Assessment of Price Risk on Agricultural Inventory Credit under Sparse Data Conditions

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Resumen

El crédito prendario es ampliamente utilizado como un instrumento para satisfacer las necesidades de capital de trabajo. Existen metodologías para evaluar el riesgo de precio para estos esquemas crediticios, tales como modificaciones de valor en riesgo (VaR) . La mayoría de estos métodos se basan en supuestos de distribución. Sin embargo, cuando el número de observaciones es bajo es difícil refugiarse en el teorema del límite central. La contribución de este trabajo es proponer una metodología para estimar el riesgo de precios a la baja, incluso en presencia de datos escasos. El uso de la metodología se

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ilustra con el análisis de precios para un producto en particular. El propósito de este modelo de simulación es proporcionar información de apoyo para la toma de decisiones en los procesos de concesión de crédito.

Palabras clave: crédito prendario, evaluación de riesgo precio, métodos no paramétricos, simulación.
JEL: B41, C14, C15, C18, C40, C53, C63

I. Introduction

Inventory credit is not a new concept. However, it is still considered a way of overcoming financing constraints and it is widely used in Latin American countries and in some Asian countries. Inventory credit refers to the use of stock or inventory, as collateral to raise finance. In developing countries banks may be reluctant to accept traditional collateral, for example where land title may be lacking, or when the borrower does not have additional collateral (Coutler and Sheperd, 1995).

The focus of this paper is on agricultural inventory credit in Mexico. In particular, the methodology is applied to conduct an analysis on beans. The methodology can easily be extended to analize different commodities. Following the usual method to apply for an inventory credit, the producer or borrower places the agricultural product in a certified warehouse. In exchange, the borrower receives a certificate that specifies the current value of the inventory placed in the warehouse. Next, borrower applies for bank credit, utilizing the certificate as collateral. Should a borrower defaults on a loan, a bank's recovery may depend on the value of the loan collateral at the time of the default (end of the credit lifetime).

As a risk management strategy, banks generally lend no more than 80% of the value of the certificate of collateral. However, for specific cases when the bank is willing to lend more than the usual 80%, certain conditions must be met by the borrower[1]. Credit history, risk rating of the activity and related risk concepts may need to be reviewed, in addition to price risk. In this paper, only price risk is analyzed, leaving the analysis of the rest of the factors to others.

A rich literature exists addressing issues relating to the measurement of price risk. In general, most farmers consider output prices to be their main source of risk, followed by yields and the input prices (Goodwin and Kastens, 1993).

There are methodologies that consider large series of historical prices to build a histogram of the frequencies of price decrease over a period of time. Usually 5 years of monthly prices are required to assess price risk. From this historical series a probability density can be adjusted to estimate the probability of a given percentage in price decrease (downside risk). However, in practice it is not uncommon to face the

[1] Methodologies used at a Bank.

problem of sparse data.

This paper proposes to use simulation techniques to estimate the afore-mentioned probabilities, not from historical series, but from probabilistic forecast that take into consideration the trend in price combined with the seasonal component of price. The working hypothesis is that by using the proposed approach the historic variability can be replicated in the simulation and thus an estimate of price risk can be obtained. In other words, the contribution of this paper would be to obtain an estimate of the desired probabilities even in the presence of sparse data.

II. Objective

The goal of this paper is to propose a methodology to estimate the probabilities of a price decreasing by a certain percentage with respect to the last observed historical price (the value of the collateral at the time of credit analysis), representing the potential magnitude of the loss. The model is a simple application of stochastic simulation techniques to develop a probabilistic forecast. Next, a modification of the Value at Risk (VaR) model will be used to estimate the downside risk for the desired timeframe. The contention is that these probabilities can reliably be obtained under small sample conditions.

III. Methodology

Generally, financial risk is classified into the broad categories of market risk, credit risk, liquidity risk, operational risk and sometimes legal risk. Market risk arises from movements in the level of volatility of market prices. VaR tools allow users to quantify market risk in a systematic fashion. As a formal definition, VaR is the measure of the worst expected loss over a given horizon under normal market conditions at a given confidence level. The main purpose of VAR systems is to assess market risk, which are due to changes in prices (Jorion, 2006).

As pointed out by Jorion (2006), downside risk can be measured by the quantiles of the distribution. Quantiles are defined as cutoff value q such that the area to the left represents a given probability c:

$$c = Prob\,(X \leq q) = \int_{-\infty}^{q} f(x)dx = F(x)$$

Perhaps the greatest advantages of VaR is that it summarizes in a single, easy to understand, number the downside risk due to change in prices of the collateral. Simulation is, by far, the most powerful method to compute VaR. Simulations generate the entire Probability Density Function (pdf), not just the quantile (Jorion, 2006). As such, it can be used to assess the probability of downside risk at any desired level.

It was mentioned earlier that a modification of the VaR was to be used in this paper. Such a modification consists of estimating the maximum probability of a certain loss (percentage decrease in price) instead of estimating the traditional VaR analysis described above. In other words, instead of calculating the quantile, the value of the cumulative distribution function will be calculated. That is, the probability of occurrence that the price falls to a critical level or less.

One of the shortcomings of VaR methodology is that it relies on normal distributions. One way to overcome this issue is to use empirical distributions. As defined by Vose (2000), an empirical distribution is a distribution whose mathematics is defined by the shape that is required. This author also points out that empirical distributions, or non-parametric distributions, are easy to understand, extremely flexible and are therefore very useful. Furthermore, he claims that parametric distributions should be used only under certain situations, as in the case where the theory underpinning the distribution applies to the particular problem at hand. Thus, he favors the use of non-parametric distributions over their parametric counterparts. Moreover, Horowitz (1993) has noted that there is seldom sufficient justification for assuming that the distribution of a random variable belongs to an assumed parametric family.

Additionally, observation of commodity prices as well as anecdotal evidence suggests that price distributions tend to be positively skewed. Further, the probabilities associated with extreme prices are generally greater than what is implied by a normal distribution. Thus, methods capable of accommodating departures from normality are needed. Non-parametric methods are an alternative (Goodwin and Ker, 2000). In the specific case of sparse data, since it is difficult to shelter in the central limit theorem, parameters for non-parametric empirical distributions will be estimated to simulate random variables. To justify the use of normal distributions in this paper, formal tests for normality will be conducted. In the case of not counting with statistical evidence to use normal distributions, empirical distributions will be used.

One further consideration with this model is the brief length of the forecast period and the short history of the data. Due to this, it becomes difficult to correlate prices to structural variables such as stock levels, supply shocks, agricultural policy changes, etc. In other words, the timeframe will be assumed to be a short run period, in which agricultural supply response due to change in prices is highly inelastic. For this reason, univariate estimation of price was favored over estimating the parameters of a structural regression to forecast price, since the latter option does not seem feasible.

Some of the important assumptions of this model are that inventory is the only source of repayment for the credit (no other collateral are available); due to uniqueness of the product it is not possible to get larger series of prices, nor a proxy of it; the borrower does not have the possibility to contract futures or options to manage risk (another consequence of product uniqueness in the market, where hedging could not exists); variability of prices in the future follow patterns of those in the recent past.

Specifically, the methodology to be used is described briefly as follows[2]:

[2] The description of the methodology in this section relies heavily on Richardson (2010).

1. Visual inspection of the data to identify trends.

A trend is understood to be a general up or down movement in the values of a time series over the historical period of observation. Most economic data contains at least one trend (increasing, decreasing or flat trends). A trend represents long-term growth or decay.

2. Run a trend regression. This will result in the deterministic component of the equation to be simulated later on.

If trend is not statistically significant, the historical mean of the price will be used as a deterministic forecast. That is, $\hat{Y} = \bar{Y} = \sum Y_i / N$. For linear trend forecast models, the deterministic trend model is $\hat{Y}_T = a + b\ T_T$, where T_t is the time variable expressed as T = 1, 2, 3,… in this case, T are months. For non-linear trend forecast the deterministic trend model would be $\hat{Y}_t = a + b_1\ T_t + b_2\ T_t^2 + b_3\ T_t^3$ where T_t is time variable is T = 1, 2, 3,… T^2 = 1, 4, 9,… and T^3 = 1, 8, 27, … Also for forecast, any of several functional form of trend regressions could be used. For example, to forecast a growth function: $\hat{Y} = a + b_1T + b_2T^2$ or $Log(\hat{Y}) = a + b_1\ Log(T)$ could be used. On the other hand, to model a decay function $\hat{Y} = a + b_1(1/T) + b_2(1/T^2)$ might be prepared. These functional forms, which are not limitative but certainly are illustrative, were taken from Richarson (2010).

Regressions will be run in Simetar using OLS, and proper statistical tests will be used to check for the statistical significance of linear or non-linear trends. That is, F ratios and t-tests will be significant if a trend is statistically present.

3. Conduct probabilistic forecasting including seasonal decomposition with forecast periods. If normal distribution is used, juke factor is a must to achieve stationarity of the coefficient of variation (CV).

Usually, trend forecast is not enough to capture the behavior of a price series. This is particularly common if we have monthly data. Periodic (cyclical) patterns in a time series that complete the cycle within a year may be caused by weather, production/ marketing patterns, as well as by customs and holidays. Sometimes the seasonal pattern may overwhelm the trend, so the final model will need both trend and seasonal terms.

In particular, for this model, seasonal factors will follow an empirical distribution taking into consideration the number of observations at hand. That is, if the number of observations is 24 monthly consecutive prices, the seasonal factors will be a random variable for each month. Recall that seasonal indexing is a simple way to forecast monthly data. The index represents the fraction that each's months price is above or below the annual mean. As can be expected, this index has a mean of 1.0 (Richardson, 2010). Hence, the probabilistic forecast in this model will be a combination of trend and seasonal index.

Another factor to consider, as pointed out by Richardson (2010), is the fact that simulating outside the historical range raises a problem in that the mean will likely be different from historical values causing the coefficient of variation of simulated data (CV_{Sim}) to differ from historical coefficient of variation (CV_{Hist}). In other words, CV stationarity will be a problem when simulating outside the sample period because if mean for X increases, CV declines, implying less relative risk about the future as time progresses $CV_{Sim} = \sigma_H / \bar{Y}_S$. Conversely, if the mean for X decreases, CV increases, which implies more relative risk as we get farther out with the forecast $CV_{Sim} = \sigma_H / \bar{Y}_S$. An adjustment to the standard deviation can make the simulation results CV stationary if simulating a Normal distribution. This is done by calculating a J_{t+i} value for each period (t+i) to simulate as $J_{t+i} = \bar{Y}_{t+i} / \bar{Y}_{history}$. The J_{t+i} value is then used to simulate the random variable in period t+i as: $\tilde{Y}_{t+i} = \bar{Y}_{t+i} + (\text{Std Dev}_{history} * J_{t+i} * \text{SND})$. The resulting random values for all years t+i will have the same CV, which is desired when doing multiple period simulations.

On the other hand, empirical distributions automatically adjust this factor, such that the simulated values are CV stationary if the distribution is expressed as deviations from the mean or trend, which is: $\tilde{Y}_{t+i} = \bar{Y}_{t+i} * [1 + \text{Empirical}(S_j, F(S_j), \text{USD})]$ (Richardson, 2010).

4. Get the residuals as deviation from trend and test for normality. If the hypothesis of normality is rejected, use Empirical distribution of percentage deviation from trend for the stochastic part of the price. The forecast error, or residual, is calculated as usual: $\hat{e}_i = Y_i - \hat{Y}$.

5. Simulate the forecasted values for the desired number of periods as probabilistic forecast: $\tilde{Y}_T = \hat{Y}_{T+i} + \tilde{e}$

6. Calculate the probabilities that the price reaches a critical level or below using the cumulative distribution function (cdf) of the simulated values of the probabilistic forecast for the desired period in the future. As indicated below, the critical price level will be calculated as a percentage decrease of the current price:

$$\textit{Price Critical level } T + i = T - x\%$$

Where T is the last historical observation of the monthly price; Price critical level T+i is the percentage decrease in price with respect to the last obvervation; i is the 1, 2, 3, etc. period after the last observation; and x is the desired percentage change that we are interested in assessing the probability of occurrence.

After we have the price critical value T+i, we can evaluate the probability of occurrence in every period by using the cdf of the simulated values for each period of interest. After conducting this procedure several times for different critical price levels we can get an output table to be presented to the decision makers, so they can make informed decisions when granting credit.

4. Data

Regarding data, national average wholesale monthly prices for domestic pinto beans in Mexico will be used. These are collected and published by the National System of Information and Integration of Markets (SNIIM for its name in Spanish), an agency that belongs to the Ministry of Economy. Calculations are conducted considering prices in Mexican pesos per metric ton.

The summary statistics for 24 monthly prices of pinto beans, from January 2009 to December 2010, are shown below. These observations are to be renamed, for simplicity, from *Jan Yr 1* (January year 1) to *Dec Yr 2* (December year 2). Forecasted values will be renamed as a *Jan Yr 3* to *Dec Yr 3*.

Table1. Summary Statistics

Summary Statistics		
	Pinto beans	
Mean	13,984	
StDev	1603.231	
95 % LCI	13201.84	
95 % UCI	14766.76	
CV	11.46451	
Min	10,980	
Median	14,293	
Max	16,253	
Skewness	-0.6558	
Kurtosis	-0.67203	

The price at Dec 2010 (Dec Yr 2) was 11,092.41 Mexican pesos per ton of pinto beans. Prices are nominal. Since the objective is to capture price risk, data was not deflated. This is considered to be the current value of the collateral at the time of making the decision of credit granting. Thus, the critical prices are as follows. These are going to be used to estimate probabilities of occurrence when considering simulated values as described in section V.

Table 2. Critical values of collateral

Price Decrease	Critical Price Value
5%	10,537.79
10%	9,983.17
15%	9,428.55
20%	8,873.93
25%	8,319.31

V. Model and Results

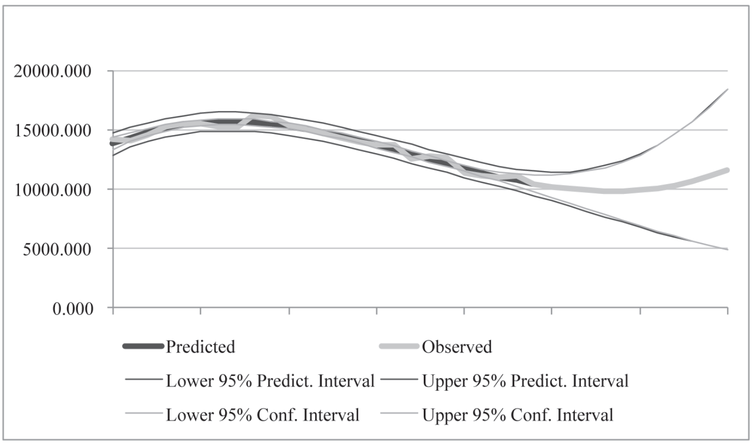
As described in the previous section, the first step is to conduct a visual inspection of the data. Since a non-linear trend was detected, the regression used was: $\hat{Y}_t = a + b_1 T_t + b_2 T_t^2 + b_3 T_t^3$. The regression results are as shown below:

Table 3. Regression results

OLS Regression Statistics for Pinto beans, 12/4/2011 2:59:47 PM					
F-test	155.077	Prob(F)	0.000	**Unrestricted Model**	
$MSE^{1/2}$	356.556	CV Regr	2.550	F-test	155.077
R^2	0.959	Durbin-Watson	1.769	R^2	0.959
$RBar^2$	0.953	Rho	0.066	$RBar^2$	0.953
Akaike Infor	11.821	Goldfeld-Quandt	1.337	Akaike Info	11.821
Schwarz Inf	11.968			Schwarz Inf	11.968
95%	**Intercept**	**Trend**	**Trend 2**	**Trend 3**	
Beta	**13150.980**	**741.777**	**-61.740**	**1.111**	
S.E.	343.272	116.495	10.712	0.282	
t-test	38.311	6.367	-5.764	3.940	
Prob(t)	0.000	0.000	0.000	0.001	
Elasticity at Mean		0.663	-0.901	0.298	
Variance Inflation Factor		122.759	688.295	261.028	
Partial Correlation		0.818	-0.790	0.661	
Semipartial Correlation		0.2890635	-0.26165	0.178843	

All three components of trend are statistically significant. Graphically, deterministic forecast looks as presented in Graph 1.

Graph 1. Observed and predicted values for pinto beans



Next, seasonal factors for 2 years of historical data were calculated as deviations from the annual mean.

Table 4. Seasonal factors

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
Yr 1	14,218	14,168	14,579	15,284	15,541	15,546	15,310	15,156	16,253	16,136	15,406	15,038	15,220
Yr 2	14,674	14,368	13,934	13,783	13,709	12,594	12,783	12,633	11,331	11,107	10,980	11,092	12,749
Seasonal Factors													
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
Yr 1	0.93	0.93	0.96	1.00	1.02	1.02	1.01	1.00	1.07	1.06	1.01	0.99	1.00
Yr 2	1.15	1.13	1.09	1.08	1.08	0.99	1.00	0.99	0.89	0.87	0.86	0.87	1.00
Average	1.04	1.03	1.03	1.04	1.05	1.00	1.00	0.99	0.98	0.97	0.94	0.93	1.00
Output for Empirical Distributions with 2 Observations Using Actual Data													
Unsorted Actual Data													
Obs.	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
1	0.93	0.93	0.96	1.00	1.02	1.02	1.01	1.00	1.07	1.06	1.01	0.99	
2	1.15	1.13	1.09	1.08	1.08	0.99	1.00	0.99	0.89	0.87	0.86	0.87	
Mean	1.04	1.03	1.03	1.04	1.05	1.00	1.00	0.99	0.98	0.97	0.94	0.93	
Min.	0.93	0.93	0.96	1.00	1.02	0.99	1.00	0.99	0.89	0.87	0.86	0.87	
Max.	1.15	1.13	1.09	1.08	1.08	1.02	1.01	1.00	1.07	1.06	1.01	0.99	

Empirical distributions for the seasonal factors for every month were developed.

Table 5. Empirical distributions for the seasonal factors

Sorted Actual Data												
F(x)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0	0.934114	0.930834	0.957806	1.004147	1.02101	0.987727	1.002602	0.990763	0.888684	0.871087	0.861129	0.869974
0.25	0.934207	0.930927	0.957902	1.004247	1.021112	0.987826	1.002702	0.990862	0.888773	0.871174	0.861215	0.870061
0.75	1.150997	1.127014	1.092982	1.081074	1.07532	1.021432	1.005909	0.99585	1.067869	1.060236	1.01226	0.988051
1	1.151112	1.127127	1.093092	1.081182	1.075428	1.021534	1.006009	0.99595	1.067976	1.060342	1.012361	0.988149
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Stoch Seasonal EMP	1.042602	1.02897	1.025442	1.042661	1.048216	1.004629	1.004305	0.993356	0.978321	0.965705	0.936737	0.929056
	=EMP(W40:W43,$V$40:$V$43)											

Additionally, test for normality was conducted on the residuals, failing to reject that the residuals were normally distributed.

Table 6. Normality test results

Test for Normality of Distribution for Residuals			
Confidence Level	95.0000%		
Procedure	Test Value	p-Value	
S-W	0.96533	0.554331	*Fail to Reject the Ho that the Distribution is Normally Distributed**
A-D	0.26478	0.664092	*Fail to Reject the Ho that the Distribution is Normally Distributed**
CvM	0.039927	0.667872	*Fail to Reject the Ho that the Distribution is Normally Distributed**
K-S	0.104645	NA	*Consult Critical Value Table*
Chi-Squared	6.583333	0.68041	*Fail to Reject the Ho that the Distribution is Normally Distributed**
			*Based on approximate p-values

Formulas for stochastic forecasting were $\tilde{Y}_{t+i} = (\bar{Y}_{t+i} \text{*Seasonal factor}_{t+i}) + (\text{Std Dev}_{history} * J_{t+i} * \text{SND})$. After performing the calculations described in step 6 of the previous section and after simulation, the results in shown in table y were obtained.

Table 7. Simulation results

Simetar Simulation Results for 500 Iterations. 4:17:21 PM 12/4/2011 (3 min. 31 sec.). © 2011.												
Variable	**Jan Yr 3**	**Feb Yr 3**	**Mar Yr 3**	**Apr Yr 3**	**May Yr 3**	**Jun Yr 3**	**Jul Yr 3**	**Aug Yr 3**	**Sep Yr 3**	**Oct Yr 3**	**Nov Yr 3**	**Dec Yr 3**
Mean	10914.19	10524.54	10293.74	10327.93	10310.59	9881.036	9955.473	10005.85	10098.61	10303.03	10413.32	10849.74
StDev	1495.918	1434.837	1335.663	1187.944	1156.331	1144.241	1136.897	1154.104	1385.459	1484.052	1442.018	1453.858
CV	13.70617	13.63325	12.97549	11.50224	11.21499	11.58018	11.41982	11.53429	13.71929	14.40403	13.84782	13.39993
Min	6835.257	6679.138	6687.171	7107.073	7132.37	5793.083	6576.752	6604.364	5716.883	5632.897	5616.679	6408.553
Max	14577.08	14753.18	13771.25	13967.09	13656.91	13475.93	13419.71	13787.58	14077.27	15318.48	14752.14	15800.45

With respect to hypothesis testing of simulated values versus historical data, it was found that the means are not statistically equal. This was expected due to the presence of trend. Moreover, there is statistical evidence that historical variability was replicated in the simulated values. As was mentioned before, this is desired to avoid bias in the probabilistic forecast.

Table 8. Distribution comparison

Distribution Comparison of Pinto beans & Jan Yr 3				
Confidence Level		95.00%		
	Test Value	Critical Value	P-Value	
2 Sample t Test	9.01	2.39	0.000	Reject the Ho that the Means are Equal
F Test	1.20	1.55	0.240	Fail to Reject the Ho that the Variances are Equal

The table of results shows the probability of occurrence of critical price values that were discussed in section IV.

Table 9. Price risk assessment

Estimation of probabilities of percentage decrease in price of domestic pinto beans in Mexico												
	Probability of ocurrence. Price decrease with respect to the actual price of Dec of Year 2.											
Price Decrease	Jan Yr 3	Feb Yr 3	Mar Yr 3	Apr Yr 3	May Yr 3	Jun Yr 3	Jul Yr 3	Aug Yr 3	Sep Yr 3	Oct Yr 3	Nov Yr 3	Dec Yr 3
5%	40.2%	51.7%	57.2%	56.3%	58.5%	71.8%	69.8%	68.3%	62.1%	57.4%	54.1%	41.3%
10%	28.0%	36.1%	39.7%	39.9%	38.4%	53.3%	51.0%	48.7%	48.9%	41.4%	37.4%	28.2%
15%	17.5%	20.8%	26.9%	22.8%	22.1%	33.6%	32.3%	30.7%	33.7%	27.5%	23.3%	17.3%
20%	9.3%	12.5%	15.7%	11.3%	10.7%	19.1%	17.3%	16.2%	17.9%	16.9%	14.5%	8.3%
25%	3.3%	6.7%	6.9%	4.3%	4.5%	8.7%	7.6%	7.3%	9.3%	9.2%	7.7%	4.3%

The content of this table can be interpreted as the probability that the price is at or below certain critical level. For example, row 4 in the table shows the probabilities that the price is below the critical value of 8,873.31 Mexican pesos per metric ton, which is a 20% reduction with respect to the reference price of December 2010 (value of the collateral at the time of signing the inventory credit). Since this model considers seasonal factors, the afore-mentioned probability is expected to be different from month to month. That is, the probability of 20% price decrease over February of year 3 is 12.5% and it increases up to 19.1% by June of the same year. Similar interpretations apply to the rest of the cells in the table.

Because inventory credits are typically written for three months and allow for renewal, several timeframes are considered in the table of results to help decision makers assess the market risk on inventory credit.

Summary and Conclusions

The VaR model was modified to estimate the maximum probability of occurrence of a certain loss. In this case, the loss is a percentage decrease in price with respect to the actual value at the time of making decisions on granting inventory credits. The probabilistic forecast was developed utilizing a simulation model in *Simetar*.

Based on the results described above, decision makers will have more information to determine the amount of money that can be lent according to the credit granting policies in place in the bank. In the specific example of domestic pinto beans, the risk seems to be quite high since the probability of a decrease of 20% in price goes from 8.3%

to 19.1% over the next 12 months. Bank executives will need to consider if they are willing to take that level of risk by granting the inventory credit under these conditions, or to make a decision on the percentage of the value of collateral to be granted as credit.

The results of this model can be considered an application of positive economics, since the probabilities of occurrence of certain level of price decrease are estimated, leaving bank executives to make decisions of credit granting. In other words, the purpose of this model is to provide information to aid in the decision making process.

The model is in early stages of validation. Up to this point, aside from the verification of formulas, only statistical validation has been conducted to check if simulated variability is not statistically different from historical variability. Validation with experts and potential users remains pending.

The next step on the validation process is to use the model of probability forecast on different series of prices and conduct backtesting to check for the accuracy of estimates. Given its properties, this model is very flexible and once validated, could be used routinely for inventory credit analysis.

With respect to limitations of this model, since only trend and seasonal factors are considered, it would not be appropriate to conduct a probabilistic forecast for a large number of periods into the future. Also, due to the sparse nature of the data another limitation of this study is that only univariate parameter estimation is considered. Although outside the scope of this paper, an extension to multivariate parameter estimation could be be achieved by using the methodology to correlate variables for simulation proposed by Clements, Mapp Jr. and Eidman (1971) and generalized by Richardson and Condra (1978).

When extending this model further, it should be noted that we are assuming historical data has all the possible risk that can affect business. One way to overcome this shortcoming is to use expert opinion to incorporate extreme events that could adversely affect prices. That is, modify the "historical distribution" based on expected probabilities of rare events, also known as *Black Swan* events as described in Taleb (2007). By adjusting the model to this type of events, estimates of probabilities of price decrease are expected to consider situations like severe drought conditions that occurred in Mexico during 2011, when more than half of beans production was lost. This type of events certainly have an effect on price risk that should not be ignored.

References

Clements Jr. A. M., H.P. Mapp Jr. and V.R. Eidman. 1971. "A Procedure for Correlating Events in Farm Firm Simulation Models". Oklahoma State University Agricultural Experiment Station.Technical Bulletin T-131. August 1971.

Coutler, J. and A.W. Shepherd. 1995. "Inventory Credit: An Approach to Developing Agricultural Markets". FAO Agricultural Services Bulletin 120.

Goodwin, B. K. and T. Kastens. 1993. "Adverse Selection, Disaster Relief, and Demand for

Insurance." Unpublished manuscript, Kansas State University.
Goodwin, B. K. and A. P. Ker."Modeling Price and Yield Risk."In A Comprehensive Assessment of the Role of Risk in U.S. Agriculture, R.E. Just and R.D. Pope Editors, Norwell, Mass: Kluwer Academic Publisher, 2000.
Horowitz, J. 1993. "Semiparametric Estimation of a Work Trip Choice Model".*Journal of Econometrics 58: 49-70*.
Jorion, P. 2006. "Value at Risk: The New Benchmark for Managing Financial Risk". Third Edition.McGraw-Hill.
Richardson, J. W. and G.D. Condra. 1978. "A General Procedure for Correlating Events in Simulation Models".
Richardson, J. W. 2010. "Simulation for Applied Risk Management with an Introduction to Simetar".Department of Agricultural Economics.Texas A&M University.
Taleb, N. N. 2007. "The Black Swan: The Impact of the Highly Improbable". New York: Random House.
Vose, D. 2000. "Risk Analysis: A Quantitative Guide". John Wiley & Sons, LTD.Second edition.