Measuring storage responses of broiler meat producers during an outbreak of Highly Pathogenic Avian Influenza

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Infectious diseases of livestock have consistently threatened global agriculture directly through decreased production and indirectly through market responses and disruptions to trade flows. The possibility of zoonosis (transmission from animals to humans) compounds the costs of infectious disease events for many diseases (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 greatly raised yields and consumer welfare, respectively, but have also increased the probability of introduction and the economic consequences of an infectious disease introduction. Government agencies face the challenge of balancing mitigation efforts with their costs while considering producers' roles in monitoring and control efforts. In the presence of elevated disease prevalence and government intervention, producers generally make rational production adjustments rather than altruistic choices. Because rational, self-interested actors typically ignore negative externalities (e.g. disease transmission), economists have explored cases where individual responses dampen the effect of central animal disease mitigation efforts and thus exacerbate the risks of infection (e.g. Wilen, Bicknell, and Howitt, 1999 and Gramig and Horan, 2011). We instead measure behavior that complements public policy by mitigating the economic consequences of large-scale control strategies. Specifically, this paper measures changes in storage—a former of temporal arbitrage—in response to infectious disease outbreaks and the ensuing export restrictions.

While numerous economic studies have examined the interplay between public and private actors' responses to infectious disease, export restrictions have received relatively less attention. A notable exception includes Marsh, Wahl, and Suyambulingam (2005), who explore disease-related trade restrictions through a game theory framework. From the perspective of the U.S., foreign importers may choose to ban or restrict exports from the U.S. of specific animal products after the verification of an infectious disease among livestock or even wildlife. While a sovereign nation determines any trade response on a case-by-case basis, diseases that appear on the International Organization for Animal Health's (OIE) notifiable disease list typically trigger import restrictions. The U.S. and foreign governments—rather than 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, storage may be used to arbitrage goods into the future when producers expect market conditions to improve.

We specifically examine the impact of the 2004 and 2014 – 2015 outbreaks of Highly Pathogenic Avian Influenza (HPAI) on cold storage decisions by producers. HPAI introduction occurs through myriad pathways. Scientists suspect that the 2004 event was caused by a mutation of a Low Pathogenic Avian Influenza (LPAI) strain (Lee et al., 2005). Wild waterfowl introduced two distinct strains of HPAI, which they carried from Canada during their southern migration. HPAI transmission to domesticated animals then resulted from numerous vectors, including fomites,[1] fecal matter, and aerosols. Both of the HPAI outbreaks caused relatively few animal losses but did result in significant trade restrictions.[2]

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

[2] 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 production and trade consequences were minimal.

We combine industry-level, time-series data on storage volumes, retail prices, production, exports, and trade restrictions to test for responses among these indicators, and then to estimate the role of dynamic arbitrage in responses to HPAI. Our approach allows for the identification of changes in storage attributable to these export restrictions—and presumably expectations of future increases in prices—that cannot be explained by changes in contemporaneous prices. We extend our approach to include other related but endogenous factors.

The national scale of our study makes a clean causal identification between policy changes and producer behavior challenging compared to simulations characterizing the interplay between disease prevalence and biosecurity investment. On the other hand, this empirical study requires fewer assumptions and uses data aggregated over unobservable heterogeneity among producers. Our approach extends a line of research that has examined behavioral responses to human disease outbreak and subsequent centralized control efforts. For example, Towers and Chowell (2012) explore the effect weekends have on interpersonal disease transmission. 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. To the best of our knowledge, no study has such approach has been employed to study animal disease outbreaks.

Data

We combine publicly available data on U.S. poultry production, prices, trade, and storage to facilitate our estimation approaches. Data are first used to individually test for correlation between HPAI outbreaks 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. The structural models—a vector autoregression (VAR) and vector error correction model (VECM)—uses the data to estimate parameters that characterize the mechanisms behind producers' storage response, to isolate the impact of the trade restriction on storage.

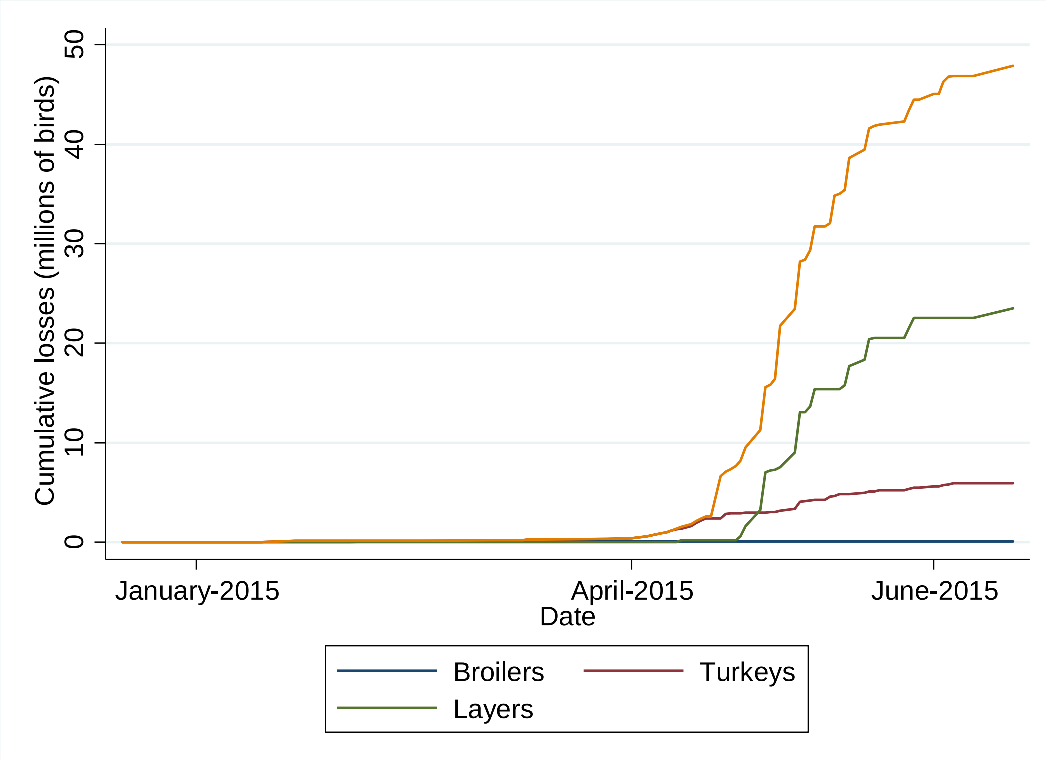
This study uses only publicly available data from federal agencies. The intervals of the time-series vary by indicator due to differences in historical data collection techniques as well as individual agency's data products. While some indicators are available as far back as January 1917, all data were available beginning in January 2000. The release of new data varies across agencies, and we, therefore, opt to omit observations after 2016. 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, causing 6,600 chickens to be depopulated. 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. This outbreaks together resulted in approximately 5.9 million broilers deaths from infection or depopulation.[3] We represent the animal losses for all three sectors below in figure 1.

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

Figure 1. Cumulative losses of poultry during the 2014 – 2015 outbreak of Highly Pathogenic Avian Influenza by production type.



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.[4] 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.

International trade responses to these events typically follow OIE guidelines, which recommend export restriction for six months after a confirmed case of HPAI. The ability of wild waterfowl to act as a reservoir for the disease encumbered perfect identification of eradication. Actual trade restrictions varied in length. As an initial specification, we opt to include every month when one or more cases of HPAI occurred and for the six months following the last observation.

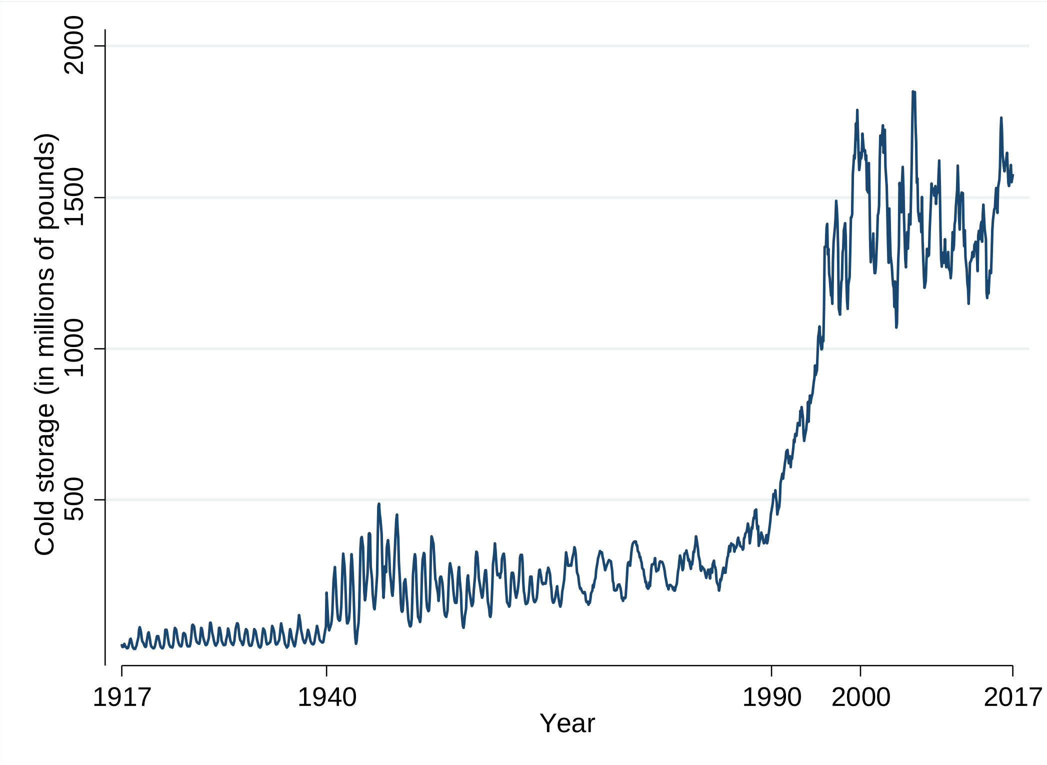
Storage

The National Agricultural Statistics Service (NASS) provides monthly broiler cold storage volume estimates through their Quickstats database. Because storage levels vary during any month, NASS opts to represent storage levels at the end of the month.

[4] Unlike the other cases of HPAI in 2004 and 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.

NASS provides over a century of monthly data, beginning in January 1917. The earliest observations only include a few product types (whole hens and young birds). Over this span, NASS introduced more finely disaggregated data based on the product type in cold storage. We represent aggregate storage across all of the product groups for the whole time horizon and product level storage from January 1917 until Month 2017 in figure 2.

Figure 2. Monthly broiler meat cold storage from January 2017 – March 2017



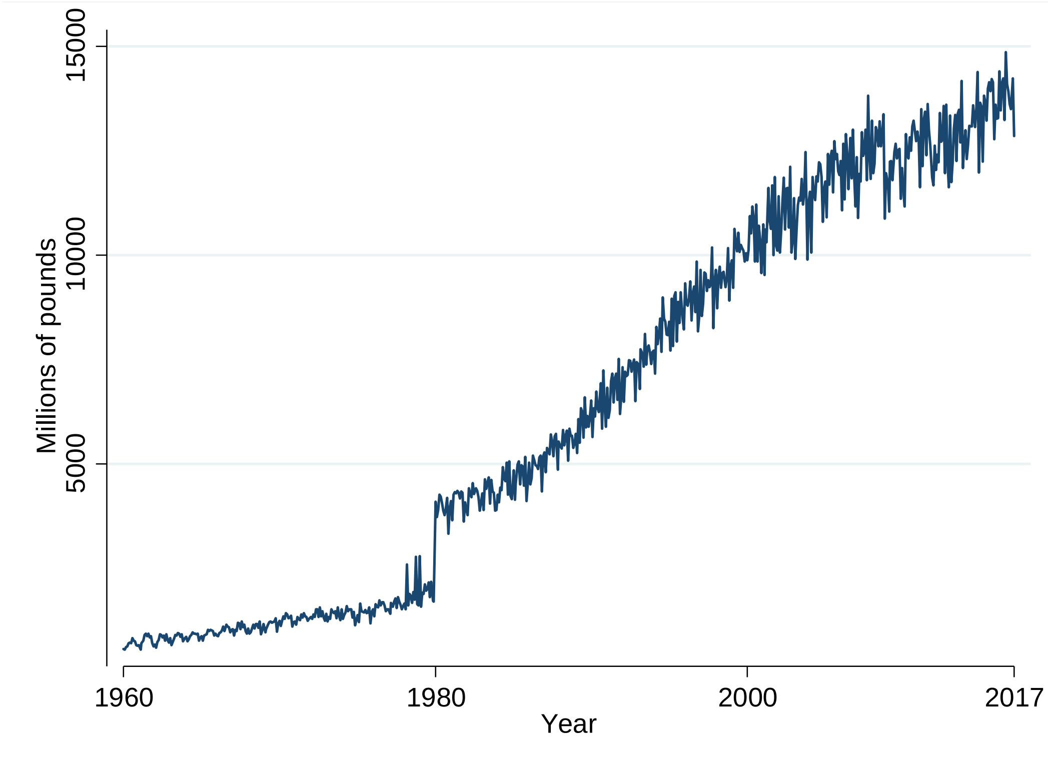
Long periods of stationarity interrupted by punctuated changes mark this time-series. Changes in record keeping practices likely caused the changes in cold storage that occurred at the beginning of 1940. NASS's database expanded from including only hens and young whole birds to also include a catchall "other" category as well as whole birds not counted as hens and or young birds. The rapid expansion of storage during the 1980s and particularly in the 1990s coincided with a corresponding expansion in production, which we explore in the next section.

Production

In addition to storage information, NASS's Quickstats data provides broiler production data. Their data include the value and the volume of production. NASS does not disaggregate to the product level—likely due to the consistent proportions of meat yielded from a slaughtered bird. The monthly data span from January 1960 through February 2017. We present the full time-series for production[5] in figure 3.

[5] The extremely high correlation between production and value—coupled with the use of price rather than value in our estimation approaches—led to the omission of value.

Figure 3. Monthly production of broiler meat, January 1960 – February 2017

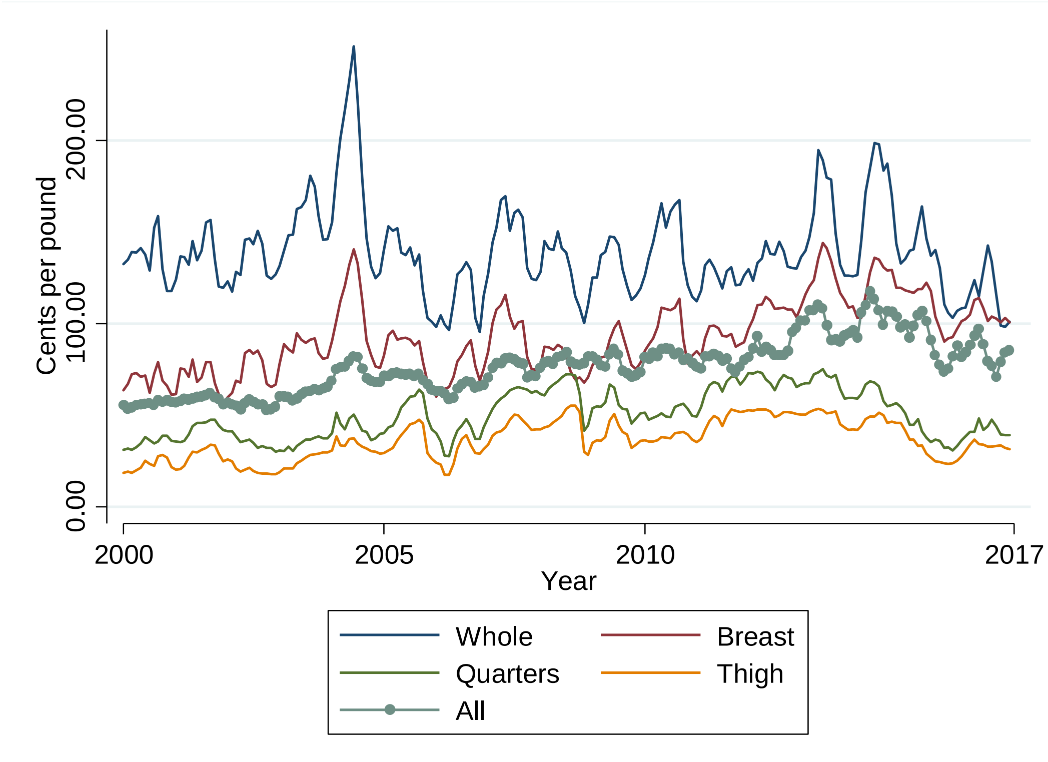


Broiler production experienced gradual and consistent growth over this period. The two discontinuities—in 1980 and 2008—respectively represent a change in data management and a shift in demand resulting from the great recession. Broiler meat production also exhibits pronounced seasonality.

Prices

Monthly nominal prices on a variety of broiler meat types are available through ERS's suite of data products: whole broilers, breast meat, leg quarters, thigh meat, and an aggregate of all broiler meat types. The complete time-series spans from January 2000 until January 2017. We represent the complete set of data in figure 4, which highlights the aggregate price (denoted "all") used during estimation.

Figure 4. Prices for broiler meat by type and month, January 2000 – January 2017



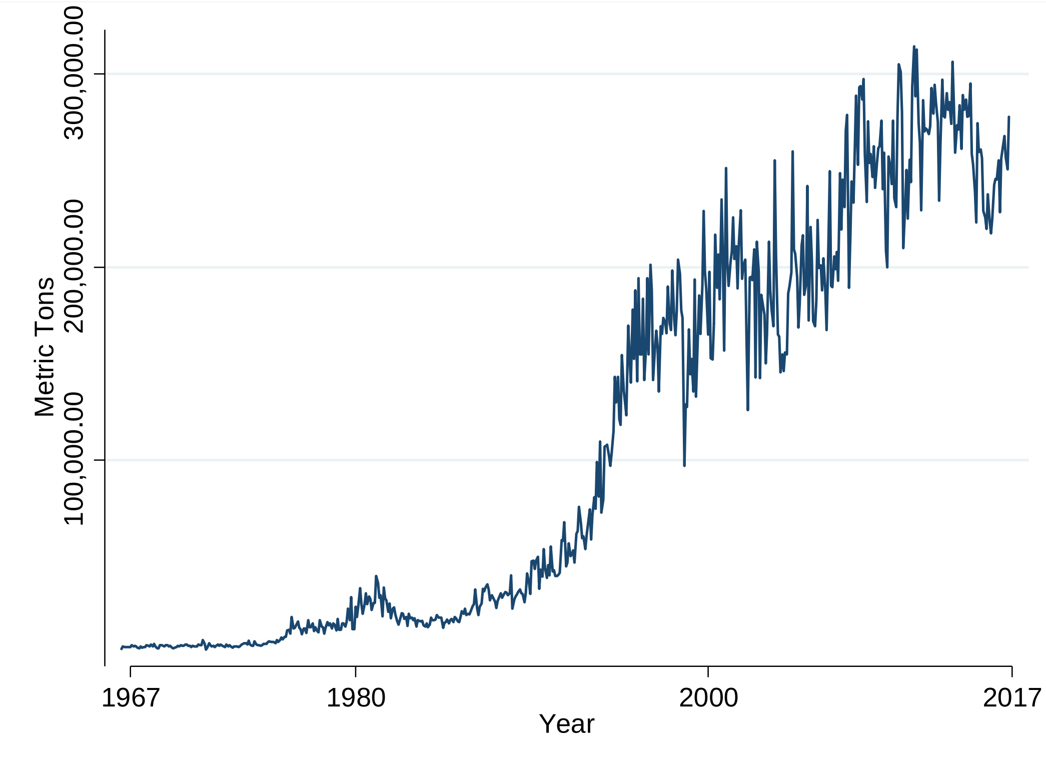
The all price category represents the price of broiler meat in the empirical sections. The last few years of the series exhibits substantially greater variance and a downward trend, which early part of the series does not express. These changes are likely in response to several macroeconomic shifts as well as the 2014 – 2015 HPAI outbreak. This series also exhibits significant seasonality.

Exports

The Global Agricultural Trade System (GATS) allows users to query a vast database of spatially explicit time-series data on storage volumes and values. The database encodes products using the Harmonized System (HS). The coding system provides shorter HS codes for broader product categories and longer codes for specific items. Because of the lack of product-specific data for other economic indicators, we select a broader category of broiler meat. We also opt to aggregate spatially across trading partners and across U.S. regions.

The GATS database includes monthly observations beginning in 1967. While we only use the subset of data after 1999 in our estimation, we include the full series in figure 5.

Figure 5. Monthly exports of broiler meat, January 1967 –December 2016



These data do not have discontinuities similar to those observed in NASS's data. Shifts in macroeconomic factors and disease events likely drive periods of rapid growth or contraction.

Testing individual indicators for changes during and after the outbreak

We test for changes in key economic indicators. In the absence of confounding events, we would expect that non-negative changes in production and non-positive changes in exports lead to non-positive changes in price and non-negative changes in storage. The empirical evidence from the previous section indicates that an exogenous international demand shift in response to HPAI alters the economic conditions and stimulates increased storage.

To disentangle the effect of HPAI outbreaks from long-term trends and seasonality, we use an autoregressive model that allows the average value to change under an outbreak of HPAI (as shown in equation 1). Restricting the time-series to observations between January 2000 and December 2016 ensures uniform time-spans across economic indicators. We model trade restrictions as occurring for all months when HPAI occurred and for the six months following each of the outbreaks.[6]

We model the evolution of each of the economic indicators, y_i, as an autoregressive process of the previous 12 periods and the presence of HPAI or an associated trade restriction, $\mathbf{1}_{HPAI}$. Removing

[6] The OIE recommends that trade restrictions be left in place for six months following a detection. The ability of HPAI to infected wild birds—which thus act as a reservoir—introduces subjectivity into the implementation of these OIE guidelines.

seasonality and taking the first difference of the data yields our converted data, denoted Δy_{it}. For each product we can generally represent this process as

$$\Delta y_{it} = \theta_{i0} + \sum_{l=1}^{12} \theta_{il}\, \Delta y_{i,t-l} + \theta_{i13} \mathbf{1}_{HPAI}(t) + \varepsilon_{it} \tag{1}$$

where ε_{it} is the error term. Not all lags are included for each models. Instead, we test for the optimal lag structure.

The Akaike Information Criterion (AIC)[7] and Bayesian information criterion (BIC) determine the relative model performance.[8] These ICs differ in their penalties for including addition parameters. Using the BIC favors parsimony, which typically manifests in the inclusion of fewer lags. Minimizing these ICs determines the included lags. We do not find cases where the optimal lag structure depends on the IC, but these measures do lead to different interpretations of the time window.

Autoregressive models depend on an assumption of stationarity. Poultry markets exhibit significant seasonality, and some of the indicators experienced positive growth. We detrended the data by first subtracting monthly averages, and then by taking the first differences. Application of Dickey-Fuller stationarity test to each of the modified time-series indicates that each series is stationary, yielding negligible test statistics, excluding the need for a more advanced approach (e.g. inclusion of a moving average).

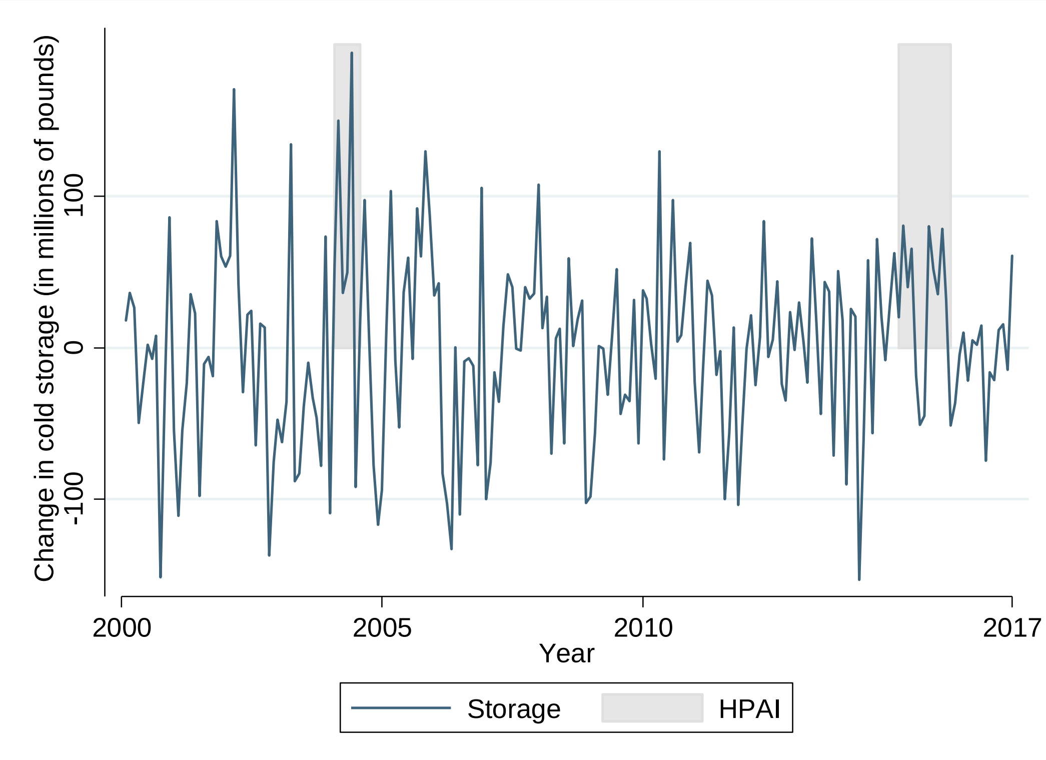
Storage

The storage responses to the HPAI outbreaks represent the primary indicator of interest within this study. Storage remains consistent—but highly variable—throughout our time-span. Figure 6 represents our seasonally adjusted, first differenced aggregate storage volumes over the span of interest. Storage increased during the outbreak windows—as shown by the positive values during the outbreak window—but did not reach unprecedented levels. This moderate response indicates that storage responds positively to disease and a variety of physical and economic factors beyond disease.

[7] The AIC is defined as twice the difference between the number of included parameters, k, and the maximized value of the log-likelihood function, $\ln(\hat{L})$: $AIC = 2k - 2\ln(\hat{L})$.

[8] The BIC is defined as the difference between the number of included parameters times the natural log of the number of observations, n, and the maximized value of the log-likelihood function: $BIC = \ln(n)\, k - 2\ln(\hat{L})$.

Figure 6. Seasonally adjusted, first differenced cold storage of broiler meat, January 2000 – December 2016



Our ICs identify identical optimal lag structures—lags at three, five, and twelve months. We define Model 1 as our baseline model that excludes an outbreak window. Model 2 includes an outbreak window. The lag structures of these models are determined using the ICs and happen to be the same regardless of the inclusion of the outbreak window. Table 1 shows these results.

Table 1. Parameter estimates and information criteria for optimal cold storage models 1 and 2.

	(1) **Storage**	**(2)** **Storage**
Trade restriction	-	75.34*** (23.62)
L3	0.22*** (0.68)	0.99*** (0.082)
L5	-0.17*** (0.067)	-0.33*** (0.083)
L12	-0.17** (0.067)	-0.12*** (0.049)
Constant	0.36 (4.13)	-12.58* (7.24)
AIC	2118.93	2113.97
BIC	2131.99	2130.28

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$
(Standard errors in parentheses)

The parameter estimates captured in Table 1 indicate a positive and statistically significant effect of the HPAI outbreaks on storage. The ICs also both indicate that including the outbreak window improves model performance. This agreement indicates a statistically significant change in storage, but also that major disease events likely played a major role in storage decisions.

Production

Poultry production has generally grown since the 1960's. Neither of the recent outbreaks of HPAI reversed this growth. The first outbreak affected only a single facility, resulting in the loss of only 7,000 birds—primarily due to depopulation. The second much larger outbreak affected just under 6 million broiler chickens (out of the 50,400,000 birds affected). Figure 7 shows deseasonalized, first differenced poultry production between 2000 and 2016 and the outbreak windows.

Figure 7. Seasonally adjusted, first differenced production of broiler meat, January 2000 – December 2016

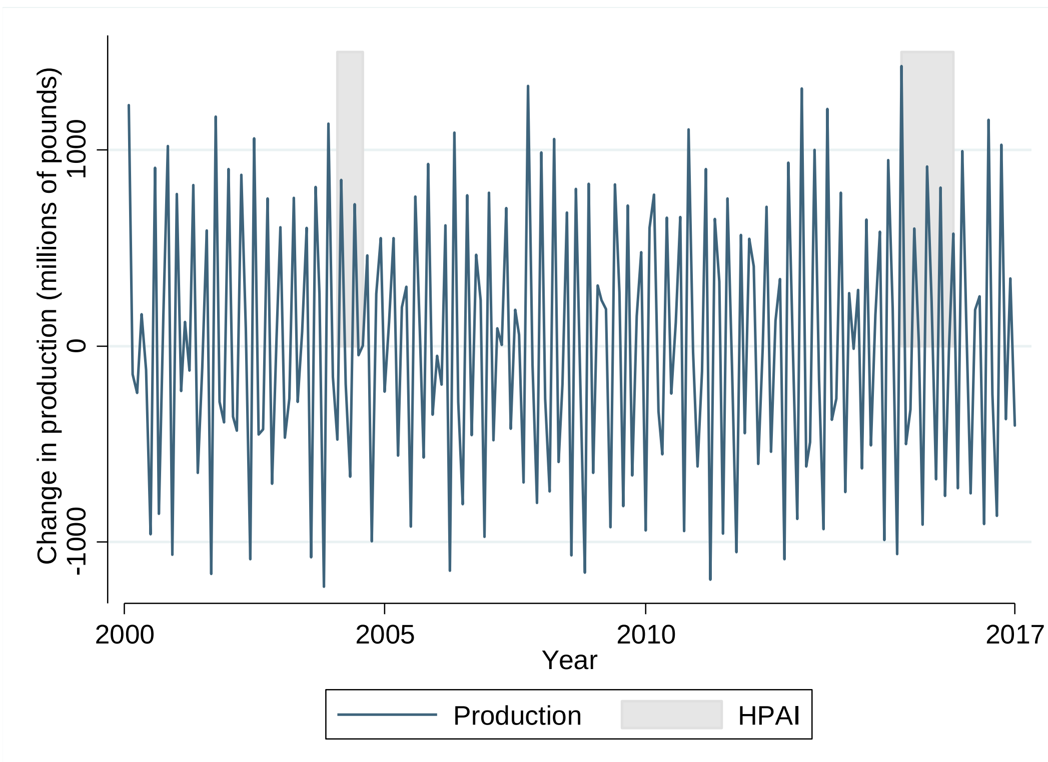


Figure 7 does not readily indicate a decrease in production in response to HPAI, but the high variability of the series could obscure HPAI's effect. To test for decreases in production during the HPAI outbreak, we test a range of lag structures for equation (1). The optimal lag structure includes lags at one, two, and twelve months. Table 2 provides parameter estimates and IC values.

Table 2. Parameter estimates and information criteria for optimal production models 1 and 2.

	(1) **Production**	**(2)** **Production**
Trade restriction	-	58.71 (79.99)
L1	-1.01*** (0.046)	-1.01*** (0.046)
L2	-0.61*** (0.057)	-0.61*** (0.057)
L12	0.19*** (0.047)	0.19*** (0.047)
Constant	42.97* (24.51)	36.92* (25.82)
AIC	2,804.53	2,805.99
BIC	2,817.58	2,822.31

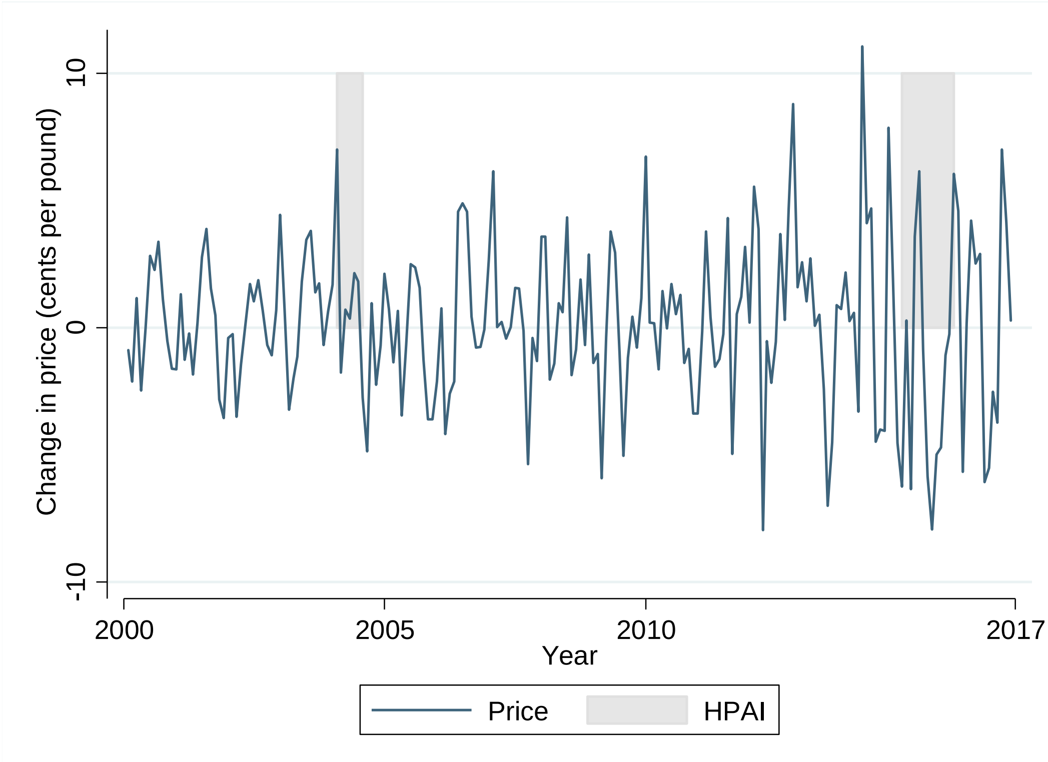
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$
(Standard errors in parentheses)

We observe an *increase* in production during the outbreak windows that is statistically insignificant. The positive but statistically insignificant increase provides evidence that production was not decreasing during the outbreak window. The ICs also indicate that the model that excludes the outbreak window performs better. These results suggest that the HPAI did not significantly impact broiler production, and the production may have grown slightly during the outbreaks.

Prices

With increases in production, which increases supply, and decreases in exports, which effectively reduces aggregate demand, we would expect prices to decline. Concurrent macroeconomic events with the HPAI outbreak, however, could have led to unexpected changes (i.e. increase) in price. We must, therefore, test for price decreases (or at least not price increases).

Figure 8. Seasonally adjusted, first differenced aggregate prices of broiler meat, January 2000 – December 2016



Interestingly, during the 2004 outbreak, the price increased while exports declined and production remained constant. The substantial decline in prices during the 2014 – 2015 outbreak more closely adheres to expectations. We test for a change in price attributable to the outbreaks in Table 3.

Table 3. Parameter estimates and information criteria for optimal production models 1 and 2.

	(1) **Price**	**(2)** **Price**
Trade restriction	-	-0.92 (0.70)
L1	0.23*** (0.066)	0.22*** (0.066)
L3	-0.19*** (0.069)	-0.19*** (0.069)
L12	0.23*** (0.071)	0.23*** (0.071)
Constant	0.09 (0.21)	0.18 (0.22)
AIC	966.52	966.80
BIC	979.55	983.09

$*p < 0.1$, $**p < 0.05$, $***p < 0.01$
(Standard errors in parentheses)

The negative estimated impact of the HPAI windows on price meets expectations. The opposing price movements during and after the two HPAI outbreaks may have contributed to a statistically insignificant relationship between the HPAI outbreak and price. The difference in ICs between Models 1 and 2 indicate that we should have a slight preference for excluding the outbreak window, which suggests that HPAI was not a significant determinant of prices during 2000 – 2016.

Exports

A downward shift in exports predictably result from an HPAI—or any other OIE reportable disease—event. Simultaneous major macroeconomic shifts make a causal identification out of reach (for more information see Ramos, 2016). Setting aside causal inference, we observe a visible decline in exports following each of the outbreaks in figure 5 that are made less obvious during the data transformation process represented in figure 9.

Figure 9. Seasonally adjusted, first differenced exports of broiler meat, January 2000 – December 2016

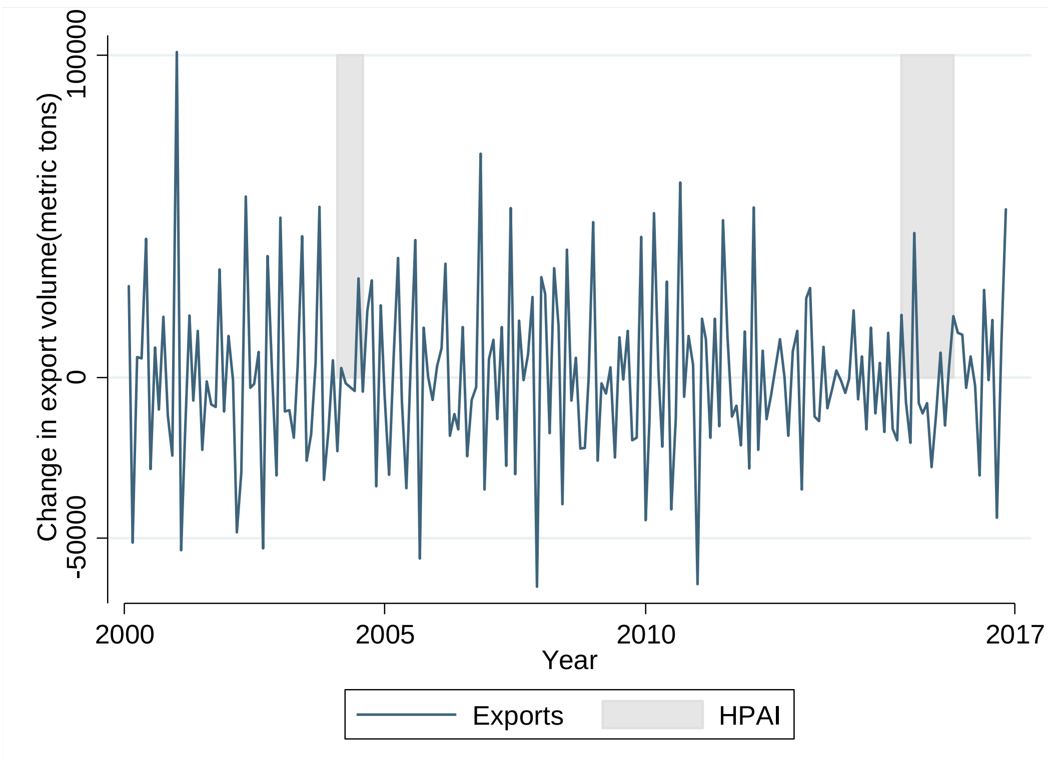


Figure 5 indicates low exports during both outbreaks, followed by periods of recovery, which figure 9 also shows to a much lesser extent. To test for statistically significant declines during this period, we follow a similar approach as our tests for changes in production. We again use both the AIC and BIC to determine our optimal number lag structure—one, three, and 12 months.

Table 3. Parameter estimates and information criteria for optimal export models 1 and 2.

	(1) Exports	(2) Exports
Trade restriction	-	-4,842.25 (5,005.63)
L1	-0.52*** (0.065)	-0.53*** (0.065)
L3	-0.35*** (0.065)	-0.35*** (0.065)
L12	0.11* (0.060)	0.11* (0.060)
Constant	331.29 (1,526.78)	841.65 (1,611.86)
AIC	4,353.54	4,354.61
BIC	4,366.55	4,370.87

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
(Standard errors in parentheses)

Our results indicate a statistically insignificant decline in exports during the outbreak window. Both ICs provide weak evidence that the model that excludes the outbreak window performs better. This result suggests potential problems in our choice for outbreak window.

Combining indicators within vector autoregressions

The univariate techniques provide suggestive evidence that storage increased in response to HPAI, while the changes in the other indicators met expectations. By unifying the indicators in a multivariate analysis, we can evaluate their interdependencies, and more clearly identify the relationship of interest. We begin by extending our autoregressive approach into a vector autoregression. This approach is extended one step further through an error correction modification. The results of both approaches indicate a significant effect of HPAI on storage.

Sims (1980) first introduced the vector autoregressive model (VAR) in levels, which is designed to evaluate dynamic responses of variables to exogenous shocks that are important sources of economic fluctuations (Kennedy, 2003). The general model follows from converting the observations y in equation 1 as vectors and accounting for correlation among the variables and serial-correlation in the error term.

Livestock price series often exhibit non-stationary error terms and may follow long-run interrelationships with other livestock price series. When such cointegration is present, first differences are used to achieve stationarity, but an error correction term is included in the model that captures the long-run equilibrium position directly. The introduction of an error correction term added to a VAR results in a vector error correction model (VECM) as first suggested by Engle and Granger (1987). It should be noted that Phillips and Durlauf (1986) argued that if data are both non-stationary and cointegrated differencing is not necessary, meaning a VAR could be used. Based on the Johansen's cointegrated vector autoregression model with k lags (Johansen, 1988), the data generating process of Y_t—an n-by-1 vector of price series—can be modeled as a VECM with $k-1$ lags:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \sum_{l=1}^{J} \theta D_l + e_t, \quad (2)$$

Where ΔY_t is an n-by-1 vector of first-order difference of prices, Y_{t-i} is the vector of lagged own commodity prices, Π is the n-by-n cointegration rank matrix, Γ is an n-by-n matrix of parameters on the lagged price differences, D_l is a matrix of dummy variables to represent seasonal or cyclic trends, and e is a n-by-1 vector of error terms (Lütkepohl, 2004). Detailed descriptions of VECM models can be found in Kennedy (2003) and Lütkepohl (2004).

In our application, we specify $k = 13$ and omit θD.

VAR

The VAR approach yields estimates that describe the relationships between each endogenous variable and lags of itself and the other variables. We use the first differenced and adjusted data described in the univariate analyses. Table 5 reports the parameter estimates *only* for storage, given the optimal lag structure of one, two, and twelve months. We suppress other estimates for brevity.

Table 5. Parameter estimates and information criteria for optimal VAR models 1 and 2—storage only.

	(1) **Storage**	**(2)** **Storage**
Trade restriction	-	36.57*** (14.10)
Storage		
L1	0.13* (0.075)	0.11 (0.074)
L2	0.021 (0.073)	-0.017 (0.073)
L12	-0.20*** (0.071)	-0.19*** (0.07)
Prices		
L1	-2.19 (1.40)	-1.98 (1.38)
L2	2.90** (1.42)	3.05** (1.40)
L12	-1.24 (1.42)	-1.23 (1.40)
Exports		
L1	-7.4e-5 (2.0e-4)	-4.1e-5 (1.9e-4)
L2	2.3e-4 (1.9e-4)	2.6e-4 (1.8e-4)
L12	-2.0e-4 (1.8e-4)	-1.7e-4 (1.7e-4)
Production		
L1	0.016* (0.0085)	0.016* (0.0083)
L2	0.13 (0.010)	0.13 (0.010)
L12	0.012 (0.0083)	0.012 (0.0081)
Constant	-0.20* (4.19)	-4.07* (4.38)

AIC	10,180.18	10,180.08
BIC	10,349.3	10,362.21

$*p < 0.1$, $**p < 0.05$, $***p < 0.01$
(Standard errors in parentheses)

Within this framework, the HPAI window has a statistically significant effect on storage. The magnitude of this effect, however, is smaller than yielded by the univariate analysis. This change may partially be explained by the significant relationship between storage and lagged prices, which declined during the outbreak.

The coefficient obtained from this approach provides stronger evidence that there was a significant storage response to HPAI. One explanation for this effect is that producers held onto their products expecting improved market conditions in the future.

VECM

The VECM approach differs from the VAR in several important ways. First, we do not seasonally adjust the data ex-ante. Instead, we include monthly fixed-effects. Second, we cannot define the lag structure beyond the number of included lags. To identify the optimal number of lags, we again use our AIC and BIC. The AIC is monotonically decreasing in the number of lags up to 24 lags. We, therefore, opt to use the model that is identified as optimal using the BIC, which identified 19 lagged differences as optimal. Because of the large number of lags, we only report the parameter on trade restrictions and the ICS

Table 6. Parameter estimates and information criteria for optimal VECM models 1 and 2—storage only.

	(1) **Storage**	**(2)** **Storage**
Trade restriction	-	38.7158*** (18.80)
AIC	9,784.444	9,771.961
BIC	10,927.02	10,927.38

$*p < 0.1$, $**p < 0.05$, $***p < 0.01$
(Standard errors in parentheses)

The parameter estimate of the effect of trade restrictions on storage is very similar—both in magnitude and statistical significance—to those of the VAR. At the same time, the AIC provides evidence that the model that includes storage is preferred. The change in BIC is negligible and does not suggest that either model is preferred.

Conclusion

Our univariate analysis allows us to rule out counterintuitive changes in our series before proceeding into our structural approaches—VAR and VECM. The point estimates derived from each of these univariate tests aligned with our intuition. During and after the HPAI event, storage increased, production remained constant, prices fell, and exports declined.

Our structural model allowed for measurement of the effect of HPAI while accounting for the influence of other economic factors (i.e. production, price, and export volume). This measurable effect indicates that producers indeed increase their storage in response to a disease event, and not just related changes in prices. We are unable to identify the producers' motivations, but storage is frequently used to temporally arbitrage to future periods with improved economic conditions or due to unforeseen frictions (i.e. challenges in finding a buyer).

The widespread and highlight infectious nature of HPAI has presented challenges to modern poultry production. The recent outbreaks throughout the world indicate that HPAI will continue to present challenges for agencies charged with animal disease control. An understanding of producers' responses to regulation improves estimation of losses and may contribute to improved public policy.

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