Effects of Alternative Marketing Arrangements on Spot Market Price Distribution in the U.S. Hog Market[1]

Jong-Jin Kim and Xiaoyong Zheng
Department of Agricultural and Resource Economics
North Carolina State University
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Abstract

We propose a stylized model that elucidates the two channels through which alternative marketing arrangements (AMAs) can affect the spot market price in livestock markets. The direct effect of AMAs on spot market price works through its effect on demand and supply conditions in the spot market. This effect has been widely studied in the literature. The indirect effect of AMAs on spot market price works through its effect on spot market price volatility. This effect has been ignored in the literature. We then estimate a dynamic (time series) model with data from the U.S. hog market to test our model implications and quantify the two effects. We find increases in the use of AMAs increase spot market price volatility and decrease spot market price level. The short-run effects are small but the long-run effects are nontrivial.

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1. Introduction

During the past 20 years, one of the most important changes in the U.S. livestock markets is that packers have relied more and more heavily on alternative marketing arrangements (AMAs) to satisfy their slaughter needs. As a result, the share of transactions conducted on the spot market has decreased. For example, in 1999, 36% of the market hogs were transacted on the cash/spot market (Grimes and Plain, 2009). By the 2004-2005 period, this share had decreased to 24% (Vukina et al. 2007) and our data, which will be detailed below in Section 3, shows that by 2010, this share had further decreased to only 5.4%.

AMAs in livestock markets mainly take the form of marketing contracts and production contracts. The main characteristic of both of them, as well as their main difference from the spot market, is that animals are committed to buyers long before they are finished for slaughter. As we know, innovations improve social welfare. Just like the introduction of a new good increases the total welfare of producers and consumers, the emergence of new marketing channels also improve the welfare of packers and farmers as a whole. This is confirmed by a recent study by Wohlgenant (2010), who shows that banning the use of AMAs in the hog industry would decrease social welfare. But the welfare effects of innovations on different groups of economic agents can be quite different. Some may gain a lot from the innovation, while others gain little or even lose. In the context of livestock markets, it is generally believed that AMAs benefit packers and those farmers who contract with packers for two reasons. First, they are the users of AMAs. If they didn't benefit from using these new marketing channels, they would not use them at the first place. Indeed, Key and McBride (2003) show one of the main reasons for AMAs to become popular is packers can reduce transaction costs by contracting with fewer and larger producers. Second, since the animals are committed to buyers well in advance, AMAs help buyers and sellers minimize, or in some cases eliminate, the price and marketing access risks they usually face when they trade in the spot market. Zheng, Vukina and Shin (2008) find that more risk-averse farmers are more likely to contract with packers and Franken, Pennings, and Garcia (2009) find both risk preferences and transactions costs are key determinants of a packer's decision in choosing market arrangements.

On the other hand, economists do not agree on the effects of AMAs on the spot market. Some argue that AMAs remove a large percentage of demand away from the spot market and if the supply adjusts slowly, there will be a surplus on the spot market and the price will go down (Schroeder et al. 1993). Others argue that AMAs decrease both the demand and the supply to the spot market and hence the resulting effect on price will be minimal (USDA-AMS 1996). Hence, examining the effects of AMAs on the spot market is an empirical question. Many studies have been devoted to study this question. One strand of literature focuses on analyzing the effect of AMAs on spot market price level. Most of these studies use data from the U.S. fed cattle market and find AMAs either have a mild negative or an unambiguous effect on the spot market price level (e.g. Elam 1992; Hayenga and O'Brien 1992; Schroeder et al. 1993; Ward, Koontz and Schroeder 1998; Schroeter and Azzam 2003). Another strand of literature studies the impact of AMAs on price volatility. For example, Hayenga and O'Brien (1992) find little evidence that AMAs decrease spot market price volatility. Also, using experimental methods, Ward et al. (1999) find that the use of an exclusive marketing agreement between a packer and a feeder in the fed cattle industry increases both the spot market price level and volatility.

Though studies in the literature have examined the effects of AMAs on spot market price level and volatility separately, to the best of our knowledge, no study has identified and studied the second channel through which AMAs influence the spot market price level. The direct effect of AMAs on spot market price level works through their effects on the demand and supply conditions in the spot market. The indirect effect, on the other hand, works through their effect on spot market price volatility. Economic theories predict that risk is an important determinant of producer supply behavior when producers are risk averse and future output price is uncertain. Empirical studies have also confirmed this prediction in several agricultural markets (e.g. Just, 1974; Aradhyula and Holt 1989; Antonovitz and Green 1990). As equilibrium price level is determined by demand and supply, this in turn implies that risk is also an important determinant of the price level. Furthermore, many empirical studies also find risk plays an important role in determining the marketing margin, which is defined as the difference between price and marginal cost (e.g. Brorsen et al. 1985; Schroeter and Azzam 1991; Holt 1993). If risk is a determinant of the price level and AMAs have an effect on price volatility or risk, then in addition to the direct effect of AMAs on spot market price level, AMAs can also affect spot market price level indirectly, that is, they affect spot market price volatility first, which in turn causes a change in spot market price level.

In this article, we first propose a simple model that elucidates the two channels through which AMAs affect spot market price level. We then estimate an autoregressive distributed lag (ARDL)-autoregressive moving average (ARMA)-generalized autoregressive conditionally heteroscedastic-in-mean (GARCH-M) time series model to test the implications of our model using hog transactions data from the Mandatory Price Reports (MPR) of U.S. Department of Agriculture (USDA). The same approach has been applied in other markets to study similar issues (e.g. Hubbard and Weiner 1992 for copper; Kavussanose, Visvikis, and Batchelor 2004 for dry-bulk shipping; Mohapatra et al. 2010 for strawberry). The ARDL-ARMA-GARCH-M model serves our purpose very well. It consists of two equations. The first equation is a standard GARCH equation for the conditional volatility of spot market price, in which the percentage of transactions that can be categorized as AMAs is included as a control variable to capture the effect of increases in AMAs on spot market price volatility. The second equation is an ARDL-ARMA model for the spot market price level, in which the conditional volatility of spot market price, or the price risk of the spot market, is included as a determinant, in addition to the AMAs variable (which captures the direct effect of increases in AMAs on spot market price level) and other control variables. Our study contributes to the literature on examining the effects of AMAs on spot market in livestock markets in several aspects. First, most of the previous studies in the literature focus on the cattle market, while we study the hog market. Second, we identify the second channel through which AMAs affect the spot market price level and our empirical analysis shows this effect mitigates the direct effect of AMAs on spot market price level. Third, in previous studies estimating the effect of AMAs on spot market price level, risk is not included as a control variable. Hence, these studies suffer from the omitted variable problem and the estimated effect of AMAs on spot market price level is likely to be biased. Finally, previous studies estimate static models to study the effect of AMAs on spot market price level, while we estimate a dynamic model. As a result, we are able to examine both the short-run and long-run or equilibrium effects of AMAs on spot market price level, while previous studies only examine the short-run effects. Since hog price time series data are autocorrelated and the autocorrelation coefficients are large, we find the long-run effects of AMAs are quite different from the short-run effects.

Our results show that increases in AMAs increase the spot market price volatility, which in turn increases the spot market price level. Hence, the indirect effect of AMAs on spot market price level is positive. However, in terms of absolute values, this indirect effect is smaller than the direct effect, which is estimated to be negative, and hence the total effect is still negative. In terms of magnitude, the short-run total effect is fairly small, consistent with most of the previous findings, but the long-run total effect is not trivial. Together, our results show that AMAs benefit packers, as they pay lower price on the spot market, at the cost of those farmers who use the spot market, as they receive lower price and face more risk in the spot market.

The rest of this article is organized as follows. The next Section introduces the AMAs in the hog industry and discusses reasons for their rising popularity. Section 3 describes the data. A simple model that elucidates the two channels through which AMAs affect spot market price and guides our empirical analysis is presented in Section 4. Section 5 explains our empirical strategy and discusses the results. The final Section concludes.

2. AMAs in the U.S. Hog Industry

In the hog industry, both farmers and packers face nontrivial risks in their production and marketing activities. For farmers, the main risks involved are production risk, price (both input and output) risk, and market access risk. Production risk mainly comes from the fact that hog production is a time consuming and complicated process, which can be affected by many factors such as weather and animal diseases over which farmers do not have full control. Price risk comes from uncertainty in both input (e.g. feed) and output (hog) prices. Finally, market access risk can be serious because once hogs reach their optimal weight for slaughter, feed conversion rate starts decreasing and hence keeping them on hand is fairly costly to farmers.

Packers face their own risks as well. Meat packing process shows substantial economies of scale in processing and waste management due to the high fixed costs of running the packing plants and the highly automated nature of the production process (Vukina et al. 2007). Hence, market access risk is also a major risk for the packers. If packers cannot secure enough hogs with good and uniform quality, their plants cannot run at full capacity and the associated implicit cost is fairly high. In addition, packers also face price risk, both for inputs (mainly the hogs) and outputs.

Contracts provide farmers and packers a way to attenuate these risks. This is one of the major reasons for why marketing and production contracts penetrate so fast during the past two decades in the U.S. hog industry. Marketing contracts are essentially forward sales contracts between farmers and packers. These contracts are usually signed several weeks or months before the hogs are ready for slaughter. Hence the market access risk is eliminated for both parties. Marketing contracts also include clauses on how the transaction price will be determined. For some marketing contracts, the transaction price is linked to pork price or hog price on the spot market. For other marketing contracts, formulas like cost-plus, price-window and price-floor are used. In cost-plus contracts, prices are determined by the costs of producing hogs, which include feed costs and production and management costs, plus a profit margin. Therefore, the transaction price in cost-plus contacts is independent of the spot market price. Also, no matter the production costs are high or low, farmers always obtain a certain profit margin. Hence the price risk is eliminated entirely for the farmers with this type of contracts. For packers, they still face some price risks as hog production costs still fluctuate over time. In price-window contracts, there are an upper bound and a lower bound for the transaction price. If the spot market price is within this price window, the transaction price is the same as the spot market price. If the spot market price falls or rises out of the price window, then the transaction price equals either the lower bound or the upper bound. Finally, the price-floor contracts are a special type of the price-window contracts in which the upper bound is infinite. Therefore, if the spot market price is lower than the lower bound, the transaction price equals the lower bound. Otherwise, the transaction price is the same as the spot market price. In sum, the latter type of marketing contracts also attenuate the price risk for farmers and packers to a certain degree.

Under production contracts, packers rather than farmers own the hogs prior to slaughter. During the production process, packers provide weaners, feed, vaccination services, transportation services, etc. and farmers provide land, labor and production facilities. When the hogs reach the market weight, they are removed from the farms and transported to the packers' processing and packing plants. Farmers are then compensated for their growing services. Therefore, under production contracts, price and market access risks are eliminated for the farmers. Their production risk is also reduced. For the packers, market access and hog price risks are eliminated and because production contracts give them more control over the production process, the hogs produced are more likely to meet their quality requirements. In return, packers take over the input price (e.g. feed price) risk and part of the production risk from the farmers. The fact that production contracts' popularity is on the rise in recent years indicates that ensuring hogs meeting their quality standards is more important for the packers.

3. Data

The main dataset used in this paper is obtained from the Mandatory Price Reports (MPR) of U.S. Department of Agriculture (USDA).[2] Required by the Livestock Mandatory Reporting Act of 1999, Agricultural Marketing Service (AMS) of USDA has released livestock transaction data on a daily basis since April 1st, 2001. The commodities covered include cattle, hogs, sheep, and lamb. The specific dataset used is the "National Daily Direct Hog Prior Day - Slaughtered Swine" series from Jan 1st 2002 to Dec 31st 2010.[3] USDA-AMS groups different hog transactions into six marketing channels based on the pricing method used and who is the seller and then report the price and quantity data for each channel. The six channels are:

a) NEGOTIATED PURCHASES: Cash or spot market purchase of swine by a packer from a producer where there is an agreement on base price and a delivery day not more than 14 days after the date on which the livestock are committed to the packer;

b) OTHER MARKET FORMULA PURCHASES: Purchase of swine by a packer in which the pricing mechanism is a formula price based on any market other than the market for swine, pork, or a pork product. This includes formula purchases where the price formula is based on one or more futures or options contracts;

c) SWINE OR PORK MARKET FORMULA PURCHASES: Purchase of swine by a packer in which the pricing mechanism is a formula price based on a market for swine, pork, or a

[2] http://mpr.datamart.ams.usda.gov/menu.do?path=\Species.

[3] The 2001 data was not used because there are many outliers and observations with missing data in the 2001 data.

pork product, other than any formula purchase with a floor, window, or ceiling price, or a futures or options contract for swine, pork, or pork product;

d) OTHER PURCHASE ARRANGEMENTS: Purchase of swine by a packer that is not a negotiated purchase, swine or pork market formula purchase, or other market formula purchase; and does not involve packer-owned swine. This would include long term contract agreements, fixed price contracts, cost of production formulas, formula purchases with a floor, window, or ceiling price;

e) PACKER OWNED: Swine that a packer, including a subsidiary or affiliate of the packer, owns for at least 14 days immediately before slaughter.

f) PACKER SOLD: Swine that are owned by a packer, including a subsidiary or affiliate of the packer, for more than 14 days immediately before sale for slaughter, and sold for slaughter to another packer.

We categorize transactions through channels b)--f) as AMAs because contracts of types b), c) and d) are essentially marketing contracts and hogs transacted through channels e) and f) are produced using production contracts. Those transactions through channel a) are taken as spot market transactions.

Table 1 reports the annual average daily hog slaughtered volumes across the six different marketing channels. Several features are salient. First, the share of hogs transacted through the spot (negotiated) market has steadily decreased from 14.7% in 2002 to 5.2% in 2010. It is worth mentioning that the spot market was once the dominant marketing channel with a market share of 62% in 1994 (Grimes and Plain, 2009). Correspondingly, the market share for AMAs has increased steadily over the years. Among them, the most popular channels are the "Swine/Pork Market Formula Purchases" channel, which accounted for 38.7% of hog transactions in 2010, and the "Packer Owned" channel, which accounted for 26.7% of hog transactions in 2010. These statistics show that though the number of hogs transacted through the spot market has decreased, the spot market still plays a very important role in this market. This is because the transaction price for most of the "Swine/Pork Market Formula Purchases," is linked to the spot market price. Therefore, the spot market remains as the place where the hog price is discovered.

Table 2 presents the summary statistics for the price and quantity data by marketing channel and the quality measures for hogs transacted through the spot market. All prices were deflated using the 2002 CPI. The number of observations for most of the variables is 2,296, which is the number of working days between January 1st 2002 and December 31st 2010. The number of observations for the "Packer Sold" channel is slightly less because on some days, there was no such transaction reported. In addition to the data from MPR, we also obtained two time series of pork price data, which will be used in our empirical analysis below. The first pork price series is the daily settlement price of the "Pork Bellies, Frozen, 12-14 lbs" cash contracts from Chicago Mercantile Exchange (CME). We obtained this data from the Commodity Research Bureau[4] and deflated it using the 2002 CPI. The second pork price time series data we use is the monthly "Consumer Price Index—All Urban Consumers, Pork Products" from the Bureau of Labor Statistics. We deflated the index such that it takes the value of 100 for 2002. Both pork price time series have their own advantages and disadvantages. The pork bellies price series has the advantage of having the same frequency as other variables and hence providing more information. The disadvantage of this time series is the fact that pork belly is just one particular type of pork products and therefore pork bellies price may be quite different from the overall pork price. The advantage of the pork CPI data is that it is a better measure for the overall price for pork products. The disadvantage of it is it is only available at the monthly level and hence contains less information, which makes the identification of the pork price effect more difficult.

Several other features of Table 2 are also worth mentioning. First, hog transactions that can be categorized as AMAs command a slightly higher average price than hogs transacted through the spot market. This might be due to the fact that most contracts include quality clauses which state specific quality requirements in terms of lean percentage, loin eye depth, back fat, etc., (Vukina et al. 2007) and the price difference simply reflects the quality premium. Second, price volatility also varies across different marketing channels. The most volatile channels are the spot market and the "Packer Sold" channels as prices in these channels can respond freely to the current market conditions. The next volatile channel is the "Swine/Pork Market Formula" channel. This is not surprising as the price for transactions in this channel are linked directly to the spot market price. The least volatile channels are the "Other Market Formula" channel and the "Other

[4] http://crbtrader.com/.

Purchase Arrangements" channel as prices in the former channel are linked to other commodities, which are less volatile during the sample period and prices in the latter channel are often negotiated for a long period of time and only change once a while. Muth et al. (2008) report similar findings. Finally, the last few rows of the table present the summary statistics for six hog quality measures: average sort loss, average carcass weight, average backfat, loineye area, loin depth and average lean percent.[5] Except for the average backfat variable, a higher value of the measure indicates higher quality.

4. Conceptual Framework

In this section, we propose a stylized model that elucidates the two channels through which AMAs affect spot market price. As a preview, the model shows that both the number of hogs through AMAs and spot market price volatility are key determinants of spot market price level and the effect of spot market price volatility on spot market price is positive. Furthermore, the model also shows that spot market price volatility is a function of the number of hogs through AMAs.

Formally, suppose there are n identical farmers and m identical packers in the market. There are two marketing channels through which hogs are transacted. One is the contracts (AMAs) channel and the other is the spot or cash market. There are also two time periods. In the first period, farmers negotiate with packers to decide how many hogs they will supply through the contracts channel when the hogs are ready for slaughter in the second period. Suppose each farmer agrees to supply q_1 hogs to packers. Therefore, a total of nq_1 hogs are committed to the packers and each packer gets $Q_1 = \frac{n}{m} q_1 = zq_1$ hogs, where $z = \frac{n}{m}$ is the number of farmers per packer.[6] In this period, farmers also decide how many additional hogs to produce for the spot market in the second period. At the time when farmers make this decision, the spot market price in the second period has not been realized yet and hence from a farmer's point of view, the spot market price is random. We assume the spot market price follows a normal distribution with mean $\bar{p}_2$ and variance σ_p^2. Further assume that a farmer's utility function exhibits the constant

[5] For the more detailed definition of these measures, see "7 C.F.R. PART 59—LIVESTOCK MANDATORY REPORTING, Title 7 – Agriculture."

[6] We can extend the current model to a more general model in which q_1 is endogenous. All our results will survive. Since our focus here is on the spot market, we treat q_1 as exogenous for brevity purpose.

absolute risk aversion (CARA) preference structure with risk aversion parameter $r_f > 0$. With these assumptions, the expected utility for a representative farmer to produce q_2 additional hogs for the spot market can be written as an increasing concave function of the mean-variance criterion (which corresponds to the certainty equivalent value of revenue),

(1). $Eu_f = \bar{p}_2 q_2 - \frac{r_f}{2} var(p_2 q_2) - \frac{a_1}{2}[(q_1 + q_2)^2 - q_1^2]$,

In (1), $\bar{p}_2 q_2$ is the farmer's expected revenue from selling q_2 hogs on the spot market. $-\frac{r_f}{2} var(p_2 q_2) = -\frac{r_f \sigma_p^2}{2} q_2^2$ represents the negative utility the farmer receives when selling on the spot market due to the price risk. Finally, we assume the production cost function to be quadratic in the quantity produced with parameter $\frac{a_1}{2} > 0$ and hence $\frac{a_1}{2}[(q_1 + q_2)^2 - q_1^2]$ is the increase in the farmer's production cost for producing q_2 additional hogs, given the fact that the farmer has already committed to produce q_1 hogs through the AMAs channel. With these assumptions, the farmer's decision problem can be written as

(2). $max_{q_2} Eu_f$

and the optimal solution is,

(3). $q_2^* = \frac{\bar{p}_2 - a_1 q_1}{r_f \sigma_p^2 + a_1}$.

The second order sufficient condition holds trivially with the assumption that both a_1 and r_f are positive. (3) implies that the number of hogs supplied to the spot market increases when the expected spot market price mean increases, and decreases if the farmer is more risk averse, if the spot market risk is higher or if more hogs are already committed through the AMAs channel.

In the second period, given the pork price in the downstream pork market and price for hogs in the spot market, p_2, each packer needs to decide how many hogs to procure from the spot market, in addition to the Q_1 hogs it has already obtained from the contracts channel for its processing and packing business. We assume the market is competitive and hence each packer is a price taker. The profit for a representative packer to procure Q_2 additional hogs from the spot market and sell the pork produced from these hogs can be written as,

(4). $u_p = (kv - p_2)Q_2 - \frac{b_1}{2}[(Q_1 + Q_2)^2 - Q_1^2]$,

where v is the price for one pound of pork and k is the number of pounds of pork that can be produced from one hog. In (4), $(kv - p_2)Q_2$ is the packer's profit from procuring Q_2 hogs from the spot market and then sell the pork produced from these hogs, excluding the processing costs. The processing cost is assumed to be quadratic in the quantity processed with parameter $\frac{b_1}{2} > 0$ and hence $\frac{b_1}{2}[(Q_1 + Q_2)^2 - Q_1^2]$ represents the increase in the packer's processing cost when the packer processes the Q_2 hogs it obtains from the spot market, given the fact that it already needs to process the Q_1 hogs from the AMAs channel. Since in our model, the packer faces no uncertainty in the second period, no matter the packer is risk averse or not, its decision problem can then be written as

(5). $max_{Q_2} u_p$

and the optimal solution is,

(6). $Q_2^* = \frac{kv - p_2 - b_1 z q_1}{b_1}$,

where we have replaced Q_1 with zq_1. The second order sufficient condition holds trivially with the assumption that b_1 is positive. (6) implies that a packer's demand for spot market hogs decreases with the spot market price, the number of hogs through AMAs and its processing cost, but increases with the price of pork.

In equilibrium, the supply equals to the demand in the spot market, that is,

(8). $nq_2^* = mQ_2^*$,

which can be rearranged to be,

(9). $p_2 = kv - b_1 z q_1 - \frac{b_1 z}{r_f \sigma_p^2 + a_1}(\bar{p}_2 - a_1 q_1)$.

(9) yields several important implications for our study. First, (9) explains why spot market price is random from the perspective of the farmers in the first period. This is because in the first period, pork price has not been realized yet and is taken as random. Since spot market price is a function of the pork price, it is also random. Second, the pork price, the number of hogs through AMAs and the spot market price volatility, or risk, are all important determinants of the spot market price level. This will guide the specification for our empirical model below. Third, the derivative of p_2 with respect to σ_p^2 can be derived as follows,

(10). $\frac{\partial p_2}{\partial \sigma_p^2} = b_1 z(\bar{p}_2 - a_1 q_1)\frac{r_f}{(r_f \sigma_p^2 + a_1)^2}$.

In (10), z, b_1 and r_f are positive by definition. Also, (3) implies that $(\bar{p}_2 - a_1 q_1)$ must be positive. Hence, (10) implies that when spot market price risk increases, the spot market price level will increase. When the spot market price risk increases, it is clear from (3) and (6), that the supply to the spot market decreases and the demand for hogs from the spot market remains the same. As a result, the equilibrium spot market price increases. One of the main purposes of our empirical analysis below is to test this model implication. Fourth, since z and b_1 are positive by definition, (9) implies that spot market price decreases with the number of hogs through AMAs. This is another major hypothesis that will be tested in our empirical analysis below. Fifth, (9) implies that

(11). $var(p_2) = k^2\sigma_v^2$,

where σ_v^2 is the variance for the pork price. Since we assumed above that $var(p_2) = \sigma_p^2$, (11) further implies that $\sigma_p^2 = k^2\sigma_v^2$. Finally, (9) also implies that the spot market price volatility is a function of the number of hogs through AMAs. To see this, we need to use the concept of rational expectations, which has been employed in previous studies on the relationship between risk and agricultural supply such as Antonovitz and Roe (1986), Aradhyula and Holt (1989) and Antonovitz and Green (1990). The idea is to assume that economic agents form expectations rationally. In our context, it means that the farmer's expectations about the spot market price distribution are consistent with those implied by the model equilibrium (9). Put in other words, this means that if we use (9) to derive the mean and variance of the spot market price, we should get

(12). $E(p_2) = \bar{p}_2$ and

(13). $var(p_2) = \sigma_p^2$.

Taking expectations on both sides of (9) and use (12), we can obtain a closed form solution for $\bar{p}_2$ as follows,

(14). $\bar{p}_2 = \frac{k\bar{v} - (b_1 z - Ma_1)q_1}{M+1}$, where $M = \frac{b_1 z}{r_f \sigma_p^2 + a_1}$.

We can then use (9) and (14) to derive $var(p_2)$ as follows,

(15). $var(p_2) = E[(p_2 - \bar{p}_2)^2] = \sigma_p^2$,

where the second equality follows from (13). Though there is no closed form solution for σ_p^2, it is clear from (9), (14) and (15) that the rationally expected spot market price volatility σ_p^2 is a function of q_1, the number of hogs through AMAs. Our empirical analysis below will use a specification that is consistent with this implication.

Our stylized model makes it clear that there are two channels through which AMAs can affect spot market price. The direct effect works through the effect of AMAs on demand and supply conditions in the spot market. With more hogs committed through AMAs, (3) shows farmers supply less hogs to the spot market. Also, (6) shows that packers also demand less hogs from the spot market. In our model, the reduction in demand is larger than the reduction in supply and hence (9) implies that an increase in the number of hogs through AMAs causes a decrease in the spot market price level.

The indirect effect of AMAs on spot market price level works through its effect on spot market price volatility. (15) implies that spot market price volatility is a function of the number of hogs through AMAs. Our model does not predict a clear sign for the effect of AMAs on spot market price volatility. Intuitively, our model implication for this effect should be positive. This is because with the increase in the number of hogs through AMAs, the spot market becomes thinner. As a result, a given demand shock (caused by a shock in pork price) in the spot market is larger in terms of percentages and hence the effect on price is larger and the resulting price volatility is higher. (10) further implies that when spot price volatility is higher, spot market price level is higher. Hence, an increase in the number of hogs through AMAs first increases spot market price volatility, which in turn increases spot market price level.

5. Empirical Strategy and Results

Stationarity Test

Before we move on to regression analysis, we first need to examine whether the times series data we have are stationary or not. As pointed out by Ng (1995), it is well known in the literature that if two time series variables are non-stationary, then regressing one on the other will produce spurious estimates and the standard asymptotic analysis will be invalid. If the dependent variable is stationary and the independent variable is non-stationary, then the estimate will be consistent but the standard asymptotic analysis will still be invalid. Therefore, if the time series data we have are found to be non-stationary, then they need to be transformed into stationary time series data first before we can use them for regression analysis.

One model that has been frequently used to characterize non-stationary time series data is the so-called unit root or random walk model. As a result, testing for non-stationarity is often the same as testing whether the time series under consideration can be characterized by a unit root or not. Many tests have been proposed in the literature. The most widely used ones are the augmented Dickey-Fuller test (ADF) and the Phillips-Perron test (PP). The early and pioneering work on unit root test was done by Dickey and Fuller (1979). Specifically, they use the following AR(1) specification for a time series variable x_t,

(16). $x_t = a + \phi x_{t-1} + bt + \epsilon_t,$

where ϵ_t is a white noise. The time trend variable and the intercept term need to be included in the model when the time series shows a trend over time and a non-zero intercept. If the model has a unit root ($\phi = 1$), then this series is non-stationary. So we can test the null hypothesis that $\phi = 1$ against the alternative that $|\phi|<1$, which means this series is stationary. However, this specification depends on the assumption that ϵ_t is a white noise. Quite often the dependence structure in x_t is more complicated than that of an AR(1) process and hence if the AR(1) specification of (16) is used, the resulting error is not a white noise. To address this issue, Dickey and Fuller (1981) propose an augmented version of their original test, now called the augmented Dickey-Fuller test, which augments the model (16) with lags of Δx_t, that is,

(17). $x_t - x_{t-1} = \mathrm{a} + (\phi - 1)x_{t-1} + \mathrm{bt} + \beta_1 \Delta x_{t-1} + \cdots \beta_p \Delta x_{t-p} + \epsilon_t,$

where p is an appropriately chosen lag such that the resulting ϵ_t is a white noise series. Again, the null hypothesis to be tested is whether $\phi = 1$ or $\phi - 1 = 0$. Phillips and Perron (1988) propose another way to address the same issue by allowing serial correlation and heteroskedasticity in the error term ϵ_t and using the Newey-West (1987) procedure to correct for it. We test for the stationarity of our time series data using both the ADF test and the PP test.

Table 3 reports the results of the ADF and the PP tests for the time series variables that will be used in our regression analysis below. Whether the time trend variable or/and the intercept term are included as controls in (16) and (17) are determined from eyeballing the time series plots of the data[7] and the specification used for each variable is reported in column 2 of the Table.

[7] These time series plots are at the end of the paper.

Column 3 of the Table reports the τ-statistics of the ADF test.[8] For each variable, the optimal number of lags used in (17) was chosen using the Bayesian Information Criterion (BIC) (for details, see pp. 644 of Greene (2005)) and is reported in the parenthesis. The last column of the table reports the τ-statistics of the PP test, with the number of lags used in the test taken to be the integer part of $4(T/100)^{\frac{2}{9}}$, where T is the number of time series observations. The results are almost identical across the two tests. For most of the variables, we reject the hypothesis that there is a unit root, or the time series is non-stationary, at the 1% significance level. For the spot market hog price series, we cannot reject the null hypothesis at the 1% level but the MacKinnon approximate p-values for the test statistics are 0.0139 and 0.0109 in ADF and PP tests, respectively. For the pork CPI series, we fail to reject the hypothesis that the time series is non-stationary at conventional significance levels. We, therefore, first differenced the pork CPI series and re-tested the resulting series for unit root. Results from both tests reject the first differenced pork CPI series is non-stationary. As a result, in our regression analysis below, we use the first difference of the pork CPI series. For other series, we use the untransformed series directly.

GARCH-M Model

To consider both the direct and the indirect effects of AMAs on the spot market price, we adopt the generalized autoregressive conditional heteroskedasticity-in-mean (GARCH-M) model. The GARCH-M model consists of two equations, one for spot market price level and the other for spot market price volatility. For the price level equation, we use an autoregressive distributed lag (ARDL) $(m, 0)$—autoregressive moving average (ARMA) (p, q) specification as follows,

(18). $A(L)[D(L)y_t - z_{1t}\beta_1] = R(L)\varepsilon_t$,

where y_t denotes the spot market hog price time series, $A(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \cdots - \alpha_p L^p$, $D(L) = 1 - d_1 L - d_2 L^2 - \cdots - d_m L^m$, $R(L) = 1 - r_1 L - r_2 L^2 - \cdots - r_q L^q$, and L is the lag operator. z_{1t} is a vector of control variables including the variable of our main interest, AMAs%, the price volatility term, $\sigma_t^2 = var(\varepsilon_t)$ (hence the name of the model, GARCH-in-mean), and pork price. From (9), these are the main determinants of the spot market price level for hogs. In addition, we also include in z_{1t} a set of monthly dummies to control for seasonality, the intercept

[8] The t-statistics from unit root tests no longer follow the Student t distribution. Therefore, a different notation, τ, is used.

term and the trend variable to control for non-zero intercept and long-term trend effect in the time series data, and 5 quality measures to control for quality differences across different transaction days.[9] We use the ARDL$(m,0)$-ARMA(p,q) specification rather than the standard ARMA(p,q) specification that is often used in GARCH-M models because the former is a more parsimonious way to capture the dependence structure of the dependent variable. Finally, ε_t is an error term that is not serially correlated.

The second equation in the GARCH-M model models the behavior of the spot market price volatility. We allow the possibility that the volatility varies over time and use the following GARCH(u,v) specification,

(19). $\sigma_t^2 = \exp(z_{2t}'\beta_2) + \sum_{i=1}^{u} \gamma_i \epsilon_{t-i}^2 + \sum_{i=1}^{v} \delta_i \sigma_{t-i}^2.$

We use the specification of $\exp(z_{2t}'\beta_2)$ rather than $z_{2t}'\beta_2$ in (19) because with this specification, the non-negativity restriction of the GARCH model (Bollerslev, 1986) is more likely to be satisfied. As the GARCH model is a model for the conditional variance, which, by definition, is non-negative, the fitted value from the estimated model needs to be non-negative as well. With the specification of $\exp(z_{2t}'\beta_2)$ in (19), the sufficient condition for the non-negativity restriction to be satisfied reduces to be that all of the γ and δ coefficients in (19) are non-negative. Again, z_{2t} is a vector of control variables including the variable of our main interest, AMAs%, as well as monthly dummies, the trend variable and the intercept term.

We estimated many specifications of our ARDL-ARMA-GARCH model (18)-(19). Each different combination of the lag values m, p, q, u and v is a different specification. Below, we present and discuss results from the specification that has the best fit in terms of model fitness measures AIC and BIC.

Estimation Results

Table 4 presents the estimation results when the pork CPI is used as pork price. The ARDL(3,0)-ARMA(2,7)-GARCH(1,1) specification turns out to be the specification that fits the data the best. The results show the model is well specified. The non-negativity restriction and

[9] The Loineye Area quality measure is not included in the regression analysis because it is highly correlated with another quality measure, Loin Depth, with a correlation coefficient of 0.998.

the stationarity condition for the GARCH model (Bollerslev, 1986) are satisfied, since all of the ARCH and GARCH coefficients (γs and δs) in the conditional variance equation (19) are positive and the sum of them is smaller than 1. Also, results from the Ljung-Box Portmanteau (Q) test[10] show that we cannot reject the hypothesis that the residual series from the ARDL-ARMA model (18) is not serially correlated. This is consistent with the model assumption we made earlier. Finally, since the ARDL-ARMA specification for the price level equation is essentially a dynamic model, there is a stability condition that needs to be satisfied for the dependent variable to converge in equilibrium. In our context, this means the roots of the characteristic function $A(z)D(z) = 0$ must be greater than one in absolute value, where functions $A(\cdot)$ and $D(\cdot)$ are defined above in (18). Using the estimated coefficients for αs and ds, we find this stability condition is satisfied as well.

Several other results are also worth discussing. We first examine the results from the price level equation. First, the coefficient for the AMA% variable is estimated to be negative and the estimate is highly significant. Though not reported, we also found that this estimate was very robust across different model specifications, always around -0.075 and highly significant. This means that the short-run direct effect of a 1 percent increase in the share of transactions through AMAs is a reduction in the spot market price by about 7.5 cents per 100 carcass lb (about 0.13% of the average spot market price in the data). This result is consistent with those results from studies in the literature, which estimate static instead of dynamic models and hence only compute the short-run effect. For example, Elam (1992), Schroeder et al. (1993), Ward, Koontz and Schroeder (1998), Schroeter and Azzam (2003) all reported a mild negative effect of AMAs on spot market price level in the cattle market. This finding is also consistent with the industry arguments that AMAs decrease spot market price by removing spot market demand while spot market supplies tend to stick to their original volumes. Second, the coefficient for the price volatility term, or the GARCH-in-mean term, is estimated to be positive and significant. This indicates that when there is more price risk in the market, farmers are compensated for that. Third, pork price has a positive, though insignificant, effect on hog price level. All these three

[10] The Q test depends on the following two facts: 1) The autocorrelation (ρ) of residuals should be small; 2) $\lim_{T\to\infty} P(Q > q) = P(\chi_J^2 > q)$ where $Q = T(T+2)\sum_{j=1}^{J} \frac{1}{T-j}\hat{\rho}^2(j)$, T is the sample size and $\hat{\rho}(j)$ is the sample autocorrelation at lag j. To reach solid conclusions, we tried several values of J such as 10, 20, 30 and 40.

findings are consistent with the implications of our model presented above. Fourth, all but one quality measures have significant effects on the hog price and their signs are all correct, that is, better quality hogs command higher price. Finally, coefficients for some of the monthly dummy variables (March, April, August, September, October) are estimated to be negative and the estimates are significant. This indicates that the spot market hog prices are significantly lower in those months than in January (the reference month).

Turning to the price volatility equation, we find that as the percentage of transactions through AMAs increases, the price volatility in the spot market increases. This result is again consistent with the arguments of market thinning effects which say that prices will more vigorously reflect a shock in the thinner spot market resulting from the rising popularity of AMAs. This result, together with the result that AMA% has a positive effect on price level, implies that the indirect effect of AMAs on the price level is positive. In addition, we also find the trend variable has a negative and statistically significant effect on price volatility. This implies that over time, the spot market becomes less volatile. On the other hand, not much seasonality pattern is detected in the price volatility as the estimates for all but one of the monthly dummy coefficients in the variance equation are insignificant.

We then repeated the analysis using the other measure of pork price, that is, the daily settlement price for cash contracts for pork bellies. Results are reported in Table 5. Almost all of the coefficient estimates are similar to those of Table 4, both in terms of the signs and the magnitudes. The only difference is now the pork price measure has a positive and statistically significant effect on hog price. This is not surprising as the pork bellies price is available daily rather than monthly and hence there is more variation in the data, which makes the identification of the coefficient easier.

Long-run or Equilibrium Effects of AMAs on Spot Market Price Distribution

With the parameter estimates, we can compute the effects of AMAs on spot market price distribution. We first examine the effect of AMAs on price volatility. Since the price volatility equation (19) is essentially a dynamic model, the long-run or equilibrium effect of AMAs on price volatility can be quantified using the formula

(20). $\frac{\exp(z'_{2t}\beta_2)\beta_{2,AMA\%}}{1-\delta_1}$,

where $\beta_{2,AMA\%}$ is the coefficient for the AMA% variable in the price volatility equation. It is clear that the effect of AMAs on price volatility varies across observations. Therefore, in Table 7 we report the minimum, median, mean and maximum of this effect. When pork CPI is used as the measure for pork price, the results indicate that one percent increase in the use of AMAs increase price volatility by 0.0185 on average. This amounts to about 6.19% of the mean value of the fitted price volatility, that is, $\hat{\sigma}_t^2$, in the dataset. We also note this effect varies across observations quite a bit, ranging from less than 1% to over 30%. The results from the case where pork bellies price is used as the measure for pork price are quite similar.

We now turn to the effects of AMAs on spot market price level. With the ARDL-ARMA specification (18), the long-run direct effect of AMAs on spot market price level can be computed as

(21). $\frac{A(1)\beta_{1,AMA\%}}{A(1)D(1)} = \frac{\beta_{1,AMA\%}}{1-d_1-d_2-d_3}$,

where $\beta_{1,AMA\%}$ is the coefficient for the AMA% variable in (18). The long-run indirect effect of AMAs on spot market price level is the product of the effect of price volatility on price level and the effect of AMAs on price volatility, that is,

(22). $\frac{A(1)\beta_{1,\sigma^2}}{A(1)D(1)}\frac{\exp(z'_{2t}\beta_2)\beta_{2,AMA\%}}{1-\delta_1}=\frac{\beta_{1,\sigma^2}}{1-d_1-d_2-d_3}\frac{\exp(z'_{2t}\beta_2)\beta_{2,AMA\%}}{1-\delta_1}$,

where β_{1,σ^2} is the coefficient for the price volatility term in (18). Again, the indirect effect varies across observations and we report its minimum, median, mean and maximum. Tables 8 and 9 report the direct effect, the indirect effect and the net effect of AMAs on spot market price level. For the case where pork CPI is used as pork price, on average, the direct effect of one percent increase in AMAs decreases the spot market price by about 5 cents, and the indirect effect increases the spot market price for about 1.75 cents. Therefore, the net effect is a reduction of about 3.3 cents per 100 pounds of carcass meat. This amounts to about 6% of the mean spot market price during the sample period. Results from the case where pork bellies price is used as pork price show smaller effects. On average, one percent increase in the use of AMAs leads to a 3.7% reduction in the spot market price level. These long-run or equilibrium effects are significantly larger than the short-run effects and are non-trivial. This is driven by the fact that the spot market hog price time series data is highly autocorrelated and hence a small short-run effect can accumulate over time into a large long-run effect.

Since the increase in the use of AMAs increases spot market volatility and decreases spot market price level, we conclude that farmers who use the spot market lose because of this structural change. On the other hand, packers gain as they pay a lower price for hogs obtained from the spot market.

6. Conclusions

In this paper, we estimate the effects of AMAs on spot market price distribution in the U.S. hog markets. We find increases in the use of AMAs increase spot market price volatility and decrease spot market price level. The effect on price level is further decomposed into a direct effect, which works through the effect of AMAs on demand and supply conditions in the spot market and an indirect effect, which works through the effect of AMAs on spot market price volatility. The direct effect is found to dominate the indirect effect. Increases in the use of AMAs benefit the packers and those farmers who rely on the spot market lose.

Having obtained the results that increases in the use of AMAs have a negative direct effect on spot market price level and this direct effect is larger than the indirect effect, the next natural question to ask is what the main underlying driving force for this negative direct effect is. In our model, the direct effect comes from the fact that increases in the number of hogs transacted through AMAs causes a larger reduction in demand than in supply on the spot market. This is worrisome as this represents a structural change that favors the packers. On the other hand, this effect can also come from the fact that AMAs divert hogs of good quality away from the spot market, as studied in Wang and Jaenicke (2006). If this is the case, then the decrease in spot market price level is less worrisome as it simply reflects the fact lower quality hogs receive lower prices. Most likely, both effects are at work. It is an interesting and challenging task to distinguish the two sources of the direct effect and examine which one is the driving force. This is left for future research.

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Table 1: Average Daily Transaction Volume (# of Heads in Thousands)

Year	2002	2003	2004	2005	2006	2007	2008	2009	2010
Negotiated (Spot)	51.6 14.7%	47.5 13.3%	40.3 11.0%	40.5 11.0%	35.5 9.6%	33.6 8.7%	35.1 8.5%	27.6 6.8%	20.3 5.2%
Other Market Formula	32.6 9.3%	27.3 7.6%	33.5 9.2%	32.5 8.8%	32.1 8.7%	33.2 8.6%	40.9 9.9%	27.8 6.9%	42.3 10.7%
Swine or Pork Market Formula	152.9 43.4%	140.1 39.1%	147.9 40.5%	150.2 40.8%	139.7 37.8%	146.8 37.9%	154.7 37.6%	176.2 43.5%	152.4 38.7%
Other Purchase Arrangement	46.0 13.1%	68.1 19.0%	65.8 18.0%	60.2 16.4%	58.2 15.7%	56.7 14.7%	54.9 13.3%	47.7 11.8%	51.7 13.1%
Packer Owned	61.4 17.4%	67.3 18.8%	70.2 19.2%	75.3 20.5%	81.5 22.0%	91.7 23.7%	100.2 24.4%	102.2 25.2%	105.2 26.7%
Packer Sold	7.9 2.2%	7.5 2.1%	7.7 2.1%	9.1 2.5%	23.1 6.2%	25.1 6.5%	25.5 6.2%	23.5 5.8%	22.0 5.6%
Total	352.5	357.9	365.3	367.9	370.0	387.0	411.4	405.0	394.0

Table 2: Summary Statistics for the Finished Hog Purchase Data

	Variable	Unit	Obs.	Mean	Std. Dev.	Min	Max
Volume (% of heads)	Negotiated	% of heads	2296	0.098	0.032	0.02	0.22
	Other Market Formula	% of heads	2296	0.089	0.025	0.03	0.17
	Swine or Pork Market Formula	% of heads	2296	0.400	0.031	0.29	0.50
	Other Purchase Arrangement	% of heads	2296	0.150	0.034	0.05	0.32
	Packer Sold	% of heads	2296	0.044	0.021	0.00	0.10
	Packer Owned	% of heads	2296	0.220	0.035	0.06	0.36
Average Net Price	Negotiated	$ per 100 carcass lb	2296	56.125	9.342	27.53	79.37
	Other Market Formula	$ per 100 carcass lb	2296	56.860	5.507	38.80	68.67
	Swine or Pork Market Formula	$ per 100 carcass lb	2296	56.896	8.933	32.17	79.95
	Other Purchase Arrangement	$ per 100 carcass lb	2296	58.272	5.226	48.72	73.78
	Packer Sold	$ per 100 carcass lb	2294	58.421	9.079	31.57	82.19
Pork Price	Pork CPI	2002=100	108	98.277	3.401	89.15	105.61
	Pork Bellies	$ per 100 carcass lb	2296	76.185	14.94	38.76	128.48
Quality of hog transacted by 'Negotiated' channel	Average Sort Loss	$ per 100 carcass lb	2296	-1.336	0.266	-2.68	-0.69
	Average Carcass Weight	lb	2296	196.506	3.345	186.60	208.17
	Average Backfat	Inch	2296	0.740	0.028	0.66	0.82
	Loineye Area	Inch	2296	6.854	0.160	6.05	7.36
	Loin Depth	Inch	2296	2.285	0.053	2.02	2.45
	Average Lean Percent	%	2296	53.782	0.444	51.53	55.45

Table 3: Unit Root Test Results

Variables		Controls	Augmented Dickey-Fuller Test	Phillips–Perron Test
Spot Market Price		a (Intercept)	-3.32(12)**	-3.40**
AMA (%)		a and t (Trend)	-6.77(14)***	-35.96***
Pork Price	Pork CPI	a	-2.46(1)	-2.43
	First Diff. of Pork CPI	-	-5.61(1) ***	-7.77***
	Pork Bellies	a	-4.10(1)***	-4.23***
Quality (Spot Market Channel)	Average Sort Loss	a and t	-3.94(9)***	-17.86***
	Average Carcass Weight	a and t	-4.26(11)***	-15.77***
	Average Backfat	a and t	-4.40(9)***	-28.25***
	Loin Depth	a and t	-5.28(9)***	-22.89***
	Average Lean Percent	a and t	-3.60(9)**	-23.35***

Notes: ** and *** denote the null hypothesis of a unit root is rejected at the 5% level and the 1% level, respectively. The optimal lag numbers chosen using Bayesian Information Criterion are in the parenthesis. The numbers of Newey-West lags used in the PP test are taken to be the integer part of $\{4(T/100)^{2/9}\}$.

Table 4: GARCH-M Estimation Results: Using Pork CPI as Pork Price

Dependent: Spot Price		Price Level Equation		Variance Equation	
		Coef.	Std. Err.	Coef.	Std. Err.
D(L)	Lag=1	0.511***	0.050		
	Lag=2	0.313***	0.041		
	Lag=3	0.161***	0.049		
AMA%		-0.075***	0.006	0.192**	0.079
σ_t^2		1.405***	0.508		
First Diff. of Pork CPI		0.039	0.029		
Quality	Average Sort Loss	0.806***	0.066		
	Average Carcass Weight	0.030***	0.008		
	Average Backfat	-11.023***	1.213		
	Loin Depth	1.002**	0.396		
	Average Lean Percent	-0.042	0.072		
GARCH	ARCH L1.			0.039***	0.008
	GARCH L1.			0.931***	0.015
A(L)	Lag=1	0.226*	0.135		
	Lag=2	-0.509***	0.104		
R(L)	Lag=1	0.754***	0.128		
	Lag=2	1.198***	0.115		
	Lag=3	0.975***	0.109		
	Lag=4	0.783***	0.088		
	Lag=5	0.581***	0.061		
	Lag=6	0.330***	0.039		
	Lag=7	0.191***	0.027		
Trend		0.000	0.000	-0.001*	0.000
Month	February	-0.201	0.151	-1.357*	1.212
	March	-0.476***	0.152	-0.943	0.626
	April	-0.289*	0.161	0.450	0.347
	May	-0.083	0.171	-1.010	0.926
	June	-0.212	0.180	0.287	0.347
	July	-0.197	0.188	-1.567	1.509
	August	-0.476**	0.184	0.341	0.341
	September	-0.313*	0.173	-1.335	1.225
	October	-0.446***	0.170	-0.339	0.411
	November	-0.234	0.178	-0.179	0.405
	December	-0.011	0.140	-0.662	0.613
Constant		10.753**	4.318	-21.077***	6.837
AIC		3689.11			
BIC		3970.25			
Portmanteau (Q) statistic when m=40		25.39			
p-value		0.965			

Note: *, **, and *** denotes significance at the 10%, 5% and 1% level.

Table 5: GARCH-M Estimation Results: Using Pork Bellies Price as Pork Price

Dependent: Spot Price		Mean Price Equation		Variance Equation	
		Coef.	Std. Err.	Coef.	Std. Err.
D(L)	Lag=1	0.521***	0.050		
	Lag=2	0.315***	0.037		
	Lag=3	0.140***	0.043		
AMA %		-0.077***	0.007	0.182**	0.080
σ_t^2		1.364***	0.480		
Pork Bellies		0.011***	0.003		
Quality	Average Sort Loss	0.812***	0.067		
	Average Carcass Weight	0.030***	0.008		
	Average Backfat	-10.896***	1.255		
	Loin Depth	0.917**	0.408		
	Average Lean Percent	-0.016	0.074		
GARCH	ARCH Lag=1			0.042***	0.009
	GARCH Lag=1			0.925***	0.016
A(L)	Lag=1	0.864***	0.108		
	Lag=2	-0.303***	0.116		
	Lag=3	-0.545***	0.114		
	Lag=4	0.829***	0.113		
	Lag=5	-0.366***	0.079		
R(L)	Lag=1	0.094	0.115		
	Lag=2	0.349***	0.089		
	Lag=3	0.739***	0.085		
	Lag=4	-0.167	0.112		
	Lag=5	0.183***	0.047		
Trend		0.000	0.000	-0.001*	0.000
Month	February	-0.244	0.149	-1.239*	1.028
	March	-0.528***	0.149	-0.931	0.583
	April	-0.331**	0.159	0.381	0.336
	May	-0.073	0.167	-0.908	0.774
	June	-0.178	0.176	0.246	0.334
	July	-0.177	0.181	-1.404	1.225
	August	-0.500***	0.179	0.251	0.334
	September	-0.287*	0.168	-1.238	1.027
	October	-0.431***	0.167	-0.225	0.365
	November	-0.275	0.171	-0.222	0.399
	December	-0.039	0.135	-0.723	0.591
Constant		9.212**	4.471	-20.144***	6.929
AIC		3687.95			
BIC		3974.83			
Portmanteau (Q) statistic when m=40		32.91			
p-value		0.779			

Note: *, **, and *** denotes significance at the 10%, 5% and 1% level.

Table 7: Effect of AMAs on Spot Market Price Volatility

	Using Pork CPI	As a Percentage of Mean Value of Fitted σ_t^2	Using Pork Bellies Price	As a Percentage of Mean Value of Fitted σ_t^2
Minimum	0.0022	0.74%	0.0028	0.93%
Median	0.0165	5.52%	0.0183	6.11%
Mean	0.0185	6.19%	0.0202	6.75%
Maximum	0.0914	30.59%	0.0897	30.00%

Table 8: Effect of AMAs on Spot Market Price Level: Using Pork CPI

	Direct Effect	Indirect Effect	Net Effect	As a Percentage of Mean Spot Market Price
Minimum	-5.069	0.209	-4.860	-8.7%
Median	-5.069	1.557	-3.512	-6.3%
Mean	-5.069	1.747	-3.322	-5.9%
Maximum	-5.069	8.637	3.568	6.4%

Table 9: Effect of AMAs on Spot Market Price Level: Pork Bellies Price

	Direct Effect	Indirect Effect	Net Effect	As a Percentage of Mean Spot Market Price
Minimum	-3.271	0.163	-3.108	-5.54%
Median	-3.271	1.065	-2.206	-3.93%
Mean	-3.271	1.177	-2.094	-3.73%
Maximum	-3.271	5.228	1.957	3.49%

Figure 1: Plot of Spot Market Price

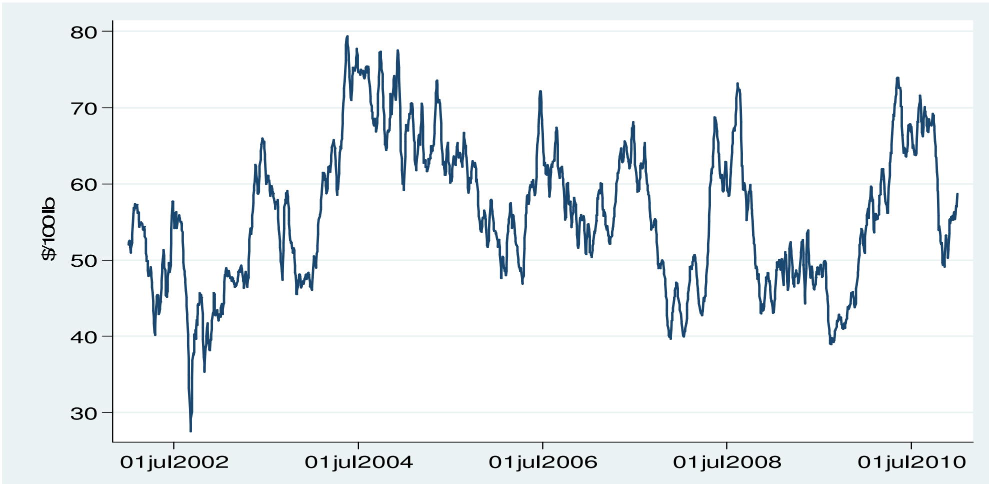

Figure 2-1: Plot of Pork CPI

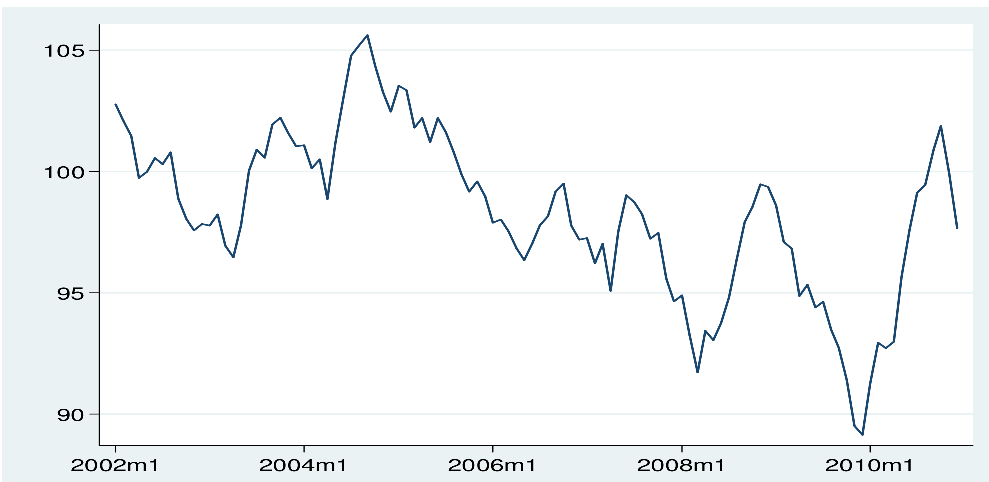

Figure 2-2: Plot of the First Difference of Pork CPI

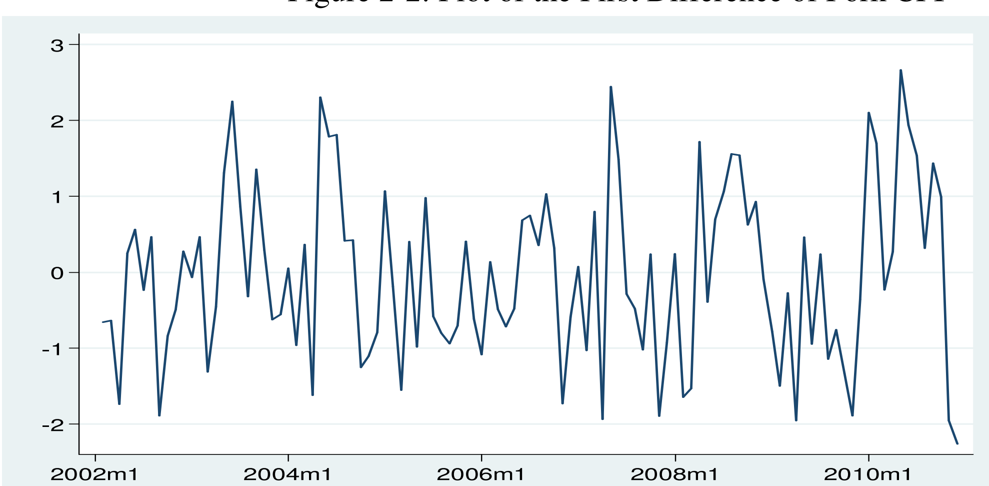

Figure 2-3: Plot of Pork Bellies Price

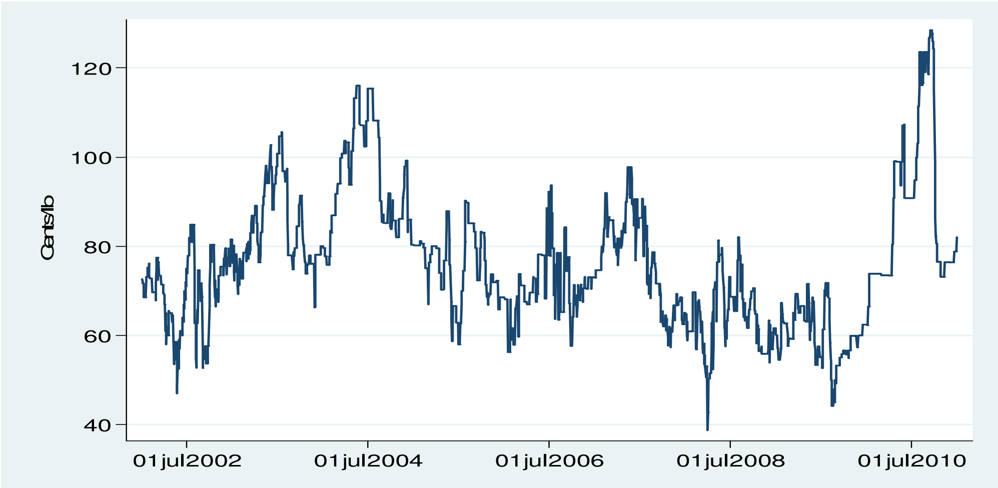

Figure 3: Plot of CS (%)

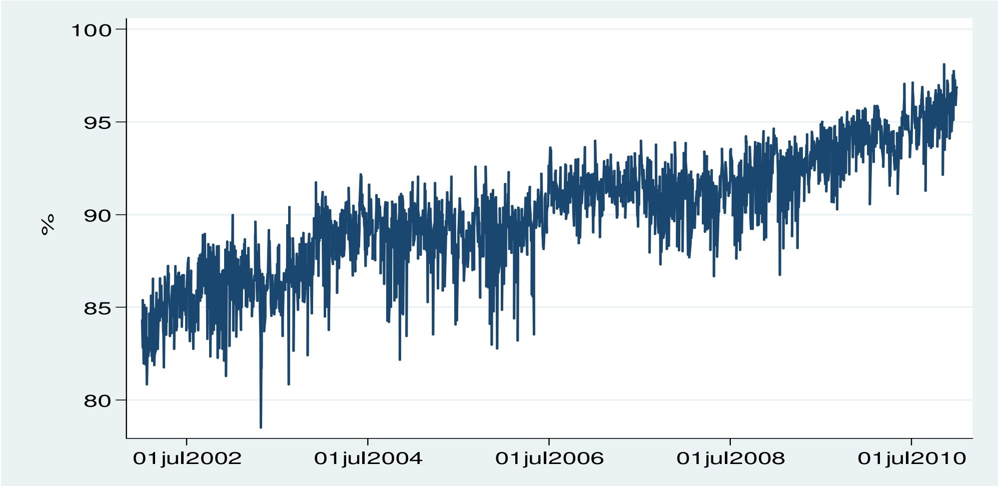

Figure 4: Plot of Average Sort Loss

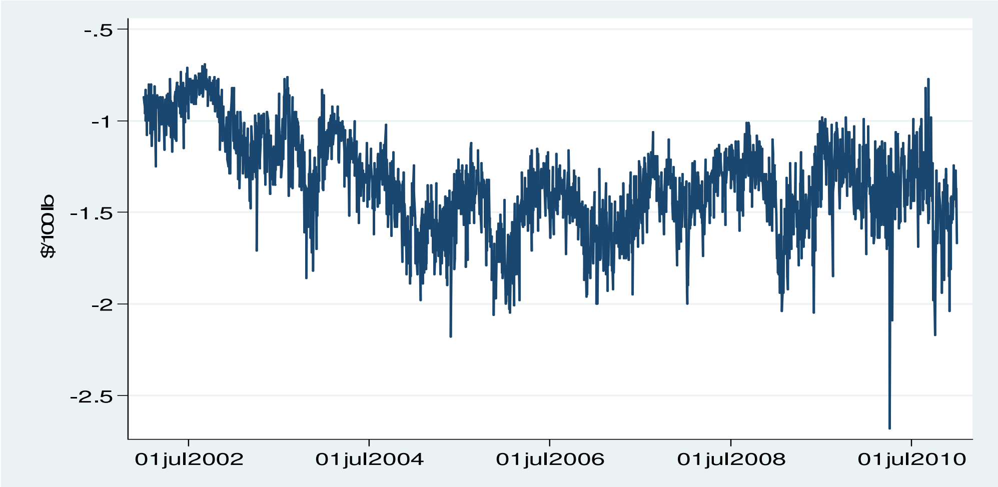

Figure 5: Plot of Average Carcass Weight

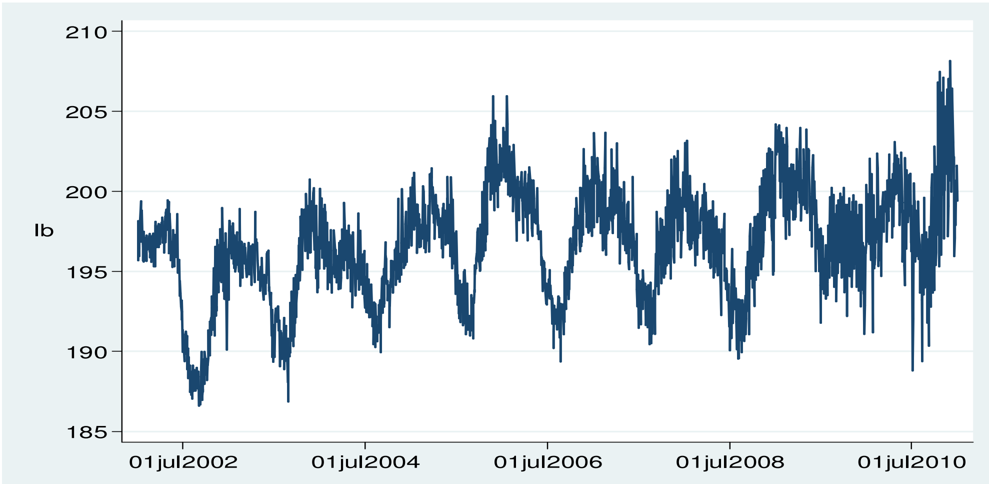

Figure 6: Plot of Average Backfat

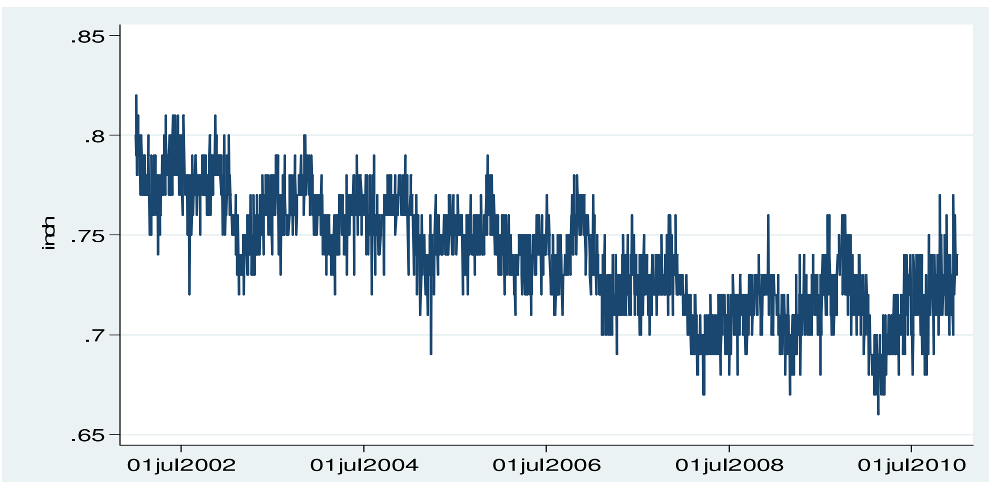

Figure 7: Plot of Loin Depth

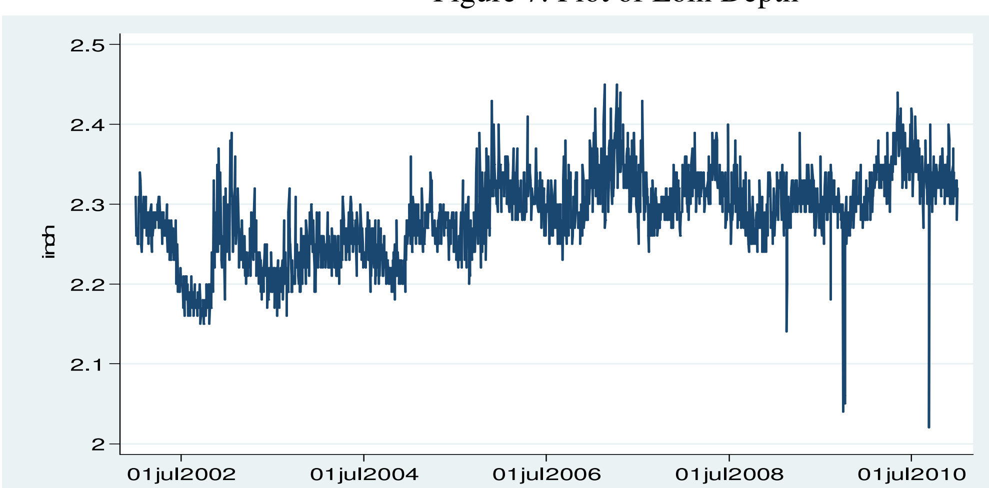

Figure 8: Plot of Average Lean Percent