Magaña Lemus, David
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Economía y Sociedad, vol. XX, núm. 34, enero-junio, 2016, pp. 106-118
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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
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 analyze 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 $c$:

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

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

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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, \( \hat{Y} = \bar{Y} = \frac{\sum Y_i}{N} \). 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 \( T = 1, 2, 3, \ldots \) 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 \( T = 1, 2, 3, \ldots \). \( T^2 = 1, 4, 9, \ldots \) and \( T^3 = 1, 8, 27, \ldots \).

Also for forecast, any of several functional form of trend regressions could be used. For example, to forecast a growth function: \( \hat{Y} = a + b_1 T + b_2 T^2 \) 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 Richardson (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: Ỹ_{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: Ỹ_{t+i} = \bar{Y}_{t+i} * [1 + \text{Empirical}(S_j, F(S_j), 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{\epsilon}_i = Y_i - \hat{Y}.

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

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:

\begin{equation}
\text{Price Critical level } T + i = T - x% \nonumber
\end{equation}

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 observation; 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.

Table 1. Summary Statistics

<table>
<thead>
<tr>
<th>Summary Statistics</th>
<th>Pinto beans</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>13,984</td>
</tr>
<tr>
<td>StDev</td>
<td>1603.231</td>
</tr>
<tr>
<td>95% LCI</td>
<td>13201.84</td>
</tr>
<tr>
<td>95% UCI</td>
<td>14766.76</td>
</tr>
<tr>
<td>CV</td>
<td>11.46451</td>
</tr>
<tr>
<td>Min</td>
<td>10,980</td>
</tr>
<tr>
<td>Median</td>
<td>14,293</td>
</tr>
<tr>
<td>Max</td>
<td>16,253</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.6558</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>-0.67203</td>
</tr>
</tbody>
</table>

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.
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 2. Critical values of collateral**

<table>
<thead>
<tr>
<th>Price Decrease</th>
<th>Critical Price Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>5%</td>
<td>10,537.79</td>
</tr>
<tr>
<td>10%</td>
<td>9,983.17</td>
</tr>
<tr>
<td>15%</td>
<td>9,428.55</td>
</tr>
<tr>
<td>20%</td>
<td>8,873.93</td>
</tr>
<tr>
<td>25%</td>
<td>8,319.31</td>
</tr>
</tbody>
</table>

**Table 3. Regression results**

| OLS Regression Statistics for Pinto beans, 12/4/2011 2:59:47 PM |
|---------------------------------|-----------------|-----------------|
| F-test                          | 155.077         | 0.000           |
| MSE\(^{1/2}\)                   | 356.556         | CV Regr 2.550   |
| R\(^2\)                         | 0.959           | 1.769           |
| RBar\(^2\)                      | 0.953           | 0.066           |
| Akaike Info                     | 11.821          | 1.337           |
| Schwarz Inf                     | 11.968          | 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**

![Graph 1](image)

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

**Table 4. Seasonal factors**

<table>
<thead>
<tr>
<th></th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yr 1</td>
<td>0.93</td>
<td>0.93</td>
<td>0.96</td>
<td>1.00</td>
<td>1.02</td>
<td>1.01</td>
<td>1.00</td>
<td>1.07</td>
<td>1.06</td>
<td>1.01</td>
<td>0.99</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Yr 2</td>
<td>1.15</td>
<td>1.13</td>
<td>1.09</td>
<td>1.08</td>
<td>1.08</td>
<td>1.09</td>
<td>1.00</td>
<td>0.99</td>
<td>0.87</td>
<td>0.86</td>
<td>0.87</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>1.04</td>
<td>1.03</td>
<td>1.03</td>
<td>1.04</td>
<td>1.05</td>
<td>1.00</td>
<td>0.99</td>
<td>0.98</td>
<td>0.97</td>
<td>0.94</td>
<td>0.93</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>

**Output for Empirical Distributions with 2 Observations Using Actual Data**

<table>
<thead>
<tr>
<th></th>
<th>Obs</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>0.93</td>
<td>0.93</td>
<td>0.96</td>
<td>1.00</td>
<td>1.02</td>
<td>1.01</td>
<td>1.00</td>
<td>1.07</td>
<td>1.06</td>
<td>1.01</td>
<td>0.99</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1.15</td>
<td>1.13</td>
<td>1.09</td>
<td>1.08</td>
<td>1.08</td>
<td>0.99</td>
<td>1.00</td>
<td>0.99</td>
<td>0.89</td>
<td>0.87</td>
<td>0.86</td>
<td>0.87</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td>1.04</td>
<td>1.03</td>
<td>1.03</td>
<td>1.04</td>
<td>1.05</td>
<td>1.00</td>
<td>1.00</td>
<td>0.99</td>
<td>0.98</td>
<td>0.97</td>
<td>0.94</td>
<td>0.93</td>
</tr>
<tr>
<td>Min.</td>
<td></td>
<td>0.93</td>
<td>0.93</td>
<td>0.96</td>
<td>1.00</td>
<td>1.02</td>
<td>0.99</td>
<td>1.00</td>
<td>0.99</td>
<td>0.89</td>
<td>0.87</td>
<td>0.86</td>
<td>0.87</td>
</tr>
<tr>
<td>Max.</td>
<td></td>
<td>1.15</td>
<td>1.13</td>
<td>1.09</td>
<td>1.08</td>
<td>1.08</td>
<td>1.02</td>
<td>1.01</td>
<td>1.00</td>
<td>1.07</td>
<td>1.06</td>
<td>1.01</td>
<td>0.99</td>
</tr>
</tbody>
</table>
Empirical distributions for the seasonal factors for every month were developed.

Table 5. Empirical distributions for the seasonal factors

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

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

Table 9. Price risk assessment

<table>
<thead>
<tr>
<th>Price Decrease</th>
<th>Jan Yr 3</th>
<th>Feb Yr 3</th>
<th>Mar Yr 3</th>
<th>Apr Yr 3</th>
<th>May Yr 3</th>
<th>Jun Yr 3</th>
<th>Jul Yr 3</th>
<th>Aug Yr 3</th>
<th>Sep Yr 3</th>
<th>Oct Yr 3</th>
<th>Nov Yr 3</th>
<th>Dec Yr 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>5%</td>
<td>40.2%</td>
<td>51.7%</td>
<td>57.2%</td>
<td>56.3%</td>
<td>58.5%</td>
<td>71.8%</td>
<td>69.8%</td>
<td>68.3%</td>
<td>62.1%</td>
<td>57.4%</td>
<td>54.1%</td>
<td>41.3%</td>
</tr>
<tr>
<td>10%</td>
<td>28.0%</td>
<td>36.1%</td>
<td>39.7%</td>
<td>39.9%</td>
<td>38.4%</td>
<td>53.3%</td>
<td>51.0%</td>
<td>48.7%</td>
<td>48.9%</td>
<td>41.4%</td>
<td>37.4%</td>
<td>28.2%</td>
</tr>
<tr>
<td>15%</td>
<td>17.5%</td>
<td>20.8%</td>
<td>26.9%</td>
<td>26.9%</td>
<td>22.8%</td>
<td>22.1%</td>
<td>33.6%</td>
<td>32.3%</td>
<td>30.7%</td>
<td>33.7%</td>
<td>27.5%</td>
<td>23.3%</td>
</tr>
<tr>
<td>20%</td>
<td>9.3%</td>
<td>12.5%</td>
<td>15.7%</td>
<td>15.7%</td>
<td>11.3%</td>
<td>10.7%</td>
<td>19.1%</td>
<td>17.3%</td>
<td>16.2%</td>
<td>17.9%</td>
<td>16.9%</td>
<td>14.5%</td>
</tr>
<tr>
<td>25%</td>
<td>3.3%</td>
<td>6.7%</td>
<td>6.9%</td>
<td>6.9%</td>
<td>4.3%</td>
<td>4.5%</td>
<td>8.7%</td>
<td>7.6%</td>
<td>7.3%</td>
<td>9.3%</td>
<td>9.2%</td>
<td>7.7%</td>
</tr>
</tbody>
</table>

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 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


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