MODELING WITH @RISK:

A TUTORIAL GUIDE

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Purdue University

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Abstract

Excel @RISK is a helpful modeling tool used to analyze under uncertain and risky conditions. This paper aims to provide a starting resource for the use of @RISK analysis and allow readers the ability to make more productive and insightful business decisions. This paper covers the fundamentals of concepts such as simulation, measuring correlations, parent distributions, time series modeling, analysis tools and NPV analysis. This tutorial guide is intended to provide a detailed resource for the conceptual understanding and practical application of @RISK modeling.

Keywords: Excel, model, risk, business modeling, NPV analysis

JEL codes: E37, C61, M21

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Introduction

In today's business world, the only thing that is certain is that everything is uncertain. This may sound like a cliché, but the idea that today's business leaders struggle with risk and uncertainty is as true as ever. In fact, as the world becomes smaller and economies more integrated, concerns once mitigated by distance are quickly becoming top issues for even mid-sized companies. This is particularly true for many commodity-based agricultural businesses that can be impacted by events occurring in other countries or continents (Anderson, 2010). Their financing decisions and the processes driving those decisions must be versatile enough to account for multiple possibilities and states of nature.

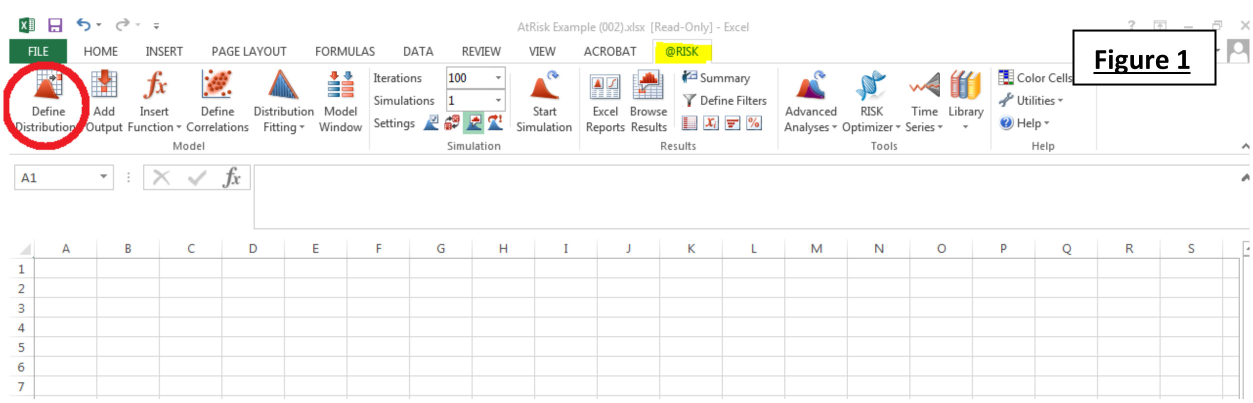
Although the pessimist may find the growth of risk unsettling, companies and individuals have substantially more options and power to combat modern business and financial risk than in the past. With proper analysis, today's uncertainty can provide an opportunity for development and advancement. Indeed, the use of tools such as @RISK have helped enterprising managers understand how risk and uncertainty can affect a business or project. This paper aims to provide a starting resource for the use of @RISK analysis and allow readers the ability to make more productive and insightful business decisions.

@RISK is an Excel add-in and is one of the most used risk analysis tools. As of 2016, 64 major universities and 214 large corporations purchases the software (Palisade *Our Customers*, 2016). The software uses simulation to combine uncertainties and risks and allow easy graphical analysis. Historically, most business spreadsheet modeling was done with individual variables being changed to examine their impact on the project. This occurred because analyzing the impact of two or more shifting variables on a model at a time was time consuming and labor intensive. In fact, this process still occurs in standard excel models that use expected values of variables. For example, a certain project's net present value may be calculated using the assumption that the product can be sold at a given price, but what if the price ends up higher or lower than expected? The project can be remodeled under the assumption that the product's price is higher or lower, but should the analysis of these alternative situations carry the same weight as the expected price? Perhaps price probabilities are not uniformly distributed and this characteristic needs consideration. A weighting system could be assigned, but a product's price varies across a wide range of values and without accounting for all possibilities, oversights in analysis are inevitable. Even a miniscule difference in price can become substantial if the quantity sold is great. Analyzing this multitude of possibilities in a clear and succinct manner is exactly the opportunity @RISK provides its users.

The Steps of Identifying a Stochastic Variable in @RISK

As previously stated, @RISK is an excel add-on. The program is a useful extension to those already familiar with Excel in a business context. The basic steps to using @RISK to define a stochastic variable are as follows (Palisade *Define Distributions*, n.d.):

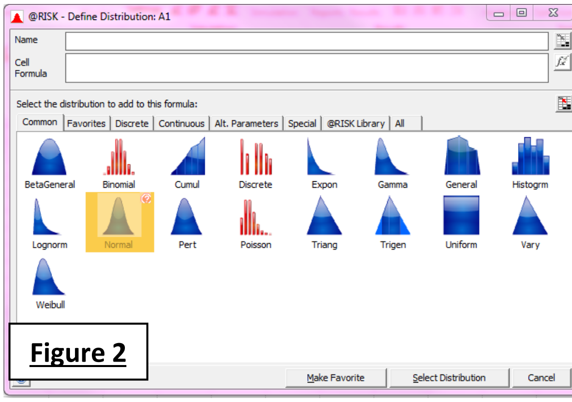
1) Access Excel through the start menu or an icon shortcut
2) Select the @RISK tab in Excel (Figure 1, yellow highlighted tab)
3) Select a cell that has been chosen to be stochastic and click the define distribution button

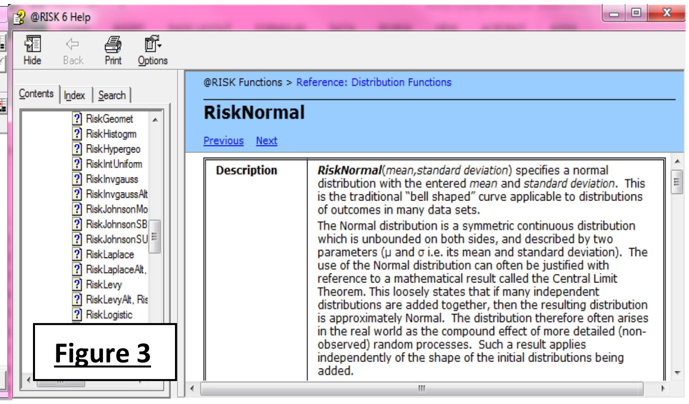


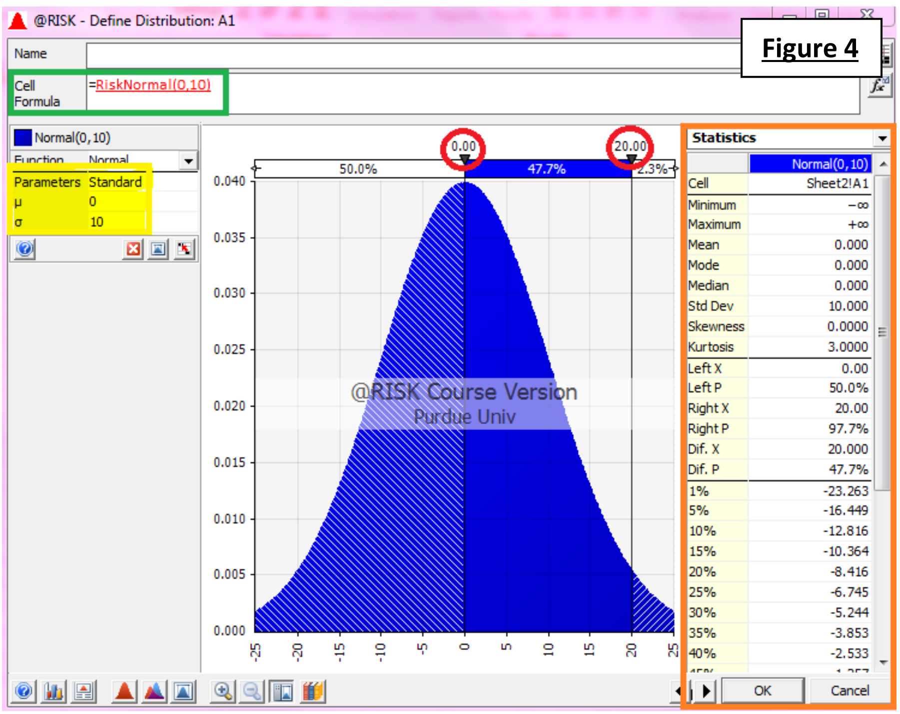
(Figure 1, red circle)

4) Select a type of distribution (Figure 2)

5) Define the parameters for the distribution (Figure 4, yellow highlight)







As noted above, Figure 1 displays where the @RISK tab can be found in an excel document. The next step in using @RISK is to click on the define distributions button (Figure 1, red circles). This opens a window showing distributions which can be modeled (Figure 2). Here, the normal distribution has been selected (Figure 2). Clicking on the question mark in the top right corner of the normal distribution icon opens an information box (Figure 3). The distribution, its purposes and the variables it can model are explained here.

Double clicking on a distribution (Figure 2) allows a user to specify the parameters of the distribution. This action opens a pop-up (Figure 4) which allows the user to enter parameters which characterize the distribution being modeled. In many cases a user has a data set and the parameters of the distribution are not yet known. In these cases, the distribution parameters can be estimated by fitting the data to a distribution. This process is described on page 15. The defined parameters of the normal distribution chosen here are highlighted in Figure 4. Other distributions can have more or fewer parameters; the normal distribution displayed was given a mean of zero and a standard deviation of ten. @RISK displays commonly used statistics and attributes of the distribution in the red box on the right side of the image given these parameters.

This window has several other useful features. By dragging the black arrows above the distribution (Figure 4, red circles), a user can analyze how likely the variable is to fall into a certain range. The example in Figure 4 shows that 47.7% of the distribution lies between zero and 20. The cell formula for an @RISK variable modeled by the normal distribution is also displayed here (Figure 4, green box). By duplicating this syntax, a user can enter a variable and its parameters directly into a cell. A syntax list of common distributions is included at the end of this paper (Table 3).

Illustrative Example

Example Introduction

The following example shows how powerful @RISK can be in analyzing business decisions. In this example, the decision being considered is investment in the commercialization and production of a new product. The example uses net present value (NPV) and the discounted cash flow (DCF) method to assess the investment. Attachment A at the end of this paper includes the projected cash flows of the project. The product is not patentable. Management does not expect to have its market share increase, but it does believe that growing demand will increase the overall market size during the next ten years. Rapid growth in sales is expected during the first three years and more sustainable growth during the following seven years. The product is sold by the case and is expected to have an initial market quantity of 300,000 cases, with an increase to 450,000 cases once it is shelved in additional stores.

Price is believed to remain at an expected value of $3.50 during phase I and is modeled to start increasing at a 2% inflation rate during phase II. Given the per unit production cost, investment outlay, and other assumptions displayed in the colored boxes of Attachment A, the project is expected to have a deterministic net present value (NPV) of $219,199. Note that this is only one possible future reality. However, the analysis shown in Attachment A has only used standard Excel features and does not provide insights concerning the risks and uncertainties of the project. All variables shown use only their expected values, without considering what other values are possible. The next analysis will use several @RISK tools to obtain further insights.

Reviewing the second analysis (Attachment B), one can note that many numbers have changed and the project's NPV is now negative. Several variables have been set to draw from an assigned distribution and attachment B shows another outcome of the project given a different state other than the expected state (Attachment A). The variables that are being selected from distributions are identified at the end of this paper (Table 1). The two alternate states of nature compared above demonstrate the impact that stochastic variables can have on a project's outcome. The next step is to create several thousand versions of future realities to enrich the analysis and understand probable outcomes.

Running a Simulation

Attachment B illustrates the impact that risk can have on the net present value of the project by using stochastic variables. However, this does not provide a great understanding about the overall risks and uncertainties of a project. Generating many possible solutions, each with different values for the variables, can give a more detailed understanding of the project. This process of generating many possible solutions by selecting values from distributions is called Monte Carlo simulation (Mooney, 1997). A simulation is composed of iterations; a single iteration can be generated by clicking F9 on the keyboard. The dice in the @RISK tab of Excel are used for switching from the deterministic solution (at the expected values) to a stochastic solution (Figure 5, orange circle). The Start Simulation button in the @RISK tab runs the model (Figure 5, green box) (Palisade *Run*, n.d.). Generally, simulations with more iterations provide more accurate inference than those with fewer.

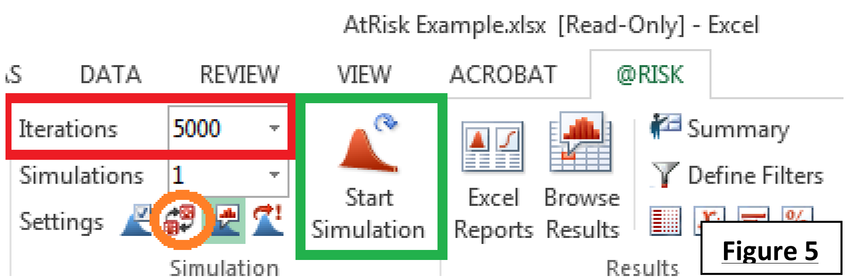
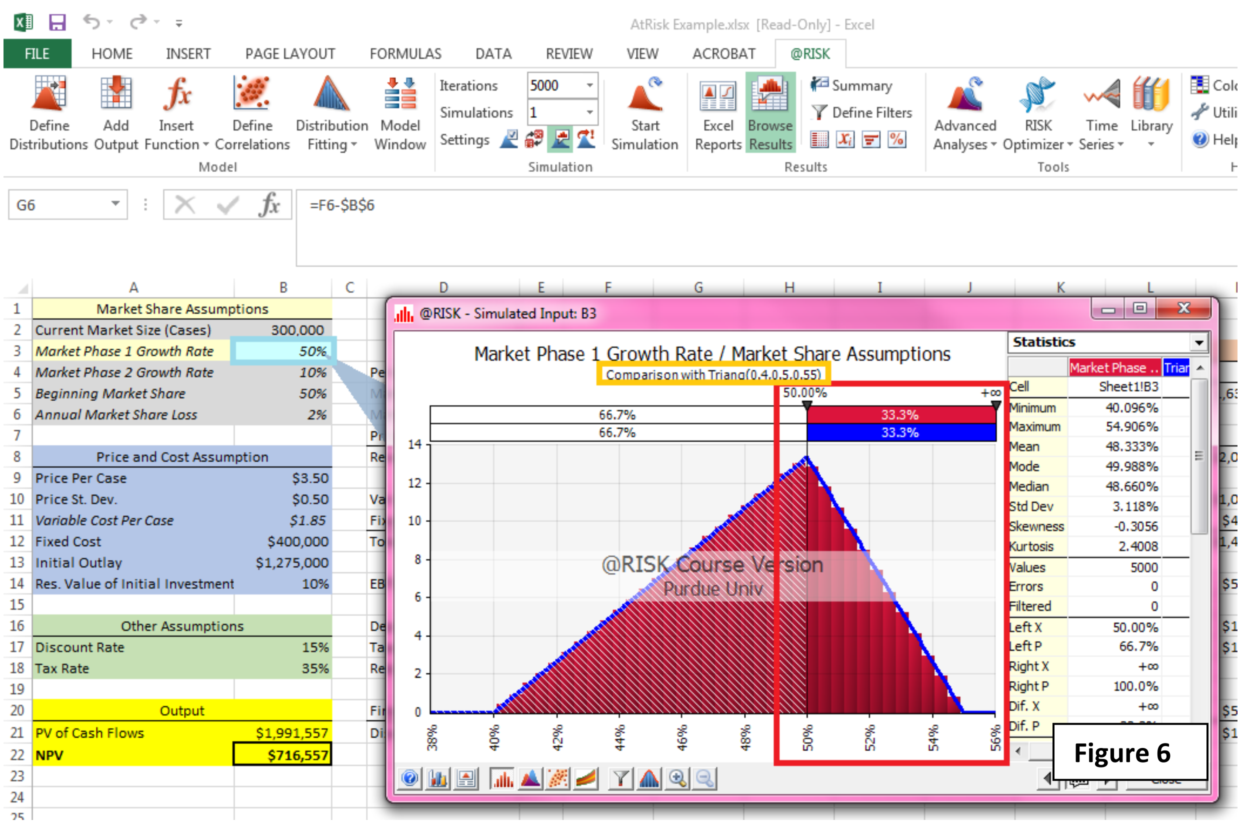


Figure 5

Analyzing Simulation Results

Figure 6 shows the characteristics of the first stochastic variable used in the analysis of the project, Market Phase 1 Growth Rate (MP1GR). The simulation results can be accessed by clicking on the variable's cell after a simulation has been run (Palisade *Results*, n.d.). In this example, MP1GR is displayed in the cell B3 (Figure 6, teal box). The parameters given for this triangular distribution are displayed in the orange rectangle. The distribution's characteristics can be seen by using the black click and drag arrows (Figure 6, red box). These results show that only a third of the iterations in the simulation experienced a market phase 1 growth rate above the 50% used in the deterministic model (Attachment A). Other important statistics are displayed in the section to the right of the distribution (Figure 6). The blue line around the triangle shows the shape of the modeled distribution, while the red represents the values used during iterations



of the simulation. Because of the high number of iterations (5,000), the simulation closely mirrors the distribution.

Figure 7 displays the characteristics of the stochastic variable Market Phase 2 Growth Rate (MP2GR) and Figure 8 shows the distribution for Beginning Market Share Growth Rate (BMSGR). These distributions show the control a user can have over how a variable is defined. MP2GR is characterized by the normal distribution and BMSGR is modeled using a uniform distribution. The moveable black bars have been adjusted to show the percent of iterations where MP2GR is within 1% of its expected value and BMSGR is within 5% of its expected value. Annual Market Share Loss (AMSL) is modeled by a symmetric triangular distribution but is not shown graphically here.

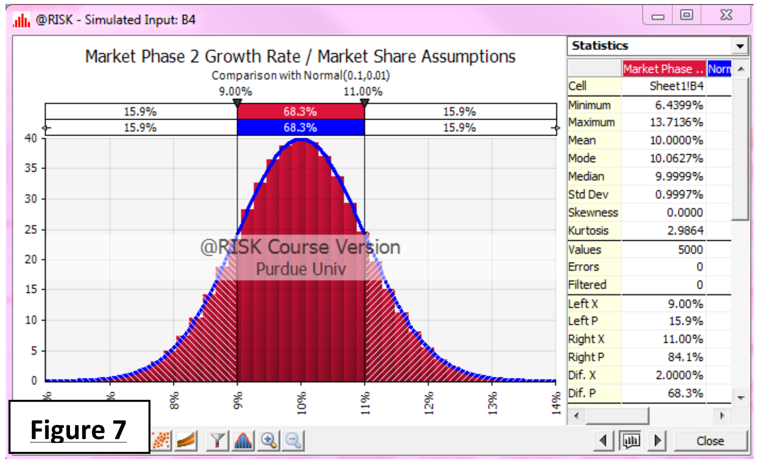


Figure 7

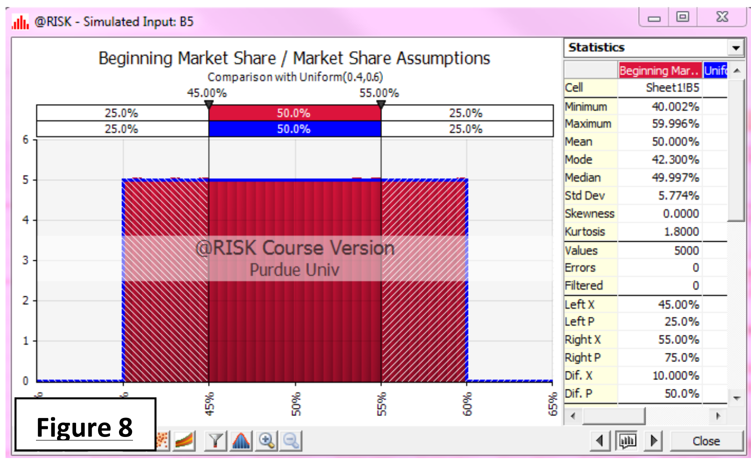


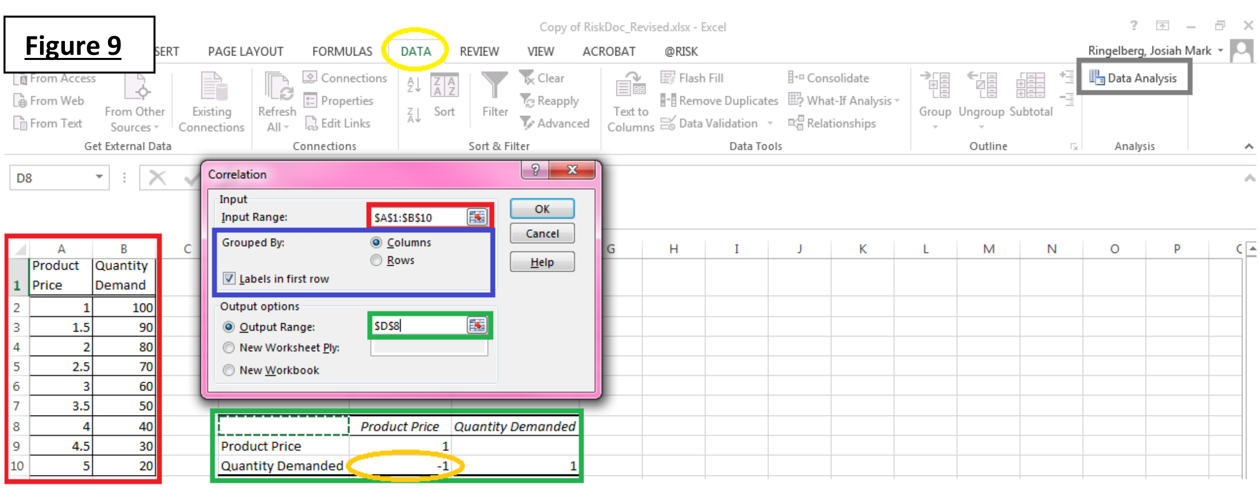
Figure 8

Measuring Correlations in @RISK

In many cases, the variables of a project may be related to each other. For example, in economics there is often a negative correlation found between price and quantity demanded. This suggests that as the price of a product goes up, the quantity demanded decreases. The relationship between price and quantity illustrates one possible correlation an @RISK user could define. Correlations can be assigned due to intuition or through empirical analysis. For an empirical example, Figure 9 shows how a correlation can be calculated empirically using the following steps (Palisade *How*, 2016).

1. Gather historical data on the variables in which a correlation is believed to exist. Price and quantity demanded data is used here (Figure 9, red box). This data has been selected as input for the correlation pop-up as shown by the smaller red rectangle.
2. In order to open the correlation pop-up an @RISK user must select the DATA tab circled in yellow and click the Data Analysis icon in the gray rectangle.
    a. If you don't see this tab, be sure Analysis ToolPak is enabled. You can enable it by going to File>Options>Add-ins. In the manage window at the bottom of the screen choose Excel Add-ins and click "Go". Check Analysis ToolPak in the pop up and click OK.
3. As the pop-up shows, a user must first select the input range, clarify how the data is organized (Figure 6, blue box), and select an output location (Figure 6, green box).
4. Once step three is finished and the user clicks the OK button, the correlation matrix shown in the green rectangle will be generated. The correlation between the variables in this example is circled in orange. This correlation can then be used in future modeling.

Figure 9



Defining Correlations in @RISK

In the model provided for this analysis, a correlation was created between the price per case variable in the first year and the variable cost per case. This could reflect a company's decision to price their product with production costs in mind. If the company finds the variable cost to produce the product is higher, the market price the product is sold at will typically be higher. In many cases, a negative correlation between price and product sales may be a reasonable assumption, but sales in our model are considered to be independent of the product's price.

There are five steps to defining a correlation between variables. They are as follows:

1. Click on a cell defined by a distribution
2. Click the Define Correlations button in the @RISK tab
3. Name the correlation matrix and select a location for it in Excel
4. Add the variables that are to be correlated
5. Enter the correlation coefficient

To begin, Figure 10 shows where the Define Correlations button can be found in the @RISK tab. This button opens the pop-up shown in the figure (Figure 10, red circle). The second step is to choose a location for the output (Figure 10, purple box). @RISK will auto generate a generic name for the matrix, but the user must select the correlation matrix's location in Excel. For this example, the cells A27:C29 have been selected.

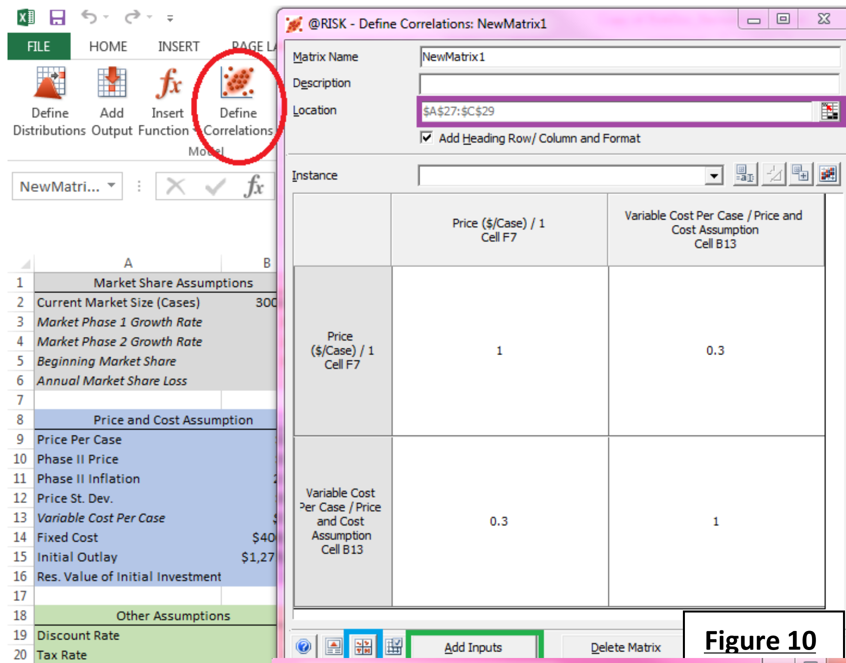


Figure 10

When a user initially opens the pop-up shown in Figure 10, the table will be blank. Variables must be selected before the table is filled. To do this, a user selects the Add Inputs button (Figure 10, green box). This opens another pop-up prompting a user to enter the cells containing the variables that will be correlated. This pop-up is not displayed but is intuitive and follows the format of standard excel data entry prompts.

Once the data for a correlation has been entered, the correlation must be defined. This can be done several ways, but the best method is to use the define correlation button (Figure 10, blue box). Figure 11 shows a scatter plot analysis of

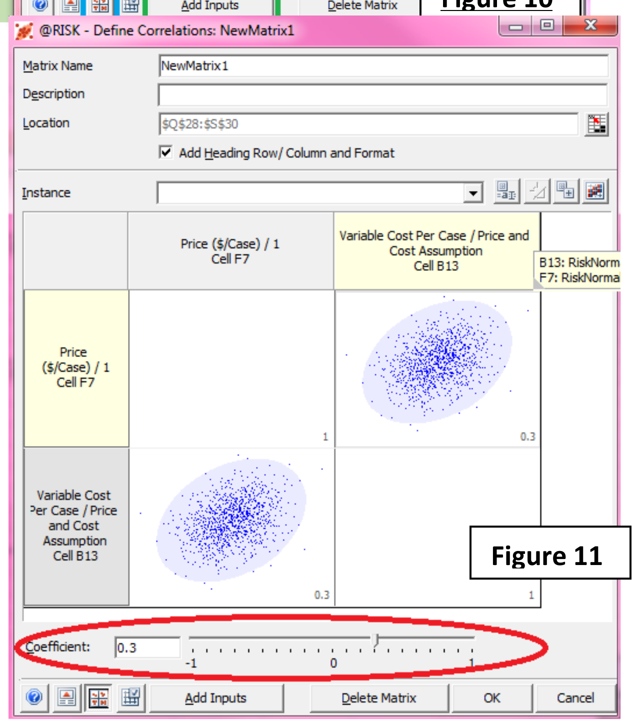


Figure 11

the correlation matrix. Use the slider at the bottom of the window to define the strength of the correlation (Figure 11, red oval). By using the slider or entering in a new correlation coefficient, a user can define the relationship between two variables. The scatter plots illustrate the strength of these correlations graphically (Figure 10).

Figure 12

@RISK Correlations	Price ($/Case) / 1 in F7	Variable Cost Per Case / Price and Cost Assumption in B13
Price ($/Case) / 1 in F7	1	
Variable Cost Per Case / Price and Cost Assumption in B13	0.3	1

After a correlation has been established between two variables, it can be altered using the correlation matrix displayed (Figure 12). Once a variable has been correlated, its formula will display the syntax RiskCorrmat(matrix cell range or name, variable position). This is shown below with the formula of Variable Cost per Case (Figure 13). A similar adjustment has been made to the cell containing the formula for the price per case in year one -- the correlated variable.

Price and Cost Assumption			Revenue		$787,500	$1,134,000
Price Per Case	$3.50					
Phase II Price	$3.50					
Phase II Inflation	2.00%					
Price St. Dev.	$0.10		Variable Cost		$416,250	$599,400
Variable Cost Per Case	*=RiskNormal(1.85,0.075,RiskStatic(1.85),RiskCormat(NewMatrix1,2))*					
Fixed Cost	$400,000		Total Cost		$816,250	$999,400
[illegible]	$1,275,000					
nitial Investment	10%		EBTD		-$28,750	$134,600

Figure 13

Complex Variables, Parent Distributions, and Analysis

So far the distribution for specific variables have been specified by the @RISK user. Furthermore, once a variable has a value in an iteration, that value is maintained throughout the entire ten-year model. For example, if the variable Annual Market Share Loss is found to be 1.8% in an iteration, the model has AMSL of 1.8% for every year of the ten-year simulation. Wouldn't it be more realistic to have the value be different each year of the model? And what if a connection exists between subsequent year values of a variable? If AMSL was 2.3% this year, one might suspect next year's to be higher than the 2% expected value. Likewise, a lower first year AMSL may signal a lower AMSL in every subsequent year. @RISK provides the power to allow a user to identify a parent distribution of a variable and code time series dependency into its models. This has been done with the Price ($/Case) variables and will be discussed shortly. First though, we will discuss how this variable distribution was found.

Identifying a Parent Distribution of a Variable

In order to identify the distribution of a variable, a sample of the population is needed. In our example, the real prices per case of the product at the first of each month since the year 2007 have been recorded. Figure 14 provides an example of this data. @RISK allows for a user to fit distributions to a dataset. This is done in three steps (Palisade *Distribution*, n.d.):

1) Select the Distribution Fitting icon (Figure 15, red oval). Click "Fit…" from the list of drop down options.
2) Name the dataset, select the data, and identify the type of data (Figure 15, green box).
3) Fit the data to a distribution.

Obs. Month	Real Price
1/1/2000	$ 3.96
2/1/2000	$ 3.80
3/1/2000	$ 3.20
4/1/2000	$ 3.50
...	

Figure 14

The distribution fitting icon opens the window shown to the right (Figure 15). The price per case data has been selected and the data set has been named real price (Figure 15, green box). The data type is continuous since prices are able to assume any value so the "Continuous Sample Data" option was selected. Click the "Fit" button.

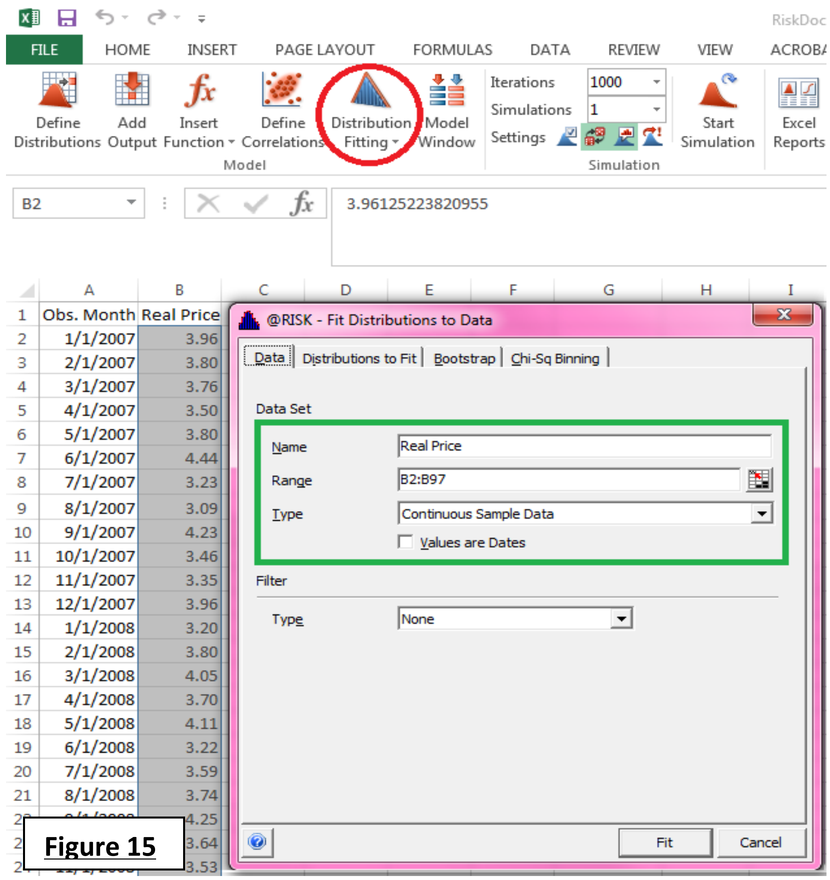
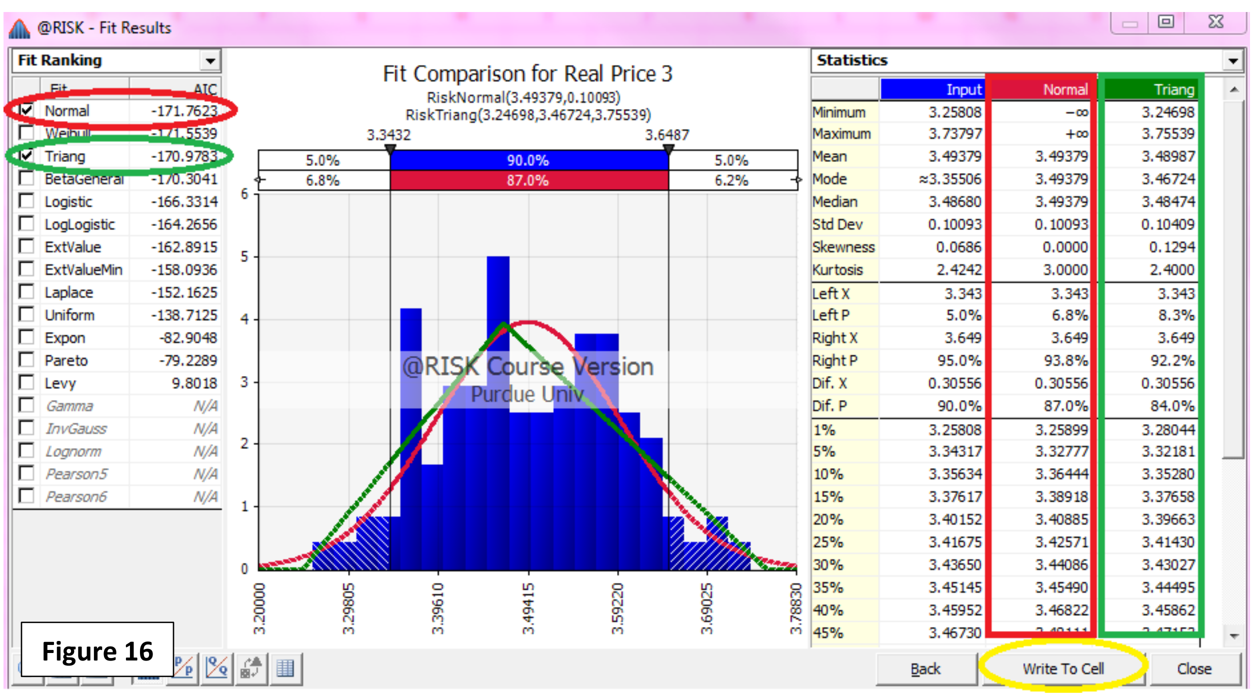


Figure 15

This opens the next window in the distribution identification process (Figure 16). An @RISK user can fit multiple distributions to the data and examine their fit. A



	Input	Normal	Triang
Minimum	3.25808	−∞	3.24698
Maximum	3.73797	+∞	3.75539
Mean	3.49379	3.49379	3.48987
Mode	≈3.35506	3.49379	3.46724
Median	3.48680	3.49379	3.48474
Std Dev	0.10093	0.10093	0.10409
Skewness	0.0686	0.0000	0.1294
Kurtosis	2.4242	3.0000	2.4000
Left X	3.343	3.343	3.343
Left P	5.0%	6.8%	8.3%
Right X	3.649	3.649	3.649
Right P	95.0%	93.8%	92.2%
Dif. X	0.30556	0.30556	0.30556
Dif. P	90.0%	87.0%	84.0%
1%	3.25808	3.25899	3.28044
5%	3.34317	3.32777	3.32181
10%	3.35634	3.36444	3.35280
15%	3.37617	3.38918	3.37658
20%	3.40152	3.40885	3.39663
25%	3.41675	3.42571	3.41430
30%	3.43650	3.44086	3.43027
35%	3.45145	3.45490	3.44495
40%	3.45952	3.46822	3.45862
45%	3.46730	[illegible]	[illegible]

Figure 16

triangle and a normal distribution have been selected here. The input data as well as the characteristics of the best-fit triangle and normal distributions are displayed on the right (Figure 16, red and green boxes). Other distributions are available to be fit on the left (Figure 16, red and green oval). Lastly, each distribution can be re-created by using the data provided in the Statistics section, or by using the Write to Cell button (Figure 16, yellow oval). Although this example has estimated a normal distribution with a mean of $3.49 and a standard deviation of just over $0.10, unless otherwise stated this paper uses $3.50 and $0.10 to define the price per case variable.

Time Series Dependency

Reviewing Attachment B, understand that the price per case variable has actually been defined by three separate variables during phase I. before the standard inflation of 2% each year starts in phase II. Although the phase I prices of each year are their own variables, they are dependent on each other in Attachment B. This linkage reflects the idea that price will fluctuate in the initial years of the product's release but will stabilize during phase II. Figures 17 and 18

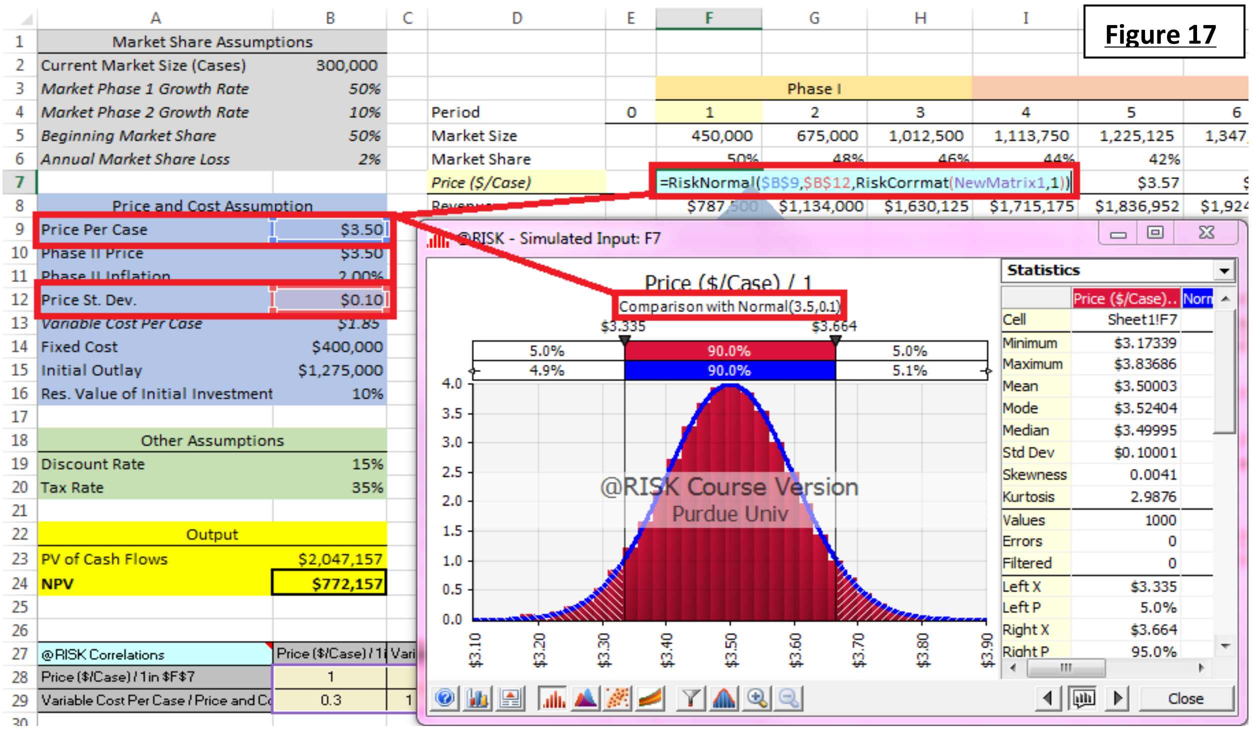


Figure 17

display this relationship. The price per case of the product in year one is defined by a normal distribution with mean price of $3.50 and a standard deviation of $0.10 (Figure 17, red boxes). The red boxes show both the coding for a normal distribution variable and the values referenced by the cell. The results of the estimation are compared to the distribution from which it was taken in the graph (observe how the red rectangles mirror the blue line). However, it is believed that the price of the product in year one will be the mean price and impact the probable distribution of prices in year two. Figure 18 shows the effect of this relationship.

Looking at the second year price per case values in, it is evident that uncertainty is increasing under these assumptions (Figure 18). Note that the mean value expected in year two is the value of the price in the first year (chosen from the normal distribution characterized by a mean of $3.50 and standard deviation of $.10). The second year has a wider interval of price values than the first. This trend of increasing variation occurs in subsequent years as well. The spread is evident by comparing the red bars to the blue line, which shows the first year's price distribution (Figure 18). The tails of the second year price distribution are thicker, which suggest that as time increases, price per case could be either substantially higher or lower than its current expected value of $3.50. Looking at the values that categorize 90% of the data in the first year and second year distributions, the red bar above the distribution has a higher range in year two than year 1. For instance, 90% of the prices in the simulation fell between the values $3.335 and $3.665 in year one, but only 75.5% of iterations had a year two price in this range. Increasing price variation implies the more volatile profits, and this risk is not captured in the deterministic example (Attachment A).

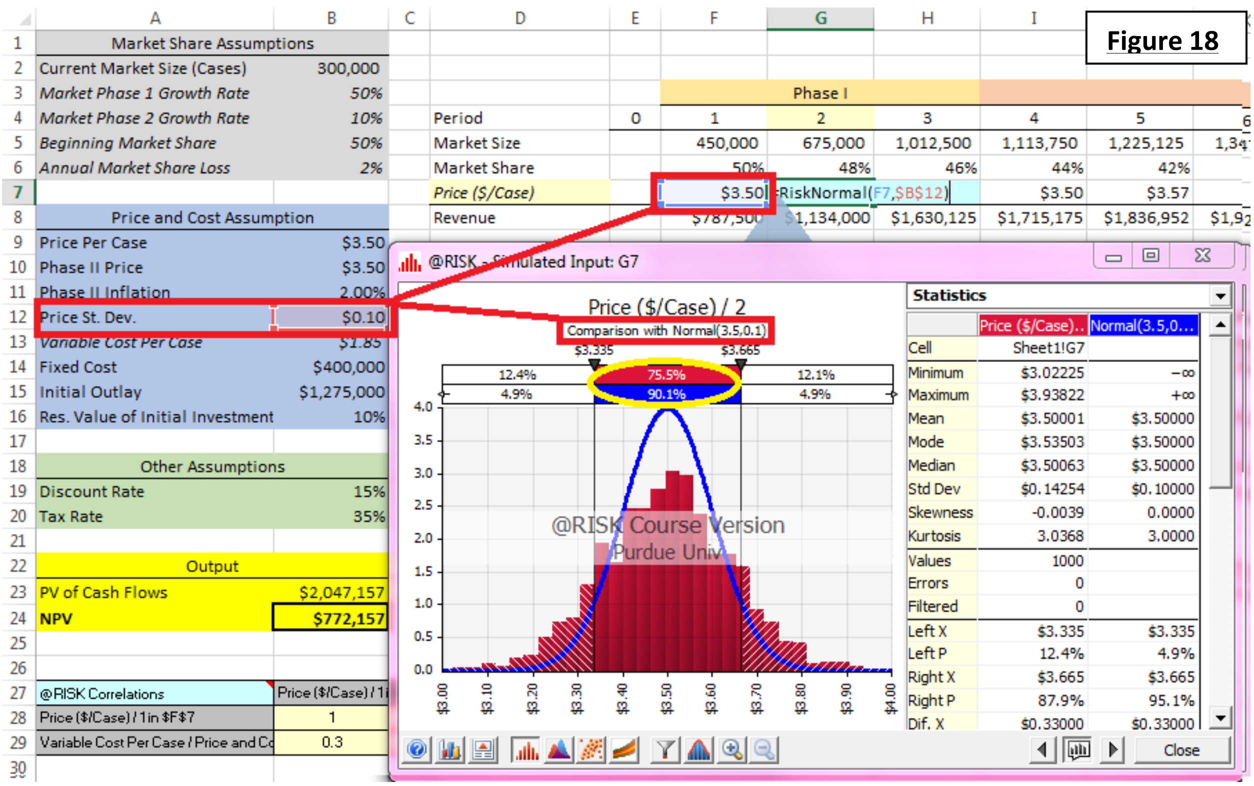


Figure 18

Built in Analysis Tools

Although these graphs allow a user to explore how variables such as prices change over time, @RISK allows for much more versatile analysis. By clicking on the icons in the simulate inputs window, a user can graphically display data in many different ways (Figure 19, yellow box). Scatter plots, graph overlays, or distribution modeling are just some of the options available to an @RISK user. Here, a time series graph displays the simulation’s price per case variable across phase I (Figure 19). The standard deviation and range increases of each year’s price per case can be easily viewed.

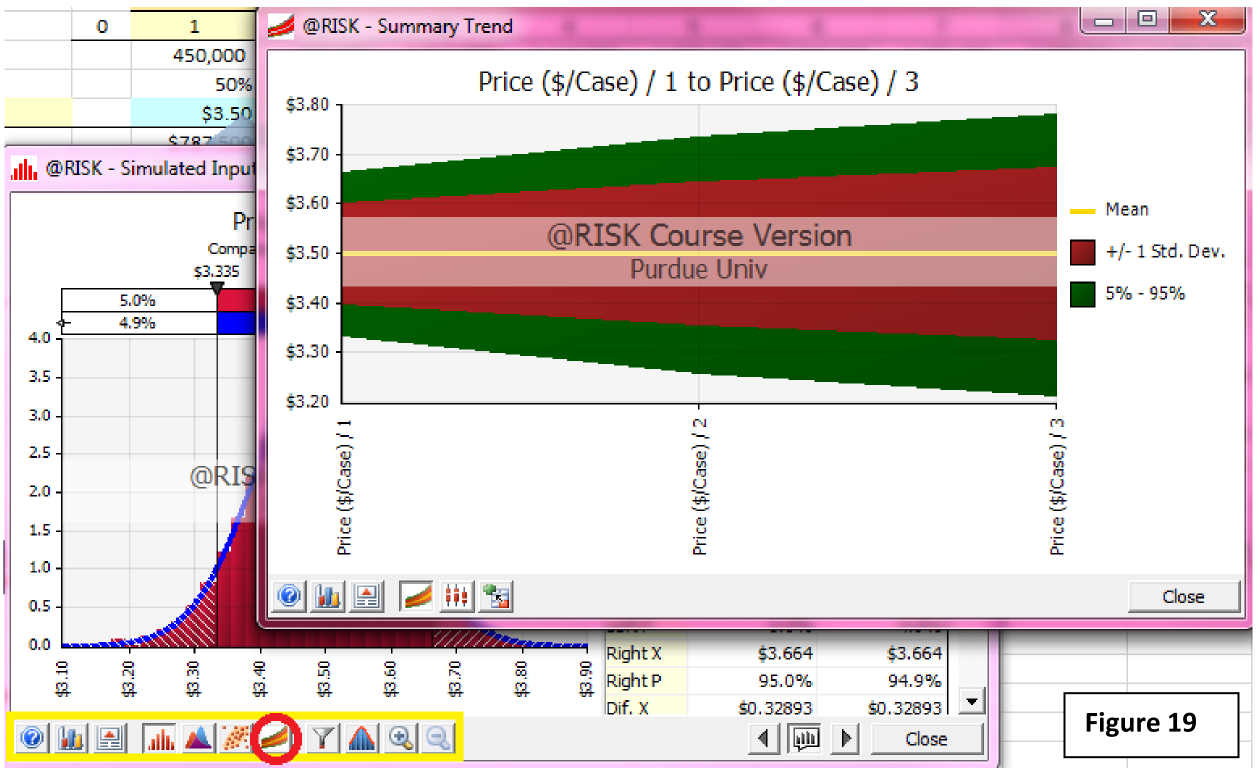


Figure 19

Analysis of NPV

The end result of this analysis is to evaluate if this project is a profitable endeavor. Before we analyze the NPV values of the simulation, a specific coding necessary for a simulation output variable like the net present value NPV calculation should be noted. As Figure 20 shows, the cell B22 must include the syntax Riskoutput() in order to properly run (Palisade *Define Outputs*, n.d.). In an @RISK simulation, the RiskOutput function identifies any cells with that function as a simulation output and records their values.

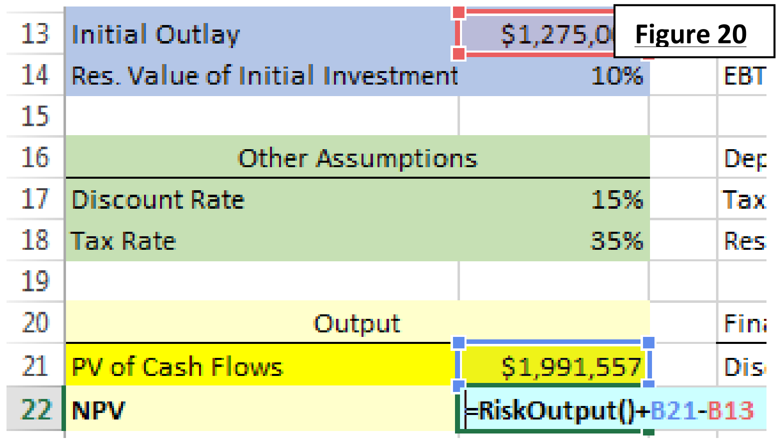


Figure 20

Regarding the project's profitability, Figure 21 shows the results of the net present value analysis (Palisade *Results*, n.d.). Although the output appears similar to graphs previously discussed for variables used in this paper's model, the implications and insights are far more

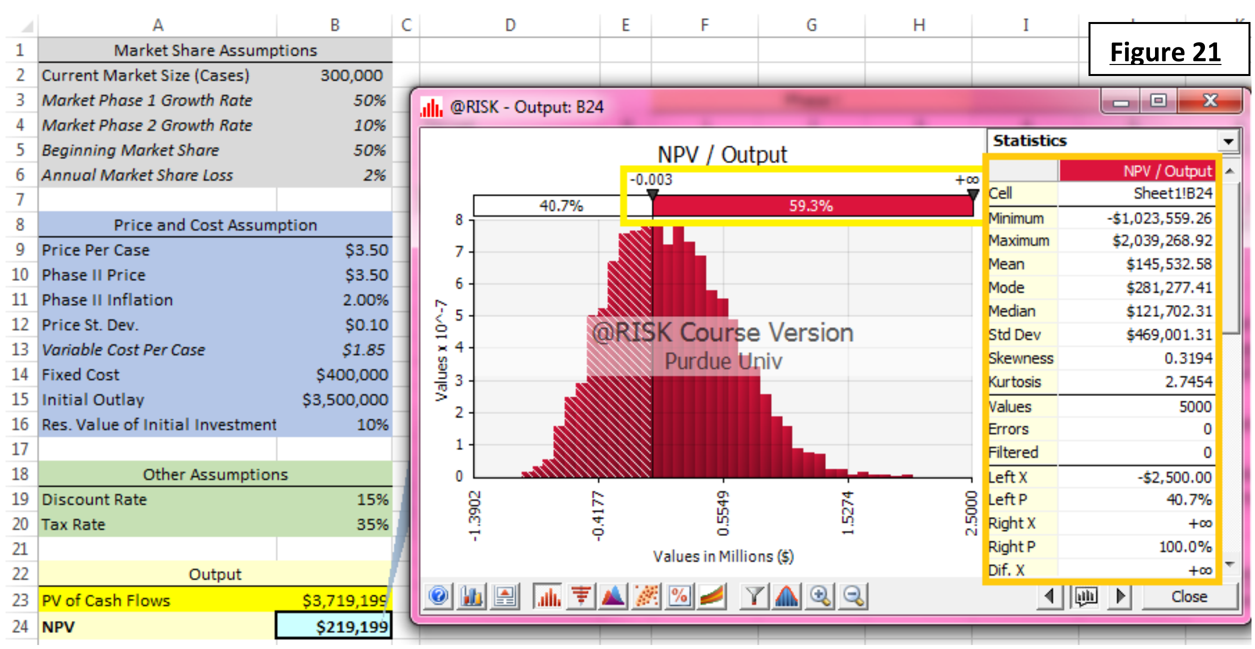


Figure 21

important. It is clear that this project has a good probability of being profitable as suggested by a mean NPV of $145,532.58 and the NPV probability distribution in the NPV space. However, there is some risk involved. To measure this risk, the user can review the NPV statistics (Figure 21, yellow box). Approximately 60% of the iterations in the simulation returned a positive net present value. However, 40% of the iterations returned a negative net present value.

The statistics are also very valuable in the final project analysis. For instance, in the most extreme case, this project could lose over one million dollars (see minimum value). Is that a risk the investor is willing to take? The maximum ($2,039,268.92) is also shown, but it is more appropriate to consider where the mean and standard deviation lie in the NPV distribution. A cursory analysis using the mean and one standard deviation above and below suggests the project is most likely to have a net present value somewhere between roughly -$300,000 and $600,000. Lastly, some consideration should be given to the skewness of the distribution. Although @RISK lists the project's skewness as 0.3194, this characteristic is best understood by looking at the shape of the project's distribution. This positive skewness is apparent from the elongated tail on the right side of the distribution. Given the assumptions and simulated results of this project, it appears to be an attractive venture; however, it is not without its risks and the sizeable number of iterations with negative net present values may be cause for concern to those more risk averse.

The Importance of Iterations

Choosing a sufficient number of iterations can be critical to obtaining accurate results. Unless otherwise stated, the graphs in this paper have used 5,000 iterations. This number may or may not be sufficient for a model, depending on its intricacy and the assumptions of the project. It is always better to err on the side of caution and perform more iterations than less. Complicated models may take longer to simulate when more iterations are selected; however, the tradeoff is rarely sufficient to merit fewer iterations when trying to draw inference. To help conceptualize the impact fewer iterations can have on the analysis of a project, Figure 22 displays the project under a fifty iteration simulation. The real risk and NPV distribution is far less easy to observe and the minimum and maximum returns from the project are substantially different from the 5,000 iteration simulation. Using this analysis, a manager might make a poor decision regarding the project. If a user is unsure about how many iterations to use, they can also select the automatic option for the number of iterations which will cause the simulation to run until the solution converges.

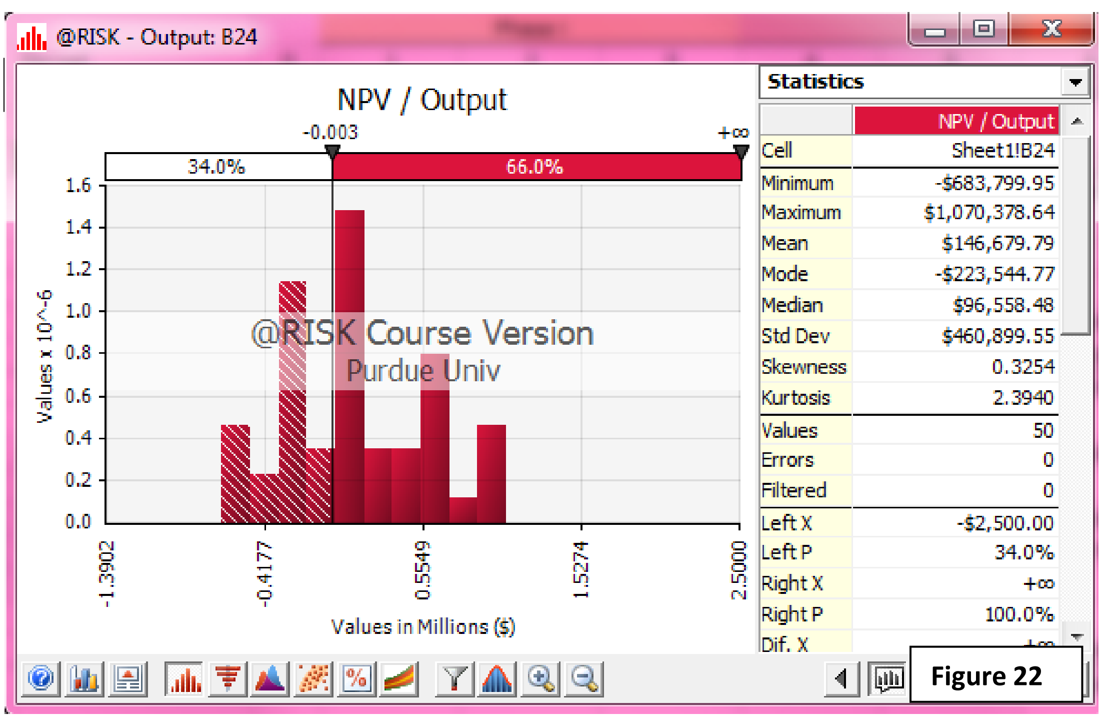


Figure 22

The Tornado Plot and Variable Influence Analysis

Although there are many other analytical tools available, one is particularly worth mentioning. The tornado plot is shown below in Figure 23. The goal of a tornado plot is to aid in sensitivity analysis. Essentially, it allows for the quick comparison of variables and their relative importance to the risk or variability of an output like NPV. The process for calculating a project's sensitivity to a particular variable is performed by @RISK, using the expected NPV as a baseline. @RISK orders the results into 10 equally probable bins from the simulation and calculates the mean of the highest and lowest bins (Palisade *Interpreting*, 2016). The extreme values in each bar are the means of these deciles. The value of this analysis is that an @RISK user is able to quickly identify the most important drivers of the variability a project.

From Figure 23, it is clear that variability in Beginning Market Share is by far the most impactful variable to the variability project's net present value. Given baseline assumptions for other variables, expected NPV falls to -$408,414 at the mean of the lower decile for Beginning Market Share. The price per case variables are also important according to the tornado plot. One

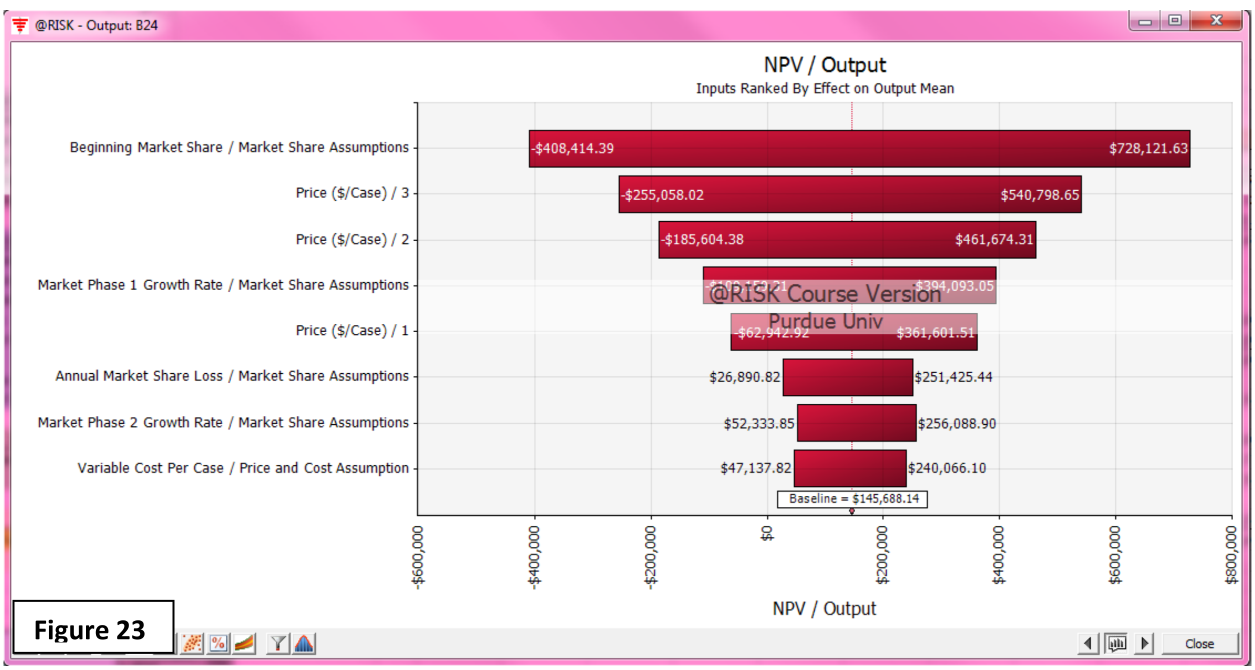


Figure 23

might think that the first year price should be higher than later years because its income experiences less discounting, but it is interestingly fourth in the plot. It is likely that the increasing range of price possibilities in later years exacerbates their impact on NPV. This unintuitive conclusion demonstrates the value of tornado plots in analysis. These insights allow @RISK users to prioritize uncertainties in the project. For example, after considering Figure 23 it may be beneficial to consider if there are ways to ensure a larger Beginning Market Share through aggressive marketing early in the venture.

Conclusion

@RISK is an extremely powerful tool for the modern day business analyst. As a continuously improving add-on to Excel, it will certainly be part of the future of risk management and project analysis. By allowing its users to actively manipulate and analyze variables, @RISK allows its users to understand and model real life business environments. Furthermore, its ability to analyze multiple possibilities and states of nature through simulations makes it an incredibly powerful tool for assessing not only projected NPV, but also the variables and assumptions built into the project. Users of @RISK can better identify whether a project will be profitable and understand the driving variables that influence profitability.

Variables and Distributions

Variable	Abbreviation	Distribution	Note
Market Phase 1 Growth Rate		Triangular	Skewed
Market Phase 2 Growth Rate		Normal	
Beginning Market Share		Uniform	
Annual Market Share Loss		Triangular	Symmetric
Price		Normal	Unique Each Year
Variable Cost Per Case Year 1		Normal	Correlated With Price in Year 1
Variable Cost Per Case Year 2		Normal	Linked to Year 1
Variable Cost Per Case Year 3		Normal	Linked to year 2

Additional Resources

The following table includes tutorial videos to complete the actions listed. You can access these videos by clicking on the title of a specific one on the left hand side of the document or going to the url home page on the right.

Additional Resources and Links
a. @RISK Library b. All Tutorials c. Correlating Inputs d. Customizing Results Graphs e. Data and Statistics Windows f. Defining Distributions g. Defining Outputs h. Distribution Fitting i. Histograms and Cumulative Curves j. Model Window k. Overlaying Results Graphs l. Reports in Excel m. Results Summary Windows n. Running a Simulation o. Scatter Plots p. Sensitivity and Scenario Analysis q. Simulation Settings r. Summary Box Plots and Trend Graphs s. Tornado Graphs t. User Guide

Coding Syntaxes

Distribution Function	Notes
RiskBetaGeneral(*alpha1, alpha2,minimum, maximum*)	beta distribution with defined *minimum*, *maximum* and shape parameters *alpha1* and *alpha2*
RiskBinomial(*n,p*)	binomial distribution with *n* draws and *p* probability of success on each draw
RiskDiscrete(*{X1,X2,...,Xn}, {p1,p2,...,pn}*)	discrete distribution with *n* possible outcomes with the value *X* and probability weight *p* for each outcome
RiskDuniform(*{X1,X2,...Xn}*)	discrete uniform distribution with n outcomes valued at *X1* through *Xn*
RiskGamma(*alpha,beta*)	gamma distribution with shape parameter *alpha* and scale parameter *beta*
RiskGeneral(*minimum,maximum, {X1,X2,...,Xn}, {p1,p2,...,pn}*)	general density function for a probability distribution ranging between minimum and maximum with *n* (*x,p*) pairs with value *X* and probability weight *p* for each point
RiskHistogrm(*minimum,maxi-mum,{p1,p2,...,pn}*)	histogram distribution with *n* classes between *minimum* and *maximum* with probability weight *p* for each class
RiskIntUniform(*minimum,maximum*)	uniform distribution which returns integer values only between *minimum* and *maximum*
RiskNormal(*mean,standard deviation*)	normal distribution with given *mean* and *standard deviation*
RiskTriang(*minimum,most likely, maximum*)	triangular distribution with defined *minimum*, *most likely* and *maximum* values
RiskUniform(*minimum, maximum*)	uniform distribution between *minimum* and *maximum*
RiskWeibull(*alpha,beta*)	weibull distribution with shape parameter *alpha* and scale parameter *beta*
RiskOutput()	identifies a cell in a spreadsheet as a simulation output

Attachments

Attachment A

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Market Share Assumptions														
2	Current Market Size (Cases)	300,000													
3	*Market Phase 1 Growth Rate*	*50%*				Phase I			Phase II						
4	*Market Phase 2 Growth Rate*	*10%*		Period	0	1	2	3	4	5	6	7	8	9	10
5	*Beginning Market Share*	*50%*		Market Size		450,000	675,000	1,012,500	1,113,750	1,225,125	1,347,638	1,482,401	1,630,641	1,793,706	1,973,076
6	*Annual Market Share Loss*	*2%*		Market Share		50%	48%	46%	44%	42%	40%	38%	36%	34%	32%
7				*Price ($/Case)*		$3.50	$3.50	$3.50	$3.50	$3.57	$3.64	$3.71	$3.79	$3.86	$3.94
8	Price and Cost Assumption			Revenue		$787,500	$1,134,000	$1,630,125	$1,715,175	$1,836,952	$1,962,915	$2,092,271	$2,223,974	$2,356,671	$2,488,645
9	Price Per Case	$3.50													
10	Phase II Price	$3.50													
11	Phase II Inflation	2.00%													
12	Price St. Dev.	$0.10		Variable Cost		$416,250	$599,400	$861,638	$906,593	$951,922	$997,252	$1,042,128	$1,086,007	$1,128,241	$1,168,061
13	*Variable Cost Per Case*	*$1.85*		Fixed Cost		$400,000	$400,000	$400,000	$400,000	$400,000	$400,000	$400,000	$400,000	$400,000	$400,000
14	Fixed Cost	$400,000		Total Cost		$816,250	$999,400	$1,261,638	$1,306,593	$1,351,922	$1,397,252	$1,442,128	$1,486,007	$1,528,241	$1,568,061
15	Initial Outlay	$3,500,000													
16	Res. Value of Initial Investment	10%		EBTD		-$28,750	$134,600	$368,488	$408,583	$485,030	$565,663	$650,143	$737,967	$828,430	$920,584
17															
18	Other Assumptions			Depreciation		$350,000	$350,000	$350,000	$350,000	$350,000	$350,000	$350,000	$350,000	$350,000	$350,000
19	Discount Rate	15%		Taxes		-$132,563	-$75,390	$6,471	$20,504	$47,261	$75,482	$105,050	$135,788	$167,451	$199,704
20	Tax Rate	35%		Residual Value											$227,500
21															
22	Output			Final Cash Flow		$453,813	$559,990	$712,017	$738,079	$787,770	$840,181	$895,093	$952,178	$1,010,980	$1,298,379
23	PV of Cash Flows	$3,719,199		Discounted Cash Flow		$394,620	$423,433	$468,163	$421,999	$391,661	$363,233	$336,499	$311,269	$287,384	$320,940
24	**NPV**	**$219,199**													

Attachment B

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Market Share Assumptions														
2	Current Market Size (Cases)	300,000													
3	*Market Phase 1 Growth Rate*	*49%*				Phase I			Phase II						
4	*Market Phase 2 Growth Rate*	*9%*		Period	0	1	2	3	4	5	6	7	8	9	10
5	*Beginning Market Share*	*45%*		Market Size		446,803	665,443	991,073	1,079,902	1,176,692	1,282,157	1,397,075	1,522,292	1,658,733	1,807,403
6	*Annual Market Share Loss*	*2%*		Market Share		45%	43%	41%	39%	37%	35%	33%	31%	29%	27%
7				*Price ($/Case)*		$3.40	$3.53	$3.47	$3.47	$3.54	$3.61	$3.68	$3.75	$3.83	$3.90
8	Price and Cost Assumption			Revenue		$688,177	$1,015,381	$1,415,459	$1,465,981	$1,544,471	$1,622,253	$1,698,193	$1,770,917	$1,838,764	$1,899,746
9	Price Per Case	$3.50													
10	Phase II Price	$3.32													
11	Phase II Inflation	2.00%													
12	Price St. Dev.	$0.10		Variable Cost		$375,754	$534,420	$758,395	$785,464	$811,293	$835,442	$857,403	$876,588	$892,326	$903,842
13	*Variable Cost Per Case*	*$1.86*		Fixed Cost		$400,000	$400,000	$400,000	$400,000	$400,000	$400,000	$400,000	$400,000	$400,000	$400,000
14	Fixed Cost	$400,000		Total Cost		$775,754	$934,420	$1,158,395	$1,185,464	$1,211,293	$1,235,442	$1,257,403	$1,276,588	$1,292,326	$1,303,842
15	Initial Outlay	$3,500,000													
16	Res. Value of Initial Investment	10%		EBTD		-$87,577	$80,961	$257,064	$280,516	$333,178	$386,811	$440,791	$494,329	$546,439	$595,903
17															
18	Other Assumptions			Depreciation		$350,000	$350,000	$350,000	$350,000	$350,000	$350,000	$350,000	$350,000	$350,000	$350,000
19	Discount Rate	15%		Taxes		-$153,152	-$94,164	-$32,528	-$24,319	-$5,888	$12,884	$31,777	$50,515	$68,754	$86,066
20	Tax Rate	35%		Residual Value											$227,500
21															
22	Output			Final Cash Flow		$415,575	$525,124	$639,592	$654,836	$689,066	$723,927	$759,014	$793,814	$827,685	$1,087,337
23	PV of Cash Flows	$3,257,840		Discounted Cash Flow		$361,370	$397,069	$420,542	$374,404	$342,587	$312,974	$285,341	$259,499	$235,280	$268,773
24	**NPV**	**-$242,160**													

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