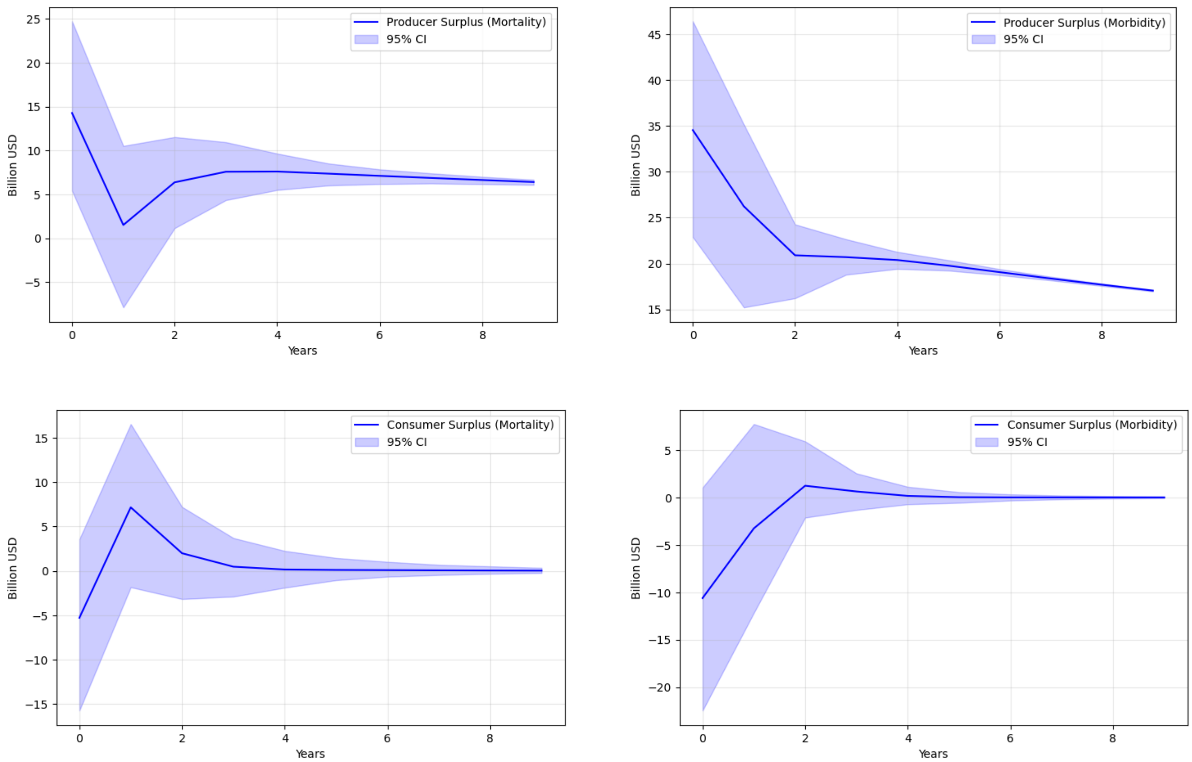

Figure 6: Present value of the welfare changes for 1% improvement in cattle health

Figure 6 (upper left panel) illustrates that the producer surplus for mortality improvement is statistically significant at the current period only. This further justifies our selection of using short-run supply elasticity for computing producer surplus due to mortality shock. Since producer surplus due to morbidity (upper right panel) is valid for a longer period of time, we use the long-run supply elasticity, which is 0.14 over five-year period, by equation (9) in order to measure the producer surplus for morbidity.

Figure 6 illustrates that the 1% improvement in mortality yields about USD 15 billion in surpluses in the short run. An 1% improvement in morbidity yields about USD 35 billion in total surpluses in the short run.

5. Discussion

We estimate a global demand and supply system of cattle meat using a structural vector autoregressive model (SVAR). SVARs offer valuable insights, including a dynamic lens on structural effects using impulse response functions (IRF); elasticities estimated with IRFs conditional on specific shocks to the system; and changes in producer and consumer surplus can be measured from these outcomes (Ghanem and Smith, 2022; Thurman and Wohlgenant, 1989).

A primary interest is to estimate the impact of shocks on demand and supply at the global level. After estimating supply elasticities from both mortality and morbidity shock, we observed that the estimated supply elasticity from mortality shock are greater in magnitude than the estimation from the morbidity shock. We also observe that the estimated demand elasticity from a mortality shock is larger in magnitude than demand elasticities estimated from, e.g., supplier inventory decision.

From the discussion above, it is evident that both the producers and consumers shows strong response to the market disruptions due to diseases. For example, we can estimate another producer surplus using demand shock, which is 0.04. This shows us that the producers' reaction to both morbidity and mortality related market disruptions is larger than the regular market disruptions such as demand shock as mentioned above. This is also true for the consumers, who exhibit larger reaction to disease shock (mortality) than disruptions caused by supply decisions.

The distribution of gains and losses are different for the two disease related shocks studied in this paper. As an immediate impact of the live cattle stock increase, producers surplus increase from the increased price. This price increase could be a result of the added cost of larger inventory. This price increase makes the consumers worse off at the beginning. However, the market adjusts in the following years due to oversupply and the consumers gain is realized by the second year (figure 6). In case of yield per cattle, the price increase in the immediate year could be due to increase in demand for better quality meat. As a biological consequence of the improvement in morbidity related production loss, live cattle stock increase in the following year and price adjustment happens years after that. Consumer demand increase due to better quality of meat and, therefore, the producers' gain is higher in positive shock in morbidity.

In section 4.6, we have calculated short run welfare effects using equations (7) and (8). Here, we discuss welfare impacts over longer-run using the epidemiological inputs from the literature as discussed in section 4.6. Since IRF reflects the magnitude of response to a 1% impulse, to estimate the total impact of the disease shock, the IRFs need to be multiplied by the epidemiological shock (Barratt et al., 2019), which is 5% and 15% in the case of mortality and 33% and 45% in case of morbidity. Since producer surplus for mortality case is valid for only the current year, the NPV of surplus loss due to disease mortality lies between USD 70 to 210 billion (figure 7). The net present value of surplus loss due to morbidity for one-year ranges between USD 1250 to 1800 billion.

Together with both mortality and morbidity due to diseases, the global annual loss in the beef cattle sector ranges between USD 1300 to 2000 billion, which is about 1.2% to 1.9% of world GDP[4].

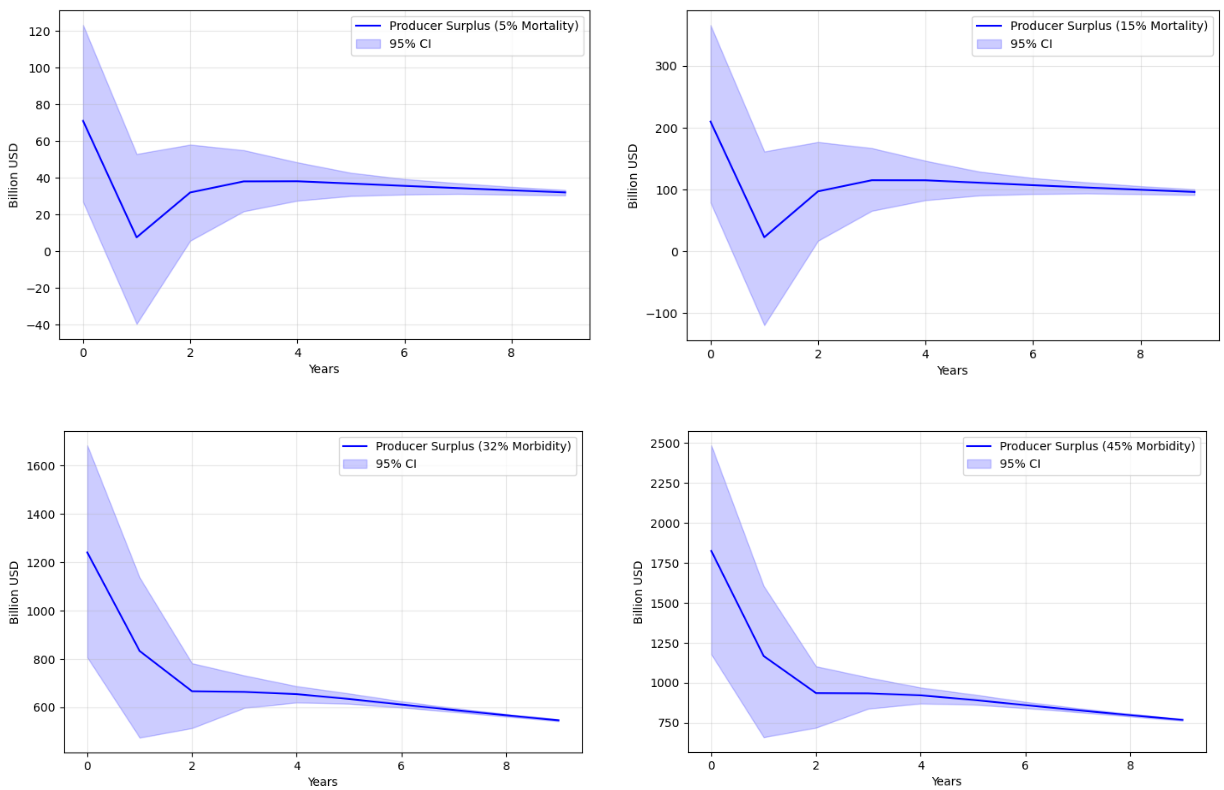

Figure 7: Present value of the changes in producer surplus for mortality (5% and 15%) and morbidity (32% and 45%) improvement in global beef cattle

[4] World GDP for the year 2023 is reported as 107 trillion by World Bank. https://data.worldbank.org/indicator/NY.GDP.MKTP.CD

6. Conclusion

This study provides an econometric framework to quantify the short- and long-run economic impacts of livestock diseases using a SVAR model, where mortality and morbidity shocks are treated as exogenous disturbances to the global beef market. We use the model to trace the redistribution of welfare between producers and consumers in response to animal health shocks. We estimate demand and supply elasticities that may serve as benchmark measures for different market regimes under disease outbreaks. Our estimates suggest that producers and consumers reacts to disease related shocks more than the other regular market shocks. Furthermore, our finding show that the distribution of gains or losses across the beef supply chain differs due to market disruptions caused by mortality and morbidity shocks. We also show that the global loss due to livestock diseases in the cattle beef industry alone is about 1-2% of the global GDP.

Overall, this framework demonstrates how integrating epidemiological insights with structural econometric modeling can identify and decompose the welfare implications of livestock disease shocks. Data driven estimation of welfare effects of livestock diseases allows us to inform the policymakers how improvements in animal health and livestock disease impact the redistribution of wealth across the economic agents of livestock and agricultural sector at large.

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Appendix A

Let us start with a reduced-form VAR(p):

$$Y_t = \Pi_1 Y_{t-1} + \cdots + \Pi_p Y_{t-p} + \varepsilon_t \tag{A.1}$$

Where,

$$Y_t = [y_{1t}, \dots, y_{kt}]';$$

$$\Pi_p = \begin{bmatrix} \pi_{p1} & \cdots & \pi_{pk} \\ \vdots & \ddots & \vdots \\ \pi_{kp} & \cdots & \pi_{kk} \end{bmatrix}$$

$$\varepsilon_t = [\epsilon_{1t}, \dots, \epsilon_{kt}]'$$

The regressors are the same in all equations. The error terms ε_t are i.i.d., i.e., $Cov(\varepsilon_t, \varepsilon_s) = 0; t \neq s$ with zero-mean and they are uncorrelated with regressors. Residuals *i.i.d.* check can be done by Autocorrelation Function (ACF) plot. Independence check can be done with ACF plots of residuals, ε_t and identical distribution (homoskedasticity) test can be established by ACF plots of squared residuals, ε_t^2. Apart from ACF plots, tests exist for *i.i.d.* check such as Ljung-Box / Portmanteau Test and Nonparametric Runs Test. If the residuals are *i.i.d*, then the appropriate estimator is OLS (Hamilton, 1994) which is unbiased, consistent and efficient. Advantage of OLS estimator is that no system estimation is needed and each equation can be estimated separately. IRFs are partial derivatives that measure how a system variable responds over time to an impulse, holding other shocks constant. Equation (A.1) can be written as

$$Y_t = \sum_{i=1}^{p} \Pi_i Y_{t-i} + \varepsilon_t \tag{A.2}$$

MA representation of equation (A.2) is

$$Y_t = \sum_{h=0}^{\infty} \Phi_h \, \varepsilon_{t-h} \tag{A.3}$$

Now, IRF can be derived from equation (A1.3) as a partial derivative.

$$IRF(h) = \frac{\partial Y_{t+h}}{\partial \varepsilon_t} = \Phi_h \tag{A.4}$$

$\Phi_h[i, j]$ effect on variable i at $(t + h)$ from shock to j.

However, in VAR, the residual ε_t is not necessarily a "clean" shock. It can be correlated across equations. Therefore, it is not identified and not orthogonalized. Hence, it is not interpretable as real-world shocks (e.g. policy shock, disease shock, supply shock). Whereas, in SVAR, such as in equation (1), matrix A_0 structures the relationships between the endogenous variables. If we compare with equation (1) with equation (A.1):

$$A_0^{-1} A_p = \Pi_p \text{ and } A_0^{-1} v_t = \varepsilon_t$$

Moreover, if we have $\widehat{\Pi_p}$ and $\widehat{\varepsilon_t}$ from (A.1), then

$$\widehat{A_p} = \widehat{A_0} \widehat{\Pi_p} \text{ and } \widehat{v_t} = \widehat{A_0} \widehat{\varepsilon_t}$$

Now, in order to estimate a triangular SVAR, we can Cholesky decompose of the covariance matrix

$$\Sigma_{\varepsilon} = LL'$$

Where, L is a lower triangular matrix. For unique identification of $A_0^{-1} = L$, the following must hold:

$$\Sigma_{\nu} = cov(\nu_t) = A_0 \Sigma_{\varepsilon} A_0' = I$$

Relationship between impulse response of the SVAR with equation A.4

$$IRF(h) = \frac{\partial Y_{t+h}}{\partial \nu_t} = \frac{\partial \Phi_h A_0^{-1} \nu_t}{\partial \nu_t} = \Phi_h A_0^{-1} \tag{A.5}$$

IRF given in equation (A.5) can trace dynamic effects on the Y_i from structural shocks in the v_t. For example, Ghanem and Smith (2022), shows how shocks from weather effect yield and then translate to prices and quantities and how shocks on demand effect the system. This allows a rich insight into both short- and long-run responses.

Bootstrap Confidence Interval

We use bootstrap method for the IRF confidence interval. We choose a sample from the residuals of the fitted model to generate bootstrap samples. Once the bootstrap sample is generated, we follow the same procedure as described above for each sample. Finally, we have the distribution to compute percentiles for 95% CI.

Appendix B

B.1 Data Cleaning

We need to first remove any non-stationary components from the time series under consideration.

Let us first plot the ACFs of the log-transformed data.

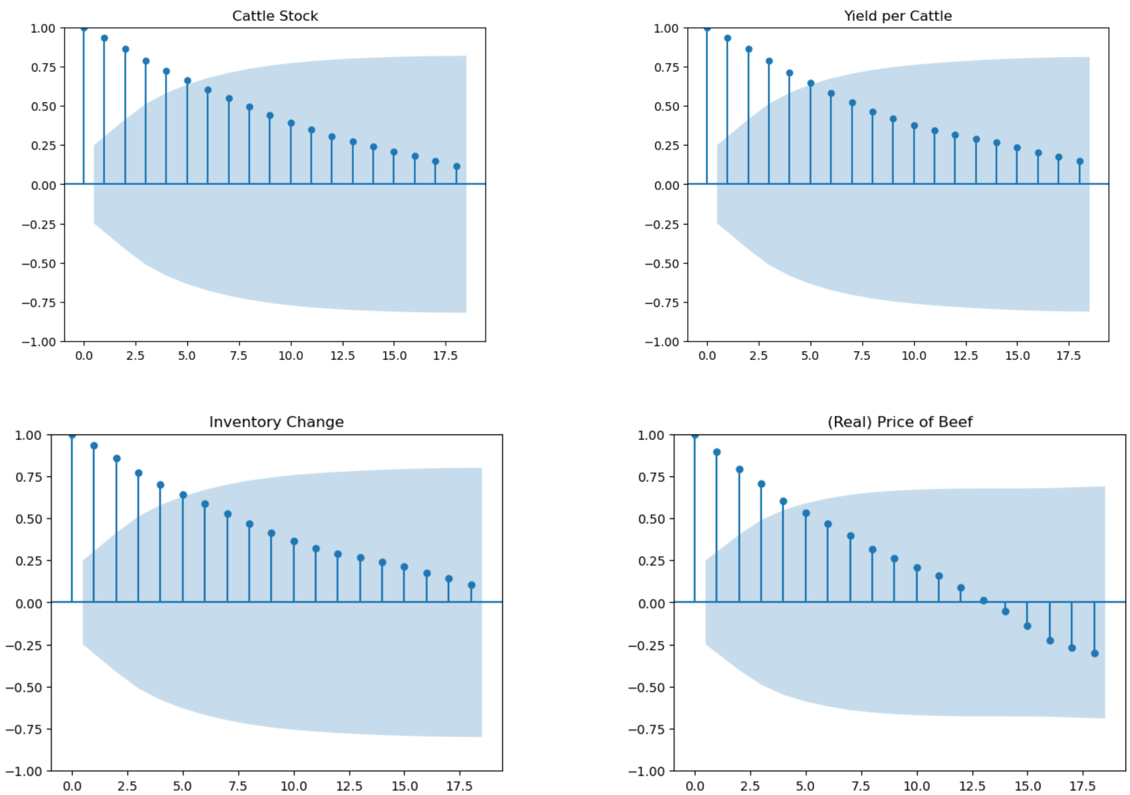


Figure B.1: ACF plot of log transformed variables

Figure B.1 and ADF test results in the Table B.1 show evidence of trend in the data.

Table B.1: ADF test results for log-transformed variables

Variable	**ADF Test Statistic**	**p-Value**
Stock	-3.19	0.0862
Yield	-1.90	0.6541
Inventory	-3.22	0.0811

Price	-1.52	0.8233

We first try to remove deterministic trend from the data and observe the ACF plots in figure B.2.

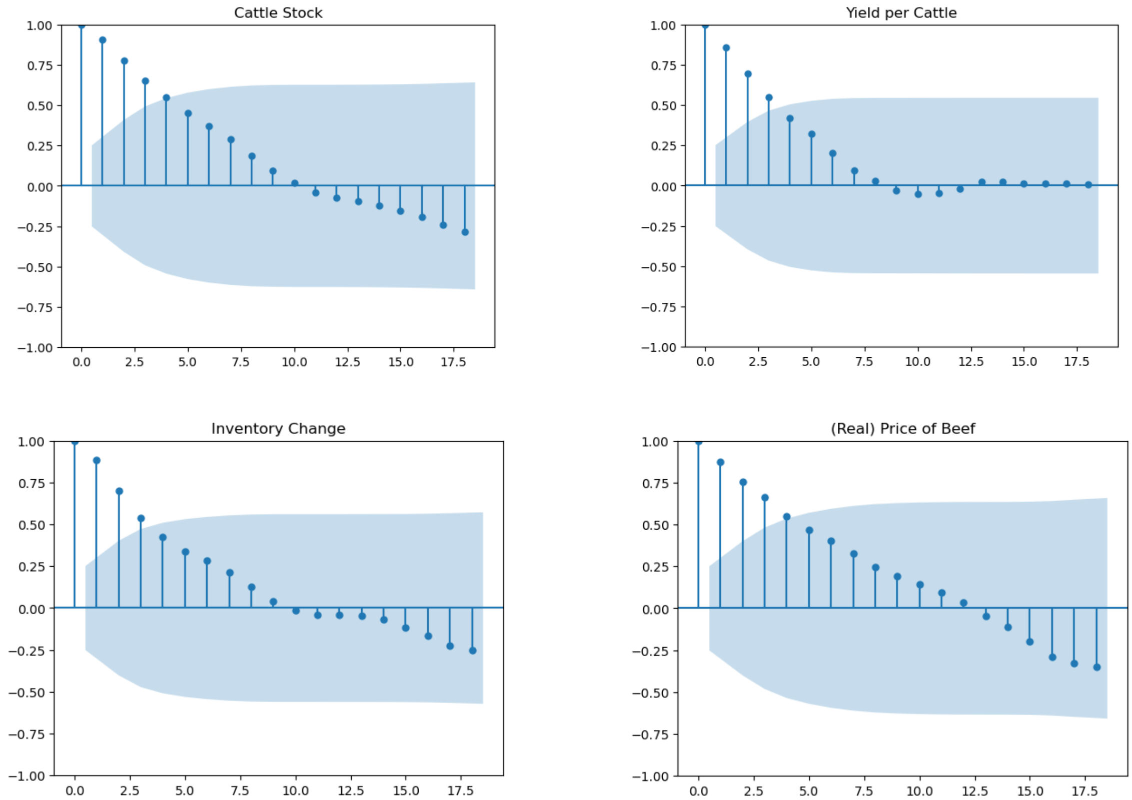
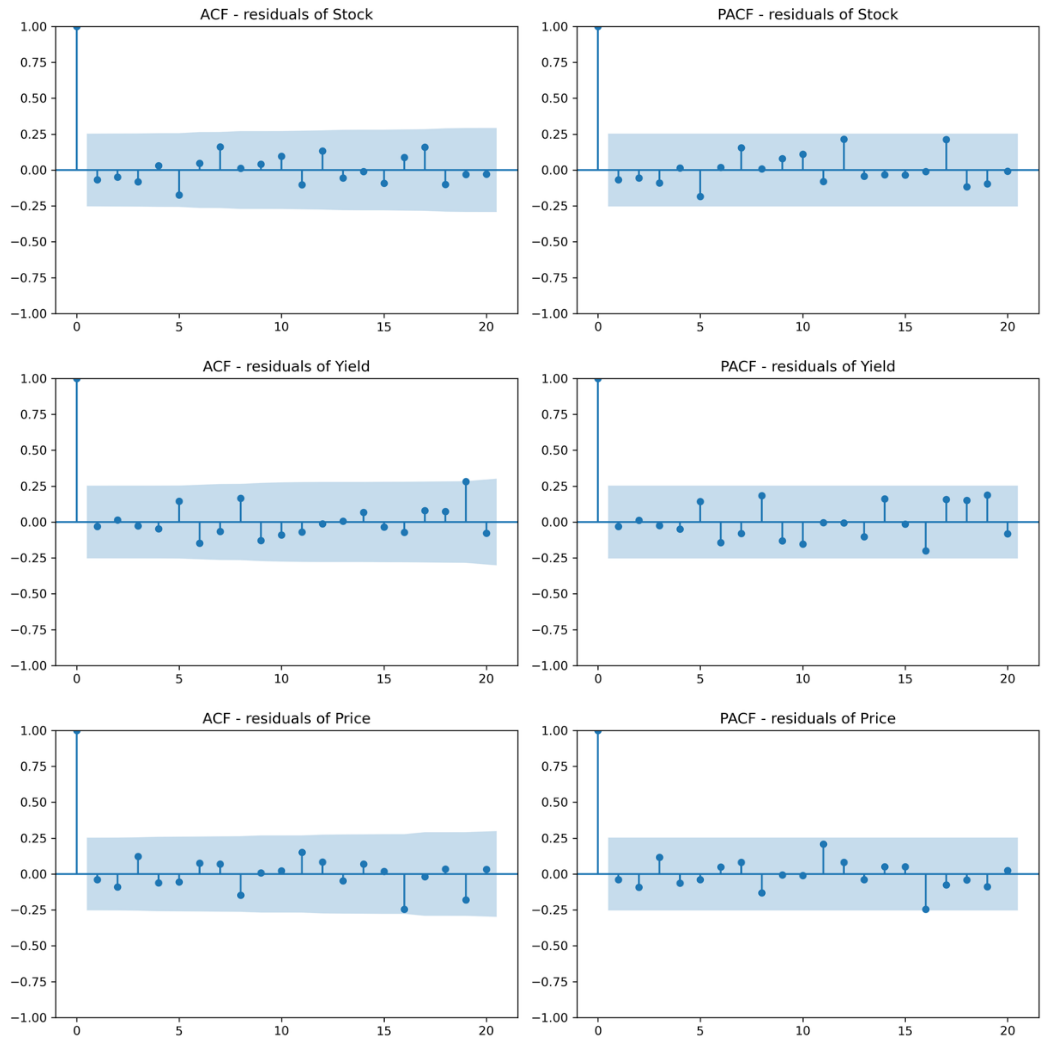


Figure B.2: ACF plot of detrended log transformed variables

ACF plots in figure B.2 illustrates that removing deterministic trend does not make the series stationary. This led us to believe that the time series might be non-stationary due to stochastic trend. In order to deal with the non-stationarity, we take first difference for all the four series. We now have the stationary series for our analysis as evidenced by figure 3 and table 1.

B.1 Residual Diagnostic

Let us start with the ACF and Partial ACF (PACF) plots of the VAR (1) residuals in Figure B.3.



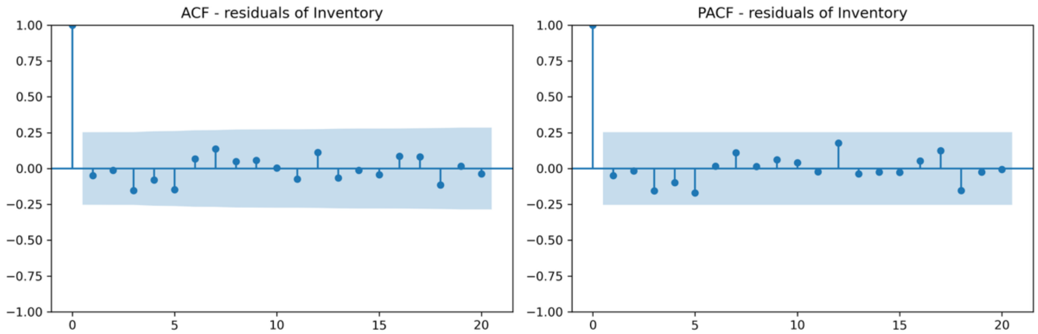


Figure B.3: ACF and PACF plots of residuals of reduced form VAR (1) model

ACF and PACF plots of Figure B.2 shows no particular pattern in the residuals. Yield PACF shows a spike around the 18th period, although within the 95% CI. To formally test for its significance, we do Breusch-Godfrey (BG) test on these residuals with lag length of 20. Table B.2 illustrates both the Lagrange Multiplier (LM) and F statistics of the BG test.

Table B.2: BG test results for VAR (1) residuals

Equation	**LM**	**LM p-value**	**F**	**F p-value**
Stock	22.1964	0.329949	1.027513	0.458528
Yield	19.6585	0.479469	0.852776	0.640097
Inventory	15.2675	0.760899	0.597289	0.888081
Price	15.2981	0.759105	0.598892	0.886875

Table B.2 shows that the p-values for both the test statistics are high. So, we cannot reject the null hypothesis of no autocorrelation at 10% level of significance.

Appendix C

In the cattle industry, there is an 8-12 year biological and economic cycle that is documented in the literature (AAA, 2022; USDA ERS, 2025). Keeping that in mind and also due to the fact that there might be a long-term spike with the yield residual ACF plot of the fitted VAR, we fit a Structural Vector Error Correction (SVEC) model and compare the estimated elasticity with the one we have from the SVAR model.

We use the same recursive structure of the impact matrix as SVAR in the SVEC model. We choose a lag-order $(p - 1)$ of 0 in the SVEC model. The cointegration rank detected by the Johansen test is 4. We present and compare the mortality elasticities estimated from the SVEC model in Table B.3.

Table B.3: Elasticities estimated from mortality shock

Elasticity	**SVEC**	**SVAR**
Supply	0.57	0.38
Demand	-0.21	-0.18

We observe from table B.3 that both the demand and supply elasticities estimated by the SVEC model is slightly higher in magnitude than the SVAR model. Since the results from the SVEC and SVAR models are broadly consistent, we proceed with the SVAR framework, which provides a more parsimonious parameterization and a simpler structure for interpreting short-run dynamic relationships without imposing additional long-run restrictions.