Identifying the Price Determinants of Animal Products in the Presence of Structural Breaks

Matthew J. MacLachlan, USDA- Economic Research Service

matthew.maclachlan@ers.usda.gov

David Boussios, USDA- Economic Research Service

david.boussios@ers.usda.gov

Keywords: disease, livestock markets, structural break, vector autoregression

Abstract: *Macroeconomic fluctuations, trade disputes, and infectious disease outbreaks alter the markets for broiler meat products, as well as markets for other animal products. Each of these events represents declines in demand as they reduce the pool of consumers or individual consumer's willingness to pay. Macroeconomic shifts—such as the Great Recession—have coincided with a decrease in supply. The ability of producers to store their durable animal products further complicates the identification of these market distortions. We first empirically test for changes in prices, storage, exports, and production among broiler meat producers during two outbreaks of Highly Pathogenic Avian Influenza. These results are then compared to a model where regime shifts can occur anytime during our time-series. We find a brief but significant storage increase at the end of both outbreaks. The inability of these approaches to identify significant events at the national-level suggests a resilient market capable of withstanding negative shocks.*

Domestic and international production and demand for U.S. chicken (broiler) meat products have undergone substantial changes over the past few decades. Within the U.S., production intensification, consumers' preferences for lower fat meats, and globalization have led to increased exports and production. Since the turn of the millennium, several infectious disease outbreaks, a historic recession, and trade conflicts have all influenced the broiler meat market. These persistent negative shocks affected producers at a national-level and consumers internationally. This paper focuses on estimating the market responses to these negative shocks. We begin by exploring the market responses to two outbreaks of Highly Pathogenic Avian Influenza (HPAI), a particularly damaging infectious disease, within a model that allows for structural breaks. We then compare these results to a model that more flexibly captures changes between two regimes.

We initially explore the role of infectious diseases in the domestic broiler meat market. Infectious diseases of livestock have threatened global agriculture directly through decreased productivity and indirectly through market responses and disruptions to trade. The possibility of zoonosis (specifically transmissions from animals to humans) leads to more severe restrictions among trading partners, even when zoonosis does not occur (Sumner, Bervejillo, and Jarvis, 2006). The modern era of production has witnessed a dramatic intensification of production and increased international connectivity, particularly within U.S. production systems (MacDonald and McBride, 2009; Perrings et al., 2009). These changes have boosted yields and consumer welfare, but have also expanded the channels of infectious disease transmission and the economic consequences of disease introductions.

While numerous economic studies have examined the interplay between public and private actors' responses to infectious disease (for example, see Bicknell, Wilen, and Howitt (1999) and Gramig and Horan (2011)), export restrictions have received relatively little attention from economists. A notable exception, a paper by Marsh, Wahl, and Suyambulingam (2005) explore disease-related export restrictions using a game theory framework. From the perspective of the U.S., foreign importers may choose to ban or restrict U.S. exports of live animals or specific animal products after the verification of an infectious disease among livestock or even wildlife or companion animals. While any sovereign nation selects trade responses on a case-by-case basis, diseases that appear on the International Organization for Animal Health's (OIE) notifiable disease list typically trigger severe import restrictions (e.g., treatment of animal products to reduce the likelihood of contamination by pathogens) or outright bans. The U.S. and foreign governments—rather than individual producers—

determine the nature and extent of any trade restriction. Producers, in turn, respond to the decreased international demand. In addition to decreasing prices and altering production choices, cold storage[1] may be used to arbitrage goods into the future when producers expect market conditions to improve.

HPAI introduction into poultry production occurs through several pathways, including interactions with wild hosts, mutation of low pathogenic strains, and farm equipment and labor. Scientists suspect that a mutation of an endemic Low Pathogenic Avian Influenza strain caused the 2004 event (Lee et al., 2005). Wild waterfowl introduced two distinct strains of HPAI during the 2014 – 2015 outbreak, which they carried from Canada during their southern migration. HPAI transmission to domesticated birds then resulted from numerous vectors including fomites,[2] fecal matter, and aerosols (APHIS, 2015). The outbreaks differ substantially in their duration and magnitude but share several important qualities. Importers imposed restrictions on U.S. poultry products following both events, and broiler chickens (young chickens raised for meat) experienced relatively low mortality rates.[3]

We combine national, broiler industry-level, time-series data on cold storage quantities, retail prices, production, exports, trade restrictions, and industrial energy prices to test for structural breaks and estimate average changes in the economic indicators (including cold storage). A vector autoregressive model (VAR) accounts for the endogenous relationships among these variables and accommodates structural shifts. We test a wide range of outbreak response window durations and select the model that minimizes information loss. These estimates shed light on the nature of structural, market shifts in responses to HPAI. Our results identify only brief increases in storage volumes. These changes occur during two short periods at the end of the disease outbreaks.

Using the same dataset, a Markov Switching VAR (MS-VAR) allows for the more flexible identification of the relationship between policy changes and broiler meat markets. This framework allows for a market to transition between two (or more) regimes at any point in our time-series, which relaxes some of the assumptions introduced in our model with structural breaks. It also allows for shocks other than HPAI to cause persistent market distortions.

The national scale of our study encumbers a clean characterization of the relationships between policy changes and producer behavior compared to simulations that characterize the interplay between, for example, disease prevalence and biosecurity. On the other hand, this empirical study requires fewer assumptions and uses data aggregated over the unobservable heterogeneity of producers. Our approach contributes to a line of research that has examined behavioral responses to human disease outbreaks and subsequent centralized control efforts. For example, Towers and Chowell (2012) explore changes in interpersonal disease transmission during the weekend. Springborn et al. (2015) characterize the role of social avoidance during an outbreak of swine flu, using television viewership to proxy for time spent at home. Methodologically, it contributes to a growing body of literature on the econometric identification of the relationship between agricultural policy and the agricultural markets (e.g., Jansen, Smith, and Carter, 2018). We modify these

---

[1] Cold storage includes any storage of food products at temperatures below 50 degrees Fahrenheit, typically for 30 days or more.

[2] Fomites are inanimate objects capable of carrying a pathogen between locations.

[3] An outbreak of Exotic Newcastle Disease (END) also occurred in California in 2002 – 2003. This outbreak led to the depopulation of 3.16 million birds to control the disease. This outbreak, however, was largely confined to backyard flocks, and the impacts on industrial production and the trade consequences were minimal.

approaches to explore producer responses to the infectious disease outbreaks *and* their ensuing trade restrictions.

Shocks to chicken meat markets

The recent shocks to the broiler market have varied in their form and intensity. While market conditions are always in a state of flux, infectious disease outbreaks, trade conflicts, and the recession led to more pronounced changes in the broiler market. Changes in feed prices—which have corresponded to other natural disasters—may also shift supply.

International policy responses to Highly Pathogenic Avian Influenza

HPAI has not led to significant losses of broiler chickens or substantially decreased production (Ramos, MacLachlan, and Melton, 2017). Trade restrictions resulting from the presence of HPAI in other poultry, however, led to significant losses of market access.

The International Organization for Animal Health (OIE) provides recommendations to exporters and importers of animal products when an OIE-listed[4] disease is present. OIE characterizes the status of an exporting country or compartment[5] and suggests methods to reduce the risk of spread from traded live animals or animal products. OIE guidelines allow importing nations to choose to ban or restrict imports of live animals and animal products from a nation or compartment without a disease-free (hereafter referred to as "HPAI free") status. Alternatively, importing nations may choose to ignore the guidelines altogether, particularly if these riskier goods can be purchased at a lower price. These guidelines also provide latitude in determining the size of compartments and the duration of trade restrictions, particularly for diseases with wild hosts or long incubation periods.

In the case of HPAI, restrictions are typically placed on both live animals *and* animal products because of risks to poultry production in the importing country and because of human health concerns.[6] OIE states that an area that was previously HPAI free *may* regain its free status three months after the completion of a stamping out process (OIE, 2017).[7] The presence of infected wildlife—which was a prominent feature of the 2014–2015 HPAI outbreak—can slow the recovery of HPAI free status because of the difficulty in demonstrating zero prevalence within these populations. OIE does not provide clear guidance on the best practices in these cases. As a result, the duration of trade restrictions often varied by trading partner.

---

[4] OIE maintains two lists of particularly damaging infectious animal diseases. List A includes the most damaging disease such as HPAI, foot and mouth disease, and African horse sickness. The more extensive List B includes other damaging diseases such as bovine tuberculosis, rabies, and Marek's disease.
[5] A compartment refers to a region within a country. In the U.S., this could include the entire country, a state, a county, or an area that does not follow political boundaries.
[6] While there were no cases of HPAI transmission from poultry or wild birds to humans during the outbreaks of interest, HPAI's propensity to mutate motivates stricter safety precautions.
[7] Stamping out includes disinfection of infected premises, which itself takes at least 21 days.

Changes in trade patterns

Exports of U.S. broiler meat depend on market access as well as non-tariff trade barriers imposed by trading partners. Changes in the production of other exporting nations consequently change the demand for U.S. products. While trade has changed almost constantly throughout our period of interest, several events stand out. Circa 2010, China accused the U.S. of dumping broiler meat products, which led to the imposition of significant duties (43% – 105%) (Li, Gutner, and Epperson, 2011). The World Trade Organization (WTO) eventually ruled in favor of the U.S. in 2013.

The annexation of Crimea led to trade conflicts between the U.S. and Russia. As part of this dispute, Russia banned imports of U.S. broiler meat products. This example highlights potential problems of identifying simultaneous shocks as Russia's ban went into effect only months before the first case of HPAI was observed in U.S. poultry in 2014.

Changes in production and exports from other broiler producing nations alter the international demand for U.S. broiler meat. For example, Thailand and Vietnam experienced outbreaks of HPAI in 2003 – 2004 that led to significant trade restrictions (Blayney, 2005).

The Great Recession

The Great Recession led to significant declines in disposable income, which, consequently, led to declines in per capita meat consumption (Darko, 2013). The decline coincided with a large decline in broiler meat production beginning in late 2009.

Data

We combine publicly available time-series data on U.S. poultry production, prices, exports, storage, industrial energy prices, and HPAI related mortality of poultry[8] to facilitate our empirical analyses. Data are first used to individually test for a correlation between HPAI outbreaks and the ensuing trade restrictions and changes in economic indicators. These tests ensure that the observed changes align with our expectations and that the data support the assumptions embedded in our structural approaches.[9] Our first estimation approach—a vector autoregression (VAR) with structural breaks—uses the data to estimate parameters of this endogenous system, and allows for the isolation of the impact of HPAI and ensuing trade restrictions on exports, prices, storage, and production.

This paper uses only publicly available data from federal agencies. The available time-series vary in length due to differences in historical data collection techniques as well as individual agency's data products. While some indicators are available as far back as January 1917, all data were available beginning in January 2000. The release of new data varies across agencies, and we, therefore, opt to

---

[8] Birds were depopulated when they were exposed to other infected birds to slow or prevent spread. Because the number of infected birds was never determined, we define infections as the number of birds lost to or in response to HPAI.

[9] The results of individual estimation approaches are presented in the Appendix. They generally follow expectations with the exception prices. While prices decline during the outbreak response window, the change is not statistically significant.

omit observations after 2017. The empirical sections do not use data outside of this span, but we note when these data are available in each product subsection.

Outbreaks

The U.S. Department of Agriculture's (USDA) Animal and Plant Health Inspection Service (APHIS) provides information regarding the 2004 and 2014 – 2015 outbreaks. APHIS (2004) notes that a single HPAI event occurred in 2004, leading to the depopulation of 6,600 broiler chickens on a single facility. APHIS (2016) provides time-series data on the number and type of birds affected by two strains of HPAI between December 2014 and June of 2015. These outbreaks together resulted in approximately 153,000[10] broilers lost to HPAI infection or depopulation.[11] We represent the cumulative poultry losses across broilers, egg layers, turkeys, and other poultry birds below in figure 1. Broilers represented approximately 0.3 percent of the total birds lost.

Figure 1. Cumulative losses of all poultry and broiler birds* during the 2014 – 2015 outbreak of Highly Pathogenic Avian Influenza.
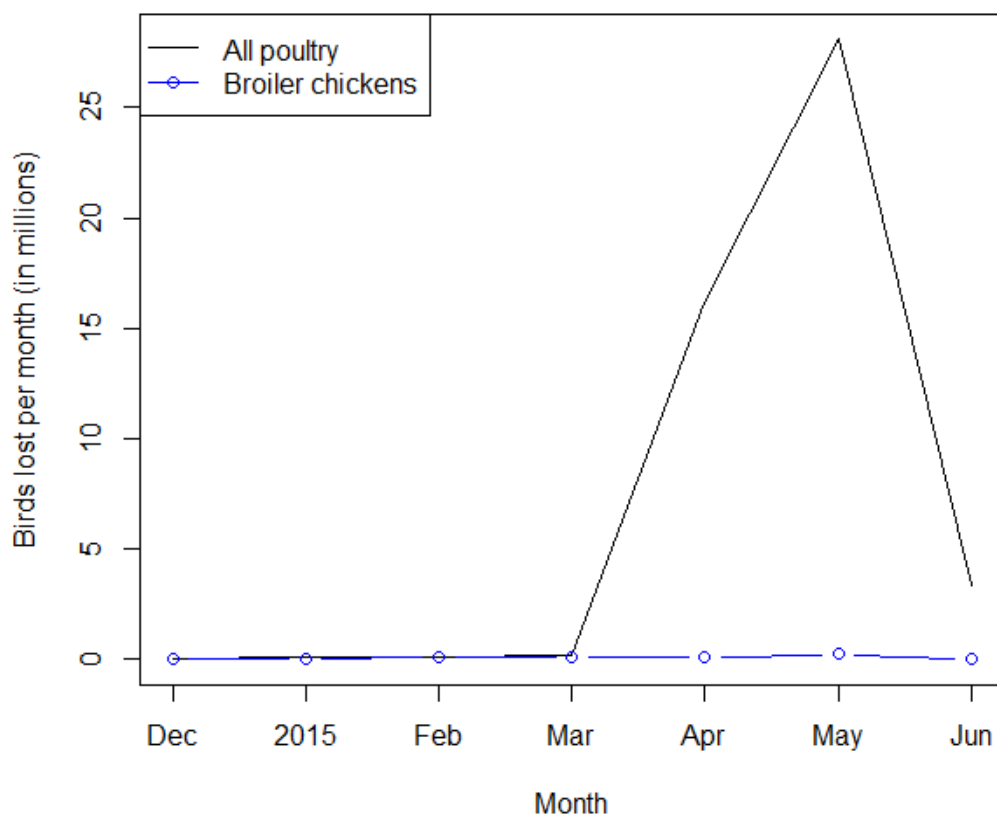
Note: The estimate of broiler birds lost includes "mixed poultry," which could contain other birds

---

[10] This estimate represents a lower bound. APHIS categorized several facilities as "mixed poultry," which could include broilers and other poultry.

[11] For context, 9.2 billion broiler chickens were placed into production during 2016.

Figure 1 shows that, while the outbreak lasted from December 2014 through June of 2015, the vast majority of poultry losses came between April and May. The vast majority of these lost birds were not broiler chickens (mainly, egg-laying hens and turkeys). We would expect that the higher prevalence in bird losses in these months to be associated with the imposition of stricter trade restrictions by more destination markets *if* importing nations had not already imposed restrictions after the first observed cases of HPAI (in December and January).[12]

The limited losses of broiler chickens indicate that the majority of revenue losses incurred by this industry[13] cannot be directly attributed to HPAI, but possibly resulting market distortions.

In addition to the two outbreaks considered in this paper, a single case of HPAI occurred in a turkey flock in February 2016. APHIS quickly isolated the infected birds, and the disease did not spread to other facilities or wild animals.[14] We exclude this event because of its limited impact on trade. The outbreak occurred away from concentrated broiler production and no new national-level trade bans resulted from it.[15]

As mentioned in the previous section, international trade responses to these events typically follow OIE guidelines, which recommend export restriction for at least three months after the stamping of HPAI. The ability of wild waterfowl to act as a reservoir for the disease encumbered perfect identification of eradication. As a result, actual trade restrictions varied in length.

Storage and economic indicators

The USDA collects and distributes information on cold storage and several economic indicators for the broiler meat market at the national level.[16] Different agencies within the USDA provide each indicator and do so for differing intervals. However, all agencies report each indicator at monthly time-steps. The USDA's Economic Research Service provides price data back to January 2000, which represents the latest starting point (and shortest time-series) for any dataset. We, therefore, only consider data beginning in January 2000 and ending in December 2017.

---

[12] Data on the timing and form of trade restrictions is not publicly available.

[13] Ramos, MacLachlan, and Melton (2017) noted a 12 percent year-over-year loss to broiler producers' revenues between 2014 and 2015. Revenues provide only an imperfect proxy for profits (products are stored and costs change).

[14] Unlike the other cases of HPAI in 2014 – 2015, this case of HPAI arose from a mutation in a strain of Low Pathogenic Avian Influenza (LPAI). Because of the rapid eradication, the new strain did not infect wild birds or other domesticated birds.

[15] It is difficult to determine if this outbreak contributed to continued trade restrictions from China and South Korea, but the possibility of a prolonged response is nested in our empirical strategy.

[16] The National Agricultural Statistics Service (NASS) provides production data at the state level; the Global Agricultural Trade System (GATS) reports exports of a broader category of poultry products (excluding eggs) at the state level.

Several of the time-series were estimated with a higher level of precision. GATS (2017) reports monthly broiler meat export data beginning in 1967;[17] ERS (2017) reports monthly broiler meat prices;[18] NASS reports monthly production quantities beginning in 1960.[19]

NASS provides the most extensive data on cold storage of broiler meat through their Quickstats portal.[20] Rather than a direct measurement of storage volumes, these data represent the results of a survey sent to approximately 800 public and private cold storage warehouses. NASS adjusts these data to account for non-responses. The full time-series spans 1917 through the present and includes product level information (i.e., the stored cut of meat).

We represent the truncated, raw time-series of the three economic indicators and storage in figure 2. To highlight the effect of the outbreak and the potential effect of lingering export restrictions, we overlay shaded areas that capture the 2004 and 2014 – 2015 outbreaks (grey), OIE's recommended three-month recovery to free status (darker red), and a nine-month delay to recovery (light red). The light red shading provides an example of delayed recovery, which could be attributed to the disinfection process, the wild host reservoir, and political interactions. The actual recovery likely differs from either the darker or light red shaded regions.

---

[17] GATS provides more detailed data than we include. Exports are included using the Harmonized System (HS), which provides detailed information on trading partners and product qualities.

[18] ERS provides five closely linked prices based on product categories: whole birds, quarters, breasts, thighs, and all broiler meat. We use the all broiler meat price, which is a weighted average of the other categories.

[19] NASS includes information on production for a variety of cuts and using several metrics: value, number of birds, and the

[20] NASS's cold storage data can also be found in their monthly Cold Storage Report (e.g., NASS, 2017).

Figure 2. Monthly export quantity, average prices, storage quantity, and production quantity of broiler meat, 2000 – 2017.
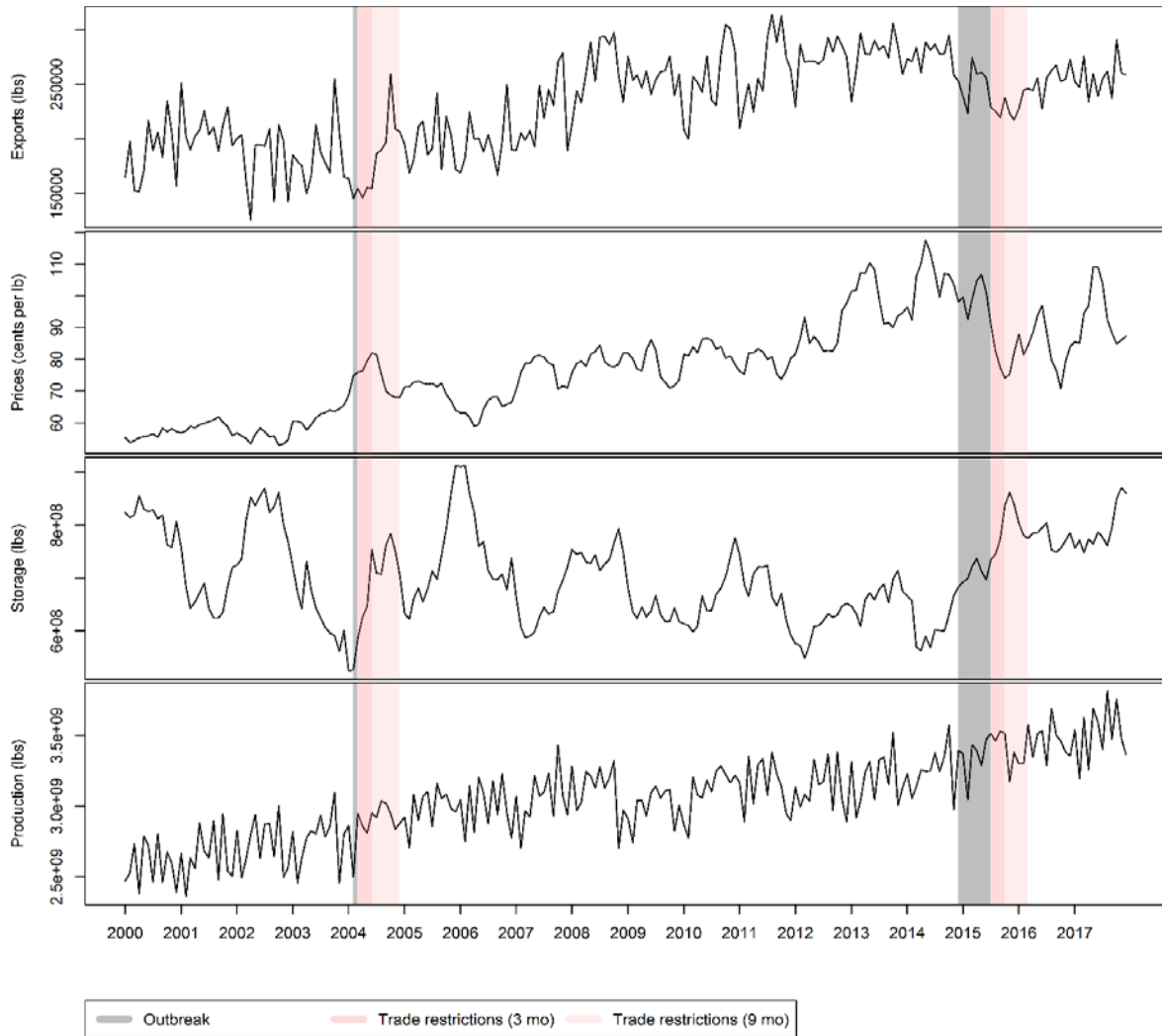
Figure 2 indicates that storage increased during both outbreaks. In contrast, exports and prices increased during and after the first outbreak and declined to begin near the end of the second outbreak. A change in production is not observed in its time-series, which follows from the low mortality rate among broiler chickens. While HPAI coincides with reversals of preceding trends, none of these changes fell outside of historical ranges.
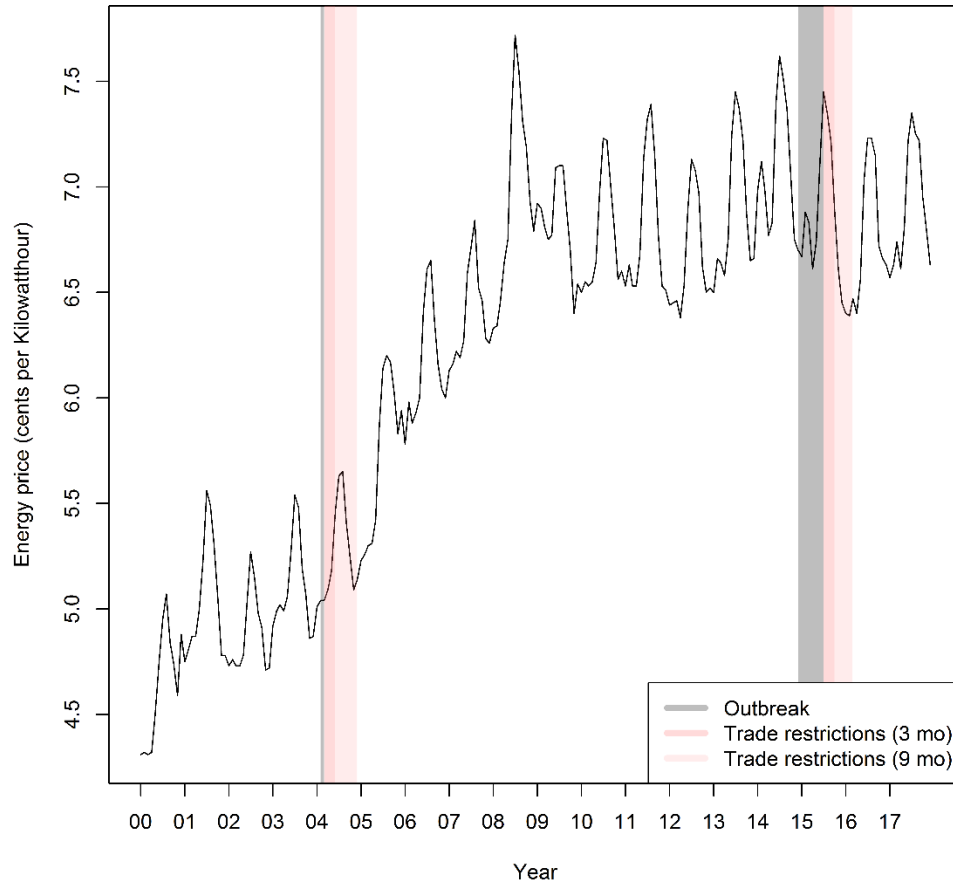
Energy prices

Storage requires substantial amounts of energy, which is a key determinant of the variable cost of cold storage. At the same time, energy prices are determined by a larger market and regulations that

are likely determined independently of cold storage of broiler meat. We, therefore, include energy prices as an exogenous source of variation in our estimation of our VAR model.[21]

We use the U.S. Energy Information Administration's (EIA) monthly data on industrial energy prices. Similar to storage and the economic indicators, we obtain the residuals from a regression with a linear long-run trend and monthly fixed effects. These residuals are reported in figure 3.

Figure 3. Monthly industrial energy prices, 2000 – 2017.

Energy prices were relatively stable, after controlling for seasonality, during our first outbreak and declined modestly during the second outbreak, which supports increased storage through lower variable costs. Measuring the relationship between energy and storage—and its importance relative to the economic indicators—is left to our empirical section.

---

[21] The available software for estimating an MS-VAR does not accommodate exogenous variables.

Methods

The 2004 and 2014 – 2015 outbreaks of HPAI introduced significant shifts in the broiler market, primarily in the form of trade restrictions.[22] To a lesser extent, the outbreaks also altered domestic production and distribution through movement restrictions and consumer confidence in the safety of broiler meat.[23]

To model these shifts, we develop a VAR framework.[24] This framework accommodates the endogenous relationships inherent among storage and the economic indicators while allowing for structural breaks (from shifts in domestic markets and international trade policy) and exogenous variables (energy prices). The inclusion of structural breaks allows for shifts in the average storage quantity and other economic indicators associated with the HPAI outbreaks. We ensure that the VAR approach is suitable for our application by first examining autocorrelation and stationarity. The absence of either of these features would rule out the use of the VAR framework. [25]

Econometricians generally apply VAR methods to systems where autocorrelation is a significant feature. Across our time-series, autocorrelation is a salient feature as shown for storage in figure 4.

Autocorrelation

Before examining the properties of our time-series, we transform the data by taking the first-difference of the log of the data, $\Delta \ln(y_t) = \ln(y_t) - \ln(y_{t-1})$. This transformation eliminates the need for detrending to ensure stationarity, and allows for the convenient interpretation of any coefficients from a linear model as elasticities. For the remaining estimation and figures, our observations will take on this form.

---

[22] These primarily came as export restrictions, including major export destination such as China and South Korea. Other forms of export restrictions were also observed for other poultry products. For some destination markets (e.g., Mexico), eggs could only be exported *after* heat treatment.

[23] While consumers' aversion to broiler meat would likely result from perceived health risks, there is no evidence that U.S. consumer preferences changed in response to either the 2004 or 2014 – 2015 outbreaks. A mutated form of the pathogen, however, *could* be transmitted, leading to significant disposal precautions on the part of APHIS.

[24] We show a simpler, univariate approach in the Appendix.

[25] The VECM is an alternative approach that extends the Vector Autoregressive (VAR) model to account for long-run cointegration, a common feature of macroeconomic data. The error correction allows for long-run dynamics that occur when a system deviates from equilibrium.

Figure 4. Partial autocorrelation functions for exports, prices, cold storage and production for 23 lags.
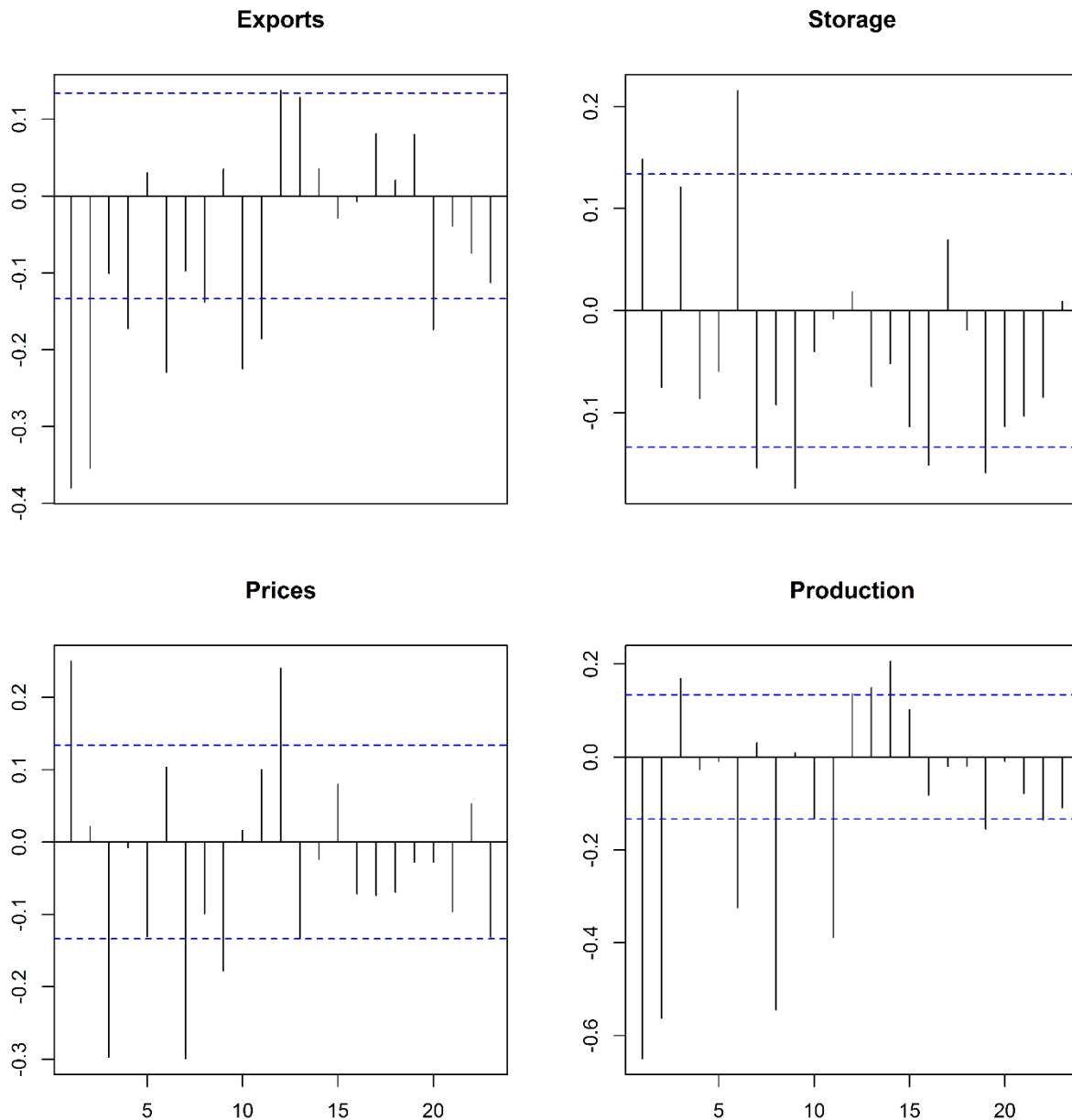
Notes. The y-axis indicate the number of lags, while the x-axis measure the auto-correlation coefficient. The horizontal blue lines indicate the 95% confidence bands around the correlation levels for the lags.

Significant autocorrelation between the contemporaneous observation and its lags is observed across indicators in figure 4, suggesting that an autoregressive specification suits our application. We apply a Durbin-Watson (DW) test to more rigorously assess this problem. The DW test statistics indicate statistically significant autocorrelation in each of the variables for one or two lags.

Table 1: Durban-Watson Test Statistic values for exports, prices, storage, and production for one or two lags

	Durban-Watson Test Statistics		
Exports (1 Lag)	Prices (2 Lags)	Storage (2 Lags)	Production (1 Lag)
0.037	8.7e-5	0.008	4.7e-8

The DW tests indicate that an autoregressive framework is indeed suitable for our data.

Stationarity

VAR models embed an assumption of stationarity. Removing trends from the data—as we did use the first difference of the natural log transformation—likely yields a stationary dataset (as shown in figure 2), but we test for stationarity in the detrended data[26] using an augmented Dickey-Fuller (ADF) test. The results of this test suggest that each of our included series are indeed stationary as shown in Table 2.

Table 2: Augmented Dickey-Fuller Test Statistic values for exports, prices, storage, production, and energy prices

	Augmented Dickey-Fuller Test Statistics			
Exports	Prices	Storage	Production	Energy
<0.01	<0.01	<0.01	<0.01	<0.01

The ADF tests provide strong evidence suggesting that all of the time-series are stationary. This stationarity indicates the appropriateness of applying a VAR identification strategy, rather than one that includes a moving average component.

Model setup

We specify a VAR framework, which is then augmented to an MS-VAR to test for regime switches. A VAR specifies a framework for endogenous variables $\boldsymbol{y} = [y_1, y_2, \ldots, y_N]$, exogenous variables $\boldsymbol{x} = [x_1, x_2, \ldots, x_M]$, and dynamic trends, $f(t)$. In our case, the dynamic trend will include monthly dummies, $\mathbf{1}_{t \in month}$ and a dummy for the outbreak window, $+\Phi_i \mathbf{1}_{HPAI}(t)$. For each endogenous variable, we can specify the following linear equation:

$$\Delta \ln(y_{i,t}) = c_i + \sum_{l=1}^{L} \sum_{j=1}^{4} a_{il} \Delta \ln(y_{i,t-l}) + b_i \Delta x_t + \Phi_i \mathbf{1}_{HPAI}(t) + \alpha_t \mathbf{1}_{t \in month} + \varepsilon_{it}, \tag{1}$$

---

[26] We also use a first-difference transformation to align the series with that used in a VECM model.

Within our specification, several specification choices not estimated within our VAR framework are unclear *ex-ante.* We, therefore, employ the Bayesian Information Criterion (BIC)[27] to identify our optimal structure. We use the BIC to identify an optimal maximum number of lags, L, the specification of the time trend, and the duration of the outbreak response windows.

We compare BICs for $L = \{1,2, \ldots 38\}$ lags and a wide range of outbreak response windows. We specifically allow the outbreak response windows to begin anywhere between the august before the first observed case of HPAI (August 2003 and August 2014 for the two outbreaks) up to 1 years after this date (August 2004 and August 2015). The outbreak window can last anywhere up to 2 years.[28] We also allowed for the exclusion of one or both outbreaks.

Results

The first step in identifying and characterizing the structural breaks in our system requires identifying the optimal number of lags and the outbreak response windows.[29] The model with the lowest BIC value included two lags and outbreak response windows for both outbreaks. The outbreak response window for the February 2004 outbreak included February – June 2004. In contrast, the December 2014 – June 2015 outbreak response window included only March 2015.

We allowed for a linear time-trend, monthly fixed effects, neither, or both. We found that the optimal specification of the time trend included only monthly fixed effects.

We present only the Φ parameter estimates, their standard errors, and significance levels in table 4. The jointly estimated parameters included in the VAR framework are in Appendix C. The columns of this table delineate the parameter estimates for each of the endogenous, dependent variables (exports, prices, storage, and production) rather than separate specifications.

Table 3: Coefficient on the mean-shifting term within VAR estimation

	Dependent Variable			
	Exports	Prices	Storage	Production
Outbreak Response Window	−0.053	0.025	0.075***	−0.004
	(0.045)	(0.016)	(0.018)	(0.013)

---

[27] Several information criteria are available to test for optimal specifications within ML estimation, the most popular being the BIC (also referred to as the Schwarz criterion) and the Akaike information criterion (AIC). The BIC imposes a larger penalty on the number of parameters, which often leads to the inclusion of fewer lags in our application. It would also favor the omission of the outbreak response window altogether.

[28] We initially allowed the outbreak response window to persist until the end of our time-series. The continued import bans of U.S. broiler meat in China and South Korea following the 2014 – 2015 outbreak led to an early reviewer to suggest the existence of a continuing structural shift. The longer outbreak response window was less plausible for the 2004 outbreak, and would likely pick up structural shifts *not* attributable to HPAI.

[29] In determining the optimal model, we must also select for the integration rank of our system. This was done for each possible model using Johansen's (1991) method for comparing a test statistic to a 0.05 level of significance. The optimal model has a cointegration rank of three. The Error Correction Terms (ECT) are included in table 3.

Contrary to the univariate results presented in Appendix A, the results presented in table 3 suggest that the outbreak responses were associated with statistically significant increases in storage and unclear changes in the other variables.[30] Following expectations, production did not significantly change during the outbreaks. The decline in imports was not statistically significant. The rise in prices is puzzling and results primarily from the increase in prices during the first outbreak response window (see Figure 1). None of the economic indicators have a statistically significant link with energy prices.

Some trends are also apparent from examining the lagged terms. Exports appear to be closely correlated with lagged exports at the 0.01 level. Exports were less closely correlated with past storage and production, at the 0.1 confidence level. Prices were correlated with lagged exports, prices, and storage, but not production. Storage appears to be only correlated with second lagged exports at the 0.01 level. Production is correlated with past production at the 0.01 level, and first lagged prices (although, this correlation is surprisingly negative).

Robustness checks

To evaluate the robustness of our results, we consider alternative outbreak response windows, a different treatment of the storage data, and the omission of the industrial energy price time-series. We find a limited difference between the results for our initial specification and data treatment relative to the alternatives, indicating robustness of our central results (particularly the estimated outbreak response window, number of lags, and the cold storage response to the outbreaks). The fact that changes in the coefficients (and their statistical inference) are small indicates that our results do not critically depend on assumptions made in our specification.

Outbreak response window length

We evaluate 97,344 possible outbreak response windows. The BIC of only three other outbreak response windows fell within 2 of our optimal choice.[31] In all of these sub-optimal specifications, the outbreak response window for the February 2004 outbreak included the same dates. The December 2014 – June 2015 outbreak response window begins on either September 2014 or March 2015 and two or three months later.

The parameter estimates on our outbreak response window did not differ from those presented in Table 3. We again found only a statistically significant change in storage during the outbreak response window.

---

[30] The transition from univariate AR models to the VECM approach yields an outbreak response window-price coefficient that is larger and statistically significant. The latter result aligns better with expectations, and a visual inspection of figure 2.

[31] A difference of less than 2 between BICs from different models does not provide sufficient evidence that one model would be strongly differentiated (Kass and Raftery, 1995). Given the need to select a single model couple, many models choose the model with the smallest BIC value.

Treatment of storage data

NASS's storage data differs from the data on other economic indicators because it represents the estimated volume of storage at a given time (the first of the month). To estimate the storage volume in the middle of a month, we average that month's cold storage with the cold storage observed in the following month.

Using this averaged cold storage does lead to results very similar to those that use the storage volume at the beginning of the month. The optimal outbreak response window,[32] lag structure, and cointegration rank are identical. The coefficient estimates and their significance differ only slightly.

Omission of energy

For our optimal model, the coefficients on industrial energy prices are all statistically insignificant, suggesting limited explanatory power. Omitting these variables from the optimal model led to a decrease in the BIC of 19.48, which provides strong evidence that we should omit this variable from our analysis.

Regime Switching Model

We extend our VAR framework to include the possibility that broiler production switches between two regimes.[33] Each regime is captured by a similar VAR framework with distinct parameter estimates. Each period is then characterized by probabilities of being in each regime.

Given our results from our VAR analysis, we make specification choices to simplify this approach. First, we drop the structural break component. Second, we choose to omit industrial energy prices as an independent variable. Also, because the available software does not accommodate exogenous variables, we eliminate our monthly dummies. We do, however, include separate estimation of the model where we detrend the data using monthly dummies. With these changes, we modify Equation 1 to

$$\Delta \ln(y_{i,t}) = c_i + \sum_{l=1}^{L} \sum_{j=1}^{4} a_{il} \Delta \ln(y_{i,t-l}) + \varepsilon_{it}, \tag{2}$$

where two sets of c and a are estimated.

As shown in Figure 5, we estimate that the probability of being in each regime is always near 0.5. Furthermore, the parameter estimates of each VAR model are not statistically significantly different.

---

[32] The second best outbreak response window is also unchanged from the original cold storage time-series.
[33] Software to execute this MS-VAR framework is available in R within the MSBVAR library.

Figure 5. Probability of being in the two regimes estimated within the MS-VAR framework for months February 2000 (0) — Dec 2017 (215)
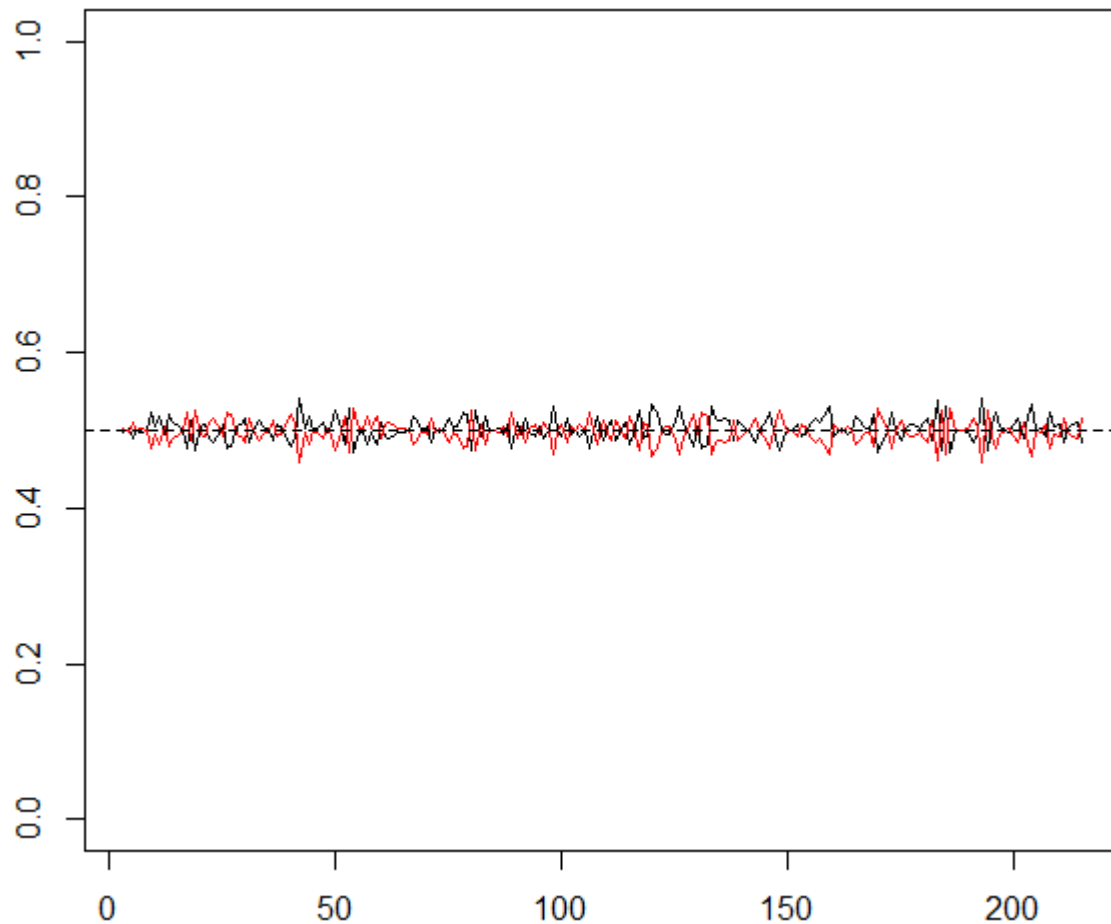
These results suggest that neither a VAR with a structural break nor an MS-VAR suit the case study. Instead, a model that more accurately characterizes the system as well as a convergence back to equilibrium is more suitable. The family of VECM models fits this description.

Conclusion

Our results suggest that there is a brief but significant increase in cold storage response among broiler meat producers to the outbreaks of HPAI. These increases were likely caused by two complementary factors, which we are unable to disentangle with our data and identification strategy. Broiler meat producers would increase storage if they believed that prices would increase after the elimination of export restrictions (dynamic arbitrage). Regardless of their expectations about future prices, producers would have to search for new trading partners once trade restrictions were imposed. It does not appear that the cold storage quantity response to the HPAI outbreaks is necessarily large or unique, as we observe stronger relationships between storage and its lags as well as lagged production.

Modeling a discrete change in the poultry market—which instead faces constant negative shocks during our period of interest—does not capture the expected market shifts. It is preferable to more accurately model the relationships within the system, then model how a market recovers from a shock within a Vector Error Correction Framework (VECM).

References

Bicknell, K.B., Wilen, J.E. and Howitt, R.E. 1999. "Public policy and private incentives for livestock disease control." *Australian Journal of Agricultural and Resource Economics*, *43*(4), pp.501-521.

Blayney, D.P., 2005. *Disease-related trade restrictions shaped animal product markets in 2004 and stamp imprints on 2005 forecasts*. Washington, DC: USDA, Economic Research Service.

Darko, F.A. and Eales, J.S., 2013. Meat demand in the US during and after the Great Recession. In *Selected paper for the Agricultural & Applied Economics Association 2013 Annual Meeting*.

Engle, R. and C. Granger. 1987. "Cointegration and error correction: representation, estimation and testing." *Econometrica*, 55:pp 251-272.

Gramig, B.M. and Horan, R.D., 2011. "Jointly determined livestock disease dynamics and decentralised economic behaviour." *Australian Journal of Agricultural and Resource Economics*, *55*(3), pp.393-410.

Janzen, J.P., Smith, A. and Carter, C.A., 2017. Commodity Price Comovement and Financial Speculation: The Case of Cotton. *American Journal of Agricultural Economics*, *100*(1), pp.264-285.

Johansen, S. 1988. "Statistical Analysis of Cointegrating Vectors. Journal of Economic Dynamics and Control, 12:pp 231-254.

Johansen, S. 2000. "A Bartlett correction factor for tests on the cointegrating relations." *Econometric Theory*, *16*(5), pp.740-778.

Kass, Robert E.; Raftery, Adrian E. (1995), "Bayes Factors", Journal of the American Statistical Association, 90 (430): 773–795

Kennedy, P. 2003. "Time series econometrics." *A guide to econometrics*. 5th edition.

Lee, C.W., Swayne, D.E., Linares, J.A., Senne, D.A. and Suarez, D.L., 2005. "H5N2 avian influenza outbreak in Texas in 2004: the first highly pathogenic strain in the United States in 20 years?" *Journal of virology*, *79*(17), pp.11412-11421.

Li, X., Gunter, F.L. and Epperson, E.J., 2011. Effects of China's Antidumping Tariffs on US–China Bilateral Poultry Trade. In *Southern Agricultural Economics Association Annual Meeting, Corpus Christi, TX, February* (pp. 5-8).

Lütkepohl, H. 2004. "Vector Autoregressive and Vector Error Correction Models." *Applied Time Series Econometrics*. H. Lütkepohl and M. Kträtzig (eds).

MacDonald, J.M. and W.D. McBride. 2009. "The Transformation of the U.S. Livestock Agriculture: Scale, Efficiency, and Risks." *Economic Information Bulletin* (EIB-43).

Marsh, T.L., Wahl, T., and T. Suyambulingam. 2005. "Animal Disease Outbreaks and Trade Bans." *World Trade Organization Impacts on U.S. Farm Policy.*

Perrings, C., et al. 2005. "How to manage biological invasions under globalization." *Trends in ecology & evolution* 20:212-215.

Phillips, P. and S. Durlauf. (1986). "Multiple time series regression with integrated processes." *Review of Economic Studies*, 53: pp473-495.

Ramos, S. 2016. "Factors Affecting the Decline in U.S. Broiler Exports." *Economic Research Service - Situation and Outlook.*

Sims, C. A. 1980. "Macroeconomics and reality." *Econometrica: Journal of the Econometric Society*, 1-48.

Springborn, M., Chowell, G., MacLachlan, M. and Fenichel, E.P., 2015. "Accounting for behavioral responses during a flu epidemic using home television viewing." *BMC infectious diseases*, *15*(1), p.21.

Sumner, Daniel A., José E. Bervejillo, and Lovell Jarvis. "The Role of Public Policy in Controlling Animal." *The Economics of Livestock Disease Insurance* (2006): 29.

Towers, S. and Chowell, G., 2012. "Impact of weekday social contact patterns on the modeling of influenza transmission, and determination of the influenza latent period." *Journal of theoretical biology*, *312*, pp.87-95.

USDA-Animal and Plant Health Inspection Service (APHIS). 2004. "Highly Pathogenic Avian Influenza, Impact Worksheet." Accessed May, 2017. www.aphis.usda.gov/animal_health/emergingissues/impactworksheets/iw_2004_files/domestic/hpaitexas032004.htm

—2015. "Epidemiologic and Other Analyses of HPAI-Affected Poultry Flocks: September 9, 2015 Report." USDA-APHIS, Washington DC.

—2016. "HPAI 2014–2015 Infected Premises." www.aphis.usda.gov/animal_health/animal_dis_spec/poultry/downloads/hpai-positive-premises-2014-2015.pdf

USDA-Foreign Agricultural Service (FAS). 2017. "Global Agricultural Trade System."

USDA-National Agricultural Statistics Service (NASS). 2017. "Quickstats portal." quickstats.nass.usda.gov. Accessed May 2017.

—2017. Cold Storage Report October 2017. USDA-NASS, Washington DC.

U.S. Energy Information Administration (EIA). 2017. "Monthly Energy Review; Previous Editions." https://www.eia.gov/totalenergy/data/monthly/previous.php

World Organization for Animal Health. 2017. Terrestrial Animal Health Code. Chapter 10.4. Infection with Avian Influenza.