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

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We propose a model that elucidates the two channels through which alternative marketing arrangements affect spot price in livestock markets. The direct effect works through their effect on demand and supply. The indirect effect works through spot price volatility, which has been ignored in the literature. We then estimate a dynamic 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 price volatility and decrease spot price level. The short-run effects are small but the long-run effects are nontrivial.

Key words: alternative marketing arrangements, captive supplies, GARCH-M, hogs

Introduction

During the past twenty years, packers have relied more and more heavily on alternative marketing arrangements (AMAs) to satisfy their slaughter needs.[1] As a result of this important change, 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), but this share had decreased to 24% by 2004–2005 (RTI International, 2007) and our data show that this share had further decreased to only 5.2% by 2010.

AMAs in livestock markets mainly take the form of marketing and production contracts. The main characteristic of these contracts (as well as their main difference from the spot market) is that animals are committed to buyers long before they are finished for slaughter. Innovations usually improve social welfare. Just as the introduction of a new good increases the total welfare of producers and consumers in most cases, the emergence of new marketing channels seems likely to improve the welfare of packers and farmers as a whole. A recent study by Wohlgenant (2010) confirmed this result by showing 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 that one of the main reasons AMAs may become popular is that 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

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[1] Although the focus of our study is on the hog and livestock markets, AMAs are also widely used in many other agricultural markets, including grain markets and the markets for fresh vegetables. Therefore, our theory and empirical results also apply to those markets.

some cases eliminate the price, marketing timing, and capacity underutilization risks they usually face when trading 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 that both risk preferences and transaction costs are key determinants of a packer's choice of marketing 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 from the spot market and there will be a surplus on the spot market if supply adjusts slowly, causing prices to go down (Schroeder et al., 1993).[2] 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 (Advisory Committee on Agricultural Concentration, 1996). Many studies have examined the effect of AMAs on the spot market as an empirical question. One strand of literature focuses on analyzing the effect of AMAs on the spot market price level. Most of these studies use data from the U.S. fed cattle market and find that AMAs have either a mild negative or an ambiguous 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 the spot market price volatility, while Ward et al. (1999) report the opposite. Other related studies include Franken and Parcell (2012), who study whether the spot market has become so thin that the price discovered there may not be an accurate reflection of true market conditions, and Lee, Ward, and Brorsen (2012), who report that the cash market remains important for price discovery in the hog and fed cattle markets.

Though studies have examined the effects of AMAs on the spot market price level and the 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 the 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 output price risk is an important determinant of producer supply behavior and hence equilibrium market price when producers are risk averse and future output price is uncertain (e.g., Just, 1974; Brorsen et al., 1985; Aradhyula and Holt, 1989; Antonovitz and Green, 1990; Schroeter and Azzam, 1991; Holt, 1993). If output price risk is a determinant of the price level and AMAs have an effect on the price volatility or price risk, then AMAs can affect the spot market price level indirectly as well as directly; that is, they affect the spot market price volatility or price risk first, which in turn causes a change in the spot market price level.

We first propose a simple model that elucidates the two channels through which AMAs affect the spot market price level. We then estimate an autoregressive distributed lag (ADL)-autoregressive moving average (ARMA)-generalized autoregressive conditionally heteroskedastic-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). Similar time series models have been applied in other markets to study different issues (e.g., Hubbard and Weiner, 1992, for copper; Kavussanose, Visvikis, and Batchelor, 2004, for dry-bulk shipping; 2010, for strawberries). The ADL-ARMA-GARCH-M model consists of two equations. The first equation is a standard GARCH equation for the conditional volatility of the 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 the spot market price volatility. The second equation is an ADL-ARMA model for the spot market price level, in which the conditional volatility of the spot market price, or the spot market price risk, is included as a determinant, in addition to the AMAs variable (which captures the direct effect of increases in AMAs on the spot market price level) and other control variables.

[2] This is likely to be a short-run effect. Over time, supply to the spot market is expected to adjust down and the old equilibrium price will probably be restored.

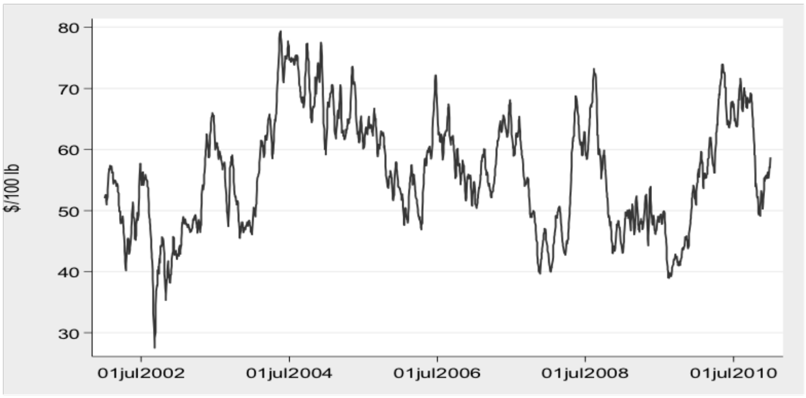

Figure 1. Spot Market Price

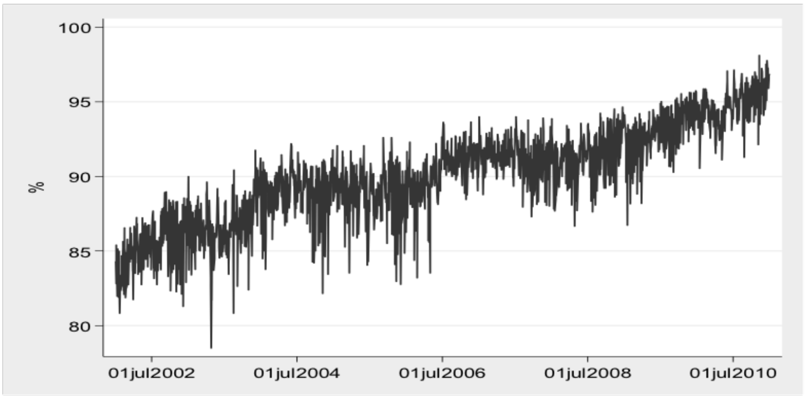

Figure 2. AMAs (%)

Our study contributes to the literature on examining the effects of AMAs on livestock spot 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 that this effect mitigates the direct effect of AMAs on the spot market price level. Indeed, no obvious relationship between the spot market price and AMAs stands out from the time series plots of the two variables in figures 1 and 2. Third, previous studies estimating the effect of AMAs on the spot market price level have not included price risk as a control variable. Hence, these studies suffer from the omitted variable problem, and the estimated effect of AMAs on the spot market price level is likely to be biased. Finally, previous studies estimate static models to study the effect of AMAs on the spot market price level, while we estimate a dynamic model. As a result, we are able to examine both the short-run and the long-run or equilibrium effects of AMAs, while previous studies only examine the equilibrium effects. Since hog price time series data are autocorrelated and the autocorrelation coefficients are large, we find the long-run effects of AMAs to be quite different from the short-run ones.

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 the 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 the total effect is therefore 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 nontrivial. Together, our results show that AMAs benefit packers, as they pay lower prices on the spot market, at the cost of those farmers who only have access to the spot market, as they receive lower prices and face more price risk in the spot market.

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 marketing timing risk. Production risk mainly comes from the fact that hog production is a time consuming and complicated process and this process 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, marketing timing risk can be serious because once hogs reach their optimal weight for slaughter, feed conversion rate starts decreasing and keeping them on hand is fairly costly to farmers.

Packers face their own risks as well. The 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 (RTI International, 2007). Hence, capacity underutilization risk is 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, which is one of the major reasons why marketing and production contracts penetrated 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 marketing timing and the capacity underutilization risks are eliminated for the farmers and packers, respectively. Marketing contracts also include clauses on how the transaction price will be determined. For some marketing contracts, the transaction price is linked to pork 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, production and management costs, plus a profit margin. Therefore, the transaction price in cost-plus contacts is independent of the spot market price and the price risk is eliminated entirely for farmers with this type of contracts. Also, no matter whether the production costs are high or low, farmers always obtain a certain profit margin. For packers, they still face some price risks as hog production costs still fluctuate over time. In price-window contracts, there are an upper and a lower bounds 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. Otherwise, the transaction price equals one of the bounds. The price-floor contracts are a special type of the price-window contracts in which the upper bound is infinity. In sum, this type of marketing contracts also attenuate the price risk for farmers and packers to a certain degree.

Under production contracts, packers 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, the price and the marketing timing risks are eliminated for the farmers. Their production risk is also reduced. For the packers, the capacity underutilization and the hog price risks are eliminated and since 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 (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 packers.

Data

The main dataset used in this paper was obtained from the Mandatory Price Reports (MPR) of U.S. Department of Agriculture (USDA)[3] and is the same as the one used by Zheng and Vukina (2009). As required by the Livestock Mandatory Reporting Act of 1999, the Agricultural Marketing Service (AMS) of the USDA has released livestock transaction data on a daily basis since April 1, 2001.[4] 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 January 1, 2002, to December 31, 2010.[5] The USDA-AMS groups different hog transactions into six marketing channels based on the pricing method used and the seller and then reports the price and quantity data for each channel. The six channels are:

1. Negotiated purchases: Cash or spot market purchase of swine by a packer from a producer in which there is an agreement on base price and a delivery date not more than fourteen days after the date on which the livestock are committed to the packer;

2. 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 for which the price formula is based on one or more futures or options contracts;

3. 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 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;

4. 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;

5. Packer owned: Swine that a packer, including a subsidiary or affiliate of the packer, owns for at least fourteen days immediately before slaughter.

6. Packer sold: Swine that are owned by a packer, including a subsidiary or affiliate of the packer, for more than fourteen days immediately before sale for slaughter and are sold for slaughter to another packer.

We categorize transactions through channels 2)–6) as AMAs because contracts of types 2)–4) are essentially marketing contracts and hogs transacted through channels 5) are produced using production contracts. Hogs transacted through channel 6) are obtained by the selling packer either through production or marketing contracts. But no matter which type of contract is involved, these hogs are committed to the selling packer long before slaughter, the defining feature of AMAs. Transactions through channel a) are taken as spot market transactions.

Table 1 reports the annual average daily volume of hogs slaughtered 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

[3] http://mpr.datamart.ams.usda.gov.

[4] On each business day, reports for transactions conducted in the previous business day are published.

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

Table 1. Average Daily Transaction Volume (Number of Heads in Thousands)

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

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, although 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 the place where the hog price is discovered.

Table 2 presents summary statistics for the price and quantity data by marketing channel and quality measures for hogs transacted through the spot market. All prices were deflated using CPI, such that all are in terms of 2002 constant dollars.[6] The number of observations for most variables is 2,296, which is the number of working days between January 1, 2002, and December 31, 2010. The number of observations for the "Packer Sold" channel is slightly less because some days did not have any such transactions 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. 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[7] and deflated it into 2002 constant dollars using CPI. The second pork price time series data we use is the monthly "Consumer Price Index—

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[6] There are two prices reported in the Mandatory Price Reports: the "Carcass Base Price" and the "Average Net Price." The average net price is simply the carcass base price adjusted for quality premium/discount. We therefore use the "Average Net Price" as this is the price farmers get paid for their hogs.

[7] http://crbtrader.com/

Table 2. Summary Statistics for the Finished Hog Purchase Data

Variable	Unit	N	Mean	Std. Dev.	Min	Max
Volume (% of heads)						
Negotiated	% of heads	2,296	0.098	0.032	0.02	0.22
Other Market Formula	% of heads	2,296	0.089	0.025	0.03	0.17
Swine or Pork Market Formula	% of heads	2,296	0.400	0.031	0.29	0.50
Other Purchase Arrangement	% of heads	2,296	0.150	0.034	0.05	0.32
Packer Sold	% of heads	2,296	0.044	0.021	0.00	0.10
Packer Owned	% of heads	2,296	0.220	0.035	0.06	0.36
Average Net Price						
Negotiated	$ per 100 carcass lb	2,296	56.125	9.342	27.53	79.37
Other Market Formula	$ per 100 carcass lb	2,296	56.860	5.507	38.80	68.67
Swine or Pork Market Formula	$ per 100 carcass lb	2,296	56.896	8.933	32.17	79.95
Other Purchase Arrangement	$ per 100 carcass lb	2,296	58.272	5.226	48.72	73.78
Packer Sold	$ per 100 carcass lb	2,294	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	2,296	76.185	14.94	38.76	128.48
Quality (Spot Market Channel)						
Average Sort Loss	$ per 100 carcass lb	2,296	−1.336	0.266	−2.68	−0.69
Average Carcass Weight	lb	2,296	196.506	3.345	186.60	208.17
Average Backfat	Inch	2,296	0.740	0.028	0.66	0.82
Loineye Area	Inch	2,296	6.854	0.160	6.05	7.36
Loin Depth	Inch	2,296	2.285	0.053	2.02	2.45
Average Lean Percent	%	2,296	53.782	0.444	51.53	55.45

All Urban Consumers, Pork Products" (pork CPI) from the Bureau of Labor Statistics. We deflated the index such that it takes an average 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 provides more information. The disadvantage of this time series is the fact that pork belly is just one particular type of pork product and the price may therefore 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, but it is only available at the monthly level and hence contains less information, which makes estimating 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 that state specific quality requirements in terms of lean percentage, loin eye depth, back fat, etc. (RTI International, 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 because prices in these channels can respond freely to current market conditions. The next most 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" and the "Other Purchase Arrangements" as prices in the former are linked to other commodities that were less volatile during the sample period and prices in the latter are often negotiated for a long period of time and change infrequently. 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, loin eye area, loin depth, and average lean percent.[8] Except for the average backfat variable, a higher value of the measure indicates higher quality.[9]

Conceptual Framework

We propose a stylized model that elucidates the two channels through which AMAs affect the spot market price. The model shows that both the number of hogs sold through AMAs and spot market price volatility are key determinants of the spot market price level and that the effect of the spot market price volatility on the spot market price level is positive. Furthermore, the model also shows that the spot market price volatility is a function of the number of hogs sold 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: the contracts (AMAs) channel and the spot or cash market. There are also two time periods. In the first stage of 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.[10] 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. We further assume that farmers and packers agree to settle their transactions through the AMAs channel using the pricing formula $p_1 = \gamma_0 + \gamma_1 p_2$, where $\gamma_0 > 0$, $0 < \gamma_1 < 1$, and p_2 is the spot market price realized in the second period. As explained in the previous section, we categorize AMAs as marketing channels 2)–5) as defined by the USDA-AMS. Different pricing methods are used in these different marketing channels. At one extreme, hogs in the "Packer Owned" and "Packer Sold" channels are produced using production contracts. In this case, farmers get a fee for each hog they raise, and that fee is independent of the spot market price realized in the second period ($\gamma_1 = 0$). The contract price used in the fixed price contracts in the "Other Purchase Arrangements" channel is independent of the spot market price as well. On the other hand, the settlement price is closely linked to the spot market price realized in the second period for hogs transacted through the "Swine or Pork Market Formula Purchases" channel. In the extreme case of the "top-of-the-market" pricing method studied by Xia and Sexton (2004), the contract settlement price equals to the spot market price realized later ($\gamma_0 = 0, \gamma_1 = 1$). Therefore, our pricing formula here provides a parsimonious way of characterizing the pricing method used in the AMAs channel, and we believe it to be a good approximation for how price is settled in the AMAs channel on average.

In the second stage of the first period, farmers also decide how many additional hogs (q_2) to produce for the spot market. When farmers make this decision, the spot market price in the second period has not yet been realized and hence the spot market price is random from a farmer's point of view. We assume that the spot market price follows a normal distribution with mean $\overline{p}_2$ and variance σ_p^2.

In the second period, given the realized pork price in the downstream pork market and price for hogs in the spot market, p_2, each packer decides how many hogs (Q_2) 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.

Therefore, our model is a sequential one. First, farmers and packers make decisions on the supply and demand for hogs through the AMAs channel and the contract market clears. Second, given their decisions in the AMAs channel, they make decisions on the supply and demand for hogs transacted on the spot market and then the spot market clears. The entire model can be solved using backward

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

[9] Some packers also penalize farmers for producing hogs that are too heavy (>350 pounds).

[10] Changing the interpretation of the quantity variable in our model from the number of hogs to the pounds of live weight will not affect any of our theoretical results. Therefore, in our model, raising more hogs is equivalent to marketing larger animals.

induction; that is, one first solves for the equilibrium price and quantity in the spot market and then those in the AMAs channel. As all of the model implications we will test in the next section come from the equilibrium for the spot market, below we only solve for the equilibrium price and quantity in the spot market. Solving for the equilibrium price and quantity in the AMAs channel is omitted for purposes of brevity.

To solve for the equilibrium price and quantity in the spot market, we first examine a farmer's decision on q_2. Assuming that a farmer's utility function exhibits the constant absolute risk aversion (CARA) preference structure with risk aversion parameter $r_f > 0$, the expected utility for a representative farmer to produce q_1 hogs for the AMAs channel and q_2 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):

$$(1) \qquad Eu_f = (\gamma_0 + \gamma_1\overline{p}_2)q_1 + \overline{p}_2 q_2 - \frac{r_f}{2} var[(\gamma_1 q_1 + q_2)p_2] - \frac{a}{2}(q_1 + q_2)^2,$$

where $(\gamma_0 + \gamma_1\overline{p}_2)q_1$ and $\overline{p}_2 q_2$ are the farmer's expected revenue from selling q_1 hogs through the AMAs channel and q_2 hogs on the spot market, respectively, and $-\frac{r_f}{2} var[(\gamma_1 q_1 + q_2)p_2] = \frac{r_f \sigma_p^2}{2}(\gamma_1 q_1 + q_2)^2$ represents the negative utility the farmer receives because of the price risk.[11] Finally, we assume the production cost function to be quadratic in the quantity produced with parameter $\frac{a}{2} > 0$. With these assumptions, the farmer's decision problem in the second stage of the first period (q_1 is already determined in the first stage of the first period and is taken as given here) can be written as

$$(2) \qquad max_{q_2} Eu_f$$

and the optimal solution is

$$(3) \qquad q_2^* = \frac{\overline{p}_2 - \gamma_1 q_1 r_f \sigma_p^2 - a q_1}{r_f \sigma_p^2 + a}.$$

The second-order sufficient condition holds trivially with the assumption that both a and r_f are positive. Equation (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 price risk is higher, if the slope of the marginal cost function is larger, if the contract price is more closely linked to the spot market price (higher γ_1), or if more hogs are already committed through the AMAs channel.

Now we address the packer's problem. In the second period, given the realized 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 that the market is competitive and hence each packer is a price taker. The profit for a representative packer to procure Q_1 hogs through the AMAs channel and Q_2 hogs from the spot market and sell the pork produced from these hogs can be written as

$$(4) \qquad u_p = (kv - \gamma_0 - \gamma_1 p_2)Q_1 + (kv - p_2)Q_2 - \frac{wb}{2}(Q_1 + Q_2)^2,$$

where v is the price for one pound of pork, k is the number of pounds of pork that can be produced from one hog, and $(kv - \gamma_0 - \gamma_1 p_2)Q_1$ and $(kv - p_2)Q_2$ are the packer's profit from procuring Q_1 hogs from the AMAs channel and Q_2 hogs from the spot market and then selling the pork produced from these hogs, excluding processing costs. The processing cost is assumed to be quadratic in

[11] Of course, financial instruments like futures and options are available to the farmers to hedge against the price risk. Therefore, the negative utility here can also be interpreted as the farmer's risk management costs.

the quantity processed with parameter $\frac{b}{2} > 0$ and hence $\frac{b}{2}(Q_1 + Q_2)^2$ represents the increase in the packer's processing cost. In addition, w in equation (4) represents a productivity shock for the packer that is realized in the second period. The productivity shock is assumed to be a normally distributed random variable with mean 1 and a small variance σ_w^2, such that negative values of w happen with almost 0 probability. A w less of than 1 indicates a productivity gain, possibly due to a technology improvement. A w of greater than 1 indicates a productivity loss, such as a machine breakdown.

Since in our model the packer faces no uncertainty in the second period, regardless of whether the packer is risk averse or not, its decision problem can then be written as (Q_1 is already determined in the first period and is given here)

$$max_{Q_2} u_p \tag{5}$$

and the optimal solution is

$$Q_2^* = \frac{kv - p_2 - wbzq_1}{wb}, \tag{6}$$

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

Since this is perfect competition model in which many buyers and sellers buy and sell for the same good, in equilibrium, the supply is equal to the demand in the spot market; that is,

$$nq_2^* = mQ_2^*, \tag{7}$$

which can be rearranged to be

$$p_2 = kv - wbzq_1 - \frac{wbz}{r_f \sigma_p^2 a}(\overline{p}_2 - \gamma_1 q_1 r_f \sigma_p^2 - aq_1). \tag{8}$$

Taking expectations on both sides of equation (8) yields

$$\overline{p}_2 = k\overline{v} - bzq_1 - \frac{bz}{r_f \sigma_p^2 + a}(\overline{p}_2 - \gamma_1 q_1 r_f \sigma_p^2 - aq_1), \tag{9}$$

where $\overline{v}$ is the mean of the pork price. Rearranging equation (9) and plugging it back into equation (8), we have

$$p_2 = kv - wbzq_1 - \frac{wbz}{r_f \sigma_p^2 + a + bz}(k\overline{v} - bzq_1 - \gamma_1 q_1 r_f \sigma_p^2 - aq_1), \tag{10}$$

which yields several important implications for our study. First, equation (10) explains why the spot market price is random from the perspective of the farmers in the first period. This is because, in the first period, pork price and packers' productivity shocks have not been realized yet and are taken as random. Since the spot market price is a function of these two variables, it is also random. Second, the pork price, the number of hogs sold through AMAs, and the spot market price volatility, or the price 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:

$$\frac{\partial p_2}{\partial \sigma_p^2} = [k\overline{v} - (1 - \gamma_1)(bzq_1 + aq_1)]\frac{wbzr_f}{(r_f \sigma_p^2 + a + bz)^2}, \tag{11}$$

where z, b, and r_f are positive by definition and w is assumed to be positive with a probability close to 1. Also, equation (3) implies that $\overline{p}_2 - \gamma_1 q_1 r_f \sigma_p^2 - aq_1$ must be positive and hence $\overline{p}_2 - aq_1$

must be positive as well. With these results, equation (9) implies that $\overline{p}_2 < k\overline{v} - bzq_1$ and hence $k\overline{v} - bzq_1 - aq_1 > \overline{p}_2 - aq_1 > 0$. Therefore, we have

$$k\overline{v} - (1 - \gamma_1)(bzq_1 + aq_1) > k\overline{v} - bzq_1 - aq_1 > \overline{p}_2 - aq_1 > 0, \tag{12}$$

where the first inequality follows from the assumption that $0 < \gamma_1 < 1$. As a result, equation (11) implies that when the spot market price risk increases, the spot market price level will increase. When the spot market price risk increases, it is clear from equations (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, the derivative of p_2 with respect to q_1 is

$$\frac{\partial p_2}{\partial q_1} = -\frac{wbz(1 - \gamma_1)r_f\sigma_p^2}{r_f\sigma_p^2 + a + bz}. \tag{13}$$

Under the same set of assumptions discussed above, equation (13) implies that the spot market price level decreases with the number of hogs sold through AMAs. This is another major hypothesis that will be tested in our empirical analysis below. Fifth, equation (10) implies that

$$var(p_2) = k^2\sigma_v^2 + \left[q_1^2 = \frac{(k\overline{v} - bzq_1 - \gamma_1 q_1 r_f\sigma_p^2 - aq_1)^2}{(r_f\sigma_p^2 + a + bz)^2}\right] b^2 z^2 \sigma_w^2, \tag{14}$$

where σ_v^2 is the variance of the pork price. Since we assumed above that $var(p_2) = \sigma_p^2$, equation (14) further implies that

$$\sigma_p^2 = k^2\sigma_v^2 + \left[q_1^2 + \frac{(k\overline{v} - bzq_1 - \gamma_1 q_1 r_f\sigma_p^2 - aq_1)^2}{(r_f\sigma_p^2 + a + bz)^2}\right] b^2 z^2 \sigma_w^2. \tag{15}$$

Though not a closed-form solution, equation (15) implies that the spot market price volatility is a function of the number of hogs sold through AMAs. Our empirical analysis below will use a specification consistent with this implication.

Our stylized model makes it clear that there are two channels through which AMAs can affect the 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, equation (3) shows that farmers supply fewer hogs to the spot market. Each farmer supplies $\frac{\gamma_1 r_f\sigma_p^2 + a}{r_f\sigma_p^2 + a}$ fewer hogs and hence the market supply decreases for $\frac{\gamma_1 r_f\sigma_p^2 + a}{r_f\sigma_p^2 + a}n$. Also, equation (6) shows that packers also demand fewer hogs from the spot market. Each packer demands z fewer hogs and hence market demand decreases for zm hogs. The reduction in demand is larger than the reduction in supply because $zm > \frac{\gamma_1 r_f\sigma_p^2 + a}{r_f\sigma_p^2 + a}n$.[12] Hence, equation (13) implies that an increase in the number of hogs sold through AMAs causes a decrease in the spot market price level.

The indirect effect of AMAs on the spot market price level works through its effect on the spot market price volatility. Equation (15) implies that the spot market price volatility is a function of the number of hogs sold through AMAs. Total differentiating equation (15) with respect to σ_p^2 and q_1

[12] That the reduction in demand is greater than the reduction in supply is driven by our specification $p_1 = \gamma_0 + \gamma_1 p_2$, where $\gamma_0 > 0$ and $0 < \gamma_1 < 1$. When the spot market price decreases, the contract price also decreases but the pass-through rate is incomplete. As a result, packers have incentives to further reduce their demand on the spot market to offset this incomplete pass-through effect. When $\gamma_1 = 1$, the reduction in demand exactly equals the reduction in supply.

yields

$$(16)\qquad \frac{\partial \sigma_p^2}{\partial q_1} = \frac{2[q_1 - (a + \gamma_1 r_f \sigma_p^2 + bz)(k\overline{v} - bzq_1 - \gamma_1 q_1 r_f \sigma_p^2 - aq_1)(r_f \sigma_p^2 + a + bz)^{-2}]b^2 z^2 \sigma_w^2}{1 + 2(k\overline{v} - bzq_1 - \gamma_1 q_1 r_f \sigma_p^2 - aq_1)[k\overline{v} - (1-\gamma_1)(bzq_1 + aq_1)](r_f \sigma_p^2 + a + bz)^{-3} r_f b^2 z^2 \sigma_w^2}.$$

The denominator in equation (16) is positive because, as proved in equation (12), $k\overline{v} - (1-\gamma_1)(bzq_1 + aq_1)$ is positive. Furthermore, equation (12) implies that $k\overline{v} - bzq_1 - \gamma_1 q_1 r_f \sigma_p^2 - aq_1 > \overline{p}_2 - aq_1 - \gamma_1 q_1 r_f \sigma_p^2$ and we know that $\overline{p}_2 - aq_1 - \gamma_1 q_1 r_f \sigma_p^2 > 0$ from equation (3). As a result, $k\overline{v} - bzq_1 - \gamma_1 g_1 r_f \sigma_p^2 - aq_1$ is also positive. Therefore, equation (16) shows that the spot market price volatility can either increase or decrease depending on the sign of $q_1 - (a + \gamma_1 r_f \sigma_p^2 + bz)(k\overline{v} - bzq_1 - \gamma_1 q_1 r_f \sigma_p^2 - aq_1)(r_f \sigma_p^2 + a + bz)^{-2}$. But intuitively, we expect that the spot market price volatility increases with the number of hogs sold through AMAs. This is because with the increase in the number of hogs sold through AMAs, the spot market becomes thinner. As a result, a given productivity shock in the second period is larger in terms of percentages and the effect on the spot market price level is therefore larger and the resulting price volatility higher. This can be seen more clearly from the derivative of p_2 with respect to w using equation (10):

$$(17)\qquad \frac{\partial p_2}{\partial w} = -bzq_1 - \frac{bz}{r_f \sigma_p^2 + a + bz}(k\overline{v} - bzq_1 - \gamma_1 q_1 r_f \sigma_p^2 - aq_1),$$

which implies that when the productivity shock is less favorable, p_2 decreases and the effect is larger with a higher value of q_1, the number of hogs transacted through AMAs. The latter can be seen more clearly from

$$(18)\qquad \frac{\partial^2 p_2}{\partial w \partial q_1} = -\frac{(1-\gamma_1) bz r_f \sigma_p^2}{r_f \sigma_p^2 + a + bz} < 0.$$

Together with the result from equation (11) that when the spot price volatility is higher, the spot market price level is higher, we expect an increase in the number of hogs sold through AMAs first to increase the spot market price volatility, which in turn increases the spot market price level.

Empirical Strategy and Results

Stationarity Test

Before we move on to regression analysis, we first need to examine whether our times series data are stationary. As pointed out by Ng (1995), it is well known that if two time series are nonstationary, then regressing one on the other will produce spurious estimates and the standard asymptotic analysis will be invalid. If the dependent variable is stationary but the independent variable is nonstationary, then the estimate will be consistent but the standard asymptotic analysis will be invalid. Therefore, if the time series we have are found to be nonstationary, then they need to first be transformed into stationary time series before we can use them for regression analysis.

One model that has been frequently used to characterize nonstationary time series is the so-called unit root or random walk model. As a result, testing for nonstationarity 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). Dickey and Fuller (1979) did early, pioneering work on unit root tests. Specifically, they use the following AR(1) specification for a time series x_t:

$$(19)\qquad x_t = a + \phi x_{t-1} + bt + \epsilon_t,$$

where ϵ_t is 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 nonzero intercept. If the model has a unit root ($\phi = 1$), then this series is nonstationary. We can test the null hypothesis that $\phi = 1$ against the alternative that $|\phi| < 1$, which means the series is stationary. However, this specification depends on the assumption that ϵ_t is white noise. Quite often the dependence structure in x_t is more complicated than that of an AR(1) process, and if the AR(1) specification of equation (19) is used, then the resulting error is not 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 equation (19) with lags of Δx_t; that is,

$$(20) \qquad x_t - x_{t-1} = a + (\phi - 1)x_{t-1} + bt + \beta_1 \Delta x_{t-1} + \ldots \beta_p \Delta x_{t-p} + \epsilon_t,$$

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 and West (1987) procedure to correct for it. We test for the stationarity of our time series using both tests.

Table 3 reports the results of the two tests for the time series that will be used in our regression analysis below. Whether the time-trend variable or/and the intercept term are included as controls in equations (19) and (20) are determined by eyeballing the time series plots of the data;[13] the specification used for each variable is reported in column 2 of the table. Column 3 of the table reports the τ-statistics of the ADF test.[14] The optimal number of lags used for each variable in equation (20) was chosen using the Bayesian Information Criterion (BIC) (for details, see Greene, 2003, p. 644) 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 to correct for serial correlation and heteroskedasticity 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 variables, we reject the hypothesis that there is a unit root—or the time series is nonstationary—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 the two tests, respectively. For the pork CPI series, we fail to reject the hypothesis that the time series is nonstationary at conventional significance levels. Therefore, we first differenced the pork CPI series and retested the resulting series for unit roots. Results from both tests reject the hypothesis that the first differenced pork CPI series is nonstationary. As a result, we use the first difference of the pork CPI series in our regression analysis. 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 the spot market price level and the other for the spot market price volatility. For the price-level equation, we use an autoregressive distributed lag (ADL) (m,0)-autoregressive moving average (ARMA) (p,q) specification as follows:

$$(21) \qquad A(L)[D(L)y_t - z_{1t}\beta_1] = R(L)\varepsilon_t,$$

where y_t denotes the spot market hog price time series, $A(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \ldots - \alpha_p L^p$, $D(L) = 1 - d_1 L - d_2 L^2 - \ldots - d_m L^m$, $R(L) = 1 - r_1 L - r_2 L^2 - \ldots - r_q L^q$; L is the lag operator; z_{1t} is a vector of control variables, including the variable of our main interest, AMAs%, the

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

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

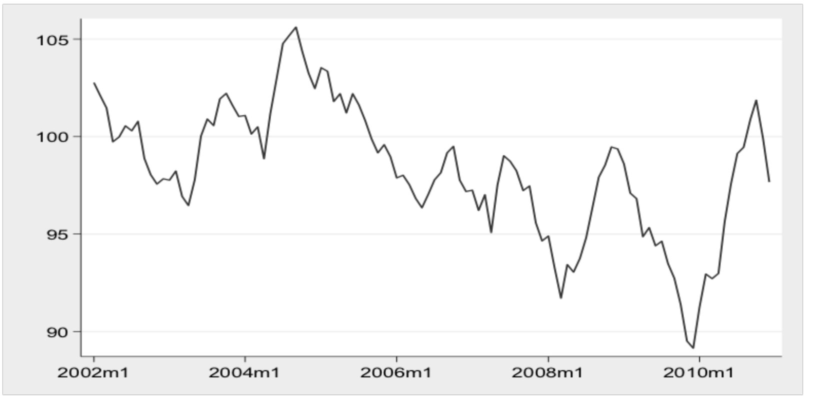

Figure 3a. Pork CPI

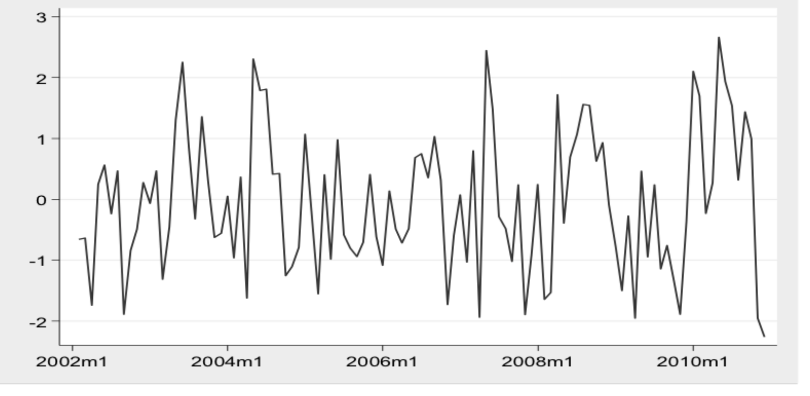

Figure 3b. First Difference of Pork CPI

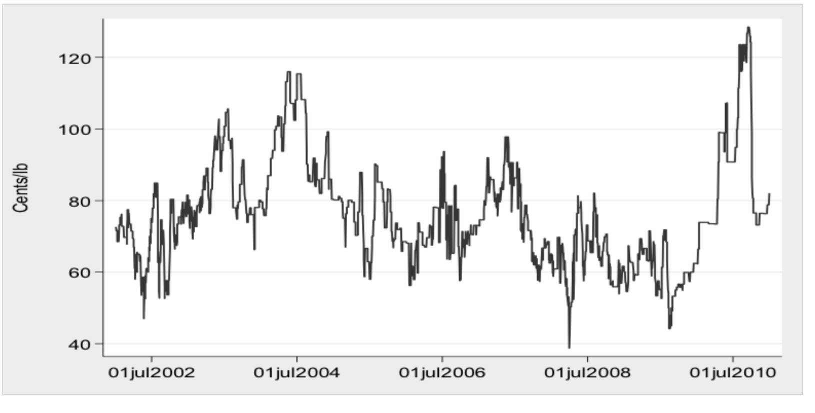

Figure 3c. Pork Bellies Price

price volatility term, $\sigma_t^2 = var(\varepsilon_t)$ (hence the name of the model, GARCH-in-mean), and the pork price. From equation (11), 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 term and the trend variable to control for the nonzero intercept and the long-term trend effect, and five quality measures to control for quality differences across different transaction

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: Double and triple asterisks (**, ***) denote that the null hypothesis of a unit root is rejected at the 5% level or 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 $\{4(T/100)^{2/9}\}$.

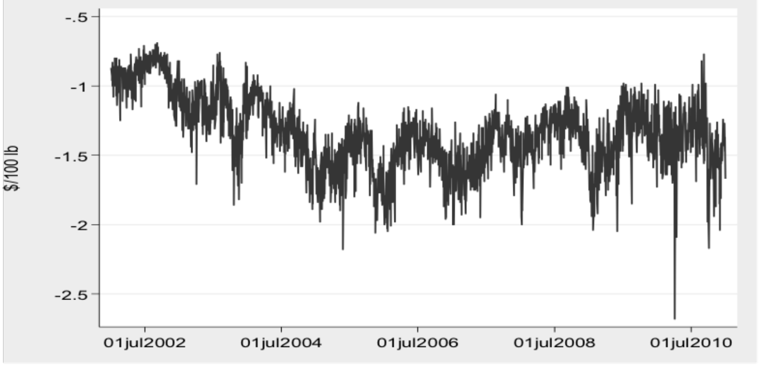

Figure 4. Average Sort Loss

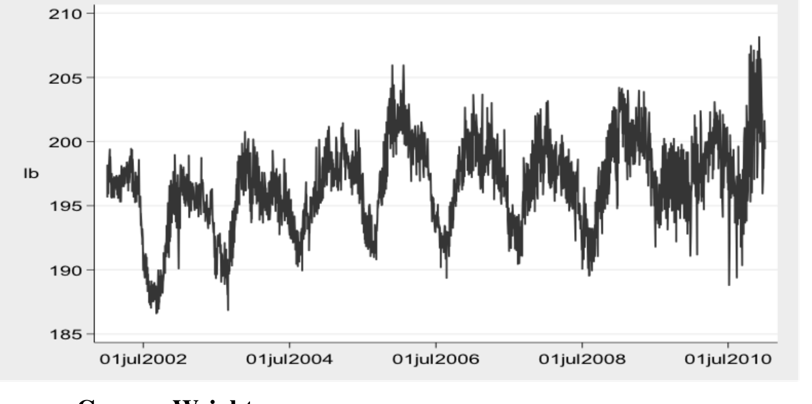

Figure 5. Average Carcass Weight

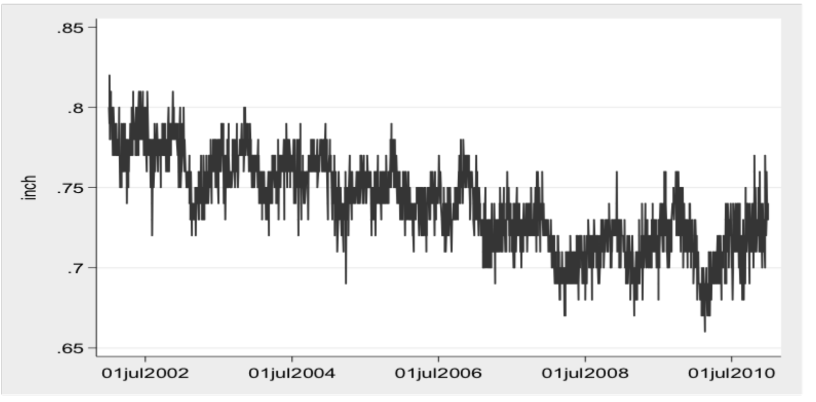

Figure 6. Average Backfat

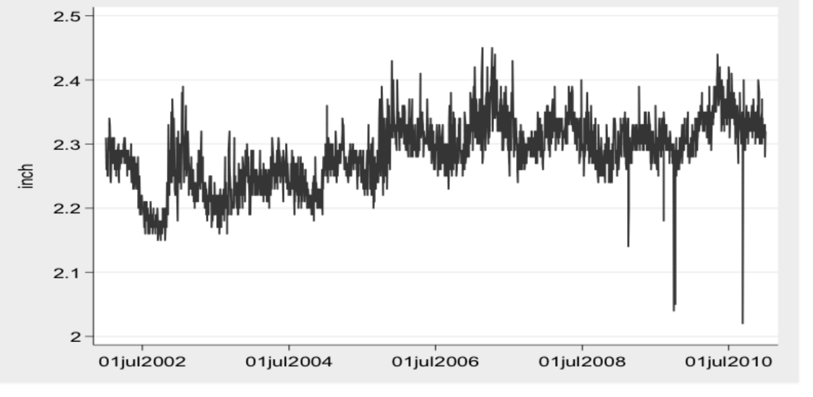

Figure 7. Loin Depth

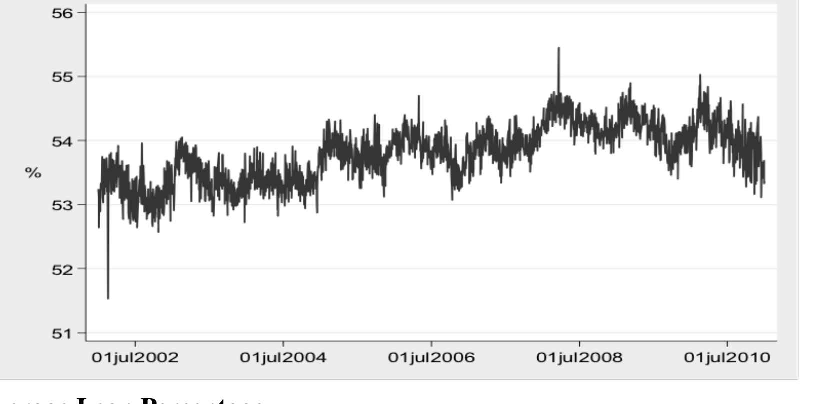

Figure 8. Average Lean Percentage

days.[15] We use the ADL(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 describes the behavior of the spot market price volatility. We allow the possibility that volatility varies over time and use the following GARCH(u,v) specification:

$$\sigma_t^2 = \exp(z_{2t}'\beta_2) + \sum_{i=1}^{u} \gamma_i \epsilon_{t-i}^2 + \sum_{i=1}^{v} \delta_i \sigma_{t-i}^2. \tag{22}$$

We use the specification of $\exp(z_{2t}'\beta_2)$ rather than $z_{2t}'\beta_2$ in equation (19) because the non-negativity restriction of the GARCH model (Bollerslev, 1986) is more likely to be satisfied with this specification. As the GARCH model is a model for the conditional variance, which is non-negative by definition, the fitted value from the estimated model needs to be non-negative as well. With the specification of $\exp(z_{2t}'\beta_2)$ in equation (19), the sufficient condition for the non-negativity restriction to be satisfied reduces to be that all of the γ and δ coefficients in equation (19) be 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 ADL-ARMA-GARCH model in equations (21)–(22). Each combination of the lag values m, p, q, u, and v is a different specification. We present and discuss results from the specification that has the best fit in terms of model fitness measures AIC and BIC below.

Estimation Results

Table 4 presents the estimation results when pork CPI is used as the pork price. The ADL(3,0)-ARMA(2,7)-GARCH(1,1) specification turns out to be the specification that best fits the data. The results show the model is well-specified. The non-negativity restriction and 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 (22) are positive and the sum of them is smaller than 1. Also, results from the Ljung-Box Portmanteau (Q) test[16] show that we cannot reject the hypothesis that the residual series from the ADL-ARMA model (21) is not serially correlated. This is consistent with the model assumption we made earlier. Finally, since the ADL-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 1 in absolute value, where functions $A(\cdot)$ and $D(\cdot)$ are defined above in equation (21). Using the estimated coefficients for αs and ds, we find that 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% increase in the share of transactions through AMAs is a reduction in the spot market price by about 7.5 cents per 100 carcass pounds (about 0.13% of the average spot market price in the data). This result is consistent with results of other studies that estimate static

[15] The loin eye 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.

[16] 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.

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

		Price Level Equation		Variance Equation	
Dependent: Spot Price		Coeff.	Std. Err.	Coeff.	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			

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5% and 1% level.

instead of dynamic models. For example, Elam (1992); Schroeder et al. (1993); Ward, Koontz, and Schroeder (1998); and Schroeter and Azzam (2003) all report that AMAs have a mild negative effect on spot market price levels in the cattle market. This finding is also consistent with the industry arguments that AMAs decrease the spot market price by removing spot market demand while spot market supplies tend to remain at their original volumes. Second, the coefficient for the price volatility term, or the GARCH-in-mean term, is estimated to be positive and significant, indicating that when there is more price risk in the market, the expected return is also higher. Third, pork price has a positive, though insignificant, effect on the hog price level. All three of these findings are consistent with the implications of our model presented above. Fourth, all but one of the quality measures have significant effects on the hog price and their signs are all correct; that is, better quality hogs command higher price.[17] Finally, coefficients for some of the monthly dummy variables (March, April, August, September, October) are estimated to be negative and the estimates are significant, which indicates that the spot market hog price is 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 the market-thinning effect discussed above. Together with the result that the spot market price increases with the price volatility, this result implies that the indirect effect of AMAs on the spot market price level is positive. In addition, we also find that the trend variable has a negative and statistically significant effect on the price volatility, which implies that the spot market becomes less volatile over time. On the other hand, not much seasonality pattern is detected in the price volatility, as the estimates for all but one monthly dummy coefficient 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 pork bellies cash contracts). 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 that now the pork price measure has a positive and statistically significant effect on the hog price, which is not surprising given that the pork bellies price is available daily rather than monthly and there is therefore more variation in the data, making the estimation of the coefficient easier.

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

With the parameter estimates, we can compute the effects of AMAs on the spot market price distribution. We first examine the effect of AMAs on the price volatility. Since the price volatility equation (22) is essentially a dynamic model, the long-run or equilibrium effect of AMAs on the price volatility can be quantified using the formula

$$\frac{\exp(z_{2t}'\beta_2)\beta_{2,AMA\%}}{1-\delta_1}, \tag{23}$$

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 the price volatility varies across observations. Therefore, in table 6 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 a 1% increase in the use of AMAs increases the price volatility by 0.0185 on average. This amounts to about 6.19% of the mean value of the fitted price volatility, $\hat{\sigma}_t^2$. This effect varies across observations, ranging from less than 1% to over 30%. The results are quite similar when the price of pork bellies is used as the measure for pork price.

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[17] Some packers stopped reporting quality measures to USDA during the sample period. As a result, the estimated effects of quality measures may also reflect the change in the coverage of the quality data. We thank a reviewer for bringing this to our attention.

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

		Mean Price Equation		Variance Equation	
Dependent: Spot Price		Coeff.	Std. Err.	Coeff.	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			

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5% and 1% level.

Table 6. 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 7. 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 8. 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%

We now turn to the effects of AMAs on the spot market price level. With the ADL-ARMA specification (21), the long-run direct effect of AMAs on the spot market price level can be computed as

$$\text{(24)} \qquad \frac{A(1)\beta_{1,AMA\%}}{A(1)D(1)} = \frac{B_{1,AMA\%}}{1 - d_1 - d_2 - d_3},$$

where $\beta_{1,AMA\%}$ is the coefficient for the AMA% variable in equation (21). The long-run indirect effect of AMAs on the spot market price level is the product of the effect of the price volatility on the price level and the effect of AMAs on the price volatility:

$$\text{(25)} \qquad \frac{A(1)\beta_{1,\sigma^2}}{A(1)D(1)} \frac{\exp(z_{2t}'\beta_2)\beta_{2,AMA\%}}{1 - \delta_1} = \frac{\beta_1,\sigma^2}{1 - d_1 - d_2 - d_3} \frac{\exp(z_{2t}'\beta_2)\beta_{2,AMA\%}}{1 - \delta_1},$$

where β_{1,σ^2} is the coefficient for the price volatility term in equation (21). Again, the indirect effect varies across observations, and we report its minimum, median, mean, and maximum. Tables 7 and 8 report the direct effect, the indirect effect, and the net effect of AMAs on the spot market price level. For the case where pork CPI is used as the pork price, on average, the direct effect of a 1% increase in AMAs decreases the spot market price by about \$5, and the indirect effect increases the spot market price by about \$1.75. Therefore, the net effect is a reduction of about \$3.30 per 100 pounds of carcass meat. This amounts to about 6% of the mean spot market price during the sample period. We observe smaller effects when the price of pork bellies is used as the pork price. On average, a 1% 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 nontrivial. This is driven by the fact that the spot market hog price time series is highly autocorrelated and a small short-run effect can therefore accumulate into a large long-run effect over time.

Since the increase in the use of AMAs increases the spot market price volatility and decreases the spot market price level, we conclude that farmers who rely solely on 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.

Conclusions

This paper estimates the effects of alternative marketing arrangements (AMAs) on the spot market price distribution in the U.S. hog market. We find that increases in the use of AMAs increase the spot market price volatility and decrease the spot market price level. The effect on the 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 the spot market price volatility. The direct effect is found to dominate the indirect effect. Increases in the use of AMAs benefit packers and those farmers who rely solely on the spot market lose.

Having found that increases in AMA usage have a negative direct effect on the spot market price level and that this direct effect is larger than the indirect effect, the next natural step is to inquire into the main underlying driving force for this negative direct effect. In our model, the direct effect is a result of 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 it represents a structural change that favors the packers. On the other hand, this effect may also derive from the fact that AMAs divert hogs of good quality away from the spot market (Wang and Jaenicke, 2006).[18] If this is the case, then the decrease in the spot market price level is less worrisome, as it simply reflects the fact that lower quality hogs receive lower prices. Most likely, both effects are at work. It will be an interesting and challenging task to distinguish the two sources of the direct effect and examine which is the driving force.

Our model also channels the positive effect of AMAs on the spot market price level through the increase in price volatility or price risk on the spot market. Another path through which this effect can be channeled could be that a shrinking spot market is associated with higher transactions costs or marketing timing risk and hence growers need to be compensated for that. Again, it will be an interesting and challenging task to collect data on transactions costs so that we can determine which channel is at work. These questions are left for future research.

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[18] The quality measures in our regression only control for the variation in hog quality across different transaction days, not across different marketing channels.

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