Real Options: DPL Tips and Techniques

In the late 90's, "real options" was one of the hottest buzzwords in management science. Companies were in a hurry to "do" real options, often hiring consultants or even whole departments in a race to use and master the most advanced decision-making methods. The authors of DPL played a leading role in the real options revolution, pioneering the practical, decision tree-based approach to valuing real options.

Today, real options is regarded with far more skepticism, and is sometimes associated with the excesses of the bubble period. Analysts are finding that real options techniques, judiciously applied, are a very good way to understand and quantify the value of management flexibility. Real options analysis is now often integrated with decision and risk analysis to form a more complete picture -- one with an upside and a downside -- of the value and risk in an investment.

What is a real option?

An *option* is the right, but not the obligation, to do something (usually buy or sell some asset) at some time in the future after learning about uncertainty. The source of uncertainty is called the *underlying*. A *real option* is an option where the underlying is not traded in the financial markets.

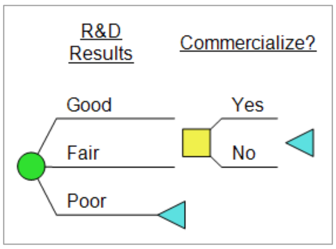

Figure 1. A Simple Real Option

In business areas with a high degree of uncertainty, management, knowingly or not, creates and exercises real options on a regular basis. For example, R&D creates real options: management has the right, but not the obligation, to commercialize the results. In a decision tree, real options are represented by "downstream" decisions -- that is, decision nodes which follow one or more chance nodes. **Figure 1** shows a simple real option modelled in DPL.

How can real options be quantified?

Techniques for quantifying real options fall broadly into two families. The first family involves the use of methods from financial option pricing theory, such as the Black-Scholes equation and binomial lattices. These techniques are appropriate for real options which are very similar to financial options. For example, the real option to acquire a controlling stake in a non-traded company that owns a gold mine might be very similar to a call option on a gold contract.

The second family uses methods that explicitly account for multiple and varied sources of uncertainty, such as decision tree analysis and Monte Carlo simulation. These techniques are appropriate for more "real world" problems where the uncertainties don't follow well defined mathematical processes. Examples include early stage companies, R&D projects and capital investments in politically unstable countries. This paper gives tips for using DPL to implement the second family of techniques.

Learning models

Simplistic real options models handle uncertainty in large chunks, with a single chance node representing all the uncertainty in a given value driver. For events that play out over time, such as sales over the lifecycle of a product, a more realistic formulation breaks the uncertainty into several parts, allowing finer grained calculations of option value. A representation of the way uncertainty is resolved over time is called a *learning model*. The tree at the far right in **Figure 2** below shows a two-period learning model on the size of a market. We see the rate of adoption in the first year, then make a decision about increasing production capacity, then resolve the longer-term uncertainty in ultimate market size.

Some of the simplest learning models use Bayesian relationships. For example, a market test may give an indication of whether a product will be a hit, but some hot products may have done poorly in similar market tests. With DPL, you can assess the relationship in either order. For example, the input probabilities in **Figure 3** (overleaf) show that the outcome of the market test is influenced by the actual market results -- this relationship may have been ascertained from past data or experience. However, the actual order of events is: decide to conduct a market test, observe its results and then decide to launch or not. With DPL, you can reverse the uncertainties in the tree and DPL will "flip" the probabilities as necessary. **Figure 3** also shows the input probabilities and Policy Tree™ for this market test example.

Link to the value of information

If you've studied decision analysis, you may be thinking that this talk of learning models sounds an awful lot like the value of information. Mathematically, the value of information and the value of optionality often work out to be the same problem. Just as the value of imperfect information is more subtle and often more relevant than the value of perfect information, a learning model can give a more realistic estimate of option value than a simpler, all-or-nothing formulation of uncertainty.

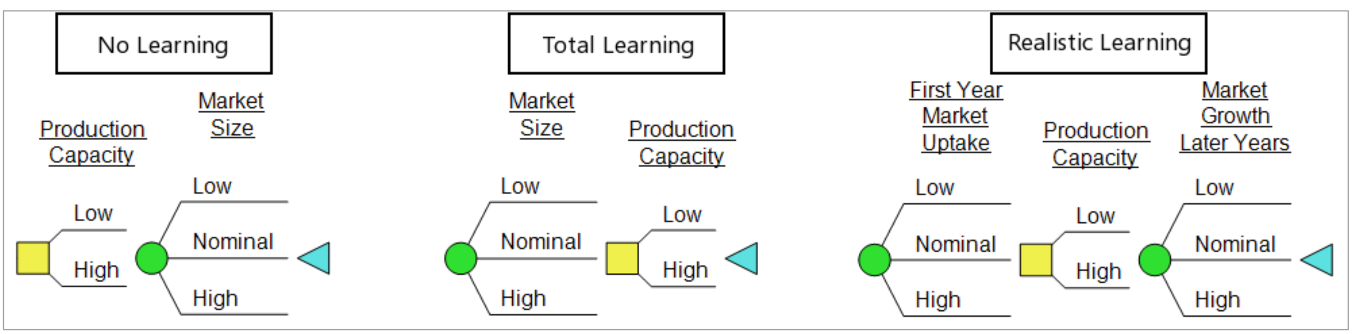

Figure 2. Degrees of Learning

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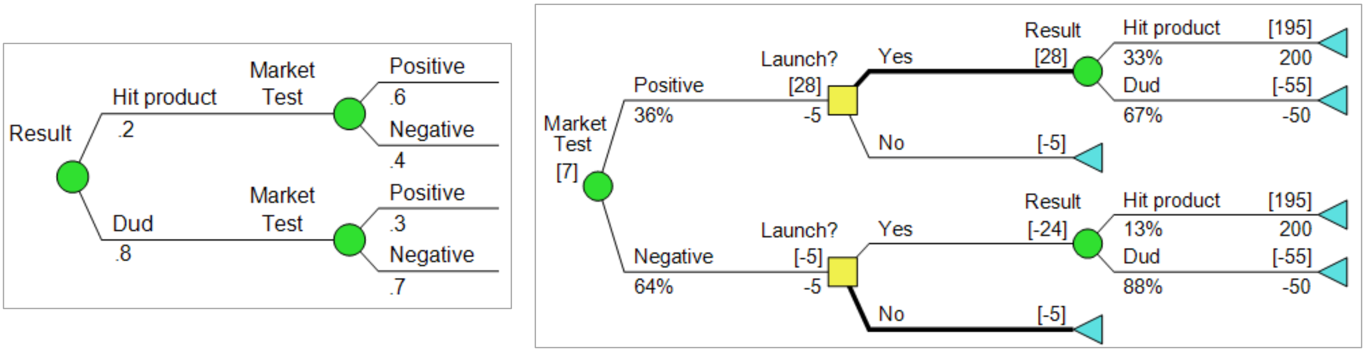

Figure 3. Input probabilities and Policy Tree™ Showing Option Exercises

Calculating the value of optionality in DPL

It's easy to calculate the value of optionality in DPL. First, build a tree which includes the option as a downstream decision and run a decision analysis. Next, temporarily disable the option using Branch Control, and run another decision analysis. The difference in expected value between the two runs is the option value. In **Figure 4**, the Production Capacity decision is fixed in its High state, effectively disabling the optionality.

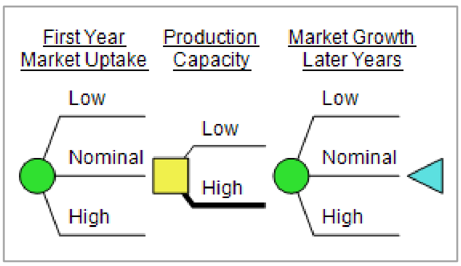

Figure 4. Controlling a Decision

Where does the option value come from?

Showing how an option creates value is as important as calculating its value. Decision-makers need to see what the option means in business terms -- when is it exercised, what is the cash flow impact -- if they are to include it in their view. DPL provides several outputs which can shed light on the sources of option value. For example, in **Figure 5**, we can see how the exit option (blue line) cuts downside risk. Other key questions about the option, such as when and how often it is exercised, can be answered by DPL's Policy Tree™ and Policy Summary™ outputs.

The importance of speed

Real options models are often computationally intensive. A decision tree with learning can have many more nodes than one which considers uncertainty only in one time period. Moreover, real world problems often come with huge cash flow spreadsheets. While these models are tough, DPL's proprietary algorithms and special performance features can make them surprisingly tractable. Keeping model runtimes short allows for more (human) iteration, leading to new insights and a higher level of comfort with the results.

Conclusions

Real options techniques can bring insight to the analysis of investments with a high degree of uncertainty. DPL provides a rich set of features for dealing with complex, real world real options problems -- from building the model to making sense of the results. DPL's unique combination of power, flexibility and transparency has made it the professional's choice for real options analysis.

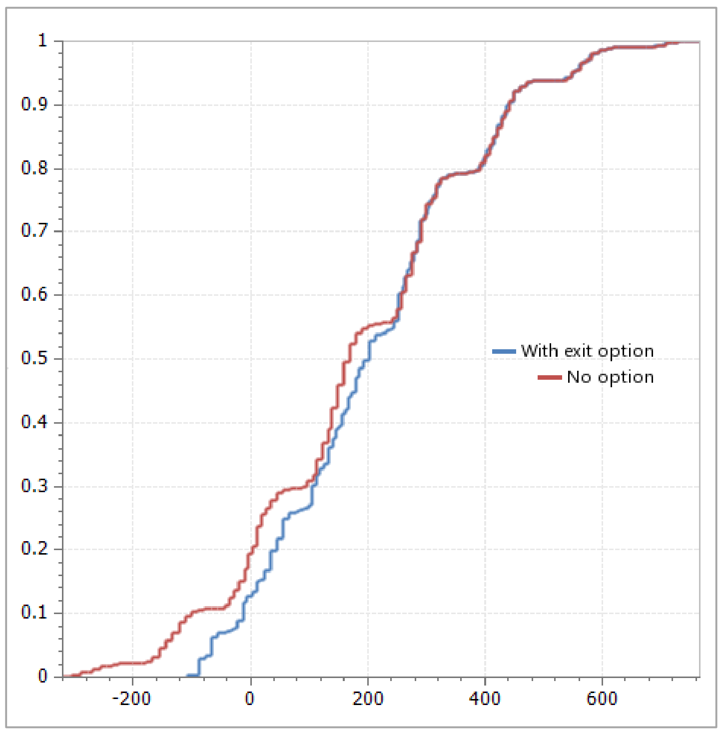

Figure 5. Risk Profile for an Exit Option

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