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 applied to analyze market dynamics in the beef demand supply system following a disease outbreak. Findings suggest that producers and consumers in the cattle beef sector are more responsive to mortality shock than to morbidity shock. The estimated net present value (NPV) of a marginal 1% animal health improvement over a five-year period is USD 13.43 billion, which is about 4% of the size of the value of global beef production.

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 provide nutrition to households across the world. Livestock diseases reduce productivity and distort markets, which results in food supply chain disruptions (Rushton et al., 2018, 2021; Hennessy and Marsh 2021) and redistributes economic welfare across the globe (Hennessy and Marsh 2021). The market distortion due to diseases are exogenous to regular market dynamics and hence could be useful in estimating market forces. For example, identification and estimation of global demand and supply of commodities has been extensively studied in the economic literature. 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.

It is important to distinguish this study from the recent trend in literature on the difference in demand and supply during an outbreak (Acosta et al., 2020; Goodwin, 2024). Instead of analyzing the difference in elasticity estimates due to small and large disease shock (Goodwin, 2024) or normal states to disease states, our focus here is to estimate the overall market behavior due to sudden changes in demand and supply, maybe due to a disease outbreak. The estimated elasticities in this study can be thought of as a benchmark (or average) of the elasticities for different regimes mentioned above. Linking the exogenous shifts with disease outbreak is an important contribution of this study, which allows us to use the outputs from this study to make inferences on the livestock disease economics.

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 this literature 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, global estimates of demand and supply of meat have not received as much attention in the 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 methodologically following Ghanem and Smith (2022), who exam global demand and supply for cereal grains. A key contribution of the current 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. 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 $f(t)$ 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 the size of the inventory, y_t is the meat yield per 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). Similar to Shakil et al., (2025), meat production is broken-down into two components: inventory size (i_t) and per animal yield (y_t).

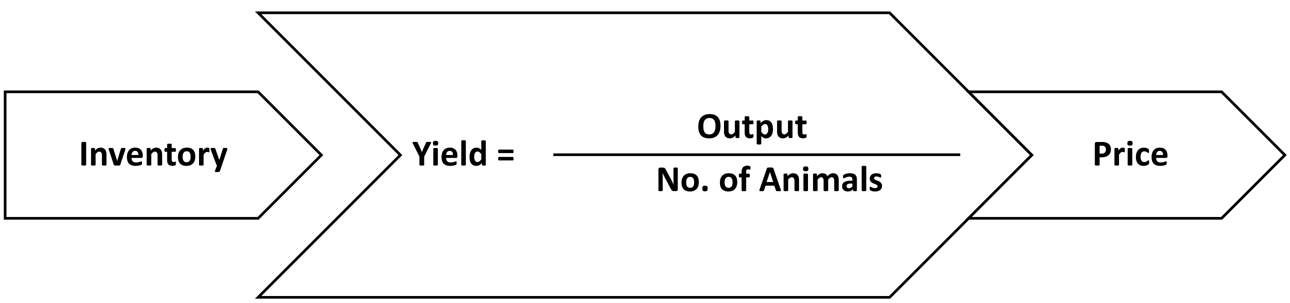

Figure 1: Causal Ordering of Global Beef Cattle SVAR Model

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

2.2. Identification of the Structural Matrix

Due to the biological nature of livestock production, at the beginning of a year t, the number of cattle in the inventory 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 inventory size in year t through the relationship described in figure1. 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:

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

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). But 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 beef supply: cattle inventory and yield per cattle. A sudden shift in inventory 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 inventory 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:

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

Here, the elasticity is estimated using the mortality shock, i.e., shock to the cattle inventory. Similarly, demand elasticity can also be estimated using the morbidity shock (ν_y). 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 inventory and yield decision for the following period. In order to estimate the supply elasticity, responses of the suppliers in the next period is under consideration.

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

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 yield data from the Food and Agricultural Organization Statistics (FAOSTAT) database. Yield data is reported in carcass weight (lb) per slaughtered animal in FAOSTAT. The per animal slaughtered data is also used as a proxy for the inventory size, as inventory decision directly influence the number of cattle supplied to slaughterhouses. 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. Figure 3(a) illustrates the log transformed time series data.

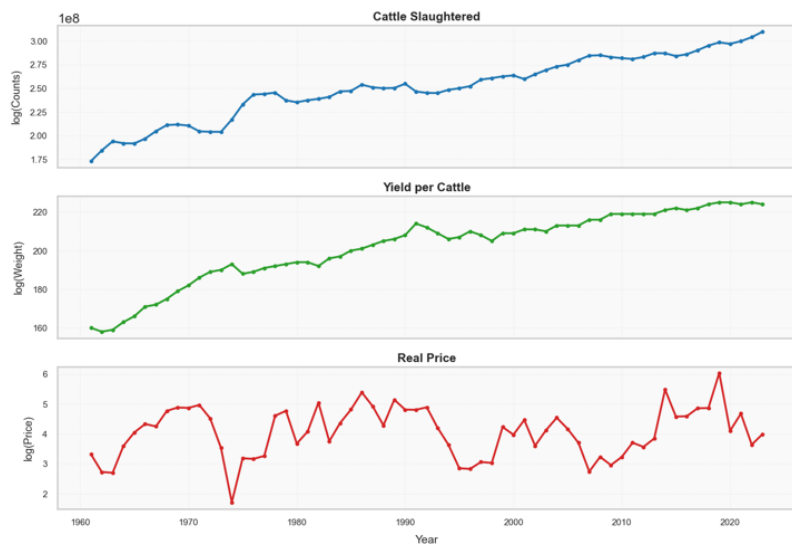

Figure 3(a): Log data over the years

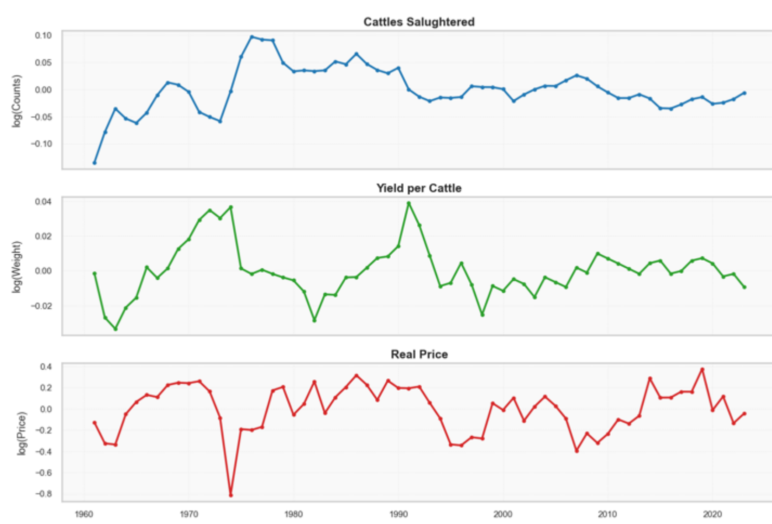

Figure 3(b): Detrended log data over the years

Figure 3: Total number of cattle slaughtered globally, yield per animal and real price over the years

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 is selection. Third, impulse response functions are estimated. Third, elasticities are reported. Fourth, economic surplus for producers and consumers are provided.

4.1. Unit Root Test

Figure 3(a) shows trend in data, especially in animal numbers and in yield. Therefore, the data were detrended as shown in figure 3(b). Augmented Dickey Fuller (ADF) test results are shown in table 3. From the left column of table 3, 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

4.2. Lag Order Selection

The length of the lag-order is an important step in the identification of demand-supply models. Ghanem and Smith (2022) used Akaike and Bayesian information criteria for selecting the lag order. Table 1 illustrates information criterion for different lag-orders, with the asterisk provided for the smallest value. We can observe from table 1 that all the criteria select the model with the first lag only.

Table 2: Lag-order selection based on information criteria

Lag-order	AIC	BIC	FPE	HQIC
1	-21.09*	-20.42*	6.956 X10^{-10}*	-20.83*
2	-21.07	-20.07	7.106 X10^{-10}	-20.69
3	-20.90	-19.56	8.623 X10^{-10}	-20.38
4	-20.64	-18.96	1.144 X10^{-9}	-19.99
5	-20.83	-18.82	9.810 X10^{-10}	-20.05
6	-20.65	-18.31	1.237 X10^{-9}	-19.75
7	-20.55	-17.87	1.476 X10^{-9}	-19.52
8	-21.03	-18.02	1.010 X10^{-9}	-19.87
9	-21.00	-17.66	1.190 X10^{-9}	-19.72

*Smallest value

However, Durbin-Watson test statistic indicate that residuals of the fitted reduced form VAR model are autocorrelated at lag-order 1. This autocorrelation gets mitigated with higher order VAR. Table 2 illustrates the Durbin-Watson test statistics for different lag orders.

Table 3: Durbin-Watson test statistics (DW)[2]

Lag-order	Inventory	Yield	Price
1	1.20	1.73	2.14
2	2.00	2.04	2.14
3	1.84	2.02	1.96

[2] DW close to 2 implies no autocorrelation, DW < 2 implies positive autocorrelation and DW > 2 implies negative autocorrelation.

Similar observation can be made from figure 1 as well. In figure 2(a), ACF and PACF plots for residuals of lag order 1 shows serial autocorrelation, especially inventory variable. Figure 2(b) illustrates that the serial correlation dissipates for the residuals for lag-order 2.

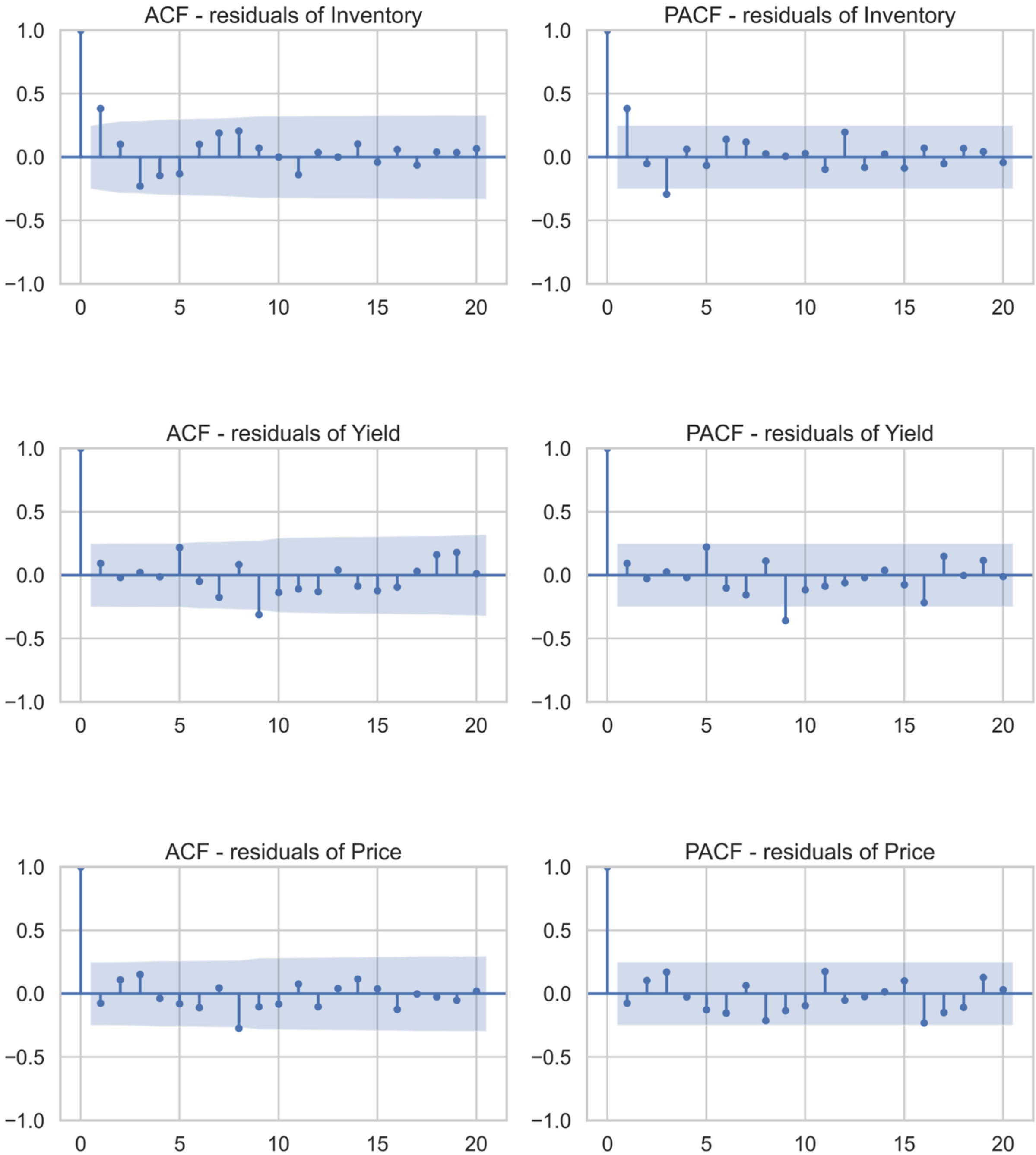

Figure 2(a): ACF and PACF plots of residuals of reduced form VAR (1) model

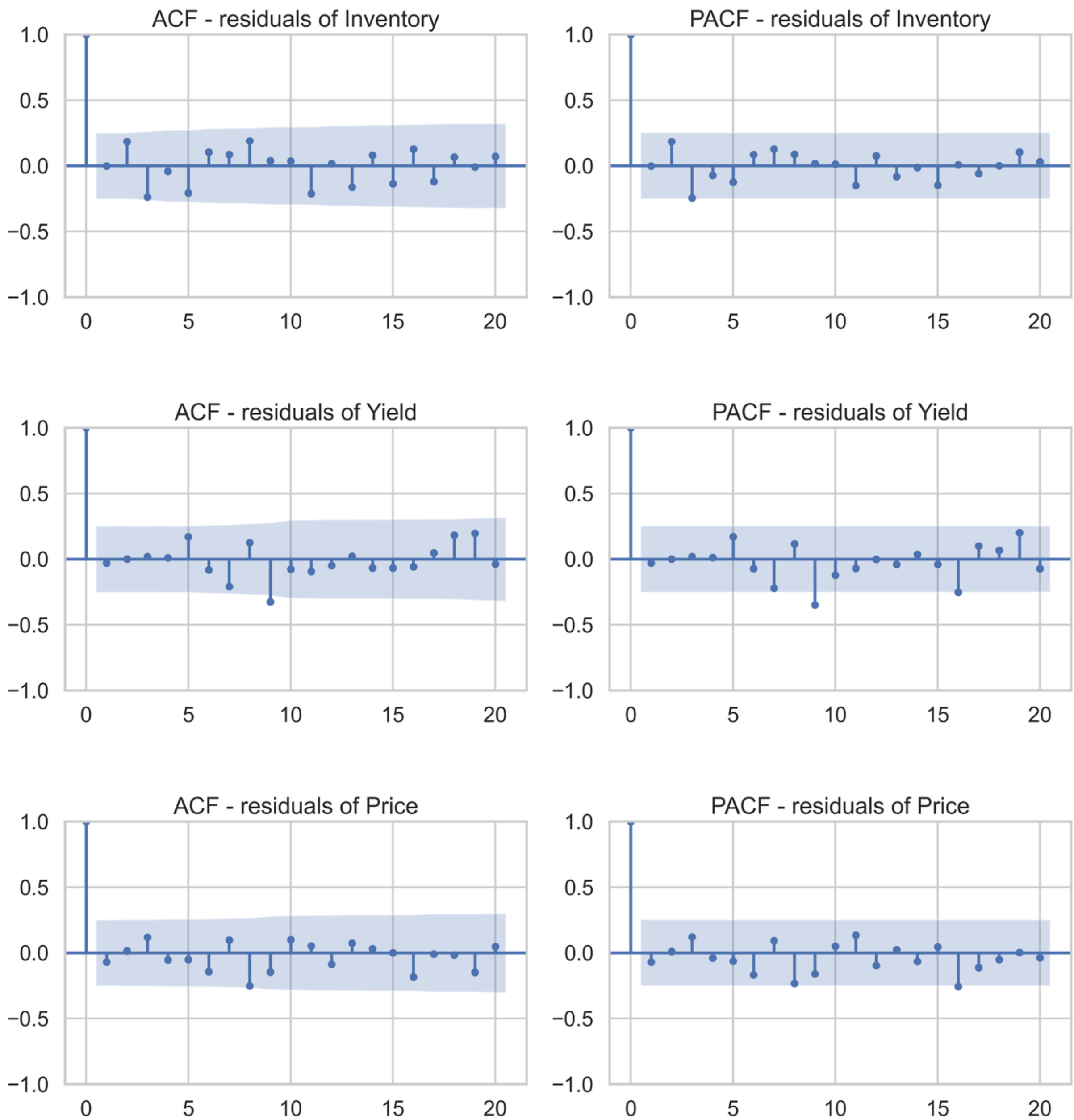

Figure 2(b): ACF and PACF plots of residuals of reduced form VAR (2) model

Figure 2: ACF and PACF plots of reduced form VAR residuals models for different lag-orders

Evidence from the literature suggests longer life cycles from calves to be slaughtered. For example, Paarlberg et al. (2008) modeled the cattle life cycle from inventory to slaughterhouses with five quarters. Industry data suggest that the time frame from birth to slaughter for calves can extend up to 22 months[3]. Therefore, to capture the supply and inventory decision, we select lag order 2 for our cattle beef SVAR model.[4]

4.3. Impulse Response Functions

The impulse response functions (IRFs) are shown in Figure 4. The main purpose is to describe the evolution of a model's variables in reaction to a shock in one or more variables.

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

[4] For a robustness check based on the lag-order of the reduced form VAR, please refer to Appendix B.

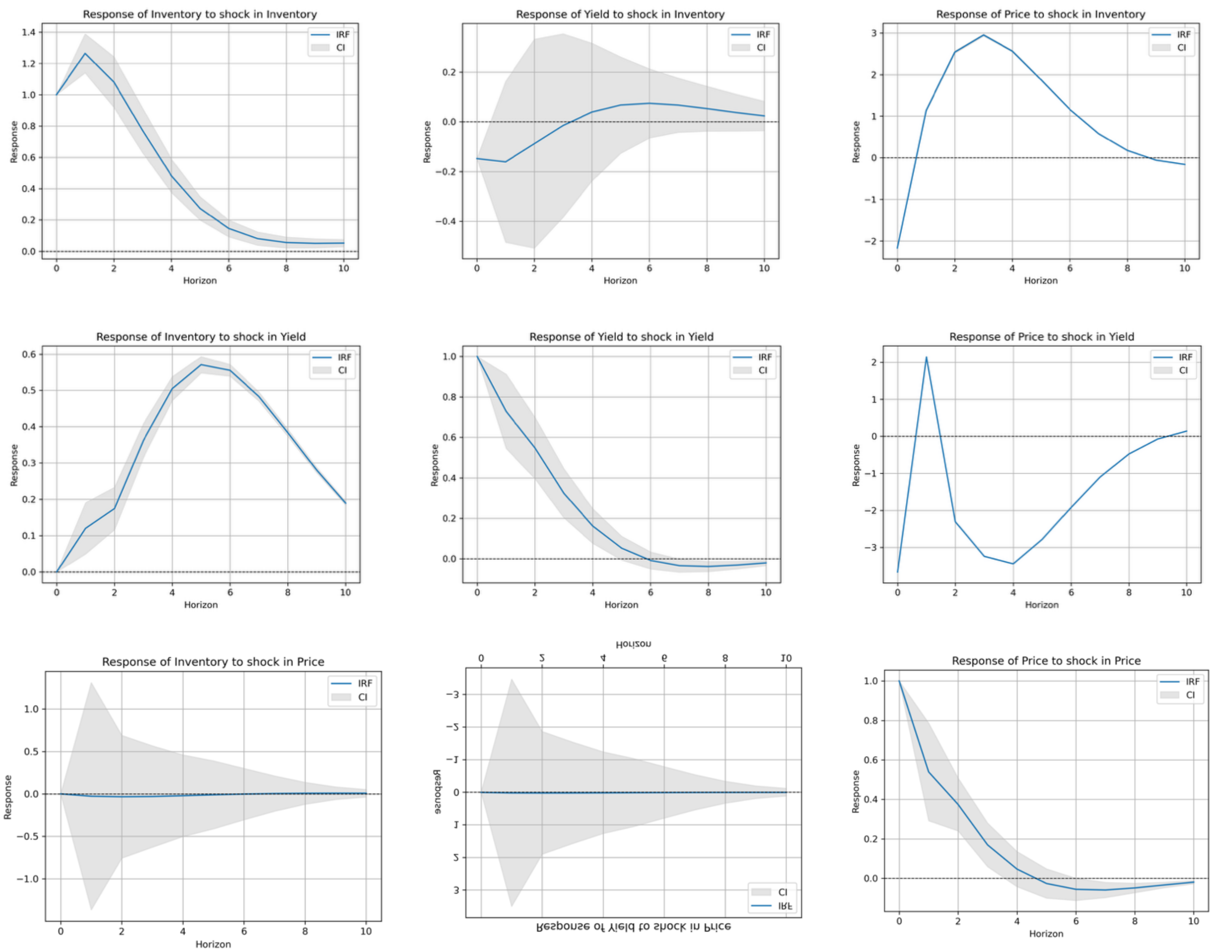

Figure 4: SVAR results of global cattle beef model: impulse response plot

From figure 4, 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

IRFs in figure 4 are used to estimate elasticities. Figure 5 illustrates the demand and supply elasticities estimated using different shocks.

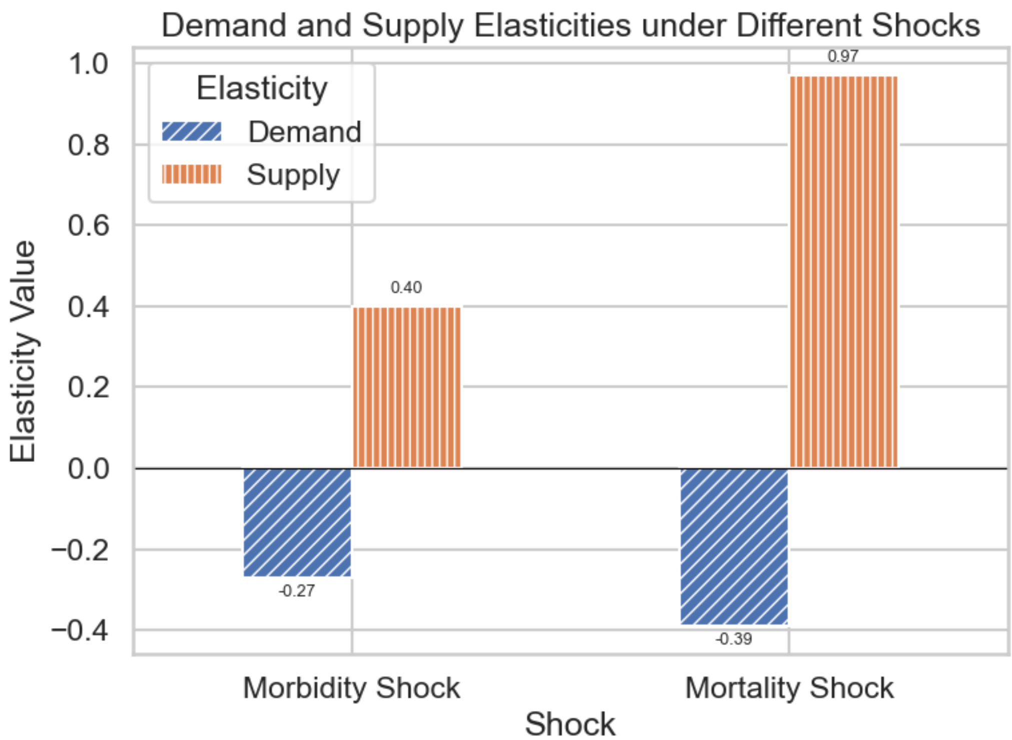

Figure 5: Elasticity estimates from cattle supply (mortality) shock and meat supply (morbidity) shock

Figure 5 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.

4.5. Redistribution of Economic Welfare

To calculate redistribution of economic welfare, we consider producer surplus (PS) and consumer surplus (CS).[5] 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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[5] 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.

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 morbidity shock than to mortality 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 6 shows the change in surpluses of the ripple effect of the 1% change in the subsequent years[6].

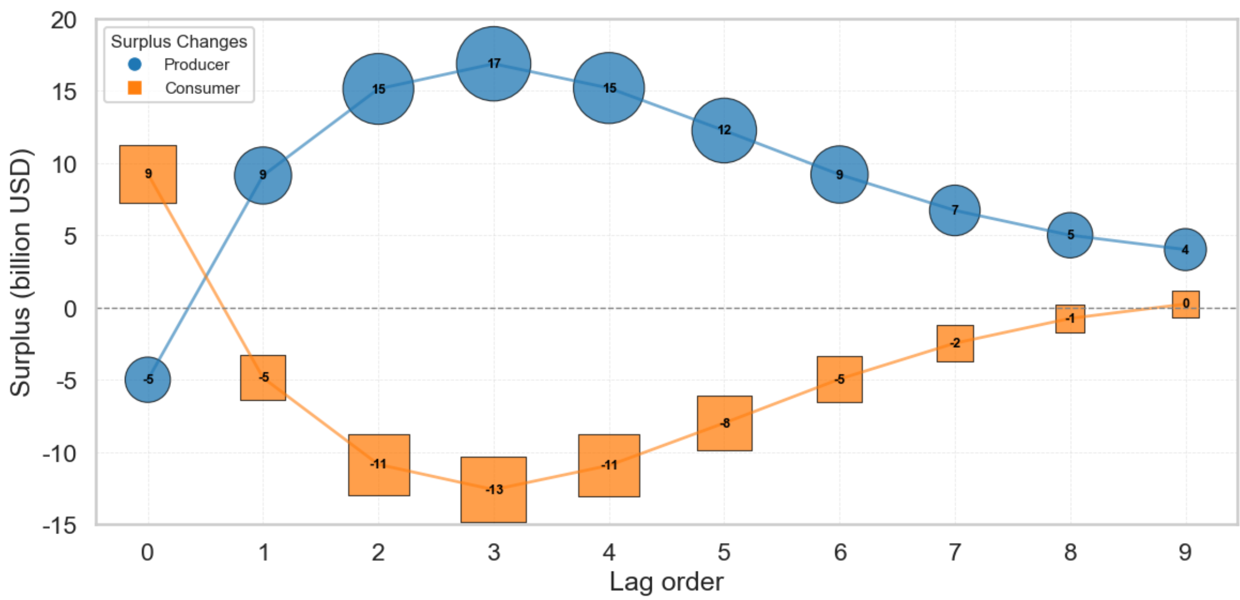

Figure 6(a): Change in producer and consumer surpluses due to mortality shock

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[6] Surpluses are calculated with base values from the year 2023. The average nominal price of beef for the year 2023 is USD 1.95/pound (WBCMO) and beef produced for the year is USD 153.14 billion pound (FAOSTAT).

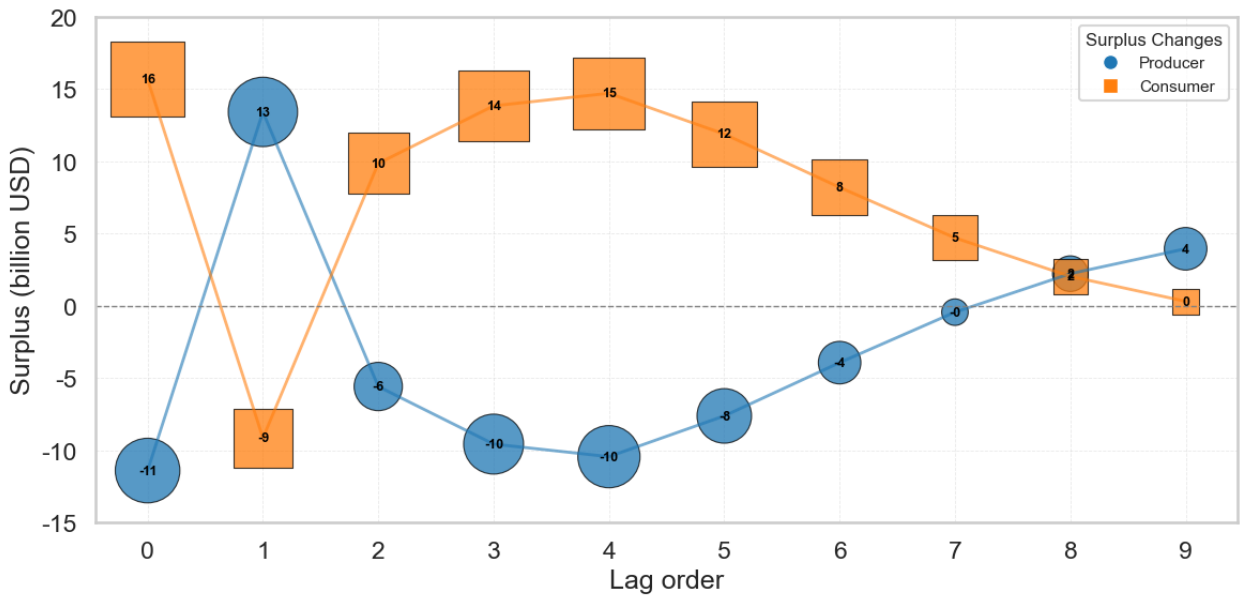

Figure 6(b): Change in producer and consumer surpluses due to morbidity shock

Figure 6: Change in producer and consumer surpluses over the years due to 1% shock

Figure 6(a) illustrates that, with a positive supply shock in animal inventory, producers lose and consumers gain as an immediate aftermath. Figure 4 (first row) illustrates that, positive shock in the size of the inventory results in immediate price drop, particularly due to a sudden oversupply. In the subsequent years, market adjusts to increased consumer demand that pushes the beef price upward. Hence, the producers gain in the following years.

Figure 6(b) shows that, with a positive morbidity shock in per animal yield, producers lose and consumers gain, similar to what we observed in the case of mortality shock. In the following year, market adjusts to increased consumer demand that pushes the beef price upward. However, as shown in second row of figure 4, suppliers react to this positive price change by increasing the inventory supply. This results in the decrease in the beef price.

It is interesting to note that, the total surplus at each period is equal, irrespective of the morbidity and mortality shock. This makes intuitive sense as surplus changes arising from both the shocks represent an equal 1% supply shock. The net present value (NPV) of a marginal 1% animal health improvement over the five years period is USD 13.43 billion which is about 4% of the size of the global beef sector.[7]

However, the distribution of gains and losses are quite different for the two supply shocks implemented in this study. Although immediate impacts are similar for both type of shock, consumers bear the burden of mortality shock in the long run. Whereas producers bear the burden of distortions due to morbidity shock. Since the producers are more responsive to distortions due to morbidity shock (see figure 5), the burden is passed to the consumers for market distortions of this nature. On the other hand, producers are stickier to respond to the distortions due to morbidity and hence the burden is borne by them in subsequent years.

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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[7] NPV is calculated with 5-year OMB discount rate of 3.8% for calendar year 2025. https://bidenwhitehouse.archives.gov/wp-content/uploads/2025/01/M-25-08-2025-Discount-Rates-for-OMB-Circular-No.-A-94.pdf

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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 D $=$ 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

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

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.

Appendix B

As a robustness check of the estimated elasticities, we compute the demand and supply elasticities estimated from SVARs of different order with respect to both the mortality and morbidity shock. Table B.1 suggests SVAR of order 1 produces a negative supply elasticity and hence reconfirms our assumption about autocorrelation to be still present in SVARs of order 1. SVARs of higher orders produce similar demand elasticities as we reported in this paper. However, the supply elasticities tends to go down as the order increases. For the principle of parsimony, we choose the SVAR of order 2.

Table B.1: Estimated elasticities with SVARs of different orders

SVAR Order	Morbidity Shock		Mortality Shock	
	Demand Elasticity	Supply Elasticity	Demand Elasticity	Supply Elasticity
1	-0.3853	-0.3304	-0.4969	1.7365
3	-0.2405	0.6185	−0.3825	0.6942
4	-0.2460	0.5873	−0.3533	0.6293
5	-0.2832	0.4255	−0.3804	0.5436