ABSTRACT

BOUCHARD, DYLAN DAVID. Essays in Agricultural Economics: Crop Insurance, Vertical Price Transmission, and Spatial Market Integration. (Under the direction of Barry Goodwin.)

The three essays of this thesis consider topics in agricultural economics. The first essay investigates moral hazard and adverse selection effects surrounding policy changes in federal crop insurance. The second and third essays investigate price dynamics and possible structural change. These two essays are motivated by alleged price-fixing in the United States broiler industry. On September 2, 2016, Maplevale Farms, Inc. filed a class-action complaint against several dominant firms in the broiler industry. According to the allegations, the defendants illegally shared detailed records with the assistance of a third-party conspirator, Agri Stats, in an attempt to restrict output and increase prices beginning as early as 2008 (Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016).

The first essay studies the moral hazard, adverse selection, and subsidy expenditure implications of recent changes in the federal crop insurance program. In the empirical analysis, we jointly estimate a model of insurance purchases, planted acres, CRP enrollment, and chemical input use using data for corn and soybeans in the Corn Belt counties. Using the parameter estimates, we conduct counterfactual analysis and examine the effects of subsidy rate changes on insurance participation, acres planted, and premium subsidy costs. Our estimation results indicate that counties using less fertilizer will purchase more revenue liability (moral hazard) and that counties with higher risk of yield-loss will have smaller responses to premium rate changes (adverse selection). Our counterfactual simulation analysis empirically confirms our theoretical predictions: subsidy expenditures increase in a convex fashion with subsidy rate.

The second essay examines the impact of an alleged price-fixing conspiracy in the United States broiler industry on the dynamics of input and output prices. In particular, we test for structural change and compare an estimated break date to the alleged start date of price-fixing. Further, we consider cointegration between the Georgia-Dock price and the AMS wholesale broiler chicken price to investigate claims of manipulation of the Georgia-Dock price. We find that the estimated breaks and cointegration tests are consistent with the alleged start date of price-fixing. To examine asymmetric price transmission (APT), we use farm-level, wholesale, and retail broiler chicken, beef, and pork price data to estimate asymmetric vector error correction models that allow for asymmetric responses to exogenous price shocks. Impulse response analysis reveals welfare gains for pork and beef wholesalers relative to the case of symmetric price transmission.

In the third essay, we aim to quantify the effects of price-fixing, if any, beginning in 2008 on the spatial price dynamics. We present dynamic impulse responses and use the timing of shocks and resulting price adjustments to shed light on the allegations of price fixing and noncompetitive pricing behavior. The size of threshold parameters indicate a significant potential for isolated market behavior but may also represent differentials in production costs and transaction costs. Important differences in long-run behavior are revealed through the application of Qu and Perron

(2007) multivariate structural break tests. These changes are compared to market developments and implications for the alleged price fixing behavior are offered.

Essays in Agricultural Economics: Crop Insurance, Vertical Price Transmission, and Spatial Market Integration

by
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DEDICATION

To my family.

BIOGRAPHY

Dylan Bouchard was born in Greenville, Maine. He graduated a from small high school and went on to study economics at the University of Maine. He graduated with a B.S. and M.A. in economics before beginning the PhD economics program at North Carolina State University.

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CHAPTER 1

Policy Changes in Federal Crop Insurance: Implications for Moral Hazard, Adverse Selection, and Subsidy Expenditures

1.1 Introduction

The Federal Crop Insurance Program has undergone substantial changes over the past several decades. Prior to the provisions adopted under the 1980 Crop Insurance Act, the program insured approximately 45 million acres or 13% of total crop acres in the US, offering only yield protection with coverage for 29 crops. One provision of the act was higher subsidies for premiums paid by farmers, which reduced costs of purchasing an insurance product. With a target subsidy level of 30% of premium costs, this required farmers to only pay 70% of the actuarially fair premium rate. The 1994 Crop Insurance Reform Act (CIRA) increased premium subsidies to roughly 40% of premium costs and offered protection against losses in revenue-per-acre on products for which viable futures prices were available (Smith, Glauber, and Goodwin, 2017). As program participation increased, costs of subsidizing premiums grew at roughly 10% per year between 1994 and 2000. As premium subsidies increased to as high as 62% in the 2000's, increased participation led to program costs increasing from $951 million in 2000 to $7.3 billion in 2013. A more detailed review of the program's history can be found in Smith, Glauber, and Goodwin (2017).

Program participation has increased as a result of two primary factors, namely, increased premium subsidies and introduction of revenue protection products. The 30% subsidy rate under the 1980 Act turned out to be too modest to substantially induce participation. However, subsidy increases enacted by the 1994 CIRA led to considerably greater of participation. Additionally, the introduction of revenue protection under the 1994 CIRA, a product shown to be more attractive to farmers than yield protection, also contributed to the increase in insured acres. Two common criticisms of federal crop insurance are related to behavior distortion among US farms (moral hazard) and concerns over the program's actuarial fairness (adverse selection), for both of which existing studies in the literature have found supporting evidence.

This paper considers moral hazard, adverse selection, and subsidy expenditure in federal crop insurance. The important contribution of this work is to provide a better understanding of how subsidy expenditures are affected by subsidy rate. Using a theoretical framework, we show that subsidy expenditures increase in a convex fashion with subsidy rate. We decompose the marginal effect into two components to tell the economic story behind this convex relationship. First, a higher subsidy rate increases the share of each dollar of premium covered by federal subsidy (share effect). Second, a higher subsidy rate increases insurance purchases (participation effect).

Our empirical analysis contains two parts. First, we estimate the system using a structural model that accounts for simultaneity of the decision processes, allowing us to examine moral hazard and adverse selection. Second, using the parameter estimates, we conduct counterfactual analysis to examine the effects of subsidy rate changes on premium subsidy costs. In particular we simulate a mapping between subsidy rate and subsidy expenditure in the Heartland region. Our counterfactual analysis confirms our theoretical prediction: an increase in subsidy rate leads to a more than proportional increase in subsidy expenditure. Given the objective function of the policymaker, this counterfactual tool can be used to determine the optimal subsidy rate.

Many argue that moral hazard effects of subsidized premiums lead to environmental costs. In particular, studies have found that subsidizing crop insurance affects both crop and livestock choice and input usage. In the context of crop insurance, moral hazard often takes the form of smaller quantities of fertilizer, pesticide, and herbicide used. Smith and Goodwin (1996) estimate a simultaneous equations model of insurance purchases and chemical input usage, recognizing the potential for simultaneity bias if the endogeneity is ignored. Their results indicate evidence of moral hazard in the form of fewer chemical inputs used by insured farms. Others have argued that crop insurance incentivizes practices that increase yield variability, which includes the use of certain chemical inputs. In contrast, Horowitz and Lichtenberg (1993) assume that input usage and insurance purchases are not jointly determined. They find that insured corn farmers use more chemical inputs. Since these estimation results will be sensitive to model assumptions, the nature of these processes should be considered carefully to avoid incorrect exogeneity assumptions. Claassen et. al (2017) find that federal crop insurance has led to some conversion of non-cropland to cropland and, more notably, affected crop rotation and crop choices. The consequences of such, the authors argue, include minor contributions to agricultural pollution.

When discussing actuarial fairness of an insurance policy, it is imperative to consider adverse selection. Actual premiums do not influence producer decisions, because maximization of expected profit depends only on subsidy-adjusted premiums. When total loss ratios are considered, i.e. indemnity over total premium, the program appears actuarially fair over the past two decades. In other words, the loss ratio is close to 1 when the premium considered is not subsidy-adjusted. This is not the case, however, when total premiums are used to calculate loss ratios. Prior to 1994, when program participation was low, the total loss ratio was almost always larger than unity, which reflects an adversely selected insurance pool. When subsidy rates were increased after 1994, total loss ratios fluctuated about unity, reflecting actuarial fairness resulting from more low-risk farms participating. However, when producer loss ratios, i.e. using subsidy-adjusted premiums, are considered, the post-1994 period is characterized by loss ratios much higher than 1. As noted by Smith, Glauber, and Goodwin (2017), "the average risk-neutral farmer can expect to receive more than $2 back for every dollar he or she spends buying federal crop insurance."[1] These authors argue that the adverse selection problem cannot be solved with product design.

To consider adverse selection effects of the program, it is useful to estimate farmer demand elasticities for insurance purchases. Goodwin (1993) estimates an equation for proportion of planted acres and an equation for liability per planted acre using panel regression. His results suggest elasticities of $-.32$ for relative acres and -0.73 for liability per planted acre. Because farmers can adjust liability by changing yield or price coverage, the higher elasticity for liability per planted acre was consistent with expectations. Additionally, the estimation results indicate that counties with higher loss-risk have more elastic demand for insurance. This finding has important moral hazard implications in that increasing premium rates for all producers (possibly in the form of lower subsidies) will raise the risk of the insurance pool. Goodwin and Smith (2012) estimate a reduced-form acreage response equation and find that subsidy and participation respond positively to subsidy rate increases after controlling for previous year's acreage. The authors note these results should be interpreted with caution and that a detailed structural model is necessary for more definitive

[1] It is worth noting that, despite this high average loss-ratio, there is a great deal of heterogeneity of risks, meaning many rational farmers do not purchase any federal crop insurance coverage.

conclusions. Woodard (2016) shows that not incorporating soil data into premium pricing in federal crop insurance has compounded the adverse selection problem. Additionally, Yu, Smith, and Sumner (2017) estimate acreage response for seven crops and find that a 10% increase in premium subsidy causes a 0.43% increase in acreage of a crop, holding premium subsidy of competing crops constant. They find larger own price acreage elasticities than exist in the literature after accounting for the small share of premium subsidies in expected crop revenue.

Goodwin, Vandaveer, and Deal (2004), (GVD), estimate a structural model to explain program participation, crop acreage, input choices, and enrollment into the Conservation Reserve Program (CRP). Recognizing the simultaneity structure of the processes examined, the authors use GMM to obtain unbiased, consistent parameter estimates. They find higher program participation leads to statistically significant, but modest, acreage increases. Further, they conduct simulation experiments to examine effects of premium changes and find that large premium decreases lead to meaningful participation increases but only minor increases in planted acres. Our model parallels that of GVD using more recent data to investigate participation effects of program changes.

The remainder of this paper is organized as follows. Section 2 presents a descriptive analysis of the data and discusses the relevant variables in detail. Section 3 outlines our estimation strategy and presents the results. Section 4 discusses a simulation approach to evaluating policy changes in the form of reduced premium subsidies. Section 5 concludes and discusses avenues for future research.

1.2 Data and Model Setup

Our structural model follows that of GVD (2004) and contains six equations. GVD sought to model three farm-level decisions made jointly, namely, which crops to plant, which input bundle to use, and the degree of participation in government programs. We restrict our analysis to include only corn and soybeans produced in the Heartland region of the US that purchased federal revenue protection, defined according to the USDA ERS Farm Resource Regions. Instruments include all exogenous variables and state dummies.

The acreage equations are given in (1) below where the subscript denotes crop. We expect to replicate findings by Goodwin and Smith (2012) and GVD (2004), who find evidence of a positive acreage response to own price, insurance participation, acres planted of alternative crop, and lagged acres. Further, we expect CRP enrollment to have a negative coefficient as crop acres may be reallocated to CRP acres if prices, rental rates, and other variables incentivize such behavior. Finally, as in the GVD model, we include county size as a regressor and expect a positive coefficient. In the estimation, we allow for the possibility that own-price may be endogenous to the model, as noted by GVD (2004). The acreage equation for $i, j \in$ {Corn,Soybeans} are as follows:

$$Acres_i = f(Price_i, Acres_j, Participation_i, Acres_{i,t-1}, NewCRP, CountySize) \tag{1.1}$$

We follow GVD (2004) in constructing an insurance participation variable. In particular, we estimate maximum possible liability and take proportion of possible liability as a measure of insurance participation rate. Maximum possible liability is taken as the product of 85% of historical yields, expected price, and acres planted. As with the acreage equations, we model participation in only corn and soybean revenue protection. The yield coefficient of variation for crop i, denoted $YieldCV_i$, reflects risk of yield-loss to producers and should therefore have a positive sign if producers are risk averse. Basic demand theory predicts the coefficient on premium rate will be negative. Note that premium rates in our model are subsidy adjusted. $LossRatio$ is the average county-level loss ratio for the previous five years and should have a positive sign, since higher loss ratios indicate higher returns from purchasing insurance. As found in previous studies, high-risk farms should have more elastic demand for insurance (see, for example Goodwin, 1993). We therefore expect a positive coefficient for the loss ratio and premium rate interaction. These predictions from the economic theory were supported by the results of the GVD (2004) estimation. The insurance participation equations for $i, j \in$ {Corn,Soybeans} are given by:

$$\begin{aligned} Participation_i = f(&Acres_i, PremiumRate_i, PremiumRate_i * LossRatio_i, \\ &LossRatio_i, LivestockSales, YieldCV_i, Fertilizer, CountySize) \end{aligned} \tag{1.2}$$

The $Fertilizer$ variable represents total county spending on fertilizer and chemical inputs for farming, not specific to any crops. The relationship between fertilizer use on insurance participation has been a topic of debate in the literature. Specifically, the question of whether the processes are jointly determined has been an important point of discussion. If the processes are jointly determined, and this is ignored by the econometrician, the estimates suffer from simultaneity bias. This endogeneity problem has motivated the use of instrumental variable techniques in examining this relationship. Goodwin and Smith (1996) and GVD (2004) estimate simultaneous equation models and find farms using more chemical inputs purchased less insurance. Hence, we expect a similar result. The converse marginal effects are discussed below.

CRP enrollment should be increasing in previous enrollment, rental rate, and county size. We expect such results. GVD (2004) find a positive and significant impact of county size and lagged CRP acres but no significant effect of CRP rental rate. The CRP Enrollment equation can be expressed as follows:

$$NewCRP = f(RentalRateCRP, NewCRP_{t-1}, Countysize) \tag{1.3}$$

As previously mentioned, the potential for joint determination of input usage and insurance participation should be carefully considered by the econometrician. Goodwin and Smith (2004) find insured farms use less fertilizer which could indicate moral hazard effects of insurance participation. Horowitz and Lichtenberg (1993) assume that insurance participation is exogenous to input usage and find that insured farms use more of risk-increasing chemical inputs. GVD (2004) find positive (negative) marginal effects of corn (soybean) acreage and insurance participation. Since corn production requires substantially more chemical inputs per acre than soybean production, this is an unsurprising result. The fertilizer equation is given by:

$$\begin{aligned} Fertilizer = f(&Participation_i, Participation_j, Acres_i, Acres_j,\\ &SoilTFactor, SoilKFactor) \end{aligned} \tag{1.4}$$

where again $i, j \in$ {Corn,Soybeans}.

Our data are annual, county-level, and span from 2002-2016. After restricting the analysis to corn and soybean production in Heartland participating counties, we obtain a dataset containing 6,474 usable observations. The data come from various sources. The USDA Risk Management Agency's (RMA) summary of business data include various county-level insurance variables including premium rate, loss ratio, indemnities and liability. The Regional Economic Information System (REIS) dataset contains county-level input and cost data. Relevant variables for our analysis from REIS include fertilizer use, livestock sales and total farm sales. Annual, county-level acreage and yields were collected for corn and soybean from the USDA National Agricultural Statistics Service (NASS) database. Data for annual county-level CRP acres enrolled and rents received come from the USDA Farm Service Agency (FSA). Descriptive statistics for the data are displayed in Table 1.1.

1.3 GMM Estimation

The model to be estimated is the system of six equations introduction in the previous section. Endogenous variables in the model include acres planted for both crops, insurance participation for both crops, CRP enrollment, fertilizer use, and prices for both crops. In the empirical analysis, we estimate the model parameters using two-stage least squares (2SLS). For each of the M equations, the moment conditions are given by:

$$g_n(\delta) = \frac{1}{nT}\sum_{t=1}^{T}\sum_{i=1}^{n}\varepsilon_{it}\otimes\mathbf{x_{it}} = \frac{1}{nT}\sum_{t=1}^{T}\sum_{i=1}^{n}(y_{it}-\mathbf{z}'_{\mathbf{it}}\delta)\otimes\mathbf{x_{it}}$$

where i indexes counties in the Heartland region over T years. The parameter vector δ for each equation is estimated by minimizing the following objective function:

$$Q(\delta,\Sigma_\delta) = [n\mathbf{g_n}(\delta)]'\Sigma_\delta[n\mathbf{g_n}(\delta)],$$

where $\mathbf{g_n}(\cdot)$ is an Lx1 vector containing $g_n(\cdot)$ for each equation, Σ_δ denotes the parameter covariance matrix, y_{it} are dependent variables, $\mathbf{z_{it}}$ is a vector of covariates, and $\mathbf{x_{it}}$ is a vector of instrumental variables.

The main focus of our estimation and simulations are the acreage response and insurance participation equations, as these will be used to estimate premium subsidy expenditures for corn and soybean farms in the Heartland region. In particular, the estimates from these equations are used to investigate effects on the system's endogenous variables from exogenous changes in subsidy rates. The estimates are compared to similar simulations conducted by GVD (2004). The GMM estimation results are displayed in Tables 1.2 and 1.3.

We first turn to the corn acreage response equation. The coefficient for corn price was correctly hypothesized and significant. The results indicate that a $1 per bushel increase in the expected real corn price per bushel is associated with a county-level increase of 1,119 corn acres planted. Acres planted for growing corn in the previous year was included as a regressor to reflect partial adjustment and was found to be positive and significant. Additionally, the coefficient for soybean acres planted was positive and significant. As noted by GVD (2004), counties that are well-suited to produce soybeans are likely to be better suited to produce corn as well. With the exception of insurance participation and CRP enrollment, the slope coefficients had the hypothesized sign. The incorrectly hypothesized signs could be due to data aggregation problems. Specifically, county level data leads to unobserved heterogeneity at the farm level that could influence the estimation results. With farm-level data, the observational units are at the decision-maker level and are not subject to unobserved heterogeneity issues associated with aggregated county-level data.

Next, we turn to the soybean acreage response equation. The coefficient on soybean price is positive and significant. The results indicate that a $1 increase in expected real soybean price per bushel is associated with an increase of 313 soybean acres planted. Interestingly, the coefficient on corn acres planted is positive and significant, but of much smaller magnitude than the converse case in the corn acreage equation. Neither tolerance factor nor erodibility factor were statistically significant determinants of soybean acres planted. With the exception of erodibility and tolerance factors, all slope coefficients had the hypothesized signs.

In the insurance participation equations, the dependent variable was revenue liability as a proportion of estimated maximum possible liability. A main parameter of interest in these equations is the chemical expenditures term. The theory of moral hazard in the context of crop insurance predicts farms who use less fertilizer will purchase more insurance. Hence, we expected a negative sign for this parameter. For both participation equations, the chemical expenditures coefficient is negative and statistically significant. This result confirms results from previous studies (Smith and Goodwin, 1996; GVD, 2004).

In the corn participation equation, the coefficient estimates were all significant with the hypothesized signs with the exception of county size. While the coefficient on premium rate was less than the coefficient estimated by GVD (2004), we included soybean participation as a regressor in our equation, and they did not.[2] The interaction term is positive and significant, reflecting the fact that high-risk farms tend to have less elastic demand for revenue liability. This result also supports findings of Goodwin (1993). Figure 1.1 displays the relationship between corn loss ratio and elasticity of demand for corn insurance. As the coefficients indicate, higher loss ratio is associated with more elastic demand for insurance. As expected, the coefficient on corn loss ratio is positive. GVD (2004) note that this variable reflects subsidy effects, since the loss ratio is calculated using subsidy-adjusted premiums. Corn yield CV was found to have no significant impact on corn insurance participation. Livestock sales were found to have a negative effect on corn insurance participation. Parameters

[2]When soybean participation is not included as a regressor, corn insurance participation was estimated to be approximately three times more responsive to premium rate changes than was found by GVD (2004). A lower liability elasticity may reflect a more adversely selected insurance pool in the data used by GVD, as participation rates are far higher in the data period used in our analysis. An analogous result was found for the soybean insurance participation equation.

that were statistically insignificant include county size, corn acres planted, the interaction term, and corn yield CV.

Similar to the corn participation equation, the coefficient on soybean premium rate was less than the coefficient estimated by GVD (2004), but we included soybean participation as a regressor in our equation, and they did not. The estimate for the soybean loss ratio coefficient was correctly hypothesized as positive, though the yield CV term was not significant. Figure 1.1 displays the relationship between soybean loss ratio and elasticity of demand for soybean insurance. As the coefficients indicate, higher loss ratio is associated with more elastic demand for insurance. Further, demand for soybean insurance is more elastic than demand for corn insurance. As with the corn participation equation, soybean yield CV was found to have no significant impact on soybean insurance participation. As in the corn insurance equation, the interaction term is positive and significant, reflecting the fact that high-risk farms tend to have less elastic demand for revenue liability, further supporting the findings of Goodwin (1993). Insignificant parameter estimates included loss ratio, soybean CV, and soybean acres planted.

Of less focus in our analysis are the CRP enrollment and chemical expenditures equations. Next, we turn to the CRP enrollment equation. As expected, CRP rental rate had a positive and significant sign. The coefficient for previous year's new CRP enrollment was positive, significant, and nearly identical to the corresponding parameter estimate obtained by GVD (2004). The sign for county acres planted was opposite our expectations. Finally, we consider the chemical expenditures equation. The coefficient signs on acres planted and insurance participation for both crops match those found by GVD (2004). The estimates suggest that increases in tolerance and erodibility factors lead to less fertilizer use. All slope coefficients were statistically significant.

1.4 Counterfactual Experiment

1.4.1 Theoretical Framework

We begin by constructing a theoretical framework to motivate predictions for our counterfactual experiment. In particular, we are interested in the effect of changing the subsidy rate for corn and/or soybeans affects acres planted, insurance participation, and most importantly, federal subsidy expenditure. First we will derive some simple comparative statics.

The government subsidy costs C for revenue protection in year t county i is given by:

$$C_{it} = s_{it}\pi_{it}L_{it}$$

where s denotes subsidy rate, π denotes premium rate (not subsidy-adjusted), L denotes total county revenue liability. Subsidy rate, by definition, must fall within the unit interval. Premium rate is assumed to be a constant, is unaffected by exogenous variation in s or endogenous variation in L, and also lies within the unit interval. Liability is non-negative and depends on both subsidy rate and premium rate.

Formally, we can write our assumptions as follows: $s, \pi \in [0,1]$ and $L : [0,1] \to (0,\infty)$, where $L \in C^2$ and $L'(s) > 0$. For notational simplicity, we drop subscripts and write liability as $L(s)$ to emphasize that liability is a function of subsidy rate:

$$C(s) = s\pi L(s).$$

The marginal effect of a change in the subsidy rate on C is given by

$$C'(s) = \pi L(s) + s\pi L'(s).$$

It is straightforward to show that $C'(s) > 0$. The first term in the above expression is positive, since $\pi, L > 0$. This term can be interpreted as the increase in subsidy expenditures due to a higher proportion of premiums paid by government. The second term, $s\pi L'(s)$ must also positive, since $s, \pi, L'(s) > 0$. $L'(s) > 0$ follows from basic demand theory for risk averse agents and implies that higher subsidy rates (and lower premium rates paid by farmers) will induce liability increases.

The second derivative of subsidy costs with respect to subsidy rate is given by

$$C''(s) = 2\pi L'(s) + s\pi L''(s).$$

For $C''(s) > 0$, i.e. for subsidy expenditures increase in a convex fashion as subsidy rate is increased, we need

$$\frac{-sL''(s)}{L'(s)} < 2.$$

If we consider the elasticity of C with respect to s, denoted $\mathscr{E}_{C,s}$, it is straightforward to demonstrate that this elasticity is greater than 1. We start with the definition of $C(s)$:

$$C(s) = s\pi L(S).$$

In logarithms we have:

$$\ln C = \ln s + \ln \pi + \ln L.$$

Since π is a constant, we have:

$$d\ln C = d\ln s + d\ln L$$

$$d\ln C = d\ln s + \mathscr{E}_{L,s}\, d\ln s$$

$$\mathscr{E}_{C,s} = (1 + \mathscr{E}_{L,s}).$$

Since $L'(s) > 0$, it follows that $\mathscr{E}_{L,s} > 0$, where $\mathscr{E}_{L,s} = \frac{d\ln L}{d\ln s}$. Thus, $\mathscr{E}_{C,s} > 1$.

1.4.2 Empirical Application

We return to our subscript notation above to better explain the calculations in our counterfactual experiment. The government subsidy costs C for revenue protection in year t county i is given by:

$$C_{it} = s_{it}\pi_{it}L_{it}$$

Define insurance participation, ℓ_{it}, as actual liability divided by maximum possible liability, $\tilde{L}_{it}$, so

$$C_{it} = s_{it}\pi_{it}\ell_{it}\tilde{L}_{it}.$$

For revenue protection in 2012, maximum possible liability can be expressed in terms of acres planted, historical average yields ($\overline{y}_{it}$), and expected price (P^e_{it}):

$$\tilde{L}_{it} = 0.85 P^e_{it}\overline{y}_{it}A_{it}.$$

Denote the set of Heartland counties as $\mathscr{H}$. The total subsidy expenditures, denoted C_t, for the Heartland region in year t is then given by:

$$\sum_{i\in\mathscr{H}} s_{it}\pi_{it}\ell_{it}\tilde{L}_{it}.$$

Given a set of endogenous variables ℓ_{it}, A_{it} and exogenous variables $s_{it}, P^e_{it}, \overline{y}_{it}$ for $i \in \mathscr{H}$, it is straightforward to recover the implied subsidy costs for year t for the Heartland region.

We conduct a series of counterfactual experiments to investigate the response in acreage and insurance participation to exogenous changes in the subsidy rate, denoted Δs_{it}. Though we do simulate values for other endogenous variables such as insurance participation and acreage, implied government subsidy costs are the focus of our simulation analysis.The steps of the simulation experiment are as follows:

1. Select which cross-section (year) to analyze.

2. Fix exogenous values for each county at the values for the year chosen in step 1.

3. Select the across-the-board change in subsidy rate ($\Delta s_{it} = -.2$).

4. Draw a parameter vector from a multivariate normal distribution based on estimated parameter covariance matrix.

5. For each county, use the parameter vector and exogenous variables to solve the system for the endogenous variables and implied subsidy costs.

6. Sum subsidy costs over counties.

7. Repeat steps 4-6 for 1000 iterations.[3]

8. Average the subsidy costs from step 6 across the 1000 iterations from step 7.

9. Repeat steps 4-8 for each selected value of Δs_{it}.

We select $\Delta s_{it} \in \{-.3, -.2, ..., .2, .3\}$ for across-the-board subsidy changes in step 9. We conduct three types of simulations: varying subsidy rates for both crops simultaneously, varying corn subsidy rates only, and varying soybean subsidy rates only for the production years 2005, 2009, 2012, and 2016. Figures 1.2-1.5 show implied government expenditures on insurance subsidies from various subsidy rates with 95 % confidence bands on each point estimate. In all cases considered, the marginal effect of subsidy rate for crop j on subsidy expenditures for crop j is increasing, i.e. a proportional increase in subsidy rate leads to a more-than-proportional increase in subsidy expenditures. Interestingly, we observe an 'income effect', where an increase in subsidy rate for crop j has a larger impact on subsidy expenditures for crop j when alternative subsidy rates are increased.

[3] We repeated the simulations for B=100 and B=10000. The size of the confidence bands and the results are robust to the number of bootstrap iterations.

Tables 1.5 and 1.6 show the implied proportional changes in subsidy expenditures for $\Delta s_{it} \in \{-.3, -.2, ..., .2, .3\}$. In the 2012 production year, for instance, during which the mean subsidy rate was 0.6082, our results indicate that increasing the corn (soybean) subsidy rate by 0.3, i.e. from 0.6082 to 0.9082, would have increased insurance subsidy expenditures for corn (soybeans) by approximately 107.14% (77.87%). These results shed light on the magnitude of the increasing marginal effect predicted by the theory.

Lastly we use our subsidy expenditure distributions generated from the simulation experiments to fit kernel distribution functions for the four years analyzed at various subsidy rates. Each plot displays the distribution function (CDF) for each of three cases: no change in subsidy rate, $\Delta s_{it} = -0.3$, and $\Delta s_{it} = +0.3$. We find that, all else equal, distributions with higher subsidy rates stochastically dominate distributions with lower subsidy rates.

1.5 Conclusion

This paper studies the moral hazard, adverse selection, and subsidy expenditure implications of changes in the federal crop insurance program. Our data are county-level, annual corn and soybean data in the Heartland region from 2002-2016 and is obtained from a variety of sources. In our empirical analysis, we estimate a structural model of insurance purchases, planted acres, CRP enrollment, and chemical input use. We then use these parameter estimates to conduct simulation experiments and examine the effects of subsidy rate changes on mean insurance participation, mean acres planted, and total premium subsidy costs.

For both crops, the sign of parameter estimates indicate the presence of adverse selection and moral hazard. However, statistically significant evidence of adverse selection is not found for corn. Specifically, the model estimates predict that counties using less fertilizer will purchase more revenue liability (moral hazard) and that counties with higher risk of yield-loss will have smaller responses to premium rate changes (adverse selection). These results are consistent with those found by Smith and Goodwin (1996) for moral hazard, Goodwin (1993) for adverse selection, and GVD (2004) for both.

We conduct counterfactual analysis to better understand how changes in the subsidy rate affects total subsidy expenditure. While the government has expressed a desire to incentivize participation in the federal crop insurance program, and has successfully achieved this goal via heavy premium subsidization, it is important to ask whether the welfare gains justify this spending in taxpayer dollars. In our counterfactual analysis, we exogenously vary the subsidy rate and use our model to predict the change in liability. From the change in liability, we calculate the implied premium costs to government for various subsidy rates.

Our results indicate that increasing the subsidy rate will increase the total subsidy expenditures in a convex fashion. The reason for this theoretically predicted and empirically demonstrated relationship between subsidy rate and subsidy expenditure can be explained by a combination of two forces. First, subsidy expenditures increase due to a higher proportion of premiums paid by government. Second, basic demand theory for risk averse agents and implies that higher subsidy rates (and lower premium rates paid by farmers) will induce liability increases. Further, our empirical results show that the elasticity of subsidy expenditures with respect to subsidy rate is greater than 1.

For future research, we propose four extensions. First, technical efficiency may influence insurance purchases. If a farm is farther from the efficient frontier (either cost or production), they may be more inclined to purchase insurance. This will be especially true if there is a downward trend in efficiency and previous yields were close to the efficient frontier. Conversely, insurance purchases may influence technical efficiency. All else equal, a deviation from the frontier will have a smaller impact on profit for an insured farm than for an uninsured farm. Hence, farm managers who purchase insurance may be less concerned about reaching the efficient frontier.

Second, another possible channel of moral hazard behavior is off-farm labor. If a farmer chooses to work more off the farm, then yield losses may be more likely. As a result, farmers with more off-farm labor would likely be more inclined to purchase insurance. Conversely, a farmer who purchases more insurance may be more apt to work off the farm, since a yield-loss would be less costly for an insured farm guaranteed a certain revenue level.

Third, the responses of acreage and participation might differ under different types of insurance, e.g. revenue protection vs. yield protection. Consequently, the magnitude of the marginal effect of subsidy rate on subsidy expenditures might be different as well. Exploring this question further could shed light on the cost effectiveness of subsidizing various types of insurance.

Fourth, further welfare analysis is worth exploring. In this paper, we consider only welfare change resulting from taxpayer dollars being spent in the form of crop insurance subsidies. To justify such subsidies, one must consider the welfare gains to farmers and insurance companies (both parties benefit from crop insurance subsidies). While it is beyond the scope of this paper, weighing these welfare gains against the spending of taxpayer dollars on subsidies is an important consideration for analyzing the consequences of this policy.

Tables and Figures

Table 1.1 Descriptive Statistics of Model Variables

Variable	Mean	Std. Dev.
Corn Acres Planted (10,000 acres)	9.7040	6.4138
Soybean Acres Planted (10,000 acres)	8.4650	4.4862
Corn Insurance Participation	0.6821	0.2564
Soybean Insurance Participation	0.6204	0.2610
CRP Acres Enrolled (10,000 acres)	1.1390	1.1691
Chemical Expenditures ($1000/acre)	0.0530	0.0261
County Acres (100,000 acres)	3.3660	1.1404
Corn Price ($/bushel)	1.8649	0.4663
Soybean Price ($/bushel)	4.1471	1.1349
Corn Premium Rate (subsidy adjusted)	0.0424	0.0150
Soybean Premium Rate (subsidy adjusted)	0.0413	0.0151
Corn loss ratio	1.8229	1.5136
Soybean loss ratio	1.3879	0.8275
Corn Yield CV	11.0679	8.3662
Soybean Yield CV	11.2637	8.0014
Livestock Sales (% of total farm sales)	0.3557	0.2066
CRP Rental Rate ($/acre)	51.6304	15.6117

Table 1.2 GMM Estimation Results

Variable	Estimate	Std. Error	t-Ratio
Equation 1: Corn Ares Planted			
Constant	-8362.85*	1729.23	-4.84
Soil T-Factor	1449.21*	310.32	4.67
Soil K-Factor	-6.49	19.06	-0.34
Soybean Acres Planted	0.062*	0.005	12.73
Lagged Corn Acres Planted	0.949*	0.004	261.94
Corn Insurance Participation	-945.29	851.13	-1.11
New CRP Enrollment	0.820*	0.34	2.44
County Size	415.464*	137.76	3.02
Corn Price	1119.749*	452.23	2.48
Equation 2: Soybean Ares Planted			
Constant	-162.71	1660.44	-0.1
Soil T-Factor	-285.39	275.325	-1.04
Soil K-Factor	9.234	16.7495	0.55
Corn Acres Planted	0.034*	0.00324	10.38
Lagged Soybean Acres Planted	0.941*	0.00408	230.53
Soybean Insurance Participation	396.66	755.86	0.52
New CRP Enrollment	-1.325*	0.29276	-4.52
County Size	222.31*	120.229	1.85
Soybean Price	313.99	215.58	1.46
Equation 3: Corn Insurance Participation			
Constant	0.1791*	0.0126	14.21
Soybean Insurance Participation	0.814*	0.01004	81.07
Corn Premium Rate	-1.0509*	0.1620	-6.48
Corn loss ratio	0.028*	0.0023	10.56
Corn Yield CV	6.96265E-06	0.00015	0.05
Corn loss ratio*PremiumRate	0.0821	0.0534	1.53
Livestock Sales	-0.032*	0.00598	-5.28
Corn Acres Planted	7.14529E-09	2.91E-08	0.25
Chemical Expenditures	-0.6856*	0.1228	-5.59
County Size	-0.00079	0.0013	-0.62

* denotes statistical significance at the 10% level.

Table 1.3 GMM Estimation Results (cont.)

Variable	Estimate	Std. Error	t-Ratio
Equation 4: Soybean Insurance Participation			
Constant	0.0132	0.0139	0.93
Corn Insurance Participation	0.927*	0.00924	100.25
Soybean Premium Rate	-0.7235*	0.1773	-4.08
Soybean loss ratio	0.0034	0.0043	0.78
Soybean Yield CV	0.0003	0.00017	1.27
Soybean loss ratio*PremiumRate	0.26435*	0.0906	2.92
Livestock Sales	0.04968*	0.0059	8.48
Soybean Acres Planted	7.12676E-08	4.58824E-08	1.55
Chemical Expenditures	-0.8329*	0.12957	-6.43
County Size	0.0079*	0.00142	5.58
Equation 5: New CRP Enrollment			
Constant	-478.57*	54.7635	-8.74
CRP Rental Rate	9.166*	0.80667	11.36
Lagged CRP Enrollment	0.343*	0.01162	29.52
County Size	-36.037*	10.378	-3.47
Equation 6: Chemical Expenditures			
Constant	0.123*	0.004	33.91
Soil K-Factor	-0.0004*	5.4E-05	-7.81
Soil T-Factor	-0.013*	0.0008	-16.08
Corn Insurance Participation	0.0805*	0.0079	10.95
Soybean Insurance Participation	-0.0703*	0.0079	-9.27
Corn Acres Planted	1.428E-07*	9.6E-09	14.83
Soybean Acres Planted	-2.21E-07*	1.2E-08	-17.71

* denotes statistical significance at the 10% level.

Table 1.4 Model Tests for Heteroskedasticity and OLS v. 2SLS

Test	Statistic	p-value
White Test: Corn Acres Planted	751.4*	<.0001
White Test: Soybean Acres Planted	1229*	<.0001
White Test: Corn Insurance Participation	837*	<.0001
White Test: Chemical Expenditure	2492*	<.0001
White Test: New CRP Enrollment	146.2*	<.0001
White Test: Corn Acres Planted	396.3*	<.0001
Hausman Test: OLS v. 2SLS	3326*	<.0001

* denotes statistical significance at the 10% level.

Table 1.5 Counterfactual: Effects of Both Subsidy Rates on Subsidy Expenditures (2005)

Δs	-0.3	-0.2	-0.1	0	+0.1	+0.2	+0.3
Corn	-80.33%	-62.20%	-36.09%	0.00%	47.35%	107.98%	183.33%
Soybeans	-80.13%	-61.73%	-35.65%	0.00%	46.26%	105.27%	177.44%

Table 1.6 Counterfactual: Effects of Corn Subsidy Rates on Corn Subsidy Expenditures (2005)

Δs	-0.3	-0.2	-0.1	0	+0.1	+0.2	+0.3
Corn	-75.78%	-57.19%	-32.22%	0.00%	40.62%	90.11%	150.22%

Table 1.7 Counterfactual: Effects of Soybean Subsidy Rates on Soybean Subsidy Expenditures (2005)

Δs	-0.3	-0.2	-0.1	0	+0.1	+0.2	+0.3
Soybeans	-67.37%	-48.22%	-25.73%	0.00%	29.55%	62.54%	100.00%

Table 1.8 Counterfactual: Effects of Both Subsidy Rates on Subsidy Expenditures (2009)

Δs	-0.3	-0.2	-0.1	0	+0.1	+0.2	+0.3
Corn	-78.69%	-60.93%	-35.19%	0.00%	46.38%	105.76%	179.03%
Soybeans	-80.08%	-62.11%	-35.95%	0.00%	47.17%	108.00%	182.22%

Table 1.9 Counterfactual: Effects of Corn Subsidy Rates on Corn Subsidy Expenditures (2009)

Δs	-0.3	-0.2	-0.1	0	+0.1	+0.2	+0.3
Corn	-72.94%	-54.99%	-31.03%	0.00%	38.63%	86.22%	143.64%

Table 1.10 Counterfactual: Effects of Soybean Subsidy Rates on Soybean Subsidy Expenditures (2009)

Δs	-0.3	-0.2	-0.1	0	+0.1	+0.2	+0.3
Soybeans	-64.57%	-46.40%	-25.12%	0.00%	28.48%	61.30%	97.62%

Table 1.11 Counterfactual: Effects of Both Subsidy Rates on Subsidy Expenditures (2012)

Δs	-0.3	-0.2	-0.1	0	+0.1	+0.2	+0.3
Corn	-70.2%	-52.2%	-28.9%	0	36.0%	78.5%	128.9%
Soybeans	-69.9%	-52.0%	-28.7%	0	35.8%	77.7%	126.5%

Table 1.12 Counterfactual: Effects of Corn Subsidy Rates on Corn Subsidy Expenditures (2012)

Δs	-0.3	-0.2	-0.1	0	+0.1	+0.2	+0.3
Corn	-65.8%	-47.8%	-26.4%	0	30.5%	65.5%	107.1%

Table 1.13 Counterfactual: Effects of Soybean Subsidy Rates on Soybean Subsidy Expenditures (2012)

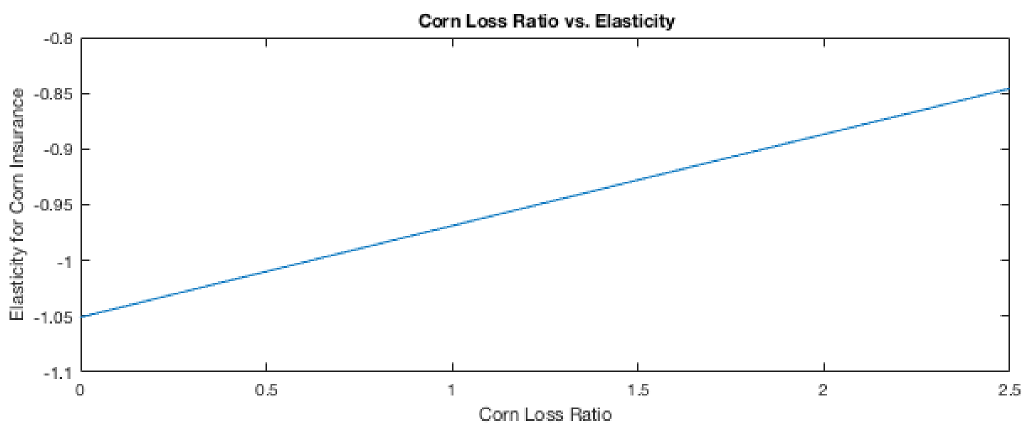
Δs	-0.3	-0.2	-0.1	0	+0.1	+0.2	+0.3
Soybeans	-58.4%	-41.3%	-21.7%	0	24.0%	50.3%	77.9%

Table 1.14 Counterfactual: Effects of Both Subsidy Rates on Subsidy Expenditures (2016)

Δs	-0.3	-0.2	-0.1	0	+0.1	+0.2	+0.3
Corn	-72.30%	-53.87%	-29.91%	0.00%	37.34%	81.99%	136.52%
Soybeans	-69.86%	-51.46%	-28.35%	0.00%	34.66%	75.36%	123.99%

Table 1.15 Counterfactual: Effects of Corn Subsidy Rates on Corn Subsidy Expenditures (2016)

Δs	-0.3	-0.2	-0.1	0	+0.1	+0.2	+0.3
Corn	-69.56%	-51.02%	-27.96%	0.00%	33.81%	73.52%	119.98%



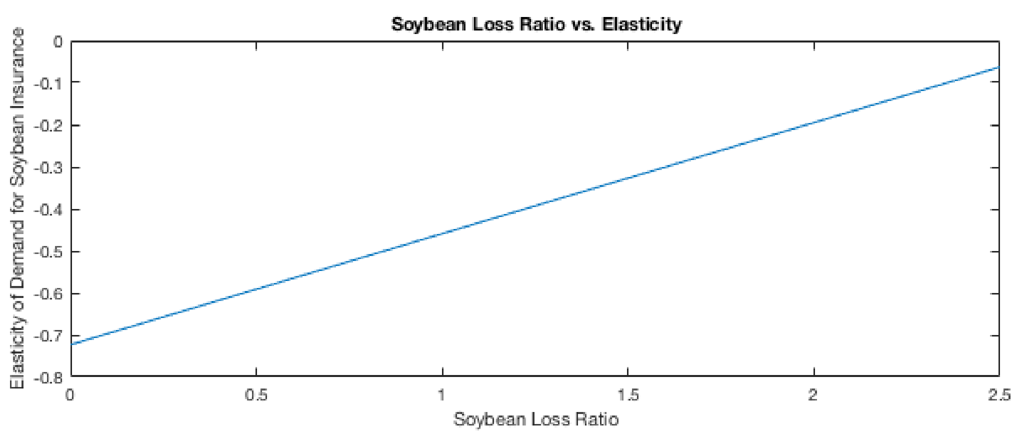


Figure 1.1 Loss-Ratios vs. Elasticity of Demand for Insurance

Table 1.16 Counterfactual: Effects of Soybean Subsidy Rates on Soybean Subsidy Expenditures (2016)

Δs	-0.3	-0.2	-0.1	0	+0.1	+0.2	+0.3
Soybeans	-57.92%	-40.22%	-20.81%	0.00%	22.71%	47.02%	73.02%

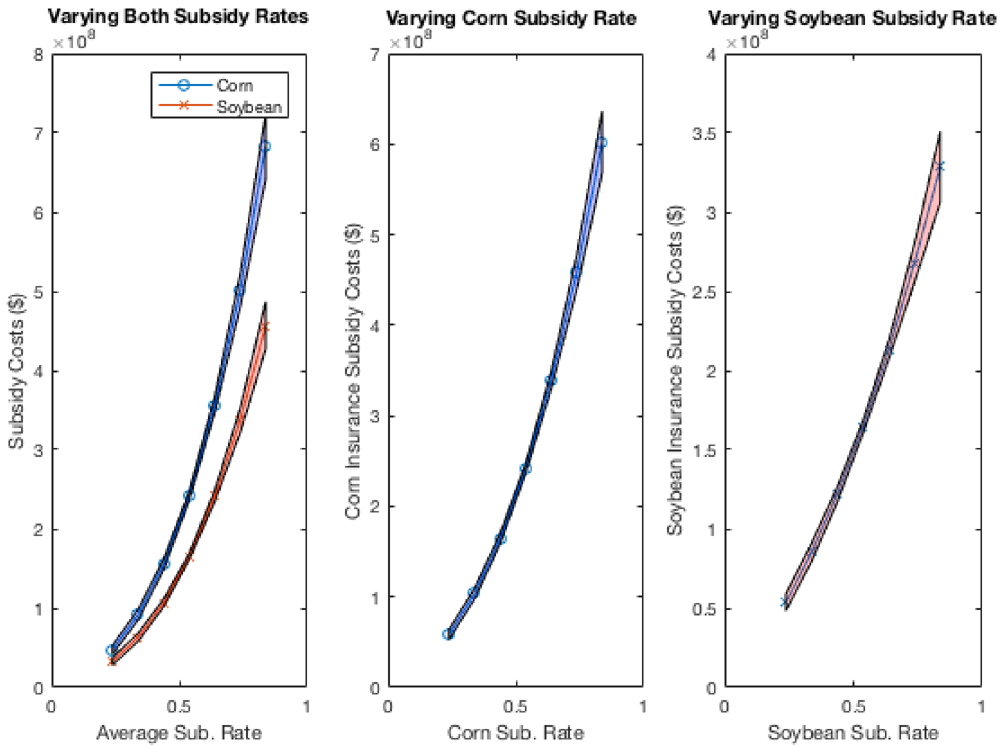


Figure 1.2 Total Heartland Subsidy Costs by Subsidy Rate (2005)

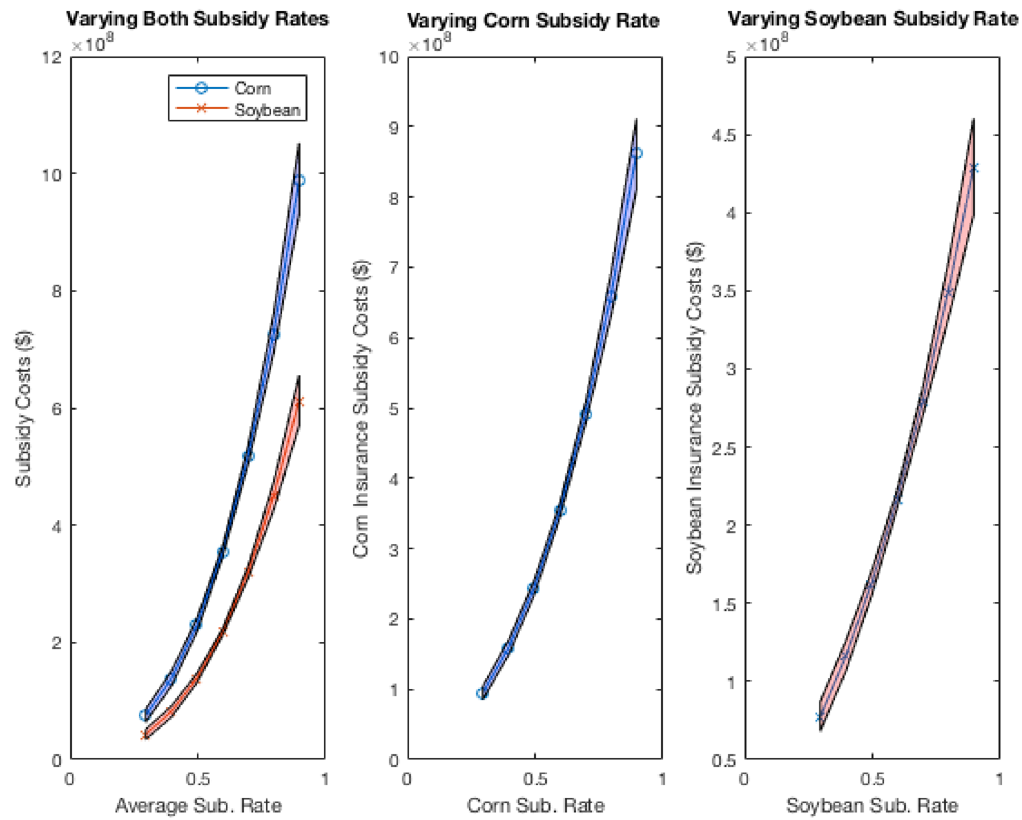


Figure 1.3 Total Heartland Subsidy Costs by Subsidy Rate (2009)

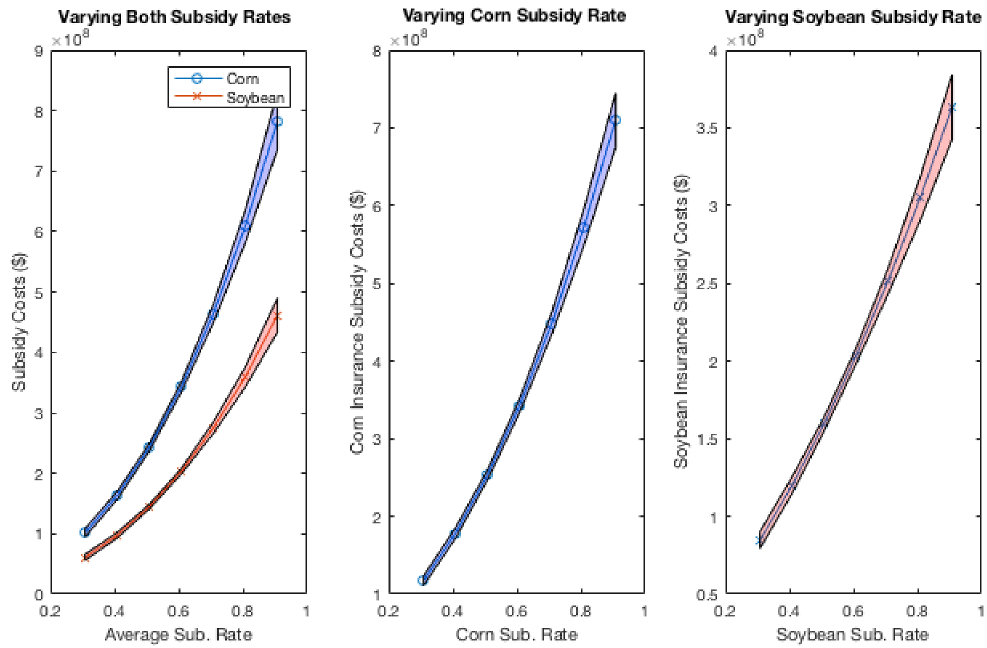


Figure 1.4 Total Heartland Subsidy Costs by Subsidy Rate (2012)

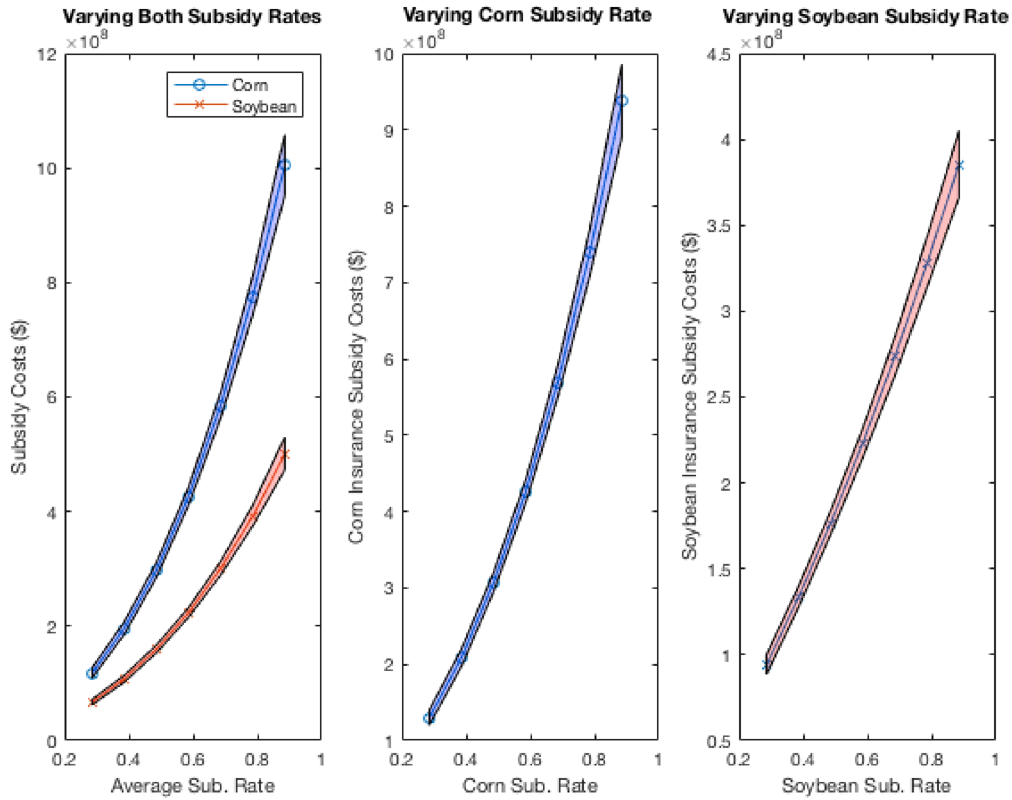


Figure 1.5 Total Heartland Subsidy Costs by Subsidy Rate (2016)

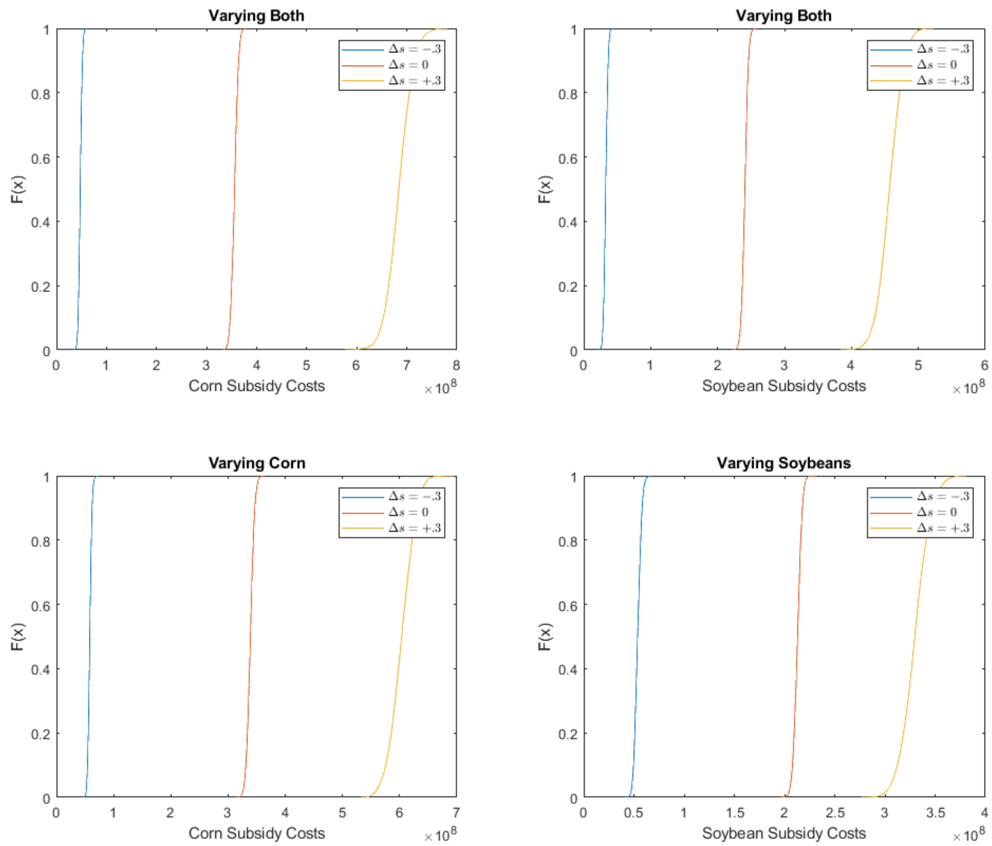


Figure 1.6 CDF's of Total Heartland Subsidy Costs by Subsidy Rate (2005)

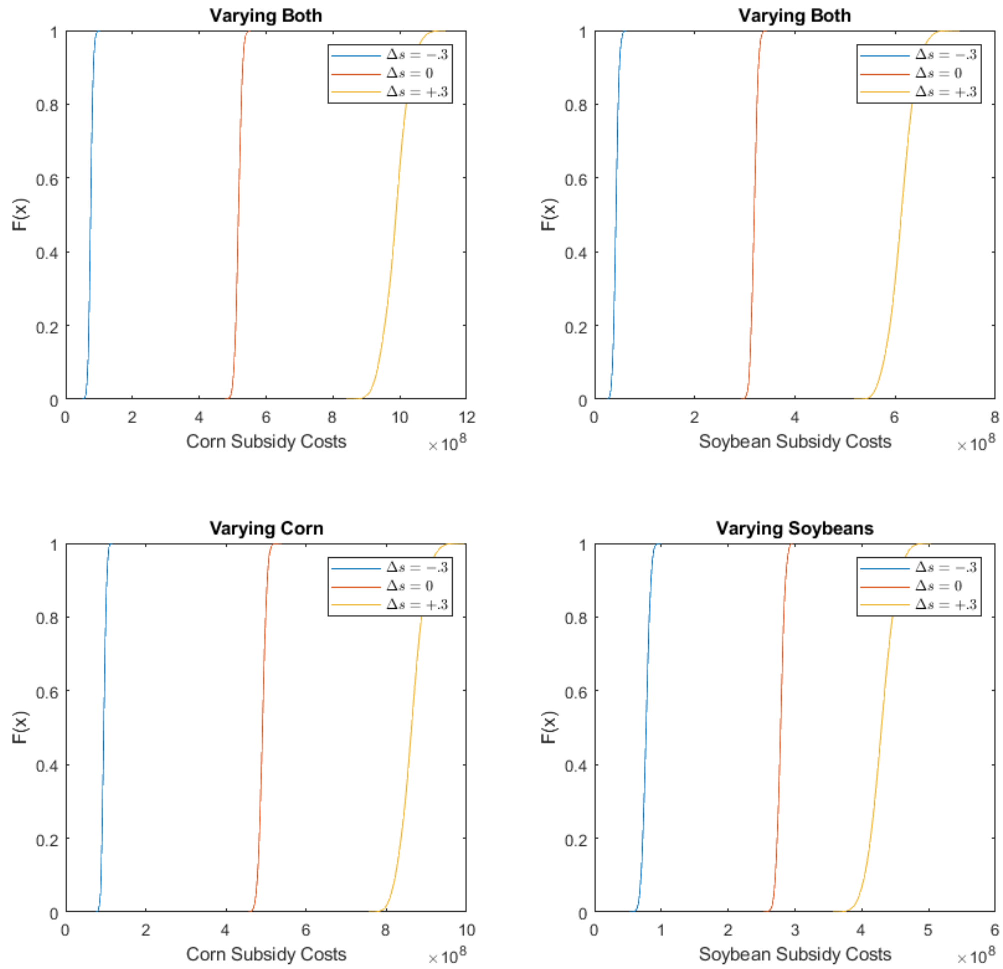


Figure 1.7 CDF's of Total Heartland Subsidy Costs by Subsidy Rate (2009)

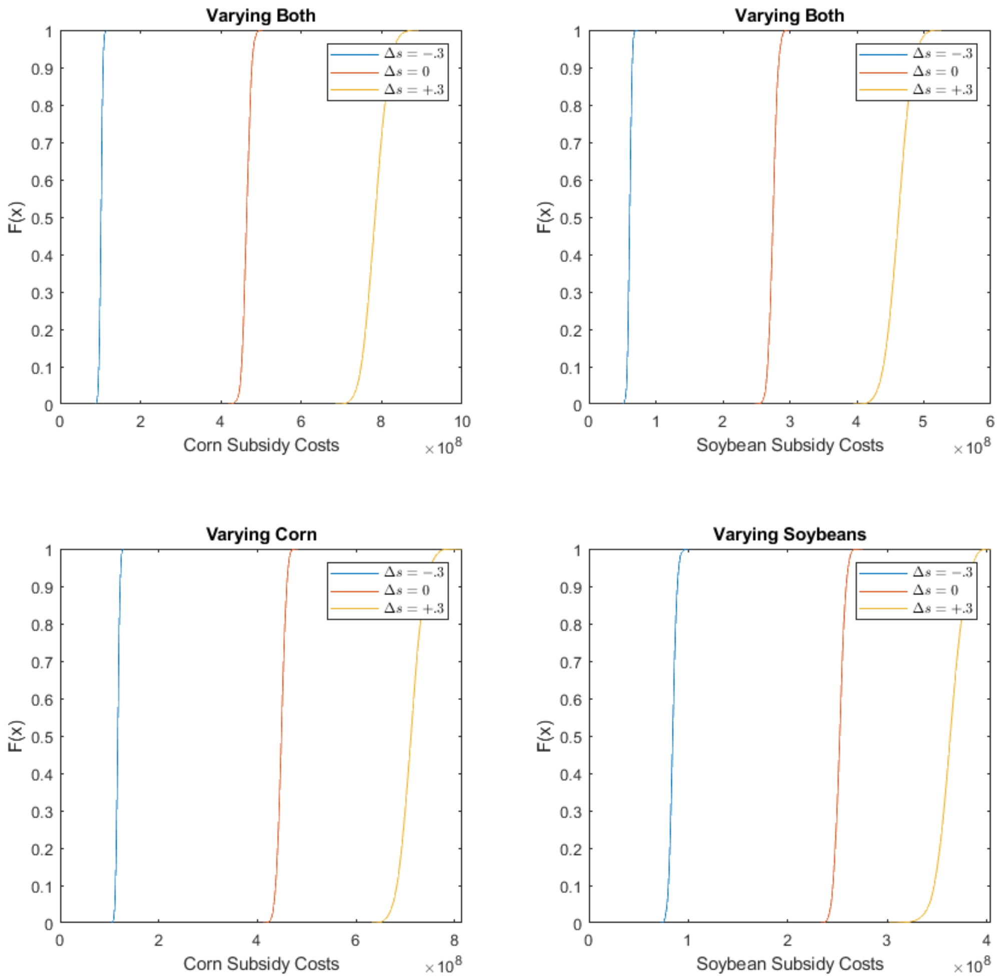


Figure 1.8 CDF's of Total Heartland Subsidy Costs by Subsidy Rate (2012)

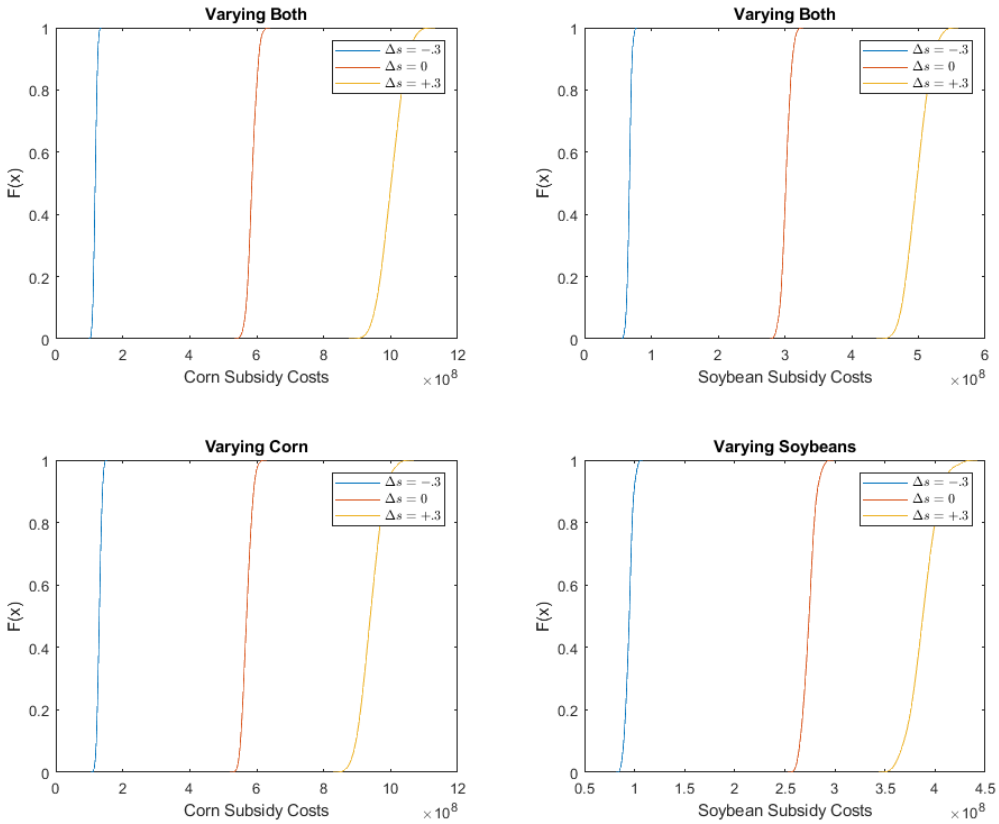


Figure 1.9 CDF's Total Heartland Subsidy Costs by Subsidy Rate (2016)

CHAPTER 2

Input-Output Price Transmission in the US Broiler Chicken Industry: An Empirical Investigation of Alleged Price-Fixing

2.1 Introduction

A vast literature has studied vertical price transmission. Typically, the focus of analysis is on asymmetries in the price transmission process where either the magnitude or speed of a shock depends on the sign of the shock. While some authors find asymmetric price transmission to be the standard (see Peltzman, 2000), others argue that existing econometric methods can generate misleading results that should be interpreted with caution (Gauthier and Zapata, 2001; von Cramon-Taubadel and Meyer, 2000). In particular, it is argued that standard tests can lead to excessive rejection of symmetry (Meyer and von Cramon-Taubadel, 2004). For a comprehensive review of the asymmetric price transmission (APT) literature, see Meyer and von Cramon-Taubadel (2004).

Meyer and von Cramon-Taubadel (2004) consider the importance of APT. Peltzman (2000) argues that APT is indicative of gaps in the existing economic theory because the existing theory treats APT as an exception rather than a rule. Additionally, APT will have important welfare implications. If a price change would have taken place sooner or have been of larger magnitude under symmetry, a redistribution of welfare results from APT. The gainers and the losers resulting from APT of course depend on the nature of APT and the sign of the price change.

Most studies of APT have focused on agricultural markets. Meyer and von Cramon-Taubadel (2004) review 40 publications of APT, 27 of which focus on agricultural products. The studies reviewed reject the null hypothesis of symmetry in 48% of tests. It should be noted that these studies use a wide variety of techniques, which Meyer and von Cramon-Taubadel categorize into first-difference methods, summed-difference methods, error-correction methods, threshold methods, and miscellaneous methods. Concerns over choice of method are worth mentioning, since rejection rate tends to depend on the method used. In the studies reviewed by Meyer and von Cramon-Taubadel, threshold methods reject symmetry in 80% of cases, while methods using summed difference reject in only 25% of cases.

Despite the general focus on agricultural products in the APT literature, to the best of the authors' knowledge, no published studies in the literature have investigated vertical price transmission in the US broiler chicken industry. A recent series of class-action lawsuits against broiler chicken processors provide motivation for studying price transmission in this industry.

The United States Broiler industry has experienced an increase in vertical integration over the past several decades. While the total number of processing and slaughter plants owned by the largest 15 firms increased only modestly from 124 in 1997 to 127 in 2013, total output of ready-to-cook (RTC) chicken meat increased approximately 38.5% during this period (Vukina and Zheng 2015). Further, the four-firm and eight-firm concentration ratios increased from 40.9% to 57.9% and from 51.3% to 79.3%, respectively. As a result of substantially high startup costs, significant barriers to entry are sometimes alleged to characterize the United States Broiler industry (see, for example, Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016).

The plaintiffs in Maplevale Farms, Inc. v. Koch Foods, Inc. et al. allege that prior to 2008, the US Broiler industry was characterized by a boom-and-bust cycle. According to allegations, this pattern was halted when collusion began in 2007 between Tyson and Pilgrim and quickly extended to include several more of the dominant broiler processing firms. When non-cooperative firms began increasing production in 2010, the plaintiffs allege that the defendants engaged in a second round of production cuts characterized by a substantial destruction of breeder flocks (Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016).

The defendants account for over 90% of the United States wholesale broiler market and record approximately $30 billion in sales annually. According to allegations, as a result of the collusion by the defendants, prices have risen 50% since 2008. During this same period, the cost of most influential inputs, namely corn and soybeans, has fallen approximately 20% (Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016). The plaintiffs also allege defendants manipulated the Georgia Dock chicken price index, to which the majority of broiler sales were tied (Morris, 2017, August 10), and earned record profits during this period (Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016). Accordingly, the plaintiffs allege that as a result of exercised market power by major poultry processors, prices paid to the processors were higher than those that would have been determined by competition (Kroh, 2016, September 2). Given the limited number of poultry processors, market power would be categorized by oligopoly in output markets and oligopsony in contract markets for grower services. Additional class action complaints against poultry processors were filed by indirect purchasers including Fargo Stopping Center LLC, though the cases were eventually combined (Meisel, 2016, December 15).

Processors filed a motion to dismiss the suit in January of 2017 following a second amended complaint in November of 2016, which is still pending. On August 7, 2017, however, direct purchasers reached a $2.25 million settlement deal with Fieldale Farms Corp. This deal was the first reached out of the 13 poultry processers involved in class action cases, but terms of the settlement may lead to more settlements from other processors. In particular, Fieldale Farms Corp. has agreed to provide phone records and financial support along with depositions from five employees (Rhodes, 2017, August 7).

A series of other suits stem from the Maplevale farms case. Specifically, Tyson Foods Inc., the alleged 'ringleader' in the price-fixing consipiracy (Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016) has become involved in litigation beyond the Maplevale Farms case. In particular Tyson Foods Inc. received a subpoena from the U.S. Securites and Exchange Commission (SEC) relating to allegations filed by food distributors and indirect producers in February of 2017 (Newsham, 2017, February 6). It was not until August 217, however that the SEC closed its investigation. Further, an antitrust suit was filed by Chicken Kitchen USA LLC against Tyson Foods Inc. et al. in April of 2017 alleging the poultry processor engaged in price-fixing behavior that prevented restaurants' ability to pay competitive prices for poultry (Hanson, 2017, April 24). The nature of these allegations is very similar to those in the Maplevale Farms case. Further, investor class actions were filed alleging Tyson Foods Inc. fixed prices, artificially raising prices and profits, and lied to investors about the source of the profit increases. This case was dismissed in July of 2017 due to insufficient evidence of price-fixing (Kroh, 2017, July 27).

The allegations against major broiler processors motivates an investigation of changes in market power. One avenue for such investigation is to look for asymmetries in the vertical price transmission. The theoretical connection between APT and market power is discussed in detail in the following section. Of course, several other factors can lead to price-transmission asymmetries aside from market power, meaning that the sources of asymmetry are likely difficult to disentangle. An alternative approach is to model processor decisions in a dynamic game framework and consider whether the equilibrium observed is consistent with a collusive equilibrium or a competitive one. Such analysis requires firm-specific data, which is difficult to obtain for this industry.

To motivate predictions for our empirical analysis of US broiler chicken prices, the authors model the processor's problem in a Cournot framework where processors have market power over retailers and farms. This framework is used to model input-output price spreads among US poultry processors. The equilibrium model is used to make hypotheses about cointegration, asymmetry, and relationships to other prices. Empirical findings are compared to the price-fixing allegations and implications are offered. Further, we test for structural breaks in the price transmission between the Retail-Wholesale and Wholesale-Farm level. We expect to find breaks in the coefficients reflecting asymmetry near the time of the alleged start-date of price-fixing. Further details on the economic link between APT and collusion is discussed in section 2.

For comparison purposes, we repeat the analysis for the United States beef and pork industries and compare findings with those from our broiler chicken analysis. Since production contracting is less common in beef and pork production than in poultry production, our beef and pork price analyses provides a good countercase. Using farm-level, wholesale, and retail beef prices at monthly frequency obtained from the Economic Research Service (ERS), we find evidence of cointegration among both the wholesale-farm and retail-wholesale price pairs. Many studies have focused on asymmetry in price dynamics in these two sectors of US agriculture. In particular, studies in the literature have found evidence that retail price responses to farm price increases are stronger and/or more rapid than farm price decreases of equal magnitude (Goodwin and Holt, 2001).

2.2 Definitions and Economic Theory

2.2.0.1 Definitions

Meyer and von Cramon-Taubadel (2004) distinguish among three criteria for classifying APT. The first criterion is whether the asymmetry is in the speed of adjustment, magnitude of adjustment, or a combination of both. These authors point out, relative to the symmetry case, that an asymmetry in adjustment magnitude will lead to a permanent welfare transfer, while an asymmetry in adjustment speed will lead to a temporary welfare transfer. Whether a permanent or temporary welfare transfer is of greater concern cannot be determined *a priori* because the answer will depend on the relative sizes of these transfers and the discount rate.

The second criterion is whether the asymmetry is positive or negative. According to these authors, positive (negative) APT exists between two prices, p^{out} and p^{in}, if p^{out} reacts more fully or rapidly to increase (decrease) in p^{in} than a decrease (increase). They argue that if, for example, p^{out} and p^{in} denote retail and farm gate prices, respectively, then negative (positive) APT increases (decreases) welfare of consumers, and hence the distinction between positive and negative APT is important. The final criterion is whether the asymmetry affects spatial or vertical price transmission. While the focus of this paper is solely on vertical price transmission, price-fixing allegations also motivates interesting research questions in the spatial price dimension.

2.2.0.2 Theoretical Motivation for APT

In order to make predictions about the impact on APT of potential price-fixing, we must first consider the possible sources of the various types of APT. Most APT studies provide one of two explanations for APT: market power and adjustment costs. In addition, a variety of other explanations have also been provided, including political intervention, asymmetric information, and inventory management (Meyer and von Cramon-Taubadel, 2004).

In most cases that consider market power, motivation for APT is due to a middleman (often in the form of an agricultural processor) exercising market power over the retail and/or farm levels of the supply chain (Meyer and von Cramon-Taubadel, 2004). Some studies in the literature have suggested that oligopoly power can lead to negative asymmetry. Ward (1982) considers firms with market power that are concerned about losing market share. In such a case, firms would be more reluctant to increase price and risk losing market share than to decrease price, leading to negative APT. Bailey and Brorsen (1989) consider oligopoly firms with a kinked demand curve. The authors point out that if firms believe that no competitor will match a price increase, but all would match a price decrease, then negative APT would result. Alternatively, if firms believe that no competitor will match a price decrease, but all would match a price increase, then positive APT would result. This illustrates the difficulty of using economic theory to determine whether APT should be positive or negative *a priori*.

A few studies have considered APT in the context of implicit collusion. Balke et al. (1998) and Brown and Yücel consider asymmetric effects of input price changes on the output price. If reputation is important in maintaining collusion, then increases in input prices would lead to rapid increases in output price, while decreases in input prices would have a delayed effect on output price. Damiana and Yang (1998) consider the effects of output demand shifts on output price. In their model, firms will be reluctant to decrease price if output demand falls, but will increase price without fear of punishment when output demand rises.

Meyer and von Cramon-Taubadel (2004) point out two difficulties in linking APT and market power. First, when studying only a single product using time series data, unless there are known changes in market power within the data period observed, then there is no variation in the 'treatment variable'. Peltzman (2000) studies a cross-section of different products with various levels of market power. Second, it is difficult to find a good proxy for market power. Most studies use Herfindahl-Hirschman index (HHI) or number of firms, though these metrics often fall short of depicting exercise of market power that is hypothesized to cause APT. However, researchers should exercise caution in drawing conclusions of market power purely based on evidence of APT. Tappata (2009) provides a theoretical framework for better understanding the 'Rockets and Feathers' phenomenon in the context of competitive markets, i.e. the common finding that prices rise faster than they fall. In Tappata's model, consumers are partially informed, while firms are competitive. The market outcome is characterized by consumers responding asymmetrically to shocks to firms' production costs.

Adjustment costs can also lead to APT. Ward (1982) suggests that with perishable products, retailers may be reluctant to increase prices to avoid spoiled inventory. On the other hand, Heien (1980) argues that perishable products have more flexible prices because changing prices for products with a long shelf-life leads to higher time costs and losses of goodwill. Though this paper focuses primarily on market power as a source of APT, these examples illustrate the difficulties of disentangling the various possible causes of APT. In response to the competing theories of the effects of perishability on APT, Santeramo and von Cramon-Taubadel (2016) investigate APT in a variety of fruits and vegetables with varying perishability. The authors exploit the perishability variation in an attempt to shed light on the causal nature of the relationship. Their results indicate that higher perishability leads to less evidence of APT, with APT nearly vanishing for very highly perishable products.

The variety of theories proposed in the literature to explain the Rockets and Feathers phenomenon illustrates the importance of proceeding cautiously in drawing conclusions about the source of APT evidence in price data. That being said, imposing symmetry without first-considering the possibility of APT poses the risk of masking important price dynamics that might otherwise be seen in impulse response functions when allowing for APT in the model.

Asymmetric price transmission has been widely studied in both US pork and beef markets, though empirical evidence of such tends to be sensitive to the model specification used. Goodwin and Holt (1999) estimate a single-threshold error-correction model and conduct impulse response analysis to investigate evidence of APT in US beef markets. They find statistically significant evidence of asymmetry, but impulse response analysis indicates the asymmetry may not be economically significant. Their analysis indicates information flows up the supply chain from the farm level up to the retail level but not in the reverse direction and retail shocks do not affect farm-level or wholesale prices. Wholgenant and Mullen (1988) consider various specifications of the relationship between farm-level and retail beef prices in the US and find the markup specification is inferior to the relative price specification. More recently, Pozo and Schroeder (2013) also test for APT in US beef markets. They distinguish between short and long-run asymmetry using an asymmetric TVEC specification and find no evidence of asymmetry, indicating beef markets might be more efficiently linked than was previously thought. Hahn (1990) investigates APT in both US beef and pork markets and finds that at all levels of the supply chain, prices respond more rapidly to price increases than to equal-magnitude price decreases.

Goodwin and Harper (2000) estimate a three-regime TVEC model to test for APT in US pork markets and find evidence of threshold cointegration. Their findings are similar to those of Goodwin and Holt (1999) in that information flows up the supply chain from the farm-level to the retail level but not in the reverse direction and that retail shocks are largely confined to retail markets. Miller and Hayenga (2001) estimate a band spectrum regression assuming that the nature of APT depends on whether high or low-frequency cycles are being considered. They find observed asymmetries in retail-wholesale transmission are not consistent with the search cost explanation and is more likely explained by retail inventory adjustment or coordination failures. Further, they find wholesale-farm asymmetries at all frequencies considered.

Emmanoulides and Fousekis (2014) employ copula models to investigate vertical price transmission in US pork markets from 1970-2012. They find that price dynamics vary along the supply chain and over time. In particular, the results indicate that the farm-wholesale price pair had symmetric extreme price co-movement, while the wholesale-retail price pair exhibited asymmetric price co-movement with decreased extreme dependence in the second half of the sample analyzed. In a similar vein, Qui and Goodwin (2013) use dynamic conditional copula models to study price co-movements in US pork markets. Allowing for time-varying transmission elasticities, the authors find that large increases in farm prices are readily transmitted to retail prices, while large price decreases at the farm-level are unlikely to affect consumer prices.

To date, the authors have not found any studies investigating vertical price transmission in US broiler chicken markets. The allegations of price-fixing provides a strong motivation for studying how prices along the supply chain move together and whether any structural change has taken place. We investigate vertical price transmission, allowing for structural change, in US broiler chicken, beef, and pork markets. The econometric techniques utilized are discussed in the following section.

2.3 Econometric Methods

We begin by investigating cointegration relationships. For such relationships to exist, each price series must be integrated of order one, $I(1)$. Thus, our analysis begins by evaluating the time series properties of the data by testing the natural logarithm of each price series in levels and first-differences for unit-root nonstationarity using Augmented dickey fuller tests. In the seminal paper by Dickey and Fuller (1979), a test is proposed of an ARIMA$(p,0,0)$. Subsequently, Dickey and Said (1981) discuss techniques for testing that $d=1$ when p and q are known. Said and Dickey (1984) propose a method for testing the null hypothesis that $d=1$ using an autoregressive approximation of an autoregressive moving average model where the number of lags p and q of the ARIMA$(p,1,q)$ are unknown. We then apply the test to price differentials, where the presence of a unit root is indicative of a lack of pairwise cointegration.

We use Ordinary Least Squares (OLS) to estimate the cointegration relationships between all market pairs, which take the following form

$$p_{i,t} = \alpha + \beta p_{j,t}. \tag{2.1}$$

where $p_{i,t}$ and $p_{j,t}$ denote the prices at time t in markets i and j, respectively. Here, markets represent different levels of the supply chain for the same product. If the both price series are stationary, employing a Likelihood Ratio (LR) test that $\alpha = 0$ and $\beta = 1$ is a test of market linkages. Goodwin and Piggott (2001) point out two useful pieces of information about this type of cointegration relationship. First, if logarithms of prices are used, the long-run equilibrium is assumed to be a constant ratio of prices, rather than a constant absolute margin. Second, if the series are nonstationary, conventional testing methods lead to poor inference in the form of inconsistent standard errors.

Next we follow Johansen's work (1988; 1991) proposing maximal eigenvalue and trace tests for cointegration. In the context of vertical price linkages, an economic equilibrium can be represented by a cointegrated $(k\text{x}1)$ vector of time series if there exist constants $(\beta_2, ..., \beta_k)$ such that

$$p_{1,t} - \beta_2 p_{2,t} - \beta_3 y_{3,t} - \cdots - \beta_k p_{k,t} = v_t \tag{2.2}$$

$$v_t = \rho v_{t-1} + \epsilon_t, \tag{2.3}$$

where p_{it} is $I(1)$ for all $i = 1, ..., k$ and v_t is a stationary time series. Additionally, Johansen tests over all series are a test for a long-run market equilibrium among the prices used. Balke and Fomby (1997) have shown that conventional cointegration tests perform reasonably well when the true model includes one or more thresholds. Hence, cointegration testing is meaningful even if the price-transmission process is characterized by a regime change at some point in the dataset.

When time series are cointegrated, an error-correction form is the appropriate specification. The literature on asymmetric price transmission proposes partitioning the error-correction term, denoted ECT, into positive shocks and negative shocks. Define $ECT_t^+ = I(ECT_t > 0)ECT_t$ and $ECT_t^- = I(ECT_t \leq 0)ECT_t$. This specification, as proposed by Endersa and Granger (1998) can be written as follows

$$y_{1,t} = c + \sum_{i=1}^{P} \phi_i \Delta y_{2,t-i+1} + \beta_+ ECT_{t-1}^+ + \beta_- ECT_{t-1}^- + \epsilon_t,$$

where $y_{1,t}, y_{2,t}$ are the prices being analyzed and ϵ_t is a noise term. If the two series are not cointegrated, i.e. no long-run equilibrium between prices exists, the terms β_+ and β_- both take the value of zero. Frey and Manera (2007) describe a more general case of the asymmetric ECM that allows for both short-run and long-run asymmetries

$$y_{1,t} = c + \sum_{i=1}^{P} \phi_{i,+} \Delta y_{2,t-i+1}^+ + \sum_{i=1}^{P} \phi_{i,-} \Delta y_{2,t-i+1}^- + \beta_+ ECT_{t-1}^+ + \beta_- ECT_{t-1}^- + \epsilon_t,$$

where $\Delta y_{2,t-i+1}^+ = I(\Delta y_{2,t-i+1} > 0)\Delta y_{2,t-i+1}$ and $\Delta y_{2,t-i+1}^- = I(\Delta y_{2,t-i+1} < 0)\Delta y_{2,t-i+1}$. Two tests of nonlinear adjustment are used to test for APT. A test of $\beta_+ = \beta_-$ is a test of long-run asymmetry, i.e. whether there is a difference in the magnitude of adjustment depending on whether the deviation from equilibrium is positive or negative, while a test of $\sum_{i=1}^{P} \phi_{i,+} = \sum_{i=1}^{P} \phi_{i,-}$ is a test for short-run asymmetry.

Next we construct generalized impulse response functions (GIRF) to better understand the equilibration process. GIRF's are applied to the above specification in a bivariate[1] setting. In par-

[1] For ease of interpretation, we chose to conduct bivariate (pairwise) price analysis. An alternative specification would

ticular, we compare responses of the downstream (upstream) price to positive and negative one standard deviation shocks to the upstream (downstream) price. In order to investigate whether any asymmetries are economically significant, we plot absolute impulse responses to more easily compare the different response to positive and negative shocks. Generalized impulse response functions are designed to be applied to linear and nonlinear time series models alike. A GIRF is defined as the expected change in the dependent variable vector $j = 1, 2, ..., n$ periods in the future conditional on a present shock and a history. A history is the information set at time $t-1$, denoted $\mathbf{I}_{t-1}$. We construct impulse response functions at the last observation in the dataset, i.e. $\mathbf{I}_{t-1} = \mathbf{I}_T$. Mathematically, a GIRF can be expressed as

$$GIRF(\mathbf{I}_{t-1}, \mathbf{y}_t, v_{i,t}) = E[\mathbf{y}_{t+j}|\mathbf{I}_{t-1}, \mathbf{y}_t, v_{i,t}] - E[\mathbf{y}_{t+j}|\mathbf{I}_{t-1}, \mathbf{y}_t], \tag{2.4}$$

for $j = 1, 2, ..., n$. These conditional expectations must be estimated using simulations. Each simulation consists of five steps:

1. Choose a shock of interest, $v_{i,t}$, upon which to condition.
2. Choose a history, I_{t-1}, upon which to condition[2].
3. Draw shocks $n = 10$ periods into the future and contemporaneous shocks, $v_{j,t}$, $j \neq i$, assuming multivariate normal distribution of errors. The distribution parameters are estimated from the residuals.
4. Calculate a path conditional on $v_{i,t}$ and a path not conditional on $v_{i,t}$: $[\mathbf{y}_{t+j}|\mathbf{I}_{t-1}, \mathbf{y}_t, v_{i,t}]$ and $[\mathbf{y}_{t+j}|\mathbf{I}_{t-1}, \mathbf{y}_t]$ for $j = 1, 2, ..., n$.
5. Repeat steps 3 and 4 for $B = 1000$ times and average across these 1000 iterations to estimate $E[\mathbf{y}_{t+j}|\mathbf{I}_{t-1}, \mathbf{y}_t, v_{i,t}]$, $E[\mathbf{y}_{t+j}|\mathbf{I}_{t-1}, \mathbf{y}_t]$, and hence $GIRF(\mathbf{I}_{t-1}, \mathbf{y}_t, v_{i,t})$ for the chosen history, $\mathbf{I}_{t-1}$.

Our impulse response analysis is applied to retail-wholesale, wholesale-farm, and AMS wholesale-Georgia Dock broiler price pairs in the pre-2008 and post 2008 periods in order to consider the timing of shocks and resulting price adjustments to shed light on the allegations of price fixing and non-competitive behavior. Additionally, we apply our impulse response functions to the retail-wholesale and wholesale-farm price pairs for both beef and pork prices.

If there is a structural change in the process that determines prices (e.g. collusion among firms began after a certain date), then a Qu-Perron structural break test can be used. This technique tests

be to simultaneously analyze all three prices.

[2]Each time we implement this procedure, we use the history corresponding to the last observation in the dataset, i.e. I_{T-1}

for the presence of an unknown breakdate and serves as a useful heuristic for suspected structural change. We adopt a specification with asymmetry and allow for a single structural break that can be expressed as follows:

$$\Delta y_{1,t} = \begin{cases} f_1(y_{2,t}, y_{2,t-1}, ... y_{2,t-P}, ECT_{t-1}) & \text{if } t < T_1 \\ f_2(y_{2,t}, y_{2,t-1}, ... y_{2,t-P}, ECT_{t-1}) & \text{if } t \geq T_1, \end{cases} \tag{2.5}$$

T_1 is the break-date, and P is the number of lags. The functions f_1 and f_2 differ only in the parameters, depend on whether cointegration is present, and can take either of the proposed functional forms described above that allow for asymmetry. This specification is estimated twice: first with retail and wholesale prices and second with wholesale and Georgia Dock prices. A further extension to the error correction model that is more commonly applied to spatial price transmission is to allow for responses to the error correction term to depend on a threshold, where a 'neutral band' (Goodwin and Piggott, 2001) exists. In this setting, shocks will only provoke a significant response if they push the error correction term outside the neutral band. Within a regime, a test that $\beta_+ = \beta_-$ is a test for symmetry.

The appeal of structural break tests proposed by Qu and Perron (2007) is that the exact date of the structural break is unknown. The estimation algorithm is composed of the following steps. First, an approximate Quasi-Maximum Likelihood Estimation (QMLE) analogue of Feasible Generalized Least Squares (FGLS) is estimated. Next, a recursive residuals approach is used to construct log-likelihood values for each segment of the time series, which yields a triangular matrix of log-likelihood values. Finally, the optimal break dates, i.e. the partition maximizing the sum of log-likelihood values, are selected using a dynamic programming algorithm. Under this procedure, LR tests are used to determine the number of structural changes. Critical values for the test statistics are obtained using simulations. In particular, we test for changes in the regression coefficients at unknown break dates, allowing for a single break.The changes proposed by the structural break tests are compared with market developments and implications for the alleged price-fixing behavior are offered. Structural changes are anticipated at the start date of the alleged broiler chicken price-fixing.

A few other points from Meyer and von Cramon-Taubadel (2004) are worth mentioning. First, estimation of the error correction form stated above allows for asymmetry only in the speed of price transmission and not in the magnitude of adjustment. Second, standard augmented Dickey-Fuller (ADF) tests may fail to reject nonstationarity of the error correction term. Enders and Granger (1998) and Enders and Siklos (2001) adapt the standard ADF test to allow for asymmetric adjustment. Third, it is possible that the nature of response to the error correction term may be non-linear and more appropriately reflected by a higher-order polynomial in the above specification. Von Cramon-Taubadel (1996) investigates this issue and finds significant evidence of non-linearity in EU pork markets.

2.4 Empirical Application

2.4.1 Application to Broiler Chicken Prices

Our analysis is first applied to broiler chicken prices in the US. Prices at the retail and wholesale level are weighted averages of whole birds and parts and are observed at a monthly frequency from 1990-2015. Prices at the Georgia Dock are used to represent wholesale prices and are observed at a weekly frequency from 2000-2015. The retail and wholesale data are obtained from USDA, while the Georgia Dock prices are obtained from the State of Georgia Department of Agriculture. Additionally, a monthly farm-level price index for broiler prices was obtained from National Agricultural Statistics Service (NASS). Finally, monthly corn meal and soybean meal (high protein) prices were obtained from the USDA Economic Research Service (ERS).

We begin by evaluating the time series properties of the price data using unit-root tests. In order to perform cointegration analysis, it is necessary that each price series be $I(1)$. Tables 2.1 and 2.2 display the results from the ADF and KPSS tests, respectively. With the exception of cornmeal price series, which the ADF test indicates to be $I(0)$, KPSS and ADF indicate all price series are $I(1)$. Hence, cointegration analysis is appropriate among these prices. Since price series are typically assumed to follow a random walk, we assume all series are $I(1)$ for the remainder of analysis.

The parameter estimates of the cointegrating relationships, $p_t^i = \alpha + \beta p_t^j$, between the retail-wholesale and wholesale-farm pairs are presented in Table 2.3. All analysis is conducted on logarithmic transformations of the data. Estimates of the intercept and slope terms are very close to zero and one, respectively. Conventional hypothesis tests are inappropriate given the nonstationarity of the price series. The slope coefficient is nearly double in the wholesale-farm regression compared to the retail-wholesale regression. This result indicates that there is a stronger link between the wholesale-farm price pair relative to the retail-wholesale price pair.

Table 2.4 displays the results of Multivariate Johansen tests for cointegration among the BLS retail, AMS wholesale, and NASS farm-level prices. The tests indicate that the presence of two long-run equilibria among these three price series. Pairwise cointegration tests are given in Table 2.5. For both the retail-wholesale and wholesale-farm pairs, pairwise Johansen tests indicate pairwise cointegration. For the Phillips-Ouliaris test, only the wholesale-farm price pair is found to be cointegrated. These results suggest that an error-correction model (ECM) should be used rather than a vector autoregression (VAR) in first-differences.

In estimating (4), or the single-regime version of (4), an appropriate lag-length ($P-1$) must be chosen. Our criterion for lag-selection is Bayesian Information Criteria (BIC) with a maximum of $P=7$. In the retail-wholesale (wholesale-farm) ECM, four (four) lags minimized BIC.

We first consider the retail-wholesale ECM. The estimates of β^+ and β^- are very close to one another, both with a negative sign. There is modest evidence in asymmetric responses to deviations from equilibrium, as the response to positive shocks is approximately 1.5 times the response to negative shocks. In the wholesale-farm ECM, the estimates of β^+ and β^- are again very close, both with a negative sign. This negative coefficient indicates that the price margin corrects toward the equilibrium in response to shocks. Again, there is little evidence in asymmetric responses to deviations from equilibrium. It should be noted that the relatively large standard errors mean these result should be interpreted with caution, particularly in the retail-wholesale pair. Table 2.9 displays the likelihood-ratio test results under $H_0: \beta^+ = \beta^-$. The null hypothesis of symmetry is not rejected at a 10% significance level for the wholesale-farm price pair. For the retail-wholesale price pair, we reject the null hypothesis of symmetry at the 1% level, indicating statistically significant evidence of positive asymmetry in the vertical price transmission. The estimation and testing results suggest that the retail-wholesale correct toward equilibrium more quickly in response to increases in the retail price than to decreases in the retail price.

Meyer and von Cramon-Taubadel (2004) point out that data frequency is another important issue in APT estimation. They argue that a possible reason many studies find no evidence of asymmetry is low-frequency data. Miller and Hayenga (2001) suggest that some causes for APT can only be observed in low (or high) frequency data. They argue that search costs and local market power take place in high-frequency price cycles and hence could not be observed in low-frequency data. They argue that instead, a possible source of APT that would be observed in low-frequency data is inventory behavior, which firms only adjust to low-frequency price changes.

We also consider the Georgia-Dock price. Allegations of Georgia-Dock price manipulation raise the question of whether Georgia-Dock price behavior was different before and after 2008. As can be seen in Figure 2.2, the Georgia-Dock price appears to follow the AMS wholesale price index[3] much more closely before 2008. To investigate regime-change, we perform cointegration tests of USDA wholesale and Georgia-Dock prices before and after 2008. As can be seen, cointegration tests indicate the two series are cointegrated from 2000-2008, but are not cointegrated from 2008-2016. These results could conservatively indicate regime change.

We use the aforementioned bivariate model estimates to construct generalized impulse response functions for the retail-wholesale, wholesale-farm, and AMS wholesale-Georgia Dock broiler price pairs in the pre-2008 and post 2008 periods, with the break estimated by aforementioned structural break tests. Figure 2.5 and Figure 2.6 display the impulse responses for the farm-wholesale and wholesale-retail price pairs, respectively, in the pre-2008 period. An examination of the absolute responses reveals some minor asymmetric responses to positive and negative price shocks, but the magnitude of these asymmetries is a maximum of 0.01, i.e. approximately $0.01 difference in real prices, indicating these asymmetries are not economically significant. The impulse responses displayed in Figure 2.7 and Figure 2.8 for the farm-wholesale and wholesale-retail price pairs, respectively, in the post-2008 period reveal a similar result.

Figure 2.10 displays the impulse responses of the AMS wholesale-Georgia Dock broiler price pair to AMS wholesale price shocks in the pre-2008 and post 2008 periods. As can be seen, minor asymmetries exist, but these asymmetries are not economically significant. Interestingly, shocks to the AMS wholesale price trigger much stronger responses in the Georgia Dock price in the pre-2008 period. In particular, responses of the Georgia Dock price in the post-2008 period to the AMS wholesale price shocks appear to essentially be non-existent. This finding is consistent with the cointegration testing results between this price pair described above, which further reinforces the notion that regime change took place starting near the estimated break-date, as consistent with the allegations of manipulation of the Georgia Dock price.

Finally, we construct impulse response response functions to analyze the how the wholesale-farm price margin is affected by changes in the price of broiler feed in the pre-2008 and post-2008 periods.[4] Interestingly, in the pre-2008 period, increases (decreases) in the broiler feed price invoke increases (decreases) in the wholesale-farm price margin in the pre-2008 period, while the reverse is true in the post-2008 period. Whether this finding is indicative of a change in the level of market power

[3]The large drop in the wholesale broiler price in mid-2015 is likely a result of the avian influenza outbreak that occurred in late 2014 into 2015.

[4]All impulse response functions are measuring change in logarithmic price. Therefore, the vertical axis can be interpreted as percentage change in price.

being exercised is uncertain, as the comparative statics from the Cournot oligopoly-oligopsony have indeterminate sign and therefore cannot be used to make predictions about how changes in market power affect price dynamics.

2.4.2 Application to Beef Prices

We use a sample of national farm-level, wholesale, and retail prices for the US beef industry obtained from the USDA ERS. All beef prices are observed at monthly frequency and span from January 1970 to December 2017. Our analysis is conducted on logarithmic transformations of prices, which assumes prices are related in a proportional fashion. Prices are deflated using the CPI before transforming the time-series.

ADF tests for nonstationarity and KPSS tests for stationarity both reveal the presence of unit roots in all time series considered. Since all three price series are $I(1)$, we test for the presence of a long-run equilibrium using a variety of cointegration tests, namely pairwise Johansen and Philips-Ouliaris tests. The R^2 values in the OLS cointegrating vector estimation indicates farm-level prices explain more variation in wholesale prices than wholesale prices explain variation in retail prices. Philips-Ouliaris tests suggest neither price pair is cointegrated, while pairwise Johansen tests indicate the opposite. Multivariate Johansen tests indicate the presence of two long-run equilibria.

Subsequently, we estimate two bivariate asymmetric VEC models, one for each price pair[5]. Lag length is selected by minimizing BIC. Likelihood-ratio tests are used to test for both short and long-run APT. In both the retail-wholesale and wholesale-farm models, we fail to reject the null hypothesis of long-run asymmetry. The null hypothesis of short-run asymmetry, however, is rejected at the 10% level in the retail-wholesale model and at the 5% level in the wholesale-farm model.

We use the aforementioned bivariate model estimates to construct generalized impulse response functions for the retail-wholesale and wholesale-farm price pairs. Figure 2.11 displays the impulse response functions for beef prices and reveals the presence of positive APT in the wholesale-farm price pair and the presence of negative APT in the retail-wholesale price pair.

[5]Since cointegration tests reveal conflicting results, it is possible that a VAR in first differences is instead the appropriate model, meaning an error-correction specification is inefficient. If instead we estimated a VAR when the true model was an error-correction form, estimates would be biased and inconsistent. We err on the side of caution, prioritizing unbiased and consistent estimates over efficiency.

2.4.3 Application to Pork Prices

We use a sample of national farm-level, wholesale, and retail prices for the US pork industry obtained from the USDA ERS. All beef prices are observed at monthly frequency and span from January 1970 to December 2017. Our analysis is conducted on logarithmic transformations of prices, which assumes prices are related in a proportional fashion. Prices are deflated using the CPI before transforming the time-series.

As with beef and broiler prices, ADF tests for nonstationarity and KPSS tests indicate the three pork prices considered follow a random walk. Subsequently, we test the wholesale-farm and retail-wholesale price pairs for cointegration using pairwise Johansen and Philips-Ouliaris tests. Similar to our findings in the beef price analysis, R^2 values in the OLS cointegrating vector estimation indicates farm-level prices explain more variation in wholesale prices than wholesale prices explain variation in retail prices. Philips-Ouliaris and pairwise Johansen tests indicate that both price pairs are cointegrated.

Subsequently, we estimate two bivariate VEC models, one for each price pair, that allow for both short-run and long-run asymmetries. Again, lag length is selected by minimizing BIC. Likelihood ratio tests applied to our models of pork prices reveal similar findings to our models of beef prices. Again, in both the retail-wholesale and wholesale-farm models, we fail to reject the null hypothesis of long-run asymmetry. The null hypothesis of short-run asymmetry, however, is rejected at the 10% level in the retail-wholesale model and at the 5% level in the wholesale-farm model.

We use the aforementioned bivariate model estimates to construct generalized impulse response functions for the retail-wholesale and wholesale-farm price pairs. Figure 2.12 displays the impulse response functions for pork prices and reveals the presence of positive APT in the wholesale-farm price pairs and the presence of negative APT in the retail-wholesale price pairs

2.5 Conclusion

This paper analyzes the vertical price dynamics in the US broiler chicken industry with an emphasis on asymmetric price transmission and structural change motivated by price-fixing allegations. We estimate structural breaks and compare our findings to the alleged start-date of price fixing. Further, we estimate bivariate asymmetric vector error-correction models to investigate the asymmetric price transmission and construct impulse response analysis.

Structural break testing reveals break dates that are consistent with the alleged start date of price-fixing in the wholesale-farm and AMS wholesale-Georgia Dock price pairs. In the retail-wholesale price pair, no break-date was found, i.e. a one-segment partition was optimal, and in the wholesale-farm price margin regressed on the broiler feed price, the break date was not consistent with alleged start date of price-fixing. Impulse response analysis reveals the presence of minor asymmetries in price responses for the wholesale-farm and retail-wholesale price pairs, though these asymmetries appear to be economically insignificant.

More substantial positive asymmetries were found in the responses of the wholesale-farm price margin to the broiler feed price. Impulse response functions indicate the Georgia Dock price responded rapidly and in the same direction in the pre-2008 period, while responses were extremely modest in the post-2008 period. This finding could conservatively support the allegation that the Georgia Dock price was manipulated from 2008-2016, as the impulse responses in the post-2008 period show the Georgia Dock price was largely unrelated to an alternative indicator of the US wholesale broiler chicken price.

We repeat our analysis for US pork and beef prices as a comparison, since these industries are less constrained to contract pricing relative to the US broiler chicken industry. In particular, bivariate asymmetric vector error-correction models, conduct hypothesis tests for asymmetric price transmission and construct impulse response functions. For both pork and beef prices, hypothesis tests indicate the presence of asymmetries in the vertical price transmission. The nature of these asymmetries for both commodities, as revealed by the impulse response analysis, indicates the presence of positive APT in the wholesale-farm price pairs and the presence of negative APT in the retail-wholesale price pairs. Interestingly, these findings of APT are indicating welfare gains for wholesalers and welfare losses for farmers and retailers relative to the case of symmetric price transmission. As wholesalers in agricultural markets are often alleged to have market power over farmers and retailers, these findings of asymmetry conservatively support such claims.

As noted by von-Cramen Taubadel (2004), it is important to exercise caution when discussing the source of asymmetric price transmission based on empirical results. He explains that asymmetric price transmission has important welfare implications, as the presence of such implies a different welfare distribution than would have occurred under symmetric price transmission. If the source of asymmetric price transmission is indeed market power, economic theory tells us market failure is present in the market at hand. However, although asymmetric price transmission implies a different welfare distribution than under symmetry, market power is not the only means by which APT can cause market failure.

Tables[6] and Figures

Table 2.1 Tests for (non)Stationarity

	ADF Test for Nonstationarity		KPSS Test for Stationarity	
	Level	First-difference	Level	First-difference
BLS retail	-0.228	-13.124*	0.621*	0.0881
AMS wholesale	-0.227	-7.078*	0.621*	0.0221
NASS farm-level	-0.270	-5.096*	0.538*	0.0178
Georgia-Dock wholesale	-0.555	-6.989*	0.538*	0.031
Cornmeal	-3.29*	-8.567*	1.681*	0.020
Soybean meal	-2.665	-11.782*	1.263*	0.039

Table 2.2 OLS Estimates of Cointegrating Vector

	α	β	R^2
Retail-Wholesale	2.847*	0.326*	0.2053
	(0.158)	(0.042)	
Wholesale-Farm	1.688*	0.644	0.7865
	(0.072)	(0.022)	

Table 2.3 Multivariate Johansen Tests

	Trace Test	Eigen. Test
$r \geq 2$	3.10	3.10
$r \geq 1$	30.46*	27.36*
$r = 0$	61.22*	30.76*

[6] * denotes statistical significance at the 10% level.

Table 2.4 Pairwise Cointegration Tests

	Retail-Wholesale	Wholesale-Farm
Max. eigen. test: r=0	26.26*	26.68*
Trace test: r=0	29.18*	29.62*
Johansen: r=1	2.91	2.94
Phillips-Ouliaris test	-1.241	-3.411*

Table 2.5 Retail-Wholesale Error Correction Model

Variable	Estimate	std. error
Intercept	0.00059	0.2958
ΔW_t	0.0023	0.032
ΔW_{t-1}	0.018	0.032
ECT^{+}_{t-1}	-0.062	0.052
ECT^{-}_{t-1}	-0.039	0.039

Table 2.6 Wholesale-Farm Error Correction Model

Variable	Estimate	std. error
Intercept	-0.00028	0.002
ΔF_t	0.274*	0.033
ΔF_{t-1}	0.321*	0.030
ECT^{+}_{t-1}	-0.237*	0.075
ECT^{-}_{t-1}	-0.267*	0.075

Table 2.7 Asymmetry Tests (Broilers)

	COIA		DLEA		MEAPA	
	LR Test	p-Value	LR Test	p-Value	LR Test	p-Value
Retail-Wholesale	1.5823	0.2084	12.618*	0.00182	0.9248	0.3362
Wholesale-Farm	0.8167	0.3661	0.8536	0.6526	27.515*	1.56E-07

Table 2.8 Bai-Perron Test for Structural Break

	Estimated Breakdate
Retail Wholesale	N/A
Wholesale Farm	May 2008
Wholesale: AMS Georgia Dock	July 2008
Wholesale/Farm Feed	April 2003

Table 2.9 Cointegration Tests: USDA Wholesale and Georgia-Dock

	Pre-2008	Post-2008
Max. eigen. test: r=0	14.88*	11.94
Trace test: r=0	18.54*	14.06
Johansen: r=1	3.66	2.12
Phillips-Ouliaris test	-2.588*	-0.828

Table 2.10 Beef Prices: (non) Stationarity Tests

	ADF		KPSS	
	Level	First Difference	Level	First Difference
Farm	-1.709	-6.6667*	5.2743*	0.0517
Wholesale	-1.7288	-7.0257*	5.5058*	0.0688
Retail	-1.8673	-6.0501*	3.5413*	0.1394

Table 2.11 Beef Prices: Estimates of Cointegrating Relations

	α	β	R^2
Retail-Wholesale	2.6483	0.5578	0.8755
	(0.043)	(0.009)	-
Wholesale-Farm	0.2886	0.9732	0.9811
	(0.027)	(0.006)	-

Table 2.12 Beef Prices: Pairwise Cointegration Tests

	Retail-Wholesale	Wholesale-Farm
Max. eigen. Test: r=0	15.83*	43.19*
Trace test: r=0	19.57*	49.72*
Johansen: r=1	3.74	6.53
Phillips-Ouliaris test	-1.9232	-2.3856

Table 2.13 Beef Prices: Multivariate Johansen Tests

	Trace Test	Eigen. Test
$r \geq 2$	3.44	3.44
$r \geq 1$	14.83*	18.27*
$r = 0$	42.90*	61.17*

Table 2.14 Retail-Wholesale AVECM (Beef)

Variable	Estimate	Std. Error	t-Value
Intercept	-0.0029*	0.001	-2.143
ΔW_t^-	0.0726*	0.025	2.848
ΔW_{t-1}^-	0.1323*	0.026	5.082
ΔW_{t-2}^-	0.1803*	0.026	6.980
ΔW_t^+	0.0955*	0.024	4.053
ΔW_{t-1}^+	0.2148*	0.023	9.259
ΔW_{t-2}^+	0.2087*	0.023	9.075
ECT_{t-1}^-	-0.0568*	0.024	-2.398
ECT_{t-1}^+	-0.0179	0.0166	-1.079

Table 2.15 Wholesale-Farm AVECM (Beef)

Variable	Estimate	Std. Error	t-Value
Intercept	-0.0013	0.002	-0.645
ΔF_t^-	0.0526	0.037	1.430
ΔF_{t-1}^-	0.7378*	0.036	20.696
ΔF_t^+	0.0281	0.035	0.812
ΔF_{t-1}^+	0.9024*	0.035	25.880
ECT_{t-1}^-	-0.1305*	0.044	-2.995
ECT_{t-1}^+	-0.2174*	0.044	-4.933

Table 2.16 Likelihood-Ratio Tests for Asymmetry (Beef)

	COIA[7]		DLEA[8]		MEAPA[9]	
	LR Test	p-Value	LR Test	p-Value	LR Test	p-Value
Retail-Wholesale	0.3126	0.5761	5.9889	0.1122	1.2995	0.2543
Wholesale-Farm	0.1684	0.6816	7.7378*	0.02088	1.3993	0.2368

Table 2.17 Pork Prices: (non) Stationarity Tests

	ADF		KPSS	
	Level	First Difference	Level	First Difference
Farm	-1.6657	-6.5954*	6.9959*	0.0124
Wholesale	-1.3861	-6.7121*	24.3708*	0.0441
Retail	-2.3092	-6.7047*	5.282*	0.0444

Table 2.18 Pork Prices: Estimates of Cointegrating Relations

	α	β	R^2
Retail-Wholesale	3.4326	0.3730	0.8629
	(0.028)	(0.006)	-
Wholesale-Farm	0.8876	0.8713	0.9246
	(0.043)	(0.010)	-

Table 2.19 Pork Prices: Pairwise Cointegration Tests

	Retail-Wholesale	Wholesale-Farm
Max. eigen. Test: r=0	23.22*	21.11*
Trace test: r=0	28.14*	27.05*
Johansen: r=1	4.92	5.93
Phillips-Ouliaris test	-2.7385*	-4.2551*

Table 2.20 Pork Prices: Multivariate Johansen Tests

	Trace Test	Eigen. Test
$r \geq 2$	4.68	4.68
$r \geq 1$	20.9*	25.59*
$r = 0$	34.48*	60.07*

Table 2.21 Retail-Wholesale AVECM (Pork)

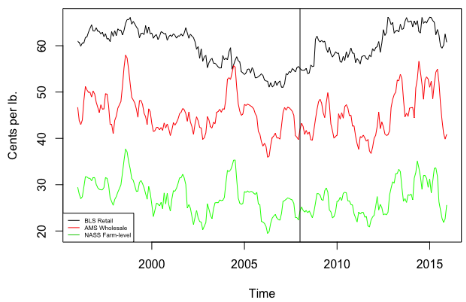
Variable	Estimate	Std. Error	t-Value
Intercept	-0.0021	0.002	-1.328
ΔW_t^-	0.0930*	0.029	3.218
ΔW_{t-1}^-	0.1250*	0.029	4.262
ΔW_{t-2}^-	0.1107*	0.028	3.943
ΔW_t^+	0.1036*	0.027	3.889
ΔW_{t-1}^+	0.2021*	0.026	7.729
ΔW_{t-2}^+	0.2009*	0.026	7.710
ECT_{t-1}^-	-0.021	0.023	-0.882
ECT_{t-1}^+	-0.062*	0.023	-2.711

Table 2.22 Wholesale-Farm AVECM (Pork)

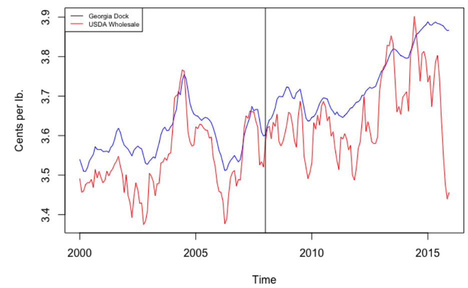
Variable	Estimate	Std. Error	t-Value
Intercept	-0.0022	0.003	-0.881
ΔF_t^-	0.0559*	0.023	2.416
ΔF_{t-1}^-	0.4365*	0.022	19.645
ΔF_t^+	-0.0096	0.021	-0.463
ΔF_{t-1}^+	0.5045*	0.022	23.452
ECT_{t-1}^-	-0.0493*	0.024	-2.090
ECT_{t-1}^+	-0.0190	0.017	-1.136

Table 2.23 Likelihood-Ratio Tests for Asymmetry (Pork)

	COIA		DLEA		MEAPA	
	LR Test	p-Value	LR Test	p-Value	LR Test	p-Value
Retail-Wholesale	0.052	0.8196	7.9509*	0.04704	1.1567	0.2822
Wholesale-Farm	3.227*	0.07243	6.1942*	0.04518	0.773	0.3793

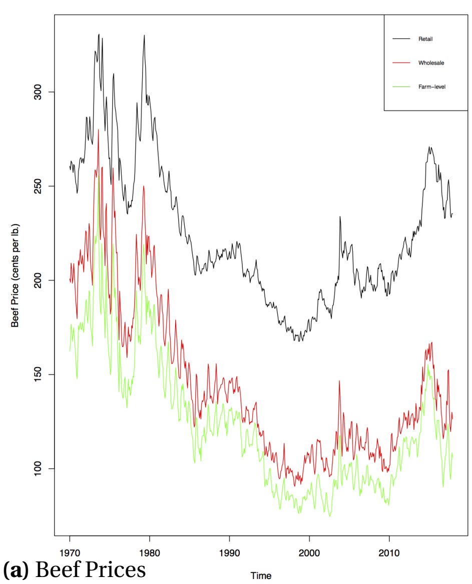


(a) Broiler Prices

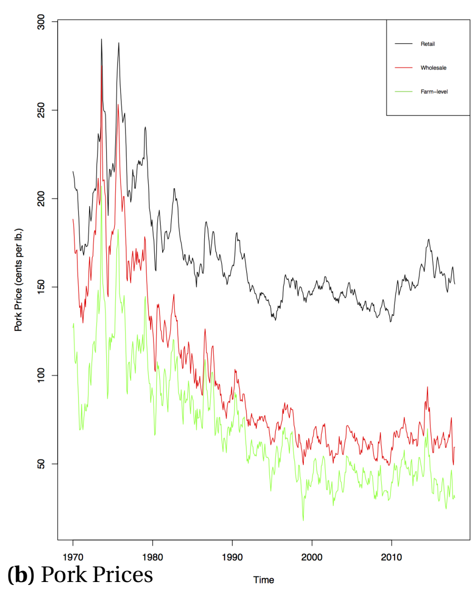


(b) Georgia Dock and USDA Wholesale Prices

Figure 2.1 Broiler Price Data

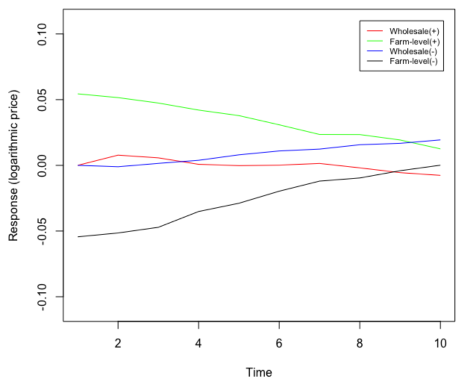


(a) Beef Prices

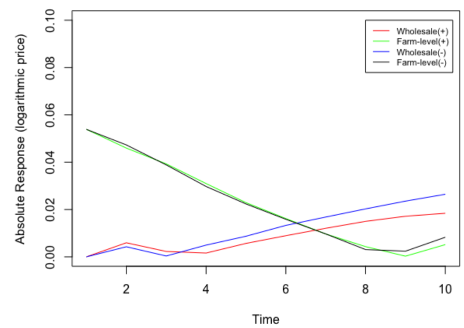


(b) Pork Prices

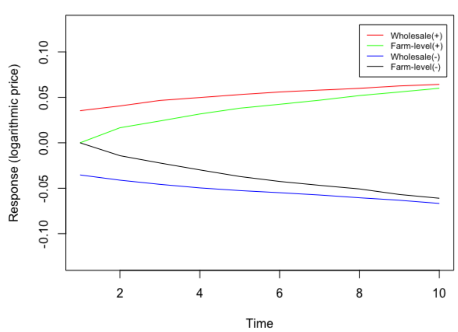
Figure 2.2 Pork and Beef Price Data



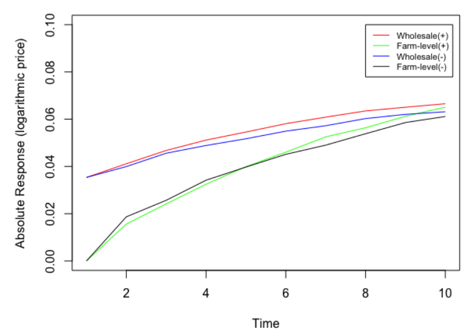
(a) Broilers: Responses to Farm-Level Shocks (pre-2008 period)



(b) Broilers: Absolute Responses to Farm-Level Shocks (pre-2008 period)

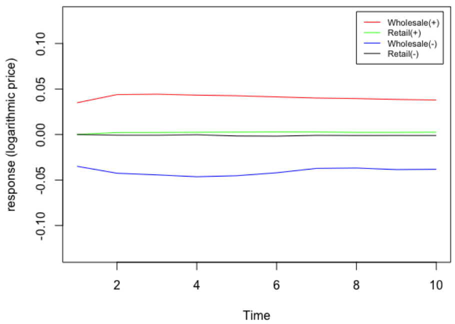


(c) Broilers: Responses to Wholesale Shocks (pre-2008 period)

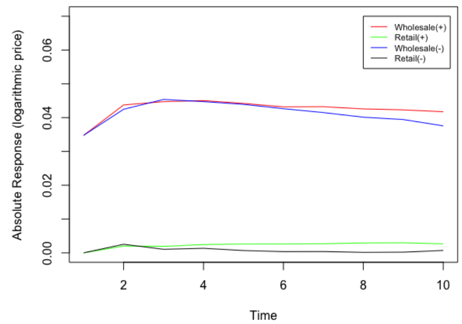


(d) Broilers: Absolute Responses to Wholesale Shocks (pre-2008 period)

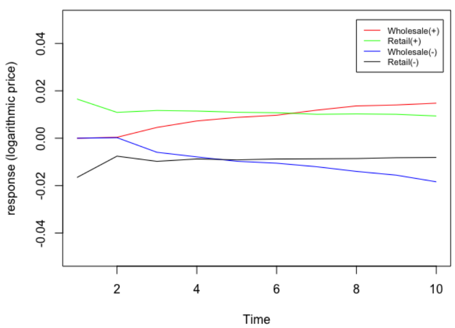
Figure 2.3 Broilers: Pre-2008 Farm-Wholesale GIRF Plots



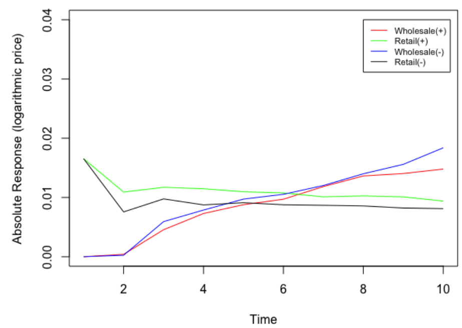
(a) Broilers: Responses to Wholesale Shocks (pre-2008 period)



(b) Broilers: Absolute Responses to Wholesale Shocks (pre-2008 period)

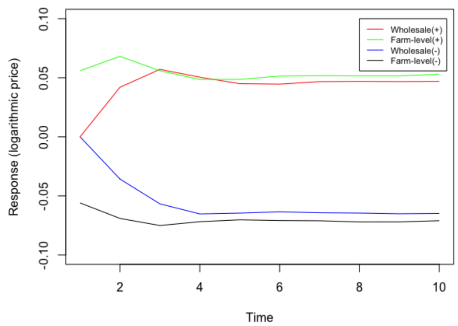


(c) Broilers: Responses to Retail Shocks (pre-2008 period)

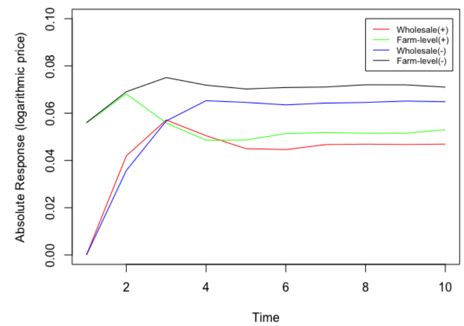


(d) Broilers: Absolute Responses to Retail Shocks (pre-2008 period)

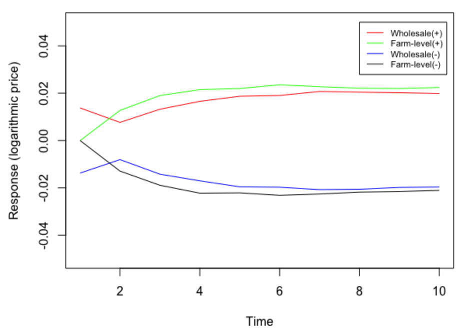
Figure 2.4 Broilers: Pre-2008 Wholesale-Retail GIRF Plots



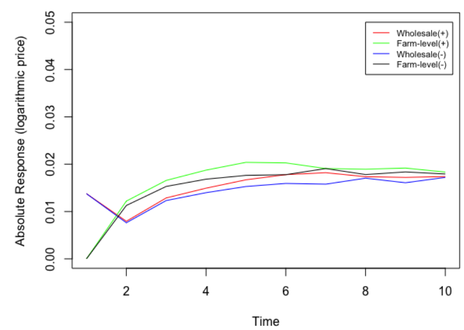
(a) Broilers: Responses to Farm-Level Shocks (post-2008 period)



(b) Broilers: Absolute Responses to Farm-Level Shocks (post-2008 period)

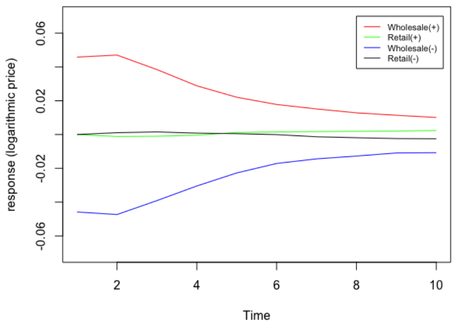


(c) Broilers: Responses to Wholesale Shocks (post-2008 period)

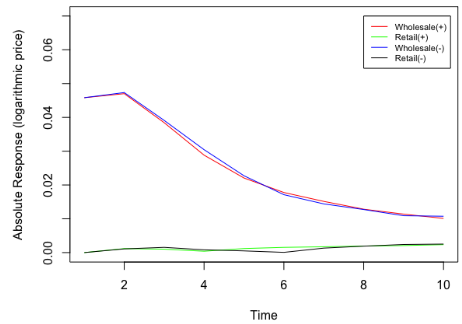


(d) Broilers: Absolute Responses to Wholesale Shocks (post-2008 period)

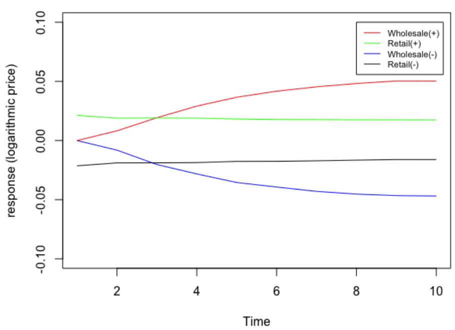
Figure 2.5 Broilers: Post-2008 Farm-Wholesale GIRF Plots



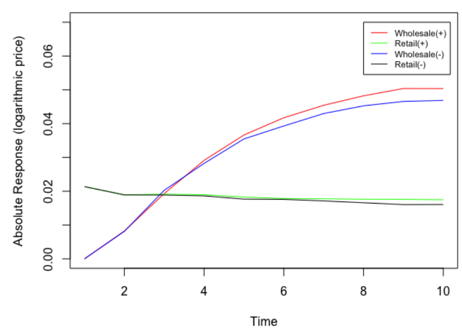
(a) Broilers: Responses to Wholesale Shocks (post-2008 period)



(b) Broilers: Absolute Responses to Wholesale Shocks (post-2008 period)

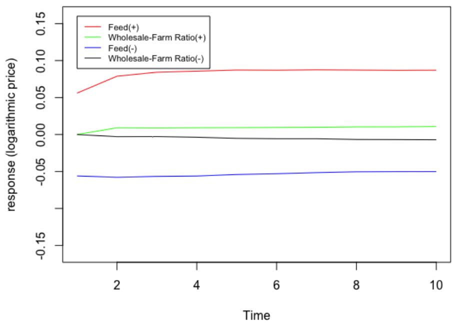


(c) Broilers: Responses to Retail Shocks (post-2008 period)

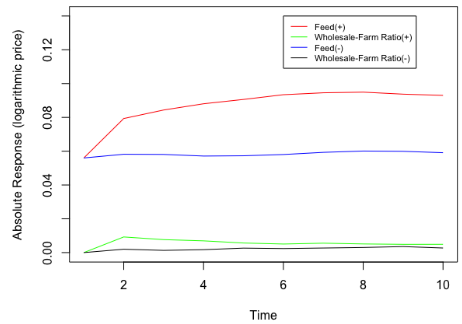


(d) Broilers: Absolute Responses to Retail Shocks (post-2008 period)

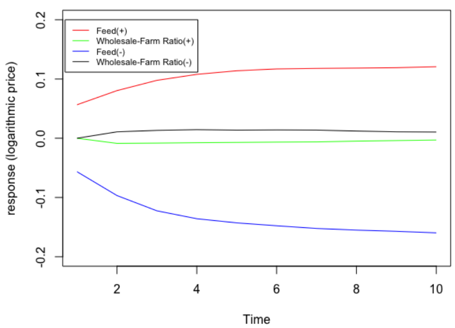
Figure 2.6 Broilers: Post-2008 Wholesale-Retail GIRF Plots



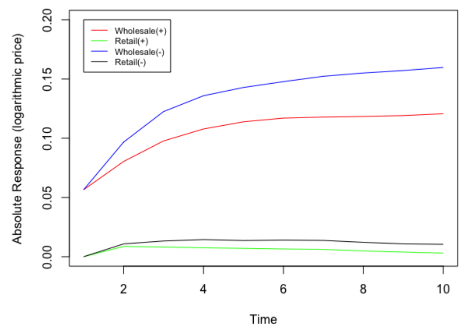
(a) Broilers: Responses to Feed Price Shocks (pre-2008 period)



(b) Broilers: Absolute Responses to Feed Price Shocks (pre-2008 period)

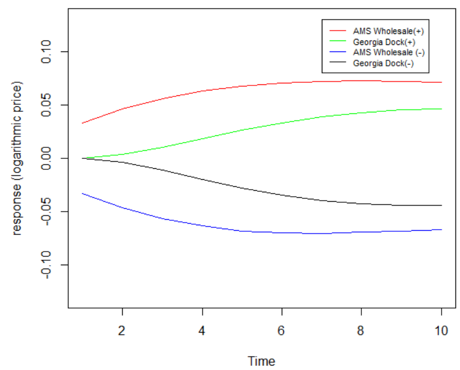


(c) Broilers: Responses to Feed Price Shocks (post-2008 period)

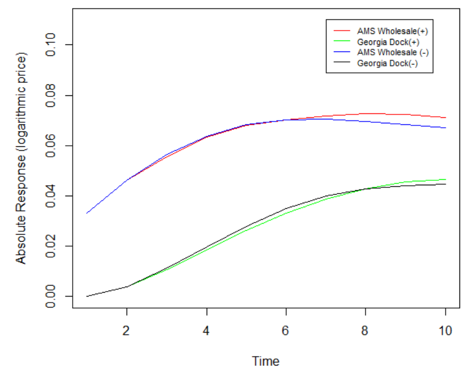


(d) Broilers: Absolute Responses to Feed Price Shocks (pre-2008 period)

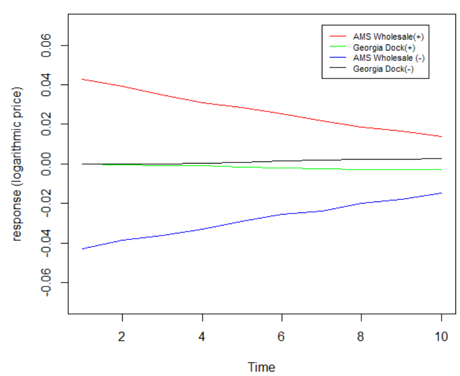
Figure 2.7 Broilers: Impulse Responses to Feed Price Shocks



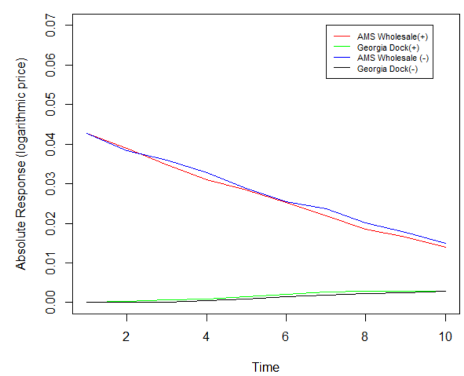
(a) Broilers: Responses to AMS Wholesale Price Shocks (pre-2008 period)



(b) Broilers: Absolute Responses to AMS Wholesale Price (pre-2008 period)

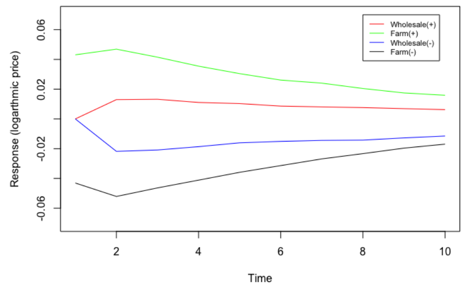


(c) Broilers: Absolute Responses to AMS Wholesale Price (post-2008 period)

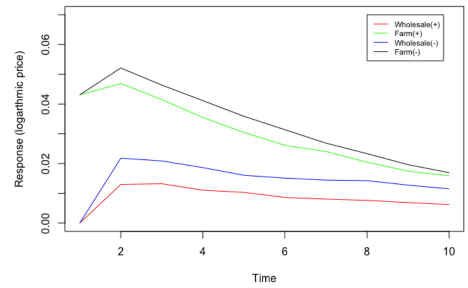


(d) Broilers: Absolute Responses to AMS Wholesale Price (post-2008 period)

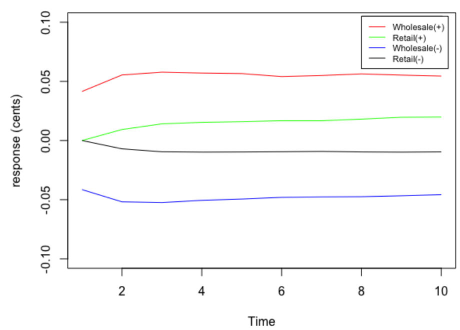
Figure 2.8 Broilers: AMS Wholesale-Georgia Dock Impulse Responses



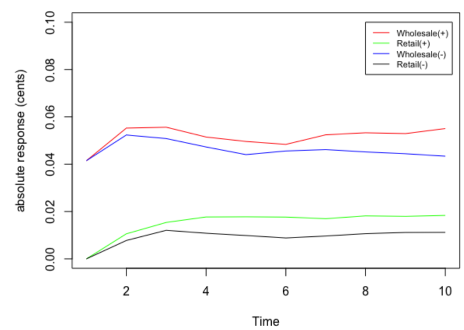
(a) Beef: Wholesale and Farm-Level Responses to Farm-Level Shocks



(b) Beef: Absolute Wholesale and Farm-Level Responses to Farm-Level Shocks

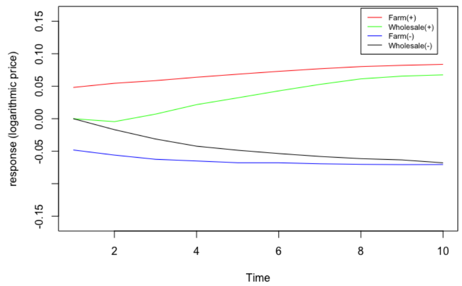


(c) Beef: Retail and Wholesale Responses to Wholesale Shocks

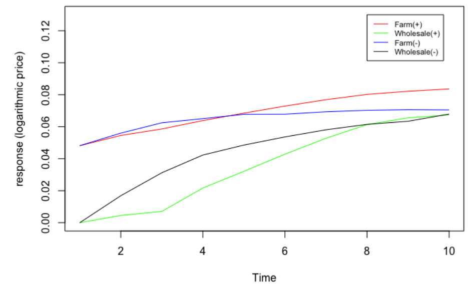


(d) Beef: Absolute Retail and Wholesale Responses to Wholesale Shocks

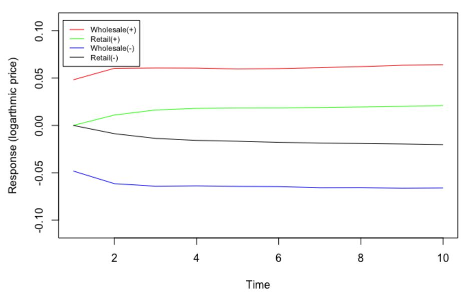
Figure 2.9 Beef: GIRF Plots



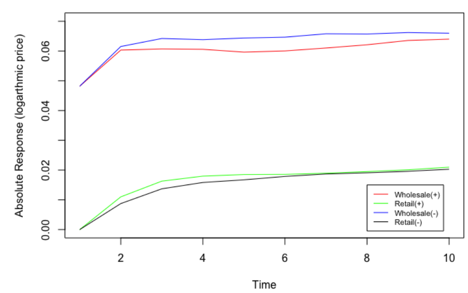
(a) Pork: Wholesale and Farm-Level Responses to Farm-Level Shocks



(b) Pork: Absolute Wholesale and Farm-Level Responses to Farm-Level Shocks



(c) Pork: Retail and Wholesale Responses to Wholesale Shocks



(d) Pork: Absolute Retail and Wholesale Responses to Wholesale Shocks

Figure 2.10 Pork: GIRF Plots

Appendix: Comparative Statics of the Cournot Oligopoly-Oligopsony

To motivate the empirical analysis of the input-output price transmission, we consider a Cournot Oligopoly-Oligopsony. Okuguchi (1998) derives conditions that guarantee an equilibrium for this model. Below we discuss a special case of Okuguchi's model and apply non-parametric techniques to estimate the relationships described by the theoretical model.

In the model, we have n firms that simultaneously choose an output level. Firm i's production function is given by:

$$f^i(x_1^i, x_2^i), i = 1, ..., n,$$

where x_1^i, x_2^i denote input quantities for firm i. Denote f_j^i as firm i's marginal product for input j for $j = 1, 2$ and $f_{jk}^i = \frac{\partial^2 f^i}{\partial x_k^i \partial x_j^i}$. Following Okuguchi (1998), we assume each firm's production function is concave, i.e.

$$f_{11}^i < 0$$

$$f_{11}^i f_{22}^i - (f_{12}^i)^2 > 0$$

$$(f_1^i)^2 f_2 2^i + (f_2^i)^2 f_1 1^i - 2 f_1^i f_2^i f_{12}^i < 0$$

$$\text{for } i = 1, ..., n.$$

The market demand is given by $P(Q)$, where Q denotes the market quantity demanded. Note that under equilibrium,

$$Q = \sum_{i=1}^{n} f^i(x_1^i, x_2^i).$$

Let X_1 and X_2 denote the market quantities . Then $X_1 = \sum_{i=1}^n x_1^i$ and $X_2 = \sum_{i=1}^n x_2^i$. Denote the inverse market supply of input x_j as $w_j(X_j)$, where w_j denotes the price of input j. We assume that firms have market power over input 1 but not over input 2, and that market supply of input 1 is weakly convex. Hence

$$w_1' > 0, w_1'' \geq 0$$

$$w_2' = w_2'' = 0.$$

Further, Okuguchi (1998) assumes that marginal revenue is positive and decreasing in quantities of other firms. That is

$$MR^i \equiv p + f^i(x_1^i, x_2^i)p' > 0$$

$$p' + f^i(x_1^i, x_2^i)p'' < 0$$

$$\text{for } i = 1, ..., n.$$

We can write firm i's profit function as

$$\pi^i(x_1^i, x_2^i; \mathbf{x_1^{-i}}, \mathbf{x_2^{-i}}) = P(\sum_{j=1}^{n} f^j(x_1^j, x_2^j)) f^i(x_1^i, x_2^i) - w_1(\sum_{j=1}^{n} x_1^j) x_1^i - w_2 x_2^i.$$

Taking first order conditions gives

$$\pi_i \frac{\partial \pi^i}{\partial x_1^i} = (P'(Q)f(x_1^i, x_2^i) + P(Q))f_1^i(x_1^i, x_2^i) - w_1'(X_1)x_1^i - w_1(X_1) = 0$$

$$\frac{\partial \pi^i}{\partial x_2^i} = (P'(Q)f(x_1^i, x_2^i) + P(Q))f_2^i(x_1^i, x_2^i) - w_2 = 0.$$

Assuming regularity conditions introduced by Okuguchi (1998) hold, we can rewrite the first order conditions as

$$x_1^i = g^i(X_1, Q; w_2)$$

$$x_2^i = h^i(X_1, Q; w_2).$$

Okuguchi shows that $g_j^i \leq 0$ and $h_j^i \leq 0$ for $j \in \{Q, X_1, X_2\}$ and $i = 1, ..., n$. Summing over firms, we get

$$X_1 = \sum_{i=1}^{n} g^i(X_1, Q; w_2) \equiv g(X_1, Q; w_2)$$

$$X_2 = \sum_{i=1}^{n} h^i(X_1, Q; w_2) \equiv h(X_1, Q; w_2).$$

Using comparative statics on the firm-specific input quantity functions g^i and h^i above, Okuguchi shows that $g_j \leq 0$ and $h_j \leq 0$ for $j \in \{Q, X_1, X_2\}$. Solving the above system for X_1 and X_2, we get

$$X_1 = X_1^*(Q; w_2)$$

$$X_2 = X_2^*(Q; w_2)$$

Okuguchi defines a function $F(Q)$ such that

$$F(Q) \equiv \sum_{i=1}^{n} f^i(g^i(X_1^*(Q; w_2), Q), h^i(X_1^*(Q; w_2), Q)).$$

Okuguchi shows that if $F' < 1$, then Q is solution to the fixed-point problem $Q = F(Q)$. Noting that the solution depends on the exogenous variable w_2, denote the solution for the equilibrium market quantity as $Q^*(w_2)$. The solution for firm-level input quantities is then given by

$$\{g^i(X_1^*(Q^*(w_2)), Q^*(w_2)), h^i(X_1^*(Q^*(w_2)), Q^*(w_2)))\}_{i=1}^{n}.$$

It follows that equilibrium prices P and w_1 are given by

$$P^*(w_2) \equiv P(Q^*(w_2))$$

$$w_1^*(w_2) \equiv w_1(X_1^*(Q^*(w_2))).$$

Define $m_1 = \frac{P^*}{w_1^*} \equiv m_1^*(w_2)$. Without knowing the functional forms of $P(Q)$, $f^i(x_1^i, x_2^i)$, and $w_1(X_1)$, we cannot determine the function form of $P^*(w_2)$, $w_1^*(w_2)$, or $m_1^*(w_2)$. We can, however, use comparative statics to derive important model results. Since w_2 is an exogenous variable, we can differentiate the equilibrium output and input quantities as well as the output and input prices with respect to w_2. These comparative statics are as follows.

$$\frac{dQ^*}{dw_2} = \frac{F'_{w_2}}{1-F'_Q}$$

$$\frac{dP^*}{dw_2} = P'(Q)\frac{F'_{w_2}}{1-F'_Q}$$

$$\frac{dX_1^*}{dw_2} = \frac{\partial X_1^*}{\partial w_2} + \frac{\partial X_1^*}{\partial Q}\frac{dQ}{dw_2}$$

$$\frac{dw_1^*}{dw_2} = w_1'(X_1)(\frac{\partial X_1^*}{\partial w_2} + \frac{\partial X_1^*}{\partial Q}\frac{dQ}{dw_2})$$

$$\frac{dm_1}{dw_2} = \frac{1}{w_1}\frac{dP}{dw_2} - \frac{P}{w_1^2}\frac{dw_1}{dw_2}$$

To analyze the signs of the comparative statics of interest, we assume all firms have identical production functions. Define

$$\pi^j = (P(\sum_{i=1}^{n} f^i(x_1^i, x_2^i))f^j(x_1^i, x_2^i) - w_1(\sum_{i=1}^{n} x_1^i)x_1^j - w_2 x_2^j$$

$$\pi_1' = (P'(nq)q + P(nq))f_1 - w_1'(nx_1)x_1 - w_1(nx_1) = 0$$

$$\pi_2' = (P'(nq)q + P(nq))f_2 - w_2 = 0$$

Define

$$\mathbf{F}(x_1, x_2, w_2, n) = \begin{bmatrix} \pi_1' \\ \pi_2' \end{bmatrix}.$$

Partially differentiate with respect to x_1 to get

$$\mathbf{F}'_{x_1} = \begin{bmatrix} (P''(nq)nq + P'(nq)(n+1))f_1^2 + (P'(nq)q + P(nq))f_{11} - w_1''(nx_1)nx_1 - w_1'(nx_1)(n+1) \\ (P''(nq)nq + P'(nq)(n+1))f_1 f_2 + (P'(nq)q + P(nq))f_{21} \end{bmatrix}$$

and with respect to x_2 to get

$$\mathbf{F}'_{x_2} = \begin{bmatrix} (P''(nq)nq + P'(nq)(n+1))f_1 f_2 + (P'(nq)q + P(nq))f_{12} \\ (P''(nq)nq + P'(nq)(n+1))f_2^2 + (P'(nq)q + P(nq))f_{22} \end{bmatrix}$$

and with respect to w_2 to get

$$\mathbf{F}'_{w_2} = \begin{bmatrix} 0 \\ -1 \end{bmatrix}.$$

Define

$$\mathbf{g}(w_2, n) = \begin{bmatrix} x_1^*(w_2, n) \\ x_2^*(w_2, n) \end{bmatrix}.$$

It follows from the implicit function theorem that

$$\frac{\partial \mathbf{g}(w_2, n)}{\partial w_2} = -\begin{bmatrix} \mathbf{F}'_{x_1} & \mathbf{F}'_{x_2} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{F}'_{w_2} \end{bmatrix} = \begin{bmatrix} \mathbf{F}'_{x_1} & \mathbf{F}'_{x_2} \end{bmatrix}^{-1} \begin{bmatrix} 0 \\ -1 \end{bmatrix}.$$

Denoting positive, negative, and indeterminate signs as $(+), (-)$, and $(?)$, respectively, it follows the signs in the above expression can be written as

$$\frac{1}{(+)-(+)} \begin{bmatrix} (-) & (?) \\ (?) & (-) \end{bmatrix} \begin{bmatrix} 0 \\ -1 \end{bmatrix} = \begin{bmatrix} (?) \\ (?) \end{bmatrix}.$$

Thus, our comparative statics of interest have indeterminate sign. Therefore, our question of interest, i.e. how the broiler wholesale to farm-level price ratio responds to changes in the price of broiler feed is a purely empirical question. We assume that the normality conditions provided by Okuguchi (1998) for the existence of an equilibrium are satisfied and construct hypothesis tests and impulse response functions to address the question of how these price dynamics are different in the pre-2008 and post-2008 period.

CHAPTER 3

Spatial Price Transmission and the Extent of the Market: Price Behavior in the United States Broiler Chicken Market

3.1 Introduction

A vast body of literature has studied integration between distinct geographic markets and the Law of One Price (LOP). Early studies of the LOP, namely Isard (1977), Richardson (1978), Thursby, Johnson, and Grennes (1986), Benninga and Protopapadakis (1988), and Giovanni (1988), find evidence contrary to economic theory. However, using a rational expectations framework, Goodwin, Grennes and Wohlgenant (1990) find evidence supporting the LOP. Further, several studies employ cointegration techniques proposed by Engel and Granger (1987) and find evidence of economic theory (e.g. Buongiorno and Uusivouri 1992; Michael, Nobay, and Peele 1994; Bessler and Fuller 1993; Jung and Doroodian 1994).

Recent studies use more sophisticated regime switching models with the aim of reflecting a transaction cost band outside which there is opportunity for profitable arbitrage (Fackler and Goodwin, 2001). In particular, the autoregressive and error correction regime-switching methods used to investigate the LOP have included discrete threshold models (Balcombe, Bailey and Brooks 2007), smooth-transition threshold models (Goodwin and Piggott 2001), and time-varying smooth-transition models (Goodwin, Holt, and Prestemon 2013). Many of these studies allowing for non-linear price adjustment between regions find evidence of asymmetric threshold effects, where large shocks lead to rapid equilibration and smaller shocks exhibit little to no price response (Goodwin and Holt, 2015). Guney, Goodwin, and Riquelme (2018) use semi-parametric generalized additive vector autogressive models to examine spatial basis dynamics and find evidence of efficiently linked markets.

Efficiently linked markets are often thought to be a signal of competitive behavior. Early studies examined spatial price transmission as a mechanism for defining the extent of the market by using output and transport cost data to measure inefficiencies (see Bressler and King 1970). Others have considered price-based methods as an alternative tool for defining markets for regulatory purposes, including correlation analysis (Stigler and Sherwin 1988), Granger causality and cointegration (Lo and Zivot 2001). Further, tests traditionally used to examine spatial market linkages have been used to test market power and non-competitive pricing (e.g. Faminow and Benson 1990).

Many investigations of the law of one price have been been applied to agricultural commodities. Some of these studies include, for example, international wheat markets (Goodwin and Schroeder 1992; Goodwin 1992; Goodwin and Grennes 1998), corn and soybean (Goodwin and Piggott 2001), US cattle (Koontz, Garcia,and Hudson 1990) and US pork and chicken markets (Goodwin and Vavra 2009). Though researchers have studied spatial price dynamics in US broiler markets (e.g. Awokuse and Bernard 2007; Chavas 1999), recent price-fixing allegations motivate a novel extension to the existing body of work. Our paper examines the impact of an alleged price-fixing conspiracy on spatial price transmission in the United States broiler Industry. On September 2, 2016, Maplevale Farms, Inc., a food distributor and plaintiff, filed a class-action complaint on behalf of end-buyer consumers against several other dominant firms in the Broiler chicken industry. According to the allegations, the Defendants illegally shared detailed records with the assistance of a third-party conspirator and defendent in the case, Agri Stats, in an attempt to restrict output and increase prices beginning as early as 2008 (Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016).

The United States Broiler industry has experienced an increase in market concentration and vertical integration over the past several decades. While the total number of processing and slaughter plants owned by the largest 15 firms increased only modestly from 124 in 1997 to 127 in 2013, total output of ready-to-cook (RTC) chicken meat increased approximately 38.5% during this period (Vukina and Zheng 2015). Further, the four-firm and eight-firm concentration ratios increased from 40.9% to 57.9% and from 51.3% to 79.3%, respectively. As a result of high startup costs and economies of scale, significant barriers to entry are sometimes alleged to characterize the United States Broiler industry (see, for example, Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016).

According to the Plaintiffs, prior to 2008, the US Broiler industry was characterized by a boom-and-bust cycle. According to allegations, this pattern was halted when collusion began in 2007 between Tyson and Pilgrim and quickly extended to include several more of the dominant broiler processing firms. When non-cooperative firms began increasing production in 2010, the plaintiffs allege that the Defendants engaged in a second round of production cuts characterized by a substantial destruction of breeder flocks (Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016).

The Defendants account for over 90% of the United States wholesale broiler market and record approximately $30 billion in sales annually. According to allegations, as a result of the collusion by the Defendants, prices have risen 50% since 2008, while the cost of most influential inputs, namely corn and soybeans, has fallen approximately 20% over the same period (Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016). The plaintiffs also allege defendants manipulated the Georgia Dock chicken price index, to which the majority of broiler sales are tied (Morris, 2017, August 10), and earned record profits during this period (Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016). Accordingly, the plaintiffs allege that as a result of exercised market power by major poultry processors, prices paid were higher than those determined by competition (Kroh, 2016, September 2). Given the limited number of poultry processors, market power would be categorized by oligopoly in spot markets and oligopsony in contract markets. Additional class action complaints against poultry processors were filed by indirect purchasers including Fargo Stopping Center LLC, though the cases were eventually combined (Meisel, 2016, December 15).

Processors filed a motion to dismiss the suit in January following a second amended complaint in November of 2016, which is still pending. On August 7, 2017, however, direct purchasers reached a $2.25 settlement deal with Fieldale Farms Corp. This deal was the first reached out of the 13 poultry processers involved in class action cases, but terms of the settlement may lead to more settlements from other processors. In particular, Fieldale Farms Corp. has agreed to provide phone records and financial support along with deposition from five employees (Rhodes, 2017, August 7).

A series of other suits stem from the Maplevale farms case. Specifically, Tyson Foods Inc., the alleged 'ringleader' in the price-fixing consipiracy (Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016) has become involved in litigation beyond the Maplevale Farms case. In particular Tyson Foods Inc. received a subpoena from the U.S. Securites and Exchange Commission (SEC) relating to the allegations filed by food distributors and indirect producers in February of 2017 (Newsham, 2017, February 6). It was not until August 217, however that the SEC closed its investigation. Further, an antitrust suit was filed by Chicken Kitchen USA LLC against Tyson Foods Inc. et al. in April of 2017 alleging the poultry processor engaged in price-fixing behavior that prevented restaurants' ability to pay competitive prices for poultry (Hanson, 2017, April 24). The nature of these allegations is very similar to those in the Maplevale Farms case. Further, investor class actions were filed alleging Tyson Foods Inc. fixed prices, artificially raising prices and goosing profits, and lied to investors about the source of the profit increases. This case was dismissed in July of 2017 due to insufficient allegations of price-fixing (Kroh, 2017, July 27).

In our analysis, we investigate potential differences in spatial price behavior before and after the alleged start date of price fixing. The chicken price data are weekly time series obtained from the Agricultural Marketing Service. These price data correspond to East, Central, and West areas of the United States over the period of January 1995 to May 2017. Analysis was conducted on logarithmic transformations of the time series. To determine whether each pair of regions is characterized by the Law-of-One-Price (LOP), we conduct pairwise Johansen tests and unit root tests of price differentials. Further, Johansen tests over all series suggest the presence of a long-run equilibrium.

Augmented Dickey-Fuller Tests of price differentials suggest stationarity for all price-pairs except Northeast-West. Non-stationarity is an unsurprising result for the market-pair having the greatest transportation costs. To examine the presence of thresholds in price equilibration, we employ non-linearity tests to both the cointegration OLS regression errors and the price differentials.

We include a nonparametric drift component as well as thresholds in an attempt to measure the potential for evidentiary price fixing behavior. We also present dynamic impulse responses and use the timing of shocks and resulting price adjustments to shed light on the allegations of price fixing and noncompetitive pricing behavior. The size of threshold parameters indicate a significant potential for isolated market behavior but may also represent differentials in production costs and transaction charges. Important differences in long-run behavior are revealed through the application of Qu and Perron (2007) multivariate structural break tests. These changes are compared to market developments and implications for the alleged price fixing behavior are offered.

The layout of this paper is as follows. In the next section, we develop the theoretical motivation and predictions for our empirical work. The third section discusses the econometric techniques used in our analysis. The fourth section applies these methods to weekly average data for wholesale prices of fresh, whole, poultry in four regions of the United States. The final section elaborates on our findings and discusses related policy implications.

3.2 Economic Theory

The law-of-one price is taken to be nearly axiomatic in the discipline of economics. If a price differential creates an opportunity for profitable arbitrage between two geographically distinct regions, the theory suggests firms will increase supply accordingly until the arbitrage gap is dissolved. This result is derived from the assumption of competitive markets. In the event of market power, the law-of-one price should not hold.

For example, suppose a monopolist has market power in n geographically distinct markets, in which consumers do not have the resources to engage in arbitrage with other markets. Marginal costs of selling to different regions will vary due to differences in transaction (transport) costs. Let $Q_i, P_i(Q_i), t_i(Q_i)$ respectively denote the quantity sold, inverse demand, and total transportation costs of selling to region i. Also let $C(\sum_{j=1}^{n} Q_j)$ denote the total cost function of producing before any output is shipped. The profit maximization problem is then:

$$\max_{Q_i} \sum_{i=1}^{n} (P_i(Q_i)Q_i - t_i(Q_i)) - C(\sum_{j=1}^{n} Q_j) \tag{3.1}$$

The monopolist first-order conditions require that

$$P_i'(Q_i)Q_i + P_i(Q_i) = C'(\sum_{j=1}^{n} Q_j) + t_i'(Q_i), \tag{3.2}$$

for

$$i = 1, ..., n$$

where $P_i'(Q_i)Q_i + P_i(Q_i)$ is marginal revenue of selling to region i. Taking this a step further, suppose without loss of generality that the monopolist is located in region 1 so that transportation cost to region 1, $t_1(Q_1)$ is zero for any Q_1. We can solve each of the n first order conditions for $C'(\sum_{i=j}^{n} Q_j)$ and identify a relationship between prices in two regions. It follows

$$(P_i'(Q_i)Q_i + P_i(Q_i)) - (P_1'(Q_1)Q_1 + P_1(Q_1)) = t_i'(Q_i) \tag{3.3}$$

or equivalently,

$$P_i(Q_i) - P_1(Q_1) = t_i'(Q_i) + P_i'(Q_i)Q_i - P_1'(Q_1)Q_1,$$

for

$$i = 2, ..., n.$$

This model implication is intuitively appealing. Of course, within each region, the monopolist produces where marginal revenue equals marginal cost. Since the marginal costs only differ by the marginal transportation costs, so should the marginal revenues. Thus, the economic theory suggests that rather than prices differing by transport costs, as suggested by the LOP in competitive markets, a monopolist produces such that the marginal revenues differ by the transportation costs. This implies that the profit-maximizing price differential may be greater than or less than the transport costs and that demand shocks may be permanent.

This notion of permanent demand shocks that is implied by the theory is consistent with the allegations that boom-and-bust price patterns were halted after the alleged price-fixing start date. In oligopolistic markets, profit maximization under collusion is characterized by market behavior of a monopolist. This model serves to demonstrate why the law-of-one price will not hold when market power is exercised and is easily extended to the dominant firm model by letting $P_i(Q_i)$ represent residual demand after accounting for the competitive supply fringe. Given the theoretical predictions, we expect to find that shocks are temporary before and permanent after the alleged start date of price-fixing.

3.3 Econometric Methods

We begin by investigating cointegration relationships. For such relationships to exist, each price series must be integrated of order one, $I(1)$. Thus, our analysis begins by evaluating the time series properties of the data by testing the natural logarithm of each price series in levels and first-differences for unit-root nonstationarity using Augmented dickey fuller tests. In the seminal paper by Dickey and Fuller (1979), a test is proposed of an ARIMA$(p, 0, 0)$. Subsequently, Dickey and Said (1981) discuss techniques for testing that $d = 1$ when p and q are known. Said and Dickey (1984) propose a method for testing the null hypothesis that $d = 1$ using an autoregressive approximation of an autoregressive moving average model where the number of lags p and q of the ARIMA$(p, 1, q)$ are unknown. We then apply the test to price differentials, where the presence of a unit root is indicative of a lack of pairwise cointegration and hence a lack of support for market integration.

We use Ordinary Least Squares (OLS) to estimate the cointegration relationships between all market pairs, which take the following form

$$p_t^i = \alpha + \beta p_t^j. \tag{3.4}$$

If the both price series are stationary, employing a Likelihood Ratio (LR) test that $\alpha = 0$ and $\beta = 1$ is a test of market linkages. It should be noted that if the series are nonstationary, conventional testing methods lead to poor inference (Goodwin and Piggott 2001).

Next we follow Johansen's seminal work (1988; 1991) proposing maximal eigenvalue and trace tests for cointegration. In the context of spatial market linkages, an economic equilibrium can be represented by a cointegrated $(k\text{x}1)$ vector of time series if there exists constants $(\beta_2, ..., \beta_k)$ such that

$$p_{1,t} - \beta_2 p_{2,t} - \beta_3 y_{3,t} - \cdots - \beta_k p_{k,t} = v_t \tag{3.5}$$

$$v_t = \rho v_{t-1} + \epsilon_t, \tag{3.6}$$

where p_{it} is $I(1)$ for all $i = 1, ..., k$ and v_t is a stationary time series. Tests indicative of pairwise cointegration relationships are said to support for the LOP between the respective regions. Additionally, Johananansen tests over all series are a test for a long-run market equilibrium. Balke and Fomby (1997) have shown that conventional cointegration tests perform reasonably well when the true model includes one or more thresholds.

We test for the presence of thresholds in the behavior of price differentials following the work of Tsay (1989). Tsay's non-parametric test for non-linearity uses recursive residuals from an arranged autoregression. Once the presence of thresholds has been identified, we estimate a regime-switching model. Our specification includes two thresholds and thus three regimes, allowing for the possibility of asymmetric adjustment to equilibrium. Additionally, we employ Hansen's (1997) modified Chow test to test for differences in parameter estimates across different regimes. The SETAR model can be expressed as:

$$y_t = \begin{cases} c^{(1)} + \phi^{(1)} y_{t-1} + \epsilon_t & \text{if } y_{t-1} \le c_1 \\ c^{(2)} + \phi^{(2)} y_{t-1} + \epsilon_t & \text{if } c_1 \le y_{t-1} \le c_2 \\ c^{(3)} + \phi^{(3)} y_{t-1} + \epsilon_t & \text{if } c_2 \le y_{t-1}, \end{cases} \tag{3.7}$$

where $y_t = p_t^i - p_t^j$, i.e. the price differential between regions i and j.

For cointegrated time series, a threshold vector autoregression (TVAR) inconsistently estimates the model parameters. To cope with this issue, an error correction term must be included in the TVAR, meaning the cointegrating relationship must be included as a regressor. This model is known as a threshold vector error correction model (TVEC) and can be expressed as follows:

$$\Delta \mathbf{p}_t = \begin{cases} \mu^{(\mathbf{1})} + \mathbf{M}^{(1)} v_{t-1} + \sum_{i=1}^{P} \backprime_i^{(1)} \Delta \mathbf{p}_{t-i} + \epsilon_{\mathbf{t}} & \text{if } v_{t-1} \leq c_1 \\ \mu^{(\mathbf{2})} + \mathbf{M}^{(2)} v_{t-1} + \sum_{i=1}^{P} \backprime_i^{(2)} \Delta \mathbf{p}_{t-i} + \epsilon_{\mathbf{t}} & \text{if } c_1 < v_{t-1} < c_2 \\ \mu^{(\mathbf{3})} + \mathbf{M}^{(3)} v_{t-1} + \sum_{i=1}^{P} \backprime_i^{(3)} \Delta \mathbf{p}_{t-i} + \epsilon_{\mathbf{t}} & \text{if } c_2 \leq v_{t-1}, \end{cases} \tag{3.8}$$

where $\mathbf{p}_t$ is a two-tuple of logarithmic prices, v_t is the cointegrating vector, and $[c_1, c_2]$ represents the transaction cost band outside which there opportunity for profitable arbitrage. A large magnitude of the estimated threshold parameters is indicative of potential for isolated market behavior, i.e. pricing behavior within the transaction cost band. Alternatively, large threshold parameters can indicate different production and transaction costs in different locations.

We modify the TVEC specification by replacing the OLS residual error correction term with the residual from a bivariate nonparametric kernel regression. As outlined by Wang and Phillips (2009), this data-driven approach to cointegration analysis allows for additional flexibility in our specification.

A nonparametric kernel regression takes the form

$$p_{i,t} = f(p_{j,t}) + v_t.$$

The residuals used for the error correction term are the difference between the dependent variable and the fitted value:

$$\hat{v}_t = p_{i,t} - \hat{f}(p_{j,t})$$

where

$$\hat{f}(p_{j,0}) = \frac{\sum_{t=1}^{T} p_{i,t} K(\frac{p_{j,0} - p_{j,t}}{h})}{\sum_{t=1}^{T} K(\frac{p_{j,0} - p_{j,t}}{h})}.$$

The function $K(\cdot)$ is a kernel function and h is the bandwidth. We estimate bivariate Gaussian kernel regressions, which have kernel function given by

$$K(u) = \frac{1}{\sqrt{2\pi}} e^{\{\frac{-u^2}{2}\}}.$$

The bandwidth value is set to be the rule-of-thumb value of $h = 1.06 * std(p_2) T^{-1/5}$.

Next we construct generalized impulse response functions (GIRF) to better understand the equilibration process. GIRF's are applied to bivariate TVEC models. In particular, we investigate how quickly prices converge (if at all) to a shock in a given region. The GIRF's are used to consider the timing of shocks and resulting price adjustments to shed light on the allegations of price fixing and noncompetitive behavior. Generalized impulse response functions are designed to be applied to linear and nonlinear time series models alike. A GIRF is defined as the expected change in the dependent variable vector $j = 1, 2, ..., n$ periods in the future conditional on a present shock and a history. A history is the information set at time $t-1$, denoted $\mathbf{I}_{t-1}$. The number of histories is simply the difference between the number of observations, T, and the number of lags in the model. In our analysis we chose to examine responses $n = 10$ periods (weeks) into the future. Mathematically, a GIRF can be expressed as

$$GIRF(\mathbf{I}_{t-1}, \mathbf{y}_t, v_{i,t}) = E[\mathbf{y}_{t+j}|\mathbf{I}_{t-1}, \mathbf{y}_t, v_{i,t}] - E[\mathbf{y}_{t+j}|\mathbf{I}_{t-1}, \mathbf{y}_t], \tag{3.9}$$

for $j = 1, 2, ..., n$. These conditional expectations must be estimated using simulations. Each simulation consists of five steps:

1. Choose a shock of interest, $v_{i,t}$, upon which to condition.
2. Choose a history, I_{t-1}, upon which to condition[1].
3. Draw shocks $n = 10$ periods into the future and contemporaneous shocks, $v_{j,t}$, $j \neq i$, assuming multivariate normal distribution of errors. The distribution parameters are estimated from the residuals.
4. Calculate a path conditional on $v_{i,t}$ and a path not conditional on $v_{i,t}$: $[\mathbf{y}_{t+j}|\mathbf{I}_{t-1}, \mathbf{y}_t, v_{i,t}]$ and $[\mathbf{y}_{t+j}|\mathbf{I}_{t-1}, \mathbf{y}_t]$ for $j = 1, 2, ..., n$.
5. Repeat steps 3 and 4 for $B = 1000$ times and average across these 1000 iterations to estimate $E[\mathbf{y}_{t+j}|\mathbf{I}_{t-1}, \mathbf{y}_t, v_{i,t}]$, $E[\mathbf{y}_{t+j}|\mathbf{I}_{t-1}, \mathbf{y}_t]$, and hence $GIRF(\mathbf{I}_{t-1}, \mathbf{y}_t, v_{i,t})$ for the chosen history, $\mathbf{I}_{t-1}$.

We estimate TVEC models and GIRF's each of the three price pairs before and after 2008 (the alleged start date of price fixing) and compare results in the two time periods to investigate the price-fixing allegations.

Lastly, we conduct multivariate structural break tests following the work of Qu and Perron (2007). The proposed tests can be applied when the exact date of the structural break is unknown. The estimation algorithm is composed of following steps. First, an approximate Quasi-Maximum Likeli-

[1] The selected histories in the pre-2008 and post-2008 periods are January 13, 2004 and November 4, 2012, respectively.

hood Estimation (QMLE) analogue of Feasible Generalized Least Squares (FGLS) is estimated. Next, a recursive residuals approach is used to construct log-likelihood values for each segment of the time series, which yields a triangular matrix of log-likelihood values. Finally, the optimal break dates, i.e. the partition maximizing the sum of log-likelihood values, are selected using a dynamic programming algorithm. Under this procedure, LR tests are used to determine the number of structural changes. Critical values for the test statistics are obtained using simulations. In particular, we test for changes in the regression coefficients and covariance matrices at unknown break dates, allowing for one through five breaks.The changes proposed by the structural break tests are compared with market developments and implications for the alleged price-fixing behavior are offered. Structural changes are anticipated at the start date of the alleged broiler chicken price-fixing.

3.4 Empirical Application

Our analysis is applied to weekly wholesale prices for whole, fresh broiler chicken in four distinct regions of the US. The price data were obtained from the Agricultural Marketing Service (AMS) and correspond to the East, Central, and West regions of the United States during the period of March 2000 to December 2012. Analysis is based on logarithmic transformations of the price data. Plots of these data and the first differences is presented in Figure 3.1.

We begin by evaluating the time series properties of the price data using unit-root tests. In order to perform cointegration analysis, it is necessary that each price series be $I(1)$. We test each series for stationarity (nonstationarity) with KPSS (Augmented Dickey Fuller (ADF)) tests. All hypothesis tests indicate the presence of a single unit root in each price series when a trend is not included. However, figure indicates the data are trending upward, suggesting a deterministic trend may be present. Implementing these tests again with a deterministic trend included yields mixed results. In particular, KPSS tests (Table 3.2) indicates unit-root nonstationarity for each series while ADF tests (Table 3.1) indicate no unit roots when a deterministic trend is included. Performing ADF tests of first-differences of each series suggests that the first differences are stationary series. For the remainder of the analysis, we treat each price series as $I(1)$.[2] Awokuse and Bernard (2007) examine spatial price dynamics of the US broiler chicken industry using a sample of BLS broiler chicken price data from June 1991 to May 2002 and find each regional price series is $I(1)$.

[2]Prices are typically presumed to follow a random walk. This distinction determines whether an autoregression model or error-correction model is appropriate. Using the former when the latter is appropriate causes bias, while the reverse causes inefficiency. We err on the side of caution and proceed as if each series is $I(1)$.

The parameter estimates of the cointegrating relationships, $p_{i,t} = \alpha + \beta p_{j,t}$, between all market pairs before 2008 and after 2008 are presented in Table 3.3. Estimates of the intercept and slope terms are all very close to zero and one, respectively. Conventional hypothesis tests are inappropriate given the nonstationarity of the price series. The value of the R^2 is notably lower for each price pair in the post-2008 period relative to the pre-2008 period.[3] This result indicates a greater degree of market integration prior to the alleged start date of price-fixing .

We utilize a series of cointegration tests for all price pairs in the pre-2008 and post-2008 period. Multivariate Johansen tests indicate the presence of 2 cointegrating relationships both in the pre-2008 period (Table 3.4) and the post-2008 period (Table 3.5) . All pairwise market integration tests (Table 3.6) provide evidence of market integration between all price pairs in the pre-2008 period and the post-2008 period. The structural Qu and Perron break tests are displayed in Table 3.8 We allow for a maximum of four unknown break dates. The tests suggest that for each price pair, four break dates are appropriate. None of the price pairs revealed a structural break in 2008.

Figures 1.2 and 1.3 display the gaussian kernel regressions for all three price pairs in the pre-2008 period and post-2008 period, respectively. For all six of the regressions, the relationship appears to be very close to linear. The plots display the 45-degree line for comparison purposes. All plots except the post-2008 East-Central plot exhibit a price transmission elasticity (slope of the kernel plot) less than 1. We save the residuals from these six kernel regressions to use as error-correction terms in the TVEC models. Table 3.9 displays the nonlinearity tests and threshold values for the two-threshold TVEC models for all price pairs in the pre-2008 period and the post-2008 period. From the table, one can see that there is minor differences in the neutral bands in the pre-2008 and post-2008 periods.

Lastly, we construct GIRF's for all price pairs in the pre-2008 period and the post-2008 period to better understand potential differences in price dynamics before and after the alleged start date of price-fixing. While traditional impulse response functions are linear and thus independent of the timing of the shock, this is no longer the case with threshold models such as TVEC. In particular, with TVEC models, the impulse response will differ for different histories, as the responses are regime-dependent. To mitigate this issue, we adopt a more flexible approach based on averaging of simulated price paths that are empirical analogs of the true expected responses. We impose one half standard deviation positive and negative shocks to construct the GIRF's. The selected histories in the pre-2008 and post-2008 periods are January 13, 2004 and November 4, 2012.[4]

[3]The pre-2008 period is March 2000-December 2007 and the post-2008 period is January 2009-December 2012. We omit all weeks in 2008 to eliminate any gray area about the exact start date of the alleged price-fixing.

[4]This selection allowed for approximately equal distance from 2008 for each period.

From examining the GIRF plots, a few conclusions are noteworthy. First, the sign of the shock matters. Most of the GIRF's exhibit asymmetric responses for an equal-sized positive and negative shock. This finding further reinforces the notion of nonlinear adjustment that is present in the price dynamics. Such evidence of nonlinear adjustments supports the chosen threshold methodology

Second, the random walk nature of the prices is evident in the lack of convergence to zero exhibited by the own price shocks in the GIRF's. In a random walk process, price shocks do not dissipate as is the case with stationary price series. Instead, the marginal effect of an own price shock k periods ago is equal to unity.

Third, for many of the price pairs, there is a notable difference in the pre-2008 and post-2008 periods for responses to other price shocks. In particular, East to Central, West to East, East to West, and West to Central exhibit very different patterns of adjustment in the two periods. How much of this difference is due to inter-temporal regime change (e.g. due to price-fixing) vs. the selected history is difficult to disentangle.

In summary, none of the analysis results point to evidence of the price-fixing allegations. In the structural break analysis, we took an agnostic approach and tested for up to four unknown break dates. None of these break dates were consistent with the alleged start date of price-fixing. Further, there is evidence of market integration in the pre-2008 and post-2008 period, indicating no substantial changes in the level of market power being exercised before and after the alleged start date of price-fixing.

3.5 Conclusion

In this paper, we study the spatial price dynamics in the US broiler chicken industry. Though researchers have already studied spatial price dynamics in US broiler markets (e.g. Awokuse and Bernard 2007; Chavas 1999), recent price-fixing allegations motivate a novel extension to the existing body of work. Our paper examines the impact of an alleged price-fixing conspiracy on spatial price transmission in the United States broiler Industry. On September 2, 2016, Maplevale Farms, Inc., a food distributor and plaintiff, filed a class-action complaint on behalf of end-buyer consumers against several other dominant firms in the Broiler chicken industry. According to the allegations, the Defendants illegally shared detailed records with the assistance of a third-party conspirator and defendent in the case, Agri Stats, in an attempt to restrict output and increase prices beginning as early as 2008 (Maplevale Farms, Inc. v. Koch Foods, Inc. et al., 2016).

Using three weekly regional price series (East, Central, and West wholesale prices) from the agricultural marketing service, we explore market integration before and after the alleged start date of price-fixing to shed light on these allegations. Our analysis indicates the presence of market integration before and after the alleged start date of price-fixing. Qu and Perron structural break tests indicate the presence of four structural breaks in our dataset for all price pairs, though none of the estimated breaks are near the alleged start date of price-fixing. Finally, impulse response analysis reveals the presence of substantial nonlinearities in the price dynamics, favoring nonlinear modeling approaches adopted in this paper over linear time series methods that are often used (e.g. VAR, VEC). Overall, the results do not point to any clear evidence supporting the price-fixing allegations.

To square this result with those from the second essay, we consider the difference in expectations of the vertical price dynamics and the spatial price dynamics. For spatial price dynamics, the expectations are very clear regarding market integration: geographically distinct competitive markets will exhibit a spatial price long run equilibrium. For vertical price dynamics, the expectations are less clear. Many factors can can cause asymmetric price transmission and structural change, so to attribute structural change or asymmetric price transmission to price-fixing is more difficult. One result appears to strongly support the allegations, however, is this the structural break in the Georgia Dock-AMS wholesale price index.

We propose two extensions to this work. First, the analysis could be repeated for monthly retail prices obtained from the Bureau of Labor Statistics (BLS). Whether these price data support the price-fixing allegations is an interesting question. Second, using the BLS data in conjunction with the ERS wholesale data in this paper, one could model the spatial price dynamics at two levels of the supply chain simultaneously. From a more sophisticated hybrid model of spatial and vertical price transmission, further analysis could be done to answer questions that are unable to be answered using only wholesale price data. For such a model with mixed frequency data, a mixed data sampling (MIDAS) approach is appropriate, as proposed by Ghysels et al. (2007). It has been shown that the MIDAS framework outperforms equal-weight aggregration to deal with mixed frequency data. Such an analysis is beyond the scope of this paper.

Tables[5] and Figures

[5] * denotes statistical significance at the 10% level.

Table 3.1 Augmented Dickey-Fuller Tests for Non-stationarity

Location	Level without trend	Level with trend	First Difference
East	-2.167	-4.088*	-14.436*
Central	-2.572	-4.070*	-15.521*
West	-1.926	-4.503*	-14.327*

Table 3.2 KPSS Tests for Stationarity

Location	Level without trend	Level with trend	First Difference
East	6.7894*	0.149*	0.0242
Central	5.1304*	0.1923*	0.0312
West	6.787*	0.1851*	0.034

Table 3.3 Estimation of Cointegrating Relationships

Market Pair	α	β	R^2
East-Central (pre-2008)	-0.2198	1.0565	0.9372
	(0.0562)	(0.0136)	
East-West (pre-2008)	-0.5071	1.1111	0.9152
	(0.0705)	(0.0168)	
Central-West (pre-2008)	0.1478	1.0221	0.9223
	(0.0619)	(0.0148)	
East-Central (post-2008)	1.1584	0.7541	0.8443
	(0.0968)	(0.0224)	
East-West (post-2008)	0.844	0.9466	0.8273
	(0.1325)	(0.0210)	
Central-West (post-2008)	-1.0532	1.2129	0.9145
	(0.1137)	(0.0257)	

Table 3.4 Johansen Multivariate Cointegration Tests (Pre-2008)

Hypothesis	Trace Test	Max. Eigenvalue Test
$r \leq 2$	5.10	5.10
$r \leq 1$	29.39*	34.50*
$r = 0$	50.05*	84.54*

Table 3.5 Johansen Multivariate Cointegration Tests (Post-2008)

Hypothesis	Trace Test	Max. Eigenvalue Test
$r \leq 2$	5.93	5.93
$r \leq 1$	20.35*	26.28*
$r = 0$	31.31*	57.59*

Table 3.6 Tests for Pairwise Market Integration

Market Pair	Cointegration Test	Test Statistic
East-Central (pre-2008)	LR Test of $\alpha = 0, \beta = 1$	72.118*
	max eigenvalue test $r = 0$	29.02*
	trace test $r = 0$	34.62*
	max eigenvalue and trace test $r = 1$	5.59
	ADF test of nonstationary differential	-3.283*
East-West (pre-2008)	LR Test of $\alpha = 0, \beta = 1$	295.25*
	max eigenvalue test $r = 0$	45.94*
	trace test $r = 0$	51.12*
	max eigenvalue and trace test $r = 1$	5.18
	ADF test of nonstationary differential	-5.1388*
Central-West (pre-2008)	LR Test of $\alpha = 0, \beta = 1$	478.33*
	max eigenvalue test $r = 0$	43.02*
	trace test $r = 0$	49.11*
	max eigenvalue and trace test $r = 1$	6.08
	ADF test of nonstationary differential	-5.0856*
East-Central (post-2008)	LR Test of $\alpha = 0, \beta = 1$	474.23*
	max eigenvalue test $r = 0$	29.55*
	trace test $r = 0$	35.54*
	max eigenvalue and trace test $r = 1$	5.99
	ADF test of nonstationary differential	-4.7815*
East-West (post-2008)	LR Test of $\alpha = 0, \beta = 1$	28.754*
	max eigenvalue test $r = 0$	27.78*
	trace test $r = 0$	35.70*
	max eigenvalue and trace test $r = 1$	7.91*
	ADF test of nonstationary differential	-3.6533*
Central-West (post-2008)	LR Test of $\alpha = 0, \beta = 1$	552.96*
	max eigenvalue test $r = 0$	21.98*
	trace test $r = 0$	33.65*
	max eigenvalue and trace test $r = 1$	11.67*
	ADF test of nonstationary differential	-4.0033*

Table 3.7 Qu and Perron Breakdate Estimates

Market Pair	Break 1	Break 2	Break 3	Break 4
East-Central	Feb-02	Jan-05	May-07	May-10
East-West	Feb-02	Jan-05	Sep-07	May-10
Central-West	Jun-03	Oct-05	Sep-07	Oct-09

Table 3.8 Threshold Estimates of 3-Regime TVEC Models

Market Pair	Regime or Test	Test Statistic
East-Central (pre-2008)	Regime I	$-\infty < v_{t-1} \leq -0.0478$
	Regime II	$-0.0478 < v_{t-1} < -0.0018$
	Regime III	$-0.0018 \leq v_{t-1} < \infty$
	Tsay's Test	1.232
East-West (pre-2008)	Regime I	$-\infty < v_{t-1} \leq -0.0908$
	Regime II	$-0.0908 < v_{t-1} < -0.0458$
	Regime III	$-0.0458 \leq v_{t-1} < \infty$
	Tsay's Test	0.4836
Central-West (pre-2008)	Regime I	$-\infty < v_{t-1} \leq -0.0859$
	Regime II	$-0.0859 < v_{t-1} < -0.0369$
	Regime III	$-0.0369 \leq v_{t-1} < \infty$
	Tsay's Test	0.1555
East-Central (post-2008)	Regime I	$-\infty < v_{t-1} \leq -0.0710$
	Regime II	$-0.0710 < v_{t-1} < -0.0240$
	Regime III	$-0.0240 \leq v_{t-1} < \infty$
	Tsay's Test	0.01848
East-West (post-2008)	Regime I	$-\infty < v_{t-1} \leq -0.0993$
	Regime II	$-0.0993 < v_{t-1} < -0.0603$
	Regime III	$-0.0603 \leq v_{t-1} < \infty$
	Tsay's Test	0.8617
Central-West (post-2008)	Regime I	$-\infty < v_{t-1} \leq -0.0926$
	Regime II	$-0.0926 < v_{t-1} < -0.0706$
	Regime III	$-0.0706 \leq v_{t-1} < \infty$
	Tsay's Test	2.235*

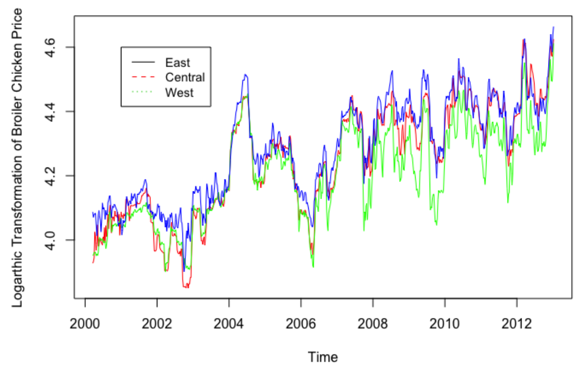


Figure 3.1 Weekly Regional US Wholesale Broiler Chicken Prices (2000-2012)

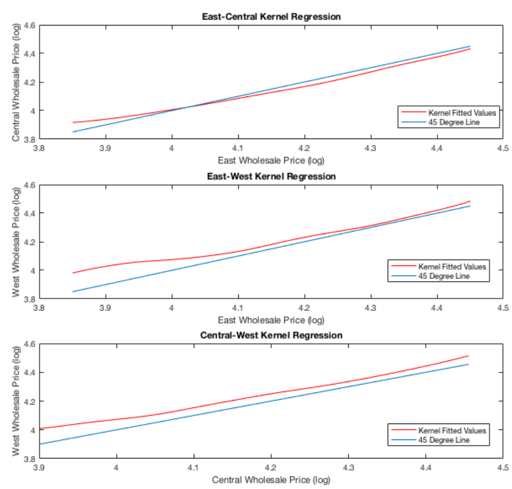


Figure 3.2 Kernel Regression Plots (pre-2008)

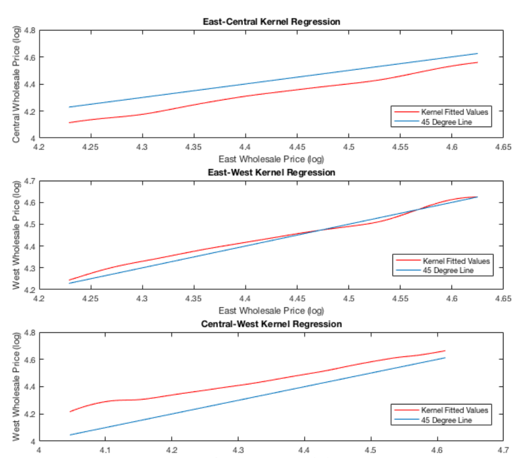


Figure 3.3 Kernel Regression Plots (post-2008)

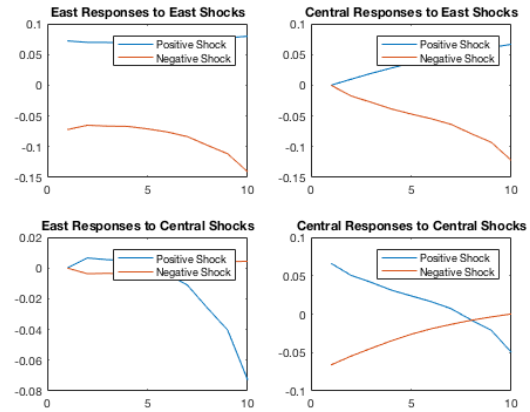


Figure 3.4 East-Central Generalized Impulse Response Functions (pre-2008)

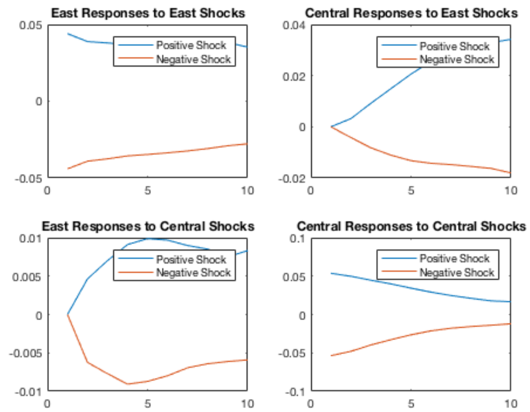


Figure 3.5 East-Central Generalized Impulse Response Functions (post-2008)

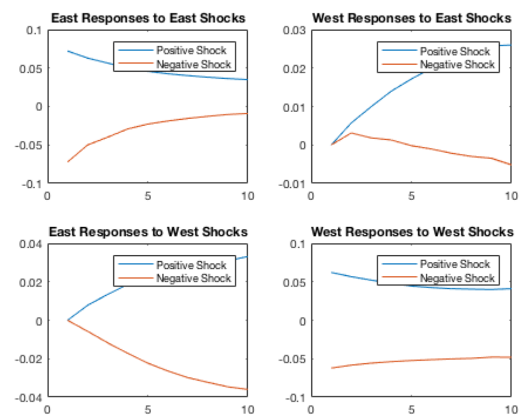


Figure 3.6 East-West Generalized Impulse Response Functions (pre-2008)

Figure 3.7 East-West Generalized Impulse Response Functions (post-2008)

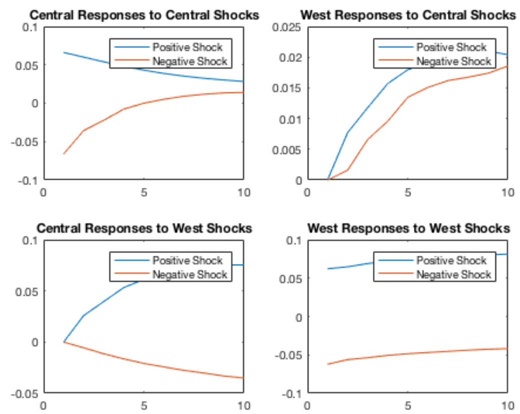


Figure 3.8 Central-West Generalized Impulse Response Functions (pre-2008)

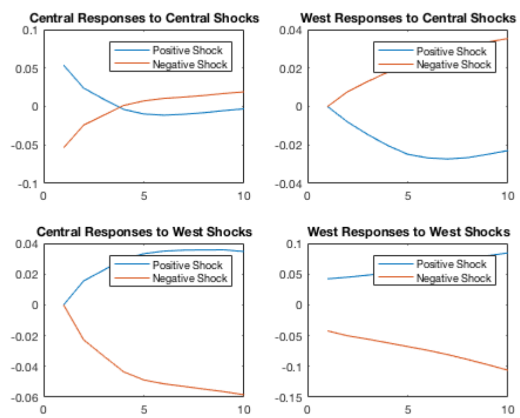


Figure 3.9 Central-West Generalized Impulse Response Functions (post-2008)

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