SVAR Estimates of Global Supply and Demand for Cattle Meat

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Abstract: This paper models the global cattle beef sector with a dynamic structural vector autoregression (SVAR) model to estimate the supply and demand for cattle meat. SVAR method is used for analyzing how market dynamics in the beef demand supply system may change following a disease outbreak. Findings suggest that producers and consumers in the cattle beef sector is more responsive to morbidity shock than to mortality shock. The estimated net present value (NPV) of a marginal 1% animal health improvement over the five years period is USD 21.78 billion which is about 5% of the size of the global beef sector.

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

1. Introduction

Livestock disease outbreaks distort markets, which results in food supply chain disruptions and redistribute economic welfare across the globe (Rushton et al 2018, 2021; Hennessy and Marsh 2021). If modeled properly, the market distortion due to diseases could be interpreted as shock, which could be useful in estimating market forces. For example, identification and estimation of global demand and supply of crop has been extensively studied in the literature.

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Roberts and Schlenker (2013) use instrumental variable (IV) method to estimate the global demand and supply of crops. Ghanem and Smith (2022) produce similar estimates with time series approach.

National and regional studies on demand and supply across the value chain of the livestock sector is a vast literature (Wohlgenant 1989; Bielik, P., & Šajbidorová, Z. 2009; Lusk and Tonsor, 2016; Delport et al., 2017). Elasticities estimated in these literature are often used in future studies, 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 outbreak estimate regional and value chain elasticities pertaining to their studies (Cakir et al, 2018; Thompson et al., 2019). However, global estimates of demand and supply of meat has not received as much attention in the literature.

This paper develops a global econometric model of cattle beef demand and supply methodologically following Ghanem and Smith (2022), who exam global demand and supply for crop grains. A key contribution of this paper is to fit a multivariate time series model, namely the structural vector autoregression (SVAR) model, and use the model and its outputs to assess the redistribution of economic welfare from shocks to the demand and supply system. This could include shocks from drought or livestock diseases. The redistribution of economic welfare through impacts on firms and consumers is vital information for global planning, for stakeholder livelihoods, and for food security. 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.

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.

We follow the standard practice of a triangular SVAR with strict restrictions (Ghanem and Smith, 2022; Kilian, 2009). The estimates from these models can be used in assessing the economic impact of livestock diseases. These estimates can also be used in welfare measurement similar to Thurman and Wohlgenant (1989). To our knowledge, no other studies on the econometric estimation of the economic impact of livestock diseases at the global scale. Also, a recent strand of literature shows that, market forces act differently at times of disease outbreak (Goodwin, 2024). Our approach of interpreting the impulse responses of a dynamic global demand-supply framework contributes to both of the literature scopes mentioned above.

2. Methods

Let Y_t be a random vector of outcomes at time t for $t = 1, \dots, T$.

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

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 $f(t) \equiv \left(f_w(t), f_p(t), f_q(t)\right)'$ are fixed functions of time, e.g., linear trend. The vector ν_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) or welfare surpluses (Thurman and Wohlgenant, 1988).

2.1. Global Cattle Beef Model

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

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

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

$$p_t = \beta_{31} i_t + \beta_{32} y_t + \rho_{31} Y_{t-1} + \cdots + f_{p(t)} + v_{pt} \tag{4}$$

Figure 1 shows the causal ordering of the three endogenous variables in equations (2), (3) and (4). Beef production is broken-down into two components: cattle slaughtered (i_t) and per animal yield (y_t).

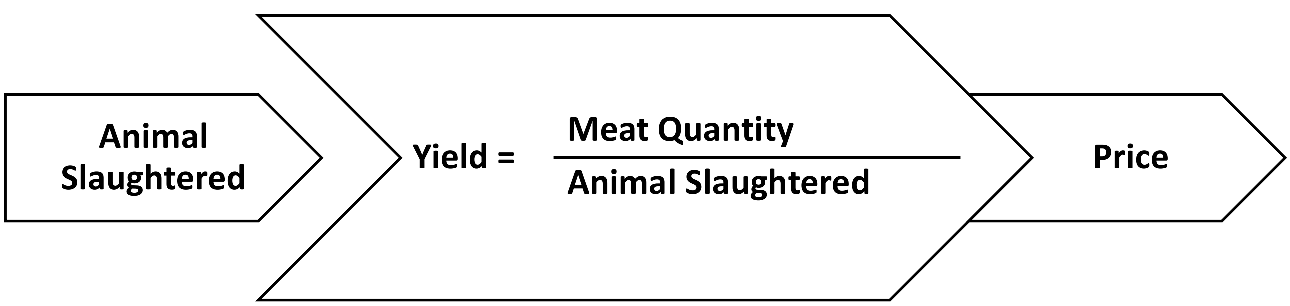

Figure 1: Causal Ordering of Global Beef Cattle SVAR Model

[1] Refer to Appendix A for details on the triangular SVAR identification methodology.

2.2. Identification of the Structural Matrix

At the beginning of a year t, number of cattle slaughtered is exogenous of the yield and price of that year t, but depends on the yield and prices of previous year. Yield is directly impacted by the number of slaughtered cattle in the year t through the relationship described in figure1. Price of beef is determined by taking both the cattle slaughtered and yield in the year t into consideration. This recursive structure gives a lower triangular shape of the contemporaneous matrix. We define the A_0 and A_i as:

$$A_0 = \begin{bmatrix} 1 & 0 & 0 \\ \beta_{21} & 1 & 0 \\ \beta_{31} & \beta_{32} & 1 \end{bmatrix} \text{ and } A_i = \begin{bmatrix} \alpha_{11}^i & \alpha_{12}^i & \alpha_{13}^i \\ \alpha_{21}^i & \alpha_{22}^i & \alpha_{23}^i \\ \alpha_{31}^i & \alpha_{32}^i & \alpha_{33}^i \end{bmatrix}; i = 1, 2, \ldots, l$$

The length of the lag-order is an important step in the identification of demand-supply models. Ghanem and Smith (2022) used lag-order 1 for to fit global crop model. Evidence from the literature suggest longer life cycles for cattle. For example, Paarlberg et al. (2008) modeled the cattle life cycle from inventory to slaughterhouses with five quarters. Industry data suggest that cattle life cycle could be as long as 22 months[2]. Therefore, to capture the supply and inventory decision, we select lag order 2 for our cattle beef SVAR model.

2.3. Estimating the Elasticities from IRFs

Short and long run elasticities can be estimated using the IRFs. Since, IRF is the partial derivative with respect to shocks, so demand elasticates can be expressed as the following:

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[2] https://www.pabeef.org/raising-beef/beef-lifecycle

$$\frac{\partial q_t}{\partial p_t} = \frac{\partial q_t/\partial \nu_i}{\partial p_t/\partial \nu_i} = \frac{\partial i_t/\partial \nu_i + \partial y_t/\partial \nu_i}{\partial p_t/\partial \nu_i} = \frac{IRF(i_t, \nu_i) + IRF(y_t, \nu_i)}{IRF(p_t, \nu_i)}$$

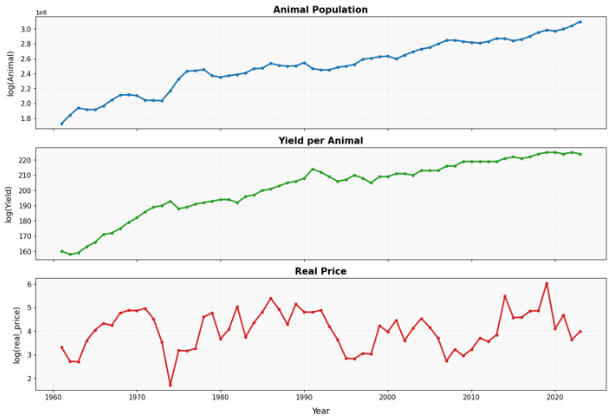
Here, the elasticity is estimated using the shock to the supply of number of cattle supplied for slaughtering. Similarly, demand elasticity can also be estimated using the shock on yield per animal (ν_y).

Suppliers cannot adjust shock due to weather or diseases in the current period. In order to estimate the supply elasticity, responses of the suppliers in the next period is under consideration.

$$\frac{\partial q_{t+1}}{\partial p_t} = \frac{\partial q_{t+1}/\partial \nu_i}{\partial p_t/\partial \nu_i} = \frac{\partial i_{t+1}/\partial \nu_i + \partial y_{t+1}/\partial \nu_i}{\partial p_t/\partial \nu_i} = \frac{IRF(i_{t+1}, \nu_i) + IRF(y_{t+1}, \nu_i)}{IRF(p_t, \nu_i)}$$

3. Data

We collected yield data from the Food and Agricultural Organization Statistics (FAOSTAT) database. Yield data is reported in carcass weight (lb) per slaughtered animal in FAOSTAT. We calculated beef demand as bovine meat production net of stock variation, which were from FAOSTAT. We use bovine meat production data as a proxy for beef production, given that beef constituted approximately 90% of total bovine meat production in 2022. We source price data from world bank commodity database (WBCMO). We take the average of monthly data for a year and convert them in real price with the food price index sourced from the sample. See Table 1 for descriptive statistics. Figure 2(a) illustrates the log transformed time series data.



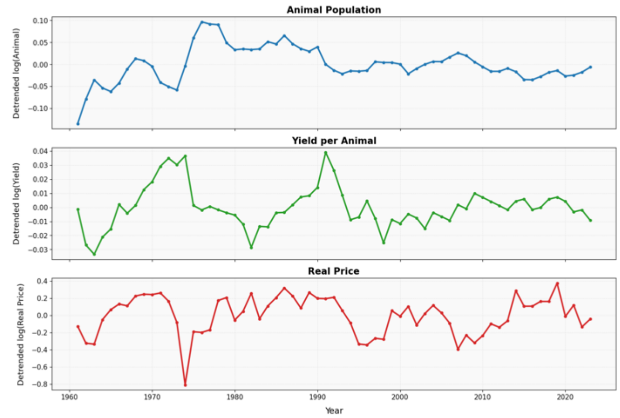


Figure 2(a): Log data over the years Figure 2(b): Detrended log data over the years

Figure 2: Total number of cattle slaughtered globally, yield per animal and real price over the years

4. Results

Figure 1(a) shows trend in data, especially in animal numbers and in yield. Therefore, the data were detrended as shown in figure 2(b). Augmented Dickey Fuller (ADF) test results are shown in table 1. From the left column of table 1, we can see that the null hypothesis of non-stationarity is rejected at the 5% level of significance for all three variables.

Table 1: ADF test results for detrended variables

Variable	**ADF Test Statistic**	**p-Value**
Animal population	-3.35	0.01279
Yield per animal	-5.00	0.00002
Price	-4.00	0.00142

4.1. Impulse Response Functions

The impulse response functions (IRFs) are shown in Figure 3. The main purpose is to describe the evolution of a model's variables in reaction to a shock in one or more variables.

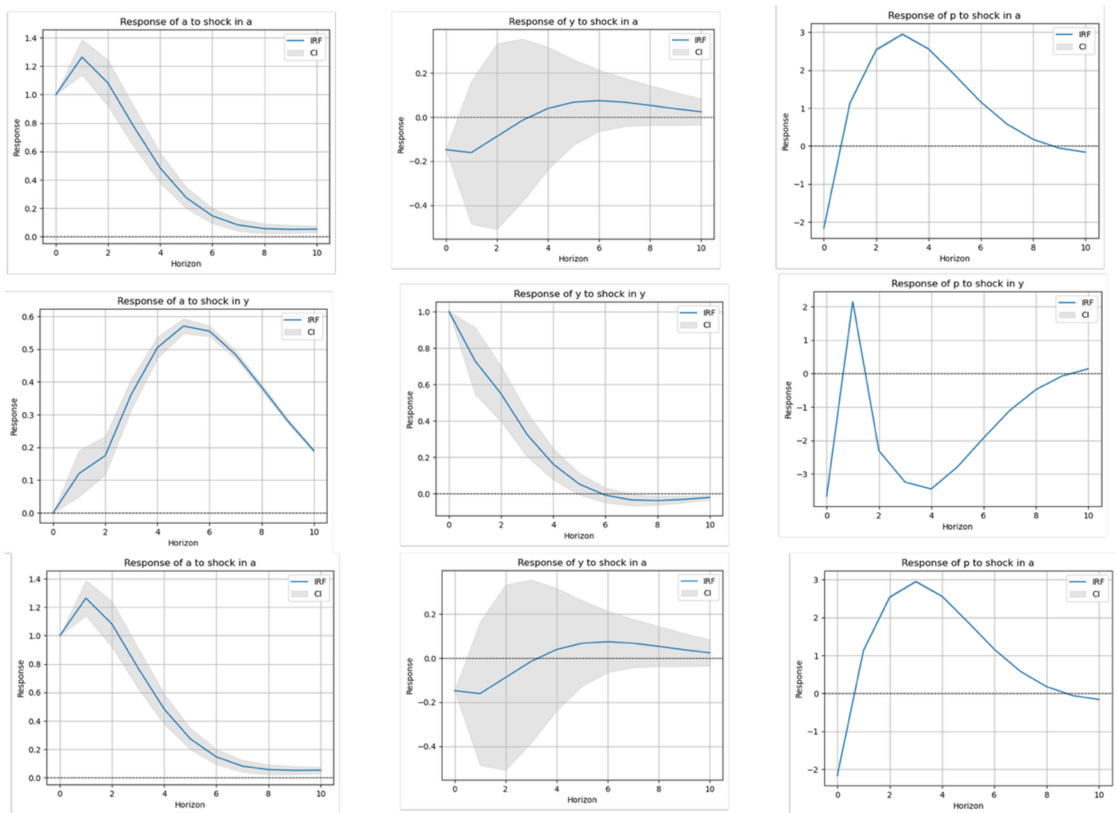


Figure 3: SVAR results of global cattle beef model: impulse response plot

From figure 3, 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.

4.2. Estimated Elasticities

IRFs in figure 3 is used to estimate elasticities. Figure 4 illustrates the demand and supply elasticities estimated using different shocks.

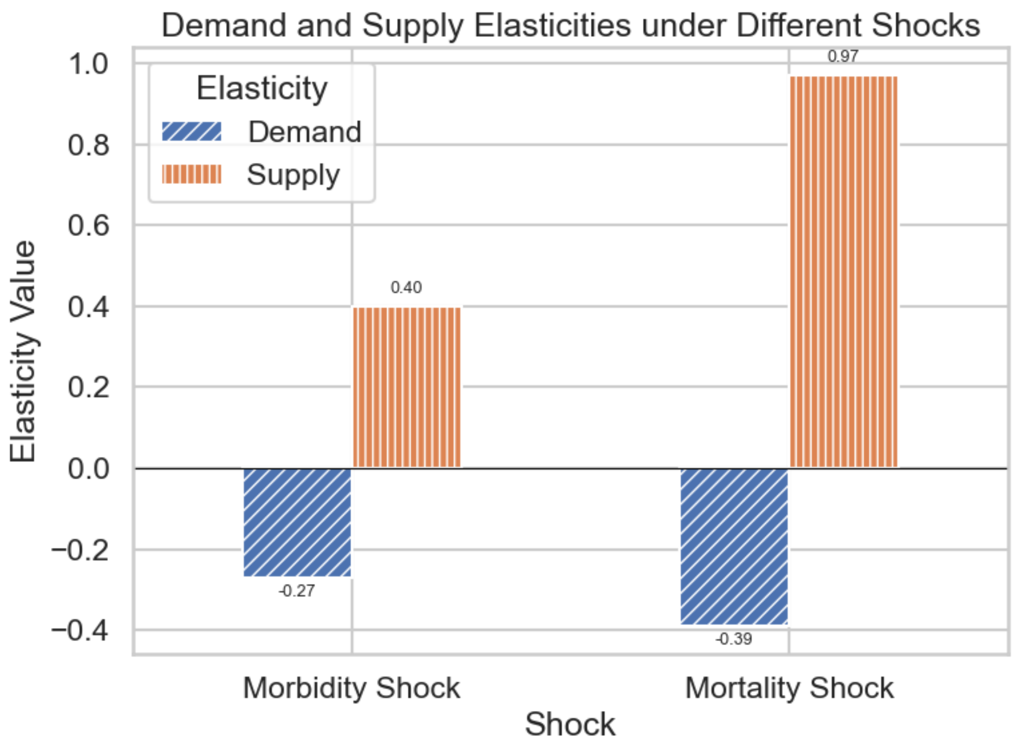


Figure 4: Elasticity estimates from cattle supply (mortality) shock and meat supply (morbidity) shock

Figure 4 illustrates that a 1% increase in yield in the short run due to positive mortality shock yields a demand elasticity of -0.39 and a supply elasticity of 0.97. Likewise, a 1% increase in yield in the short run due to positive morbidity shock yields a demand elasticity of -0.27 and a supply elasticity of 0.40.

4.3. Redistribution of Economic Welfare

To calculate redistribution of economic welfare, we consider producer surplus (PS) and consumer surplus (CS).[3] We can calculate the PS and CS by the following equations (Alston et al., 1995):

$$\Delta PS = P_0 Q_0[(0.01 + EP)(1 + 0.5 * EQ)] \tag{5}$$

$$\Delta CS = -P_0 Q_0 \times EP\ (1 + 0.5 * EQ) \tag{6}$$

where the E operator indicates percentage change ($\approx dln(.)$). Since the IRFs are calculated based on the log-transformed variables, they can be used directly into the surplus change equations (5) and (6) (Barratt et al., 2019). In order to calculate the producer and consumer surplus as in equation (5) and (6), we need baseline price and quantity, P_0 and Q_0, respectively. We get the price data from WBCMO and quantity from FAOSTAT. The average nominal price of beef for the year 2022 is USD 2.55/pound and quantity demanded for the year is USD 166.91 billion pound. Therefore, a 1% increase in yield in the short run due to positive mortality shock yields a change in producer surplus of - 4.99 billion USD and a change in consumer surplus of 9.27 billion USD for a single year.

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[3] Ghanem and Smith (2022) estimate a SVAR model of global demand and supply, calculate IRFs, and recommend following Thurman and Wholgenant (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.

On the other hand, a 1% increase in yield in the short run due to positive mortality shock yields a change in producer surplus of - 11.41 billion USD and a change in consumer surplus of 15.68 billion USD for a single year.

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 elasticities from both mortality and morbidity shock, we observed that the estimated elasticities from mortality shock are greater in magnitude than the elasticities estimated from the morbidity shock. Based on this observation, we claim that at the global level, consumers and especially, producers take more time to adjust in response to mortality shock than to morbidity shock.

We can estimate the short and long run aggregated welfare impact of livestock diseases, provided that their exogenous effects are known, for example, from the outputs of epidemiological models. In the absence of such exogenous epidemiological output, we discussed the short run welfare effect in response to 1% mortality and morbidity improvement in section 4.3. Figure 5 shows net present value (NPV) of the ripple effect of the 1% change in the subsequent years.

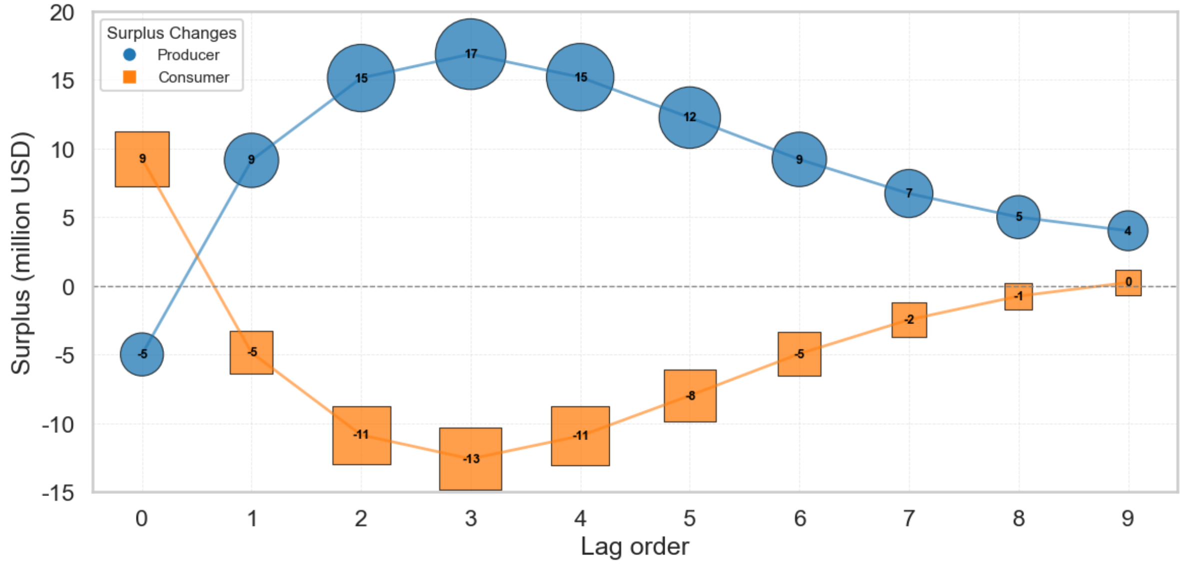

Figure 5(a): Change in producer and consumer Surpluses due to mortality shock

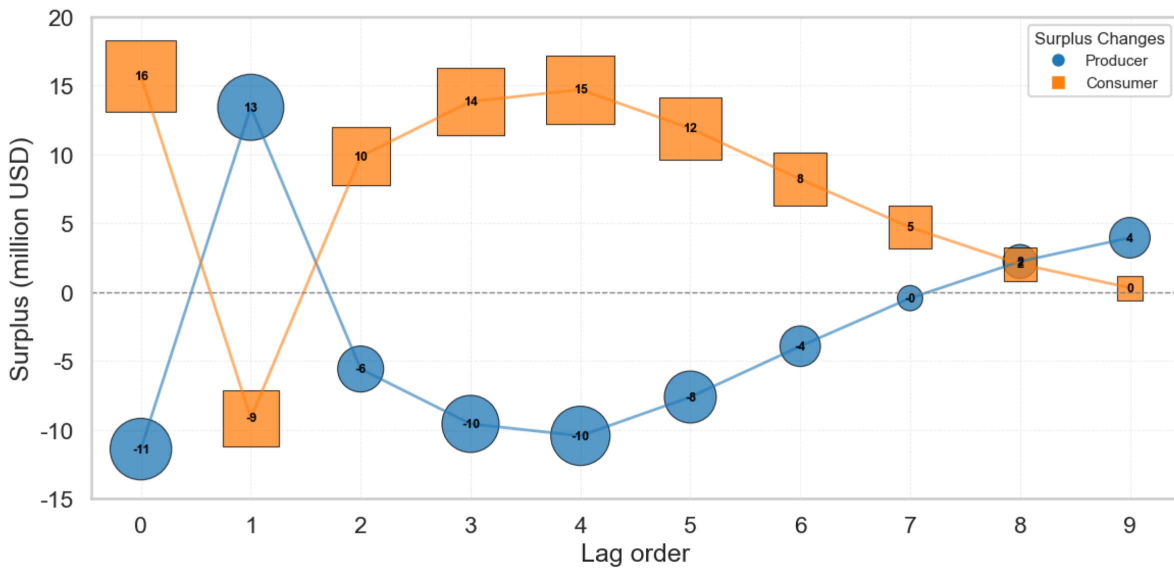

Figure 5(b): Change in producer and consumer Surpluses due to morbidity shock

Figure 5: NPV of the change in producer and consumer surpluses over the years due to 1% shock

Figure 5 strengthens our claim about the economic agents' ability to quickly adjust to morbidity shocks. We see that the producers and consumers surplus changes in the subsequent year do not change direction in case of the mortality shock. However, in case of morbidity shock, the direction changes immediately in the next period. NPV of a marginal 1% animal health improvement over the five years period is USD 21.78 billion which is about 5% of the size of the global beef sector. 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,

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

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

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

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):

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

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

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

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 $A_0^{-1} = LD^{-1}$ and $\mathrm{D} = \mathrm{diag(L)}$, 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

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

IRF given in equation (A.5) can trace dynamic effects on the Y_i from structural shocks in the ν_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.