Three Essays in Economics of U.S. Dairy Markets

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Dedication

To the U.S. dairy producers

Abstract

The Margin Protection Program for Dairy Producers, created under the Agricultural Act of 2014, is a new margin insurance program that pays indemnity when a national income-over-feed-cost margin declines below an elected coverage level. A widely speculated side effect of the program is its potential to reduce uses of CME dairy futures and options for hedging purposes. The first essay studies this issue under the assumption that dairy producers adopt private hedging practices and the Margin Protection Program as ways to protect against catastrophic margin risks rather than for speculative profits. Empirical framework is set under the safety-first assumption in that a producer minimizes hedge ratio subject to a probabilistic constraint that restricts the revenue above a critical threshold. The novelty of this study is the use of accounting data on dairy cost of production in two U.S. regions. Monte Carlo simulation results that compare the crowding-out effect on representative producers in the upper and lower Midwest show the magnitude of the effect depends on production efficiency, market risk exposure, and the timing of the Margin Protection Program sign-up.

The second essay proposes MPP-DL as a supplemental insurance program for the 2014 Farm Bill dairy title margin program MPP-D (formally known as the Margin Protection Program for Dairy Producers). MPP-DL caps an indemnity payment to $1 per hundredweight of milk under protection. A model built on cumulative prospect theory is used to predict 37 representative farms' sign-up choices. Risk attitude parameters are estimated by grid search method based on sign-up data for coverage year 2015. Fiscal cost analysis shows that MPP-DL is able to smooth payment streams over the years studied in this essay. Notably, MPP-DL can redirect producers to choose MPP-DL instead of MPP-D when margin forecast at sign-up is above the historical average margin while also keeping the overall cost of the program lower than MPP-D.

The third essay investigates asymmetric transmission between farm-gate raw milk prices and retail fluid milk prices in 15 U.S. regional markets. A two-threshold three-regime error correction model is first estimated on individual price pairs. Threshold effect is then studied through Common Correlation Effect Mean Group panel data time series model for each regional market. A rich set of econometric tools are employed in empirical analysis to deal with discontinuous long-term price relationships. Structural break unit root tests and cointegration tests are performed to ensure the long-term relationship of retail-farm prices exists. Symmetry test results suggest that the majority of the regions feature positive asymmetric price transmission. In addition, there is evidence to suggest that asymmetry is sensitive to the presence of temporary retail sales price.

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1.1 Introduction

In the decade prior to 2015, due to the volatile milk price and increasing feed costs, the U.S. dairy industry had been facing an ever growing challenge to stay at a healthy profit margin. The once effective Dairy Product Price Support Program (DPPSP), formerly known as the Dairy Price Support Program, became irrelevant in this new market landscape with its lower-than-market $9.90 per hundredweight (cwt) price floor for milk[1] (see Figure 1 below). Amid concerns over stabilizing income-over-feed-cost (IOFC) margin for dairy producers, the Agriculture Act of 2014, which will be referred to as the 2014 Farm Bill in the rest of the paper, authorized USDA Farm Service Agency (FSA) to administer an insurance program that pays indemnity if a national level of IOFC margin falls below a user-selected coverage level. Formally known as the Margin Protection Program for Dairy Producers (MPP), the insurance program has the potential to become a new risk management tool for the dairy industry.

[1] The DPPSP supports the milk price by purchasing a basket of dairy products whenever a product's price falls below a threshold that reflects the $9.90 milk price based on production relationship between the milk price and the product price. The program was discontinued in 2014 when the MMP was established.

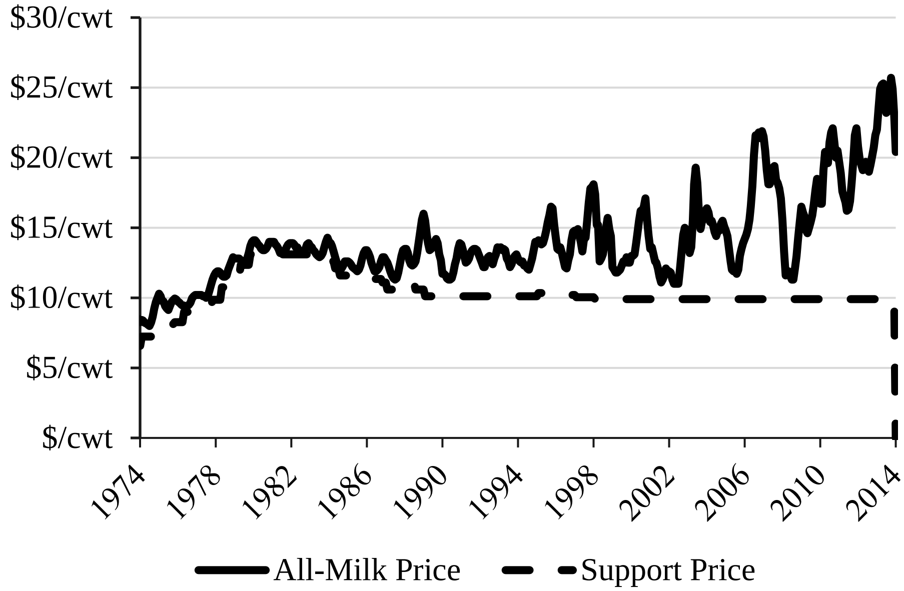

Figure 1 Historical milk price vs. support price

Throughout the passage of the 2014 Farm Bill, there has been considerable amount of speculation on the impact of the new margin protection program on the existing risk management practice through futures contracts traded on Chicago Mercantile Exchange (CME) (Stephenson, et al., 2014, Wolf, et al., 2013). One of the reasons MPP may reduce CME contract uses is rooted in the fact that MPP premiums are subsidized by the federal government while CME contracts are sold at market fair prices. The lowest protection level of MPP is free for producers of all sizes. Actuarial pricing principle suggests that an insurance is valued at zero when the probability of indemnity being paid is also zero. Given a fixed level of protection, there is no guarantee that market conditions would always be conducive to not trigger indemnity payments. This means certain levels of MPP protection are cheaper than what the market would have charged for.

A recent survey among dairy producers and market experts states that 10% to 50% of the trading volume on CME Class III milk contracts were placed by producers directly or through their cooperatives (Stephenson, et al., 2014). The upward sloping open interest curve presented in Figure 2 suggests that the interest in using Class III contracts for risk management purpose has been growing since the commodity was first introduced in 1996.

Part of the reason that contributes to the growing interest is that CME is the go-to place for dairy exporters to offset their risk associated with the commitments specified in forward contracts they signed with foreign importers. For example, a long position in Class III milk contracts effectively reduces a dairy exporter's risk exposure to matters typically highly sensitive in the buyer's home country. Without CME futures contracts, dairy exporters will find themselves unable to promise a fixed export price for long period of time[2], therefore losing their comparative advantage to competitors in EU and New Zealand.

Figure 2 Class III futures and options open interest

The market concern about the MPP negatively affecting private risk management practice is founded in a historical precedent roughly five decades ago. The butter futures contract was first traded in the namesake Chicago Butter and Egg Board – the former entity of CME before 1919 – since the inception of the board. On October 1st, 1949, the DPPSP was established under the Agricultural Act of 1949. The DPPSP greatly reduced the price risk faced in dairy production and effectively sidelined butter contracts as a risk management

[2] The earliest a person can trade a Class III milk futures contract is about 24 months ahead of the named expiration month of the contract. If an exporter uses such futures to hedge sales prices, they can secure the sales prices up to 24 months ahead of the delivery of their milk.

tool for decades. The interest in butter contracts waned and the contract was ultimately delisted.

Compared to the MPP that is designed at a national level, CME futures and options contracts as risk management tools provide great flexibility. Individual producers can customize their hedging strategies using one or several contracts to fit their specific production and risk profile. Therefore, it is of vital importance to maintain trading volumes of CME contracts. However, because the MPP provides an alternative to the traditional risk management tools through CME and only allows dairy producers to participate, many dairy risk management experts believe that the MPP may reduce the use of futures for risk management purpose if producers find it provides satisfactory risk protection (Stephenson, et al., 2014). In the rest of the paper, I refer to this reduction as the "crowding-out" effect. This paper seeks to answer this question: what is the magnitude of the crowding-out effect, if any, that the MPP poses to the dairy futures market?

Newton, et al (2013a) argue that the margin protection program is not designed to be actuarially fair. An insurance program that is not actuarially fair is prone to the plague of adverse selection and moral hazard. This argument supports the heated speculation on the crowding-out effect. To take one step further on the issue, Wolf, et al. (2013) theoretically analyzed the change in hedge ratio with and without MPP under a mean-variance utility framework. Their findings confirm the existence of the crowding-out effect.

This paper adds empirical analysis to previous studies. The results of this paper support the theoretical findings in Wolf, et al. (2013). But the model in this paper is built on a set of less restricted assumptions. The empirical study of this paper is also in line with the 9-month mean-reversion theory in Bozic, et al. (2012) and suggests that MPP may better serve its purpose if the program sign-up period is further removed from the start of the coverage year. A novel dairy financial benchmark dataset utilized in this study allows us to look at the crowding-out effect by different regions, which is something that has not been done in previous studies.

The rest of the paper can be divided into several sections. The first section introduces the margin protection program and paves the way for the derivation of the empirical model in the second section. The third section details empirical methods and documents additional assumptions regarding the characterization of the multivariate log-normal distribution. Empirical results follow in the section after. The paper concludes in the last section by reiterating key findings and discussing directions for further research.

1.2 Background: Margin Protection Program for Dairy Producers

The Margin Protection Program for Dairy Producers (MPP) in the 2014 Farm Bill allows dairy producers to protect their income-over-feed-cost (IOFC) margin against adverse market conditions. Much like a put option on the IOFC margin, the MPP is a voluntary program that pays an indemnity if a national level bi-monthly IOFC margin falls below a coverage level that a dairy producer elects to purchase. The coverage period always starts in January and ends in December of the same year. Coverage year 2015 is the first coverage year under the current authorization of the farm bill and opened its sign-up period on Sept 2nd, 2014. Subsequent coverage years (2016 - 2018) will start enrollment between July and September of the preceding year. There are four major components of the MPP: Actual Dairy Production Margin (ADPM), Production History (PH), Coverage Percentage (CP) and Coverage Level (CL).

The Actual Dairy Production Margin (ADPM) is a type of IOFC margin that equals the average milk price for all grades of milk minus the cost of three key components of feed. The 2014 Farm Bill states that the ADPM is calculated from the following formula:

$$\begin{aligned} ADPM\ (\$/\mathrm{cwt}) = & \ \textit{All-Milk Price}\ (\$/\mathrm{cwt}) \\ & -1.0728 \times \textit{Corn Price}\ (\$/\mathrm{bu}) \\ & -0.00735 \times \textit{Soybean Meal Price}\ (\$/\mathrm{ton}) \\ & -0.0137 \times \textit{Alfalfa Hay Price}\ (\$/\mathrm{ton}) \end{aligned} \tag{1}$$

where *All Milk Price* is the national average wholesale milk price; *Corn Price* and *Alfalfa Hay Price* are national average prices reported by National Agricultural Statistics Service (NASS); and *Soybean Meal Price* is the Dectaur-Central Illinois high protein soybean meal price reported by Agricultural Marketing Service. Though $ADPM$ can be calculated from monthly USDA data, the determination of the indemnity payment event is based on the two-month average ADPM. The two-month periods over which indemnity payment is determined start at the first two-month period of Jan/Feb and end at Nov/Dec with six in total in a coverage year. The formula implies that the ADPM is a national level IOFC margin and individual participants cannot tailor the ADPM to reflect their actual margin structure.

The Production History (PH) determines the upper bound of the amount of milk production (in pounds) that one can cover in the MPP. The PH level for coverage year 2015 equals the highest annual production of a participating producer in the calendar years of 2011, 2012 and 2013. PH in subsequent years are increased by a fixed percentage FSA announces in the summer of each year. The percentage increase applies to the coverage year after the year the percentage is announced. There are other rules in place to determine PH for new dairy producers whose production history has not been 3 years old. In this paper, PH is assumed known and the determination of its value is irrelevant to the research question.

Coverage percentage (CP) is the percentage of PH that is covered in the MPP. Individual participants can elect to cover as low as 25% to as high as 90% of their PH with an increment of 5% in between. Coverage Level (CL) is the IOFC margin level that may trigger the indemnity payment if the ADPM slips below CL. It is between $4.00/cwt and $8.00/cwt in an interval of 50 cents.

Annual premium of the MPP insurance depends on the CL and PH. The premium is priced to encourage small scale producers to participate by charging them less than larger dairy farms even though both may face the same risk environment. In order to entice high participation rate, the program offers a 25%-off discount to Tier 1 rates for all levels of CL except the $8.00/cwt coverage for coverage year 2015 and 2016. Detailed premium charges can be seen in Table 1.

Table 1 MPP Premiums under different coverage level and production history

Coverage Level ($/cwt)	Tier 1 for 2015-2016 ($/cwt)	Tier 1 for 2016-2018 ($/cwt)	Tier 2 ($/cwt)
$4.00	$0.000	$0.000	$0.000
$4.50	$0.008	$0.010	$0.020
$5.00	$0.019	$0.025	$0.040
$5.50	$0.030	$0.040	$0.100
$6.00	$0.041	$0.055	$0.155
$6.50	$0.068	$0.090	$0.290
$7.00	$0.163	$0.217	$0.830
$7.50	$0.225	$0.300	$1.060
$8.00	$0.356	$0.475	$1.360

The tier 1 rates (2^{nd} – 3^{rd} columns in Table 1) apply to the first four million pounds of the covered production. The covered production is calculated as the product of production history and coverage percentage. The tier 2 rates apply to the rest of the covered production. For example, if a producer chooses to cover 50% (CP = 50%) of its 10 million pounds PH, the covered production equals 5 million pounds. The producer will pay the tier 1 rate for the first 4 million pounds of milk and the tier 2 rate for the remaining 1 million pounds. The premium calculation on a per hundredweight basis can be summarized in equation (2):

$$Premium = \min\left(\frac{4\ million}{CP \cdot PH}, 1\right) \cdot R_1 + \max\left(1 - \frac{4\ million}{CP \cdot PH}, 0\right) \cdot R_2 \qquad (2)$$

where R_1 is the tier 1 rate and R_2 is the tier 2 rate. Both rates are functions of the coverage level.

Because MPP requires a single sign-up to cover a whole calendar year, it is of dairy producer's interest to select a proper coverage level for the entire coverage period. If a dairy producer believes the profit margin will be high during the coverage period, they may choose the lowest coverage level to minimize premium payment. If the dairy producer envisions the profit margin to be low, they may opt to purchase a higher coverage level to maximize the expected net indemnity payment (indemnity minus premium).

1.3 Model Framework: Hedging alongside the MPP

Telser (1955) proposed a "safety-first" hedging model in which the primary goal of a risk-averse producer is to keep below a chosen probability level the risk of his or her net income falling below a certain threshold. From there a long list of studies examined a variety of problems under mean-variance framework, such as Pyle and Turnovsky (1970), Ederington (1979), Anderson and Danthine (1980), and Anderson and Danthine (1981). Because the mean-variance framework considers upside risk and downside risk equally (Levy, 1974, Quirk and Saposnik, 1962, Tsiang, 1972), a second generation of risk analysis articles focused on the lower partial moments to measure hedging effectiveness. Examples of previous work on this topic include Berck and Hihn (1982), Turvey and Nayak (2009), Mattos, et al. (2008), Power and Vedenov (2010).

Because hedging with futures curbs the overall profit when the market moves in favor of the cash market where the actual sales take place, it is not always a very profitable move to fully hedge one's production. Therefore, it is safe to assume that as long as a producer's action expose themselves under their tolerated risk level, they are willing to make a tradeoff between a locked-in profit margin with less upside potential and the opportunity to profit from favorable market environment. Therefore, a dairy producer's risk behavior can be thought as to seek the lowest amount of risk protection in futures markets as long as the producer is comfortable with the risk they take. This assumption holds with or without MPP participation because MPP only pays indemnity in an adverse market environment. MPP alleviates the loss dairy producers may suffer when milk price is low or feed cost is high.

Other assumptions I make for the empirical model:

1. No production risk: the expected production turns out to be the actual production.

2. There are only two types of producers: feed growers and feed purchasers. Feed growers grow feed on site to meet ration needs completely. Feed purchasers buy all feed from open markets.

3. Futures contract size is perfectly divisible: one can always find an integer number of futures contracts to cover their production no matter the hedge ratio or production level.

4. Producers set up the hedge portfolio for the entire production in an MPP coverage year at the time they sign up for the program. There are twelve hedging portfolios targeting 12 months of the coverage year. All contracts are held until contract expiry. Hedge for feed is at a fixed proportion to the milk output according to feed ration.

5. A producer's creditworthiness does not depend on MPP participation. This assumption ensures the minimum short-term financial obligation a producer must meet to operate their business is independent of MPP participation.

A dairy producer who seeks to find the least hedge coverage while having the risk in check solves the following problem

$$\begin{array}{ll} \min & h \\ s.t. & \Pr[revenue \leq RTL] \leq \gamma \\ & h \in [0,1] \end{array} \tag{3}$$

where h, the hedge ratio, is defined as the proportion of the milk production being hedged over the overall production; $\Pr[\cdot]$ denotes the probability of a catastrophic event; RTL denotes a revenue threshold level and is typically set around the variable cost of production; γ represents the maximum risk the producer can tolerate in terms of the probability of the revenue being below the RTL. The inequality constraint in the problem is termed the risk constraint. Everything in the problem is deterministic except the $revenue$ term. The term is subject to milk and feed price shocks. The hedge ratio is bound between 0 and 1 to eliminate over-hedging. Given that the hedge ratio is being minimized here, if the optimized hedge ratio still turns out to be greater than 1, either the risk tolerance level (γ) is unrealistically strict against the risk environment or the cost of production is too high resulting in a very large RTL.

The $revenue$ term in the risk constraint is further specified by the following formula:

$$revenue = \alpha\left(\frac{1}{6}\sum_{j=1}^{6} I_j - P^{MPP}\right) + \left(\sum_{T}^{12} \beta_T \cdot MI(T)\right) + h\left(\sum_{T}^{12} \beta_T \cdot HG(T)\right) \qquad (4)$$

This formula defines the monthly average revenue on a per hundredweight basis. The three terms separated by the plus signs respectively represent the MPP net indemnity payment, income from milk sales and the hedging Profit & Loss (P&L). In the formula, t denotes the date when the producer registers for the program. T represents an MPP coverage month with value 1 denoting January, value 2 denoting February and so on. β_T adjusts for production seasonality for month T. It is equal to the ratio of average monthly production in month T over the average annual production in the period between 2008 and 2014. The actual values of β_T can be found in Table 13. $HG(T)$ defines the per hundred weight hedging P&L for month T's milk production. Similarly $MI(T)$ denotes the per hundred weight income from milk sales in month T. Furthermore, j represents a bi-monthly indemnity payment period in a coverage year. It starts with the Jan-Feb period and ends with the Nov-Dec period. I_j denotes the MPP indemnity payment made for the jth period. P^{MPP} denotes the MPP premium calculated from equation (2). Since MPP is not actuarially fair, the first term in equation (4), which represents the expected indemnity payment, does not vanish to zero under normal conditions. Finally, α represents the coverage ratio whose sole purpose is to sale the net indemnity payment to match with the expected production level. For an MPP non-participant, α is set to zero, whereas for a participant, it is defined as

$$\alpha = \frac{CP \cdot PH}{Y} \qquad (5)$$

where $CP \cdot PH$ calculates the covered production level and Y denotes the expected annual production.

The income from the milk sales is defined as

$$MI(T) = P_T^{Milk} - \xi(\omega^C P_T^C + \omega^{SM} P_T^{SM} + \omega^H P_T^H) \qquad (6)$$

where P_T^{Milk}, P_T^C, P_T^{SM} and P_T^H are the monthly average mailbox milk price, spot corn price, spot soybean meal price and alfalfa hay price respectively. The subscript T denotes the month over which these prices are averaged. ω^C, ω^{SM}, ω^H collectively denote the feed ration (of corn, soybean meal and hay) for producing one hundredweight of milk. ξ is an indicator that takes the value of 1 for feed purchasers and 0 for feed growers.

Under the minimization setup of problem (3), one can expect the minimum milk sales income that satisfies the risk constraint is lower under MPP participation due to the added indemnity revenue in equation (4) under MPP participation ($\alpha \neq 0$). This is partially achieved by making RTL fixed regardless of MPP participation. RTL in the model represents the lowest amount of revenue at which a producer is able to conduct their business. It is a producer-specific number that reflects the cost of production and line of credit. None of the two factors affecting RTL depend on MPP participation. For example, if a producer with no access to line of credit has to spend 80 cents in feed and other expenses to produce a hundred pounds of milk, production would have to stop if the producer is unable to pay that amount. In this case, RTL equals 80 cents and is independent of MPP participation.

Since feed growing cost is not included in the definition of $MI(T)$, it is added back to the right-hand side of the catastrophic event inequality. In other words, RTL for feed growers is set to be the feed growing cost plus other operating expenses. As for feed purchasers, since $MI(T)$ takes into account the feed purchasing cost, RTL equals the operating cost net feed purchasing cost.

The hedging P&L is specified as the following:

$$\begin{aligned} HG(T) = w\,\Delta F_{t,T}^{DE} + (1-w)\Delta F_{t,T}^{DK} \\ -\ \xi\left[(\omega^C + \omega^H B^{H,C})\Delta F_{t,T}^{C} + (\omega^{SM} + \omega^H B^{H,SM})\Delta F_{t,T}^{SM}\right] \end{aligned} \tag{7}$$

In the above equation, $\Delta F_{t,T}^{DE}$ and $\Delta F_{t,T}^{DK}$ respectively denote the hedging P&L from a short Class III milk position of one contract and the P&L from a short Class IV milk position of the same size. The position is set up at time t and targets the production in coverage month T. Similarly, $\Delta F_{t,T}^{C}$ and $\Delta F_{t,T}^{SM}$ denote the hedging P&L from a short Corn position and a short soybean meal position respectively. The position size of each grain hedge equals the size of one contract. These positions are then resized by the terms they are multiplied with. The milk sales is cross-hedged with Class III and Class IV contracts. The size of the milk hedge is split between these two futures by the weight w. Hay is cross hedged with corn and soybean meal contracts. $B^{H,C}$ and $B^{H,SM}$ are coefficients for corn and soybean meal futures in the cross hedge. They are multiplied by the feed ration coefficient for hay ω^{H} to align with the milk production level.

The indemnity payment is modeled as a simple put option. The strike price of a put option is analogous to the MPP coverage level (CL) and the price of the underlying asset is analogous to the ADPM.

$$I_j = \max\left(CL - ADPM_j\ ,0\right) \tag{8}$$

where $ADPM_j$ is obtained by using equation (1) with monthly prices and averaging the obtained ADPM's over the two months in the jth bi-monthly period.

As discussed in the previous section, a producer may optimally choose a coverage level to maximize the expected net indemnity received from the MPP. This behavior can be modeled as the following optimization problem:

$$CL^{*} = \arg\max_{CL} \frac{1}{6}\sum_{j=1}^{6} E_t\left[I_j(CL)\right] - P^{MPP}(CL) \tag{9}$$

where I_j and P^{MPP} are now functions of CL; and $E_t[\cdot]$ denotes the expected value conditioned at time t that reflects a producer's belief of the market.

It is worth noting that if we view RTL and γ in the problem (3) deterministic, the probability of the catastrophic event is the cumulative distribution function of the random variable $revenue$. As a cumulative distribution function, the probability is monotonically increasing in the threshold RTL. This means the probability of a catastrophic event is higher when the cost of production is higher. The relation between the catastrophic probability and the hedge ratio depends on whether or not the hedge is "good". A hedge is termed "good" if it makes the catastrophic probability monotonically decreasing in hedge ratio. A "good" hedge makes the hedge-locked-in revenue greater than the revenue threshold. To see that, imagine a world of one commodity and no basis risk. Let's further simplify it to have only three possible states of the market: conducive, neutral, and adverse to cash sales with equal probability. Consider the following example in Table 2.

Table 2 Three-state hedge monotonicity example

			$h = 0.9$	$h = 0.5$	$h = 0.1$
Market	Hedge P&L	Cash Sales	Revenue Income		
Conducive	-$1	$4	$3.1	$3.5	$3.9
Neutral	$0	$3	$3.0	$3.0	$3.0
Adverse	$1	$2	$2.9	$2.5	$2.1
Cost	Hedge Outcome		Catastrophic Probability		
$RTL = 3.6$	Bad hedge		100%	100%	66.7%
$RTL = 3.2$	Bad hedge		100%	66.7%	66.7%
$RTL = 2.8$	Good hedge		0%	33.3%	33.3%
$RTL = 2.4$	Good hedge		0%	0%	33.3%

The average hedge-locked-in sales income is $3.0 in the above example. As one can see from the table, when the cost of production (RTL) is above the locked-in level, catastrophic probability decreases as the hedge ratio decreases. The opposite is true when the cost of production is below the locked-in level. Problem (3) is not defined in case of a "bad" hedge where more hedged production incurs higher probability of a catastrophic event. "Bad" hedge is not of particular interest of this study because they are not desired form of conventional risk management.

1.4 Empirical Strategy

The empirical study follows closely a method used in Newton, et al. (2013a), Newton, et al. (2013b), and Bozic, et al. (2014). Their method derives market outlooks from futures and options markets, and simulates different price scenarios in line with the outlooks. The derivative markets used to derive price scenarios include the CME corn, soybean meal, Class III milk and Class IV milk markets. Once price scenarios are simulated, the optimal hedge ratios are calculated for an MPP participant ($\xi = 1$) and a non-participant ($\xi = 0$). Comparison of the difference in hedge ratios is then carried out to measure the degree of crowding-out.

Data sources include "Understanding Dairy Markets" website [3] for mailbox milk price and futures and options close prices, and USDA National Agricultural Statistics Service for other USDA prices. I also use regional aggregate accounting data from Genske Mulder & Co, LLP to study the crowding-out effect by regions. These regions are upper Midwest (Illinois, Indiana, Iowa, Minnesota, North Dakota, Ohio, South Dakota, Wisconsin, and Michigan) and lower Midwest (Kansas, Missouri, Nebraska, Oklahoma, and Utah).

There are two major parts that compose the method. The first part consists of several basis models that convert CME corn and soybean meal futures prices, announced USDA Class III and Class IV prices to the NASS corn, soybean meal, hay prices and all-milk price used in equation (1) and the milk spot price P_T^{Milk} as in equation (5). The second part derives a joint distribution of the futures prices of the four commodities.

1.4.1 Estimating Actual Dairy Production Margin and Spot Price

Because all USDA prices are only observed once in real life for a given month, counterfactual scenarios are derived from distributional assumptions made for CME futures contract. This section explains how these USDA prices are approximated by the simulated CME futures prices. Regression models are estimated to convert CME prices to USDA prices at national and local levels. National level prices comprise the right-hand-side of equation (1) and determine the $ADPM$ level for indemnity calculation. The local level prices are used to derive the hedge ($HG(T)$) and sales ($MI(T)$) part of equation(4). Data from Jan, 2000 to Feb, 2014 are collected for these models. These include NASS revised prices that appear in equation (1) and settlement prices on the last traded day of Class III, IV, corn and soybean meal futures. Because Class III and IV futures cease to

[3] Web address: http://future.aae.wisc.edu/

trade on the day USDA announces Class III and IV prices, the settlement prices on the last trading day of those two contracts are the announced USDA prices. Prices for upper and lower Midwest model are spatial averages of each region's component states. The period for each series is from Jan 2001 to Jan 2014. Model estimates can be found in Table 15 and Table 16 in Appendix B.

The NASS all-milk price in equation (1) is the national average milk price dairy producers receive. Here I use the classified milk prices under federal milk marketing order to model the all-milk price. The Class I and Class II prices can be approximated by the Class III and Class IV prices in the same period and the higher of the lagged Class III or Class IV prices. This is because (a) the Class I and Class II prices are derived from the same component value formula used to derive Class III and Class IV prices and (b) the lagged term can account for the advanced pricing in Class I and Class II. The last point is supported by a regression of Base Class I price on max(Class III_{t-1}, Class IV_{t-1}) without a constant term. The regression R-squared is at 99%. Figure 3 below illustrates the predictive power of the lag-max term on base Class I.

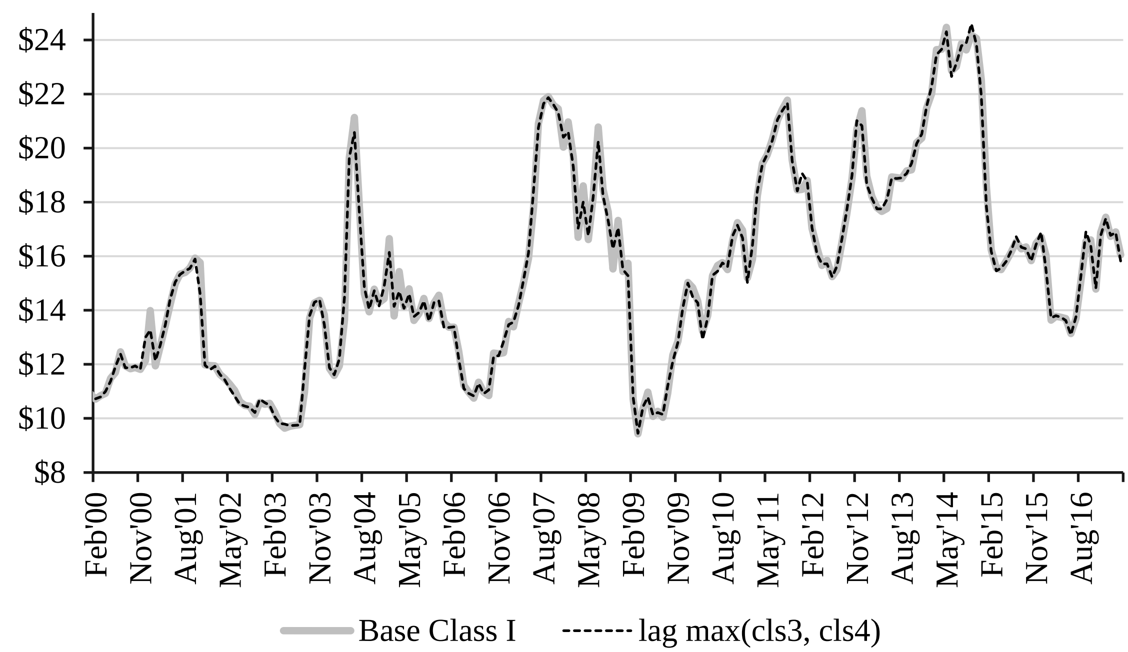

Figure 3 Base Class I price and the higher of lagged Class III and Class IV price

NASS corn price and soybean meal price are approximated by the CME corn futures and soybean meal futures prices respectively. However, there are only 5 corn contracts and 8 soybean meal contracts in a calendar year. This means not every NASS price in a calendar month has its suited futures contract. A data stacking rule employed by Newton, et al. (2013a), Newton, et al. (2013b), and Risk Management Agency (2005) is adapted to deal with this issue. For those NASS prices that don't have a futures contract that expires in the same month, the weighted average terminal price of the two contracts that expire right before and after the NASS price is paired with the NASS price for regression. Table 3 shows how corn and soybean meal futures prices are paired with NASS prices. A month in the first column represents a calendar month in which a USDA price is averaged over. A month in the second or third column represents a futures contract expiration month.

Table 3 Weights on grain futures to pair with USDA price

USDA Price Month	Corn Contracts	Soybean Meal Contracts
Jan	⅔ Dec + ⅓ Mar	Jan
Feb	⅓ Dec + ⅔ Mar	½ Jan + ½ Mar
Mar	Mar	Mar
Apr	½ Mar + ½ May	½ Mar + ½ May
May	May	May
Jun	½ May + ½ Jul	½ May + ½ Jul
Jul	Jul	Jul
Aug	½ Jul + ½ Sep	Aug
Sep	Sep	Sep
Oct	⅔ Sep + ⅓ Dec	Oct
Nov	⅓ Sep + ⅔ Dec	½ Oct + ½ Dec
Dec	Dec	Dec

Although NASS hay price does not have a CME counterpart, a regression model of hay price on corn, soybean meal and lagged hay price is developed to convert simulated CME prices to the hay price ((Newton, et al., 2013a, Newton, et al., 2013b). This specification is justified for at least two reasons: (a) Competition for land to grow corn, soybean or hay makes corn and soybean meal prices correlated with hay prices; and (b) Some persistent unexplained factors can be dealt with by the lagged term to correct for autocorrelation.

Milk is cross-hedged with Class III and Class IV futures contracts. OLS estimates are obtained for the regression model of local mailbox milk price on the terminal prices of the two futures (see Table 14). The justification of model specification is the same for the aforementioned all-milk price models. The sum of the coefficient on the futures is very close to 1[4] for both regions. Due to this finding, the hedged milk is split into two portions. The first one is covered by Class III futures while the second by Class IV futures. Because the sum of the coefficients is close to 1, a restricted regression of the same specification but with the constraint of the sum being 1 is estimated. This gives an estimate of w=0.6863 for upper Midwest and w=0.3136 for lower Midwest. $B^{H,C}$ and $B^{H,SM}$ in equation (6) are estimated in the similar fashion but without a constraint (see cross-hedge models in Table 17). In light of the above analysis, absolute value of the constant coefficients in equation (1) are used as the estimates for the ration weights ω^{C}, ω^{SM} and ω^{H} in equation (5) and (6).

1.4.2 The Joint Distribution of CME futures

Futures prices are assumed to follow log-normal distributions. Their joint distribution is modeled by a multivariate Gaussian copula. These two distributional assumptions are part of the official rating method of Live Stock Margin insurance program. They are also widely used by other studies in the dairy risk management field (see Newton, et al. 2013a, Newton, et al. 2013b, Bozic, et al. 2014). Because a multivariate Gaussian distribution is equivalent to a multivariate Gaussian copula with Gaussian marginal distributions, logarithmic futures prices can be viewed as jointly following a multivariate Gaussian distribution. A Spearman's rho correlation coefficient between two price shocks is used to populate the variance-covariance matrix parameter for the multivariate Gaussian. A price shock η_{τ}^{T} is the difference between a futures' terminal price at time T and its price quoted τ time units

[4] The sum of the OLS coefficients on milk futures is 0.0058 above 1 for upper Midwest model and 0.0126 above 1 for lower Midwest model. See Table 14 for detail.

before T. Assume the time series $\{\eta_{\tau}^{T_i}\}$ with element shocks of a same commodity is autocovariance-ergodic as $i \rightarrow \infty$. In other words, autocovariance made from shocks taken over a period of τ time units regardless of contract expiration is treated as the autocovariance of a latent shock variable η_{τ}. Given the shock is τ time units ahead of contract expiration regardless what contract it is, the ergodicity assumption implies that the new information made available in the period of τ time units before contract expiration has the same effect on determining the price movement leading to the terminal price. In other words, it is assumed here that the effect of information uncertainty is a function of the length of the time period leading to the terminal price. Information uncertainty has little to do with when the contract expires. To estimate the correlation coefficient matrix, a sequence of τ's in an increment of one month is set up to calculate the Spearman's rho coefficient between $\left\{\eta_{\tau_j}^{T_i}\right\}$ and $\left\{\eta_{\tau_k}^{T_i}\right\}$ for the (j,k) element of the matrix. Table 3 is used to compute the weighted futures price to make sure each τ has a grain shock to match with. The correlation matrix measures intra- and inter-commodity co-movements up to 24 months before contract expiration. Appendix A explains in detail about the simulation process. Its general steps are described as the following:

Step 1: Gather settlement prices of Class III, Class IV, corn and soybean meal futures and the corresponding At-The-Money (ATM) put and call options on a particular trading day together with U.S. Treasury Bill rates that match the last trading day of each option. If no such rate matches, linear interpolation of the two rates that surround the option expiration date is used as the risk-free rate.

Step 2: Calculate implied volatility for each futures. This is done by inverting trinomial tree option pricing model (Boyle, 1986) with ATM options prices, risk-free rate and option expiry in years as inputs.

Step 3: Simulate each futures price from multivariate Gaussian distribution. The mean and standard deviation of a marginal distribution depend on the logarithm of the current futures price and the implied volatility calculated from Step 2. A Spearman's rho correlation matrix that meets the ergodicity assumption is used to model the dependence structure. For details, please see Appendix A.

Step 4: Convert futures prices into USDA prices by models specified in Table 14 and Table 15.

The prices generated from step 3 and 4 are component prices used in the formulae mentioned in the previous section.

1.5 Results: How big is the crowding-out effect?

The optimal hedge ratio is first calculated as a function of production cost RTL and MPP participation parameter ξ. A producer profile has to be determined before the function can be uniquely defined. Three representative farms are assumed with production history of 4 million, 6 million and 60 million pounds. The 4-million-pound production history is the tier 1 premium threshold. Any operation with production history less than 4 million pounds is charged by the same rate. The 6-million-pound production history is around the national average production history in coverage year 2015 and 2016. The 60 million production history is an approximation of an extremely large producer whose effective premium rate is close to pure tier 2 rate. Overall, these three cases represent small, average and large producers in the nation. Their risk tolerance level γ is set to be 5%. The optimal hedge ratio function is empirically determined by a heuristic algorithm. The algorithm starts off by attempting a very low cost level, for example 0. If production is free or very low, there is no need to hedge at all. This assumption is reasonable when the output is a good rather than a bad. For the same reason, the catastrophic probability shall be zero when the cost of production is negligible. Keeping the hedge ratio at zero, the algorithm moves up the cost level RTL until the catastrophic probability violates the risk constraint. As argued in the previous section, the catastrophic probability is monotonically decreasing in hedge ratio. Hence, increasing the hedge ratio may bring the catastrophic probability down to the risk tolerance level γ. Any further attempts to lower catastrophic probability would result in a sub-optimal solution with a higher hedge ratio. In this case, the algorithm finds an interior solution and minimization of the hedge ratio can be simplified to a root finding problem that makes the risk constraint binding. Empirically this is done by the bisection root finding method (Burden & Faires, 1985).

Hedge ratio functions are determined for hypothetical coverage years 2008 to 2014 with 1 million simulated scenarios in each case. For each coverage year, three different sign-up periods are considered: the April, October and January sign-up. The April and October sign-up are set on the closest business day to the first day of the month in the year before the coverage year. The January sign-up is assumed to be done on the closest business day to January 1st of the coverage year. Had the MPP existed in those years, the results show what the expected effect on the hedge ratio would have been given the market condition at sign-up. There are 240 combinations of optional hedge ratio functions with respect to representative farms and sign-up periods. Each can be represented by a graph where the x-axis indicates the production cost and the y-axis shows the hedge ratio. A sample of those charts can be found from Figure 15 to Figure 68[5] in Appendix B. The downward sloping curve in black depicts the percentage change in the hedge ratios caused by MPP participation.

Several quick observations can be made from those figures. First, regardless of MPP participation, the upward-sloping optimal hedge ratio curves suggest that producers need more hedge protection when their production cost is high. Second, in most cases with optimal coverage level at $4.00/cwt, the difference in hedge ratio between a participant and non-participant is almost zero. This is possibly because the baseline MPP coverage provides too little protection to influent hedging choices between the hedging portfolios. Third, the percentage drop in hedge ratios is larger at lower cost levels than that at higher ones. This suggests that highly efficient producers experience stronger crowding-out effect than their inefficient peers. As an interesting case to note, some figures for example, those for 2009 and 2012, suggest that extremely inefficient producers may need more hedging protection on top of MPP compared to the case with the same producer but in the absence

[5] Only charts for coverage year 2009, 2012 and 2013 are provided. Charts for other coverage years are not presented in this paper because they add no additional insights to what the three years have already revealed.

of MPP. Fourth, many of the hedge ratio curves for MPP participants and some of those for non-participants do not reach 100%. This does not mean a full hedge is an infeasible solution. The problem lies in the computational limitation of the numerical analysis. If the number of simulation scenarios were increased to more than 1 million, one should be able to observe the curves getting closer to 100%.

To study the actual crowding-out effect in different regions, production cost is derived from data provided by Genske Mulder & Co, LLP. Because of the model setup, the RTL level for feed growers is taken as the sum of feed growing cost and other operating expense. The RTL level for feed purchasers is simply the other operating expense from Genske accounting data. The other operating expense accounts for costs not related to feed and herd replacement. It includes, for example, equipment leases, employee benefits, insurance premium, etc. These costs are reported in terms of dollar per total annual production. It is reported this way because dairy producers are more interested in protecting average profit margin of an entire year rather than that of a single month (Bozic, et al., 2012). Occasional shocks can be smoothed out by lines of credit or cash reserves.

Table 4 reports the average percentage decline in hedge ratios in each region for each producer type. In general, Table 4 shows that the Upper Midwest region experiences stronger crowding out effect than the Lower Midwest region. One may also find from Table 4 that feed purchasers face stronger crowding-out effect than feed growers across regions and producer sizes. This observation seems to reflect the fact that feed growers assume zero feed cost risk while feed purchasers face full exposure to the feed market. Since feed growers and feed purchasers sit on two ends of the feed risk spectrum, the reduction in hedge ratio with these two groups may suggest the boundaries of the crowding-out effect for producers with somewhat feed cost risk. Interestingly, the difference in crowding-out effect between the two groups diminishes as the gap between sign-up and the start of coverage is removed. This implies that the level of feed cost risk becomes less of a concern once everyone has a better grip on future market movements in the coverage year. When inspecting the hedge ratio reduction along the sign-up periods for each producer group, one may notice that feed growers experience increasing crowding-out effects whereas feed purchasers see the opposite. This might be due to the fact that diminishing sign-up gap reduces feed cost uncertainty and leaves milk price risk as the main driver for hedge ratio reduction. Finally, larger producers experience weaker crowding-out effect than smaller producers. This observation might be the result of two forces: one being larger producers are generally more efficient due to economies of scale. Second, MPP is much more expensive for larger producers therefore their appetite for the program is much smaller on a per hundred weight basis than smaller producers. To fill the gap in their hedging needs, large producers are more inclined to use CME contracts.

Table 4 Average percentage decline in hedge ratio

	4 million PH	**April Sign-up**	**Oct Sign-up**	**Jan Sign-up**
Upper Midwest	Feed Grower	0.00%	20.35%	40.00%
	Feed Purchaser	87.52%	40.00%	25.00%
Lower Midwest	Feed Grower	0.00%	23.20%	19.31%
	Feed Purchaser	72.01%	40.85%	25.00%
	6 million PH	**April Sign-up**	**Oct Sign-up**	**Jan Sign-up**
Upper Midwest	Feed Grower	0.00%	21.08%	38.04%
	Feed Purchaser	66.37%	39.88%	25.00%
Lower Midwest	Feed Grower	0.00%	23.69%	39.17%
	Feed Purchaser	40.26%	37.24%	25.00%
	60 million PH	**April Sign-up**	**Oct Sign-up**	**Jan Sign-up**
Upper Midwest	Feed Grower	0.00%	14.85%	10.52%
	Feed Purchaser	49.83%	19.94%	10.26%
Lower Midwest	Feed Grower	0.00%	10.55%	20.82%
	Feed Purchaser	25.41%	15.17%	7.52%

Detailed percentage drop in hedge ratios are reported from Table 20 to Table 31. An “N/A” in those tables indicates the cost of production is too high and the hedging strategy the model utilizes cannot keep the producer’s revenue above water. If producers were able to lock in at better futures prices, they might be able to cover a higher cost of production. The average percentage reduction reported in Table 4 excludes those cases with “N/A” values.

The dairy industry suffered a historical blow to the margin in 2009. As a special case study, it is worth looking at what the empirical results show for 2009. A quick inspection of the realized ADPM in Figure 4 reveals that the ADPM profit margin reached its bottom at the end of the second quarter in 2009. Coincidentally January sign-up happened at a time when the market was trapped in the middle of the drastic margin decline. Given the market situation at the time, it is hard to believe that any bullish signal could be picked up in the January, 2009 market. The possible bearish signal may have given rise to the highest indemnity payment ($2.30/cwt) and the lowest cash sales income across producer types and regions (see Table 19). One may question why the $8.00/cwt MPP coverage appeared ineffective in keeping the margin above the cost. Note that the model optimally picks the best coverage level for each sign-up period. Any other coverage level will bring less net indemnity payment to the overall revenue. This only leaves us to suspect a bad hedge is the issue. Indeed, with the market in the middle of the downward spiral, it would be too late for any hedge that were made at that time to lock in a promising margin. Does the hedge made three months earlier fare better than the January hedge? The absence of "N/A" values for October sign-up from Table 20 to Table 31 suggest that producers were able to cover their cost of production 3 months before coverage starts.

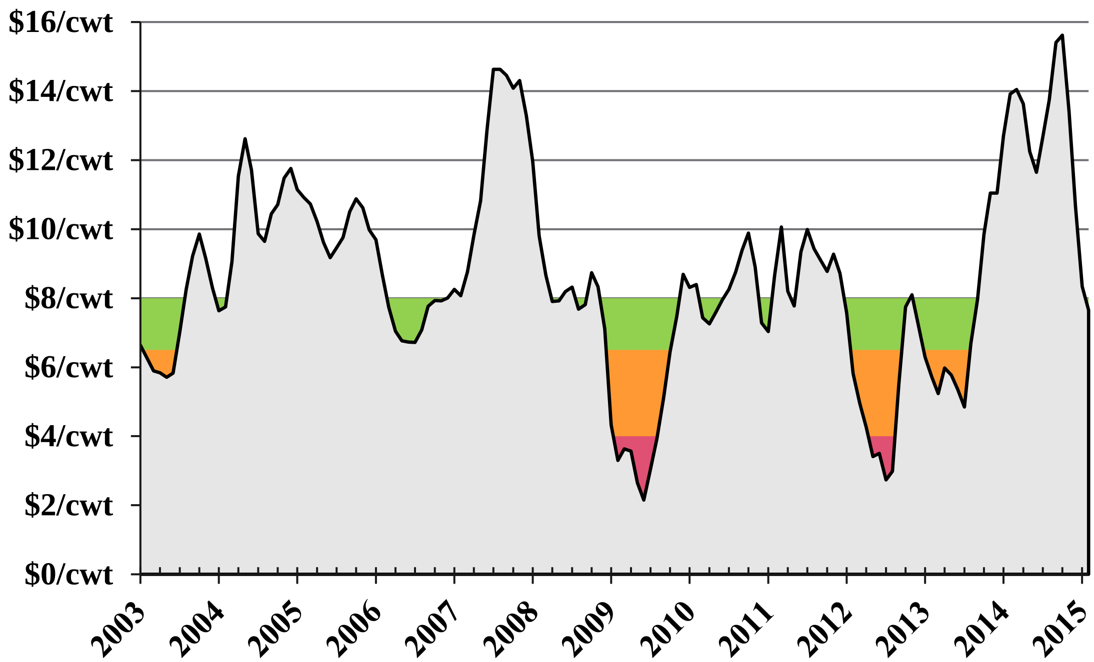

Figure 4 Realized ADPM from Jan, 2003 to Feb, 2015

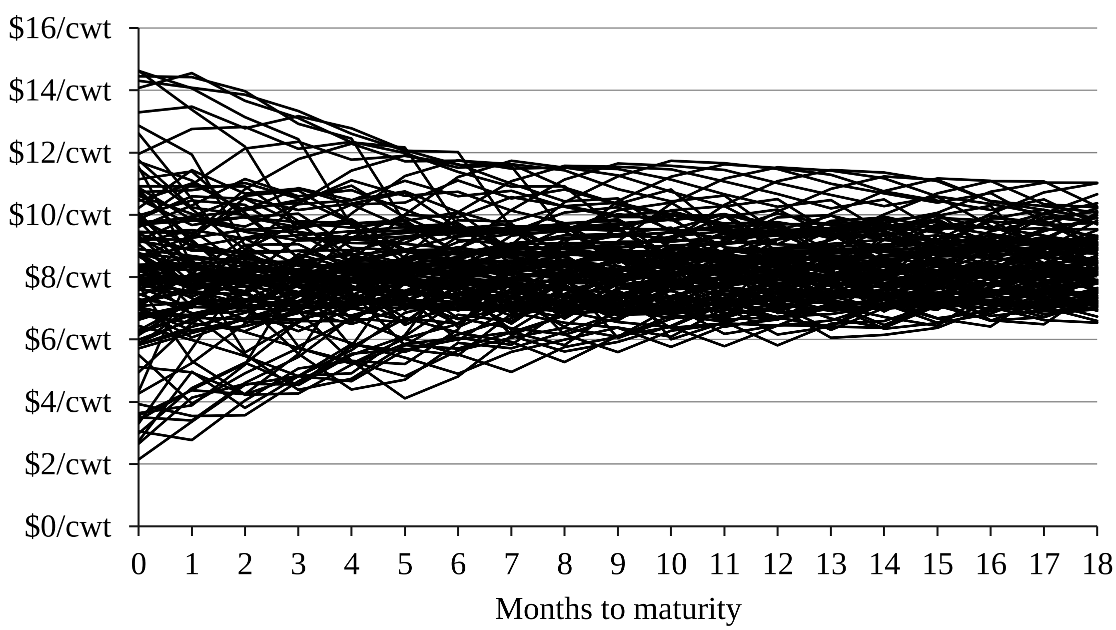

Figure 5 Forward ADPM

Bozic, et al. (2012) show that there exists a 9-month mean reversion in IOFC margin in the dairy industry. Figure 5 above shows the forward ADPM up to 18 months before the ADPM is realized. A forward ADPM at n months to maturity equals the ADPM calculated from the futures prices quoted n months before they mature. In Figure 5, futures prices are taken around the first day of a month. The dispersion in forward ADPM peaks at the realized level (at 0 month to maturity) and wanes its way out as it moves away from its named month. The dispersion becomes relatively stable at the 9-month mark. This fact suggests that any gap less than 9 months between the MPP sign-up and program kick-off cannot lock in a long-term average margin in the futures market. There is still plenty of room within those 9 months for the market consensus to evolve on what the coming calendar year would be like. If producers were to use market outlook embedded in futures market to speculatively choose MPP coverage level, they may find it difficult to do so once the sign-up/kick-off gap is 9 month long or more. Results seem to suggest this is the case. The standard deviation of the coverage level for the April sign-up is 1.36 while the standard deviation of the coverage level for the October sign-up is 1.24. From an insurance issuer's standpoint, a diverse pool of coverage levels selected among producers is an indicator of less occurrence of the adverse gaming behavior.

1.6 Conclusion and Discussion

Empirical results suggest that MPP is likely to crowd out hedging uses of CME contracts. Between the two regions studied here, the Upper Midwest region experiences more pronounced crowding-out effect than the Lower Midwest region. Besides the geographic locations, this study also shows that the crowding-out effect depends on the production efficiency, feed market risk exposure, size of the producer, and the timing of the program sign-up. More efficient producers experience more pronounced crowding-out effect. Higher market risk exposure induces higher crowding-out effect. But the feed exposure matters less and less as the time of the year progresses closer to the start of the coverage period. Larger producers see less effect on their use of CME contracts from MPP participation. Feed growers experience little crowding-out effect when they enter the program early while feed purchasers endure less crowding-out effect when they sign up late. Although longer sign-up gap should in theory reduces speculative use of MPP, it may also introduce more crowding-out among certain producer groups. A strategic choice of the gap is required to strike the balance between curbing adverse selection and keeping CME markets vibrant.

Shortcomings of the model and method in this paper call for future studies in several areas. First, this paper assumes futures prices follow multivariate log-normal distribution. A refined distributional assumption can be made to deal with tail dependency issues. Second, the theoretical model assumes producers hedge on the day of the MPP sign-up. This assumption may not always meet producer's risk protection need. A further study on hedging ahead of MPP sign-up period to cover variable cost is needed to fully address the issue of crowding-out effect. Third, it is important to understand how long a gap between MPP coverage period and sign-up deadline needs to be in order to thwart adverse gaming and to minimize the crowding-out of private dairy risk markets. Finally, MPP crowding-out may be sensitive to changes in component prices of the ADPM formula. Sensitivity analysis on this topic can shed light on the adequacy of the national level ADPM formula.

2 Methods for Evaluating Fiscal Costs of Alternative Policy Designs of Margin Protection Program for Dairy Producers

2.1 Introduction

Margin Protection Program for Dairy Producers (MPP-D) is a federal dairy safety-net program promulgated in the Agricultural Act of 2014 (2014 Farm Bill). The program makes a payment when a national average Income-Over-Feed-Cost (IOFC) margin falls below a producer-selected level. Since its commencement, the program received wide acceptance among dairy producers. Based on National Agricultural Statistics Service (NASS) Milk Production reports and signup information made public on United States Department of Agriculture Farm Service Agency (FSA) website, 55% of dairy operations entered the program in 2014 to cover milk production in the next year. The number went up to 59% the year after. The program covered 69% of the national milk produced in 2015 and 76% in 2016.

MPP-D's popularity however does not mask its shortcomings. Among several discussed in Newton et al. (2013) and Wolf, et al. (2013), MPP-D is not priced in an actuarially fair way. Though program premia were initially set to subsidize producers for entering the program, the feed cost portion of the formula that calculates the benchmark IOFC margin was marked down by 10% in Congress just before it was passed in the 2014 Farm Bill (NMPF, 2017)[6]. This last-minute mark-down artificially inflates benchmark dairy margin and consequently makes premia more expensive relative to the indemnities paid under new formula. Recent conducive market conditions further exacerbate the imbalance between the Farm Bill fixed MPP-D premia and the actuarially fair premia. Figure 6 presents the implied subsidy of each coverage level (on horizontal axis) for a producer with less than 4 million pounds of average annual production. The implied subsidy is the percentage by

[6] Congressional leaders at the time wanted to achieve a balanced budgetary target for the 2014 Farm Bill. If feed cost coefficients were not taken down by 10%, they would have had to find savings from other parts of the bill. However, two full coverage years of MPP-D suggested that the 10% cut may not generate enough benefits for dairy producers.

which actuarially fair premium differs from the official MPP-D premium. Because the catastrophic coverage at $4.0/cwt is free, all three years shown in the figure reports the highest subsidy level at that coverage. However, 2017 has seen premia for all other coverage levels higher than actuarially fair prices. It is not surprising that the number of producers opted in for free coverage level rises every year (see Figure 7).

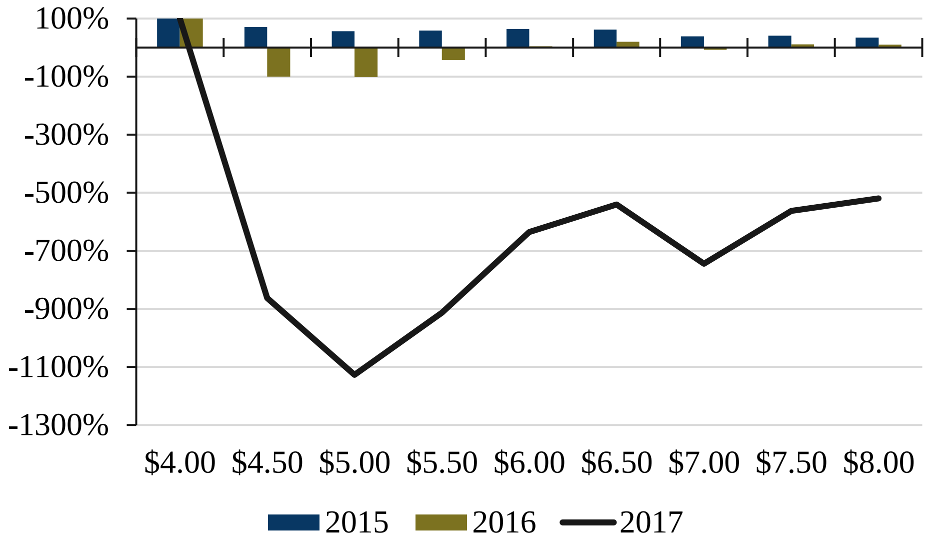

Figure 6 Implied subsidy as the percentage of actuarially fair premium

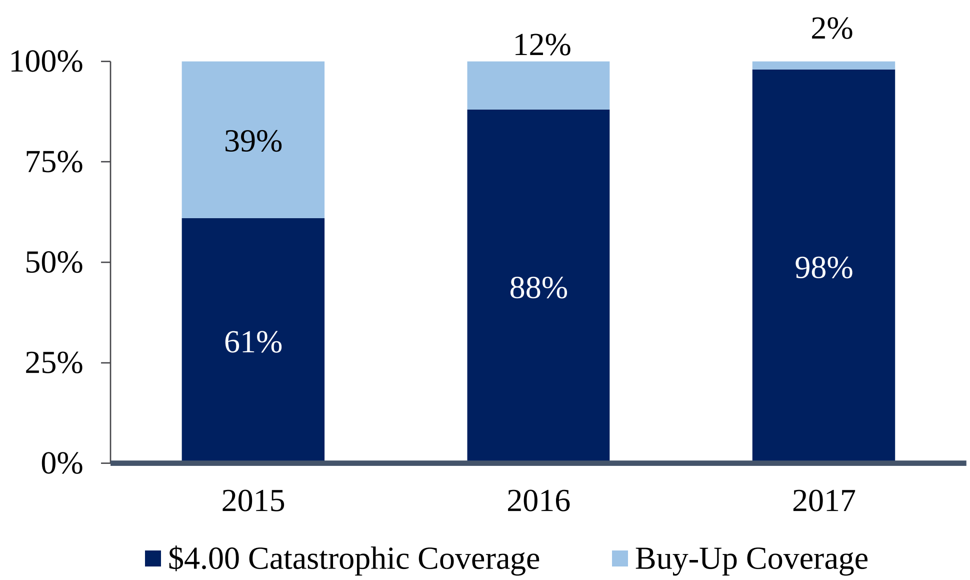

Figure 7 Percent of milk covered under catastrophic coverage and other coverage levels (Source: Bozic (2017, p. 30))

NMPF (2017) proposed to restore benchmark margin formula to the original coefficients and replace the use of NASS prices with Agricultural Marketing Service (AMS) prices. Higher feed coefficients directly reduce benchmark margin so that indemnity payouts are more likely. NMPF argues that AMS prices represent actual farm feed costs better because too many non-dairy related price points are averaged into NASS prices. Applying 2015 signup choices to hypothetical coverage years prior to 2015, one can calculate the policy costs shown in Table 5 and analyze fiscal implications in a static way. When looking at NMPF's two suggestions separately, based on 2015-2016 signup information, one may find that the first suggestion would increase the average annual net payout from 2000 to 2016 by 185% while the second increases the payout by 52%. The increase based on full NMPF solution skyrockets to 276%.

To smooth indemnity payments across years, policy makers are also seeking more payouts in years when margins are below historical average but still not catastrophically low. The NMPF solution is unable to properly achieve this objective. In fact, the majority of increased payments in the NMPF solution come from only a handful of years. Producers would still have been left with no indemnity payments in 10 out of 17 years under NMPF solution. As Table 5 illustrates, the number of indemnity-paying years is only increased by 2. The NMPF solution (S3) increases the net indemnity payment (= indemnity - premium) by 1805% in 2003 and 2040% in 2013. When only feed cost coefficients are restored (S1), the number of years with positive payments remains the same. When only AMS data are used (S2), only 5 of 17 years yield positive net payments to producers. For most of other years, the percentage increase in net indemnity is less than 10%. Since S2 has marginal impact on policy cost compared to S1 and S3, it is not separately analyzed in the remaining text.

This paper addresses the non-smooth payout issue NMPF fails to solve and proposes a shallow loss version of the existing MPP-D. The new version, which is referred to as MPP-DL in the rest of the text, is intended to be a supplemental program to address MPP-D's non-smooth payout issue. A producer can only choose either MPP-D or MPP-DL for a given coverage year. MPP-DL also caps an indemnity payment by a user selected level and is priced in such a way that producers would only purchase MPP-DL when margin forecast is beyond the coverage range offered by MPP-D. The current program, MPP-D, would still be selected when the margin forecast is low but would be deemed too expensive in comparison to MPP-DL when the forecast is high. Because MPP-DL pays out in years the current program does not, it smooths out payment over the years.

Table 5 National net indemnity in million dollars based on 2015 - 2016 signup

	National Indemnity Payment Net Premium in Million				Percentage Increase from Current Program		
Year	Current	S1: 10% Higher Feed	S2: Use AMS data	S3: NMPF solution	S1: 10% Higher Feed	S2: Use AMS data	S3: NMPF solution
2000	($20)	($18)	($18)	($15)	9%	3%	24%
2001	($20)	($20)	($20)	($20)	0%	0%	1%
2002	($12)	$8	$9	$50	167%	9%	510%
2003	$4	$39	$32	$76	871%	18%	1805%
2004	($20)	($20)	($20)	($19)	2%	0%	7%
2005	($20)	($20)	($20)	($20)	0%	0%	0%
2006	($18)	($12)	($17)	($6)	32%	34%	67%
2007	($20)	($20)	($20)	($19)	1%	1%	8%
2008	($20)	($17)	($20)	($13)	17%	18%	36%
2009	$858	$1,811	$1,058	$1,938	111%	42%	126%
2010	($20)	($17)	($19)	($9)	12%	8%	53%
2011	($20)	($19)	($18)	$5	8%	2%	125%
2012	$556	$1,565	$858	$1,996	181%	45%	259%
2013	$27	$190	$86	$576	604%	55%	2040%
2014	($20)	($20)	($20)	($20)	0%	0%	0%
2015	($20)	($17)	($19)	($7)	17%	13%	64%
2016	($9)	$20	($0)	$29	326%	102%	439%

Cost for years before 2015 assumes 2015 producer sign-up choices.

The main contribution of this paper is the use of cumulative prospect theory to model producer sign-up choices in MPP-D. Expected utility theory is not able to correctly predict about 50% of producer sign-up choices. The model built on cumulative prospect theory only fails to explain sign-up choices of about 4% of all producers. To the best of my knowledge, this is the first paper that applies the cumulative prospect theory pioneered by

Tversky & Kahneman (1992) to dairy margin programs. Babcock (2015) introduced the concept of loss aversion to modeling risk management behaviors in crop insurance. Sproul and Michaud (2017) analyzed field elicited risk attitude parameters from Tanaka, et al. (2016) and emphasized the importance of heterogeneity of loss aversion in policy analysis. This study allows for risk attitude heterogeneity by modelling U.S. dairy sector as consisting of 37 representative producers. Fiscal cost implications are then analyzed using representative dairies to model aggregate costs for 4 dairy margin program alternatives.

2.2 MPP-DL Program Specification

MPP-DL share most of program specification with MPP-D. One notable addition to MPP-D is that MPP-DL indemnity payment is capped at a user selected Payment Cap (PC). The recommended choice of PC is $1.0/cwt, even though initial analysis in later text includes higher payment caps. Serving as a brief review, the rest of the section introduces the shared components of MPP-D and MPP-DL.

The indemnity payment is triggered when a bimonthly average Actual Dairy Production Margin (ADPM) falls below a selectable Coverage Level (CL). MPP-D coverage level ranges from $4.0/cwt to $8.0/cwt in an increment of 50 cents. MPP-DL coverage level extends from MPP-D's range to $12.0/cwt while maintains the same 50 cents incremental change. The formula that determines monthly ADPM is the same in both programs. The formula is:

$$\begin{aligned} ADPM\ (\$/\text{cwt}) = {} & \textit{All-Milk Price}\ (\$/\text{cwt}) \\ & -1.0728 \times \textit{Corn Price}\ (\$/\text{bu}) \\ & -0.00735 \times \textit{Soybean Meal Price}\ (\$/\text{ton}) \\ & -0.0137 \times \textit{Alfalfa Hay Price}\ (\$/\text{ton}) \end{aligned} \tag{10}$$

The all-milk, corn and alfalfa hay prices are monthly national average prices reported by NASS. The soybean meal price is the monthly average price of high protein soybean meal delivered by rail to Dectaur-Central Illinois and can be found in AMS Market News reports.

The mechanism that determines the eligible amount of milk production that can be covered is kept intact in MPP-DL as well. The base Production History (PH) is the average pounds of milk a producer made in 2011 – 2013. PH is increased every year across the nation by a fixed percentage that FSA publishes in the summer of every year.

The actual pounds of milk under coverage depends on another producer-selectable variable called Coverage Percentage (CP). The choices of CP are between 25% and 90% with 5% apart from one another. The Covered Production History (CPH) determines the actual amount of milk under the coverage of MPP-D and MPP-DL. $CPH = PH \times CP$.

Table 6 MPP-D premium rates

Coverage Level ($/cwt)	MPP-D Tier 1 ($/cwt)	MPP-D Tier 2 ($/cwt)
$4.00	$0.000	$0.000
$4.50	$0.010	$0.020
$5.00	$0.025	$0.040
$5.50	$0.040	$0.100
$6.00	$0.055	$0.155
$6.50	$0.090	$0.290
$7.00	$0.217	$0.830
$7.50	$0.300	$1.060
$8.00	$0.475	$1.360

Both MPP-D and MPP-DL charge two-tiered rates to support smaller producers. The tier 1 rates apply to covered PH that is less than 4 million pounds. The tier 2 rates apply to the portion of covered PH that is above 4 million pounds. For a producer with less than 4 million-pounds of covered PH, the producer only pays the cheaper tier 1 rate. For a large producer whose covered PH crosses the four-million-pound threshold, the effective premium rate is a linear combination of tier 1 and tier 2 rates with weights determined by how much covered PH is above the threshold. Table 6 above shows MPP-D premium rates for each coverage level. MPP-DL premium rate depends on coverage level and payment cap. MPP-DL tier 1 rates can be found in Table 32. The corresponding tier 2 rates are reported in Table 33. These numbers are explained in a later section.

2.3 Data

This study uses producer level MPP-D signup data obtained from USDA FSA as part of research co-op agreement. The data include all records of signup forms CCC-781 and CCC-782 MPP-D participants submitted to FSA county offices across the country for coverage year 2015 and 2016. Covered production history and selected coverage level are two fields of particular interest and used to determine risk attitude parameters. Table 7 below displays the covered production history break-down by coverage levels in these two years.

Table 7 National covered production history in million pounds for each coverage level in million dollars

	Coverage Level ($/cwt)								
Year	4.0	4.5	5.0	5.5	6.0	6.5	7.0	7.5	8.0
2015	874	4	57	24	246	171	8	30	6
2016	1402	2	31	9	92	48	2	4	2

Due to the lack of monotonicity in the prospect utility function with respect to the 3 risk attitude parameters, brute force search in three-dimensional parameter space is very computationally expensive. The problem is compounded by the sheer size of the signup dataset. Overall, it is not computationally feasible to find all prospect theory parameters for more than 20 thousand operations in the dataset. In light of this limitation, a cohort of 49 representative operations are created to simplify the fiscal cost analysis. Each representative operation features a unique combination of coverage level and covered production history. These representative operations are created from the following steps: first all operations with 4 million or more covered production history are sorted according to the covered production history; then the range of the nation's covered production histories is divided into 5 representative groups with the cut-off covered production history of each group equally apart from one another; third, within each group, a representative operation is created for each coverage level with the covered production history being the average among those of the same coverage level within the group. These steps create 40 representative operations. Since not all coverage levels were purchased within each group, this number does not reflect the number of combinations among 9 coverage levels and 5 representative groups. Similarly, additional 9 representatives (corresponding to 9 coverage levels) are created among producers with less than 4 million covered production history.

Other data usage includes NASS all-milk price, NASS and AMS corn prices, NASS and AMS alfalfa hay prices, and AMS soybean meal price for calculating realized indemnity payments under different programs. For simulating indemnity distributions, daily settlement prices on dates closest to the start of (hypothetical or real) coverage years between 2008 and 2016 of Class III, Class IV, corn and soybean meal futures and options are used.

2.4 Program Design

Let the net indemnity under program $M \in \{\text{MPP-D}, \text{MPP-DL}, S1, S3\}$ for coverage level CL and payment cap PC be the following:

$$I_j^M(CL, PC; CPH) = min\left(max\left(CL - \frac{1}{2}\sum_{m=2j-1}^{2j} ADPM_m, 0\right), PC\right) - P^M(CL, PC; CPH) \tag{11}$$

where m represents the mth month in a coverage year and j represents the jth payment period; $ADPM_m$ is calculated from equation (4) when $M \in \{\text{MPP-D}, \text{MPP-DL}\}$ and from equation (9) when $M \in \{\text{S1}, S3\}$; $CPH = CP \times \frac{PH}{1{,}000{,}000}$ is the covered production history in million pounds; $P^M(CL, PC; CPH)$ denotes the indemnity payment for program M. When $M \in \{\text{MPP-D}, \text{S1}, \text{S3}\}$, the payment cap $PC \equiv \infty$ and $CL \in \{4{,}4.5{,}5, \dots, 7.5{,}8\}$. When $M = \text{MPP-DL}$, the domain of I_j^M is

$$(CL, PC) \in \{4{,}4.5{,}5, \dots ,7.5{,}8\} \times \{\infty, 1{,}1.5{,}2, .., PC^{Max}\} \\ \cup \{8.5{,}9, \dots ,11.5{,}12\} \times \{1{,}1.5{,}2, .., PC^{Max}\}$$

where PC^{Max} is the maximum payment cap offered in MPP-DL whose value is yet to be determined. For producers, PC^{Max} is assumed known. The insurance premium $P^M(CL, PC; CPH)$ in equation (2) is defined as the following:

$$\begin{aligned} P^M(CP, PC; CPH) \\ &= \min\left(\frac{4}{CPH}, 1\right) r_1(CP, PC) \\ &+ \max\left(1 - \frac{4}{CPH}, 0\right) r_2(CP, PC) \end{aligned} \tag{12}$$

where $r_1(\cdot)$ and $r_2(\cdot)$ represent tier 1 and 2 rates respectively. When $M \in \{\text{MPP-D, S1, S3}\}$, $r_1(\cdot)$ and $r_2(\cdot)$ take values defined in Table 6. When $M = MPP\text{-}DL$, later text shows that $r_1(\cdot)$ takes values reported in Table 32 whereas $r_2(\cdot)$ takes values defined in Table 33.

Under Nelson and Loehman (1987) theoretical framework, the insurer's problem is to solve for the maximum available payment cap PC^{Max} and the actuarially-fair premium schedule (r_1 and r_2) to arrive at a Pareto optimal contract. Such a contract is made possible under complete and symmetric information. Another important aspect of their framework is that under Pareto optimal contract design, producers behave as if they were risk neutral. This means actuarially fair premium can be calculated under risk-neutral distribution independent of individual producer's risk preference. However, for time-invariant MPP-DL premia, this is difficult to achieve even with perfect knowledge about every producer in the country. Nelson and Loehman (1987) suggest that one of the second-best solutions is to use the average of actuarially fair premiums over the years.

To determine the time invariant program premia, actuarially fair premia over 2008 to 2017 are calculated first. Given a coverage level (CL) and payment cap (PC), the actuarially fair premium of a given year t is the expected value of the indemnity payment:

$$\tilde{P}_t^{MPP-DL}(CL, PC) = \frac{1}{6} E_t \left[\sum_{j=1}^{6} min\left(max\left(CL - \frac{1}{2} \sum_{m=2j-1}^{2j} ADPM_m, 0 \right), PC \right) \right] \quad (13)$$

where j, m, CL, PC, and $ADPM_m$ represent respectively the jth bimonthly payment period, the mth month, coverage level, payment cap and the benchmark margin calculated from equation (10). The distribution of $ADPM_m$ is derived by simulating commodity futures prices and converting the simulated futures prices to component prices in equation (10). Marginal distribution of a single futures is assumed to be log-normal. Their joint distribution is modelled by a multivariate Gaussian copula. Simulation details can be found in section 1.4. Marginal distributions are calibrated from futures and options settlement prices on trading days closest to Dec. 15th in the year proceeding coverage year t.

MPP-DL actuarially fair premia for payment cap = \$1/cwt and several coverage levels from 2008 to 2017 are shown in Figure 8. Results for other payment caps are similar and thus omitted. Premium variation over the years are more pronounced for middle-range coverage levels (~\$8.0/cwt). As the coverage level moves away from \$8.0/cwt, the premium variation becomes more tapered. Premium for the \$12.0/cwt coverage level almost reaches the payment cap in several years. This suggests that for the upper range coverage levels (> 8.0/cwt), the payment cap is the upper limit of MPP-DL indemnity and thus restricts the otherwise unlimited payment to the cap. For lower range coverage levels, however, the coverage level itself is the limiting factor and therefore excludes a vast majority of possible ADPM values capable of generating indemnity payments at a higher coverage level.

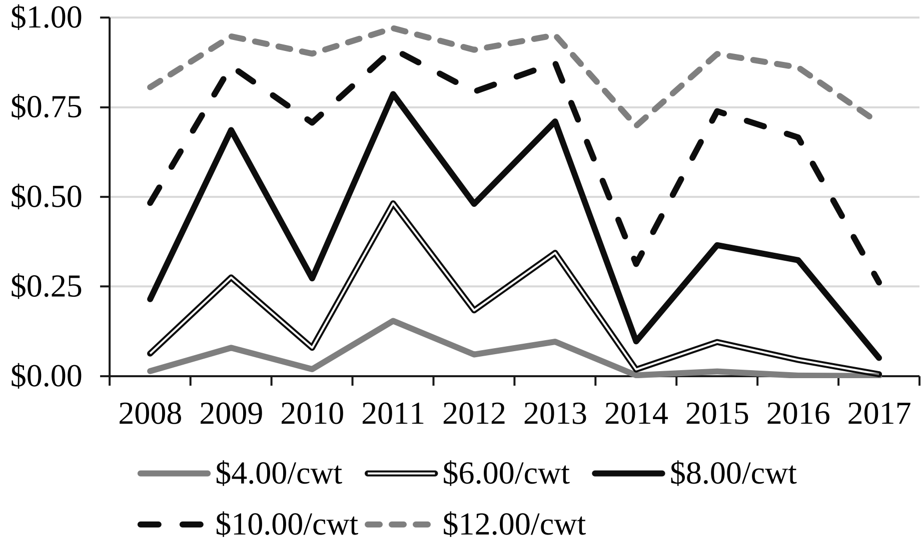

Figure 8 MPP-DL actuarially fair premia with $1.0/cwt payment cap

Figure 8 also shows that several years with low margin forecasts induce higher actuarially fair premia. Because MPP-DL is intended as an alternative program for years of high margin forecasts, special exclusion criteria are applied in the derivation of MPP-DL premia. The final MPP-DL tier 1 rate for a given CL and CP is the average actuarially fair premia of the given CL and CP over the years whose actuarially fair premia are more than 0.25 standard deviations above the average of the full period. This calculation effectively excludes premia in 2009, 2011 and 2013 for all coverage levels and 2012 for lower and higher range coverage levels. The resulting tier 1 rates can be found in Table 32 on page 109. The tier 2 rate is derived from similar calculation but with added exclusion of years that are less than 0.25 standard deviations below the average of the whole period. Years entered the calculation of tier 2 rates are 2008, 2010, 2015 for all coverage levels, plus 2012 for middle range coverage levels and 2016 for middle to higher range coverage levels. Table 33 on page 110 reports tier 2 rates.

The determination of PC^{Max}, however, is a matter of policymaker's choice. If PC^{Max} is set too low, producers may not be enticed to switch to MPP-DL as designed. If PC^{Max} is set too high, the program may be too expensive for policy makers. Maximum payment caps from $1.0/cwt to $5.0/cwt with $0.5/cwt increments are considered. To eliminate some of the payment cap candidates, a simple "Choice Score" is devised such that over the period between 2008 and 2016, the score tallies the temporal average of the percent of representative dairy operations that choose MPP-D when average annual forecasted margin is at or below \$8.5/cwt. \$8.5/cwt is selected as the threshold for two reasons. First, the average monthly realized margin from January 2000 to December 2016 is \$8.56/cwt which is close to \$8.5/cwt. Second, \$8.5/cwt is the first coverage level in MPP-DL above the maximum coverage level offered in MPP-D. Experiment with the \$8.0/cwt threshold does not result in any change in score rankings among maximum caps. Table 8 displays the "choice score" of each possible maximum payment cap PC^{Max}. The \$1.0/cwt maximum cap incentivizes on average 61% of producers to choose MPP-DL as designed. Ranked after \$1.0/cwt cap are \$1.5/cwt, \$2.0/cwt and \$3.0/cwt. They managed to make MPP-DL favorable among more than 50% of the producers. However, as the maximum payment cap PC^{Max} reaches \$4.5/cwt and \$5.0/cwt, the choice score falls below 50% because MPP-DL becomes too appealing even at lower coverage levels that are supposed to be only preferable under MPP-D.

Table 8 Evaluation of different maximum payment caps

Maximum Cap PC^{Max} (\$/cwt)	Choice Score	Average Annual Program Cost (in million \$)	Percentage of MPP-D Average Annual Cost
1.0	61%	303	87%
1.5	59%	331	96%
2.0	57%	378	109%
2.5	56%	436	126%
3.0	55%	478	138%
3.5	51%	520	150%
4.0	48%	574	166%
4.5	47%	594	171%
5.0	46%	624	180%

Of particular interest are maximum payment caps at \$1.0/cwt, \$1.5/cwt, \$2.0/cwt and \$3.0/cwt. To provide further insight on each of those choices, average annual program cost over 2008 - 2016 is calculated for them. The annual program cost for a single year is based on the prospect theory model introduced in the next section. The model matches the 2015 sign-up choices and predicts choices over other years based on estimated producer risk attitude parameters. The 9-year average policy cost for MPP-D is 346 million dollars. The highest payment occurs in 2009 at 2.4 billion dollars. Compared to MPP-D, the \$3.0/cwt cap on average costs 37% more than MPP-D and is roughly 20% of the highest payment under MPP-D. This makes PC^{Max} = \$3.0/cwt a less viable option for policy makers to offer. Similar analysis can rule out payment caps \$2.0/cwt and \$2.5/cwt. Given that the result for \$1.5/cwt payment cap is not too different from the \$1.0/cwt payment cap, \$1.5/cwt payment cap is also excluded from further analysis.

2.5 Modeling Producer Risk Attitude with Cumulative Prospect Theory

Expected utility models typically fail to predict risk behaviors. Though capable of accounting for risk aversion, they usually lack the ability to express loss aversion in any meaningful way. A loss averse producer is more sensitive to the displeasure of loss than to the contentment of gain. Loss aversion is consistent with the assumption that producers view government sponsored insurance as investment and evaluate insurance outcomes in disconnection with its effect on producers' actual income (Brown, et al., 2008). Loss aversion and risk aversion are two similar but different aspects of risk attitude. While loss aversion puts different psychological weights on losses and gains that may be induced by a same risk factor, risk aversion discriminates against risk regardless of the outcome it may produce. Loss aversion and risk aversion are not mutually exclusive. Although a producer may not be very risk averse, they may still (risk-seekingly) appreciate the possibilities of high rises of milk prices and steep drops of feed costs while at the same time disproportionally remain opposed to the loss the opposite may bring.

The cumulative prospect theory pioneered by Tversky and Kahneman (1992) offers a promising framework to model both risk aversion and loss aversion. Two main pieces of the cumulative prospect theory are the distortion of the psychological values of loss and gain and the unequal weighting of probabilities.

Let the annual net indemnity for program M equal:

$$G^M_{CL,PC,CPH} = \frac{1}{6}\sum_{j=1}^{6} I^M_j(CL, PC; CPH) \tag{14}$$

where $I^M_j(\cdot)$ is defined in equation (11). $G^M_{CL,PC,CPH}$ represents insurance gain that equals the net indemnity payment over the six payment periods under program M with coverage level CL, payment cap PC and covered production history CPH. Note that a negative $G^M_{CL,PC,CPH}$ represents a loss.

The psychological distortion of the gains and losses in the cumulative prospect theory is achieved by the value function v defined in equation (15) below. Here I adopt the specification used by Liu (2013), and Sproul and Michaud (2017):

$$v\left(G^M_{CL,PC,CPH}; \alpha, \lambda\right) = \begin{cases} \left(G^M_{CL,PC,CPH}\right)^{1-\alpha}, & G^M_{CL,PC,CPH} \geq 0 \\ -\lambda\left(-G^M_{CL,PC,CPH}\right)^{1-\alpha}, & G^M_{CL,PC,CPH} < 0 \end{cases} \tag{15}$$

The reference point to divide gains from losses in $G^M_{CL,PC,CPH}$ is naturally zero in this context. In non-monetary settings, the reference point is usually normalized to zero nonetheless. α is the risk aversion parameter and controls the curvature of the value function. A producer is risk neutral if $\alpha = 0$, risk averse if $\alpha > 0$, or risk seeking if $\alpha < 0$. λ is the loss aversion parameter. If $\lambda = 2$, it means the producer views the impact of a loss twice significant as the impact of the gain of the same magnitude. Since non-positive λ pertains little economic meaning, the parameter is restricted to $(0, \infty)$.

The unequal weighting of probability is achieved by the following probability weighting function.

$$w_t(x; \gamma) = \frac{(p_t(x))^\gamma}{\sqrt[\gamma]{(p_t(x))^\gamma - (1 - p_t(x))^\gamma}} \tag{16}$$

with

$$p_t(x) = \begin{cases} \Pr\left[G^M_{CL,PC,CPH} \geq x\right], & x \geq 0 \\ \Pr\left[G^M_{CL,PC,CPH} \leq x\right], & x < 0 \end{cases} \tag{17}$$

In the above formulation, x denotes any possible deterministic value of the annual net indemnity payment. $G^M_{CL,PC,CPH}$ is viewed as a random variable. $p_t(x)$ takes the survival distribution value of $G^M_{CL,PC,CPH}$ when x is positive and the cumulative distribution value when x is negative. The subscript t denotes the year of the indemnity distribution. $\Pr[\cdot]$ denotes the probability function of the distribution. γ and δ are probability weighting parameters. They are assumed to be positive. When $\gamma = 1$, the probability weighting function returns the actual probability. When $\gamma < 1$ producer overweighs low probability events and underweighs high probability events.

The decision weighting function in prospect theory weighs the phycological value of every possible net indemnity. It is defined as

$$\pi_t(x;\gamma) = \begin{cases} \lim\limits_{\varepsilon \to 0^+} \dfrac{w_t(x;\gamma) - w_t(x+\varepsilon;\gamma)}{\varepsilon}, & x \geq 0 \\ \lim\limits_{\varepsilon \to 0^-} \dfrac{w_t(x;\gamma) - w_t(x+\varepsilon;\gamma)}{\varepsilon}, & x < 0 \end{cases} \tag{18}$$

The role of the decision weighting function is analogous to the role of probabilities under expected utility theory. A producer's "utility" with coverage level CL, payment cap PC and covered production history CPH under program M is defined as below:

$$\begin{aligned} &V^M_t(CL, PC, CPH, \alpha, \lambda, \gamma) \\ &\qquad = \int_{\boldsymbol{\mathcal{X}}} v(x; \alpha, \lambda, CL, PC, CPH)\pi_t(x; \gamma, CL, PC, CPH)dx \end{aligned} \tag{19}$$

where $\boldsymbol{\mathcal{X}}$ represents the set of all possible annual net indemnity values; $v(\cdot)$ and $\pi(\cdot)$ are defined in equation (15) and (18) respectively with CL, PC and CPH explicitly expressed as parameters. Tversky and Kahneman (1992) only referred to the $V^M(\cdot)$ function as "a number" that orders prospects, which is not informative. In this study, $V^M(\cdot)$ is thus referred to as the prospect utility function to draw reference from the expected utility theory.

The determination of risk attitude parameters is completed through the following maximization problem: find all $(\alpha_i, \lambda_i, \gamma_i)$ such that

$$CL_i = \arg\max_{CL} V_{\tilde{t}}^{MPP\text{-}D}(CL, \infty, CPH_i, \alpha_i, \lambda_i, \gamma_i) \tag{20}$$

where CL_i and CPH_i are respectively representative i's chosen coverage level and covered production history; $\tilde{t} = 2015$ is the coverage year for which the data are matched. 2016 data are not used in estimating risk attitude parameters because of the high forecasted margin for 2016. Data for that year simply may not show wide variety of risk behaviors due to the favorable market outlook (see Table 7).

As mentioned in section 2.3, I attempt to solve equation (20) for 49 representative operations to find their respective set of risk attitude parameters. For 37 of them I am able to find at least one set of parameters that satisfy equation (20). Since each representative operation represents all producers in the covered production history group who selected the same coverage level as the representative did, this loss of representation can be evaluated in terms of lost number of represented operations and represented covered production histories. In that sense, the prospect theory is unable to account for 4.1% of all operations or 2.3% of all milk covered under MPP-D in 2015. To put this loss of representation into perspective, the expected utility theory fails to explain sign-up choices of 48.9 % of all operations or 34.4% of all milk.

Because the set of risk attitude parameters that satisfy equation (20) is not unique, producer behaviors in other coverage years cannot be uniquely predicted either. Because the true distribution of $(\alpha_i, \lambda_i, \gamma_i)$ is not unknown[7], it is not possible to condense the wide range of fiscal costs induced by wide range of risk attitude parameter values into an expected value

[7] Although all sets of possible risk attitude parameters that are consistent with data are known, there is no telling which set is not realistic in real life or agrees with more operations than others. Therefore, the true distribution of these parameters is unknown.

based on the joint distribution of those parameters. To find a single set of parameters for each representative operation, policy cost for other hypothetical coverage years are calculated among all possible sets of risk attitude parameters. The set that produces the median policy cost over 2008 - 2016 is selected as the representative's risk attitude parameters. These are the years in which realized margins are available and the liquidity of Class IV options are high enough for simulation purpose. Among these 37 representatives, 10 of them are risk neutral and none is risk seeking. These representatives also exhibit various degrees of loss aversion. 9 of the representative operations show no degree of loss aversion and 5 of them exhibit slight opposite of loss aversion (where $0.7 \leq \lambda_i \leq 0.9$). To bring loss aversion values of other representatives into perspective, I benchmarked them with the values from two other studies. Tversky and Kahneman (1992) find the median loss aversion value in their study is 2.25 whereas Liu (2013) observes 3.47 as the median loss aversion value in a separate field elicitation experiment. Among the rest 21 representative operations who exhibit loss aversion, 20 of them have loss aversion parameter higher than 3.47, and 4 have the loss aversion value higher than twice Liu's value. Probability weighting parameter γ_i varies without a pattern. However, 3 representatives do not seem to psychologically distort actual distribution while the rest of them put more emphasis on low probability market scenarios, which is consistent with other studies.

The optimal sign-up choices are solved from equation (21) by assuming $CPH_i, \alpha_i, \lambda_i, \gamma_i$ are fixed:

$$\left(CL_{i,t}, PC_{i,t}, M\right) = \arg\max_{CL,PC,M} V_t^M(CL, PC;\ CPH_i, \alpha_i, \lambda_i, \gamma_i, \delta_i)\ , \forall t \neq \tilde{t} \qquad (21)$$

where

$$M = \{\text{MPP-D, MPP-DL, S1, S3}\}$$

$$t \in \{2008, 2009, \ldots, 2013, 2014, 2016\}$$

Results of equation (8) and the associated fiscal costs will be discussed in the next section.

2.6 Program Evaluation

The two objectives of MPP-DL are (1) to incentivize producers to choose MPP-DL in years when margin forecast is high and (2) to increase indemnity payouts in those years for producers who would otherwise purchase MPP-D. The first objective is achieved by the design of MPP-DL and evidenced by the choice score introduced in previous text. To evaluate the second objective, counterfactual national policy cost based on realized ADPM has to be calculated for MPP-DL and MPP-D. This section discusses these policy costs over 2008-2016 among MPP-D, MPP-DL and two NMPF solutions.

Under NMPF's first suggestion (S1), the coefficients of the feed cost portion of equation (10) are restored to the levels before the 10% cut Congress made. Equation (22) below is used instead to calculate the ADPM distribution for NMPF's first suggestion. Under NMPF's second suggestion, the original ADPM formula is maintained but the data source for corn and alfalfa hay prices is changed from NASS to AMS Marketing News reports. In addition, the soybean meal price is the average of all AMS locations rather than the current "Decatur-Central Illinois" location used by MPP-D.

$$\begin{aligned} \widetilde{ADPM}\ (\$/\mathrm{cwt}) = {} & \textit{All-Milk Price}\ (\$/\mathrm{cwt}) \\ & -1.192 \times \textit{Corn Price}\ (\$/\mathrm{bu}) \\ & -0.00817 \times \textit{Soybean Meal Price}\ (\$/\mathrm{ton}) \\ & -0.0152 \times \textit{Alfalfa Hay Price}\ (\$/\mathrm{ton}) \end{aligned} \tag{22}$$

National policy cost is used as the measure to compare 4 different programs. It is the sum of policy cost for each representative operation. The policy cost for a representative operation is the product of the covered production history the operation represents and the per-hundredweight indemnity payments based on realized market data and optimal choices under its risk attitude parameter values.

Table 9 Comparison of national policy cost in million dollars

Year	Average Forecasted Margin ($/cwt)	Realized Average Margin ($/cwt)	MPP-D Alone (mil $)	MPP-DL with MPP-D (mil $)	S1: NMPF 10% Feed Cost (mil $)	S3: NMPF Full Solution (mil $)
2008	9.48	8.55	(44)	(24)	(54)	16
2009	6.78	4.55	2426	1860	3619	4399
2010	8.62	8.28	(62)	47	(45)	27
2011	5.77	8.86	(386)	(295)	(339)	117
2012	7.71	5.31	979	906	2824	4221
2013	6.53	7.15	302	234	1933	2743
2014	10.41	13.31	(26)	(129)	(40)	(68)
2015	8.36	8.30	(65)	40	(71)	50
2016	8.85	8.18	(7)	86	112	225
Average			346	303	882	1303
Std. Dev.			867	673	1498	1920

Shaded rows indicate the years when forecasted margins are above MPP-D insurable range.

Table 9 above reports national policy costs for all four programs. Positive numbers in the table represent positive net indemnity payments to producers. Aggregate net indemnities are negative in those years in which the realized margin finished unexpectedly above MPP-D's insurable range (≤ $8/cwt). These years are 2008, 2011, and 2014. In all these years, the best hindsight strategy is to select the free $4.0/cwt coverage. In 2008 or 2014, the forecasted margin that guides sign-up choices is already above the historical average margin ($8.56/cwt) and thus prompts many to choose the free $4.0/cwt coverage. However, the presence of risk aversion and loss aversion can deviate producer behaviors from such profit-maximizing choice and lead many to choose other coverage levels. In 2011 when producers received the least payment from MPP programs, the forecasted margin is below historical average and induces a lot of producers to buy higher coverage levels. What makes 2011 very unprofitable is that the margin ends up above the historical average. Those who select buy-up coverages cannot get their premium recovered through indemnity payments.

This is possibly why 2011 pays the least among two other years when realized margin is high.

The most expensive coverage year to policy makers is 2009 when the average realized margin is 33% lower than the forecasted margin around sign-up time. In 2009, all four programs pay out more than 1 billion nationally. The full NMPF solution costs 4.4 billion dollars in that year alone. In comparison, the stand-alone MPP-D would spend $2.4 billion. With the addition to MPP-DL, possibly due to risk aversion among some producers who prefer the less profitable MPP-D in that year, the MPP-D/DL combination reduces the payout to $1.9 billion.

On average, MPP-DL with MPP-D as an option costs the least to policy makers while the full NMPF solution costs the most. The annual cost of the stand-alone MPP-D is 346 million dollars. The two NMPF programs cost more than twice MPP-D with the full NMPF solution skyrocketing to a whopping $1.3 billion. In general, MPP-DL as an addition to MPP-D has a smoothing effect on program payout over the period inspected here. The standard deviation among annual program payout is at the lowest with MPP-DL and at the highest with NMPF full solution.

Such smoothing effect MPP-DL brings allows it to achieve the second objective: MPP-DL pays out more in years when margin forecast suggests MPP-D coverage range does not offer effective protection. Among the five years that meet this criterion, except 2014, MPP-DL is able to offer more indemnity payout than stand-alone MPP-D. Notably in 2010, 2015 and 2016 when margin forecast is around the historical average, MPP-DL increases MPP-D payout to positive zones[8]. The other program that is able to achieve the same result is the full NMPF solution. However, due to its high cost to policy makers, the program is not recommended by this study.

[8] Besides the fact that $4.0/cwt is the only "profitable" (as in $0/cwt profit rather than loss) choice for 2014 when maximum insurable margin is $8.0/cwt, MPP-DL's maximum coverage level of $12/cwt with $1/cwt payment cap may contribute to its high loss in that year compared to theother three programs. Had the coverage level raised to $14/cwt, MPP-DL may be slightly more profitable.

2.7 Conclusion

This paper proposes MPP-DL as a shallow loss version of the dairy title margin insurance program MPP-D. The new program is a supplemental program to the existing MPP-D established in the 2014 Farm bill. MPP-DL offers coverage from $4.0/cwt to $12.0/cwt with maximum payout limited at $1.0/cwt. The primary design objective for MPP-DL is to address policy makers' concern that the existing MPP-D does not pay enough in years when margin forecast is above 8.0/cwt.

Empirical analysis condenses the sign-up information of more than 20,000 producers in MPP-D coverage year 2015 into 37 representative operations, and then estimates cumulative prospect theory risk attitude parameters of the representatives. With the risk attitude parameters at hand, counterfactual sign-up behaviors in other coverage years are predicted. Fiscal costs of variations of MPP-D are analyzed after.

The results show that both MPP-DL and a solution proposed by National Milk Producers Federation (NMPF) are able to increase insurance payout in years that margin forecasts are above MPP-D insurable range. However, NMPF's "rising tide lifts all boats" approach also increases payout for other years and can put considerable fiscal burden on federal budget. MPP-DL on the other hand is able to reduce the overall cost of dairy title program with a more smoothed payment stream over the years.

This paper estimates representative operations risk attitude parameters from two observed sign-up choice variables. Producer heterogeneity can be further achieved with additional variables (i.e. producer locations, financial situations) to achieve better representation and more accurate risk attitude parameter values. A field elicitation experiment across the country may also provide better estimates of risk attitude parameters. These potential improvements may broaden the ability of the cumulative prospect theory model used in this study to explain more, if not all, representatives' choices.

3 Asymmetric Price Transmission in U.S. Fluid Milk Markets

3.1 Introduction

Asymmetric price transmission is not only an economic intrigue among scholars but a matter of practical implications for market participants and policy makers. Among a series of stylized facts, Li, Sexton and Xia (2006) claimed that “Transmission of farm price changes to retail is (i) delayed, (ii) incomplete, and (iii) asymmetric.” Asymmetry usually manifests itself in how retailers react to changes in farm price. Retail prices are described by Peltzman (2000) as “rise faster than they fall”. Since Kinnucan and Forker (1987) seminal work that supported the claim of price asymmetry in U.S. dairy markets, asymmetric transmission has been the default assumption for almost all empirical studies in the dairy filed. Awokuse and Wang (2009) later take advantage of advances in threshold cointegration analysis and reconfirm Kinnucan and Forker’s results. Further more, Peltzman (2000) extended asymmetry claim to include hundreds of producer and consumer goods beyond the dairy sector.

As pointed out by Peltzman (2000), prevalent economic theories do not explain why retail price reacts to one kind of farm price shocks faster than the other. Empirical studies on asymmetric transmission may indicate inadequacies of our theories. Asymmetric price transmission could also suggest that retailers reap the benefit at the expense of consumers and producers. Among many speculated causes of asymmetry in the literature is the retailer market power along value chain. Increased retail market concentration with the emergence of mega grocery stores and national chains may force price reactions to become inconsistent with competitive market results. Xia and Sexton (2009), Bolotova & Novakovic (2005), and Carman and Sexton (2005) found varying degrees of retailer oligopoly/monopoly in several U.S. dairy markets. If retailer market power is confirmed as a contributing factor to asymmetric price transmission, lowering farm-gate price may not translate to consumer welfare in its fullness or in a timely fashion. Consequently, milk producers may not receive adequate feedback from retail markets to adjust short term production through changes in feed ration. Sexton, et al. (2003) argued that retailer market power can press commodity prices downwards and divert more fresh produce to lower-valued uses. With changing consumer taste and ample choices of non-dairy beverages[9] gaining popularity, milk producers are facing competition that did not exist decades ago. On top of the competition from non-dairy beverages, asymmetric price transmission may add another layer of complication to producer profitability. "The person in the street" – the industry folks Peltzman (2000) facetiously referred to – observes increasing empirical evidence to justify their concerns about alternative labeled-as-milk beverages. The year-to-date volume share of all non-dairy beverages in 2016 is increased by 5.4% while the total fluid milk sales volume declined by 1.9% (Dairy Management Inc., 2016).

This study sets to empirically test asymmetric price transmission in U.S. retail fluid milk markets. Fifteen most populous Metropolitan Statistical Areas (MSA) are selected for this study. The novelty of this study is the empirical methods used. A two-threshold three-regime error correction model is first employed to investigate threshold cointegration relation between the retail price of a product type in one MSA and the corresponding Class I milk price. Then panel technique pertains to large data time series is used to test hypothesis of symmetry in each MSA.

Among empirical methods that appear in asymmetric price transmission literatures, the Houck model (Houck, 1977) was the first widely accepted specification in which downstream price change is regressed on cumulative positive and negative changes in upstream price. Ward (1982) made the Houck model more operational by including lagged terms of upstream prices. Separately, von Cramon-Taubadel and Loy (1996) added a (non-split) error correction term to Ward's specification. Splitting the error correction term soon followed in Granger and Lee (1989). In an attempt to unify Houck type models and error correction methods, Capps and Sherwell (2007) argued that an error correction specification developed by von Cramon-Taubadel and Loy (1999) nests the Houck approach and comparisons between the two methods show "statistically indistinguishable"

[9] Non-dairy beverages include almond, soy, coconut, cashew, rice milk, chocolate drinks, goat milk, Horchata drinks.

results in U.S. dairy markets. An interesting "outlier" study to mention here is Xia and Sexton (2009) who applied a symmetry test model developed by Chavas and Mehta (2004) but found that asymmetry is statisticially insignificant in fluid milk markets of all four California cities they studied. Chavas and Mehta (2004) themselves applied the method to the U.S. butter market and found strong evidence for asymmetry. All these models mentioned above and analyzed in Capps and Sherwell (2007) assume the threshold that splits the variable is zero. Enders and Dibooglu (2001) broke such convention and estimated several one-threshold two-regime models. Goodwin & Piggott (2001) estimated a one-threshold three-regime model where the two regime cut-off points share a same absolute value. To my best knowledge, Jeon and Seo (2003) are the first to use one-threshold two-regime Threshold Vector Error Correction Model (TVECM-12) in empirical work. Meyer (2004) brought forth the use of TVECM-12 into price transmission studies. Other notable studies with this method are Balcombe, et al., (2007), Ben-Kaabia and Gil (2007), and Rezitis and Reziti (2011). As an interesting addition to the empirical TVECM-12 applications, Park, et al., (2007) developed time-varying thresholds deduced from estimated TVECM thresholds. However, they did not split error correction terms by those time-varying thresholds possibly due to conventional tests' inability to check if cointegration remains under time-varying thresholds. Fitting time-varying thresholds into TVECM framework requires further econometric research. Recently, Loy, et al., (2015) employed a two-threshold three-regime error correction specification to study asymmetric price transmission in German milk and butter markets.

As mentioned before, the contribution of this study is primarily methodological. This study's methods provide a ready-to-use recipe to empirically test asymmetry for large time series datasets. First, to my best knowledge, this study is the first to apply two-threshold error correction models to U.S. fluid milk markets. A band of no-reaction is explicitly built into the model with adequate tests to assure underlying econometric properties and model selection. The threshold error correction model used in this study is close to the one Loy, et al., (2015) employed. One major difference from Loy, et al., (2015) is the extensive care this study takes to account for structural breaks in price series. The premise of error correction model is the linear long-term relationship between two price series. The presence of structural break can easily break such assumption. Second, this is the first study to use Common Correlated Effects Mean Group (CCEMG) estimator to study panel effects of asymmetric price transmission in the U.S. fluid milk markets. Only recently developed by Chudik & Pesaran (2015), an autoregressive distributed lag panel data model is used to investigate this topic based on threshold results from individual retail-farm price pairs.

This paper is organized as such: the next section introduces the empirical framework of price asymmetry that methods of this study belong to. The paper then offers a general description of the data used in this study as well as the data manipulation involved prior to formal empirical analysis. The next section delves into several aspects of the empirical analysis with detailed steps of each method and results after performing them. A discussion of the symmetry test results follows after.

3.2 Empirical Framework

There are several aspects of asymmetric price transmission that the literature has studied so far. The speed of price transmission measures how fast downstream price reacts to upstream price change in one direction than another. Peltzman (2000) statement "Prices rise faster than they fall" is a statement about different speed of such price reaction. The magnitude of price transmission characterizes the extent of downstream price reaction to an upstream price change. A statement like "downstream price adjusts fully to upstream price hikes but not upstream price decline" is a statement about the transmission magnitude. Traditionally, the Houck method is used to look at the speed and magnitude of asymmetric price response. A typical example of a classic Houck model is this:

$$\Delta R_t = a + \sum_{j=0}^{q_1} b_{\mathrm{j}}^{+} \Delta F_{t-j}^{+} + \sum_{j=0}^{q_2} b_{\mathrm{j}}^{-} \Delta F_{t-j}^{-} + v_t \tag{23}$$

where $\Delta R_t = R_t - R_{t-1}$ is the change in downstream price for time period t; $\Delta F_t^+ = \sum_{s=1}^{t} \max(F_s - F_{s-1}, 0)$ is the cumulative positive shocks in upstream price with F_t being the downstream price for period t; similarly $\Delta F_t^- = \sum_{s=1}^{t} \max(F_{s-1} - F_s, 0)$ is the cumulative negative shocks in upstream price; and v_t is the error term. b_j^+ and b_j^- are speed parameters. Comparison between them is the main analytical tool to study asymmetry speed. The magnitude of the asymmetry is measured by the sum of the speed parameters $\sum_{j=0} b_j^+$ and $\sum_{j=0} b_j^-$. Asymmetry is usually tested against the hypothesis that $\sum_{j=0} b_j^+ = \sum_{j=0} b_j^-$.

Asymmetry can also be termed “positive” or “negative”. Positive asymmetry refers to the speed and/or the magnitude of the downstream price reaction to the upstream price increase is more intense than those to upstream price decrease. In other words, if margin decline causes stronger downstream price reaction, the asymmetry is positive. In a Houck model, $\sum_{j=0} b_j^+ > \sum_{j=0} b_j^-$ serve as evidence of positive asymmetry.

As simple and effective as the Houck method is, it fell out of favor in asymmetry literature once advances in cointegration analysis bore fruit in non-linear threshold regime models. Cointegration models, with its most common Error Correction Model (ECM) specification, have unique advantage over the Houck method. If cointegrating relationship is present in the data, ECM directly models the long-term transmission relationship between two prices. Short term deviates from the long-term relationship is either explicitly or implicitly parameterized into the model. The long-term transmission relationship engrained in the model can be empirically tested via various cointegration tests. ECM is particularly primed to model positive / negative asymmetry due to the explicit parameterization of the short-term deviation (or the error correction term). One thing worth noting however is that the existence of a long-term transmission relationship assumes the two prices do not drift away or collide into each other over long period of time. This essentially “models” out the possibility of varying magnitude of asymmetric price transmission. Therefore, cointegration models can only test for the speed of asymmetry. In empirical studies, cointegration model is only appropriate if the dataset passes cointegration tests. Otherwise, the rejection of a stable long-term price dynamic necessitates the use of the Houck method.

This study employs a two-threshold three-regime error correction model. Aside from the advantage it has over the Houck method, it is also capable of modeling a band of no-reaction when changes fall between the two thresholds. Figure 10 adopted from Meyer (2004) provides a visual illustration of this point: smaller deviations from long-run equilibrium do not trigger price reactions. Such behavior can be plausible in the presence of retailer menu cost. Fear of losing market share and the associated cost of changing signage, retailers may not find price adjustment appealing if changes in upstream price is small.

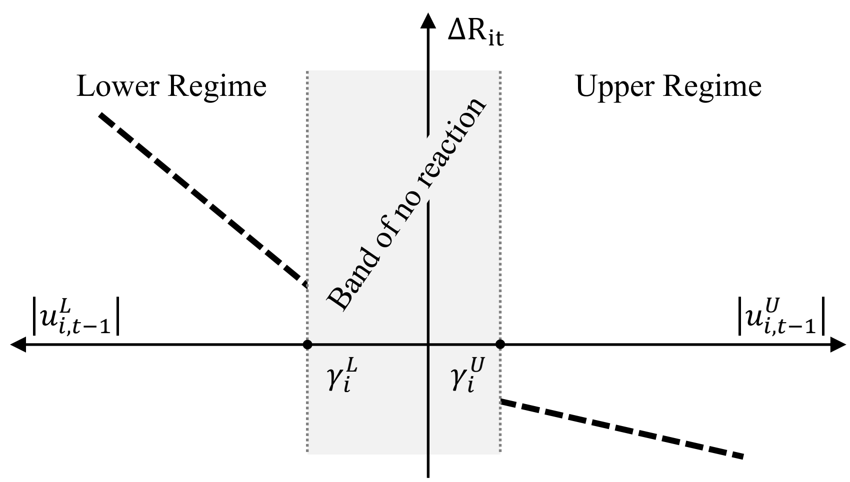

Figure 9 Error correction term on price adjustment

Let R_{it} and F_{it} denote respectively monthly retail and farm-gate prices for milk type i in month t in one single geographic area. If R_{it} and F_{it} are threshold cointegrated with thresholds γ_i^L and γ_i^U ($\gamma_i^L \leq \gamma_i^U$), they admit the following error correction specification:

$$\Delta \mathrm{R_{it}} = \alpha_i^0 + \theta_i^L u_{i,t-1}^L + \theta_i^U u_{i,t-1}^U + \sum_{j=1}^{p_i} \alpha_i^j \Delta \mathrm{R_{i,t-j}} + \sum_{j=0}^{q_i} \beta_i^j \Delta \mathrm{F_{i,t-j}} + v_{it} \tag{24}$$

$$\forall t \in \{s \in [1,T]: u_{is} \leq \gamma_i^L \ or \ u_{is} > \gamma_i^U\}$$

where Δ denotes the first difference operator; v_{it} is the regression error term; the lower and upper regime error correction terms u_{it}^L and u_{it}^U are defined as the following

$$u_{it}^L = u_{it} \cdot I_{u_{it} \leq \gamma_i^L}$$

$$u_{it}^{U} = u_{it} \cdot I_{u_{it} > \gamma_i^U}$$

with u_{it} being the error correction term, and indicator function $I_A = 1$ if A is true or $= 0$ otherwise. The speed of price transmission (θ_i^L or θ_i^U) in each regime is the slope of the dashed line in Figure 10. The lower regime (where $u_{it} \leq \gamma_i^L$) corresponds to the cases when upstream price is increased. Therefore, positive asymmetric transmission in this context means $|\theta_i^L| > |\theta_i^U|$.

Under Engle-Granger two-step cointegration procedure, the error correction term u_{it} is the residual from the long-run equilibrium regression of R_{it} on F_{it}. Note that equation (24) does not have a middle regime term $u_{it}^M = u_{it} \cdot I_{\gamma_i^L < u_{it} \leq \gamma_i^U}$. Besides the economic interpretation of the band of no-reaction, the omission also has its econometric reason. For u_{it} to be stationary, only the outer regimes need to be well behaved (Chan, et al., 1985, and Balke and Fomby, 1997). The middle regime can exhibit non-convergent or unit root behavior. Equation (24) also nests the one-threshold two-regime model when $\gamma^L = \gamma^U$. Since farm-gate prices under Federal and California milk marketing orders are derived from component prices in previous month, I also include the contemporaneous farm-gate price term $\Delta F_{i,t}$ on the right-hand side of equation (24). This is why the lagged term $\Delta F_{i,t-j}$ starts at $j = 0$ instead of 1.

For a specific type of milk, the null hypothesis of symmetric transmission is phrased like below:

$$H_0^i \colon \theta_i^L = \theta_i^H \tag{25}$$

For the entire geographic region, the hypothesis of symmetric transmission is instead

$$H_0 \colon \frac{1}{N} \sum_{i=1}^{N} \theta_i^L = \frac{1}{N} \sum_{i=1}^{N} \theta_i^U \tag{26}$$

where N denotes the number of milk product types in the region. H_0 tests the average (symmetric) effect of price transmission in a region.

3.3 Data Analysis

This study uses Nielsen Retail Scanner data in 15 Metropolitan Statistical Areas (MSA) to analyze price transmission. Farm-gate prices are California Class I milk price for three California MSAs and Class I milk price of appropriate Federal Milk Market order for the other regions. Temporary Sales Prices (TSP) are detected by Chahrour (2011) filter. Individual series are aggregated to sales-weighted series for each product type within an MSA. Two separate datasets are produced to compare the effect TSP has on transmission. The first dataset is created after aggregating UPC level prices with TSP excluded. The second is produced with TSP retained. Due to similarities in these two datasets, time series property tests only report results of the TSP-excluded dataset. Unless otherwise noted in the text, readers can assume these test results speak for the TSP-included dataset as well. Details of temporary sales price and price aggregation are explained in subsections 3.3.2 and 3.3.3.

3.3.1 Data Description

The retail price data used in this study come from Nielsen Retail Scanner Dataset. The dataset includes weekly price and sales volume of 8,234 milk products in retail locations across the United States. A product is defined by a Universal Product Code (UPC) and packaging size[10]. The available time periods at the onset of this study span from the first week of 2006 to the last week of 2014. Depending on the region, the farm level price may be either the Class I milk price for a Federal Milk Marketing Order (FMMO) or California Class I price.

Among the 8,234 milk products, many are only sold in regional markets. Some products are excluded due to short price series or unconventional product attributes such as 0.5% fat

[10] Companies sometimes use a same UPC for milk sold in bottles of different sizes. Neilson scanner dataset assigns a version number to each UPC to deal with such situation.

content. Organic products are also removed from this study because of the different cost structure compared to regular milk products. After further data manipulations detailed in the next two subsections, the total number of products in the 15 regions studied is 2,898.

3.3.2 Temporary Sales Price

Price promotion and royalty discounts are common tools retailers use to increase sales. However, these price cuts are usually temporary and have nothing to do with fluctuations in wholesale price or production cost. Most literatures refer to these price cuts Temporary Sales Prices (TSP). TSP can be described by two measures: frequency and depth. Frequency measures how often TSP occurs while depth measures the difference between TSP and regular price. Volpe (2013) argued that competition among retailers affects both frequency and depth. Hosken and Reiffen (2004) examined 20 categories of perishable foods sold in U.S. and found that 25% - 50% of annual price variance for most categories can be attributed to TSP. In an empirical study of butter products in Germany, Tifaoui and Cramon-Taubadel (2016) showed that the inclusion of TSP makes price recovery from reduced retail price look more rapid and hence increases the appearance of asymmetric price transmission. They pointed out that TSP exaggerates the temporary deviation between retail price and wholesale price, and creates the illusion that the retail profit margin is squeezed from upstream value chain. When the retailer removes sales promotion after a short period, it would appear in empirical analysis that the reduced margin is corrected in a rapid fashion. Given that retail-driven temporary price increase is less common than TSP, retail price data typically do not feature quicker correction of temporary price hikes and therefore exhibit different reactions from margin expansion compared to the case of squeezed margin.

Though the literatures appear to agree on the distortion factor of TSP in price transmission studies, the research field still has not reached a consensus on proper ways of dealing with TSP in data analysis. In their extended study of the topic, Tifaoui and Cramon-Taubadel (2016) categorized various methods into two groups. The goal of either group is nonetheless to separate a price series into two components: the regular price component and the sales price component. The first group of methods focuses on the definition of sales prices and removes them from a price series. The method used in Hosken and Reiffen (2004) falls into this group. The second group redirects a researcher's attention to what constitutes a regular price and seeks to preserve those in a time series. Tifaoui and Cramon-Taubadel (2016) argued that though the first group of methods is straight forward they usually incorporate some arbitrary components, such as the 10% sales price cut-off point in Hosken and Reiffen (2004). Those methods also implicitly assume temporary price hikes do not exist. In comparison, methods in the second group are usually robust against different values of parameters up to a certain extent and admits spurious price hikes. For example, Tifaoui and Cramon-Taubadel (2016) mentioned that the width of their modal price window is robust between 9 to 17 weeks. The method Tifaoui and Cramon-Taubadel used is the Chahrour method (Chahrour, 2011), which forms the basis of the method used in this study.

The Chahrour method utilizes a 13-week moving window centered at the week under evaluation and calculates the modal price based on prices within that window as the reference price for the week. The size of the window is consistent with the 2.66 months of regular price duration found in Narasimhan, et al. (1996). In a published online appendix of the paper, Chahrour detailed four special adjustments to the modal price when the modal price suddenly changes from a previous period.

The basis of the Chahrour method is the assumption that the regular price component of a retail price series fluctuates infrequently. Graphically this assumption translates to the presence of many visible plateaus among downward spikes or trenches in time series plot. For example, Figure 11 is a typical example of a price series assumed under the Chahrour method. Although price in the graph dips periodically at high frequency, several price plateaus are still visibly present even to a casual observer. While many price series in Nielsen retailer scanner dataset resemble the one in Figure 11, many others do not share the same look of price stickiness and regions of flat progression. Figure 12 shows the price of the same product sold in a different store of the same region. The price series in Figure 12 would render the Chahrour method ineffective since a modal price can no longer represent the "common theme" of price movement in the 13-week window. For many price points in the series plotted in Figure 12, a unique modal price does not even exist. Chahrour resolved this issue by assigning the first modal price in the order of appearance as the reference price. His resolution does not work too well if the number of occurrence of competing modal prices in the 13-week window is very low. In an extreme case where all 13 prices are different, the Chahrour method uses the price that is 6 weeks earlier as the reference price. Another issue the Chahrour method has with price series like the one in Figure 12 is that it would exclude too many price points. The series shown in Figure 12 would lose 73% of the 251 price points if exclusion takes place when the observed price does not equal the reference price.

Because of these two issues, I made two changes to the Chahrour method. First, I used average price instead of the modal price if the occurrence of competing modal prices is less than 4 weeks (~25% of the window width). Second, exclusion criterion is loosened such that only sales price of more than 10% below the reference price and spurious price hike of more than 15% of the reference price are removed from further analysis. However, due to the use of these two arbitrage cut-off thresholds (the 10% and 15%), data with sales prices retained are separately analyzed to study the impact the price filter has on asymmetric transmission.

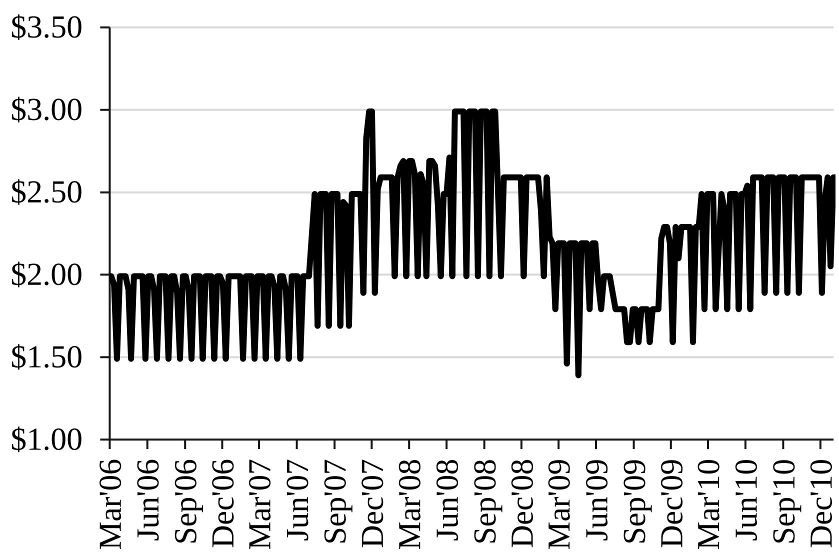

Figure 10 Sample price series 1

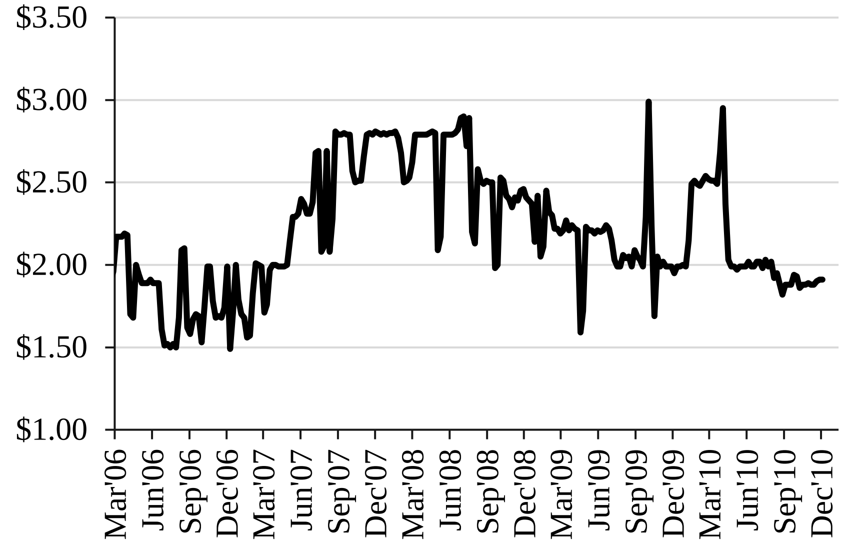

Figure 11 Sample price series 2

3.3.3 Product Type and Price Aggregation

After purging sales prices from every series, I aggregated price series by product types to Metropolitan Statistical Area (MSA) level. The resulting set of series consists of sales-weighted monthly prices of each product type in every MSA. Due to the use of 13-week moving window in the process of determining sales prices, price observations in the first and last two months are excluded from subsequent analysis. The final dataset used in threshold analysis represents about 24 - 27 product types in each of the 15 MSA's from March 2006 to Oct 2014. In other words, a balanced panel of 24 – 27 products with 104 monthly time series observations is constructed for each MSA. Totally number of series is 387. Summary statistics about each product type can be found in Table 34 on page 111.

There are several problems such aggregation addresses. First, the granularity of Nielsen retail scanner data is much higher than that of Class I milk price. Nielsen offers weekly sales-weighted average price series whereas Class I milk is published every month. Second, the sheer size of Nielsen retailer scanner data makes it very difficult to run panel data analysis that includes every individual price series. The average number of price series in an MSA is 32,226. Given that threshold estimation involves gird search, this large number of series simply renders analysis based on individual series computationally infeasible.

Table 10 Price series count in each MSA

MSA	Principal City	Number of Series	Product Count
New York-Newark-Jersey City, NY-NJ-PA	New York	1,079,814	918
Los Angeles-Long Beach-Anaheim, CA	Log Angeles	700,208	487
Chicago-Naperville-Elgin, IL-IN-WI	Chicago	523,839	510
Dallas-Fort Worth-Arlington, TX	Dallas	345,896	446
Houston-The Woodlands-Sugar Land, TX	Houston	330,767	389
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Philadelphia	335,740	569
Miami-Fort Lauderdale-West Palm Beach, FL	Miami	184,932	312
Atlanta-Sandy Springs-Roswell, GA	Atlanta	297,518	481
Boston-Cambridge-Newton, MA-NH	Boston	255,647	396
San Francisco-Oakland-Hayward, CA	San Francisco	220,330	399
Phoenix-Mesa-Scottsdale, AZ	Phoenix	259,015	353
Riverside-San Bernardino-Ontario, CA	Riverside	205,719	474
Detroit-Warren-Dearborn, MI	Detroit	168,390	280
Seattle-Tacoma-Bellevue, WA	Seattle	271,141	411
Minneapolis-St. Paul-Bloomington, MN-WI	MPLS-St Paul	180,498	444

To narrow down price observations to a manageable size but still preserve product heterogeneity, I picked 15 most populous MSA's and grouped individual products into 32 product types. Product types are defined by the following set of attributes: product size, container type, lactose-free label and fat content. I further excluded price series that does not offer conventional values of any of those attributes. For example, product size is only limited to the three most common retail sizes: 32 oz., 64 oz. and 128 oz. (1 gallon). Table 35 on page 112 describes permissible values for all attributes in detail. The number of product types does not equal the theoretical number of combinations of attribute values. This is because many combinations do not exist or the corresponding price series does not span all months. For example, it is not common to see a one-gallon lactose-free whole milk sold in a plastic container.

The decision to include the four attributes in the definition of product type is assisted by a machine learning technique called Random Forest (Breiman, 2001). I started with a larger set of product attributes that also includes kosher designation and various vitamin labels marketed on containers. All these attribute values are parsed from UPC descriptions Nielsen retail scanner dataset offers.

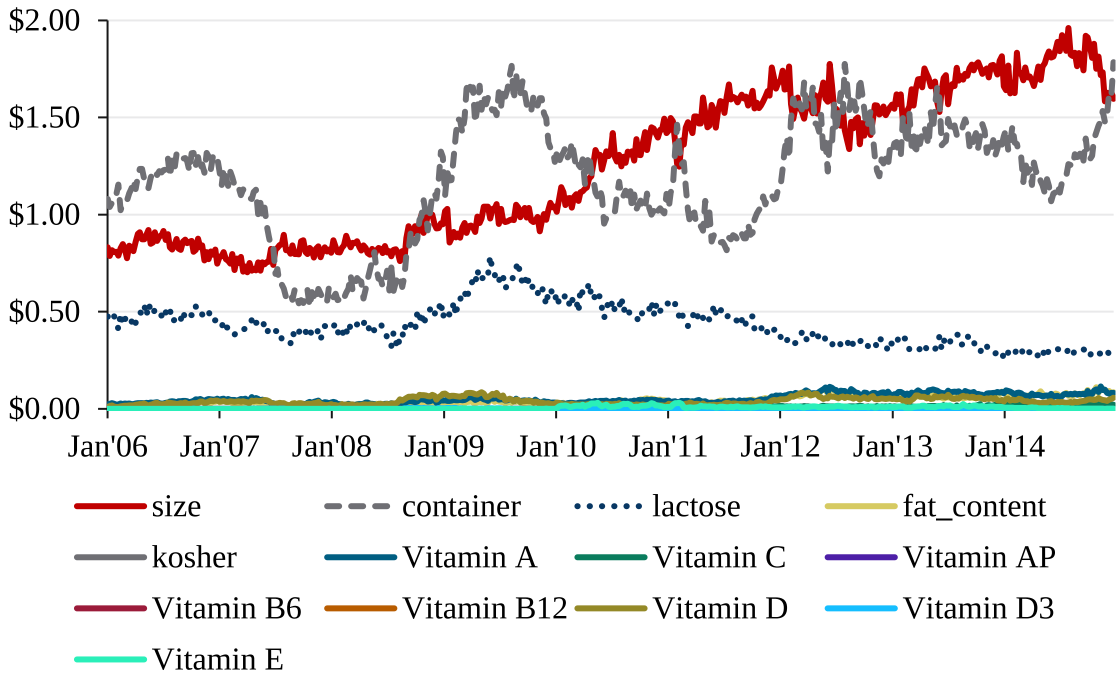

Figure 12 Temporal progression of product attribute significance with sales prices excluded

The technical details of random forest are not of interest to this study. The basic idea behind random forest is to "grow" decision trees with bootstrap sampling on random subsets of all observations. A decision tree separates observations by attribute values in binary fashion, i.e. is container size 32 oz. or not. In this study, the tree keeps splitting observations until doing so no longer decreases the lack of fitness by a factor of 1%. In the context of determining product types, the method identifies the most obvious price differentiators among other product attributes. A typical question the random forest can answer is, do price points cluster around different values of a product attribute given other attributes equal. To reduce temporal effect on shifting price clustering, I separated the entire dataset into weekly slices and ran random forest on each slice once at a time. A measure called mean decrease in accuracy can be calculated for each variable after a forest is constructed. A product attribute is a meaningful price differentiator if its mean decrease in accuracy is large in comparison to other attributes. Figure 13 shows time progression of mean decrease in accuracy of all product attributes when sales prices are excluded. It is very clear in Figure 13 that three attributes stand out in their importance of separating prices in all weekly periods. These three attributes are product size, container type and lactose-free label. These attributes remain significant when sales prices are retained. On top of those attributes, I also included fat content because milk is horizontally differentiated by fat content at retail level (Davis, et al. 2012 and Xia & Sexton 2009).

3.4 Empirical Analysis

After the detection of temporary sales prices and the aggregation of individual series by product type and geographic region, I ran extensive tests on the aggregated panel series. Augmented Dickey-Fuller (ADF) tests are performed on individual series in each panel. Due to the appearance of structural breaks in many series, HTL structural break unit root tests (Harvey, et al., 2013) are carried out on individual series. Choi panel unit root tests (Choi, 2001) with modifications to account for cross sectional dependence proposed by Demetrescu, et al. (2006) are then performed to check for panel unit roots. These tests suggest that both the retailer price and farm-gate price are I(1) processes.

Subsequently, the original Engle-Granger two-step cointegration tests are performed on individual series. Structural break cointegration tests of Gregory and Hansen (1996) and Hatemi-J (2008) are then executed. Individual series cointegration effect cannot be confirmed by these tests. In light of these test results, Westerlund (2007) method is used on panels and confirms panel cointegration in 13 of 15 panels.

Due to possible misspecification issue, Enders and Siklos (2001) threshold cointegration tests are used to test threshold cointegration on individual series. The test is extended to two-threshold models with structural breaks and unknown breakpoints. Thresholds are also estimated in the test by procedures described in Chan (1993). Because the distributions of test statistics are not known, critical values are simulated by Monte Carlo simulation detailed in Enders and Siklos (2001) with modifications consistent with methods in Gregory and Hansen (1996) and Hatemi-J (2008). Threshold cointegration tests show that most regions sport more than 90% of individual price pairs that are threshold cointegrated. Once thresholds are estimated and threshold cointegration is confirmed, Common Correlated Effects Mean Group (CCEMG) estimators are obtained on panel series. Tests on symmetry are based on CCEMG estimators. The rest of the section explains details of these tests and their results.

3.4.1 Unit Root Tests

Cointegration requires both the retail and farm-gate price series to be integrated of order one ($I(1)$). ADF results suggest that both California and FMMO Class I series are indeed $I(1)$ processes. This finding is further confirmed by a separate run of KPSS (Kwiatkowski, et al., 1992) tests. Because test results from individual retail series do not benefit from the extra information provided by cross sections, panel unit root tests are carried out for retail price series. In what follows is a brief literature review of panel unit root tests before details of the test adopted in this study is given.

A pooled version of ADF test on panel data was developed by Lavin and Lin (LL) in 1992, and later published in Lavin and Lin (2002) with improvements. Implicitly assumed in the pooled model of Lavin and Lin (2002) is that each cross section follows a same data generating process. Due to this restriction, the LL test suffers low power and is of limited use. The IPS test (Im, et al., 2003) relaxes this restriction and allows for different ADF t-statistics for each cross-section. However, the asymptotic results of IPS depend on the assumption that the number of cross sections (N) goes to infinity, whereas in time series analysis, it is more appropriate to assume the number of time periods (T) approaches infinity. Maddala and Wu (1999) subsequently proposed to use Fisher's p_λ-test (Fisher, 1932) for such reason. Choi (2001) considered not only the case where N is fixed as $T \to \infty$ but also the case where both N and T approach infinity. Literatures up to Choi (2001) assume cross section independence. This assumption is unrealistic in this study where each cross section represents a milk product type sold within a single geographic region. There is no reason to believe that the price of a carton of 2% milk does not correlate with the price of a carton of whole milk sold next to it. Demetrescu, et al. (2006) made a modification to Choi (2001) to account for cross section dependence.

According to Demetrescu, et al. (2006), the test statistic for the null hypothesis that all series in the panel have unit roots is:

$$t_{0.2} = \left(\sum_{i=1}^{N} t_i\right) \Bigg/ \sqrt{N + (N^2 - N) \cdot \left(\hat{\rho}^* + \frac{1 - \hat{\rho}^*}{5}\sqrt{\frac{2}{N+1}}\right)} \sim \mathcal{N}(0,1) \qquad (27)$$

with

$$\hat{\rho}^* = \max\left(-\frac{1}{N-1}, \hat{\rho}\right), \qquad \hat{\rho} = 1 - \frac{1}{N-1}\sum_{i=1}^{N}\left(t_i - \frac{1}{N}\sum_{i=1}^{N} t_i\right)^2$$

$$t_i = \Phi^{-1}(p_i)$$

where N represents the number of cross sections; p_i is the p-value of a unit root test statistic for series i; $\Phi^{-1}(\cdot)$ denotes the inverse standard normal cumulative distribution function; $\mathcal{N}(0,1)$ represents the standard normal distribution. Typically, p_i is the p-value of an ADF test statistic, but can also be the p-value of other unit root tests.

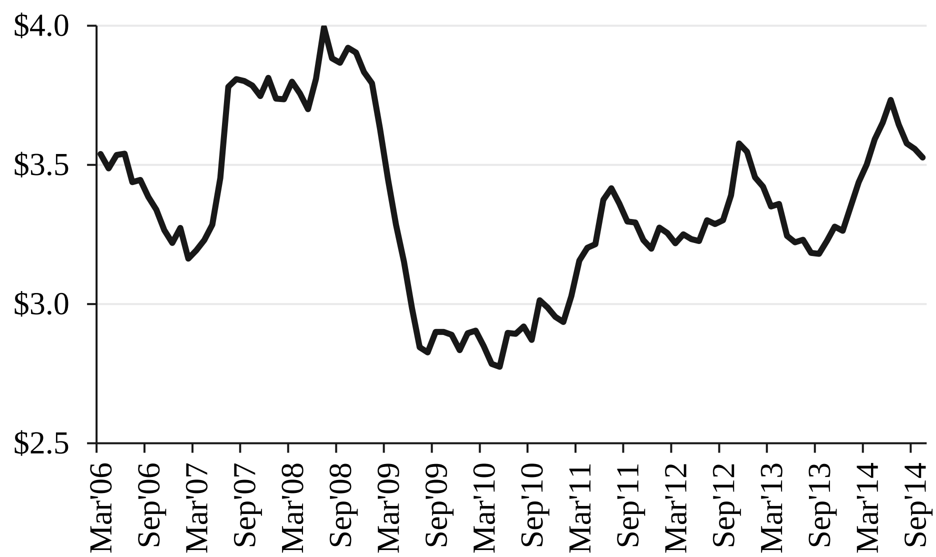

Figure 13 Sample price series suggesting structural breaks

Since some retail price series show signs of structural change (see Figure 14 above), structural break unit root test is also performed on individual series. Because ADF test has limited power in the presence of structural changes, Zivot and Andrews (1992) proposed an ADF type of unit root test for a single structure break. Zivot and Andrews (1992) test is not suitable for long horizon time series because the test does not allow for a structural break in trend. Due to such shortcoming, Carrion-i-Silvestre, et al. (2009) developed a General Least Square (GLS) based structural change unit root test that is capable of detecting multiple breakpoints. Harvey, et al. (2013) pointed out that the power of the Carrion-i-Silvestre, et al. (2009) test is dependent on the size of a break and proposed the HLT method – a GLS-based "detrended" version of ADF test.

The test statistic of HLT is the minimum ADF t statistic among all possible breakpoint locations.

$$MDF_m = \min_{\boldsymbol{\tau} \in \boldsymbol{\mathcal{T}}} DF_{\bar{c}}^{GLS}(\boldsymbol{\tau}) \tag{28}$$

where m denotes the number of breaks; $\boldsymbol{\tau} = [\tau_1, \tau_2, \dots, \tau_m]'$ denotes a vector of breakpoint locations; $\boldsymbol{\mathcal{T}}$ defines the set of all permissible locations subject to a user defined minimum inter-break length; $\bar{c}$ is the noncentrality parameter whose value depends on m; MDF_m is the HLT test statistic of the null hypothesis that structural changes occur at $\boldsymbol{\tau}$; and $DF_{\bar{c}}^{GLS}(\boldsymbol{\tau})$ is ADF t-statistic of the residual term $\tilde{u}_t$.

$$\tilde{u}_t = y_t - \tilde{\mu} - \tilde{\beta} t - \tilde{\gamma}\, D(t, \boldsymbol{\tau}) \tag{29}$$

where y_t represents the time series data; $D(t, \boldsymbol{\tau}) = max(t - \boldsymbol{\tau}, 0)$ is a vector function and the max(·,·) function is applied piece-wisely; $\tilde{\mu}$, $\tilde{\beta}$ and $\tilde{\gamma}$ are GLS estimators of $\hat{\boldsymbol{y}} = [y_1, (1-\rho)y_2, (1-\rho)y_3, \dots, (1-\rho)y_T]'$ on $\hat{\boldsymbol{x}} = [x_1, (1-\rho)x_2, (1-\rho)x_3, \dots, (1-\rho)x_T]'$ with $x_t = [1, t, D(t, \boldsymbol{\tau})]'$ and $\rho = 1 - \bar{c}/T$. Harvey, et al. (2013) provided both the value of $\bar{c}$ and critical values for MDF_m.

ADF tests on individual retail price series are first performed. Then ADF t-values are used in the panel unit root test proposed by Choi (2001) and Demetrescu, et al. (2006). Panels are organized by MSAs. HTL structural break unit root tests are performed for further diagnostics. ADF test on individual price series show that roughly 90% of the series fail to reject unit root. The results for the remaining 10% series are assumed to be type II errors. All series reject the unit root hypothesis when differenced to the first order. HTL structural break tests add four more series as neither I(0) nor I(1). However, the ADF tests on these series show they are I(1) under the assumption that there is no structural break. These results suggest that all individual series are I(1) processes. The Choi panel unit root test shows that two-thirds of panel time series have unit-roots on levels. When differenced, they all reject panel unit root hypothesis. Since the estimation of threshold is based on individual series rather than panel series, the presence of non-unit root panel series in panel threshold error correction model may not present problems.

3.4.2 Linear Cointegration Analysis

Engle-Granger and Johansen cointegration tests are performed for each product type. Results show only 10% of retail-farm prices are cointegrated when sales prices are excluded. When sales prices are not excluded, 15% of the price pairs are cointegrated.

Given the possibility of structural breaks, I carried out a structural change cointegration test based on Gregory and Hansen (1996) and Hatemi-J (2008). The test procedure is similar to the unit root version of the test in that all possible breakpoints are evaluated until the breakpoint that produces the lowest ADF t-statistic on the residuals of a structural change specification is found. The specification of the first stage cointegration test is detailed in the next section. Structural cointegration tests show that 6% of all retail-farm price pairs are cointegrated with one breakpoint. This number climbs to 44% when two breakpoints are assumed. In total, cointegration relationship is confirmed in 49% of retail-farm price pairs by either the original Engle-Granger test or the structural change cointegration test.

A test proposed by Westerlund (2007) is used to check for panel cointegration effect. Though residual based tests like Pedroni (1999) may seem more compatible with the threshold estimation procedure described in the next subsection, Westerlund (2007) accounted for cross sectional dependence with bootstrap simulation, and is not susceptible to the common factor restriction analyzed by Kremers, et al. (1992). When cross section dependence is not accounted for, every panel is cointegrated as whole with the exception that only one panel failed to reject no cointegration in the G_a test. However, the corresponding G_t test is able to reject the no cointegration hypothesis for the same panel. Tests on whether at least one series in the panel are not cointegrated are rejected for all panels. When cross section dependence is assumed, four panels fail to reject the no cointegration hypothesis. All others can reject no cointegration at least at 10% confidence level.

3.4.3 Threshold Cointegration

Because linear cointegration tests may suffer low power due to misspecification of the data generating process (Enders & Siklos, 2001), threshold cointegration is tested for each product type along the estimation of threshold values.

In the presence of structural breaks, the long-run equilibrium equation is specified as:

$$R_{it} = \mu_i^0 + \delta_i^0 F_{i,t} + I_{t>\tau_i^1}(\mu_i^1 + \delta_i^1 F_{it}) + I_{t>\tau_i^2}(\mu_i^2 + \delta_i^2 F_{it}) + u_{it} \quad \forall t \in [1, T] \tag{30}$$

where R_{it} and F_{it} are respectively the retail and farm-gate prices for milk type i in month t in an MSA; u_{it} is the error correction term; τ_i^1 and τ_i^2 are the breakpoint locations; I_A again denotes the indicator function such that $I_A = 1$ if A is true or $= 0$ otherwise. Equation (30) nests the case of no structural break (when $\tau_i^1 = \tau_i^2 = T$) and the case of one structural break (when $\tau_i^2 = T$). The values of τ's are unknown and must be estimated.

To test if R_{it} and $F_{i,t}$ are threshold cointegrated, I follow a test procedure proposed by Enders and Siklos (2001). The threshold specification of the error-term autoregressive model is

$$\Delta u_{it} = \rho_i^L u_{i,t-1}^L + \rho_i^M u_{i,t-1}^M + \rho_i^U u_{i,t-1}^U + \sum_{j=1}^{k_i} \zeta_i^j \Delta u_{i,t-j} + \varepsilon_{it} \qquad (31)$$

where

$$u_{it}^L = u_{it} \cdot I_{u_{it} \le \gamma_i^L}$$
$$u_{it}^M = u_{it} \cdot I_{\gamma_i^L < u_{it} \le \gamma_i^U}$$
$$u_{it}^U = u_{it} \cdot I_{u_{it} > \gamma_i^U}$$

$u_{i,t-1}^M$ vanishes when there is only one threshold ($\gamma_i^L = \gamma_i^U$). This is the case Enders and Siklos (2001) examined. To test for cointegration with two thresholds, Loy, et al. (2015) exploit a sufficient condition for unit-root threshold autoregressive series found in Chan, et al. (1985). Two tests proposed by Enders and Siklos (2001) can be used. First, explosive behaviors of the outer regimes need to be ruled out by a "$tMax$" test. Then a F-test called ϕ-test on unit root can be carried out. Unit root is rejected when either test rejects their null hypotheses. The test statistic for the $tMax$ test is the maximum t-value ($tMax$) between ρ_i^L and ρ_i^{U}. The test statistic for the ϕ-test is the F-statistic for $\rho_i^L = \rho_i^M = \rho_i^U = 0$. The $tMax$ test tests if the error correction process converges. For a threhold AR(1) process, as long as outer regimes are well-behaved, the entire process is ergodic (Chan, et al., 1985). When $\rho_i^L < 0$ and $\rho_i^U < 0$, equation (31) does not exhibit explosive behavior. Enders and Siklos (2001) found the $tMax$ test powerful enough for checking convergence. The $tMax$ is an important first step because the F-test for $\rho_i^L = \rho_i^M = \rho_i^U = 0$ can be easily rejected if one of the outer regime coeffecient is positive. Since the distributions of these test statistics are unknown in the presence of nuisance parameters τ_i^1, τ_i^2, γ_i^L and γ_i^U, critical values are simulated based on Zivot and Andrews (1992), Gregory and Hansen (1996), Enders and Granger (1998), and Enders and Siklos (2001). These values are reported in Table 37 and Table 38 on page 115.

Threshold estimation is based on Chan (1993). Estimation of the structural break location parameters τ_i^1 and τ_i^2 is analogous to Gregory and Hansen (1996). Hansen and Seo (2002) proposed a threshold estimation method under VECM framework. The threshold optimality condition is the minimized determinant of the correlation matrix of the residuals between VECM equations. This condition accounts for cross correlation among VECM equations. However, Serra and Goodwin (2002) found in Monte Carlo experiments that cross correlation between VECM equations does not increase accuracy of parameter estimates. Hansen and Seo (2002) method also requires a grid search for the cointegration coefficients (μ_i's and δ_i's) together with threshold parameters (γ_i's). Given the complexity of equation (30), I maintain the two-step structure of Engle-Granger cointegration test. The cointegration coefficients in this study are simplified to be OLS estimates contingent upon values of breakpoint parameters τ_i^1 and τ_i^2. Given a pair of breakpoint parameters and the associated error correction terms from equation (30), the optimality condition for thresholds is the minimized sum of squared residuals of equation (31). The breakpoint estimates are such that they produce the lowest $tMax$ statistic after the optimality condition for thresholds is met.

Detailed steps of the estimation process are provided below:

Step 1: Pick a pair of feasible values of breakpoint parameters τ_i^1 and τ_i^2. Let $(\tilde{\tau}_i^1, \tilde{\tau}_i^2)$ be any feasible values for (τ_i^1, τ_i^2). To ensure there are enough observations in each structural break period, a minimum of 10% of all observations are required for each period. This means, for one-break models, $\tilde{\tau}_i^1 \in [0.1T, 0.9T)$ and $\tilde{\tau}_i^2 = T$; for two-break models, $\tilde{\tau}_i^1 \in [0.1T, 0.8T)$ and $\tilde{\tau}_i^2 \in [\tilde{\tau}_i^1 + 0.1T, 0.9T)$. Estimate equation (30) based on the assumed pair $(\tilde{\tau}_i^1, \tilde{\tau}_i^2)$. Collect residuals $\{\tilde{u}_{it}\}$ from equation (30) after excluding the residual in the last period $\tilde{u}_{iT}$.

Step 2: Sort $\{\tilde{u}_{it}\}$ ascendingly. Let $\{\tilde{u}_{it}^j\}$ be the resulting ordered sequence where $j \in [1, T-1]$. A minimum of 15% of all observations are assumed in each regime. The pair of thresholds $(\tilde{\gamma}_i^L, \tilde{\gamma}_i^U)$ that minimizes the sum of squared residuals is the appropriate estimator for (γ_i^L, γ_i^U) under the structural breakpoints $(\tilde{\tau}_i^1, \tilde{\tau}_i^2)$ assumed in step 1. The feasible values of $(\tilde{\gamma}_i^L, \tilde{\gamma}_i^U)$ are as the following. For one-threshold models, $\tilde{\gamma}_i^L \in \{\tilde{u}_{it}^j : j \in [0.15(T-1), 0.85(T-1))\}$ and $\tilde{\gamma}_i^U = \tilde{\gamma}_i^L$. For two-thresold models, $\tilde{\gamma}_i^L \in \{\tilde{u}_{it}^j : j \in [0.15(T-1), 0.70(T-1))\}$ and $\tilde{\gamma}_i^U \in \{\tilde{u}_{it}^j : j \in [j^1 + 0.15(T-1), 0.85(T-1))\}$ where j^1 is such that $\tilde{u}_{\mathrm{it}}^{j^1} = \tilde{\gamma}_i^L$.

Step 3: Let $(\tilde{\gamma}_i^L, \tilde{\gamma}_i^U)$ be the threshold estimators under $(\tilde{\tau}_i^1, \tilde{\tau}_i^2)$. Calculate the $tMax$ statistic for equation (31). The pair of breakpoints $(\hat{\tau}_i^1, \hat{\tau}_i^2)$ that minimizes $tMax$ among all $(\tilde{\tau}_i^1, \tilde{\tau}_i^2)$ is the final estimator for (τ_i^1, τ_i^2) in equation (30). The corresponding threshold estimators $\left(\hat{\gamma}_i^L, \hat{\gamma}_i^U\right) \coloneqq (\tilde{\gamma}_i^L, \tilde{\gamma}_i^U)$ are the final estimators for equation (31).

The above steps are done for zero to two breakpoints in equation (30). For each number of breakpoints, both one-threshold and two-threshold cases are considered. The error correction values $\{\hat{u}_{i,t}^L\}$ and $\{\hat{u}_{i,t}^U\}$ for a product type i are chosen if unit root is rejected under a set of the numbers of breakpoints and thresholds.

Table 11 below reports threshold cointegration results for all 15 MSAs with TSP excluded. The TSP-included results are in Table 36 on page 113. A more detailed version of these results can also be found in Table 40 and Table 41. Table 11 shows high degree of non-linear cointegration relationship between farm gate milk price and retail milk price. As the number of breakpoints increases together with the number of thresholds, 97% of all price pairs exhibit cointegration relationship in the TSP-excluded dataset. In TSP included case, the overall number of cointegrated pairs is close and only increased to 98%. However, Houston and San Francisco have the most non-cointegrated pairs in the TSP-excluded dataset. When TSP are included, numbers of cointegrated pairs in these two locations are increased. However, Houston remains the least cointegrated MSA in both datasets.

Table 11 Number of linear or nonlinear cointegrated price pairs in each MSA (TSP excluded)

		Number of Breaks			Number of Thresholds			
MSA	Series	0	1	2	0	1	2	Total
New York	28	46%	79%	93%	61%	96%	96%	100%
Log Angeles	28	57%	82%	96%	61%	96%	96%	100%
Chicago	25	64%	88%	96%	48%	96%	96%	100%
Dallas	26	46%	77%	92%	42%	88%	92%	92%
Houston	25	52%	64%	76%	48%	84%	88%	88%
Philadelphia	27	41%	74%	96%	15%	96%	93%	96%
Miami	22	36%	64%	95%	50%	91%	100%	100%
Atlanta	26	50%	77%	92%	54%	96%	92%	96%
Boston	26	58%	88%	100%	62%	96%	100%	100%
San Francisco	28	29%	61%	86%	39%	82%	86%	89%
Phoenix	26	81%	81%	92%	54%	100%	100%	100%
Riverside	28	61%	71%	96%	54%	93%	100%	100%
Detroit	23	65%	91%	100%	70%	100%	100%	100%
Seattle	22	73%	68%	91%	36%	86%	100%	100%
Minneapolis-St Paul	27	63%	93%	93%	37%	100%	100%	100%
Total	387	55%	77%	93%	49%	94%	96%	97%

Finally, if a farm-retail price pair is threshold cointegrated with more than 1 number of thresholds, a sequential test developed by Strikholm & Teräsvirta (2006) is performed to determine the optimal number of thresholds. If an error correction process can reject unit root when the number of breakpoints is not unique, the higher number of breakpoints is favored due to the flexibility breakpoints introduce.

3.4.4 Panel Estimation and Testing

To consistently estimate panel time series, Pesaran (2006) developed a Common Correlated Effects Mean Group (CCEMG) estimator that allows for heterogenous slope coefficients and are consistent when N and T jointly approach infinity. It also assumes cross-sectional dependence through the introduction of unobserved common factors in data generating processes. Pesaran (2006) argue that OLS estimators are consistent estimators with the inclusion of cross-sectional averages of the repressors. Chudik and Pesaran (2015) extend the CCEMG estimator to panel autoregressive distributed lag models like the one specified in equation (24). The consistency of Chudik and Pesaran (2015) estimator is obtained when sufficient number of lagged terms are included.

Equation (24) can be consistently estimated by the following regression model

$$
\begin{aligned}
\Delta R_{it} &= \theta_i^L \hat{u}_{i,t-1}^L + \theta_i^U \hat{u}_{i,t-1}^U + v_{it} \\
&\quad + \kappa^L \hat{u}_{t-1}^L + \kappa^U \hat{u}_{t-1}^U + \sum_{j=1}^{p_i} \kappa_{i,j}^R \Delta \bar{R}_{t-j} \\
&\quad + \alpha_i^{10} + \sum_{j=1}^{p_i} \alpha_i^{1j} \Delta R_{i,t-j} + \sum_{j=0}^{q_i} \beta_i^{1j} \Delta F_{i,t-j} \\
&\qquad + I_{t>\tau_i^1}\left(\alpha_i^{20} + \sum_{j=1}^{p_i} \alpha_i^{2j} \Delta R_{i,t-j} + \sum_{j=0}^{q_i} \beta_i^{2j} \Delta F_{i,t-j}\right) \\
&\qquad + I_{t>\tau_i^2}\left(\alpha_i^{30} + \sum_{j=1}^{p_i} \alpha_i^{3j} \Delta R_{i,t-j} + \sum_{j=0}^{q_i} \beta_i^{3j} \Delta F_{i,t-j}\right)
\end{aligned}
\tag{32}
$$

where $\hat{u}_{i,t}^L$ and $\hat{u}_{i,t}^U$ are estimated threshold error correction terms from equation (30), v_{it} is the error term. Terms in the second line of equation (31) are required terms to consistently estimate CCEMG estimator. Particularly, $\hat{u}_t^L = \frac{1}{N}\sum_{i=1}^N \hat{u}_{i,t}^L$, $\hat{u}_t^U = \frac{1}{n}\sum_{i=1}^N \hat{u}_{i,t}^U$; $\Delta \bar{R}_t = \frac{1}{N}\sum_{i=1}^N \Delta R_{it}$. The remaining terms in equation (31) control for autocorrelation in the presence of breakpoints from the first-stage cointegration estimation. τ_i^1 is the first breakpoint for product i. τ_i^2 is the second. Note that there is no cross-sectional average term of the differenced Class I price in equation (31). This is because within each region, the farm price is the same for all price pairs in the panel. Adding cross-sectional average is equivalent to adding the $\Delta F_{i,t}$ term twice. Equation (31) is estimated separately for each i. The lag length p_i and q_i are determined by Bayesian Information Criterion (BIC).

Note that κ^L and κ^U are not CCEMG estimators for θ_i^L and θ_i^U. Their sole purpose in the equation is to control for cross sectional correlation. The CCEMG estimators of interest are $\hat{\theta}^L = \frac{1}{N}\sum_{i=1}^{N}\hat{\theta}_i^L$ and $\hat{\theta}^U = \frac{1}{N}\sum_{i=1}^{N}\hat{\theta}_i^U$ where $\hat{\theta}_i^L$ and $\hat{\theta}_i^U$ are OLS estimators of θ_i^L and θ_i^U. The null hypothesis of the panel symmetry test specified in equation (26) is equivalent to $\hat{\theta}^L = \hat{\theta}^U$. This test can be further transformed into a significance test. Equation (32) is thus reformulated as below:

$$\begin{aligned} \Delta R_{it} = {} & \theta_i^{LU}\hat{u}_{i,t-1}^{LU} + \theta_i^U\hat{u}_{i,t-1}^U + v_{it} \\ & + \kappa^L\hat{u}_{t-1}^L + \kappa^U\hat{u}_{t-1}^U + \sum_{j=1}^{p_i}\kappa_{i,j}^R\Delta\bar{R}_{t-j} \\ & + \cdots \end{aligned} \tag{33}$$

where $\hat{u}_{i,t}^{LU} = \hat{u}_{i,t}^L + \hat{u}_{i,t}^U$. The terms represented by "..." in equation (33) are the ones from the third line onwards in equation (32). Product type specific asymmetry test specified in equation (25) can be easily carried out through a t-test on $\theta_i^U = 0$. Panel asymmetry from equation (26) is tested through the CCEMG estimator $\bar{\theta}^U = \frac{1}{N}\sum_{i=1}^{N}\tilde{\theta}_i^U$ with $\tilde{\theta}_i^U$ being OLS estimator for θ_i^U in equation (33). To test $\bar{\theta}^U = 0$, let z_U be the test statistic defined as

$$z_U = \bar{\theta}^U\sqrt{\frac{N(N-1)}{\sum_{i=1}^{N}\left(\hat{\theta}_i^U - \bar{\theta}^U\right)^2}}$$

Chudik and Pesaran (2015) proved that $z_U \sim \mathcal{N}(0,1)$. Test results are discussed in the next section.

3.5 Results and Discussion

Results for symmetric price transmission tests specified in equations (25) and (26) with TSP excluded are summarized in Table 12 below. The second and third columns in Table 12 show CCEMG estimates for the lower and upper regime error correction terms. The fourth column displays the number of series within each MSA that reject symmetry. The last column reports CCEMG estimate of $\bar{\theta}^U$. A rejection of the panel symmetry test is equivalent to a rejection of $\bar{\theta}^U = 0$.

The second and third columns of Table 12 show that at least one of the two CCEMG estimates of the error correction regimes is significant at 10% level for all but one MSA. It suggests that there is error correction effect in these regions. Houston however does not exhibit any error correction effect. This is not surprising given that Houston has least amount of price pairs that are cointegrated (see Table 10 and Table 11). Just because the CCEMG regime estimates are significant does not guarantee there is threshold error correction effect.

In general, the number of series within each MSA that display threshold effect serves as an indicator to whether the panel itself may contain threshold effect. The fourth column of Table 12 shows that the region with both significant regime CCEMG estimators usually has a high rejection rate in individual symmetry tests. For example, only 36% of the price pairs in Seattle suggest the existence of threshold effect. Although Seattle's upper regime CCEMG estimate is significant, the lower regime panel estimator is not. Similar pattern can be observed for New York, Los Angeles and Houston.

Interestingly, these four regions also fail to reject the panel symmetry test. The last column in Table 12 suggests that 5 of the 15 regions studied here may not feature asymmetric transmission at all. Though the number of series in Phoenix that rejects individual symmetry test is relatively high, the insignificant upper regime CCEMG estimate may suggests that the error correction effect, however present, does not show strong signs of panel threshold effect on price transmission. Similar argument can be made for New York, Los Angeles and Seattle.

Table 12 Symmetric transmission test results with TSP excluded

Region	CCEMG Lower Regime ($\hat{\theta}^L$)	CCEMG Upper Regime ($\hat{\theta}^U$)	% of Series that Reject Individual Symmetry Test Null: Eq (11)	Panel Symmetry Test ($\bar{\theta}^U$) Null: Eq (12)
New York	-0.272 *** (0.051)	-0.081 (0.102)	46%	-0.191 (0.124)
Log Angeles	-0.517 ** (0.203)	-0.064 (0.223)	68%	-0.453 (0.590)
Chicago	-0.582 *** (0.183)	-0.395 * (0.239)	88%	-0.187 * (0.100)
Dallas	-0.530 * (0.276)	-0.074 * (0.042)	81%	0.456 ** (0.229)
Houston	-0.079 (0.275)	-0.083 (0.245)	68%	0.004 (0.015)
Philadelphia	-0.620 *** (0.189)	-0.223 *** (0.067)	70%	-0.037 *** (0.014)
Miami	-1.754 *** (0.488)	-0.065 * (0.037)	77%	0.622 ** (0.277)
Atlanta	-0.501 * (0.268)	-0.268 ** (0.121)	92%	0.233 * (0.127)
Boston	-0.673 *** (0.248)	-0.221 * (0.126)	77%	0.674 ** (0.301)
San Francisco	-0.442 *** (0.152)	-0.274 ** (0.120)	82%	-0.168 * (0.089)
Phoenix	-0.718 *** (0.212)	-0.347 (0.323)	88%	-0.371 (0.563)
Riverside	-0.394 * (0.240)	-0.115 * (0.062)	96%	0.280 * (0.146)
Detroit	0.048 * (0.027)	-1.032 * (0.565)	87%	1.080 ** (0.532)
Seattle	-0.523 (3.060)	-0.190 ** (0.086)	36%	-0.333 (0.365)
Minneapolis-St Paul	-0.409 *** (0.148)	-0.196 * (0.108)	85%	-0.213 ** (0.102)

Standard errors are shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

In terms of the speed of asymmetric transmission itself, results from Table 12 are consistent with asymmetry literature. The CCEMG lower regime estimate is larger than the upper regime estimate in absolute value in all but one region where asymmetry is significant. A direct translation of this observation is that adjustment to negative retail margin shocks is faster than reaction to positive margin shocks. This means retail price reacts faster to farm-gate price increases than to decreases.

Symmetry test results for the TSP-included case is presented in Table 39 on page 116. The narrative presented so far in this section still holds for the TSP-included case. The number of series that reject the individual symmetry test is still a good indicator of the panel test result. In addition, the majority of the regions show significant error correction effect. Four of them, however, do not exhibit strong threshold effect. With this dataset, positive asymmetry is still the kind that shows up among regions tested with asymmetric price transmission. The speed itself appears to be sensitive to the presence of TSP. CCEMG coefficients do not seem to stay in a narrow range between Table 12 and Table 39. Finally, it is worth noting, besides the fact that one more region is able to reject panel symmetry compared to the TSP-excluded case, the percentage of individual series that reject symmetry is higher in almost all regions. This result is consistent with Tifaoui and Cramon-Taubadel (2016) in that TSP seems to exaggerate asymmetric price transmission.

3.6 Conclusion

This study investigates asymmetric price transmission between retail milk price and farm-gate price in 15 U.S. Metropolitan Statistical Areas (MSA). Retail prices come from Nielsen Retail Scanner dataset. Farm-gate price is the regional Federal Milk Marketing Order or California Class I milk price. Due to the sheer size of the Nielsen dataset, retail prices are aggregated to product type and MSA level. The determination of a product type is assisted by the Random Forest data mining technique.

A two-threshold three-regime error correction model is first estimated for each retail-farm price pair. Due to the presence of structural break in price series, special tests on unit root and cointegration relation are performed before the estimation of error correction thresholds. Common Correlated Effect Group Mean panel estimates on the error correction terms are then estimated to study the panel effect on each MSA.

Panel data and individual-series level asymmetry tests suggest evidence to support asymmetric price transmission in two third of the regions. There is strong evidence to rule out asymmetry in New York, Los Angeles and Seattle. The entire analysis is performed twice with temporary sales prices excluded in the first time and included in the second time. Results from the two analyses suggest that though temporary sales price does not change the existence of asymmetry, it intensifies the speed of asymmetry. The intensification effect is consistent with Tifaoui & von Cramon-Taubadel (2016) in that temporary sales price exaggerates price asymmetry if not properly identified and excluded from analysis.

This study faces several limitations. First, panel series are given equal weights in CCEMG estimator. Certain product types are sold in higher volumes than others. To better model asymmetry in a geographic region, sales weighted CCEMG may be more appropriate. However, the potential correlation between sales volume and asymmetry may complicate the underlying data generating assumptions in CCEMG framework. Second, this study only utilizes data period from 2006 to 2014. Towards the middle of this period is 2009 when the dairy industry suffered historical margin decline. This rare margin scenario may take error correction terms more than 5 years (2010-2014) to recover to a true long-term equilibrium. If more data were available, structural breaks may not be needed in the first stage Engle-Granger procedure. This can greatly simplify the threshold model estimation which is intrinsically a time-consuming process.

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Appendix A: Data generating process of the futures

Let $f_{t,T}$ denote the realized price at time t of the futures contract that expires at T. Let random variable $F_{t,T}$ represent all possible terminal prices that matures at T with information available at time t. Naturally we let $F_{T,T} = f_{T,T}$ be deterministic.

The change of a commodity futures price conditioned at time t is assumed to follow geometric Brownian motion expressed by the following Wiener process (Black, 1976):

$$d\left(F_{t,T}\right) = \sigma \cdot F_{t,T} \cdot d\mathrm{W}_{\mathrm{T}}$$

where $W_T \sim N(0, \sqrt{T})$ is a Wiener process; σ is the volatility of the futures price. The solution of this stochastic differential equation is

$$\ln(F_{t,T}) = \ln(f_{t,T}) - \frac{1}{2}\sigma^2(\mathrm{T} - t) + \sigma\sqrt{T - t}Z$$[11]

where $Z \sim N(0,1)$ is a standard normal random variable. This says the price at time t of the contract that expires at T follows a log-normal marginal distribution

$$\ln(F_{t,T}) \sim N\left(\ln(f_{t,T}) - \tfrac{1}{2}\sigma^2(\mathrm{T} - t), \sigma^2(T - t)\right).$$

The volatility of a futures contract (σ) is estimated as the average of the implied volatilities from near-the-money call and put options. Bisection root-finding method is used to invert the trinomial tree option pricing model (Boyle, 1986) to get implied volatilities. Since prices of the contracts that expire in more than a year are needed, proper data imputation strategy is required to deal with the illiquidity of the deferred soybean meal and Class IV option contracts. For deferred soybean meal options that were not traded on a particular day, the implied volatility of the contract that expires the closest to the deferred contract is used as the imputed value. This can be justified for deeply deferred contracts are usually

[11] For an exposure to how this stochastic differential equation is solved, see Hull, J.C. 2009. Options, Futures, and other derivatives: Prentice-Hall Inc.(Hull, 2009).

priced based on long-term average. For Class IV options whose price cannot be found on a particular day, if they expire before the first 3 months in the coverage year, implied volatility of the Class III option with the same expiration is used as imputed value; if they expire after the first 3 months in the coverage year, the imputation rule for soybean meal applies.

To put together a multivariate normal distribution with marginal distributions, a correlation matrix $\boldsymbol{R}$ for all possible pairs of random variables has to be determined. Define realized price shock $\eta_\tau^T = f_{T,T} - f_{t,T}$. Let $\{\hat{T}_i\}$ be a sequence of months in which Class III or Class IV contracts expire. For grain futures, $f_{t,T}$ and $f_{T,T}$ are weighted prices following Table 3. Let $\{\tau_j\}$ be a sequence of 96 τ's. These 96 τ's can be further divided into 4 groups with 24 τ's in each group. These four groups represent four futures commodities: Class III milk, Class IV milk, corn and soybean meals. Within each group, τ sequentially ranges from one month to 24 months. The (j,k) element in the correlation matrix equals the correlation between sequence $\left\{\eta_{\tau_j}^{\hat{T}_i}\right\}$ and $\left\{\eta_{\tau_k}^{\hat{T}_i}\right\}$. This correlation is regarded as the correlation between $\left(F_{T_1-\tau_j,T_1} - E_{T_1-\tau_j}\left[F_{T_1,T_1}\right]\right)$ and $\left(F_{T_2-\tau_k,T_2} - E_{T_2-\tau_k}\left[F_{T_2,T_2}\right]\right)$[12] for any contract expiration months T_1 and T_2. Since expectations are deterministic, it can be interpreted as the correlation between random variables $F_{T_1-\tau_j,T_1}$ and $F_{T_2-\tau_k,T_2}$. In practice, the actual correlation matrix $\boldsymbol{R}$ is determined by removing the columns and rows from the 96x96 matrix and only leaving the ones that are relevant to a particular simulation.

Because Class IV futures market was very illiquid before 2007, not all 24 contracts of Class IV futures are traded on a particular day. Contracts that expire in 1 to 4 months are more frequently traded than those deeply deferred contracts. As a matter of fact, 61 out of 127 months sampled to construct the correlation matrix contain at least one missing price for Class IV. A simple solution of excluding data before 2007 causes the correlation coefficients between any two of the rest three commodities unrealistically high due to the 2008 financial crisis and its ripple effect over a few years after. Omitting only Class IV

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[12] If we believe futures price is a Martingale process, $E_t\left[F_{t,T}\right] = f_{t,T}$.

data before 2007 while keeping the rest of the commodities over a longer period renders the correlation matrix not positive definite[13]. In a belief that deferred contracts are priced based on long term trend, missing prices on the same day are linearly extrapolated through an OLS regression model on the available data of the term structure[14]. The extrapolation method does not apply to observations that only contain no more than 4 available prices because of the information scarcity of the term structure those observations provide. This leads to the exclusion of 10 observations from the dataset that generates the correlation matrix.

The Spearman's rho is defined as the Pearson correlation coefficient of the ranked variables. For a sample set $\mathbf{H}$, let h_t^i denotes the tth observation of the ith variable. The ranked value of the sample observation h_t^i is defined as

$$r_t^i = \sum_{s \in \mathbf{H}^{\mathrm{i}}} \mathbf{1}_{h_t^i \leq s}$$

where $\mathbf{H}^{\mathrm{i}}$ is the subset of $\mathbf{H}$ with all sample values of the ith variable in it; $\mathbf{1}_A$ is the indicator function that takes the value of 1 if condition A is satisfied or takes 0 otherwise. Since the Spearman's rho only depends on the ordinal order of the observations in a sample set, any monotonically increasing transformation preserves Spearman's rho. This interesting property of Spearman's rho is crucial to preserve dependence structure among all contracts.

Finally, the data generating process can be described as the following (Press, et al., 2007):

Let $\boldsymbol{X} = (X_1, \ldots, X_i, \ldots, X_M)'$ be a vector of standard-normally distributed random variables. Use Cholesky decomposition to factor Spearman's rho correlation matrix $\boldsymbol{R}$ into the lower triangular matrix $\boldsymbol{L}$ post multiplied by its transpose $\boldsymbol{L}'$:

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[13] The data generating process performs Cholesky decomposition of the correlation matrix. The Cholesky decomposition requires the correlation matrix to be positive definite.
[14] A term structure of a commodity is the prices of a continuous range of contract months observed on a same day. The range usually goes from the first contract that expires after the observe day to as far as the research needs or the market trades.

$$\boldsymbol{R} = \boldsymbol{L} \times \boldsymbol{L}'.$$

Then $\boldsymbol{Z} = (Z_1, \dots, Z_i, \dots, Z_M)' = \boldsymbol{L}\boldsymbol{X} \sim N(\boldsymbol{0}, \boldsymbol{R})$ follows multivariate normal distribution with mean zero and variance-covariance matrix $\boldsymbol{R}$. Thus the terminal prices of Class III milk, Class IV milk, corn and soybean meal follow multivariate log-normal distribution $\ln N\,(\boldsymbol{\mu}, \boldsymbol{\Sigma}\boldsymbol{R}\boldsymbol{\Sigma}')$:

$$\boldsymbol{Y} = \boldsymbol{\Sigma}\boldsymbol{L}\boldsymbol{X} + \boldsymbol{\mu}$$

where $\boldsymbol{Y} = \left(ln\left(F_{t,T_1}\right), \dots, ln\left(F_{t,T_i}\right), \dots, ln\left(F_{t,T_M}\right)\right)'$ is an $M \times 1$ column vector of log-prices; $\boldsymbol{\Sigma}$ is a diagonal matrix with the ith diagonal entry equal to the time scaled implied volatility $\sigma_i\sqrt{T_i - t}$ for the ith contract; and $\boldsymbol{\mu}$ is a column vector of means with $\left(\ln\left(f_{t,T_i}\right) - \frac{1}{2}\sigma^2(T_i - t)\right)$ as the ith element.

It is worth noting that the correlation coefficient matrix $corr[\boldsymbol{Y}] = \boldsymbol{R}$, because any (l, k) entry in the variance-covariance matrix $\boldsymbol{\Sigma}\boldsymbol{R}\boldsymbol{\Sigma}'$ is equal to the product of the standard deviation of each variable multiplied by the (l, k) entry of the $\boldsymbol{R}$ matrix. Furthermore let $\boldsymbol{F}_{t,\boldsymbol{T}} = \left(F_{t,T_1}, \dots, F_{t,T_i}, \dots F_{t,T_M}\right)'$ be a column vector of prices at time t obtained by taking the exponential function on $\boldsymbol{Y}$ element by element. Because the exponential function is monotonically increasing, $corr\left[\boldsymbol{F}_{t,\boldsymbol{T}}\right] = \boldsymbol{R}$. Thus the dependence structure is preserved.

Appendix B: Additional tables and figures

Table 13 Monthly seasonality production weight

Month	Upper Midwest	Lower Midwest
January	8.4%	8.3%
February	7.7%	7.6%
March	8.5%	8.5%
April	8.4%	8.3%
May	8.7%	8.7%
June	8.4%	8.4%
July	8.5%	8.5%
August	8.5%	8.5%
September	8.1%	8.1%
October	8.3%	8.4%
November	8.0%	8.2%
December	8.4%	8.5%

Table 14 Regional mailbox price models

	Upper Midwest Mailbox Milk Price	Lower Midwest Mailbox Milk Price
Intercept	1.4835^{***} (0.2068)	1.075^{***} (0.3087)
Announced Class III	0.6905^{***} (0.0306)	0.5842^{***} (0.0457)
Announced Class IV	0.3153^{***} (0.0294)	0.4284^{***} (0.0439)
Number of observations	167	167

R^2	0.9722	0.9409

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 15 National basis models

	All milk $price_t$	NASS $Corn_t$	NASS Soybean $meal_t$	NASS Hay_t
Intercept	1.8548***	0.0490	-3.6946	4.3358***
	(0.0925)	(0.0622)	(3.4031)	(1.6553)
Class III_t	0.4235***			
	(0.0147)			
Class IV_t	0.2723***			
	(0.0126)			
Max(Class III_{t-1}, Class IV_{t-1})	0.2889***			
	(0.0169)			
CME $Corn_t$		0.9250***		3.5193***
		(0.0120)		(0.5409)
CME Soybean $Meal_t$			1.0203***	-0.0184**
			(0.0102)	(0.0081)
Nass Hay_{t-1}				0.8935***
				(0.0213)
1st Quarter Dummy	-0.0405	0.0200	1.2473	3.1078***
	(0.0527)	(0.0619)	(2.9443)	(1.1360)
2nd Quarter Dummy	-0.4459***	0.0442	-2.3605	2.8151**
	(0.0535)	(0.0623)	(2.9626)	(1.1277)
3rd Quarter Dummy	-0.4815***	0.0191	1.7367	1.4895
	(0.0530)	(0.0622)	(2.9676)	(1.1250)
Number of observations	169	170	170	169
R^2	0.9950	0.9731	0.9840	0.9852

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 16 Regional basis models

	Upper Midwest Mailbox	Lower Midwest Mailbox	Upper Midwest NASS Corn	Lower Midwest NASS Corn	Upper Midwest NASS Hay	Lower Midwest NASS Hay
Intercept	1.8958*** (0.1856)	1.7506*** (0.2999)	-0.0138 (0.063)	0.066 (0.0604)	5.0392*** (1.4974)	3.0909*** (1.18)
Announced Class III	0.6775*** (0.0248)	0.5575*** (0.0401)				
Announced Class IV	0.3329*** (0.0237)	0.4541*** (0.0383)				
Weighted CME Corn			0.9257*** (0.0122)	0.9427*** (0.0117)	1.6983*** (0.4009)	2.7783*** (0.3552)
Weighted CME Soybean Meal					-0.0014 (0.0089)	-0.0177*** (0.006)
Lag Hay					0.9281*** (0.0228)	0.9368*** (0.0145)
1st Quarter Dummy	-0.1819 (0.1134)	-0.4494** (0.1832)	0.028 (0.061)	-0.0019 (0.0584)	-2.704** (1.1281)	-1.7074* (0.919)
2nd Quarter Dummy	-0.8628*** (0.1124)	-1.3392*** (0.1815)	0.0807 (0.061)	0.0468 (0.0585)	-3.6241*** (1.1352)	-0.719 (0.9308)
3rd Quarter Dummy	-0.8524*** (0.1121)	-0.8022*** (0.1811)	0.0836 (0.061)	0.0085 (0.0585)	-3.6365*** (1.1629)	0.7105 (0.9306)
# of obs	167	167	167	167	167	167
R^2	0.982538433	0.95662701	0.972791699	0.975781861	0.9815	0.9912

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 17 Regional hay models

	Upper Midwest Hay Basis Model	Lower Midwest Hay Basis Model	Upper Midwest Hay Cross-hedge Model	Lower Midwest Hay Cross-hedge Model
Intercept	5.0392*** (1.4974)	3.0909*** (1.18)	29.9032 (0.7696)	31.0558 (0.7566)
Weighted CME Corn	1.6983*** (0.4009)	2.7783*** (0.3552)	5.258 (1.3613)	12.7958 (1.6528)
Weighted CME Soybean Meal	-0.0014 (0.0089)	-0.0177*** (0.006)	0.2285 (0.0225)	0.1611 (0.0274)
Lag Hay	0.9281*** (0.0228)	0.9368*** (0.0145)		
1st Quarter Dummy	-2.704** (1.1281)	-1.7074* (0.919)		
2nd Quarter Dummy	-3.6241*** (1.1352)	-0.719 (0.9308)		
3rd Quarter Dummy	-3.6365*** (1.1629)	0.7105 (0.9306)		
# of obs	167	167	167	167
R^2	0.9815	0.9912	0.7696	0.7566

Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$
Hay basis models convert futures prices to local hay prices for the calculation of feed cost. The cross-hedge models determine the hedging P&L for the hay hedge.

Table 18 Values of key simulation variables

Coverage Year	Sign up	Quote Date	ADPM	4 million Production History[1]			6 million Production History[1]			60 million Production History[1]		
				CL[2]	Premium	Indemnity	CL[2]	Premium	Indemnity	CL[2]	Premium	Indemnity
2008	Oct	10/1/2007	10.30	4.0	0.000	0.0002	4.0	0.000	0.0002	4.0	0.000	0.0002
2008	Jan	1/2/2008	9.69	4.0	0.000	0.0004	4.0	0.000	0.0004	4.0	0.000	0.0004
2009	Oct	10/1/2008	7.71	8.0	0.475	0.8961	8.0	0.704	0.8961	6.0	0.148	0.2096
2009	Apr	4/2/2008	8.84	7.5	0.300	0.5583	6.5	0.142	0.3308	6.0	0.148	0.2507
2009	Jan	1/2/2009	5.62	8.0	0.475	2.3003	8.0	0.704	2.3003	8.0	1.294	2.3003
2010	Oct	10/1/2009	8.60	4.0	0.000	0.0012	4.0	0.000	0.0012	4.0	0.000	0.0012
2010	Jan	12/31/2009	8.56	4.0	0.000	0.0023	4.0	0.000	0.0023	4.0	0.000	0.0023
2010	Apr	4/1/2009	8.94	7.5	0.300	0.4352	6.5	0.142	0.2315	5.0	0.039	0.0817
2011	Jan	12/31/2010	5.88	8.0	0.475	2.0392	8.0	0.704	2.0392	8.0	1.294	2.0392
2011	Apr	4/1/2010	8.57	6.5	0.090	0.1059	4.0	0.000	0.0059	4.0	0.000	0.0059
2011	Oct	9/30/2010	6.72	8.0	0.475	1.3428	8.0	0.704	1.3428	6.5	0.275	0.4996
2012	Apr	4/1/2011	5.81	8.0	0.475	2.2879	8.0	0.704	2.2879	8.0	1.294	2.2879
2012	Oct	9/30/2011	7.61	8.0	0.475	0.9537	8.0	0.704	0.9537	6.5	0.275	0.3568
2012	Jan	1/3/2012	7.31	8.0	0.475	0.9829	8.0	0.704	0.9829	6.0	0.148	0.2201

All numeric values except dates and years are in $/cwt.

See next page for more rows.

Values of key simulation variables continued

Coverage Year	Sign up	Quote Date	ADPM	4 million Production History[1]			6 million Production History[1]			60 million Production History[1]		
				CL[2]	Premium	Indemnity	CL[2]	Premium	Indemnity	CL[2]	Premium	Indemnity
2013	Oct	10/1/2012	6.85	8.0	0.475	1.4191	8.0	0.704	1.4191	6.5	0.275	0.6470
2013	Apr	4/2/2012	6.90	8.0	0.475	1.3855	8.0	0.704	1.3855	6.5	0.275	0.6225
2013	Jan	1/2/2013	7.39	8.0	0.475	0.9603	8.0	0.704	0.9603	4.0	0.000	0.0103
2014	Oct	10/1/2013	9.27	4.0	0.000	0.0003	4.0	0.000	0.0003	4.0	0.000	0.0003
2014	Jan	12/31/2013	11.00	4.0	0.000	0.0000	4.0	0.000	0.0000	4.0	0.000	0.0000
2014	Apr	4/1/2013	7.57	8.0	0.475	0.9035	8.0	0.704	0.9035	6.0	0.148	0.2164

All numeric values except dates and years are in $/cwt.

1: Production history in lbs. 2: CL stands for coverage level.

Table 19 Average simulated net cash sales on $/cwt

Coverage Year	Sign up	Quote Date	Upper Midwest		Lower Midwest	
			Feed Grower	Feed Purchaser	Feed Grower	Feed Purchaser
2008	Oct	10/1/2007	17.82	9.88	17.94	10.24
2008	Jan	1/2/2008	18.44	9.31	18.78	9.86
2009	Oct	10/1/2008	16.97	7.23	17.39	8.05
2009	Apr	4/2/2008	18.84	8.11	19.22	9.02
2009	Jan	1/2/2009	13.77	5.21	14.08	5.75
2010	Oct	10/1/2009	15.41	8.11	15.92	8.70
2010	Jan	12/31/2009	16.45	8.24	16.80	8.72
2010	Apr	4/1/2009	16.76	8.21	17.09	8.91
2011	Jan	12/31/2010	16.52	5.59	16.73	6.16
2011	Apr	4/1/2010	15.73	7.99	16.16	8.65
2011	Oct	9/30/2010	15.67	6.30	15.97	6.90
2012	Apr	4/1/2011	16.61	5.00	17.06	6.02
2012	Oct	9/30/2011	18.18	6.93	18.42	8.01
2012	Jan	1/3/2012	18.46	6.65	18.79	7.97
2013	Oct	10/1/2012	19.50	5.90	19.92	6.95
2013	Apr	4/2/2012	16.97	5.99	17.38	7.08
2013	Jan	1/2/2013	19.54	6.77	19.87	7.59
2014	Oct	10/1/2013	18.48	8.56	18.68	9.09
2014	Jan	12/31/2013	20.11	10.48	20.18	10.73
2014	Apr	4/1/2013	17.59	6.61	18.00	7.49

Net cash sales = Milk revenue – Feed cost. Feed growers assume zero feed cost.

Table 20 Crowding-out effect on upper Midwest feed growers with 4-million-pound production history

Coverage Year	Sign-Up Month	Non-participant	Participant	% change
2008	2007 Oct	0.00%	0.00%	0.00%
2008	2008 Jan	0.00%	0.00%	0.00%
2009	2008 Apr	0.00%	0.00%	0.00%
2009	2008 Oct	0.00%	0.00%	0.00%
2009	2009 Jan	N/A	N/A	
2010	2009 Apr	0.00%	0.00%	0.00%
2010	2009 Oct	15.25%	15.00%	1.64%
2010	2009 Jan	0.00%	0.00%	0.00%
2011	2010 Apr	N/A	N/A	
2011	2010 Oct	N/A	N/A	
2011	2011 Jan	N/A	N/A	
2012	2011 Apr	N/A	N/A	
2012	2011 Oct	N/A	N/A	
2012	2012 Jan	59.58%	0.00%	100.00%
2013	2012 Apr	N/A	N/A	
2013	2012 Oct	66.68%	0.00%	100.00%
2013	2013 Jan	57.35%	0.00%	100.00%
2014	2013 Apr	N/A	N/A	
2014	2013 Oct	57.18%	57.13%	0.10%
2014	2014 Jan	0.00%	0.00%	0.00%

Class IV contracts are not available in April 2007.

Table 21 Crowding-out effect on upper Midwest feed purchasers with 4-million-pound production history

Coverage Year	Sign Up Month	Non-participant	Participant	% change
2008	2007 Oct	0.00%	0.00%	0.00%
2008	2008 Jan	0.00%	0.00%	0.00%
2009	2008 Apr	23.81%	0.00%	100.00%
2009	2008 Oct	44.73%	0.00%	100.00%
2009	2009 Jan	N/A	N/A	
2010	2009 Apr	27.54%	0.00%	100.00%
2010	2009 Oct	0.00%	0.00%	0.00%
2010	2009 Jan	0.00%	0.00%	0.00%
2011	2010 Apr	26.19%	9.80%	62.57%
2011	2010 Oct	N/A	N/A	
2011	2011 Jan	N/A	N/A	
2012	2011 Apr	N/A	N/A	
2012	2011 Oct	71.46%	0.00%	100.00%
2012	2012 Jan	67.03%	0.00%	100.00%
2013	2012 Apr	N/A	N/A	
2013	2012 Oct	N/A	N/A	
2013	2013 Jan	N/A	N/A	
2014	2013 Apr	N/A	N/A	
2014	2013 Oct	0.00%	0.00%	0.00%
2014	2014 Jan	0.00%	0.00%	0.00%

Class IV contracts are not available in April 2007.

Table 22 Crowding-out effect on lower Midwest feed growers with 4-million-pound production history

Coverage Year	Sign-Up Month	Non-participant	Participant	% change
2008	2007 Oct	0.00%	0.00%	0.00%
2008	2008 Jan	0.00%	0.00%	0.00%
2009	2008 Apr	0.00%	0.00%	0.00%
2009	2008 Oct	0.00%	0.00%	0.00%
2009	2009 Jan	N/A	N/A	
2010	2009 Apr	0.00%	0.00%	0.00%
2010	2009 Oct	32.91%	32.72%	0.58%
2010	2009 Jan	0.00%	0.00%	0.00%
2011	2010 Apr	N/A	N/A	
2011	2010 Oct	N/A	N/A	
2011	2011 Jan	N/A	N/A	
2012	2011 Apr	N/A	N/A	
2012	2011 Oct	81.17%	49.17%	39.42%
2012	2012 Jan	45.63%	N/A	
2013	2012 Apr	N/A	N/A	
2013	2012 Oct	95.41%	0.84%	99.12%
2013	2013 Jan	82.99%	18.88%	77.25%
2014	2013 Apr	N/A	N/A	
2014	2013 Oct	67.75%	67.71%	0.05%
2014	2014 Jan	0.00%	0.00%	0.00%

Class IV contracts are not available in April 2007.

Table 23 Crowding-out effect on lower Midwest feed purchasers with 4-million-pound production history

Coverage Year	Sign Up Month	Non-participant	Participant	% change
2008	2007 Oct	0.00%	0.00%	0.00%
2008	2008 Jan	0.00%	0.00%	0.00%
2009	2008 Apr	53.85%	5.47%	89.84%
2009	2008 Oct	81.04%	0.55%	99.32%
2009	2009 Jan	N/A	N/A	
2010	2009 Apr	46.91%	7.93%	83.10%
2010	2009 Oct	10.29%	9.83%	4.47%
2010	2009 Jan	0.00%	0.00%	0.00%
2011	2010 Apr	38.35%	21.82%	43.10%
2011	2010 Oct	N/A	N/A	
2011	2011 Jan	N/A	N/A	
2012	2011 Apr	N/A	N/A	
2012	2011 Oct	66.56%	0.00%	100.00%
2012	2012 Jan	77.16%	0.00%	100.00%
2013	2012 Apr	N/A	N/A	
2013	2012 Oct	N/A	N/A	
2013	2013 Jan	N/A	N/A	
2014	2013 Apr	N/A	N/A	
2014	2013 Oct	20.41%	20.31%	0.47%
2014	2014 Jan	0.00%	0.00%	0.00%

Class IV contracts are not available in April 2007.

Table 24 Crowding-out effect on upper Midwest feed growers with 6-million-pound production history

Coverage Year	Sign-Up Month	Non-participant	Participant	% change
2008	2007 Oct	0.00%	0.00%	0.00%
2008	2008 Jan	0.00%	0.00%	0.00%
2009	2008 Apr	0.00%	0.00%	0.00%
2009	2008 Oct	0.00%	0.00%	0.00%
2009	2009 Jan	N/A	N/A	
2010	2009 Apr	0.00%	0.00%	0.00%
2010	2009 Oct	5.49%	5.20%	5.20%
2010	2009 Jan	0.00%	0.00%	0.00%
2011	2010 Apr	N/A	N/A	
2011	2010 Oct	N/A	N/A	
2011	2011 Jan	N/A	N/A	
2012	2011 Apr	N/A	N/A	
2012	2011 Oct	N/A	N/A	
2012	2012 Jan	46.56%	4.56%	90.20%
2013	2012 Apr	N/A	N/A	
2013	2012 Oct	55.39%	0.00%	100.00%
2013	2013 Jan	41.24%	0.00%	100.00%
2014	2013 Apr	N/A	N/A	
2014	2013 Oct	42.17%	42.08%	0.20%
2014	2014 Jan	0.00%	0.00%	0.00%

Class IV contracts are not available in April 2007.

Table 25 Crowding-out effect on upper Midwest feed purchasers with 6-million-pound production history

Coverage Year	Sign Up Month	Non-participant	Participant	% change
2008	2007 Oct	0.00%	0.00%	0.00%
2008	2008 Jan	0.00%	0.00%	0.00%
2009	2008 Apr	23.81%	0.00%	100.00%
2009	2008 Oct	44.73%	0.00%	100.00%
2009	2009 Jan	N/A	N/A	
2010	2009 Apr	27.54%	2.08%	92.46%
2010	2009 Oct	0.00%	0.00%	0.00%
2010	2009 Jan	0.00%	0.00%	0.00%
2011	2010 Apr	26.19%	24.45%	6.66%
2011	2010 Oct	N/A	N/A	
2011	2011 Jan	N/A	N/A	
2012	2011 Apr	N/A	N/A	
2012	2011 Oct	71.46%	0.44%	99.38%
2012	2012 Jan	67.03%	0.00%	100.00%
2013	2012 Apr	N/A	N/A	
2013	2012 Oct	N/A	N/A	
2013	2013 Jan	N/A	N/A	
2014	2013 Apr	N/A	N/A	
2014	2013 Oct	0.00%	0.00%	0.00%
2014	2014 Jan	0.00%	0.00%	0.00%

Class IV contracts are not available in April 2007.

Table 26 Crowding-out effect on lower Midwest feed growers with 6-million-pound production history

Coverage Year	Sign-Up Month	Non-participant	Participant	% change
2008	2007 Oct	0.00%	0.00%	0.00%
2008	2008 Jan	0.00%	0.00%	0.00%
2009	2008 Apr	0.00%	0.00%	0.00%
2009	2008 Oct	0.00%	0.00%	0.00%
2009	2009 Jan	N/A	N/A	
2010	2009 Apr	0.00%	0.00%	0.00%
2010	2009 Oct	11.65%	11.44%	1.79%
2010	2009 Jan	0.00%	0.00%	0.00%
2011	2010 Apr	N/A	N/A	
2011	2010 Oct	N/A	N/A	
2011	2011 Jan	N/A	N/A	
2012	2011 Apr	N/A	N/A	
2012	2011 Oct	57.61%	34.44%	40.23%
2012	2012 Jan	16.63%	0.00%	100.00%
2013	2012 Apr	N/A	N/A	
2013	2012 Oct	70.39%	0.00%	100.00%
2013	2013 Jan	47.39%	1.96%	95.86%
2014	2013 Apr	N/A	N/A	
2014	2013 Oct	37.53%	37.47%	0.14%
2014	2014 Jan	0.00%	0.00%	0.00%

Class IV contracts are not available in April 2007.

Table 27 Crowding-out effect on lower Midwest feed purchasers with 6-million-pound production history

Coverage Year	Sign Up Month	Non-participant	Participant	% change
2008	2007 Oct	0.00%	0.00%	0.00%
2008	2008 Jan	0.00%	0.00%	0.00%
2009	2008 Apr	53.85%	20.15%	62.58%
2009	2008 Oct	81.04%	15.17%	81.28%
2009	2009 Jan	N/A	N/A	
2010	2009 Apr	46.91%	21.63%	53.89%
2010	2009 Oct	10.29%	9.83%	4.47%
2010	2009 Jan	0.00%	0.00%	0.00%
2011	2010 Apr	38.35%	36.70%	4.32%
2011	2010 Oct	N/A	N/A	
2011	2011 Jan	N/A	N/A	
2012	2011 Apr	N/A	N/A	
2012	2011 Oct	66.56%	0.00%	100.00%
2012	2012 Jan	77.16%	0.00%	100.00%
2013	2012 Apr	N/A	N/A	
2013	2012 Oct	N/A	N/A	
2013	2013 Jan	N/A	N/A	
2014	2013 Apr	N/A	N/A	
2014	2013 Oct	20.41%	20.31%	0.47%
2014	2014 Jan	0.00%	0.00%	0.00%

Class IV contracts are not available in April 2007.

Table 28 Crowding-out effect on upper Midwest feed growers with 60-million-pound production history

Coverage Year	Sign-Up Month	Non-participant	Participant	% change
2008	2007 Oct	0.00%	0.00%	0.00%
2008	2008 Jan	0.00%	0.00%	0.00%
2009	2008 Apr	0.00%	0.00%	0.00%
2009	2008 Oct	0.00%	0.00%	0.00%
2009	2009 Jan	N/A	N/A	
2010	2009 Apr	0.00%	0.00%	0.00%
2010	2009 Oct	0.00%	0.00%	0.00%
2010	2009 Jan	0.00%	0.00%	0.00%
2011	2010 Apr	N/A	N/A	
2011	2010 Oct	N/A	N/A	
2011	2011 Jan	N/A	N/A	
2012	2011 Apr	N/A	N/A	
2012	2011 Oct	77.78%	86.47%	-11.18%
2012	2012 Jan	33.67%	18.85%	44.02%
2013	2012 Apr	N/A	N/A	
2013	2012 Oct	44.09%	0.00%	100.00%
2013	2013 Jan	25.23%	23.07%	8.58%
2014	2013 Apr	N/A	N/A	
2014	2013 Oct	27.17%	27.10%	0.26%
2014	2014 Jan	0.00%	0.00%	0.00%

Class IV contracts are not available in April 2007.

Table 29 Crowding-out effect on upper Midwest feed purchasers with 60-million-pound production history

Coverage Year	Sign Up Month	Non-participant	Participant	% change
2008	2007 Oct	0.00%	0.00%	0.00%
2008	2008 Jan	0.00%	0.00%	0.00%
2009	2008 Apr	23.81%	0.00%	100.00%
2009	2008 Oct	44.73%	19.36%	56.71%
2009	2009 Jan	N/A	N/A	
2010	2009 Apr	27.54%	15.74%	42.84%
2010	2009 Oct	0.00%	0.00%	0.00%
2010	2009 Jan	0.00%	0.00%	0.00%
2011	2010 Apr	26.19%	24.45%	6.66%
2011	2010 Oct	N/A	N/A	
2011	2011 Jan	N/A	N/A	
2012	2011 Apr	N/A	N/A	
2012	2011 Oct	71.46%	40.75%	42.97%
2012	2012 Jan	67.03%	39.52%	41.04%
2013	2012 Apr	N/A	N/A	
2013	2012 Oct	N/A	N/A	
2013	2013 Jan	N/A	N/A	
2014	2013 Apr	N/A	N/A	
2014	2013 Oct	0.00%	0.00%	0.00%
2014	2014 Jan	0.00%	0.00%	0.00%

Class IV contracts are not available in April 2007.

Table 30 Crowding-out effect on lower Midwest feed growers with 60-million-pound production history

Coverage Year	Sign-Up Month	Non-participant	Participant	% change
2008	2007 Oct	0.00%	0.00%	0.00%
2008	2008 Jan	0.00%	0.00%	0.00%
2009	2008 Apr	0.00%	0.00%	0.00%
2009	2008 Oct	0.00%	0.00%	0.00%
2009	2009 Jan	N/A	N/A	
2010	2009 Apr	0.00%	0.00%	0.00%
2010	2009 Oct	11.65%	11.44%	1.79%
2010	2009 Jan	0.00%	0.00%	0.00%
2011	2010 Apr	N/A	N/A	
2011	2010 Oct	N/A	N/A	
2011	2011 Jan	N/A	N/A	
2012	2011 Apr	N/A	N/A	
2012	2011 Oct	57.61%	49.40%	14.25%
2012	2012 Jan	16.63%	0.00%	100.00%
2013	2012 Apr	N/A	N/A	
2013	2012 Oct	70.39%	37.21%	47.14%
2013	2013 Jan	47.39%	45.46%	4.08%
2014	2013 Apr	N/A	N/A	
2014	2013 Oct	37.53%	37.47%	0.14%
2014	2014 Jan	0.00%	0.00%	0.00%

Class IV contracts are not available in April 2007.

Table 31 Crowding-out effect on lower Midwest feed purchasers with 60-million-pound production history

Coverage Year	Sign Up Month	Non-participant	Participant	% change
2008	2007 Oct	0.00%	0.00%	0.00%
2008	2008 Jan	0.00%	0.00%	0.00%
2009	2008 Apr	53.45%	28.21%	47.23%
2009	2008 Oct	80.90%	64.91%	19.76%
2009	2009 Jan	N/A	N/A	
2010	2009 Apr	46.87%	35.38%	24.52%
2010	2009 Oct	10.08%	9.69%	3.88%
2010	2009 Jan	0.00%	0.00%	0.00%
2011	2010 Apr	37.51%	35.83%	4.49%
2011	2010 Oct	N/A	N/A	
2011	2011 Jan	N/A	N/A	
2012	2011 Apr	N/A	N/A	
2012	2011 Oct	66.12%	31.95%	51.67%
2012	2012 Jan	76.45%	53.46%	30.07%
2013	2012 Apr	N/A	N/A	
2013	2012 Oct	N/A	N/A	
2013	2013 Jan	N/A	N/A	
2014	2013 Apr	N/A	N/A	
2014	2013 Oct	19.83%	19.72%	0.56%
2014	2014 Jan	0.00%	0.00%	0.00%

Class IV contracts are not available in April 2007.

Table 32 MPP-DL tier 1 premium rates in $/cwt

Coverage Level ($/cwt)	Payment Cap								
	$1.00/cwt	$1.50/cwt	$2.00/cwt	$2.50/cwt	$3.00/cwt	$3.50/cwt	$4.00/cwt	$4.50/cwt	$5.00/cwt
$4.00	0.009	0.011	0.012	0.013	0.014	0.014	0.014	0.015	0.015
$4.50	0.013	0.017	0.019	0.020	0.021	0.022	0.022	0.023	0.023
$5.00	0.021	0.026	0.030	0.032	0.033	0.034	0.035	0.035	0.036
$5.50	0.049	0.062	0.047	0.050	0.051	0.054	0.054	0.055	0.055
$6.00	0.070	0.090	0.104	0.113	0.119	0.124	0.128	0.130	0.131
$6.50	0.100	0.129	0.149	0.162	0.170	0.178	0.183	0.186	0.188
$7.00	0.140	0.181	0.210	0.230	0.240	0.253	0.260	0.264	0.267
$7.50	0.192	0.251	0.292	0.321	0.334	0.354	0.364	0.370	0.375
$8.00	0.221	0.288	0.398	0.439	0.457	0.488	0.501	0.511	0.517
$8.50	0.292	0.386	0.453	0.499	0.510	0.550	0.563	0.571	0.577
$9.00	0.371	0.497	0.591	0.658	0.673	0.736	0.756	0.769	0.777
$9.50	0.408	0.616	0.743	0.836	0.855	0.950	0.981	1.001	1.014
$10.00	0.486	0.670	0.899	1.025	1.047	1.186	1.233	1.263	1.284
$10.50	0.512	0.789	0.973	1.118	1.241	1.440	1.507	1.553	1.584
$11.00	0.601	0.836	1.032	1.316	1.287	1.703	1.797	1.864	1.910
$11.50	0.689	0.967	1.202	1.398	1.982	1.843	2.095	2.189	2.256
$12.00	0.768	1.091	1.369	1.603	1.434	2.110	2.256	2.515	2.609

Payment Caps higher than $2/00/cwt are not recommended as a result of analyses done in this paper.

Table 33 MPP-DL tier 2 premium rates in $/cwt

Coverage Level ($/cwt)	Payment Cap $1.00/cwt	$1.50/cwt	$2.00/cwt	$2.50/cwt	$3.00/cwt	$3.50/cwt	$4.00/cwt	$4.50/cwt	$5.00/cwt
$4.00	0.016	0.020	0.023	0.024	0.026	0.026	0.027	0.027	0.027
$4.50	0.024	0.030	0.034	0.037	0.039	0.040	0.041	0.041	0.042
$5.00	0.036	0.046	0.052	0.056	0.059	0.061	0.062	0.063	0.063
$5.50	0.076	0.099	0.078	0.084	0.088	0.091	0.093	0.094	0.095
$6.00	0.093	0.120	0.139	0.176	0.187	0.194	0.200	0.204	0.207
$6.50	0.132	0.170	0.197	0.216	0.229	0.238	0.244	0.249	0.252
$7.00	0.183	0.238	0.277	0.303	0.322	0.335	0.344	0.350	0.355
$7.50	0.249	0.326	0.381	0.420	0.447	0.465	0.478	0.487	0.494
$8.00	0.294	0.385	0.514	0.569	0.608	0.635	0.653	0.666	0.675
$8.50	0.384	0.510	0.600	0.664	0.706	0.735	0.753	0.764	0.772
$9.00	0.526	0.710	0.773	0.864	0.928	0.970	0.998	1.017	1.028
$9.50	0.602	0.861	1.044	1.080	1.171	1.234	1.277	1.305	1.323
$10.00	0.686	0.964	1.230	1.414	1.422	1.513	1.576	1.619	1.647
$10.50	0.726	1.076	1.354	1.577	1.668	1.946	1.885	1.948	1.991
$11.00	0.712	1.017	1.445	1.767	1.816	2.228	2.364	2.285	2.348
$11.50	0.777	1.117	1.421	1.691	2.241	2.234	2.664	2.618	2.708
$12.00	0.833	1.207	1.546	1.851	2.120	2.472	2.672	2.934	3.060

Payment Caps higher than $2/00/cwt are not recommended as a result of analyses done in this paper.

Table 34 Summary statistics of product types

Size (oz)	Container Type	Lactose-Free	Fat Content	Average ($/gallon)	Std. Dev ($/gallon)	Max ($/gallon)	Min ($/gallon)
32	Carton	No	Skim	6.77	1.45	13.16	3.96
32	Carton	No	1%	6.23	0.95	7.96	3.95
32	Carton	No	2%	6.53	1.29	11.93	3.99
32	Carton	No	Whole	6.48	1.23	11.73	3.90
32	Carton	Yes	Skim	9.50	1.12	11.96	4.76
32	Carton	Yes	1%	9.91	1.40	14.76	4.32
32	Carton	Yes	2%	9.43	1.03	17.89	5.16
32	Plastic	No	Skim	6.64	1.54	13.32	3.27
32	Plastic	No	1%	6.73	1.51	12.84	3.55
32	Plastic	No	2%	6.74	1.25	9.88	3.32
32	Plastic	No	Whole	6.83	1.12	9.53	3.48
64	Carton	No	Skim	6.32	0.81	8.51	4.38
64	Carton	No	1%	5.94	0.99	8.33	3.66
64	Carton	No	2%	6.35	0.98	8.96	3.89
64	Carton	No	Whole	6.91	0.98	9.16	3.99
64	Carton	Yes	Skim	7.45	0.55	9.04	6.14
64	Carton	Yes	1%	6.94	1.04	10.58	1.79
64	Carton	Yes	2%	7.58	0.49	8.93	6.31
64	Carton	Yes	Whole	7.51	0.56	9.06	6.05
64	Plastic	No	Skim	4.34	0.75	6.44	2.27
64	Plastic	No	1%	5.24	1.13	8.26	2.30
64	Plastic	No	2%	4.57	0.75	6.22	1.93
64	Plastic	No	Whole	4.36	0.70	6.07	1.96
128	Carton	No	1%	5.73	1.22	8.23	3.05
128	Plastic	No	Skim	3.13	0.53	4.75	1.83
128	Plastic	No	1%	3.16	0.56	4.94	1.59
128	Plastic	No	2%	3.16	0.52	4.74	1.91
128	Plastic	No	Whole	3.31	0.51	4.82	2.01
32	Carton	No	Skim	6.77	1.45	13.16	3.96
32	Carton	No	1%	6.23	0.95	7.96	3.95
32	Carton	No	2%	6.53	1.29	11.93	3.99
32	Carton	No	Whole	6.48	1.23	11.73	3.90

Table 35 Description of milk product attributes

Product Attribute	Description
Size	In fluid ounce. Permissible values are 32, 64 and 128.
Container type	Binary; 0 for carton, 1 for plastic
Lactose-free label	Is “lactose-free” label shown on package
Fat content	Permissible values are skim, 1%, 2%, whole
Kosher label	Is the milk marketed kosher
Vitamin A	Is vitamin A marketed on package
Vitamin AP	Is vitamin A Palmitate marketed on package
Vitamin B6	Is vitamin B6 marketed on package
Vitamin B12	Is vitamin B12 marketed on package
Vitamin C	Is vitamin C marketed on package
Vitamin D	Is vitamin D marketed on package
Vitamin D3	Is vitamin D3 marketed on package
Vitamin E	Is vitamin E marketed on package

Table 36 Number of linear and nonlinear cointegrated price pairs in each MSA (TSP included)

		Number of Breaks			Number of Thresholds			
MSA	Series	0	1	2	0	1	2	Total
New York	28	37%	81%	96%	59%	100%	100%	100%
Log Angeles	28	71%	71%	82%	61%	93%	89%	93%
Chicago	25	72%	72%	96%	48%	96%	100%	100%
Dallas	26	40%	76%	96%	44%	96%	96%	96%
Houston	25	58%	67%	83%	58%	88%	88%	92%
Philadelphia	27	63%	78%	93%	7%	96%	93%	96%
Miami	22	55%	82%	100%	55%	95%	95%	100%
Atlanta	26	48%	68%	96%	56%	96%	92%	96%
Boston	26	54%	88%	100%	46%	96%	100%	100%
San Francisco	28	43%	64%	93%	21%	100%	96%	100%
Phoenix	26	92%	92%	100%	54%	100%	96%	100%
Riverside	28	79%	79%	89%	64%	96%	93%	96%
Detroit	23	80%	88%	100%	76%	100%	100%	100%
Seattle	22	71%	67%	86%	43%	95%	90%	95%
Minneapolis-St Paul	27	77%	92%	96%	50%	100%	96%	100%
Total	387	63%	78%	94%	49%	97%	95%	98%

Table 37 Critical values for threshold cointegration $tMax$ test with $T = 100$

No Break 1 Threshold				**No Break 2 Thresholds**			
Lags	90%	95%	99%	Lags	90%	95%	99%
0	-1.61	-1.85	-2.35	0	-2.18	-2.41	-2.87
1	-1.65	-1.90	-2.39	1	-2.24	-2.48	-2.95
4	-1.66	-1.92	-2.44	4	-2.26	-2.52	-2.99
1 Break 1 Threshold				**1 Break 2 Thresholds**			
Lags	90%	95%	99%	Lags	90%	95%	99%
0	-2.26	-2.54	-3.04	0	-2.61	-2.87	-3.31
1	-2.04	-2.33	-2.85	1	-2.29	-2.55	-3.04
4	-2.28	-2.63	-3.22	4	-2.57	-2.86	-3.40
2 Breaks 1 Threshold				**2 Breaks 2 Thresholds**			
Lags	90%	95%	99%	Lags	90%	95%	99%
0	-3.20	-3.48	-3.98	0	-3.38	-3.63	-4.12
1	-3.01	-3.25	-3.76	1	-3.19	-3.43	-3.90
4	-3.56	-3.89	-4.58	4	-3.71	-4.01	-4.59

Critical values for the case of no break and 1 threshold are from Enders and Siklos (2001). Other numbers are from own calculation.

Table 38 Critical values for threshold cointegration ϕ test with $T = 100$

No Break 1 Threshold				**No Break 2 Thresholds**			
Lags	90%	95%	99%	Lags	90%	95%	99%
0	5.95	6.95	9.27	0	5.70	6.59	8.46
1	6.02	7.08	9.51	1	5.77	6.65	8.51
4	6.35	7.41	9.88	4	5.64	6.50	8.48
1 Break 1 Threshold				**1 Break 2 Thresholds**			
Lags	90%	95%	99%	Lags	90%	95%	99%
0	12.87	14.49	18.04	0	9.88	11.19	14.00
1	10.84	12.23	15.52	1	8.32	9.44	11.87
4	10.55	11.91	14.94	4	8.28	9.32	11.58
2 Breaks 1 Threshold				**2 Breaks 2 Thresholds**			
Lags	90%	95%	99%	Lags	90%	95%	99%
0	19.13	21.03	25.06	0	14.12	15.70	18.63
1	15.39	16.87	19.83	1	11.40	12.41	14.68
4	15.84	17.47	20.88	4	11.88	13.05	15.79

Critical values for the case of no break and 1 threshold are from Enders and Siklos (2001). Other numbers are from own calculation.

Table 39 Symmetric transmission test results with TSP included

Region	CCEMG Lower Regime ($\hat{\theta}_t^L$)	CCEMG Upper Regime ($\hat{\theta}_t^U$)	% of Series that Reject Individual Symmetry Test Null: Eq (11)	Panel Symmetry Test ($\bar{\theta}^U$) Null: Eq (12)
New York	-0.720 *** (0.275)	-0.659 (0.646)	59%	-0.061 (0.232)
Log Angeles	-0.632 ** (0.271)	-0.331 *** (0.114)	68%	0.300 (0.424)
Chicago	-0.568 *** (0.168)	-0.266 ** (0.109)	76%	-0.301 ** (0.151)
Dallas	-0.407 *** (0.137)	-0.231 ** (0.110)	84%	-0.176 ** (0.087)
Houston	-0.552 * (0.312)	-0.296 * (0.155)	71%	0.256 * (0.132)
Philadelphia	-0.235 *** (0.084)	-0.191 * (0.103)	93%	0.043 * (0.024)
Miami	-0.460 *** (0.084)	-0.315 * (0.174)	91%	0.145 * (0.076)
Atlanta	-0.633 *** (0.107)	-0.361 ** (0.148)	88%	-0.273 ** (0.124)
Boston	-0.440 * (0.267)	-0.217 (0.352)	73%	-0.223 (0.550)
San Francisco	-0.364 *** (0.124)	-0.134 * (0.071)	93%	0.230 * (0.120)
Phoenix	-1.095 *** (0.298)	-0.161 * (0.088)	88%	-0.934 * (0.518)
Riverside	-0.100 * (0.056)	-0.667 * (0.400)	86%	0.567 ** (0.283)
Detroit	-0.997 *** (0.235)	-0.491 ** (0.193)	76%	-0.506 ** (0.240)
Seattle	-0.530 * (0.293)	-0.250 (0.226)	43%	-0.280 (0.551)
Minneapolis-St Paul	-0.538 ** (0.218)	-0.361 *** (0.090)	96%	0.003 *** (0.001)

Standard errors are shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 40 Detailed number of linear and nonlinear cointegrated price pairs in each MSA with TSP excluded

	No Breakpoint			**1 Breakpoint**			**2 Breakpoints**			
Threshold	**0**	**1**	**2**	**0**	**1**	**2**	**0**	**1**	**2**	**Series**
New York	4%	32%	39%	4%	61%	50%	61%	79%	89%	28
Log Angeles	4%	39%	39%	4%	68%	79%	57%	86%	93%	28
Chicago	16%	64%	52%	0%	88%	76%	40%	92%	96%	25
Dallas	8%	31%	46%	12%	77%	65%	42%	88%	92%	26
Houston	12%	36%	44%	4%	52%	60%	44%	76%	72%	25
Philadelphia	4%	33%	19%	0%	67%	52%	11%	85%	93%	27
Miami	0%	23%	23%	0%	41%	64%	50%	82%	95%	22
Atlanta	12%	46%	46%	4%	46%	65%	46%	92%	92%	26
Boston	15%	42%	38%	4%	69%	81%	54%	92%	96%	26
San Francisco	14%	21%	21%	0%	50%	54%	36%	79%	79%	28
Phoenix	23%	81%	69%	19%	73%	69%	46%	92%	88%	26
Riverside	11%	36%	50%	4%	64%	57%	54%	93%	86%	28
Detroit	17%	52%	61%	22%	83%	91%	61%	100%	100%	23
Seattle	14%	64%	50%	9%	41%	64%	27%	86%	86%	22
Minneapolis-St Paul	0%	37%	30%	7%	89%	81%	37%	85%	93%	27
Total	10%	42%	42%	6%	65%	67%	44%	87%	90%	387

Table 41 Detailed number of linear and nonlinear cointegrated price pairs in each MSA with TSP included

	No Breakpoint			**1 Breakpoint**			**2 Breakpoints**			
Threshold	**0**	**1**	**2**	**0**	**1**	**2**	**0**	**1**	**2**	**Series**
New York	19%	37%	30%	0%	74%	70%	52%	85%	96%	28
Log Angeles	29%	54%	57%	0%	57%	64%	46%	82%	82%	28
Chicago	20%	60%	56%	4%	68%	60%	28%	92%	96%	25
Dallas	12%	36%	32%	0%	72%	64%	32%	96%	96%	26
Houston	25%	50%	46%	4%	58%	54%	42%	79%	75%	25
Philadelphia	4%	59%	52%	0%	48%	70%	4%	89%	81%	27
Miami	0%	45%	32%	5%	68%	77%	55%	95%	95%	22
Atlanta	8%	44%	44%	8%	56%	68%	52%	96%	92%	26
Boston	27%	50%	42%	4%	77%	77%	35%	88%	100%	26
San Francisco	7%	25%	43%	0%	57%	54%	18%	89%	79%	28
Phoenix	15%	85%	88%	15%	88%	73%	42%	100%	92%	26
Riverside	29%	57%	61%	0%	61%	75%	50%	86%	89%	28
Detroit	4%	68%	72%	36%	84%	80%	76%	100%	100%	23
Seattle	33%	62%	67%	24%	52%	48%	24%	81%	76%	22
Minneapolis-St Paul	0%	54%	69%	8%	73%	88%	50%	96%	92%	27
Total	15%	52%	53%	7%	66%	68%	40%	90%	90%	387

Figure 14 Upper Midwest grower with 4 mm PH signing up in Apr, 2008 for 2009 (CL:7.5, CP:90%)

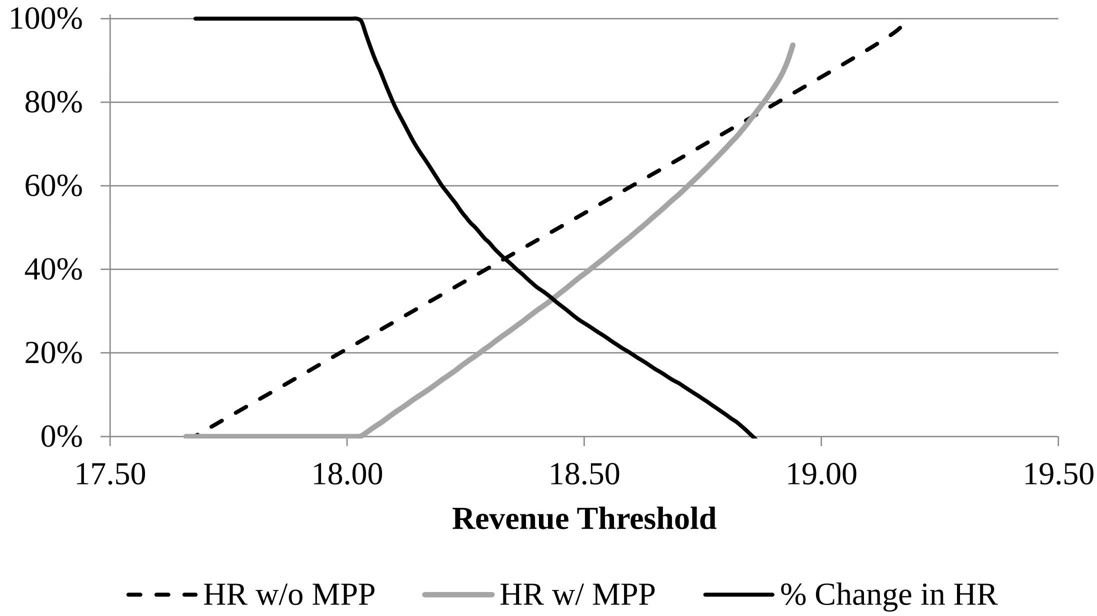

Figure 15 Lower Midwest grower with 4 mm PH signing up in Apr, 2008 for 2009 (CL:7.5 CP:90%)

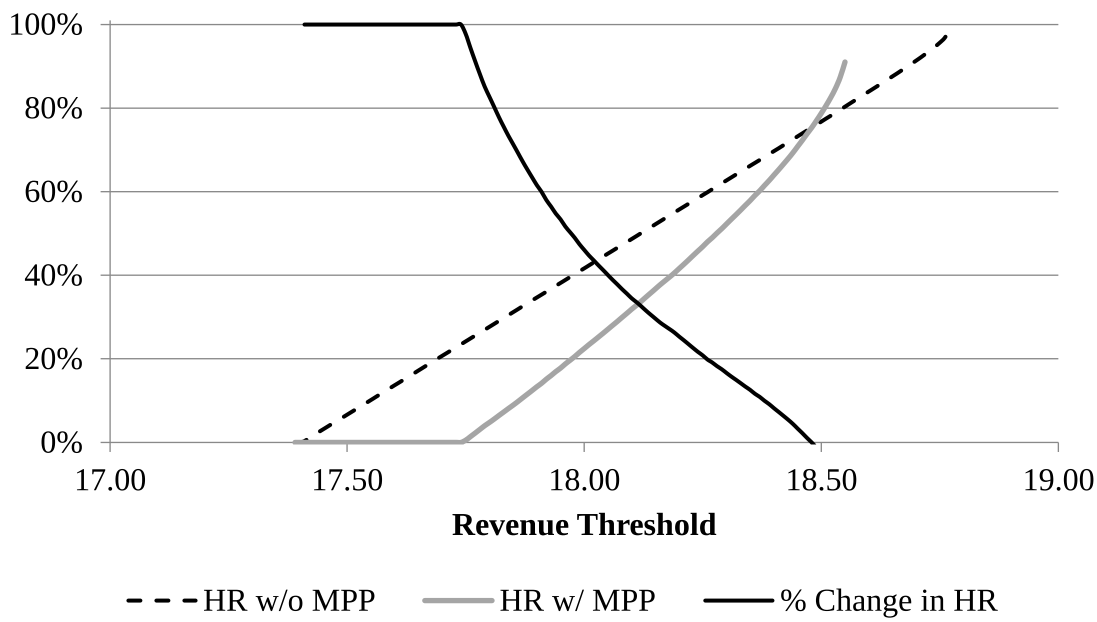

Figure 16 Upper Midwest grower with 4 mm PH signing up in Oct, 2008 for 2009 (CL:8.0 CP:90%)

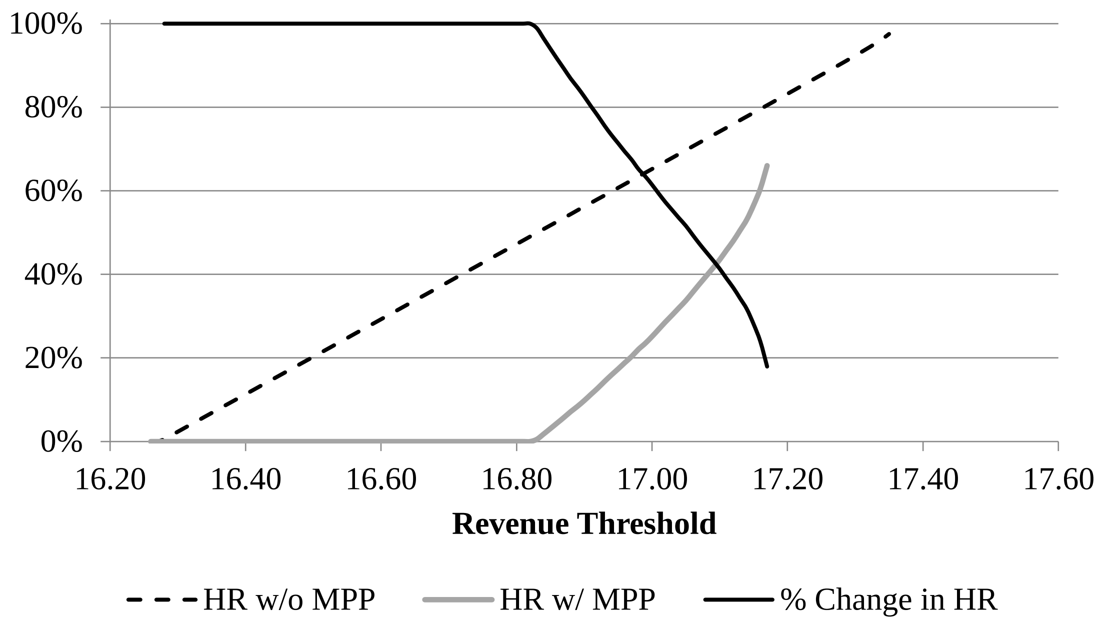

Figure 17 Lower Midwest grower with 4 mm PH signing up in Oct, 2008 for 2009 (CL:8.0 CP:90%)

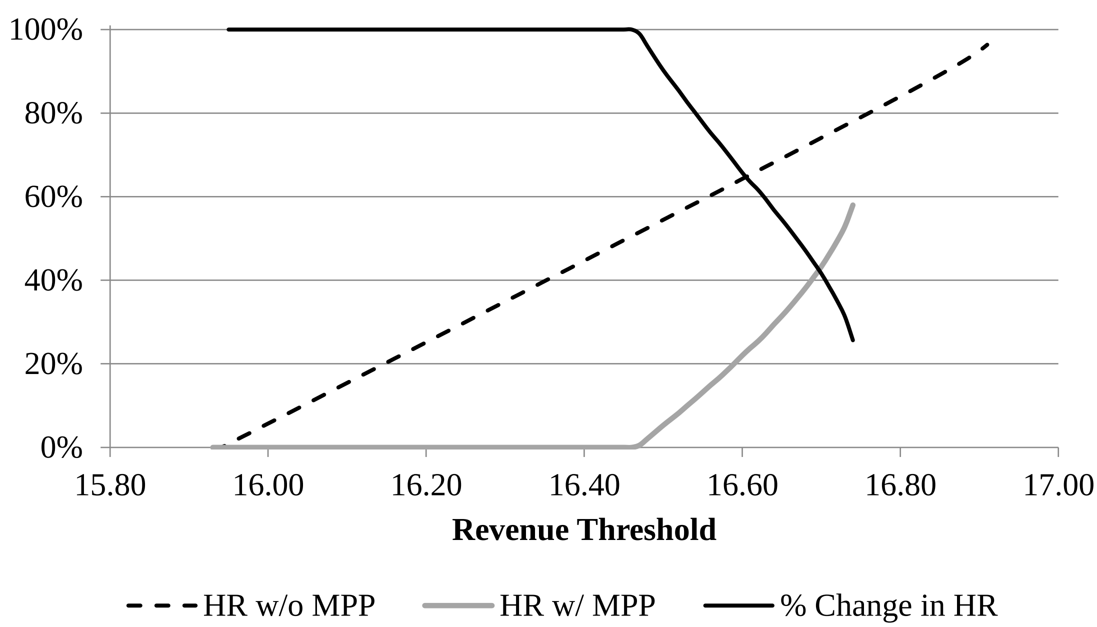

Figure 18 Upper Midwest grower with 4 mm PH signing up in Jan, 2009 for 2009 (CL:8.0 CP:90%)

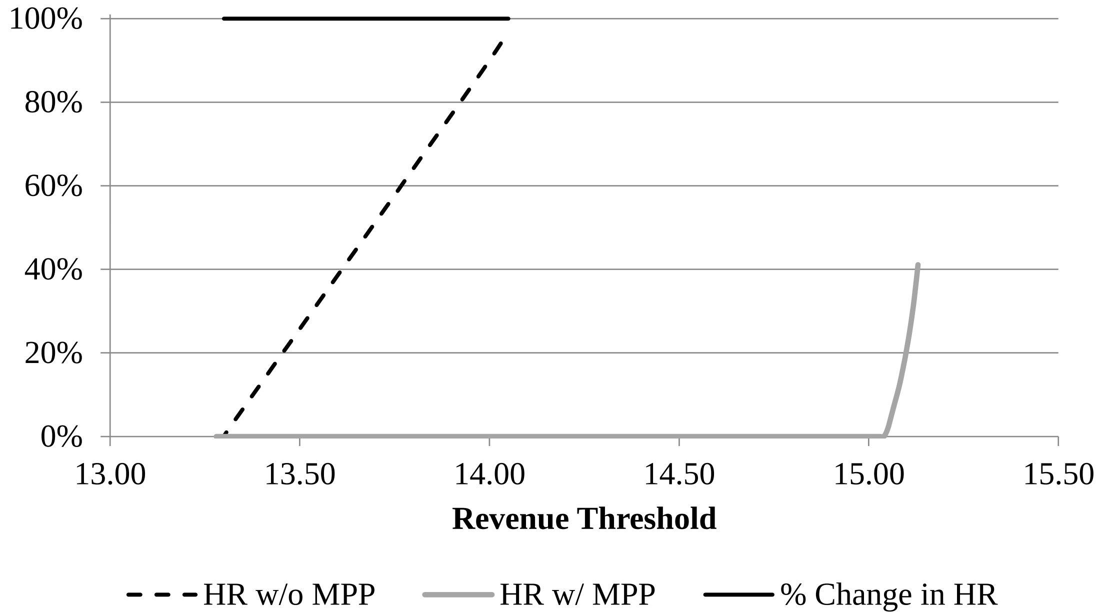

Figure 19 Lower Midwest grower with 4 mm PH signing up in Jan, 2009 for 2009 (CL:8.0 CP:90%)

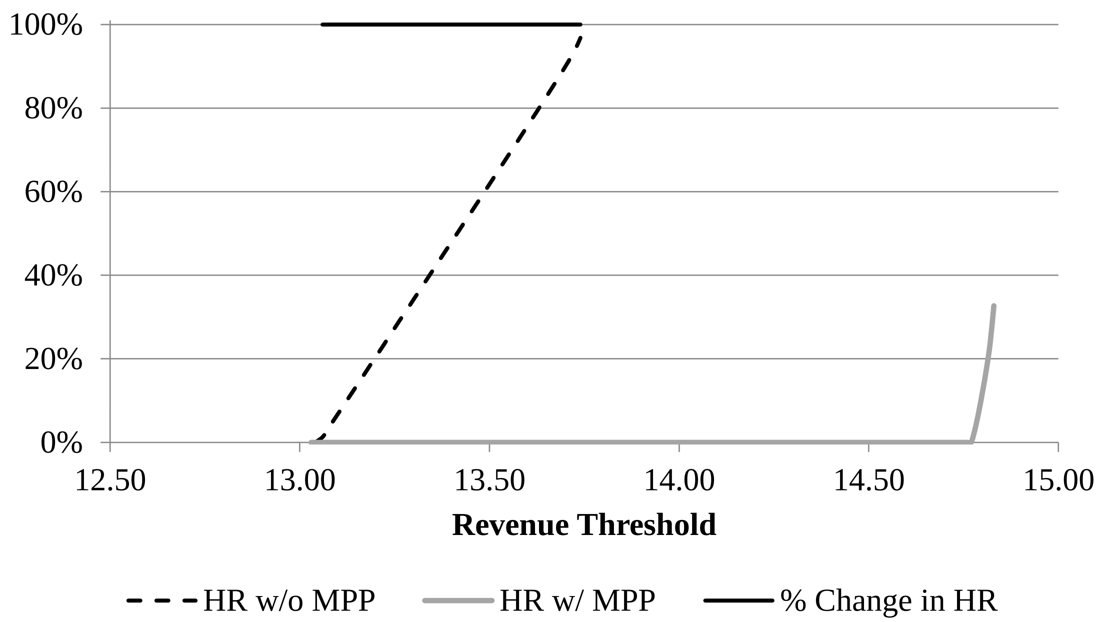

Figure 20 Upper Midwest grower with 4 mm PH signing up in Apr, 2011 for 2012 (CL:8.0 CP:90%)

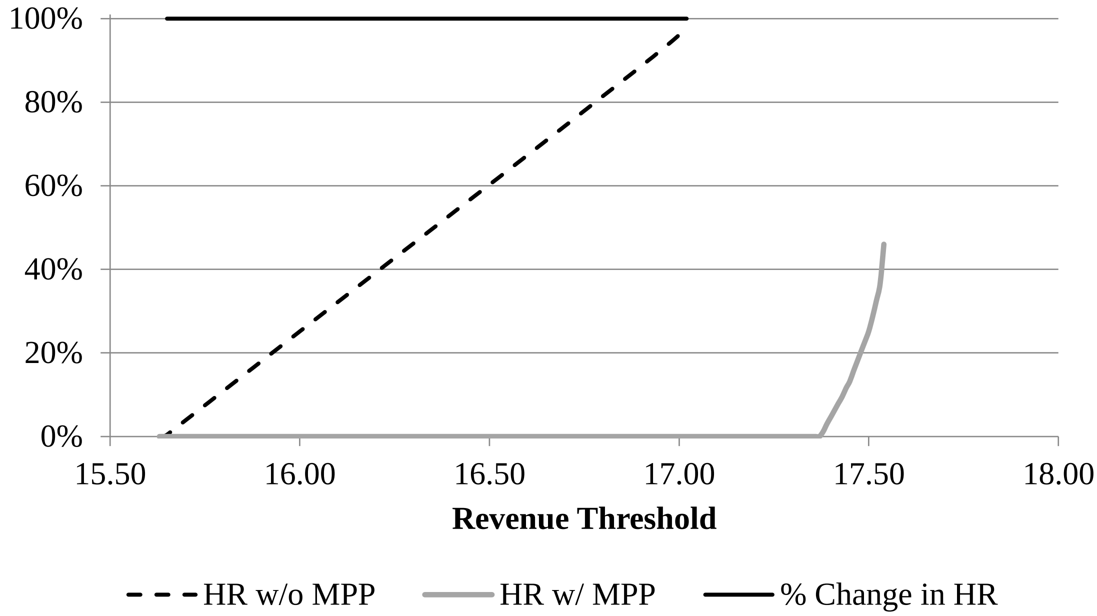

Figure 21 Lower Midwest grower with 4 mm PH signing up in Apr, 2011 for 2012 (CL:8.0 CP:90%)

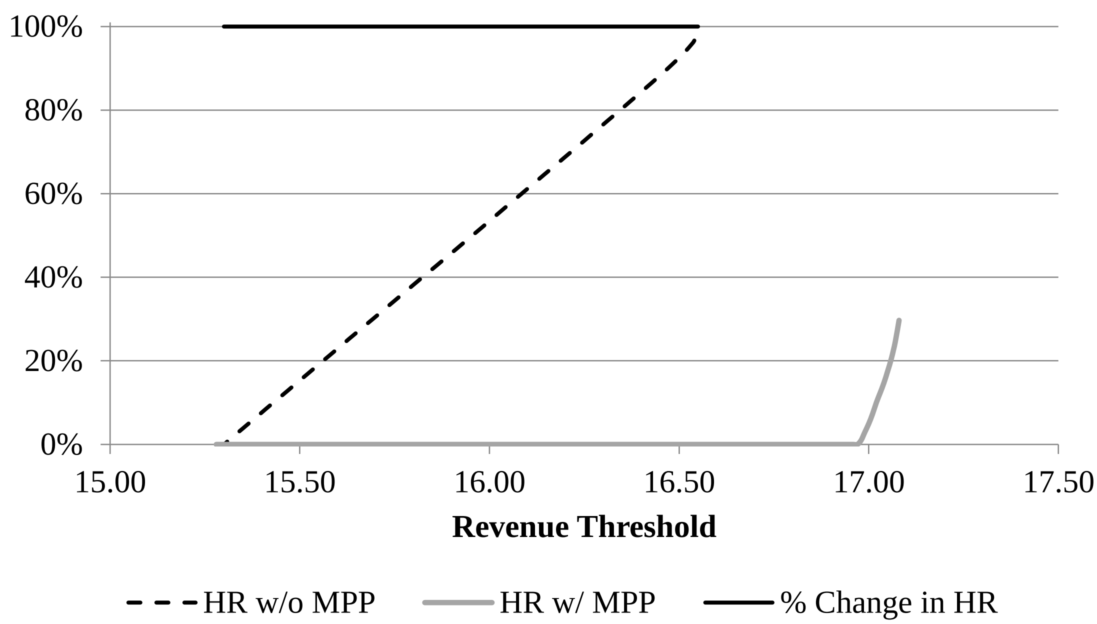

Figure 22 Upper Midwest grower with 4 mm PH signing up in Oct, 2011 for 2012 (CL:8.0 CP:90%)

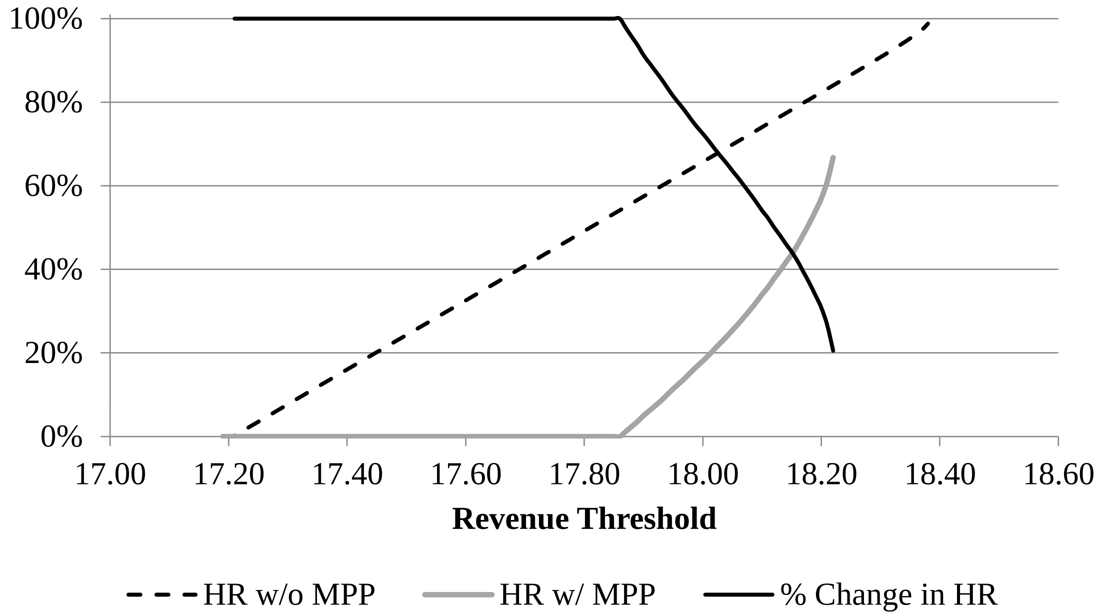

Figure 23 Lower Midwest grower with 4 mm PH signing up in Oct, 2011 for 2012 (CL:8.0 CP:90%)

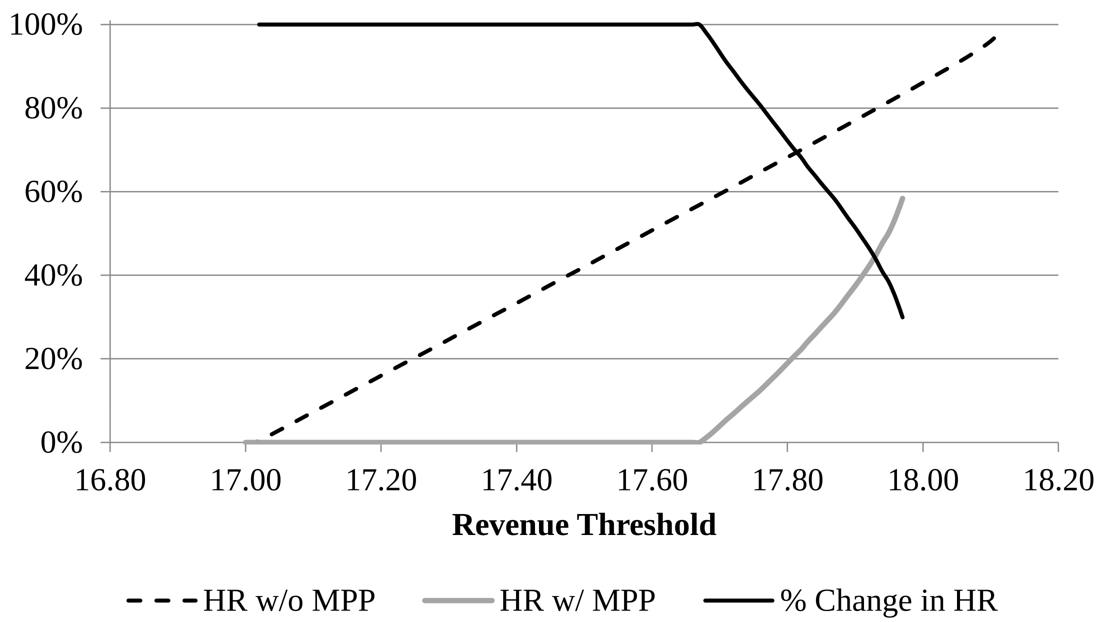

Figure 24 Upper Midwest grower with 4 mm PH signing up in Jan, 2012 for 2012 (CL:8.0 CP:90%)

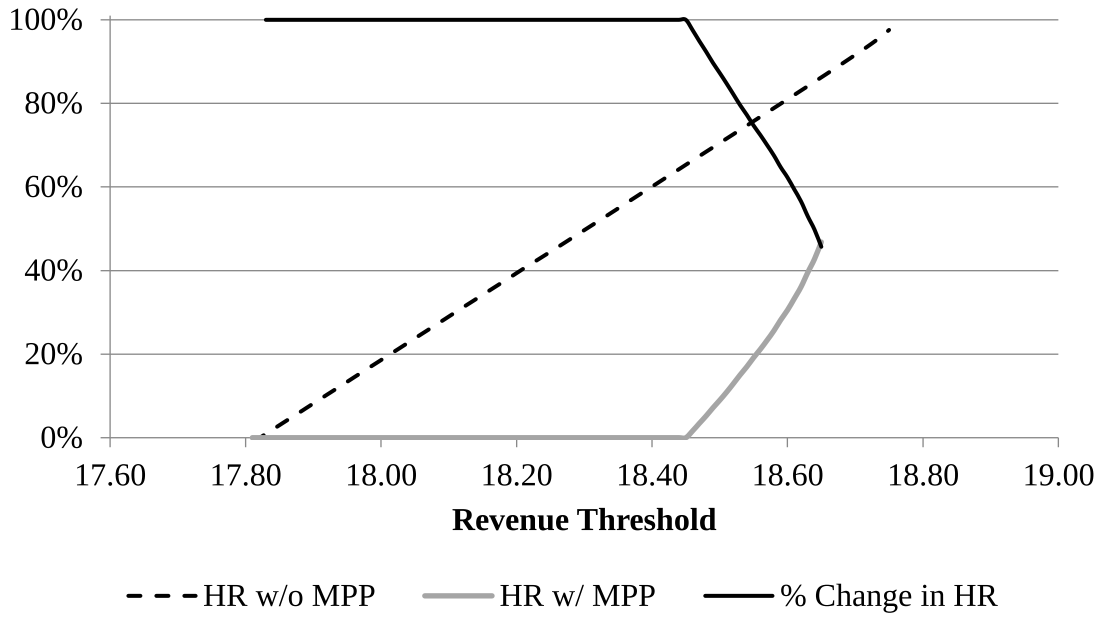

Figure 25 Lower Midwest grower with 4 mm PH signing up in Jan, 2012 for 2012 (CL:8.0 CP:90%)

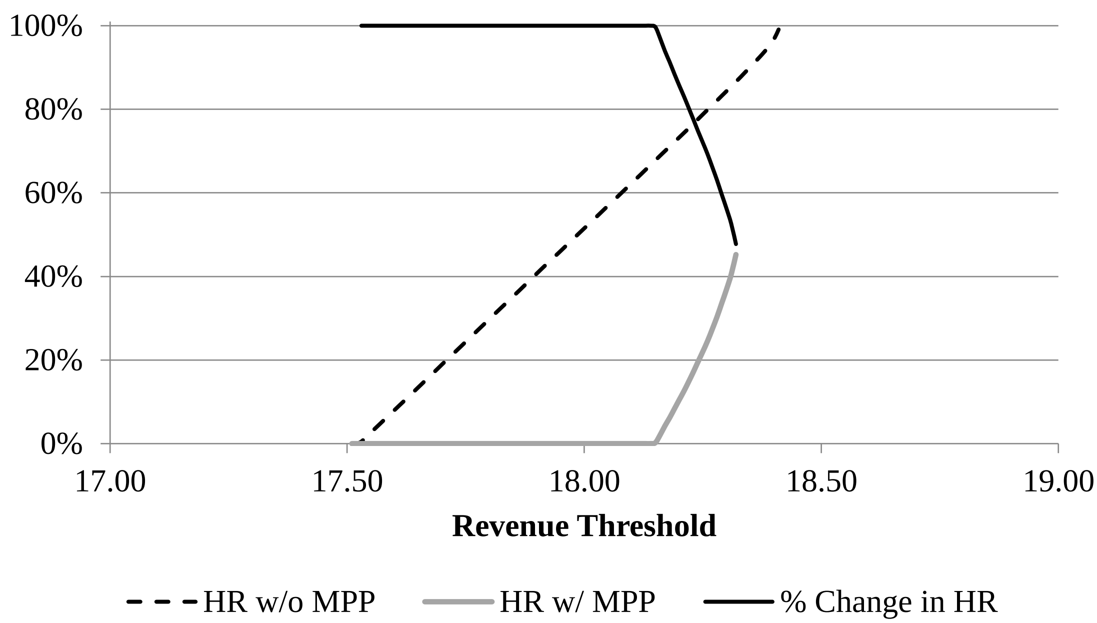

Figure 26 Upper Midwest grower with 4 million PH signing up in Apr, 2012 for 2013 (CL:8.0 CP:90%)

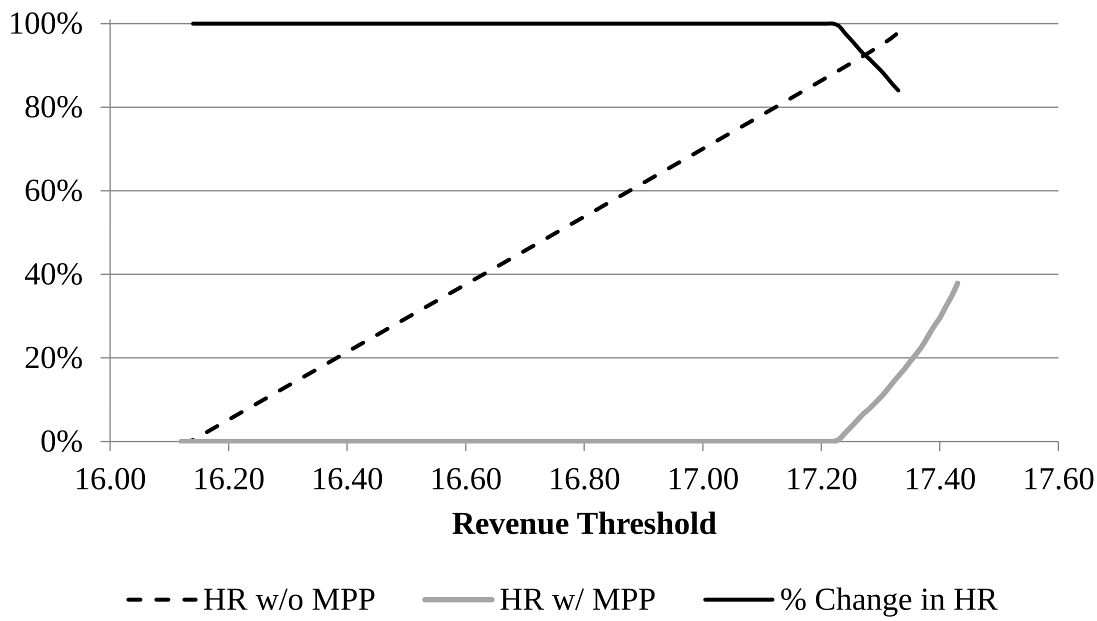

Figure 27 Lower Midwest grower with 4 million PH signing up in Apr, 2012 for 2013 (CL:8.0 CP:90%)

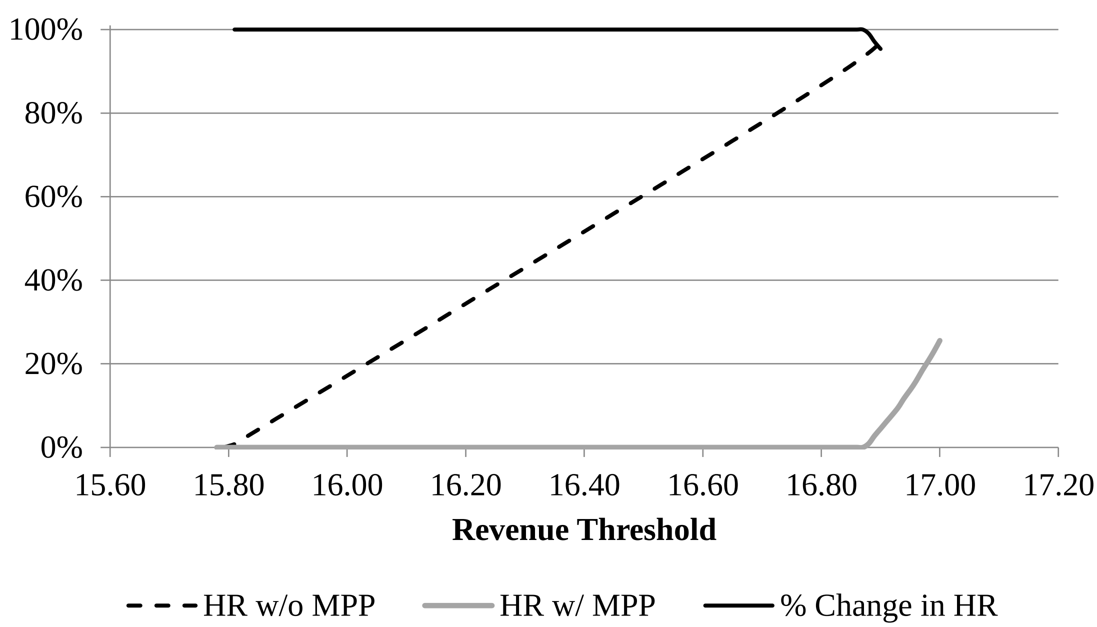

Figure 28 Upper Midwest grower with 4 million PH signing up in Oct, 2012 for 2013 (CL:6.5 CP:90%)

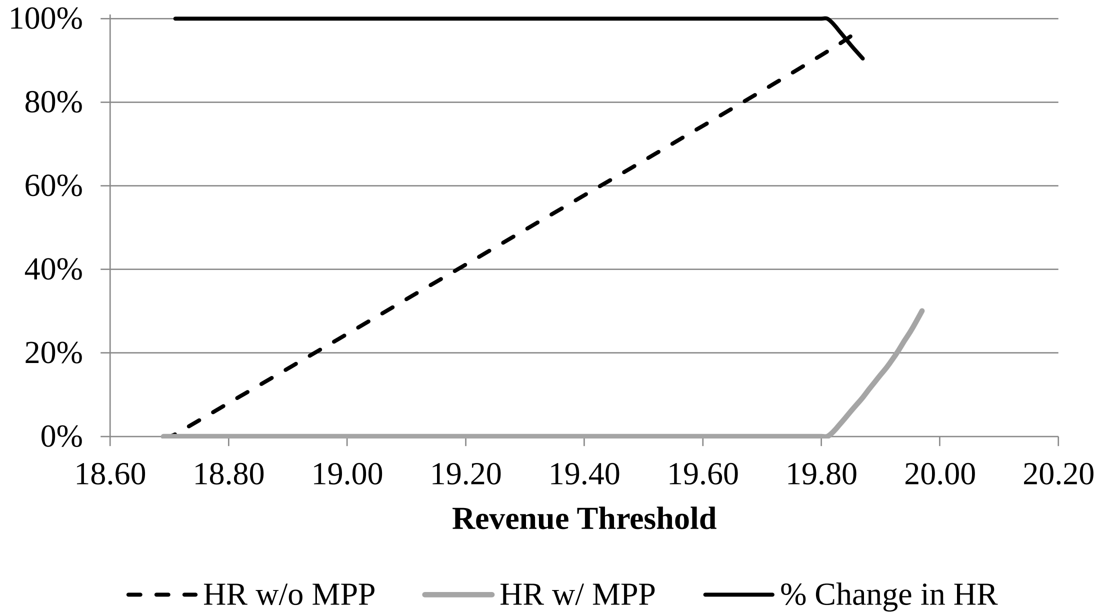

Figure 29 Lower Midwest grower with 4 million PH signing up in Oct, 2012 for 2013 (CL:8.0 CP:90%)

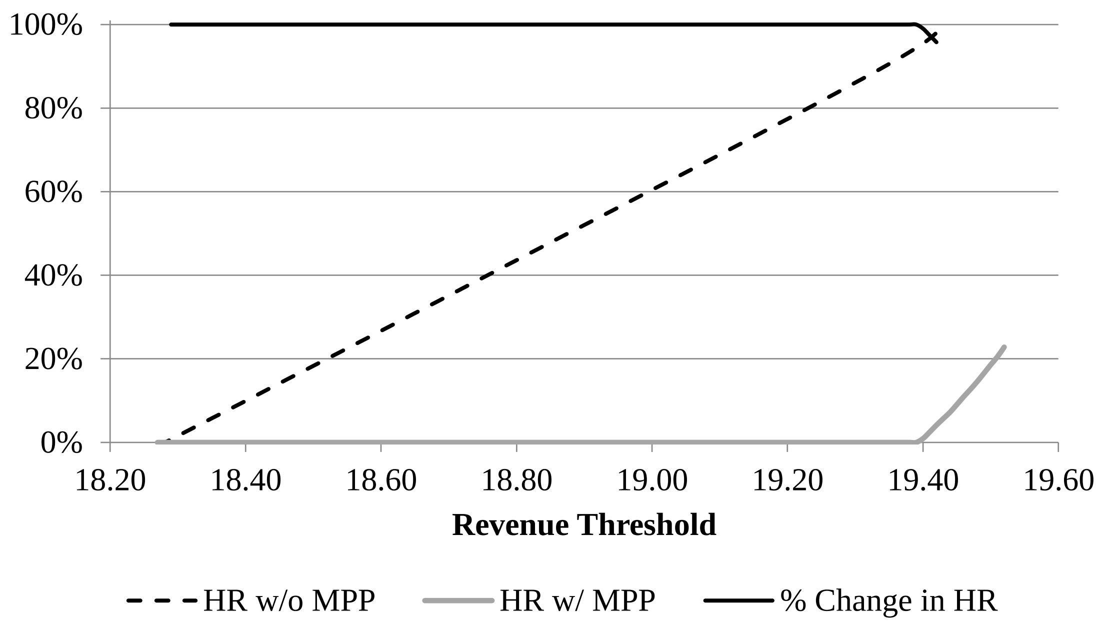

Figure 30 Upper Midwest grower with 4 million PH signing up in Jan, 2013 for 2013 (CL:8.0 CP:90%)

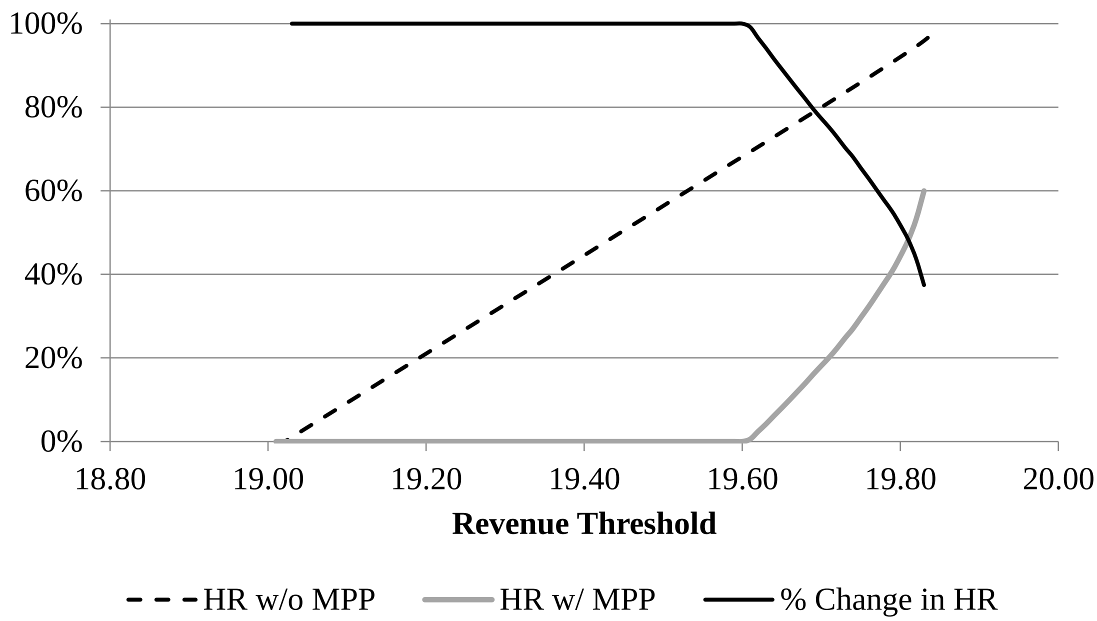

Figure 31 Lower Midwest grower with 4 million PH signing up in Jan, 2013 for 2013 (CL:8.0 CP:90%)

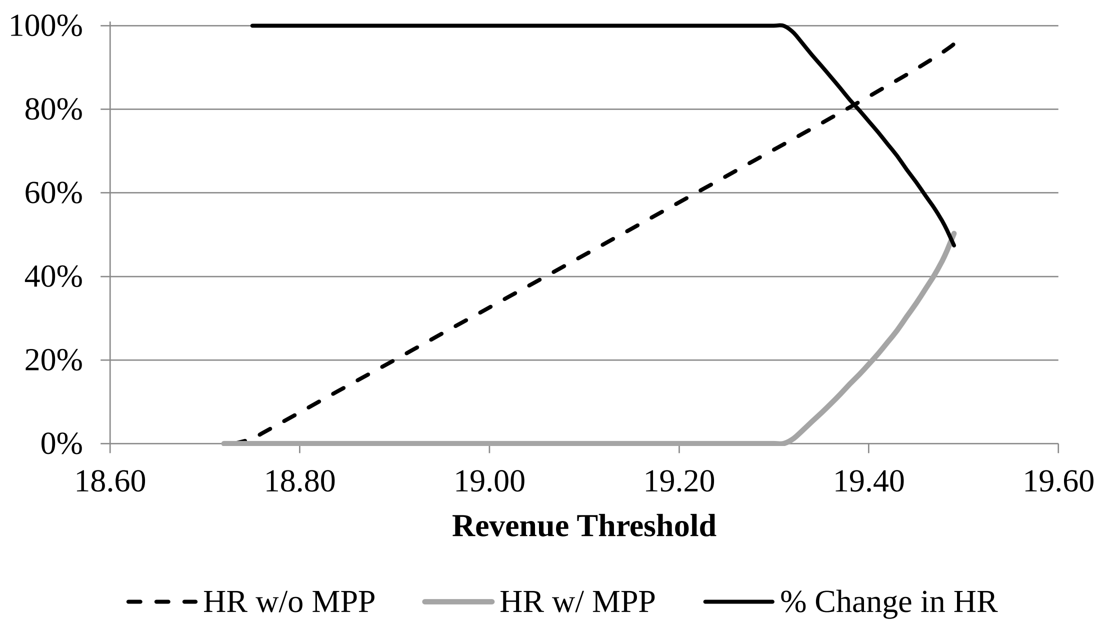

Figure 32 Upper Midwest grower with 6 mm PH signing up in Apr, 2008 for 2009 (CL:6.5, CP:90%)

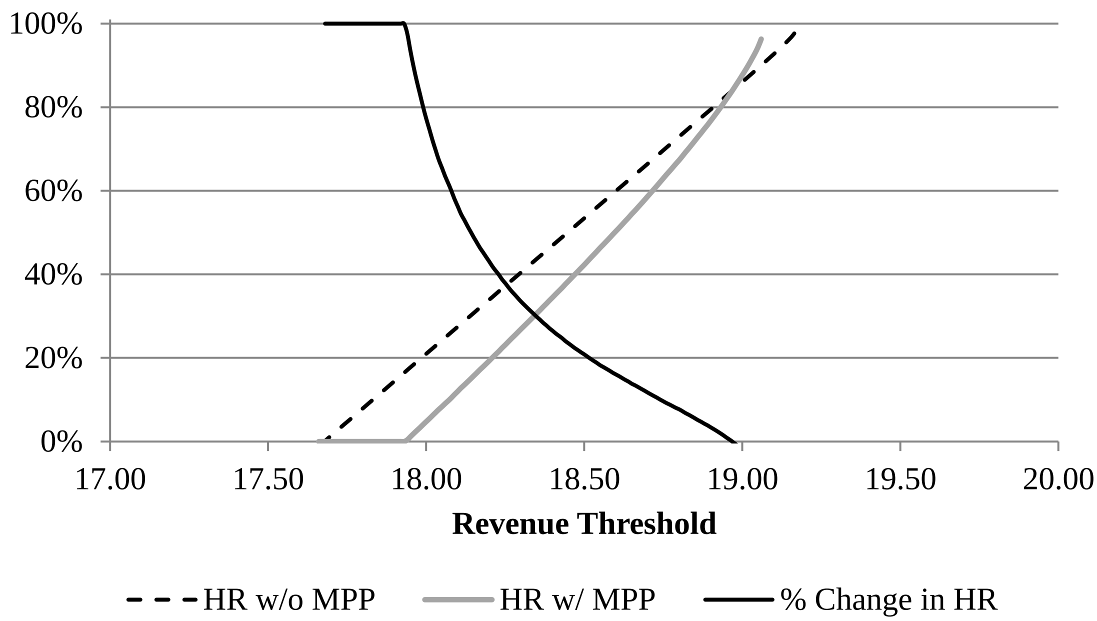

Figure 33 Lower Midwest grower with 6 mm PH signing up in Apr, 2008 for 2009 (CL:6.5 CP:90%)

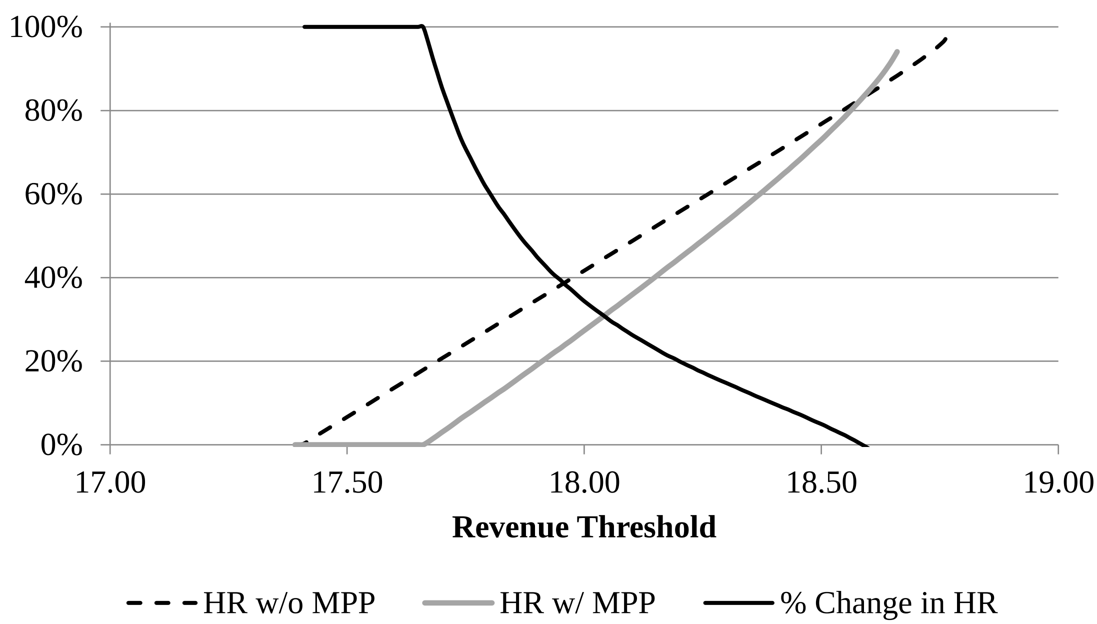

Figure 34 Upper Midwest grower with 6 mm PH signing up in Oct, 2008 for 2009 (CL:8.0 CP:90%)

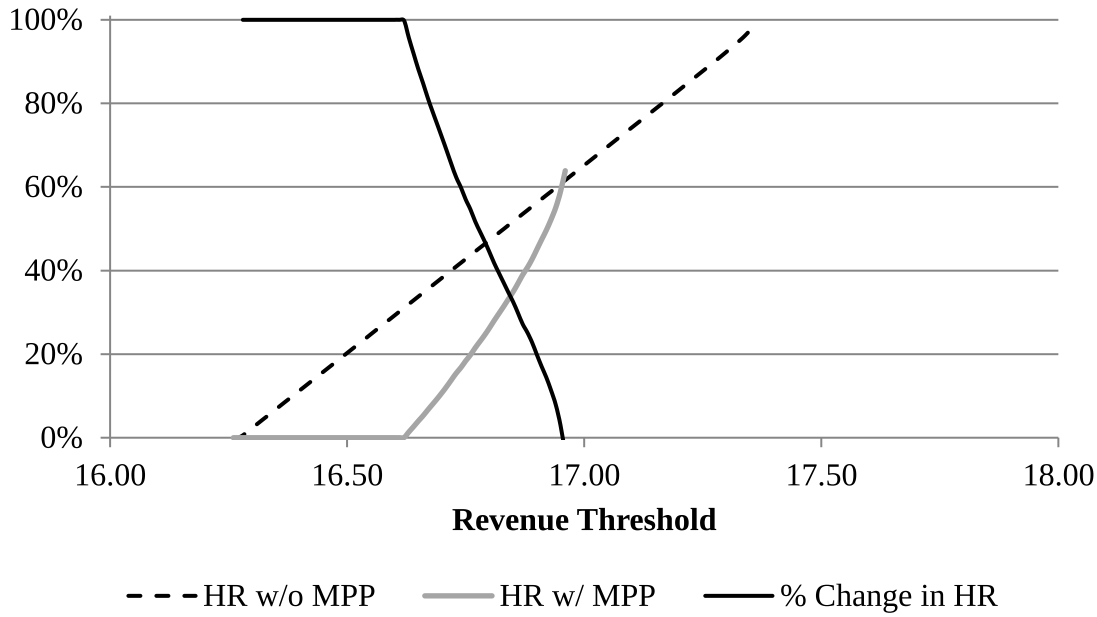

Figure 35 Lower Midwest grower with 6 mm PH signing up in Oct, 2008 for 2009 (CL:8.0 CP:90%)

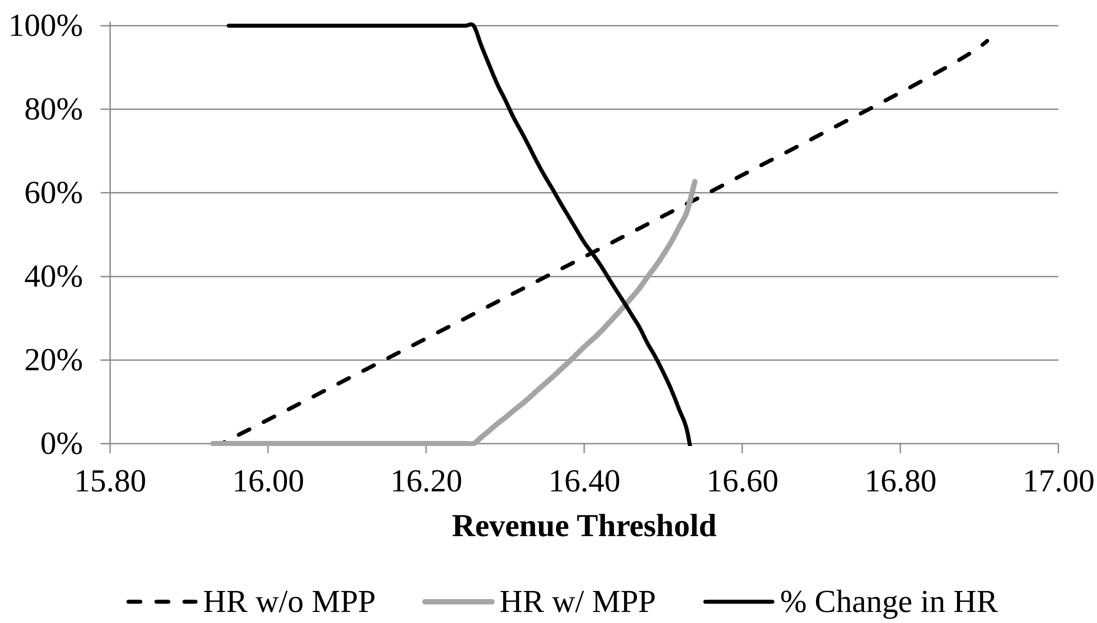

Figure 36 Upper Midwest grower with 6 mm PH signing up in Jan, 2009 for 2009 (CL:8.0 CP:90%)

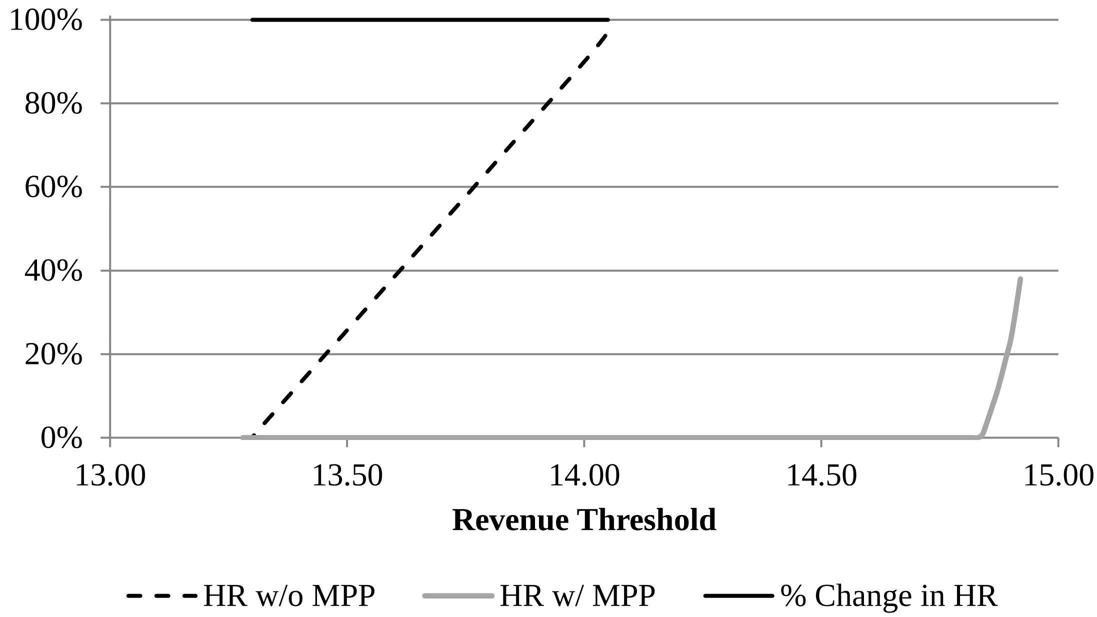

Figure 37 Lower Midwest grower with 6 mm PH signing up in Jan, 2009 for 2009 (CL:8.0 CP:90%)

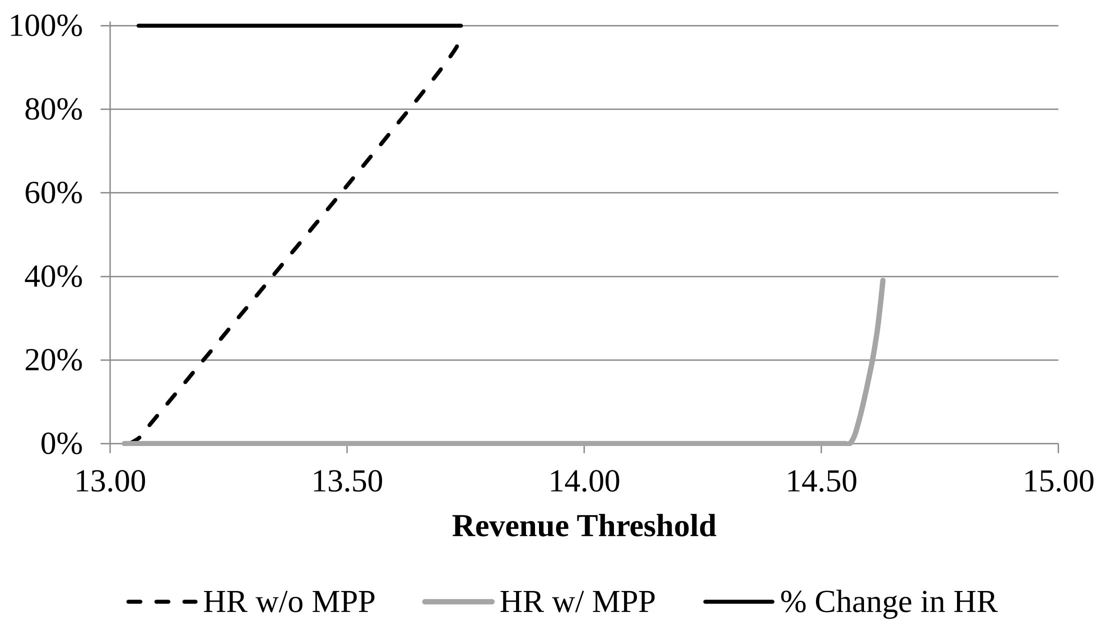

Figure 38 Upper Midwest grower with 6 mm PH signing up in Apr, 2011 for 2012 (CL:8.0 CP:90%)

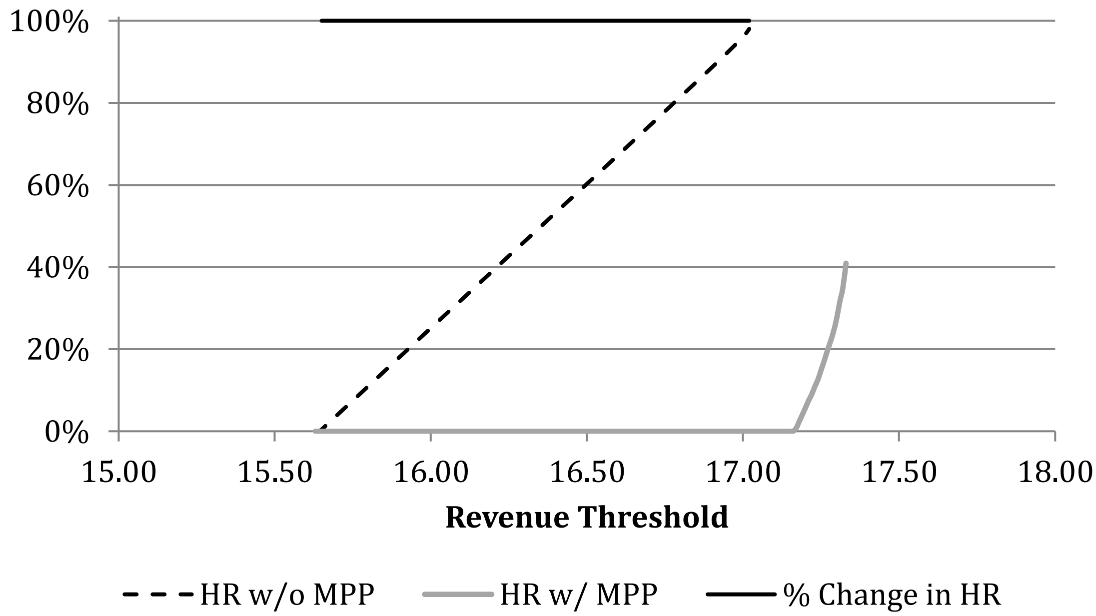

Figure 39 Lower Midwest grower with 6 mm PH signing up in Apr, 2011 for 2012 (CL:8.0 CP:90%)

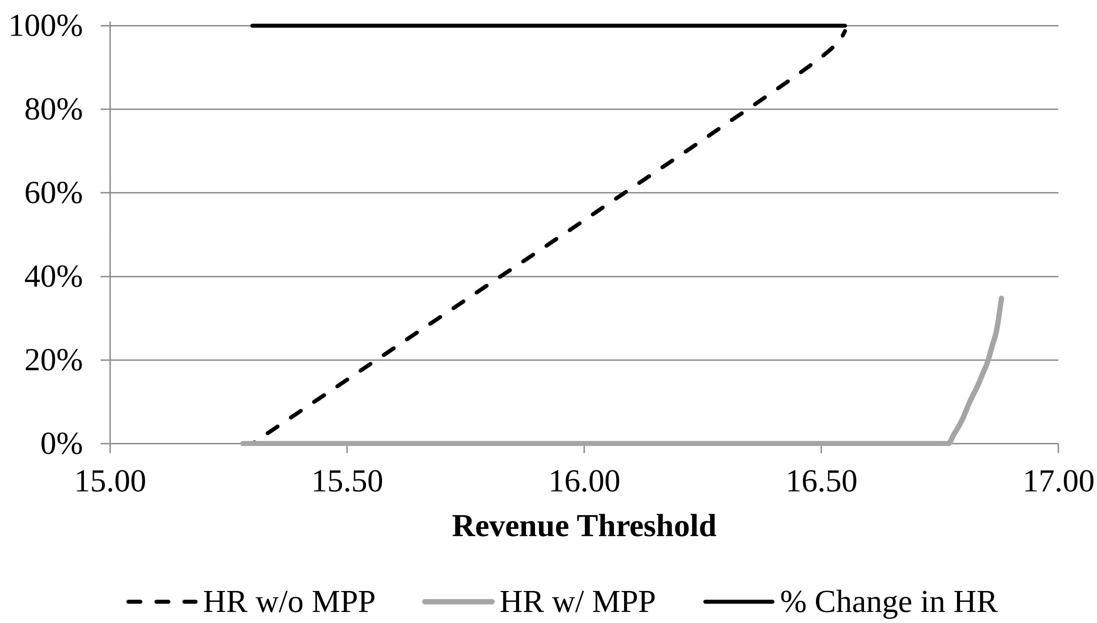

Figure 40 Upper Midwest grower with 6 mm PH signing up in Oct, 2011 for 2012 (CL:8.0 CP:90%)

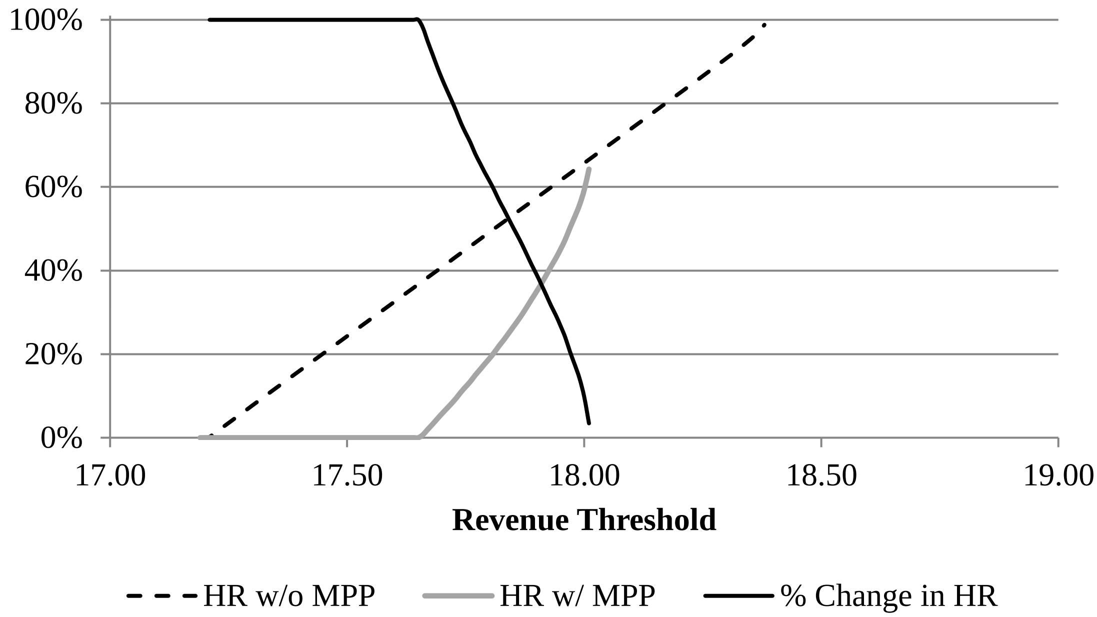

Figure 41 Lower Midwest grower with 6 mm PH signing up in Oct, 2011 for 2012 (CL:8.0 CP:90%)

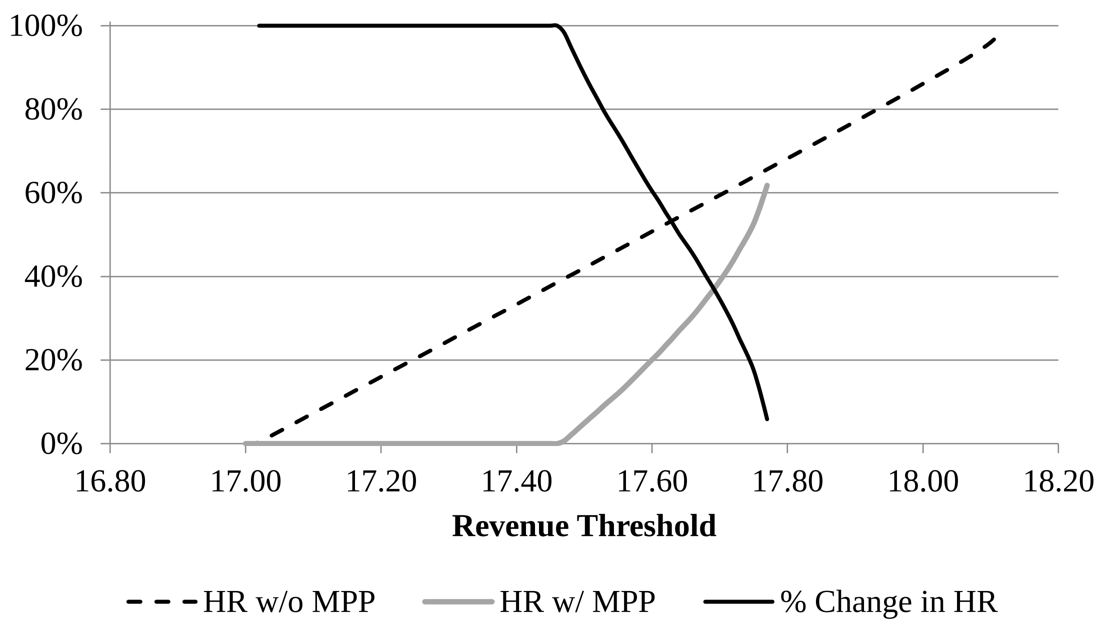

Figure 42 Upper Midwest grower with 6 mm PH signing up in Jan, 2012 for 2012 (CL:8.0 CP:90%)

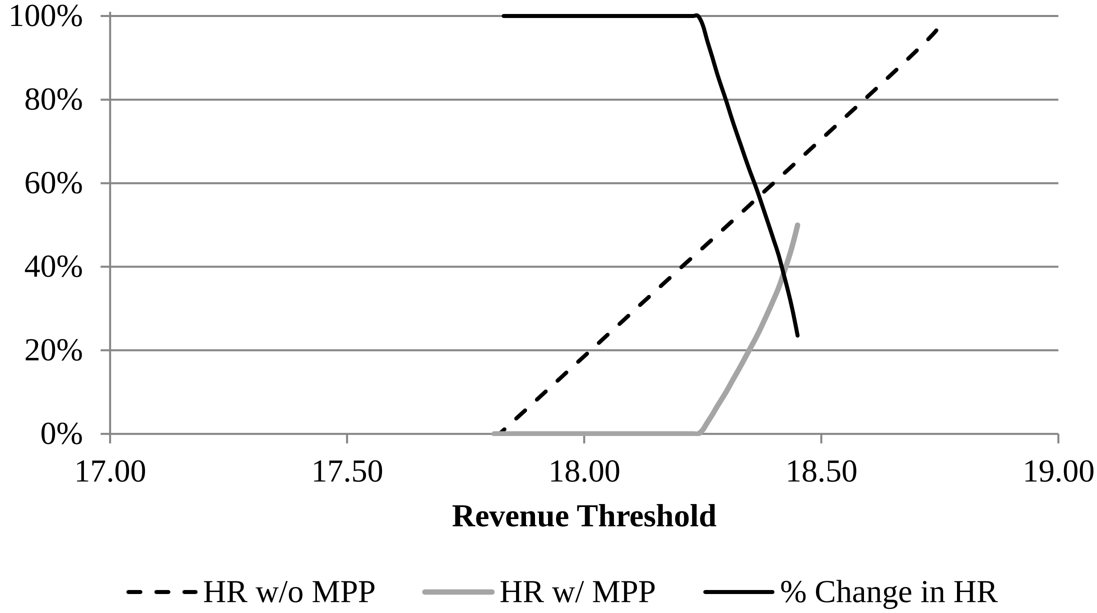

Figure 43 Lower Midwest grower with 6 mm PH signing up in Jan, 2012 for 2012 (CL:8.0 CP:90%)

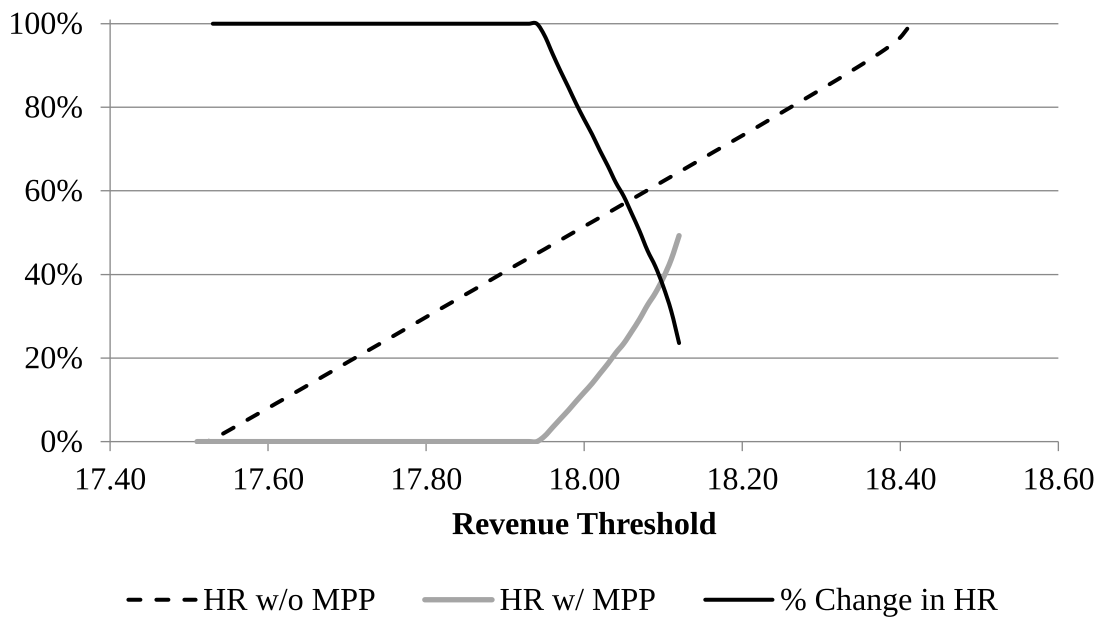

Figure 44 Upper Midwest grower with 6 million PH signing up in Apr, 2012 for 2013 (CL:8.0 CP:90%)

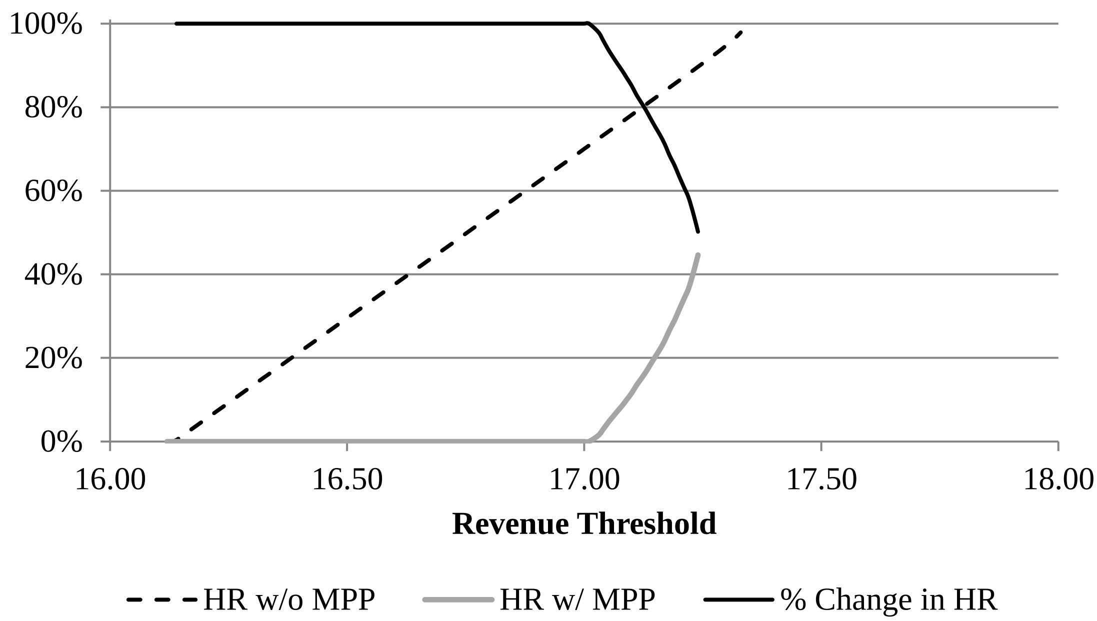

Figure 45 Lower Midwest grower with 6 million PH signing up in Apr, 2012 for 2013 (CL:8.0 CP:90%)

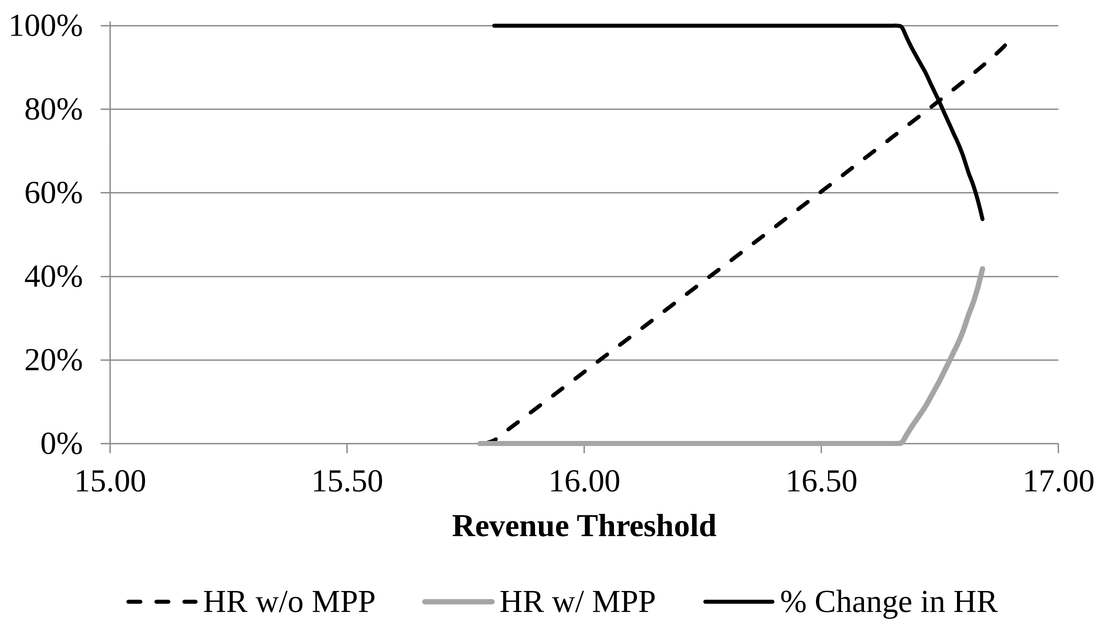

Figure 46 Upper Midwest grower with 6 million PH signing up in Oct, 2012 for 2013 (CL:8.0 CP:90%)

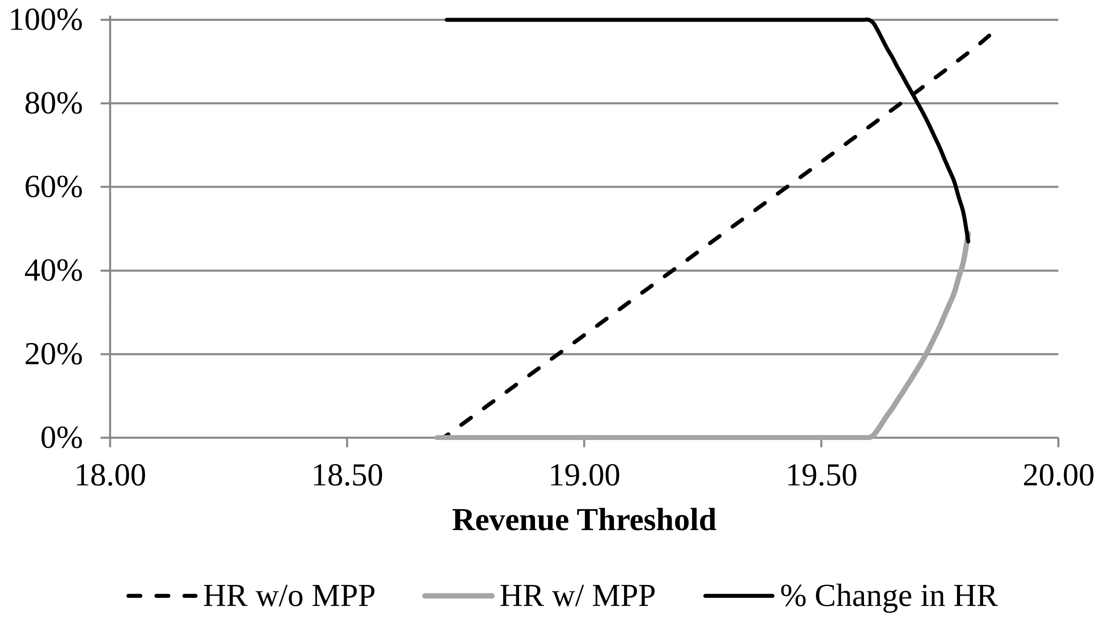

Figure 47 Lower Midwest grower with 6 million PH signing up in Oct, 2012 for 2013 (CL:8.0 CP:90%)

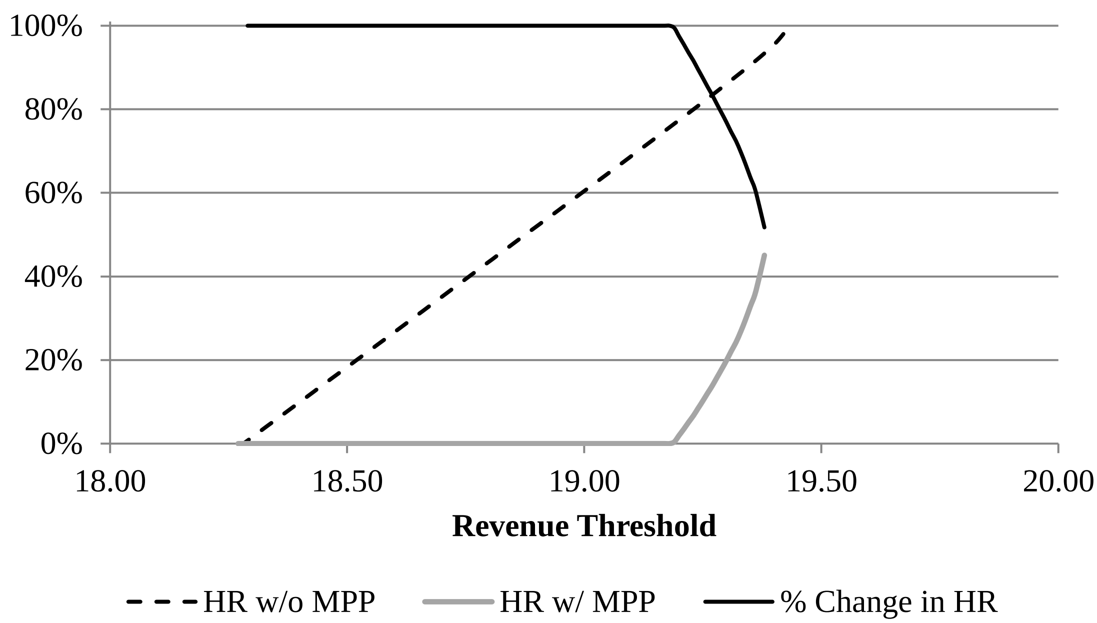

Figure 48 Upper Midwest grower with 6 million PH signing up in Jan, 2013 for 2013 (CL:8.0 CP:90%)

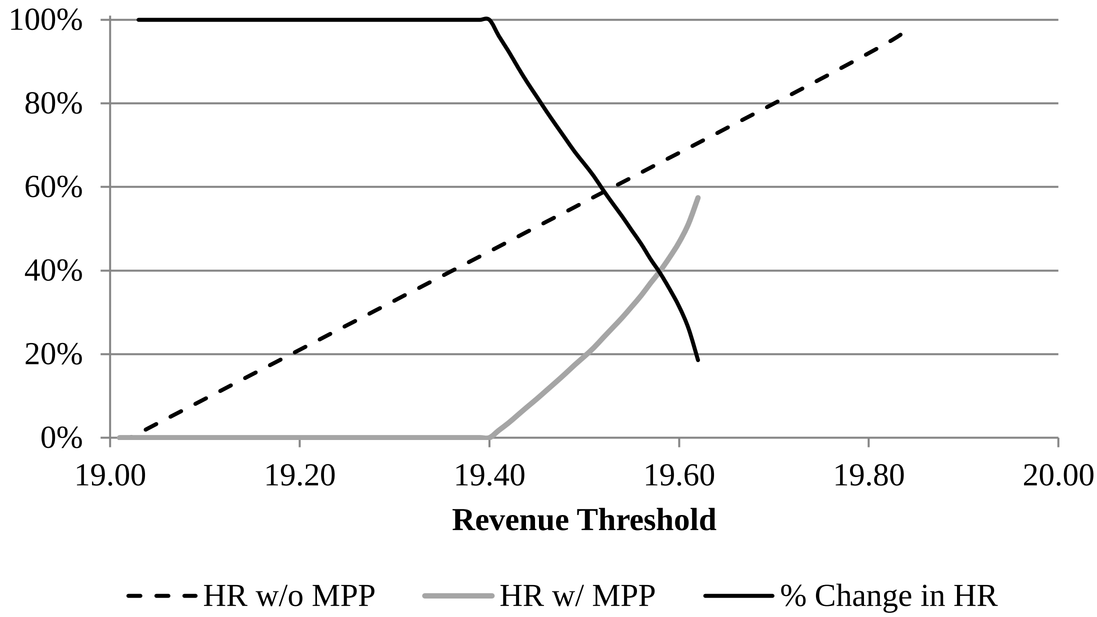

Figure 49 Lower Midwest grower with 6 million PH signing up in Jan, 2013 for 2013 (CL:8.0 CP:90%)

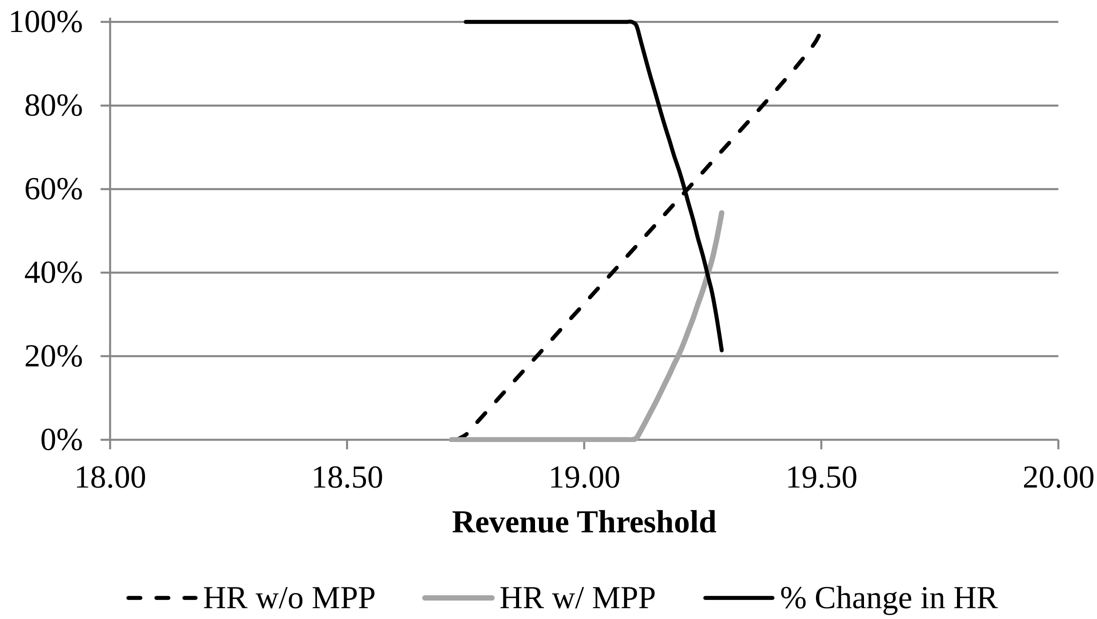

Figure 50 Upper Midwest grower with 60 mm PH signing up in Apr, 2008 for 2009 (CL:6.0, CP:90%)

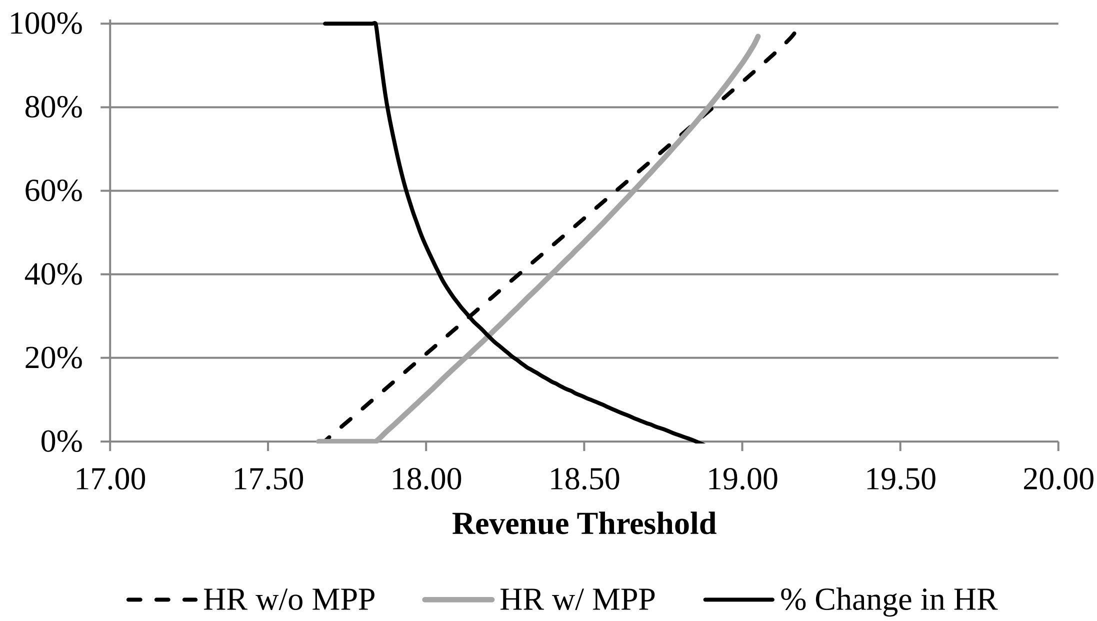

Figure 51 Lower Midwest grower with 60 mm PH signing up in Apr, 2008 for 2009 (CL:6.0 CP:90%)

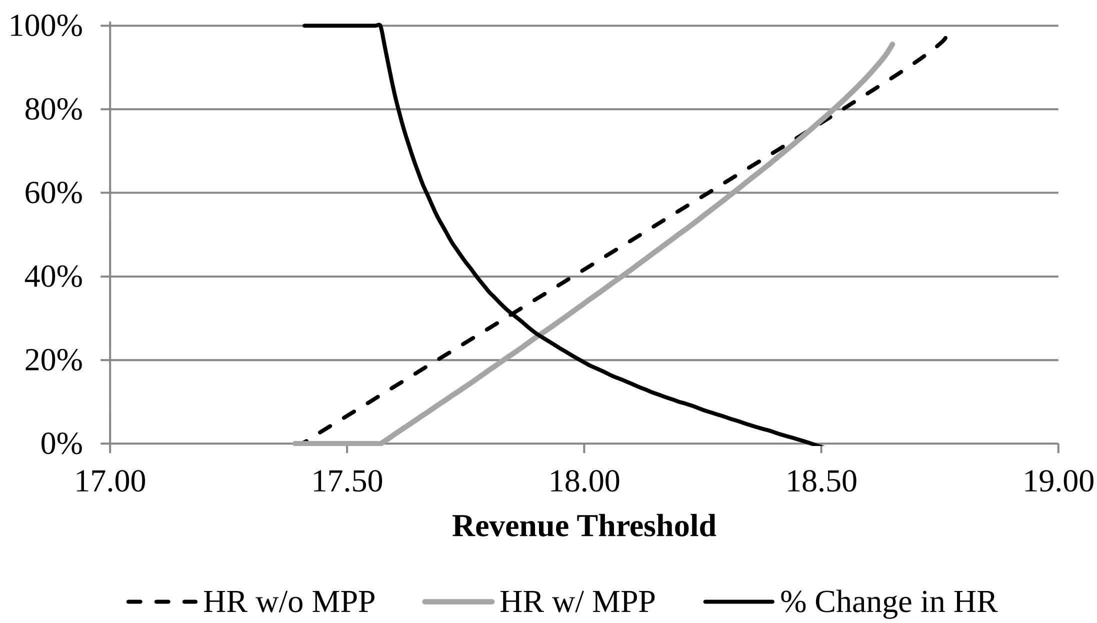

Figure 52 Upper Midwest grower with 60 mm PH signing up in Oct, 2008 for 2009 (CL:6.0 CP:90%)

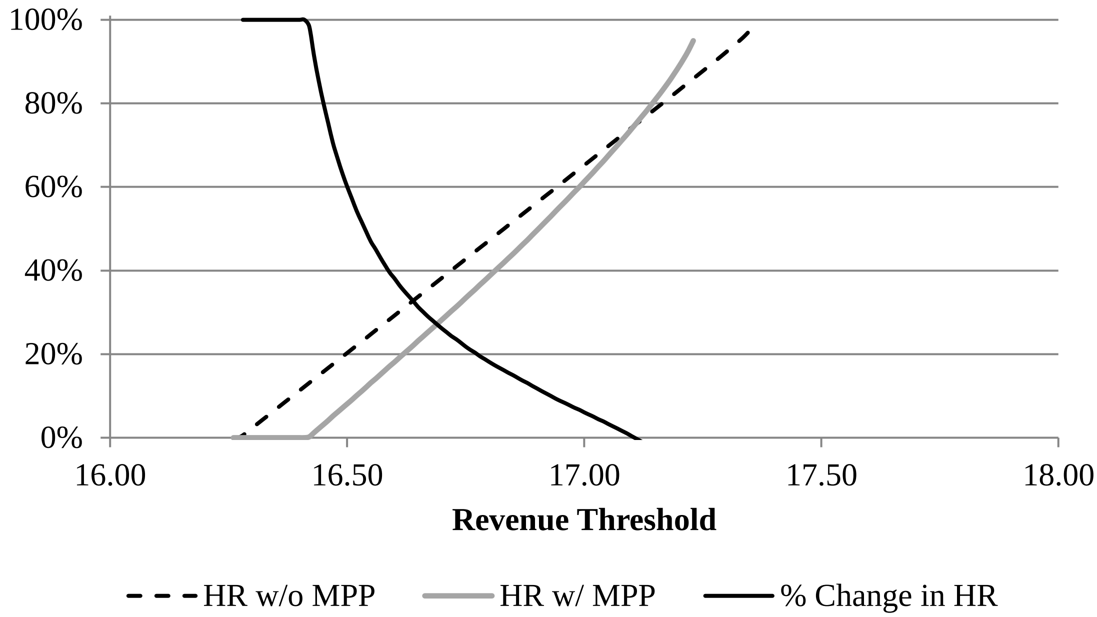

Figure 53 Lower Midwest grower with 60 mm PH signing up in Oct, 2008 for 2009 (CL:6.0 CP:90%)

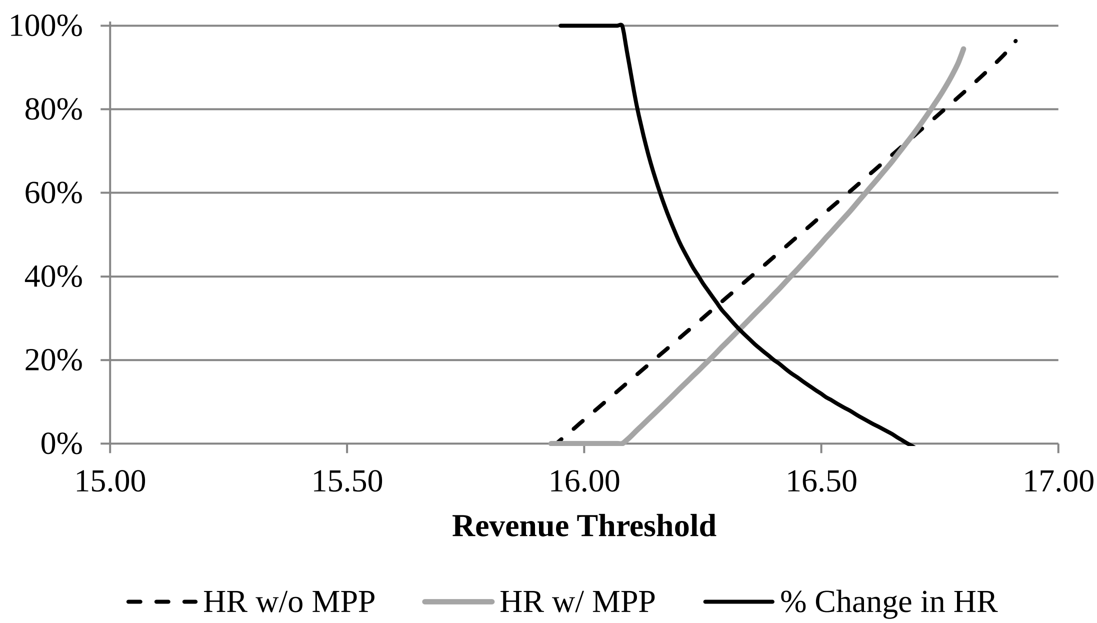

Figure 54 Upper Midwest grower with 60 mm PH signing up in Jan, 2009 for 2009 (CL:8.0 CP:90%)

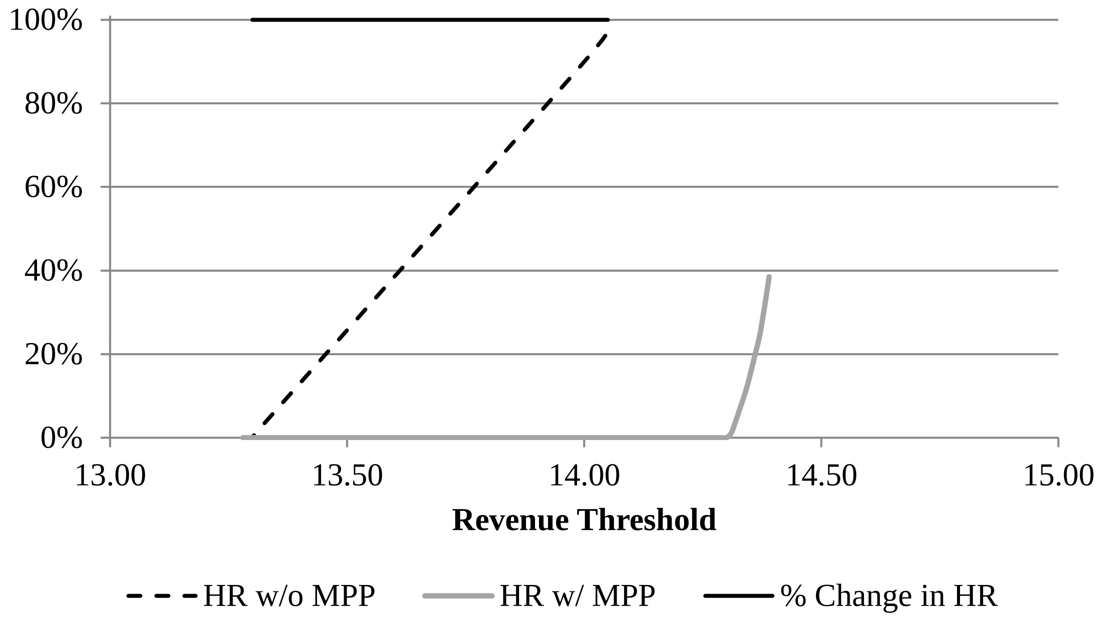

Figure 55 Lower Midwest grower with 60 mm PH signing up in Jan, 2009 for 2009 (CL:8.0 CP:90%)

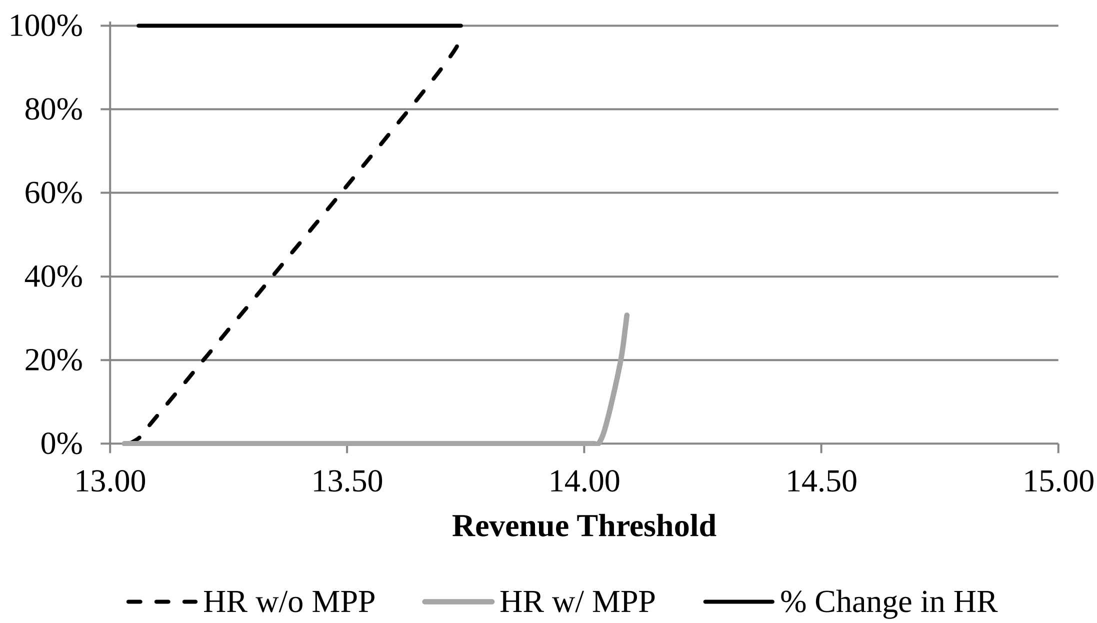

Figure 56 Upper Midwest grower with 60 mm PH signing up in Apr, 2011 for 2012 (CL:8.0 CP:90%)

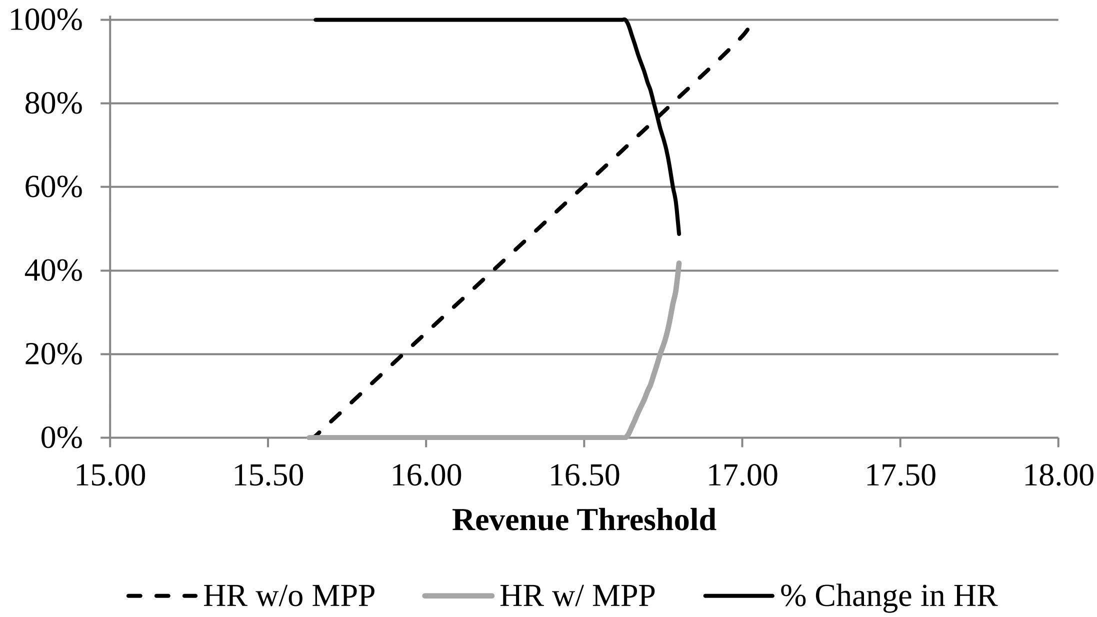

Figure 57 Lower Midwest grower with 60 mm PH signing up in Apr, 2011 for 2012 (CL:8.0 CP:90%)

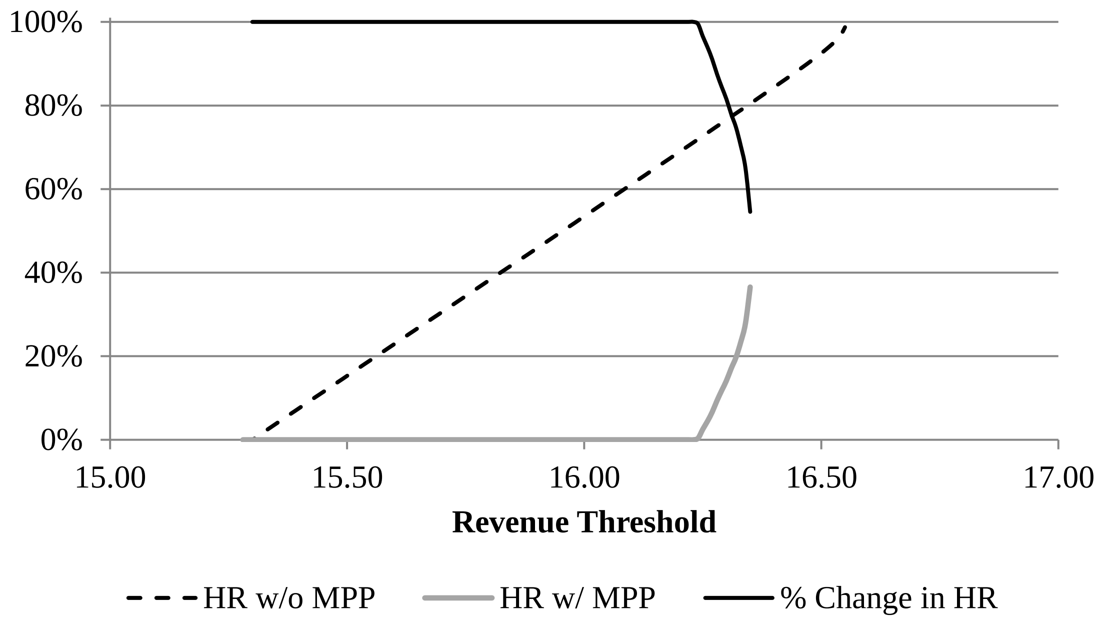

Figure 58 Upper Midwest grower with 60 mm PH signing up in Oct, 2011 for 2012 (CL:6.5 CP:90%)

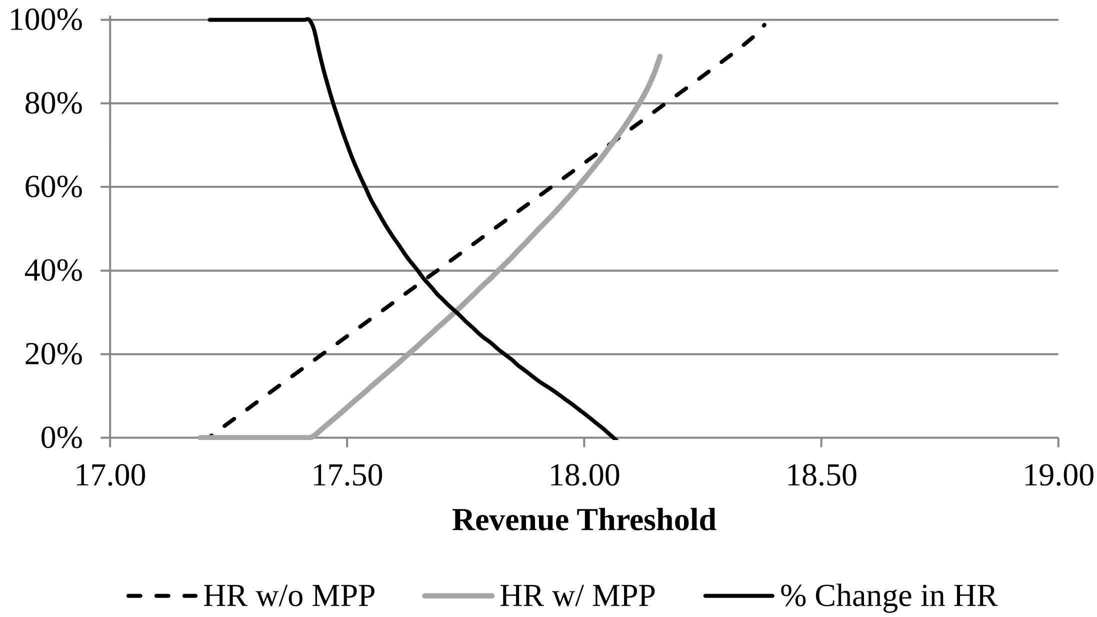

Figure 59 Lower Midwest grower with 60 mm PH signing up in Oct, 2011 for 2012 (CL:6.5 CP:90%)

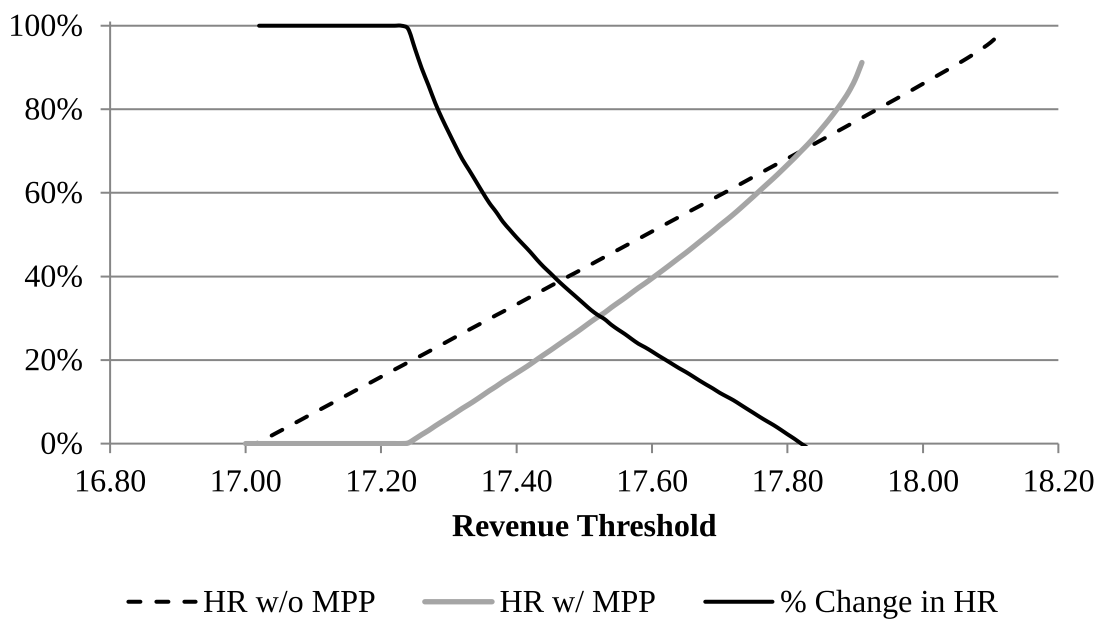

Figure 60 Upper Midwest grower with 60 mm PH signing up in Jan, 2012 for 2012 (CL:6.0 CP:90%)

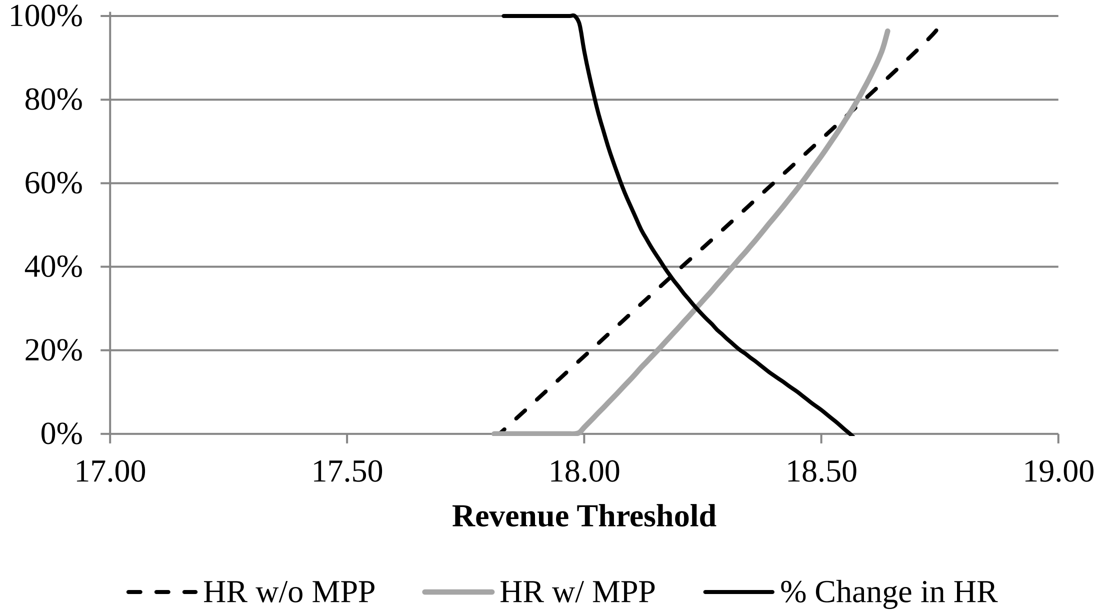

Figure 61 Lower Midwest grower with 60 mm PH signing up in Jan, 2012 for 2012 (CL:6.0 CP:90%)

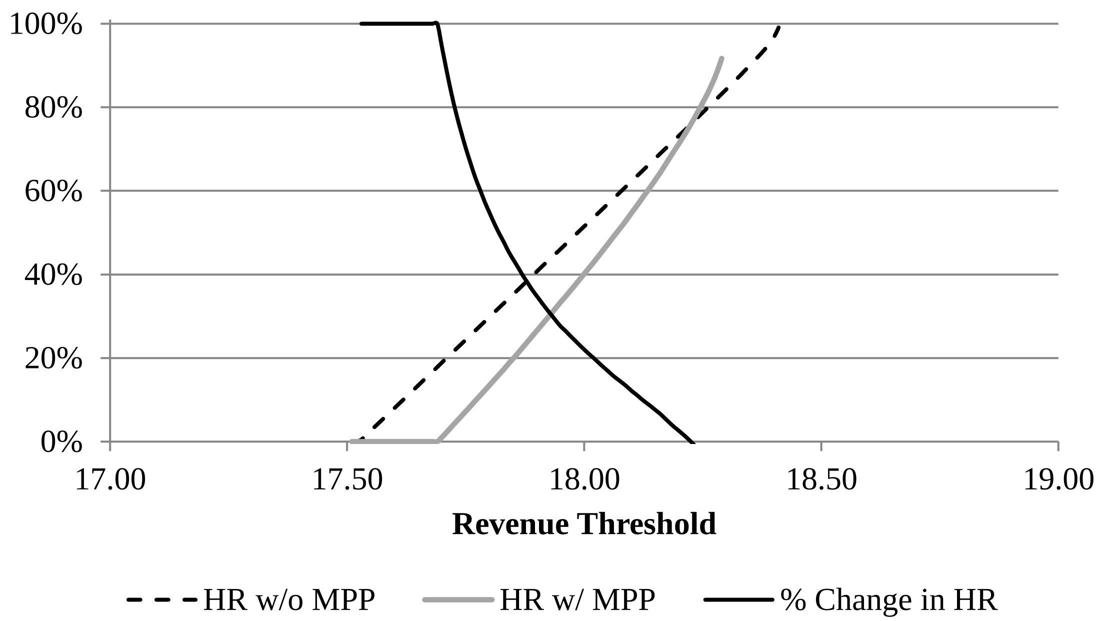

Figure 62 Upper Midwest grower with 60 million PH signing up in Apr, 2012 for 2013 (CL:6.5 CP:90%)

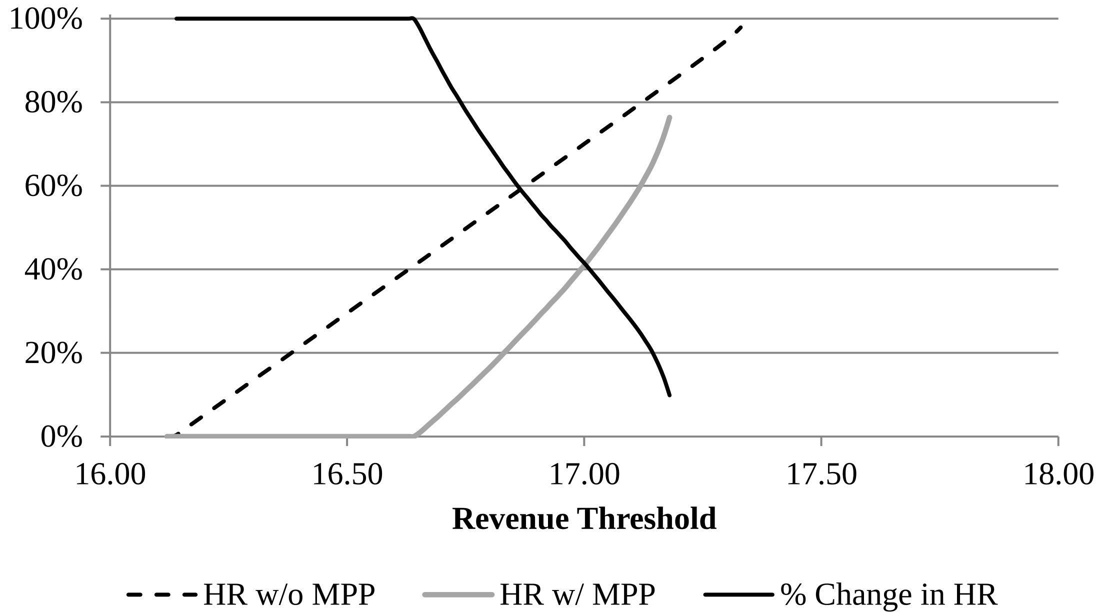

Figure 63 Lower Midwest grower with 60 million PH signing up in Apr, 2012 for 2013 (CL:6.5 CP:90%)

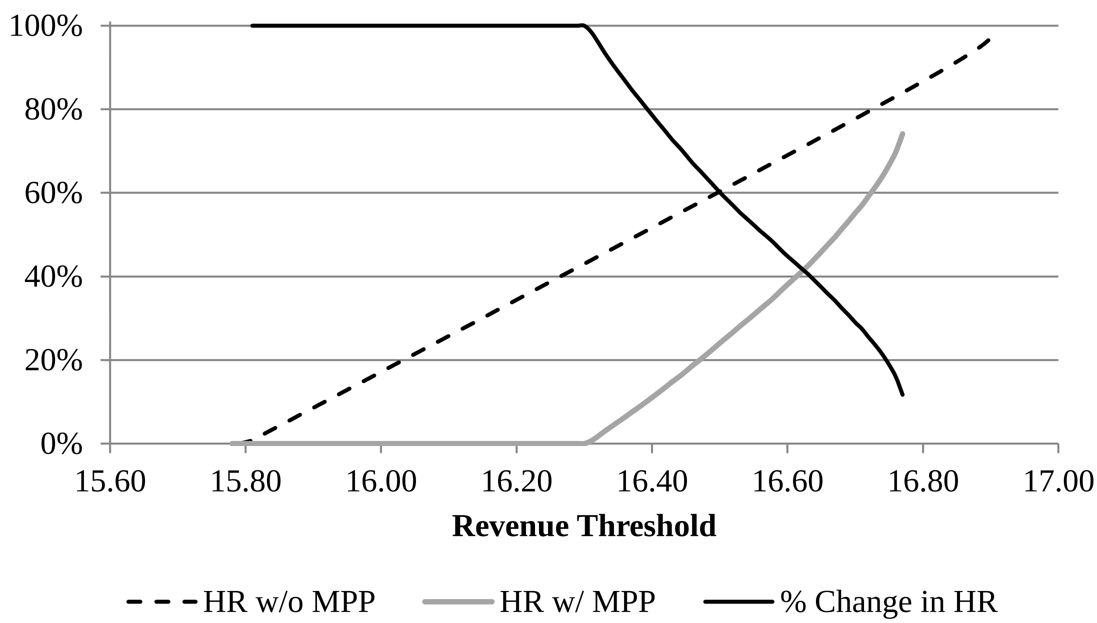

Figure 64 Upper Midwest grower with 60 million PH signing up in Oct, 2012 for 2013 (CL:6.5 CP:90%)

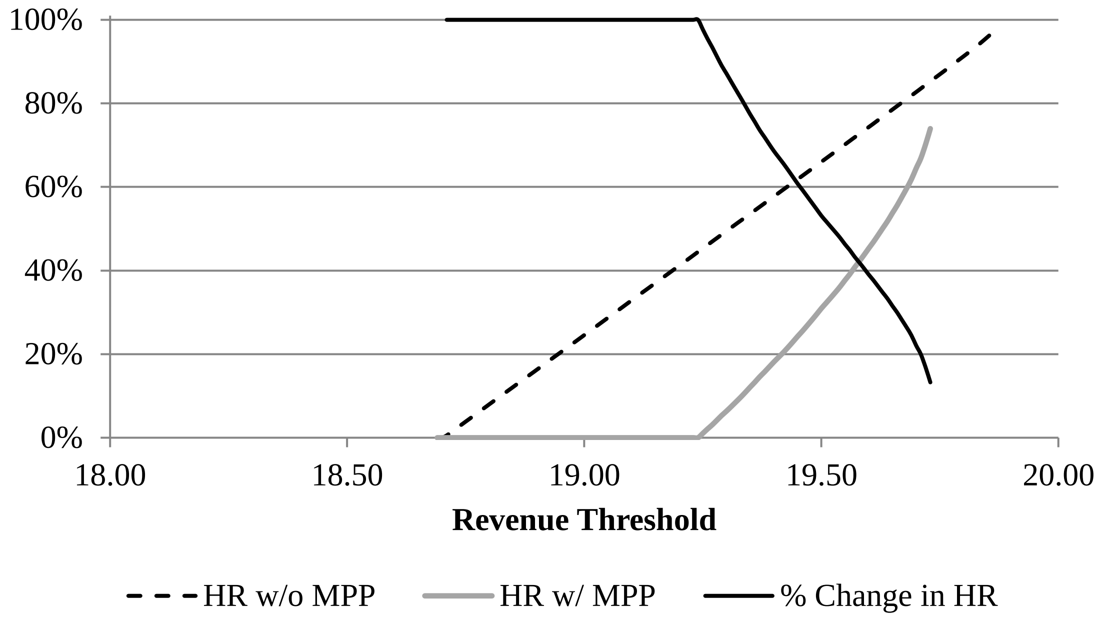

Figure 65 Lower Midwest grower with 60 million PH signing up in Oct, 2012 for 2013 (CL:6.5 CP:90%)

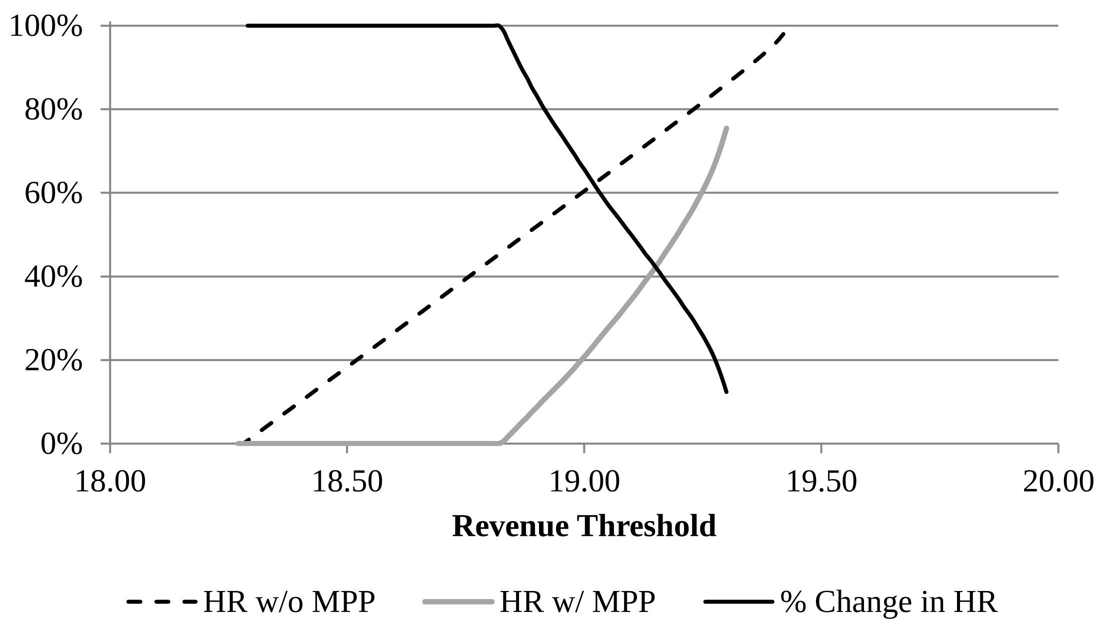

Figure 66 Upper Midwest grower with 60 million PH signing up in Jan, 2013 for 2013 (CL:4.0 CP:90%)

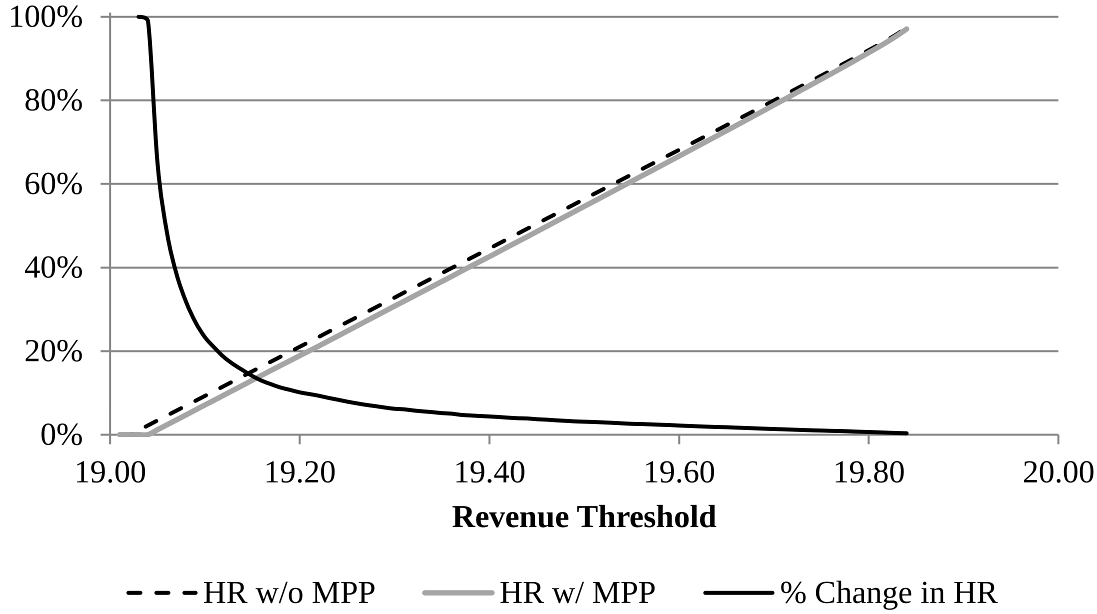

Figure 67 Lower Midwest grower with 60 million PH signing up in Jan, 2013 for 2013 (CL:4.0 CP:90%)