PLAY IT FORWARD – THE DESIGN AND DEVELOPMENT OF A FORWARD CONTRACT SIMULATION

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ABSTRACT

A game simulating commodity market prices from the perspective of an energy firm selling propane to end users. This paper describes the expectation of the sponsoring firm, includes a brief literature review and identifies 2 popular commodity futures models. A methodolgy is selected and the model is verified and tested. Screen shots of the finished simulation are displayed. The paper concludes with expected results, initial reactions of the players, facilitator, and the sponser. Lastly, the author suggests possible research extensions for this

INTRODUCTION

An energy trading firm contacted me in March 2011 and inquired if I could make a simulation / training game for their professional development program that explained the mechanics and business benefits of using future Propane contracts to hedge the riskiness of their business given the volatility of commodity prices. An additional benefit to the client is the possibility of developing a trading rule that produces an expected trading profit in addition to reducing risk. They had contracted me in 2010 to build a simulation / training game to better understand the financial impact of managing their product mix, production capacity and distribution options. Being familiar with the firm's operations and management philosophy plus having access to financial data and their management is crucial in developing an effective simulation.

The firm enters into a forward contract with a producer at a current price (F_o) for delivery of an asset in the future that it plans to use or sell. The futures price is derivative of the expected future spot price. The payoff to the buyer in a future contract is the difference between the future spot price (S_t) and the agreed upon contract price. The option to enter the contract at a price believed to be favorable currently reduces risk by identifying future cost. The hedge being modeled is not intended to be a riskless hedge at the request of the client.

In accepting the contract to build a simulation, I identified the following expectations:

Develop a simulation model that employs methods that represent actual price paths for the commodity.

Develop a tool that allows a player to experiment with hedging in a safe environment and discover the importance of forecasting and understand that hedging strategies and use of derivatives in general can both reduce risk (volatility) and improve profitability.

Develop a decision rule that if employed is more likely than not to yield higher profits (a positive expected value.

This tool is primarily a teaching and learning instrument and it is not my intention to develop new theory or create an optimal closed from solution.

BRIEF LITERATURE REVIEW

Prior to beginning the construction of this simulation I explored and drew on several excellent published sources. My search encompassed three themes; the practice of using derivatives as a risk management strategy, how can commodity price paths be modeled, and the use of simulation as a teaching, learning, and perhaps as a decision tool. Benhamou & Mamalis (2002) identified three primary reasons that a firm uses derivatives. They are to hedge against price fluctuations, speculation and arbitrage. Peterson & Thiagarajan (2000) compared two firms using different approaches to managing risk. One, American Barrick aggressively used derivatives to manage risk and the second, Homestake Mining did not. They found the volatility of earnings and the return to equity falls by 2%, the probability of financial distress lessens with the use of derivatives and there is an increase in expected profits. Non hedging firms are more likely to experience unexpected cash flow fluctuations. Hedging firms are able to remain more competitive than non hedging firms in they are able to maintain more stable prices for their customers than firms that are required to pass on input price increases.

Schwartz in 1997 published a much cited paper in the Journal of Finance. He presented three models of commodity price behavior that he tested against a set of actively traded commodities. All models incorporate the Wiener process for incorporating the Brownian motion attribute of price paths through time. A single factor model was based on the log of the spot price following a mean reverting process and including a speed of adjustment factor specified as

k. A two factor model included a convenience yield factor and a third model added interest rates. He found that over a long term (in excess of two years) models two and three demonstrated less error and more accurately captures actual volatility with model one showing less long term volatility. Over short periods of time, such as the six month window the simulation covers, it is not clear that any one of the three models is dominant.

Gamerman (1997) defined simulation as "a treatment of a real world problem through reproduction in a computer environment." Generally, it will be a smaller scale replica of the system under study. He argued that it is an appropriate tool when some components of the system are subject to random fluctuation that can only be described by probability distributions. A Markov Chain (Markov chains were introduced by Andre Andreevich Markov. Markov was led to develop Markov chains as a natural extension of sequences of independent random variables) process is an effective addition to a simulation model when successive results depend on all their predecessors only through their immediate predecessors as in a price path with a randomness term such as a Wiener Process.

M. Miller (2001) cited simulation as a beneficial risk management tool enabled by computer technology in his paper surveying financial innovations since 1960's. Both Hull and Benninga recognize that Monte Carlo Simulation (a simulation of a stochastic process sampling random outcomes) can be used to price derivatives though Benninga does assert that simulation is really an experimental technique and in general should be avoided if another closed form solution is available.

Miller and Nentl (2003) defined simulation as a replica or model designed to represent an actual or theoretical reality. They reported simulation use in business education and training increases involvement and motivation and results in deeper comprehension, better retention, and students are more self- directed.

Cheng (2009) created and tested a simulation designed to teach option trading practices to novices. They modeled commodity prices as a mean reverting process (converging on marginal cost of production) and using a Wiener Process simulating movement. Cheng found his subjects did poorly on their initial trials but improved significantly with practice and repetition. He concluded that simulation is an effective training tool if there is an opportunity to experiment with alternative scenarios, play multiple times, and a knowledgeable facilitator debriefs the players by helping them to understand and analyze results.

METHODOLOGY

Price data was collected over a 20 year period (Appendix 1) and to mirror the simulation period, from November 2009 to October 2010 (Appendix 2). It was the latter data set that was used to calculate the estimated mean and standard deviation.

Three models of commodity price behavior were considered. A standard one factor model found in Hull, and a one and two factor model presented and studied by Schwartz. Upon reflection the Schwartz two factor model was abandoned for this project and for the time being. This choice will be addressed in the paper's closing comments. The two models selected for testing are presented in Figure 1 below.

The models are developed using math techniques that are expected to be beyond the technical capabilities of players / traders and likely a workshop facilitator (and possibly readers of this paper). My expectation is users of this game will accept the model embedded under the covers to be externally valid. This paper does present the math for readers interested in evaluating the model's fidelity. Professors teaching Finance at the graduate level will recognize these models to be variations of the Black Sholes Options Pricing Model – a standard valuation technique for several decades now and centerpiece of a Nobel Prize award.

The models are more similar than different. Model 2 includes a constant k that reflects the magnitude of the speed of adjustment of the log of the spot price reversion to the mean. The value 1.5 was selected for k based on personal experimentation using the empirical range in the Schwartz data set. Model 2 also assumes a lognormal distribution. For both models 1 and 2 were derived from the

Figure 1
Models of commodity price behavior

Model 1:

$S_t = ((\mu - r) * S_{t-1} * dt) + (\sigma * S_{t-1} * dz)) + S_{t-1}$

Notation:	S_t = Predicted spot price	$\mu = .1619$	r = opportunity cost of capital = .06
	drift = .10219	S_{t-1} = Predicted spot price	dt = time increment
	σ = daily	$\sigma * 252^{.5} = .28$	dz = normsinv (rand ()) * $dt^{.5}$

Model 2:

$S_t = (k * (\mu - (\sigma^2 / 2k)) + \sigma * dt^{.5} * dz)) + S_{t-1}$

Notation:	S_t = Predicted spot price	k = 1.5	$\mu = .1619$	σ = daily $\sigma * 252^{.5} = .28$
	drift = .10339	dt = time increment	dz = normsinv (rand ()) * $dt^{.5}$	

November 2009 – October 2010 data set presented as Appendix 2.

Both models are stochastic (probability driven rather than deterministic) Markov Process incorporating Wiener's mathematical representation of Brownian motion. Both models also include an Ito process (dx = α*dt + β*dz) in which variable α (the drift) and β (the variance) are functions of underlying data – in this case historical propane prices. It is assumed the drift rate is constant over the model period. The uncertainty however increases over time as a square root function of time.

Each model will be tested over a three month period (November 2010 to January 2011). The time period of 252 days is a common interval when evaluating options as it covers a complete year of variance that considers systematic cycles. Appendix 3 lists the actual spot price each day, the predicted spot price, and the error term. The Appendix also includes a graph of three predicted and actual prices over the 3 month period and a summary statistic – the Mean Absolute Deviation.

METHODOLOGY – TEST OF MODEL

Appendix 3 contains for both model 1 and model 2 a summary of the actual spot price during the modeling period along with the prediction and error. Each table concludes with summary statistics for actual mean, predicted mean, their respective sample standard deviations, and a mean average deviation. Model 2 appears to be a better predictor using this short term data set. While the 90 day mean was price was \$1.298, the average price predicted by model 1's price path is only \$1.175 compared to model 2's \$1.293. Models 2's mean average deviation was also closer to 0 (.0047 vs. .123) which is the expected MAD for an unbiased model.

A useful and often insightful evaluation of a model is a visual inspection. Again, turning to Appendix 3 a plot of predicted vs. actual spot prices over the model period shows model 2 tracks the price path better than model 1. The scatter plots of error terms appear to indicate a system bias for model 1 whereas model 2 seems to be closer to the ideal pattern of randomness.

Based on the summary statistics cited above and the derived scatter plots of model 1 and 2's respective performance, model 2 was selected as the engine for the simulation.

THE SIMULATION – OVERVIEW

The Story:

A simulated firm, "PropaneCo" is a distributer of propane fuel to residential and commercial markets. In 6 months they will need to take delivery of enough of the commodity to meet customer demand. They face the option of buying the propane as needed on the spot market, entering into a forward contract to purchase the commodity, or some combination of both.

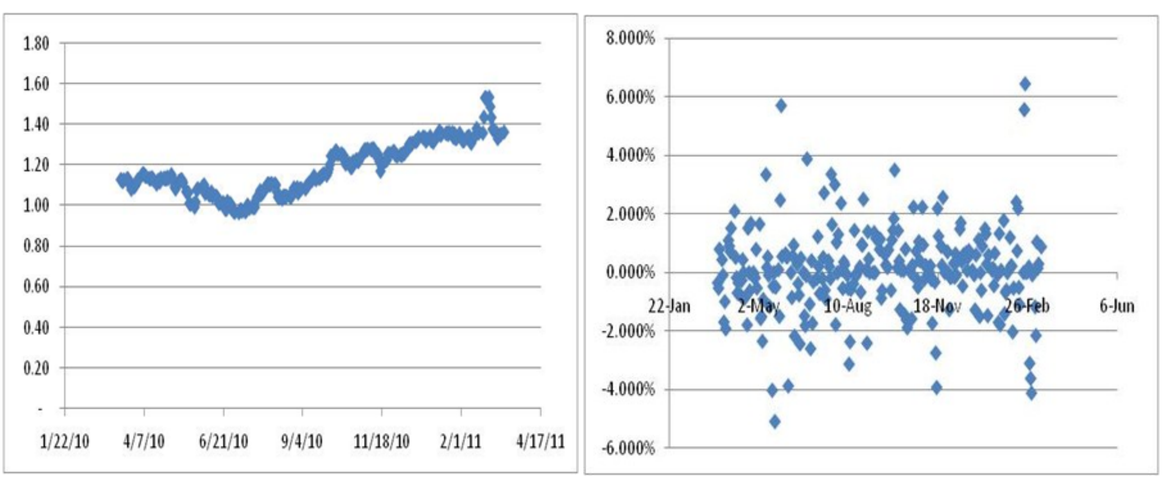
Data Sources:

Using historical demand, price, and interest rate data a probability distribution of demand will be developed with a mean of 1,000,000 gallons and variability modeled as a function of the actual variance. Spot and forward prices over the course of the simulation will be determined using a Monte Carlo process derived from actual price data over the past 1 year or 252 trading days. Spot prices and daily variability are displayed in Figure 2.

Decision Points:

At t_{-6} (6 months before delivery) the players will make a demand estimate.

Figure 2
Spot prices and daily variability



At t_{-6} the players will have an opportunity to accept or not accept a forward contract for X gallons at a price to be determined using a Monte Carlo simulated future price. Their decisions will range from contracting for enough to cover expected demand to rejecting the offer. If rejected, they can make a contract at t_{-5}, t_{-4}, or settle at t_0 at the spot price. Of course, the players will not know at this point what the forward price will be at t_{-5}, t_{-4}, or the spot price at t_0

At t_{-5}, they face the same choice as above – but only can defer to period t_{-4}.

At t_{-4}, they again have a similar decision, but if the forward contract is not accepted, they will need to buy at the spot price at t_0.

Results:

At the delivery date (t_0), a simulated sales price and "actual" demand will be generated – again using a Monte Carlo process as derived from historical data. The product of "actual" price times "actual" demand will be used to determine sales revenue. Cost of Goods Sold will be calculated using the input prices determined by the contracting decisions described above. If demand exceeds contracted supply at t_0 the excess will be filled at the t_0 spot price. Should demand be less than supply, the firm will accept delivery and incur storage and holding costs.

Expected Outcomes:

The practice and consequences of accurate forecasting will be reinforced.

Players will better understand the mechanics of a forward contract.

Using forward contracts (or other derivative instruments for that matter) need not be a speculative activity but an effective tool for managing risk.

Players will experience the sensitivity of demand, pricing, and input costs on the firm's financial results.

THE SIMULATION – DETAILS

The look and feel and navigation for the simulation named *Play it Forward* can be found as Appendix 5. To better understand this section my recommendation is for the reader to view Appendix 5, view the PowerPoint named *Play it Forward*, or better yet, experiment with the actual simulation file *Play it Forward*. (available from the author at craig.miller@normandale.edu) The simulation is based on an Excel platform and includes Visual Basic for Applications Code. For each decision period the player checks the spot price S_t and the simulation will generate a price using model 2 (presented in the methodology section). Because this model is a stochastic process, S_t will be unknown and vary as a function of a normal distribution represented by dz or N * t^.5. The assumed forward price, F_0, will be computed as $S_t e^{r\square t}$ and will converge to the spot price as time approaches the contract settlement date. The assigned value of r is 6% based on the reported short term borrowing rate of the client firm. In addition, the transaction cost of the forward contract was reported by the client firm as low – estimated at about 2 cents per gallon.

The expected value of a spot price at t_0 (six months hence) equals the current spot price plus the expected drift over the contract period. The annual drift using model 2 has been calculated to be .10339 which makes the expected spot price at t_0 = (1 + (.10339/2) = \$1.3672. From this information, I am recommending hedging with a forward contract if F_{ot} < \$1.3672. Using the optimal hedge formula from financial theory ($H^* = (\sigma_{actual} / \sigma_{predict}) * \rho$), the recommended hedge ratio is .82 (from (.0475 / .0473) * .81.) The standard deviations and correlation coefficient for model 2 data is derived and presented in Appendix 3.

After the player has made their hedging decisions at t_{-6}, t_{-5}, and t_{-4}, they game concludes by clicking the results button. A spot price for t_0 is derived from the simulation model as well as actual demand. Demand is derived in the simulation using Excel's normsinv (rand ()) function with μ and σ set to 1,000,000 and 200,000 respectively. These parameters were estimated by management of the client firm based on historical experience and future expectations.

Contribution margin is the sales revenue (final price is based on a 50 cent markup, per client direction) less cost of goods sold using a First in First out inventory flow model. Any inventory deficits will be remedied by purchasing at the T_0 spot price and excess inventory will be carried. For this game client management requested no holding costs be assessed as they would be negligible.

Finally the game compares the contribution income based on player decisions and that of an unhedged play. My hypothesis is if a player follows the suggested decision rule using the recommended hedge ratio of .82, more often than not they will experience a greater contribution margin.

This hypothesis was tested and results are reported in Appendix 4. Based on 60 plays, the average gain for a hedging strategy was \$40,049. This difference was significant at a t score of 3.67. In addition, the proportion of "gains" vs. "losses" was 75% and was significant at a t score of 4.47.

RESULTS, CONCLUSIONS, AND REFLECTIONS

Generally, I am pleased with the project and feel the time invested will be valuable to my client and the learning I experienced is of great value to me. It is my belief that over repeated play (as is the pedagogy of a teaching and learning game/simulation) players will discover that combining a hedging strategy employing decision rules such as those advocated here will be profitable more often than not.

In addition, I feel this project will satisfy the objectives presented earlier:

The practice and consequences of accurate forecasting will be reinforced.

Players will better understand the mechanics of a forward contract.

Using forward contracts (or other derivative instruments for that matter) need not be a speculative activity but an effective tool for managing risk.

Players will experience the sensitivity of demand, pricing, and input costs on the firm's financial results.

In my future work I plan to examine, better understand, test, and perhaps deploy three other models. One is the Schwartz two-factor model incorporating the convenience yield. A second model that I read about that I find intriguing is a Gabillon Markovian two factor model using two Wiener Processes; the first a short term mean reversion factor and the second is a slower long term mean reversion factor. A third area of exploration is the family of jump-diffusion models first introduced by Merton and now being more rigorously developed in response to the extreme price behavior experienced recently in some of the security markets. As I understand it, this addition of low probability extreme events suits the types of simulations I create.

With the elimination time constraints and the limits of my current technical abilities (I plan to continue working on my math), I expect to be able to able to assess and produce more sophisticated models. A big step is to know what you don't know.

The tool was employed several times in a workshop setting during the summer of 2011. Comments by both the facitiator, the participants, and sponsor were positive. To me, that suggests the game was fun and made a cplocated environment more understandable. The players that used the suggested trading rules did aceive results similar to the expected values presented earlier. The actual data was not collected, the sample size was small (approximately 30 players), andthu the extent of followup analysis is limited. An opportunity does exist to create a better controlled design making a richer statisitical analysis possible.

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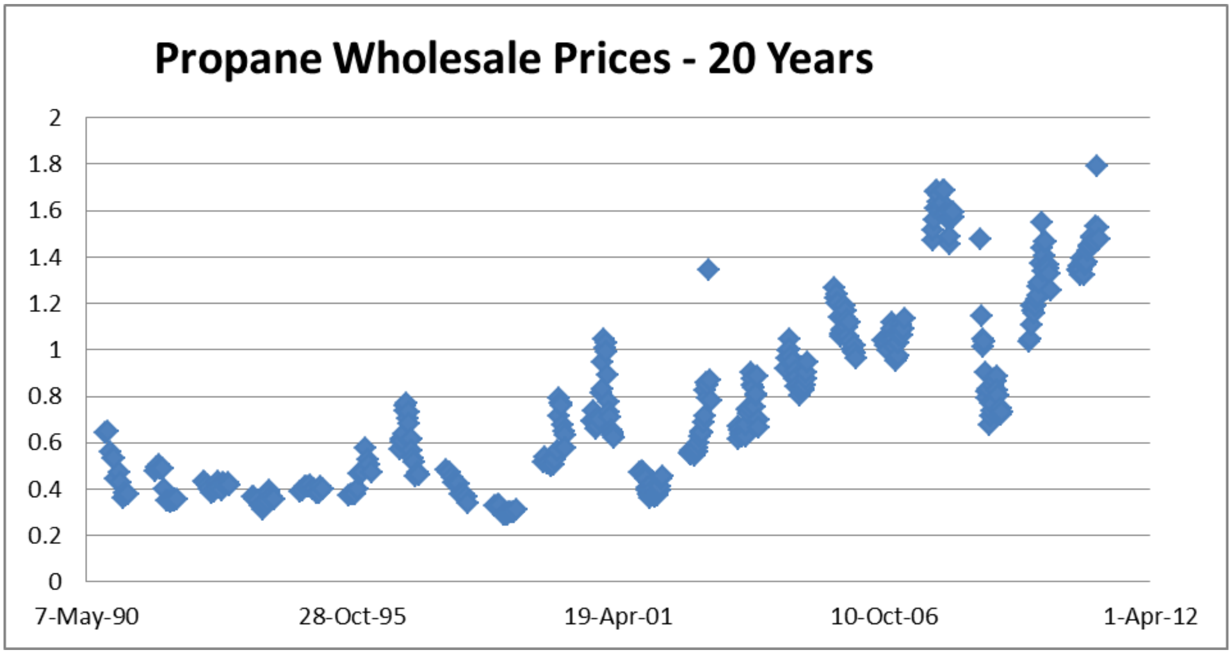
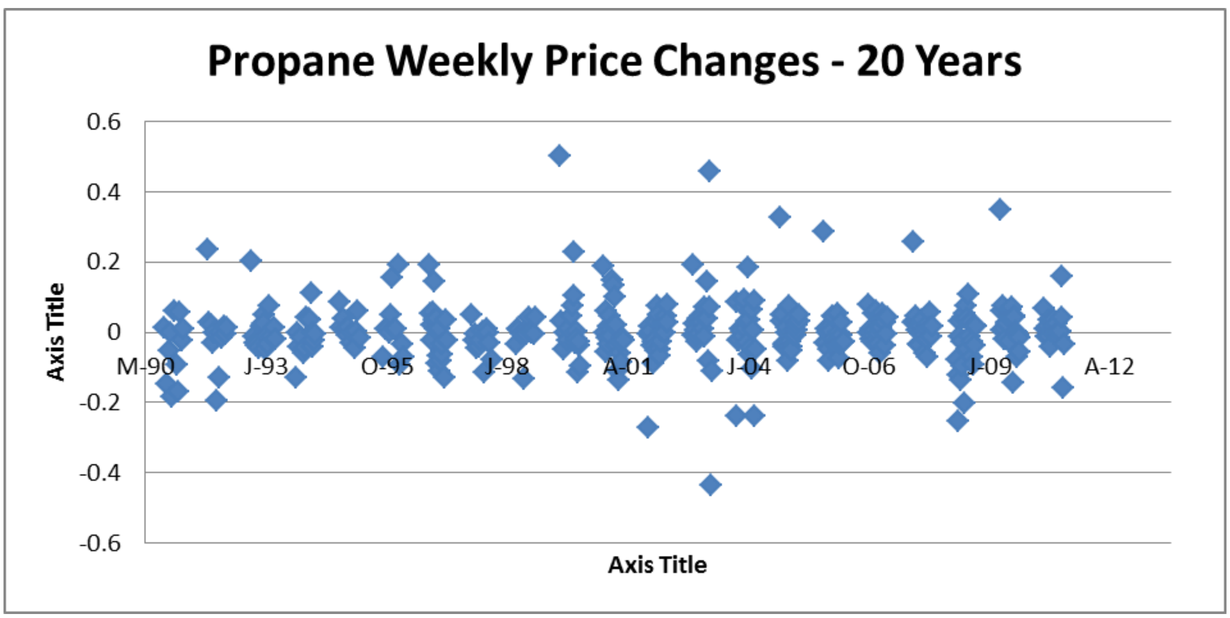
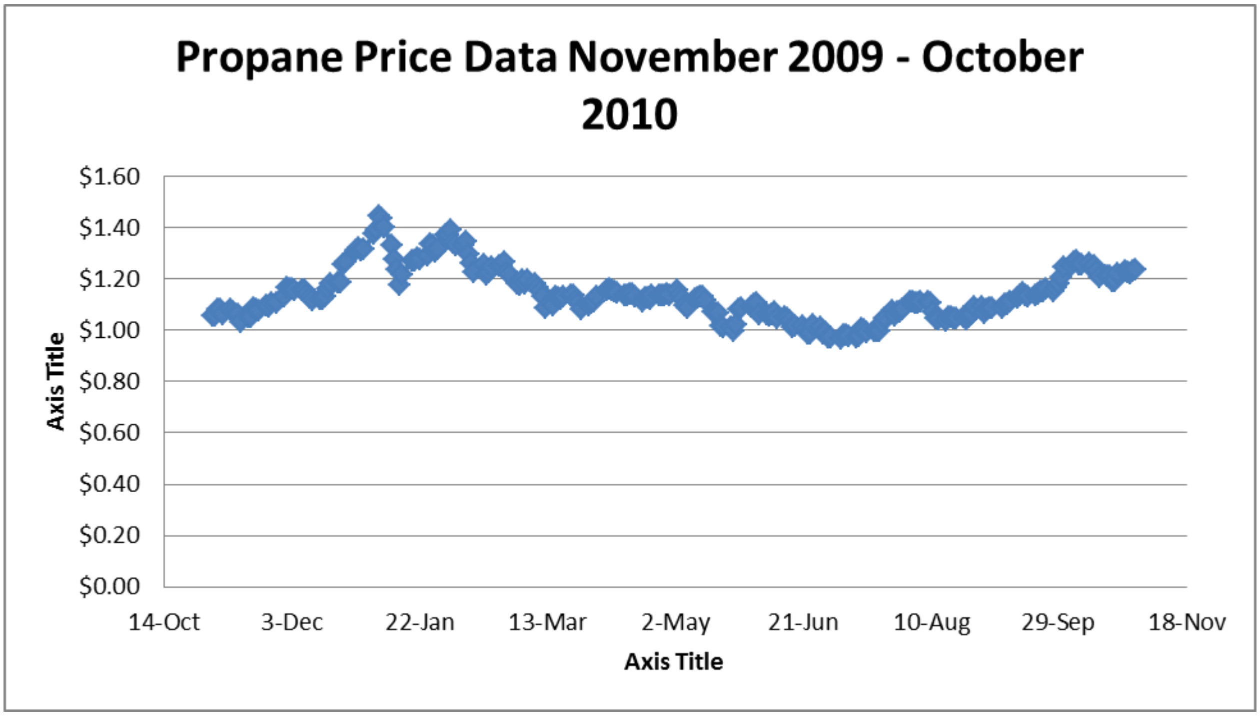
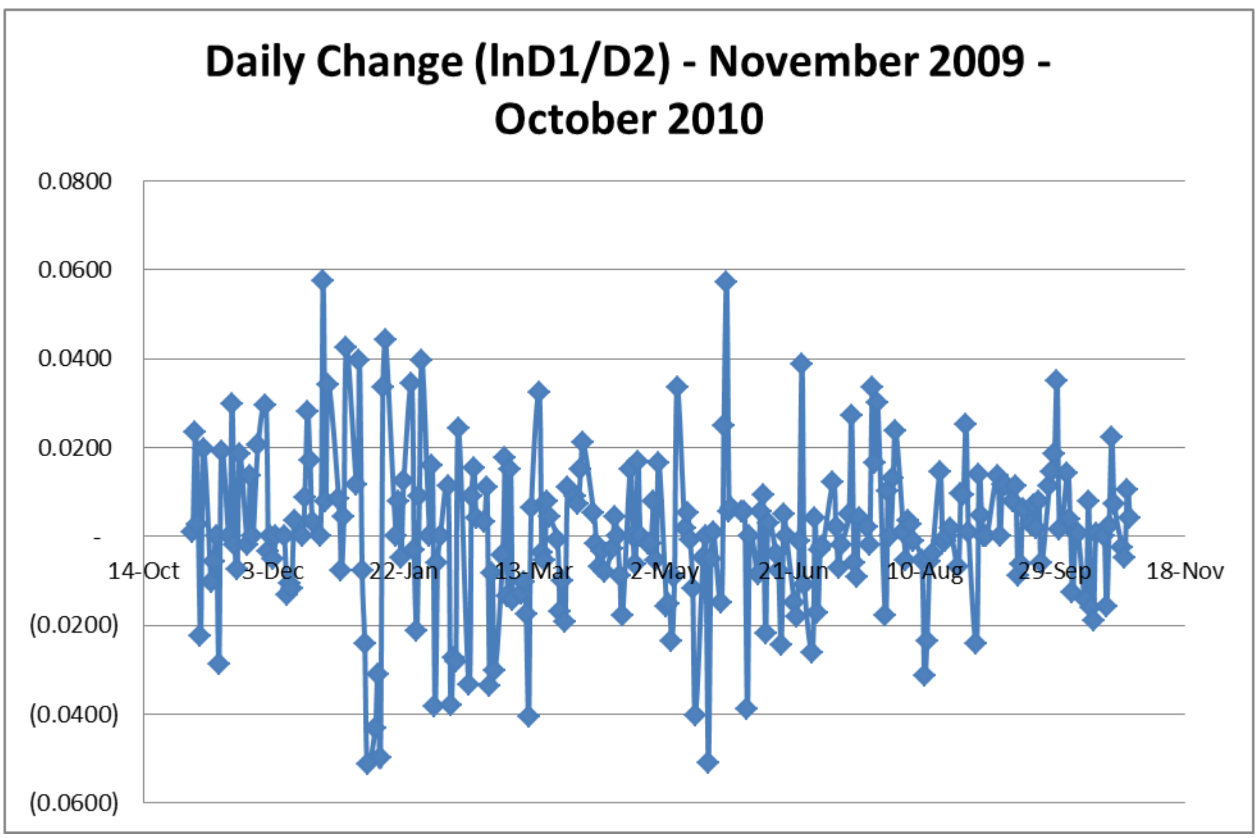
Appendix 1
Wholesale Prices – 20 years





Appendix 2
Spot Prices – November 2009 – October 2010



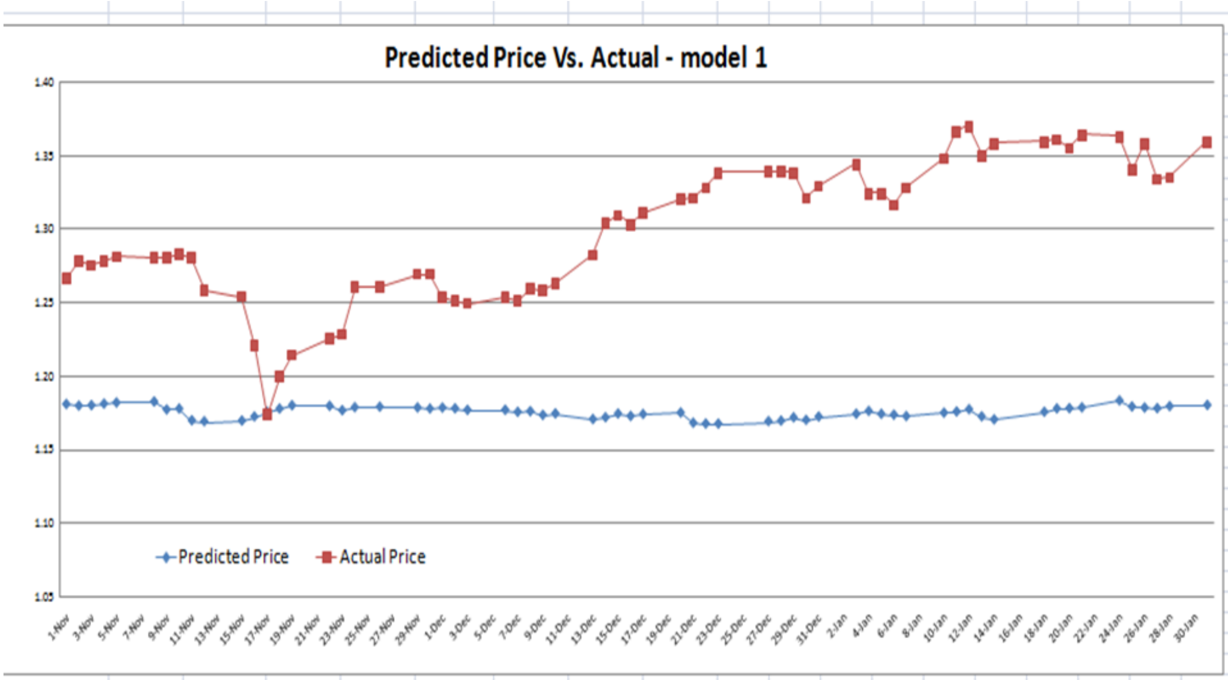


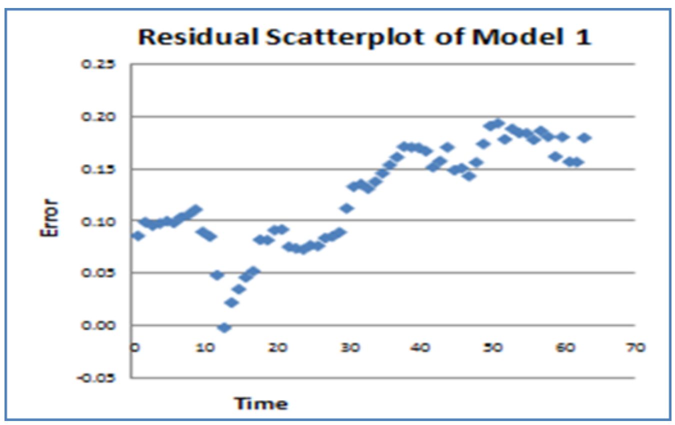
Data	Spot Price	Data	Spot Price
2-Nov	1.0540	1-Mar	1.1790
3-Nov	1.0550	2-Mar	1.1740
4-Nov	1.0800	3-Mar	1.1950
5-Nov	1.0830	4-Mar	1.1790
6-Nov	1.0590	5-Mar	1.1970
9-Nov	1.0800	8-Mar	1.1800
10-Nov	1.0690	9-Mar	1.1650
11-Nov	1.0630	10-Mar	1.1530
12-Nov	1.0630	11-Mar	1.1330
13-Nov	1.0330	12-Mar	1.0880
16-Nov	1.0530	15-Mar	1.0950
17-Nov	1.0530	16-Mar	1.1310
18-Nov	1.0850	17-Mar	1.1270
19-Nov	1.0830	18-Mar	1.1210
20-Nov	1.0750	19-Mar	1.1300
23-Nov	1.0950	22-Mar	1.1350
24-Nov	1.0930	23-Mar	1.1340
25-Nov	1.1080	24-Mar	1.1150
27-Nov	1.1080	25-Mar	1.1040
30-Nov	1.1310	26-Mar	1.0830
1-Dec	1.1650	29-Mar	1.0950
2-Dec	1.1610	30-Mar	1.1050
3-Dec	1.1610	31-Mar	1.1130
4-Dec	1.1550	1-Apr	1.1300
7-Dec	1.1550	5-Apr	1.1540
8-Dec	1.1550	6-Apr	1.1600
9-Dec	1.1400	7-Apr	1.1580
10-Dec	1.1280	8-Apr	1.1500
11-Dec	1.1150	9-Apr	1.1460
14-Dec	1.1190	12-Apr	1.1370
15-Dec	1.1190	13-Apr	1.1340
16-Dec	1.1290	14-Apr	1.1390
17-Dec	1.1610	15-Apr	1.1390
18-Dec	1.1810	16-Apr	1.1290
21-Dec	1.1850	19-Apr	1.1090
22-Dec	1.1850	20-Apr	1.1260
23-Dec	1.2550	21-Apr	1.1260
24-Dec	1.2650	22-Apr	1.1190
28-Dec	1.3090	23-Apr	1.1380
29-Dec	1.3200	26-Apr	1.1380
30-Dec	1.3100	27-Apr	1.1360
31-Dec	1.3160	28-Apr	1.1340
4-Jan	1.3730	29-Apr	1.1430
5-Jan	1.3890	30-Apr	1.1370
6-Jan	1.4450	3-May	1.1560
7-Jan	1.4340	4-May	1.1380

Data	Spot Price	Data	Spot Price	Data
5-Jan	1.3890	30-Apr	1.1370	1-Sep
6-Jan	1.4450	3-May	1.1560	2-Sep
7-Jan	1.4340	4-May	1.1380	3-Sep
8-Jan	1.4000	5-May	1.1210	7-Sep
11-Jan	1.3300	6-May	1.0950	8-Sep
12-Jan	1.2740	7-May	1.0850	9-Sep
13-Jan	1.2350	10-May	1.1220	10-Sep
14-Jan	1.1750	11-May	1.1240	13-Sep
15-Jan	1.2150	12-May	1.1300	14-Sep
19-Jan	1.2700	13-May	1.1290	15-Sep
20-Jan	1.2700	14-May	1.1160	16-Sep
21-Jan	1.2800	17-May	1.0720	17-Sep
22-Jan	1.2740	18-May	1.0670	20-Sep
25-Jan	1.2900	19-May	1.0670	21-Sep
26-Jan	1.3350	20-May	1.0140	22-Sep
27-Jan	1.3310	21-May	1.0090	23-Sep
28-Jan	1.3030	24-May	1.0100	24-Sep
29-Jan	1.3150	25-May	0.9950	27-Sep
1-Feb	1.3680	26-May	1.0200	28-Sep
2-Feb	1.3680	27-May	1.0800	29-Sep
3-Feb	1.3900	28-May	1.0860	30-Sep
4-Feb	1.3380	1-Jun	1.0930	1-Oct
5-Feb	1.3300	2-Jun	1.0990	4-Oct
8-Feb	1.3300	3-Jun	1.1050	5-Oct
9-Feb	1.3450	4-Jun	1.0630	6-Oct
10-Feb	1.2950	7-Jun	1.0630	7-Oct
11-Feb	1.2600	8-Jun	1.0540	8-Oct
12-Feb	1.2250	9-Jun	1.0600	11-Oct
16-Feb	1.2550	10-Jun	1.0700	12-Oct
17-Feb	1.2140	11-Jun	1.0470	13-Oct
18-Feb	1.2250	14-Jun	1.0500	14-Oct
19-Feb	1.2440	15-Jun	1.0460	15-Oct
22-Feb	1.2490	16-Jun	1.0380	18-Oct
23-Feb	1.2530	17-Jun	1.0130	19-Oct
24-Feb	1.2670	18-Jun	1.0180	20-Oct
25-Feb	1.2250	21-Jun	1.0180	21-Oct
26-Feb	1.2150	22-Jun	1.0030	22-Oct
		23-Jun	0.9850	25-Oct
		24-Jun	0.9840	26-Oct
		25-Jun	1.0230	27-Oct
		28-Jun	1.0120	28-Oct
		29-Jun	0.9860	29-Oct
		30-Jun	0.9900	

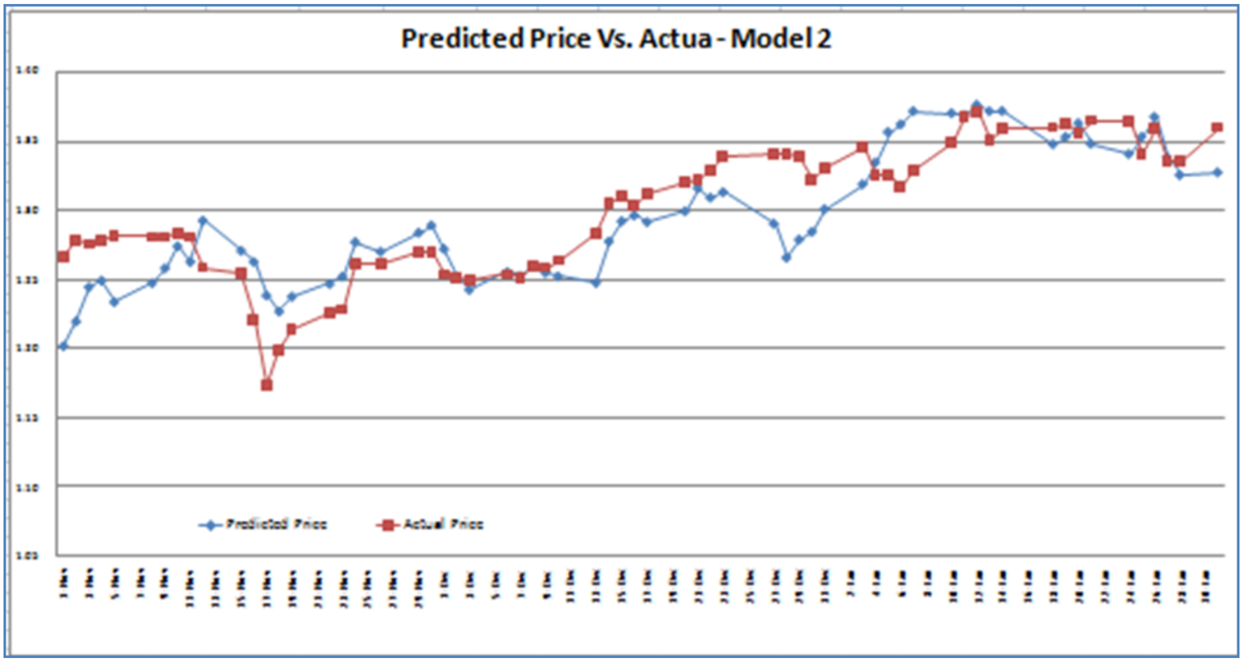
Appendix 3
Tests of Models

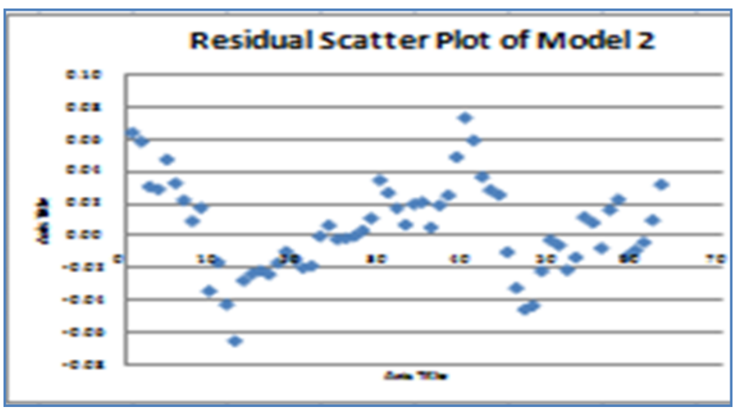
Test of Model 1						
Date	Actual	mean predict	Error		Date	Actual
11/1/2010	1.266	1.1804	0.0856		12/15/2010	1.309
11/2/2010	1.278	1.1794	0.0986		12/16/2010	1.303
11/3/2010	1.275	1.1797	0.0953		12/17/2010	1.311
11/4/2010	1.278	1.1807	0.0973		12/20/2010	1.320
11/5/2010	1.281	1.1815	0.0995		12/21/2010	1.321
11/8/2010	1.280	1.1822	0.0978		12/22/2010	1.328
11/9/2010	1.280	1.1768	0.1032		12/23/2010	1.338
11/10/2010	1.283	1.1774	0.1056		12/27/2010	1.339
11/11/2010	1.280	1.1694	0.1106		12/28/2010	1.339
11/12/2010	1.258	1.1688	0.0892		12/29/2010	1.338
11/15/2010	1.254	1.1692	0.0848		12/30/2010	1.321
11/16/2010	1.220	1.1720	0.0480		12/31/2010	1.329
11/17/2010	1.173	1.1752	(0.0022)		1/3/2011	1.344
11/18/2010	1.199	1.1774	0.0216		1/4/2011	1.324
11/19/2010	1.214	1.1796	0.0344		1/5/2011	1.324
11/22/2010	1.225	1.1793	0.0457		1/6/2011	1.316
11/23/2010	1.228	1.1762	0.0518		1/7/2011	1.328
11/24/2010	1.260	1.1783	0.0817		1/10/2011	1.348
11/26/2010	1.260	1.1787	0.0813		1/11/2011	1.366
11/29/2010	1.269	1.1781	0.0909		1/12/2011	1.370
11/30/2010	1.269	1.1774	0.0916		1/13/2011	1.350
12/1/2010	1.253	1.1780	0.0750		1/14/2011	1.358
12/2/2010	1.251	1.1776	0.0734		1/18/2011	1.359
12/3/2010	1.249	1.1765	0.0725		1/19/2011	1.361
12/6/2010	1.253	1.1766	0.0764		1/20/2011	1.355
12/7/2010	1.251	1.1751	0.0759		1/21/2011	1.364
12/8/2010	1.259	1.1756	0.0834		1/24/2011	1.363
12/9/2010	1.258	1.1731	0.0849		1/25/2011	1.340
12/10/2010	1.263	1.1741	0.0889		1/26/2011	1.358


Predicted Price Vs. Actual - model 1
Predicted Price
Actual Price


Residual Scatterplot of Model 1
Error
Time

Test of Model 2						
Date	Actual	mean predict	Error	Date	Actual	mean predict
11/1/2010	1.2660	1.2021	0.0639	12/15/2010	1.3090	1.2921
11/2/2010	1.2780	1.2197	0.0583	12/16/2010	1.3030	1.2963
11/3/2010	1.2750	1.2446	0.0304	12/17/2010	1.3110	1.2915
11/4/2010	1.2780	1.2493	0.0287	12/20/2010	1.3200	1.2993
11/5/2010	1.2810	1.2338	0.0472	12/21/2010	1.3210	1.3160
11/8/2010	1.2800	1.2474	0.0326	12/22/2010	1.3280	1.3091
11/9/2010	1.2800	1.2582	0.0218	12/23/2010	1.3380	1.3131
11/10/2010	1.2830	1.2740	0.0090	12/27/2010	1.3390	1.2903
11/11/2010	1.2800	1.2628	0.0172	12/28/2010	1.3390	1.2659
11/12/2010	1.2580	1.2925	(0.0345)	12/29/2010	1.3380	1.2789
11/15/2010	1.2540	1.2707	(0.0167)	12/30/2010	1.3210	1.2846
11/16/2010	1.2200	1.2628	(0.0428)	12/31/2010	1.3290	1.3007
11/17/2010	1.1730	1.2385	(0.0655)	1/3/2011	1.3440	1.3188
11/18/2010	1.1990	1.2270	(0.0280)	1/4/2011	1.3240	1.3344
11/19/2010	1.2140	1.2377	(0.0237)	1/5/2011	1.3240	1.3565
11/22/2010	1.2250	1.2469	(0.0219)	1/6/2011	1.3160	1.3621
11/23/2010	1.2280	1.2521	(0.0241)	1/7/2011	1.3280	1.3715
11/24/2010	1.2600	1.2771	(0.0171)	1/10/2011	1.3480	1.3701
11/26/2010	1.2600	1.2700	(0.0100)	1/11/2011	1.3660	1.3687
11/29/2010	1.2690	1.2838	(0.0148)	1/12/2011	1.3700	1.3760
11/30/2010	1.2690	1.2890	(0.0200)	1/13/2011	1.3500	1.3714
12/1/2010	1.2530	1.2720	(0.0190)	1/14/2011	1.3580	1.3716
12/2/2010	1.2510	1.2515	(0.0005)	1/18/2011	1.3590	1.3476
12/3/2010	1.2490	1.2427	0.0063	1/19/2011	1.3610	1.3531
12/6/2010	1.2530	1.2554	(0.0024)	1/20/2011	1.3550	1.3628
12/7/2010	1.2510	1.2527	(0.0017)	1/21/2011	1.3640	1.3480
12/8/2010	1.2590	1.2595	(0.0005)	1/24/2011	1.3630	1.3406
12/9/2010	1.2580	1.2549	0.0031	1/25/2011	1.3400	1.3530
12/10/2010	1.2630	1.2523	0.0107	1/26/2011	1.3580	1.3673
12/13/2010	1.2820	1.2476	0.0344	1/27/2011	1.3340	1.3382
12/14/2010	1.3040	1.2775	0.0265	1/28/2011	1.3350	1.3254


Predicted Price Vs. Actua - Model 2
Predicted Price
Actual Price

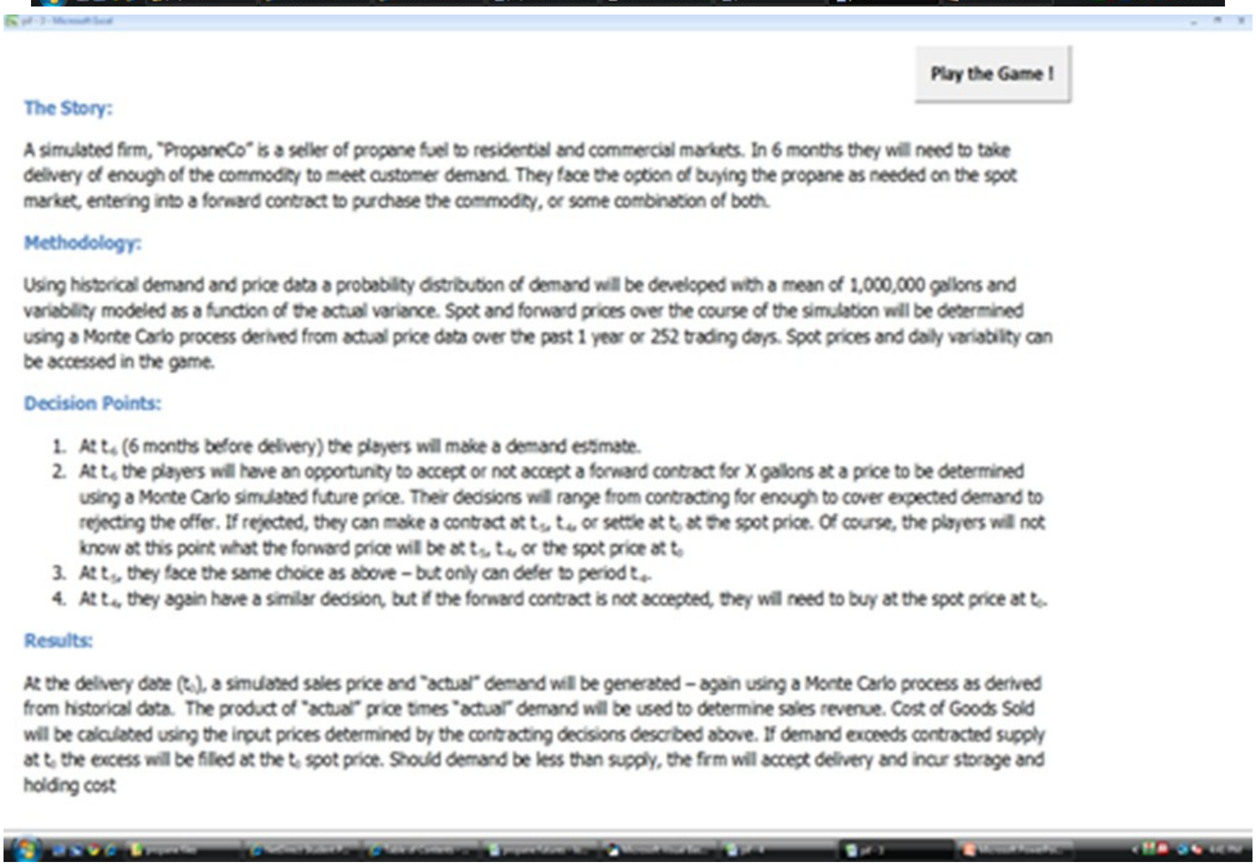

Residual Scatter Plot of Model 2

Appendix 4
Tests of Models

Test of Mean and Proportion when applying a decision rule to the simulation
null hypothesis: mean = 0, proportion = .5

12,716		(70,548)			
(70,548)		61,433		Test of mean:	
(98,120)		73,195			
1,709		60,017		sample mean:	40,049
217,144		(97,572)		sample std:	84,613
120,287		43,053		std error:	10,923
110,366		20,183			
89,553		(71,986)		t stat	3.67
97,555		69,036			
187,922		54,487			
100,879		(66,227)		Test of proportion:	
(50,825)		234,210			
27,143		8,640		sample proportion:	0.25
3,232		26,303			
110,647		(32,438)		std error:	0.0559
117,459		124,305			
107,626		(8,839)		tstat:	4.47
6,953		45,790			
85,452		80,228			
229,879		(31,979)			
(114,875)		45,821			
101,284		34,394			
(88,092)		104,979			
130,603		34,073			
(116,888)		157,161			
103,122		45,279			
(21,355)		(58,147)			
(9,020)		(69,309)			
40,294		34,338			
17,406		103,554			

Appendix 5
Model Screen Shots



Play the Game !

The Story:

A simulated firm, "PropaneCo" is a seller of propane fuel to residential and commercial markets. In 6 months they will need to take delivery of enough of the commodity to meet customer demand. They face the option of buying the propane as needed on the spot market, entering into a forward contract to purchase the commodity, or some combination of both.

Methodology:

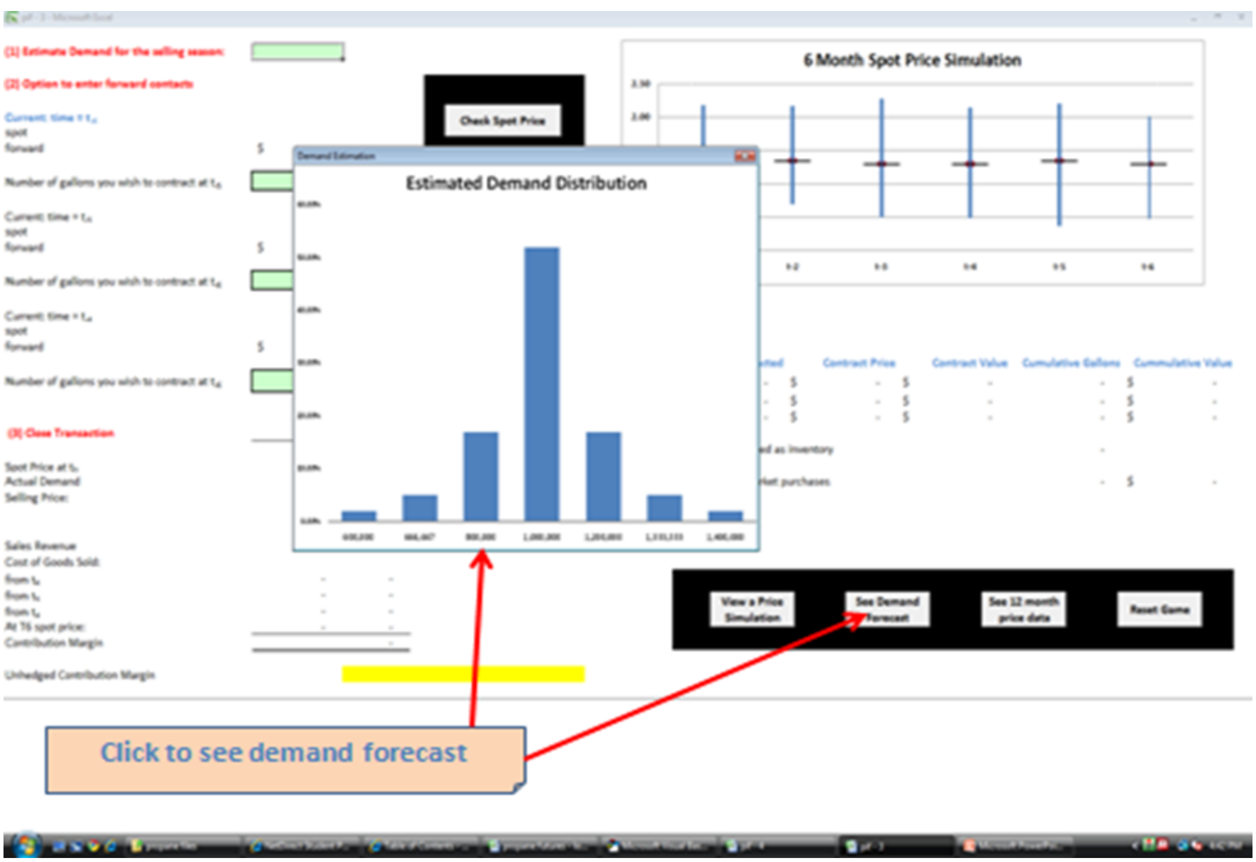
Using historical demand and price data a probability distribution of demand will be developed with a mean of 1,000,000 gallons and variability modeled as a function of the actual variance. Spot and forward prices over the course of the simulation will be determined using a Monte Carlo process derived from actual price data over the past 1 year or 252 trading days. Spot prices and daily variability can be accessed in the game.

Decision Points:

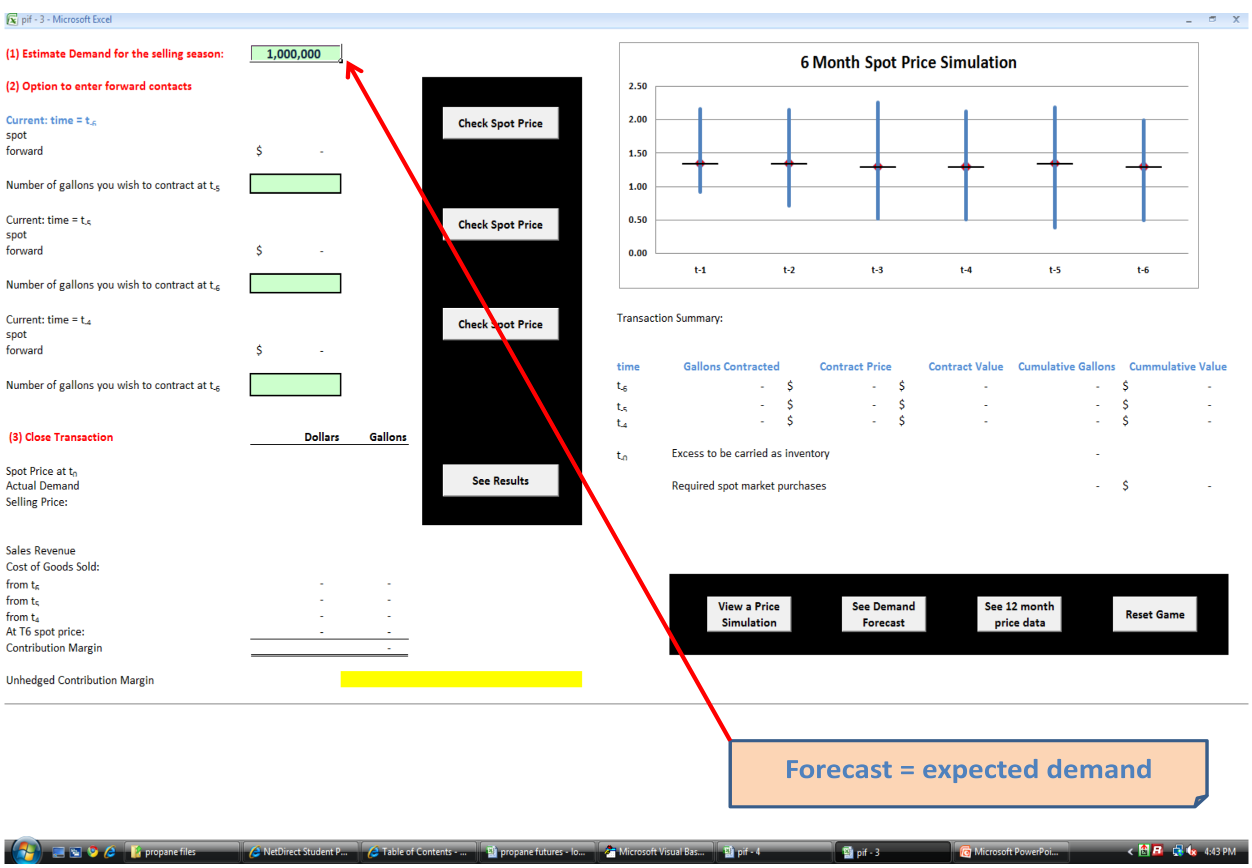
1. At t_6 (6 months before delivery) the players will make a demand estimate.
2. At t_6 the players will have an opportunity to accept or not accept a forward contract for X gallons at a price to be determined using a Monte Carlo simulated future price. Their decisions will range from contracting for enough to cover expected demand to rejecting the offer. If rejected, they can make a contract at t_5, t_4, or settle at t_0 at the spot price. Of course, the players will not know at this point what the forward price will be at t_5, t_4, or the spot price at t_0
3. At t_5, they face the same choice as above – but only can defer to period t_4.
4. At t_4, they again have a similar decision, but if the forward contract is not accepted, they will need to buy at the spot price at t_0.

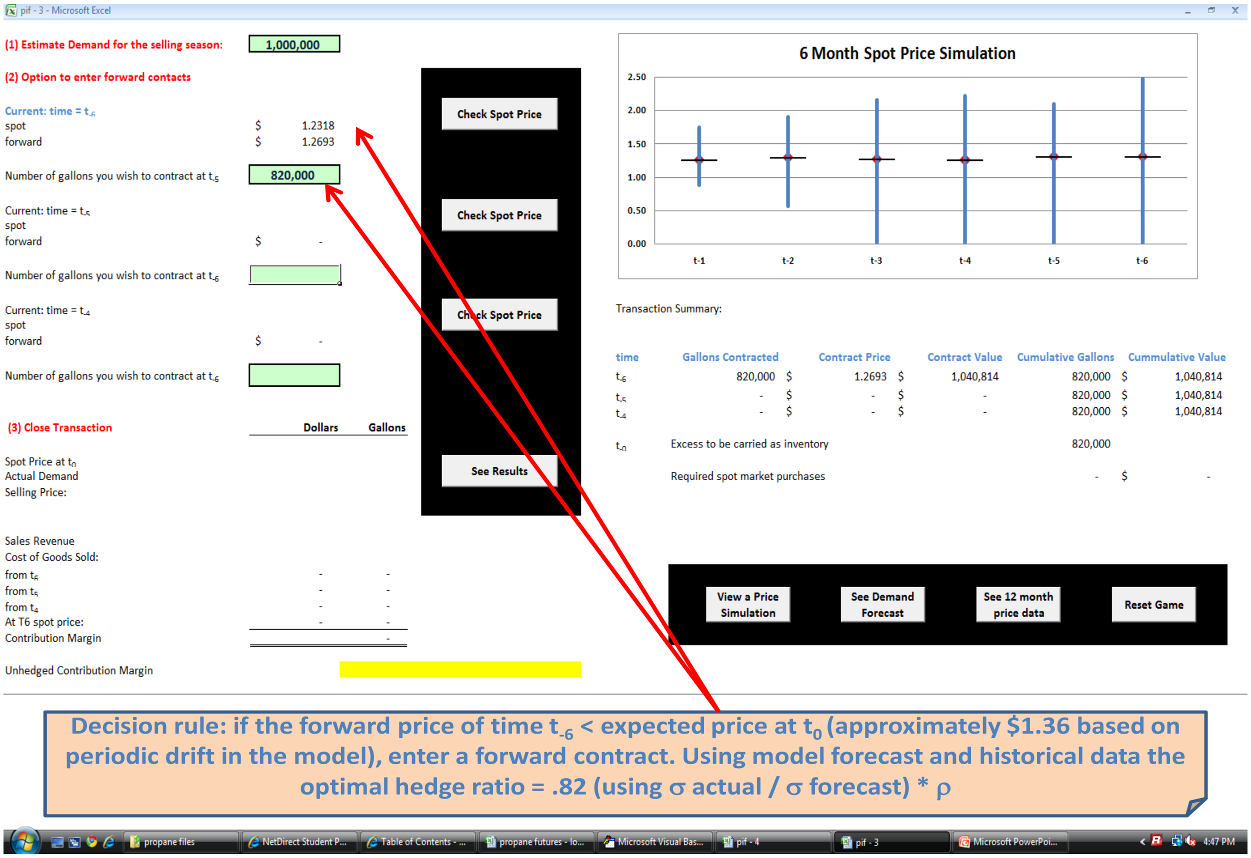
Results:

At the delivery date (t_0), a simulated sales price and "actual" demand will be generated – again using a Monte Carlo process as derived from historical data. The product of "actual" price times "actual" demand will be used to determine sales revenue. Cost of Goods Sold will be calculated using the input prices determined by the contracting decisions described above. If demand exceeds contracted supply at t_0 the excess will be filled at the t_0 spot price. Should demand be less than supply, the firm will accept delivery and incur storage and holding cost


Click to see demand forecast


(1) Estimate Demand for the selling season:
(2) Option to enter forward contacts
Current: time = t6
spot
forward
Number of gallons you wish to contract at t6
Current: time = t5
Number of gallons you wish to contract at t5
Current: time = t4
Number of gallons you wish to contract at t4
(3) Close Transaction
Spot Price at tn
Actual Demand
Selling Price:
Sales Revenue
Cost of Goods Sold:
At T6 spot price:
Contribution Margin
Unhedged Contribution Margin
Price data for past 12 months
Price Data - past 12 months
6 Month Spot Price Simulation
Summary:
Gallons Contracted
Contract Price
Contract Value
Cumulative Gallons
Cummulative Value
Excess to be carried as inventory
Required spot market purchases
View a Price Simulation
See Demand Forecast
See 12 month price data
Reset Game
Click to see price history


(1) Estimate Demand for the selling season:
1,000,000
(2) Option to enter forward contacts
Check Spot Price
Check Spot Price
Check Spot Price
See Results
(3) Close Transaction
Dollars
Gallons
6 Month Spot Price Simulation
Transaction Summary:
time
Gallons Contracted
Contract Price
Contract Value
Cumulative Gallons
Cummulative Value
Excess to be carried as inventory
Required spot market purchases
View a Price Simulation
See Demand Forecast
See 12 month price data
Reset Game
Unhedged Contribution Margin
Forecast = expected demand


pif - 3 - Microsoft Excel
(1) Estimate Demand for the selling season:
1,000,000
(2) Option to enter forward contacts
Current: time = t_{-6}
spot $ 1.2318
forward $ 1.2693
Number of gallons you wish to contract at t_{-5}
820,000
Current: time = t_{-5}
spot
forward $ -
Number of gallons you wish to contract at t_{-6}
Current: time = t_{-4}
spot
forward $ -
Number of gallons you wish to contract at t_{-6}
(3) Close Transaction
Dollars
Gallons
Spot Price at t_0
Actual Demand
Selling Price:
Sales Revenue
Cost of Goods Sold:
from t_{-6}
from t_{-5}
from t_{-4}
At T6 spot price:
Contribution Margin
Unhedged Contribution Margin
Check Spot Price
Check Spot Price
Check Spot Price
See Results
6 Month Spot Price Simulation
2.50
2.00
1.50
1.00
0.50
0.00
t-1
t-2
t-3
t-4
t-5
t-6
Transaction Summary:
time
Gallons Contracted
Contract Price
Contract Value
Cumulative Gallons
Cummulative Value
t_{-6} 820,000 $ 1.2693 $ 1,040,814 820,000 $ 1,040,814
t_{-5} - $ - $ - 820,000 $ 1,040,814
t_{-4} - $ - $ - 820,000 $ 1,040,814
t_0 Excess to be carried as inventory 820,000
Required spot market purchases - $ -
View a Price Simulation
See Demand Forecast
See 12 month price data
Reset Game
Decision rule: if the forward price of time t_{-6} < expected price at t_0 (approximately $1.36 based on periodic drift in the model), enter a forward contract. Using model forecast and historical data the optimal hedge ratio = .82 (using σ actual / σ forecast) * ρ
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pif - 3
Microsoft PowerPoi...
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pif - 3 - Microsoft Excel
(1) Estimate Demand for the selling season:
1,000,000
(2) Option to enter forward contacts
Current: time = t_{-6}
spot $ 1.2318
forward $ 1.2693
Number of gallons you wish to contract at t_{-5}
820,000
Current: time = t_{-5}
spot $ 1.3001
forward $ 1.3464
Number of gallons you wish to contract at t_{-6}
Current: time = t_{-4}
spot
forward $ -
Number of gallons you wish to contract at t_{-6}
(3) Close Transaction
Dollars
Gallons
Spot Price at t_0
Actual Demand
Selling Price:
Sales Revenue
Cost of Goods Sold:
from t_{-6}
from t_{-5}
from t_{-4}
At T6 spot price:
Contribution Margin
Unhedged Contribution Margin
Check Spot Price
Check Spot Price
Check Spot Price
See Results
6 Month Spot Price Simulation
2.50
2.00
1.50
1.00
0.50
0.00
t-1
t-2
t-3
t-4
t-5
t-6
Transaction Summary:
time
Gallons Contracted
Contract Price
Contract Value
Cumulative Gallons
Cummulative Value
t_{-6} 820,000 $ 1.2693 $ 1,040,814 820,000 $ 1,040,814
t_{-5} - $ 1.3464 $ - 820,000 $ 1,040,814
t_{-4} - $ - $ - 820,000 $ 1,040,814
t_0 Excess to be carried as inventory 820,000
Required spot market purchases - $ -
View a Price Simulation
See Demand Forecast
See 12 month price data
Reset Game
Decision rule: if the forward price of time t_{-6} < expected price at t_0 (approximately $1.36 based on periodic drift in the model), enter a forward contract. A judgment here was made not to contract at this price.
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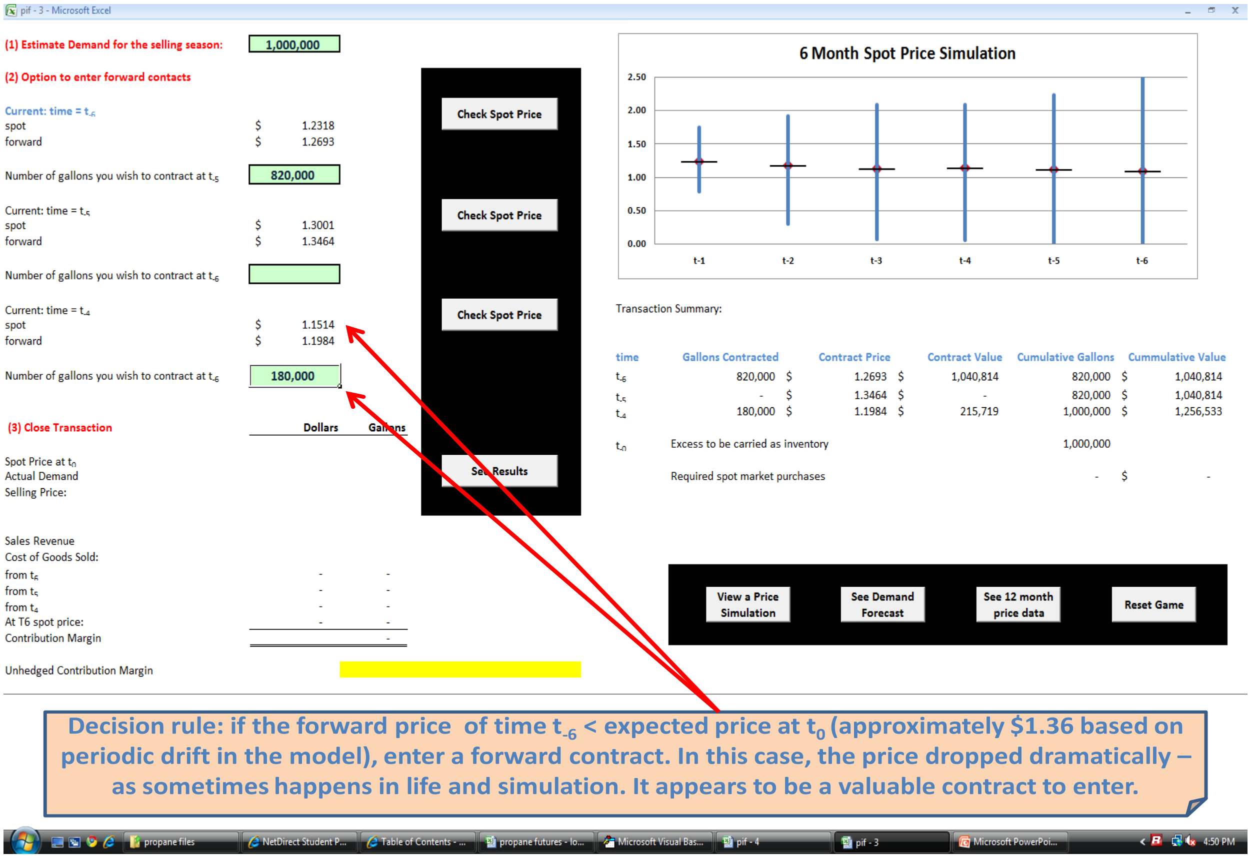
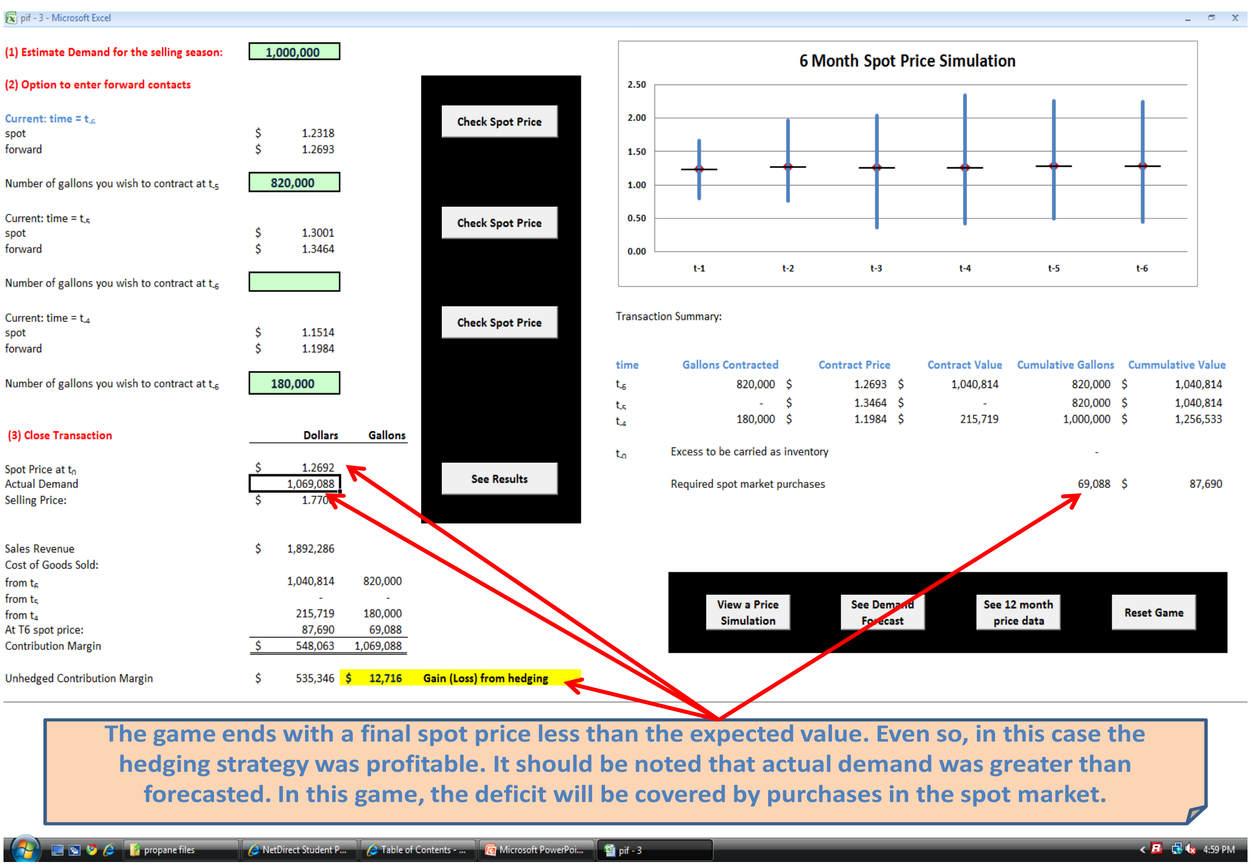


Decision rule: if the forward price of time t_{-6} < expected price at t_0 (approximately $1.36 based on periodic drift in the model), enter a forward contract. In this case, the price dropped dramatically – as sometimes happens in life and simulation. It appears to be a valuable contract to enter.



The game ends with a final spot price less than the expected value. Even so, in this case the hedging strategy was profitable. It should be noted that actual demand was greater than forecasted. In this game, the deficit will be covered by purchases in the spot market.