Modeling with @RISK: A Tutorial Guide

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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. 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 better understand how risk and uncertainty can impact 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 today. The software uses simulation to combine uncertainties and allow easy graphical analysis. Historically, most business decisions were modeled and then individual variables were altered 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 utilize 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 very intuitive to those already familiar with Excel in a business context. The basic steps to using @RISK to define a stochastic variable are as follows:

1) Access Excel through the start menu or an icon shortcut
2) Select the @RISK tab in Excel
3) Select a cell that has been chosen to be stochastic and click the define distribution button
4) Select a type of distribution
5) Define the parameters for the distribution

Figure 1 displays where the @RISK tab can be found in a normal excel document. The tab is highlighted in yellow. The next step in using @RISK is to click on the define distributions button

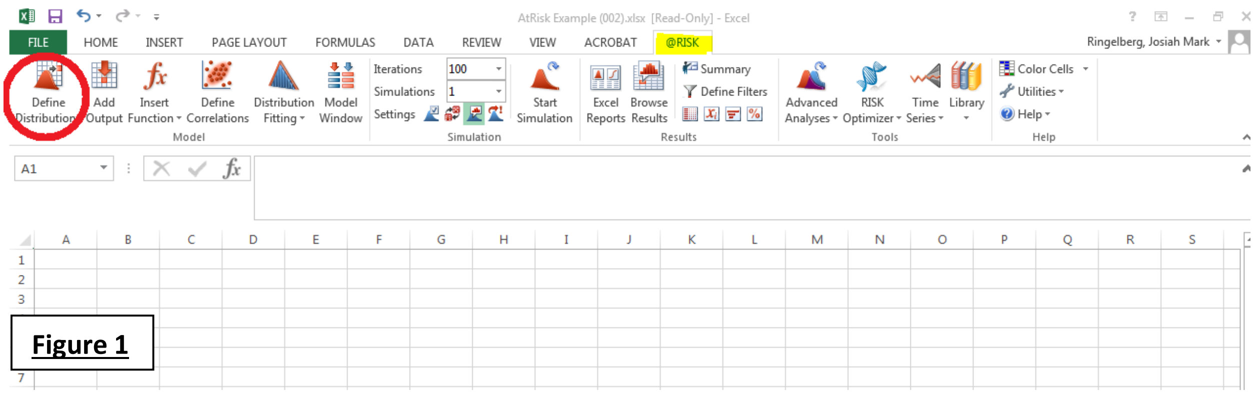


Figure 1

circled in red on Figure 1. This opens the following window shown in Figure 2. Multiple distributions are displayed. As shown in Figure 2, the normal distribution has been selected. Clicking on the question mark in the top right corner of the normal distribution icon opens the information box shown in Figure 3. The distribution as well as its purposes and the types of variables it can model are defined.

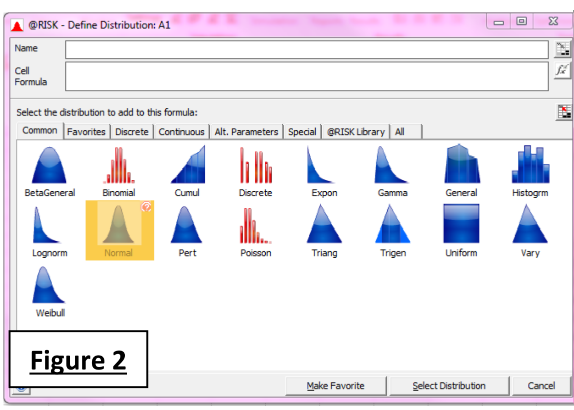


Figure 2

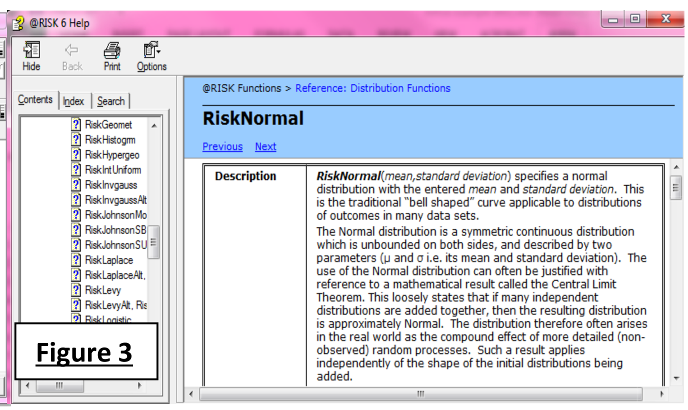


Figure 3

Double clicking on a distribution allows a user to specify the parameters of the distribution. This action opens a pop-up shown in Figure 4 that allows the user to enter parameters that characterize the distribution being modeled.

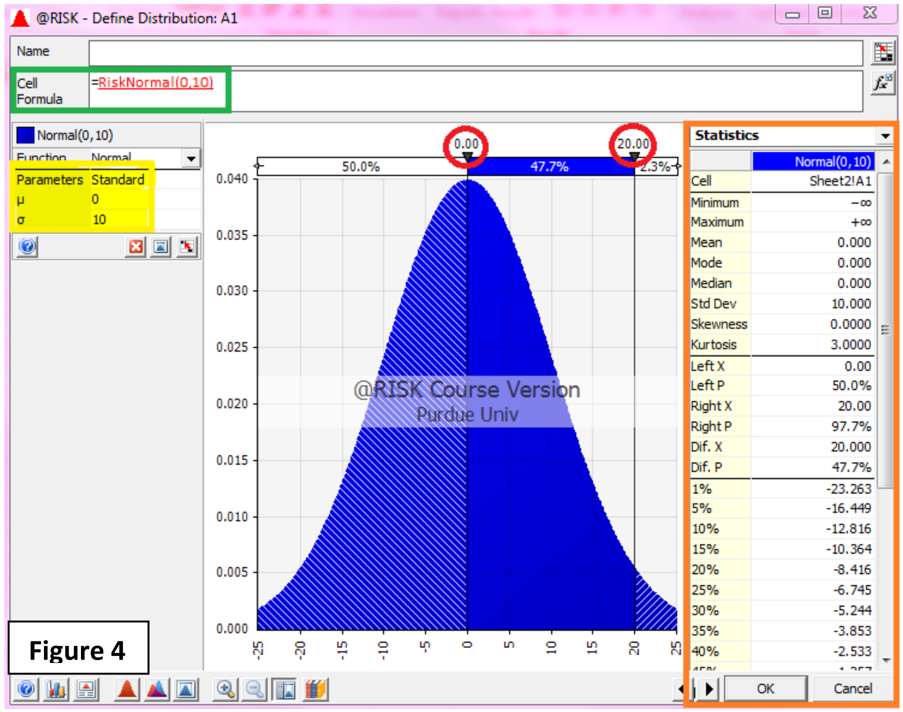


Figure 4

Highlighted on Figure 4 in yellow are the defined parameters of a normal distribution. Other distributions can have more or less parameters, but the normal distribution currently displayed has a mean set at zero and a standard deviation of ten. Given these parameters, many commonly used statistics and attributes of the distribution are displayed in the red box on the right side of the image.

One of the most powerful and interactive abilities of @RISK can be seen by looking at the red circles in Figure 4. By dragging the black arrows, 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. As a closing comment, the green box displays the cell formula for an @RISK variable modeled by the normal distribution. With the proper syntax a user can enter a variable and its parameters directly into a cell. A syntax list of common distributions is included in Table 3 at the end of this paper.

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 whether or not to invest in a particular venture. The analytical procedure being used is net present value (NPV) or discounted cash flow (DCF).The cash flows of the project are outlined in the first attached spreadsheet (Attachment A at the end of this paper). The spreadsheet summarizes the revenues and costs for a product that is being introduced into a new market. The product is not patentable, so the company 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 currently has market volume of 300,000 cases, but is expected to increase to 450,000 once it is shelved in additional stores. Price is believed to remain at an expected value of $3.50 during phase I and but is modeled to start increasing at a 2% inflation rate during phase II. Given the cost, outlay, and other assumptions displayed in the colored boxes of Attachment A, the project is expected to have a net present value (NPV) of $219,199. However, the analysis shown in Attachment A has only utilized standard Excel features and doesn’t provide insights concerning the risks of the project. All variables shown utilize only their expected values, without consideration to what other values are possible. The next analysis will utilize several @RISK tools to obtain further insights.

Reviewing the second analysis (Attachment B), it should be apparent 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 the spreadsheet of attachment B shows one possible outcome of the project given a different state other than the expected. This demonstrates the impact that randomly selected values from the distribution might have on a project. The variables that are being selected from a distribution are identified in Table 1 (shown at the end of this paper). The results of multiple runs with different values assigned to these variables will be analyzed in the following paragraphs.

Running a Simulation

Attachment B shows the impact that uncertainty can have on the net present value of the project by illustrating one possible outcome using stochastic variables. However, this still does not provide a great understanding of the overall risks of the project. To obtain a more detailed understanding of the project multiple solutions each with different values for the variables can be gathered using a procedure called simulation. A simulation is composed of iterations. An iteration is run by clicking

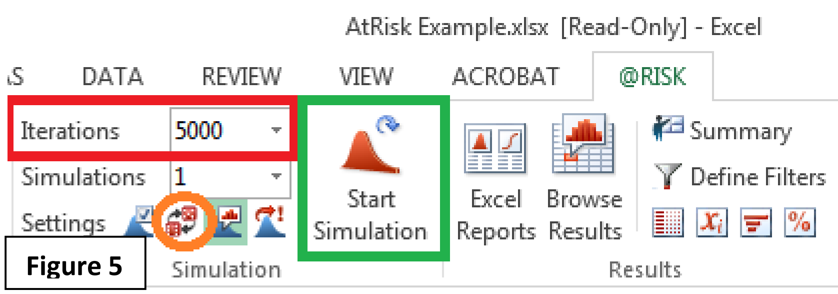


Figure 5

the dice in the @RISK tab on Excel, as circled in orange in Figure 5. As a general rule of thumb, the more iterations the more accurate the inferences derived from the simulation. The consequences of using too few of iterations will be covered in depth during the net present value analysis later in this paper. For now, it suffices to understand that by adjusting the number of iterations in a simulation (shown in the red box of figure 5) and running the simulation by clicking the icon in the green box, an @RISK user can analyze the impact of random variables across many iterations – the risk of the project.

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 results shown in Figure 6 can be accessed by clicking on the variable's cell after a simulation has been run. In this example, MP1GR is displayed in the cell B3 (teal box in Figure 6). Given the assumption that MP1GR can be defined by a triangle distribution with the parameters shown in the orange rectangle, its characteristics can be seen by utilizing the drag and click black arrows shown in the red rectangle. 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 single value expectations model of Attachment A. Other statistics like the mean, mode, and variance for this variable are displayed

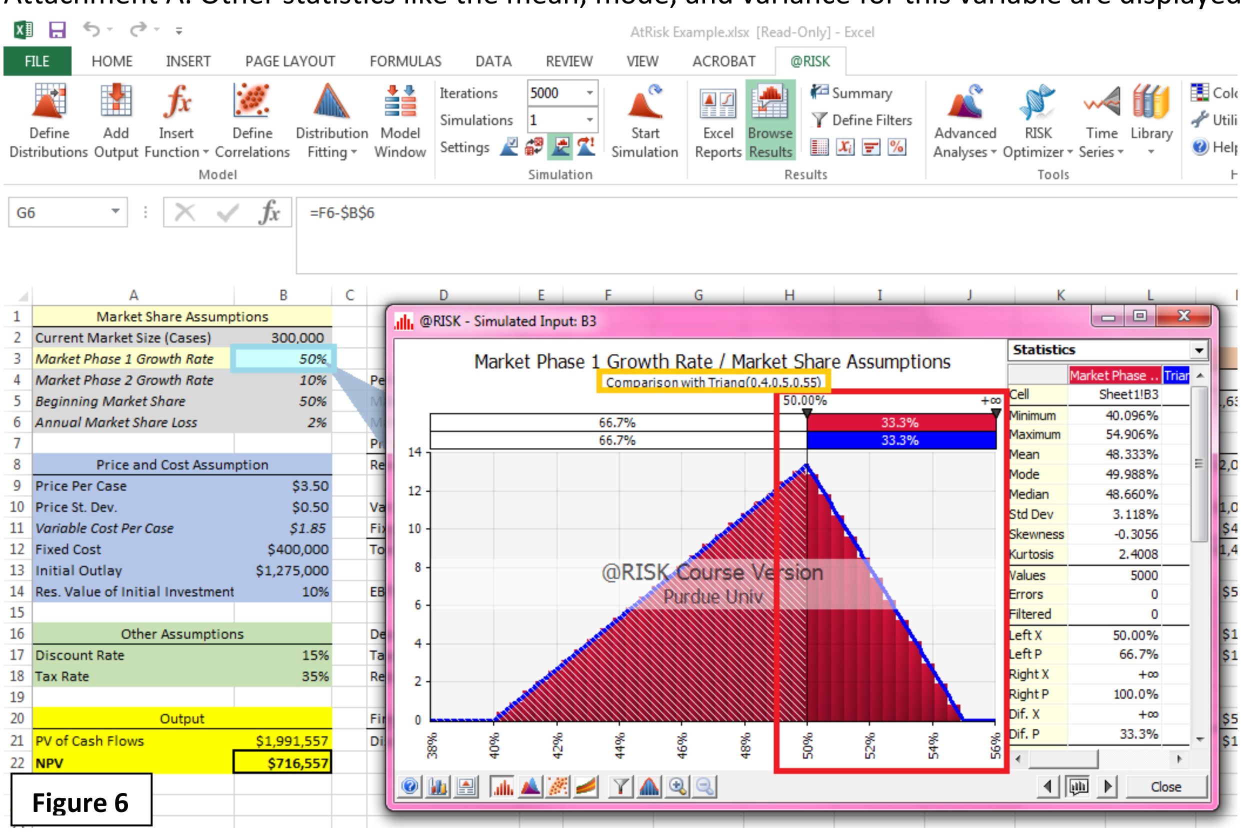


Figure 6

to the left. The blue line around the triangle shows the shape of the coded distribution, while the red represents the variable's actual values during iterations of the simulation. Because of the high number of iterations (5,000), the simulation mirrors closely the distribution. The selection of 5,000 iterations will be reviewed again during the section on the analysis of the project's net present value.

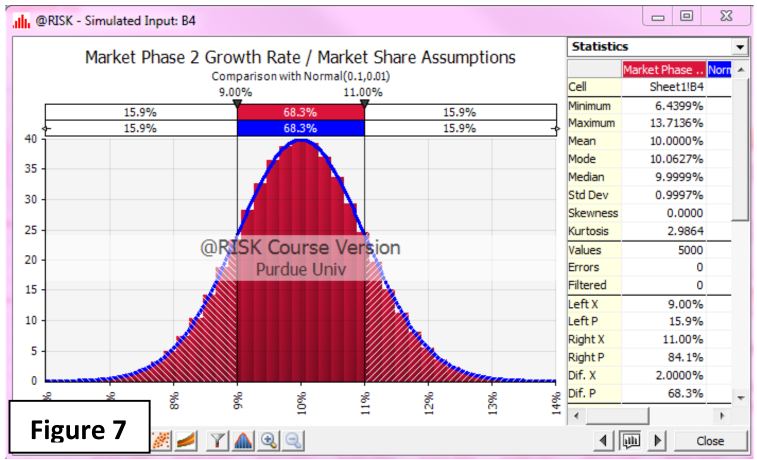


Figure 7

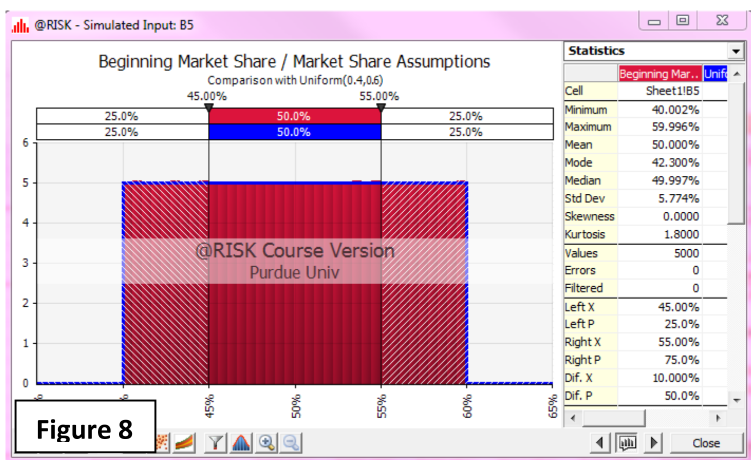


Figure 8

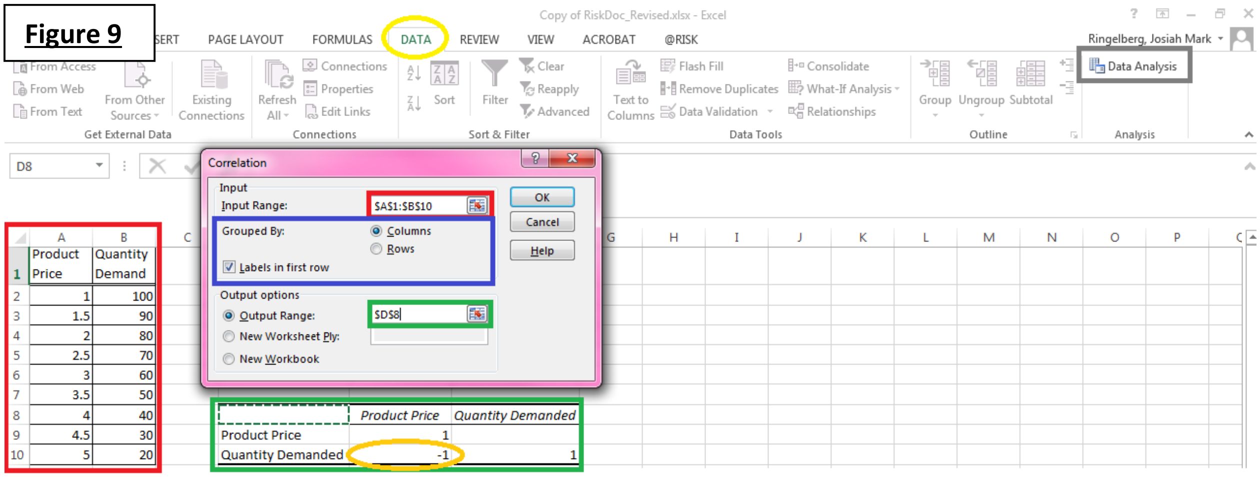
Figure 7 displays the characteristics of the variable Market Phase 2 Growth Rate (MP2GR) and Figure 8 shows the distribution for Beginning Market Share Growth Rate (BMSGR). These distributions show the versatility a user can have over how a variable is defined. MP2GR is characterized by the normal distribution and BMSGR is modeled using a uniform distribution. Again, the moveable black bars have been adjusted to show the percent of iterations where MP2GR is within 1% of the expected 10% value and BMSGR is within 5% of its expected value. Annual Market Share Loss (AMSL) is modeled by an unskewed triangular distribution but is not graphically shown.

Defining 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 is merely to suggest that as the price of a product goes up, the quantity demanded decreases. In short, 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.

1. Gather historical data on the variables in which a correlation is believed to exist. Figure 9 displays product price and quantity demanded data in the large red rectangle. 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 first select the DATA tab circled in yellow and click the Data Analysis icon in the gray rectangle.
3. As the pop-up shows, a user must first select the input range, clarify how the data is organized using the attribute features shown in the blue box, and select an output location as identified by the smaller green rectangle.
4. Once step three is finished and the user clicks the OK button, the correlation matrix shown in the larger green rectangle will be inserted into Excel. The correlation between the variables in this example is shown circled in orange. This correlation can then be used in future modeling.

Figure 9



In the model provided for this analysis, a correlation has been created between the price per case variable in the first year and the variable cost per case. This could be reflective of a company's decision to price their product with consideration to the costs they are unsure of or the assumption that, 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 three steps to defining a correlation between variables. They are as follows:

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

To begin, Figure 10 shows where the Define Correlations button can be found in the @RISK tab. This button has been circled in red and opens the pop-up shown in the figure. The second required step is highlighted in the purple box of the pop-up. Although @RISK will auto generate a generic name for the matrix, the user must select the correlation matrix's location in Excel. For the correlation matrix displayed the cells A27:C29 have been selected.

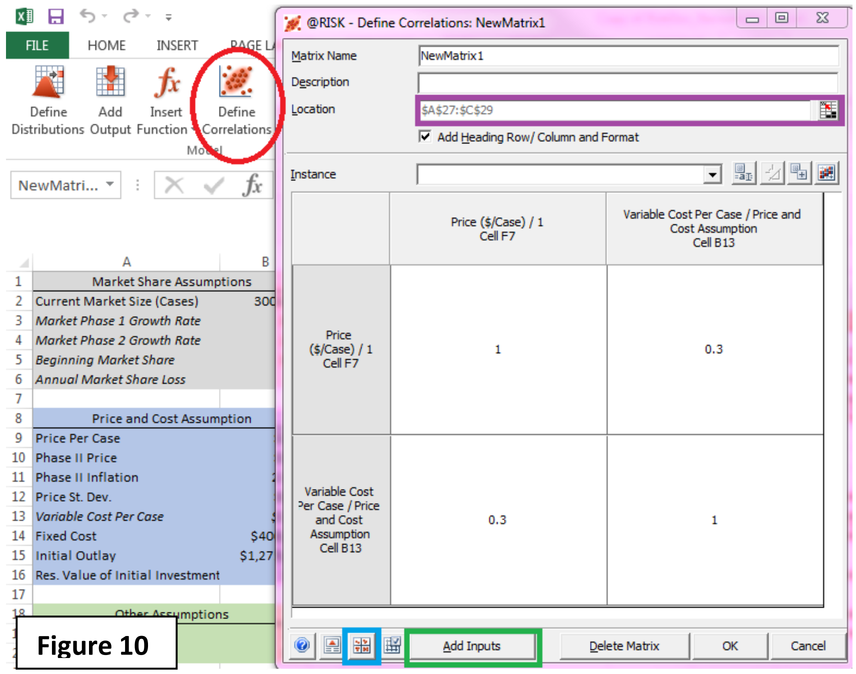


Figure 10

When a user initially opens the pop-up in Figure 10, the table displayed will be blank. Variables must be selected before the table is filled. To do this, a user selects the Add Inputs button shown in the green rectangle. This action opens a 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.

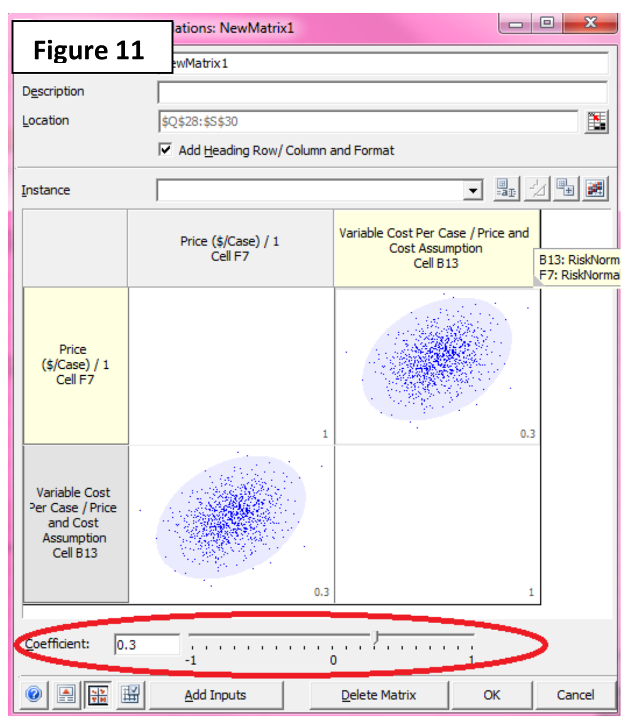


Figure 11

Once the data for a correlation has been entered, the correlation must be defined. This can be done several ways, but the best method would be to utilize the button in the blue rectangle on Figure 10. This opens a pop-up that allows a much more interactive means of defining a correlation between two variables. Figure 11 shows a scatter plot analysis of the correlation matrix. By using the slider or entering in new correlation coefficients, a user can help define the relationship between two variables. The scatter plots help to illustrate the strength of these correlations graphically. After a correlation has been established between two variables, it can be altered using the correlation matrix displayed in Figure 12. Again, this matrix appears in the location identified in the purple rectangle of Figure 10 after a correlation has been created. Lastly, once a variable has been correlated, its formula will display the syntax RiskCorrmat(matrix cell range or matrix name, variable position). This is shown below with the formula of Variable Cost per Case displayed in 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.

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

Price and Cost Assumption					
Price Per Case	$3.50	Revenue		$787,500	$1,134,000
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),RiskCorrmat(NewMatrix1,2))*				
Fixed Cost	$400,000	Total Cost		$816,250	$999,400
[illegible]	$1,275,000				
[illegible]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:

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

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

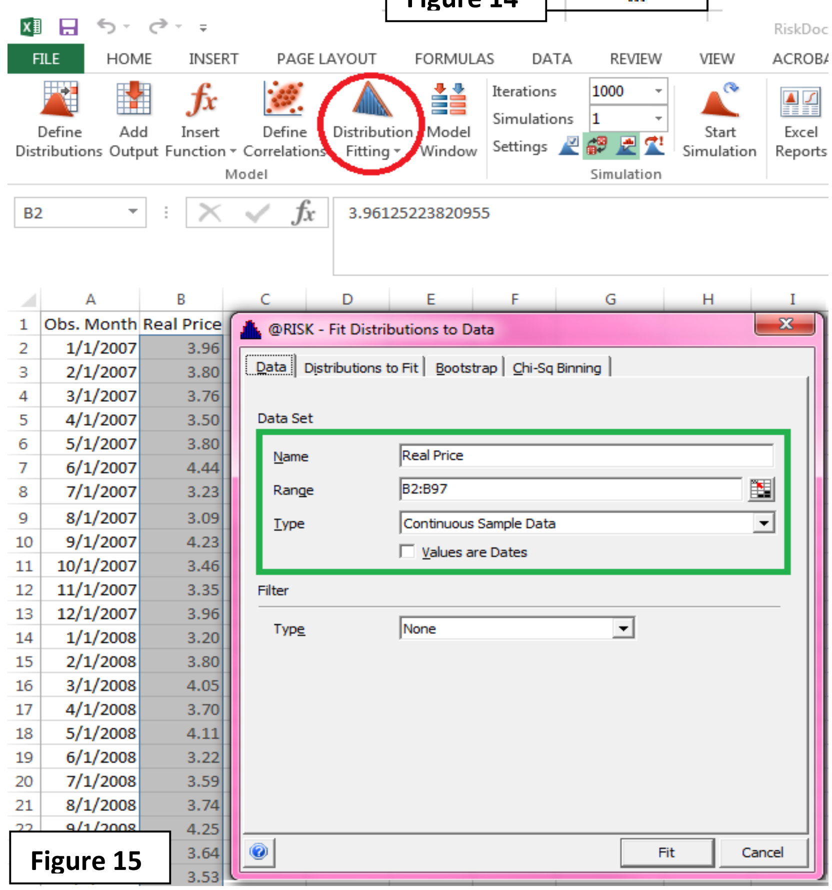


Figure 15

The distribution fitting icon is circled in red in Figure 15. Completing step 1 opens the window shown to the right in this figure. The price per case data has been selected and the data set has been named real price (see the green box in Figure 15). The data type is continuous since prices are able to assume any value so the “Continuous Sample Data” option has been selected from the available drop down menu. Clicking the “Fit” button initiates step 3.

Figure 16 shows the next window in the distribution identification process. An @RISK user can fit multiple distributions to the data and examine their fit. A triangle and a normal distribution have been selected. The input data as well as the characteristics of the best-fit triangle and normal distributions are displayed on the right. Other distributions are available to be fit on the left where the red and green ovals are shown. Lastly, each distribution can be re-created by using the data provided in the Statistics section, or by using the Write to Cell button circled in yellow. 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

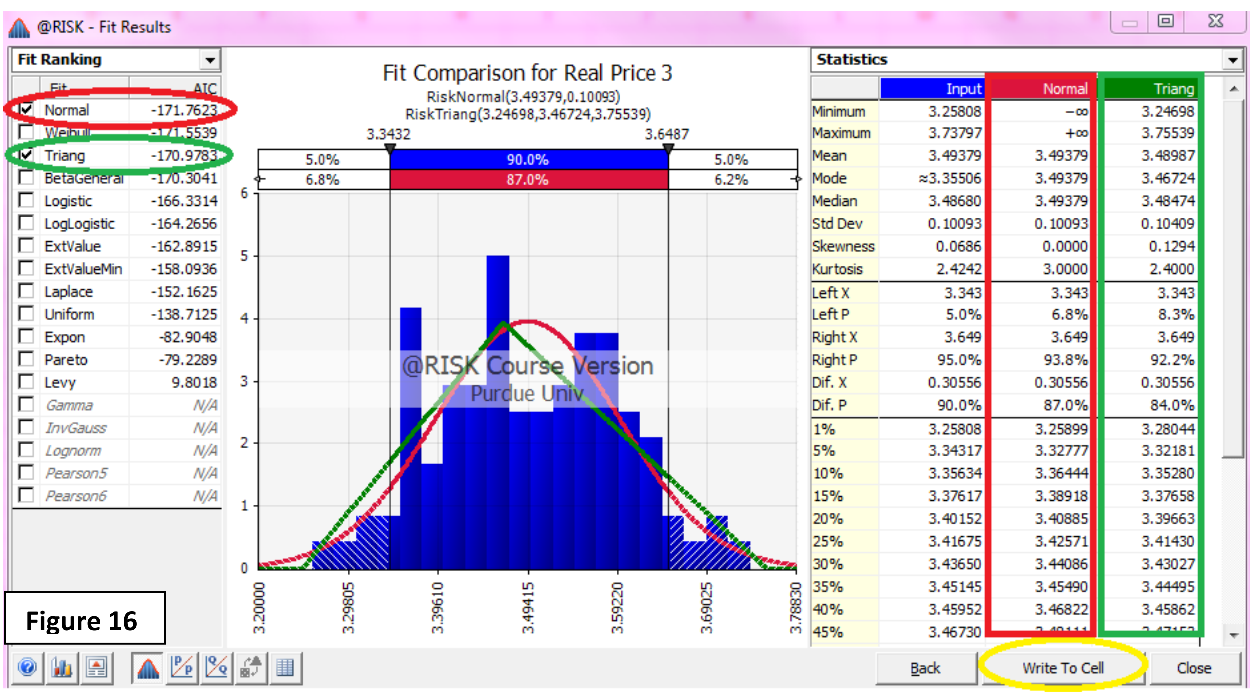


Figure 16

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 is to reflect the idea that price will fluctuate in the initial years of the product's release but will stabilize during phase II. Figure 17 and 18 will display this relationship assumption. Reviewing the Figure 17, the price per case of the product in year one (see the red boxes) is defined by a normal distribution with mean price of $3.50 and a standard deviation of $.10. 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 (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 range of prices possible in year two. Figure 18 shows the effect of this relationship.

Looking at the second year price per case values in Figure 18, it is evident that uncertainty is increasing under these assumptions. Note that the mean value expected in year 2 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 spread of price values than the first. This trend of increasing variation occurs in year three as well. The spread is evident by comparing the red bars to the blue line that shows the first year's price distribution in Figure 18. The tails of the second year price distribution are wider and thicker, which suggest that as time increases, price per case will 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

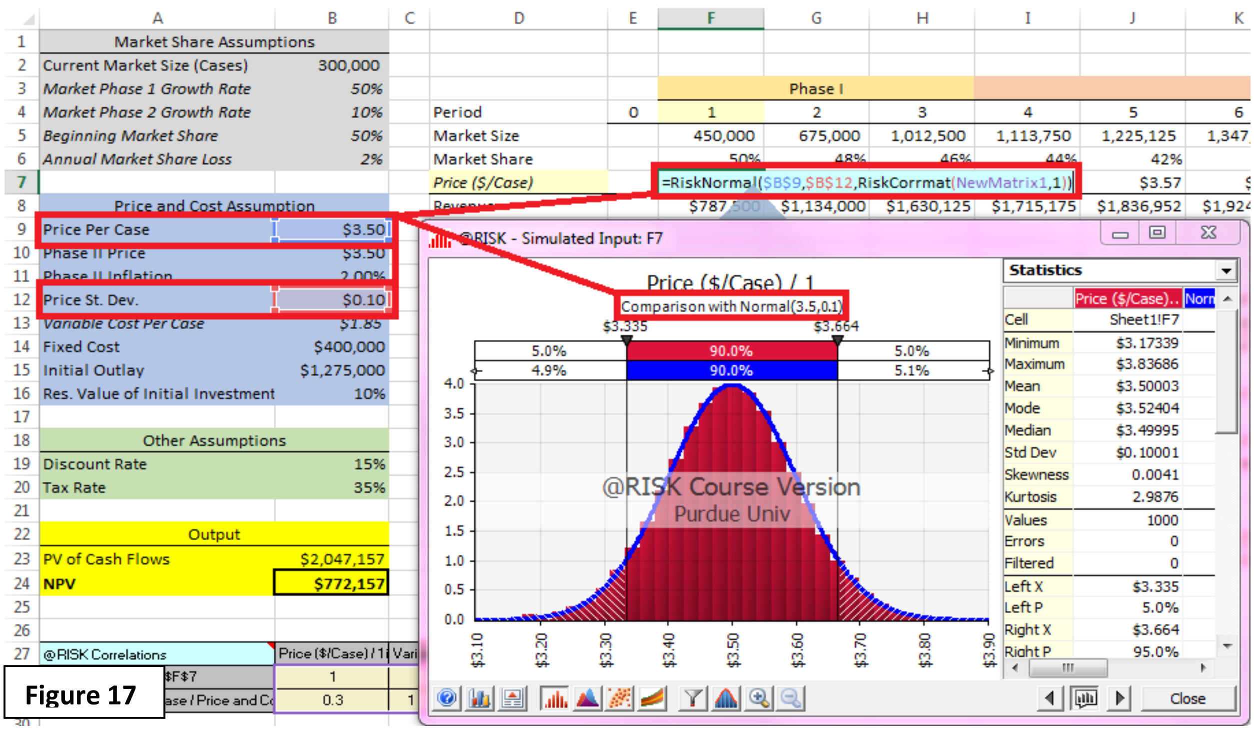


Figure 17

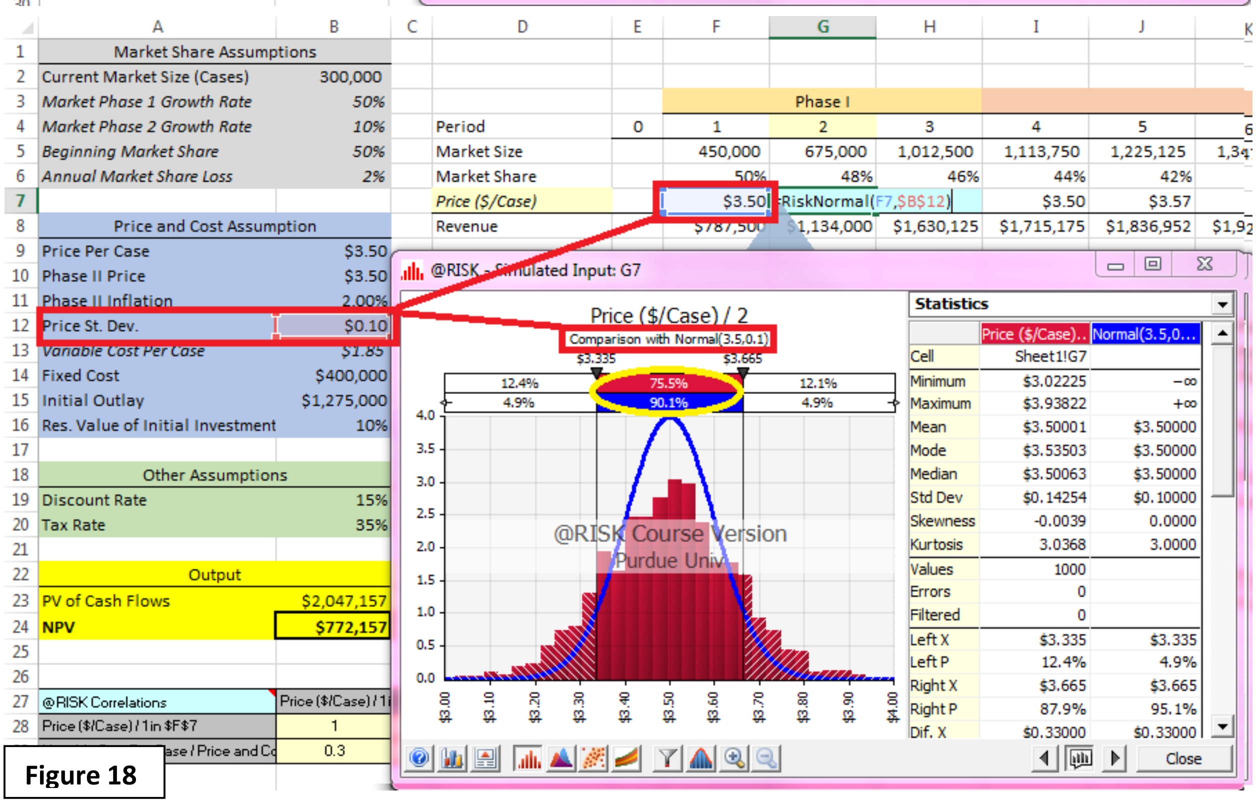


Figure 18

and second year distributions, the red bar above the distribution has increased its range in year two. 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 possibilities implies the potential for more volatile profits, and this risk is not captured in the deterministic example provided by Attachment A (although this relationship was not assumed either).

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 boxed in yellow in Figure 19, a user can graphically display data in many different ways. Scatter plots, graph overlays, or distribution modeling are just some of the options available to an @RISK user. In Figure 19, a time series graph displaying a simulation's price per case variable across phase I. The standard deviation and range increases of each year's price per case can be easily viewed.

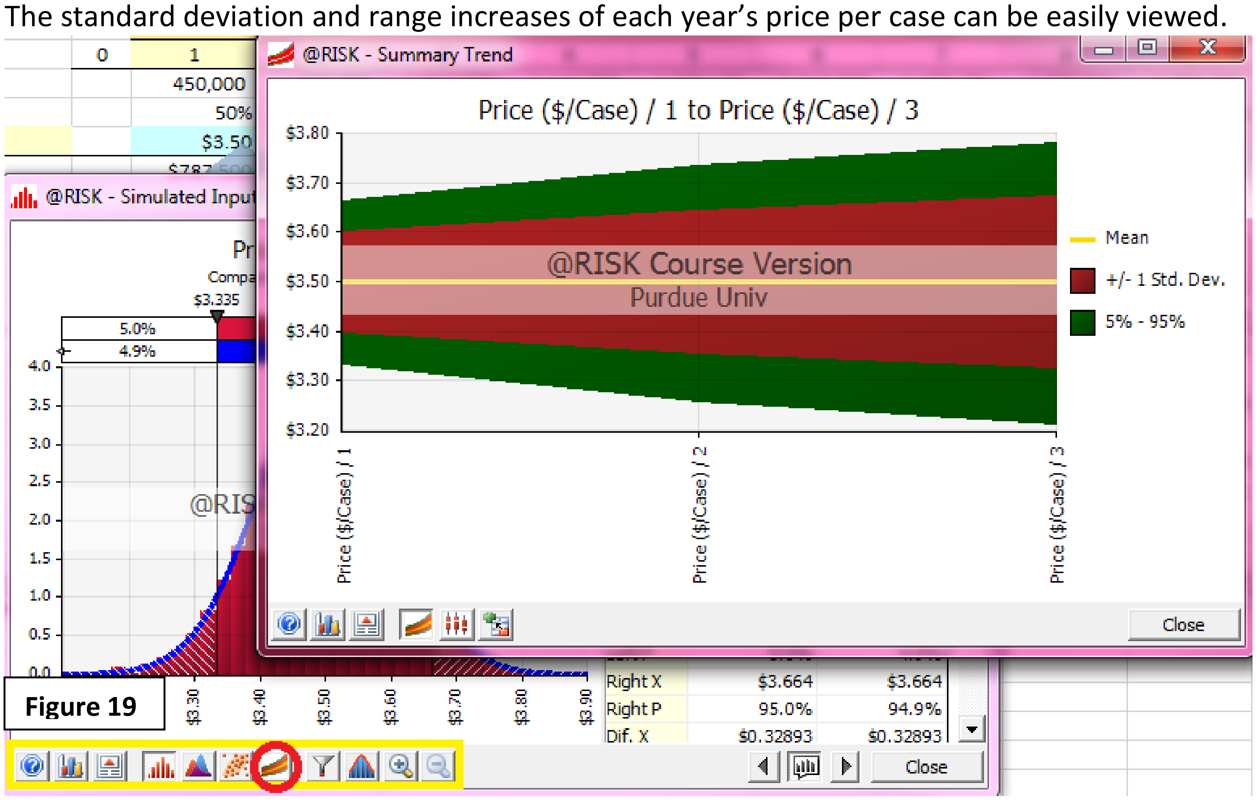


Figure 19

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. In an @RISK simulation the RiskOutput function identifies a cell in a spreadsheet as a simulation output and records its values.

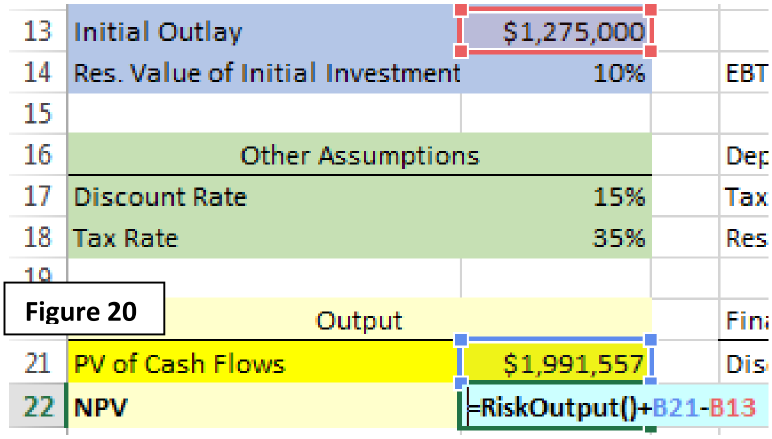


Figure 20

Regarding the project's profitability, Figure 21 shows the results of the net present value analysis. Although the output appears similar to graphs previously discussed for variables used in this paper's model, the implications and insights are far more important. It is clear that this

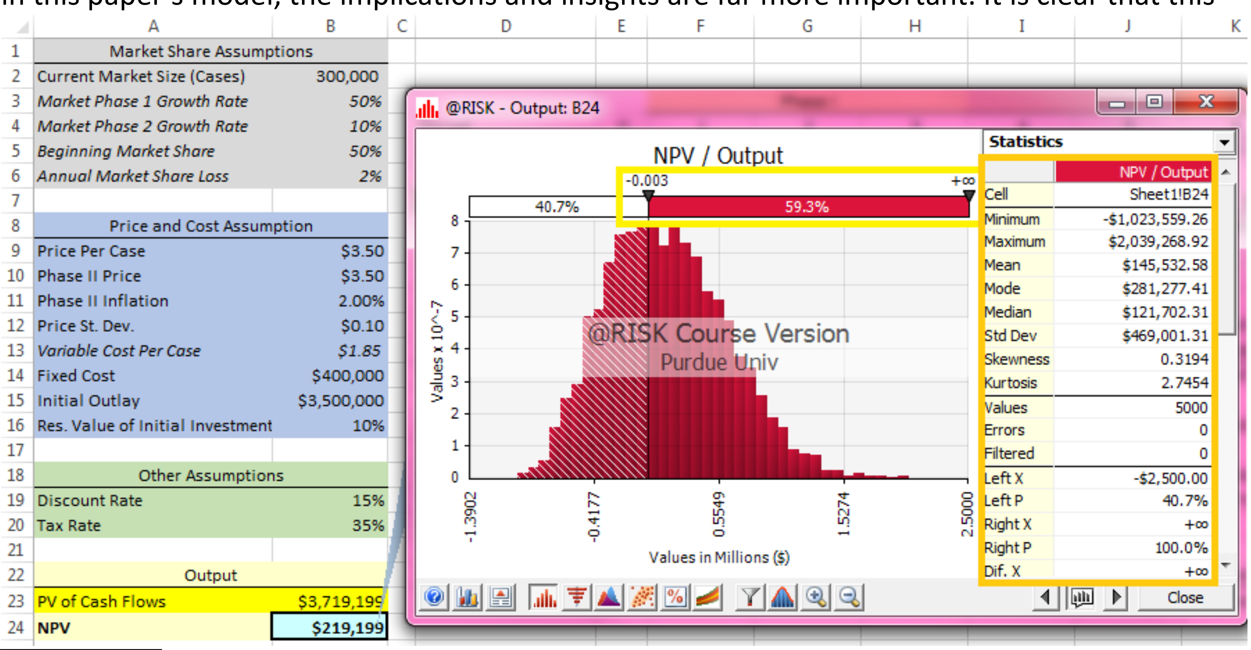


Figure 21

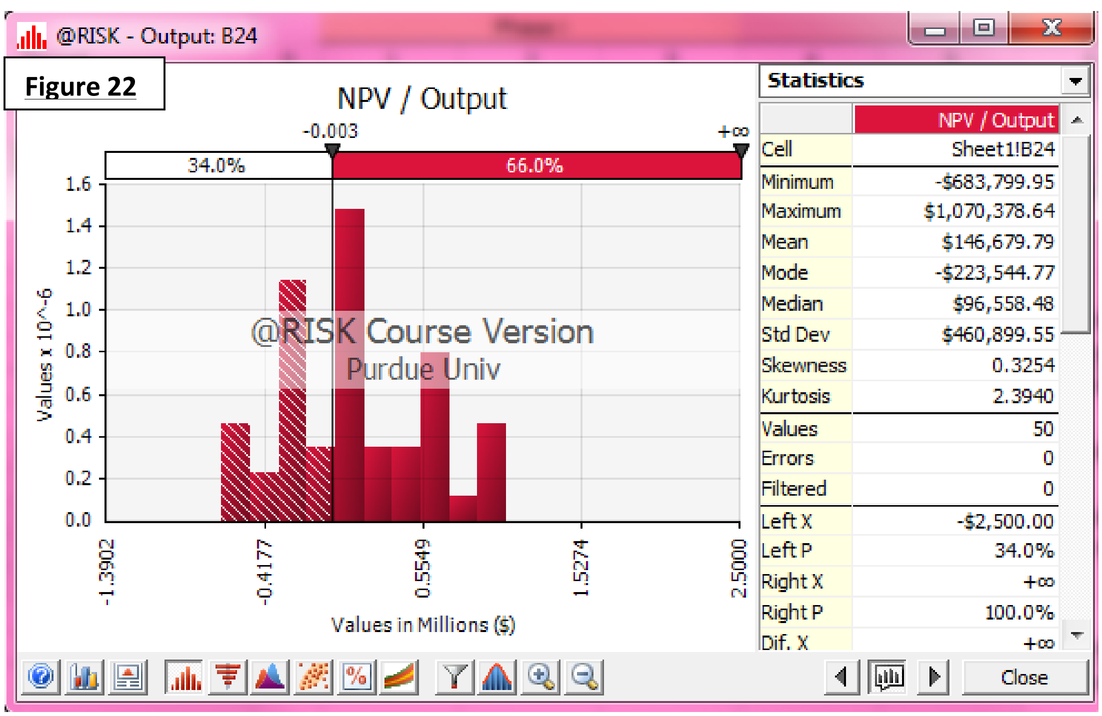
project has a good probability of being profitable as suggested by a mean NPV of $145,532.58 and the NPV probability distribution in the NPV space. However, there is some risk involved. To measure this risk, the user can review the yellow rectangle in Figure 21. Approximately 60% of the iterations in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

The statistics in the orange rectangle also become far more 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 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 all models, depending on their intricacy and the assumptions of the project. It is always better to err on the side of caution and perform more iterations than less when possible. Complicated models may take longer to simulate when more iterations are selected; however, the tradeoff is rarely sufficient to merit fewer iterations. 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. Furthermore, 66% of projects now report a positive NPV and the overall project's risk appears to have lessened. Using this analysis, a manager might make a poor or improper decision regarding the project.

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 deterministic sensitivity analysis. Essentially, it allows for the quick comparison of variables and their relative importance to an output like NPV. The process for calculating a project's sensitivity to a particular variable is performed by @RISK using baseline assumptions of highs, lows, and averages of each variable. By varying only one particular variable at a time, its potential impact on an outcome is calculated. The value of this analysis is that an @RISK user is able to quickly identify the most important drivers of a project.

From Figure 23, it is clear that the Beginning Market Share variable is by far the most impactful variable to the project's net present value. Given baseline assumptions for other variables, its impact on mean NPV can range from approximately -$408,414.39 to $728,121.63. The price per case variables are also listed rather highly up on the tornado plot. One might think that the first year price should be higher than later years because its income experiences

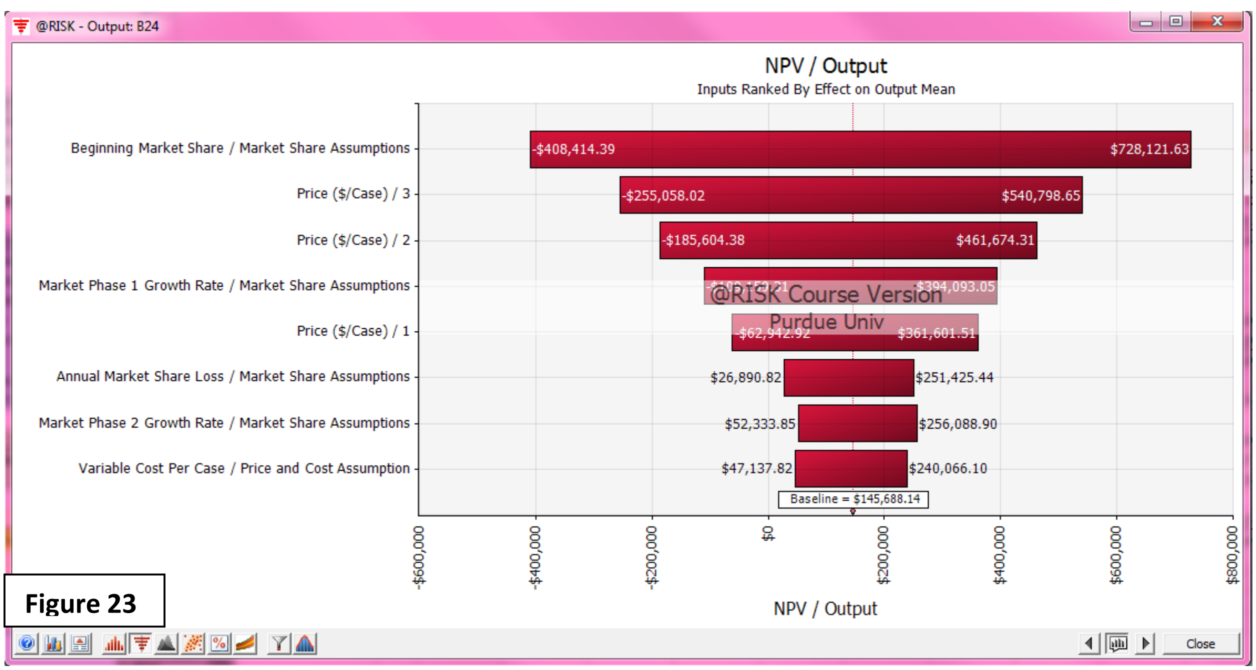


Figure 23

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 less intuitive conclusion demonstrates the power and necessity of tornado plots in analysis. Their insights allow @RISK users to prioritize uncertainties in the project. For example, after considering Figure 23 it may be beneficial to discuss if there are ways to ensure a larger Beginning Market Share through aggressive marketing early in the venture. Likewise, it does not appear that more resources should be allocated toward the lower tier variables that capture later phase growth, market share loss, and most surprisingly variable cost.

Conclusion

@RISK is an extremely powerful tool to 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 through simulations makes it an incredibly powerful tool for assessing not only a projects 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

Table 1

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.

Title of Document / Video	Location/Web url
a. Defining Distributions b. Defining Outputs c. Model Windows d. Simulation Settings e. Running a Simulation f. Histograms and Cumulative Curves g. Tornado Graphs h. Scatter Plots i. Overlaying Results Graphs j. Customizing Results Graphs k. Summary Box Plots and Trend Graphs l. Results Summary Windows m. Data and Statistics Windows n. Sensitivity and Scenario Analysis o. Reports in Excel p. Distribution Fitting q. The @RISK Library r. Correlating Inputs	http://www.palisade.com/risk/5/tips/en/gs/default.asp
Guide to Using @RISK: Risk Analysis and Simulation Add-In for Microsoft® Excel by Palisade Corporation	http://www.palisade.com/downloads/manuals/en/risk5_en.pdf

Table 2

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

Table 3

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**													