Model Risk

Alexander Sakuth, Fengchong Wang

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Both authors have contributed to all parts, conclusions were made through discussion.

1 Introduction

Models are widely used in the area of financial economics, e.g. for derivative pricing, and sometimes play an indispensable role. Unlike liquid markets which have 'price' to reflect the value of the asset, some financial instruments, such as interest rate floors, caps and so on, lack of direct indicators of asset value. As a result, when analyzing these financial instruments, people rely heavily on models to calculate the risks and decide the strategy to hedge.

Formally a model is defined as

> *A quantitative method, system, or approach that applies statistical, economic, financial, or mathematical theories, techniques, and assumptions to process input data into quantitative estimates.*[1]

To identify, build, implement and reevaluate the model is a long procedure. Errors can occur in each step. This is what is usually referred to as **Model Risk**, which is the risk of loss of trust, financial loss, wrong pricing and bad decision.

2 The Source of Model Risk: Model Building

Usually, there are several kinds of models. Crouhy et. al. [2] classified the models used in finance into three different categories.

1. Models based on observations of historical data and some statistical assumptions. This kind of model is fully statistics-driven.

2. Models based on some assumptions of behavior of agents in the market. These models try to use a system of equations to simulate the market and thus to calculate the risks.

3. Models that share the characteristics of the above categories.

No matter what category a model belongs to, the life-cycle is similiar for all models. Roughly speaking, there are usually 5 stages in the life of a model [1]:

1. The need or the problem in the business has to be clearly defined.

2. A theoretical model has to be carefully devised. This step is usually challenging and time-consuming. For example, for a model in category 2, the steps are [3]:

   (a) Collection of knowledge of the market. How is the market operated? How do the market participants behave under certain market situations?

   (b) Identifying and choosing factors that can be used to estimate risks.

   (c) Identifying the properties of the factors. Are they independent or dependent on some other factors? Are they observable? If so, can they be observed directly or indirectly?

   (d) Deciding for each factor how important its stochasticity is. It is often the case that some factors can be treated as deterministic without introducing too much inaccuracy in the model. On the contrary, the stochasticity of other factors is very crucial for the security values.

   (e) Replacing the independent factors with deterministic value or rule if applicable. If not, choosing the stochastic process that is best and reasonably fits the independent factors.

(f) Forming a mathematical model that describes the market. This is usually done in terms of many equations.

(g) Thinking of how easy the model can be solved. If it is too hard in technic or too time-consuming, the model should be simplified reasonably. In the same time, the best way of how to solve the model should be determined.

3. User-friendly Software has to be coded and tested to implement the theoretical model.

4. The model has to be used in reality to tackle business problems.

5. The model has to be refined with the feedback from the application result and with the variations in inputs as market situation changes.

3 Differnt types of model risk

Here we want to classify the different types of model risk to show the variation. The structure of Crouhy et. al. [2] is used.

Irrelevant model

The model is based on insubstantial real world data or economic theory. This risk occurs mostly in the case one builds the model strongly based on historical charts.

Incorrect model

1. Analytical solutions acquired from computation might be wrong. For example when one wants to get the global maximum of a very complicated function, it can be the case that he will finally get the local maximum instead. Sometimes, to obtain global maximum, one need to have several attempts.

2. Wrong assumption of stochastic process. When the model contains some stochastic process, it is hard to have the right assumptions about it because the process is hidden and one can only rely on the observed data set.

3. Wrong set of variables. Some complicated financial instruments include many variables, it leads to risks to misidentify or miss variables.

4. Wrong assumption of the distribution function of some parameters. For example, bonds price is more likely to be log-normal distributed than normal distributed. If one assumes it to be normal distributed, it will lead to large deviations in the result from the true data for the case of short-maturity bonds [3].

5. Wrong assumption of the natures of the markets. Markets are sometimes far from perfect and highly influenced by factors coming out of markets such as politics, natural disasters, media power, etc. For example, the market in China is in a transit from centralization to decentralization [4]. If one analyzes the market in China, he must consider both the centralization elements (which is hard to predict because politicians are easily changing) and free market elements just as in the western world. Another example is related to the opening hours of markets. Different from classical models, the market is usually not operating all the time and usually closes regularly. Under special conditions, the market can be even closed irregularly and partly [5]. This will lead to absence of essential liquidity when needed.

6. Ignorance of trading cost. A model can sometimes ignore trading cost. However, because trading cost in most cases are fluctuating and stochastic, some extreme situation might lead to extreme high trading cost.

7. Wrong assumption of the underlying assets. An asset can be a primary asset or dependent of primary assets and correlated with them in the system.

Erroneous Model Implementation

The requirements for the implementation of models nowadays are immense. Big data feeds, thousands of lines of code that has to be on the one hand very efficient in running time and on the other hand should have a clear style, so that it can be checked by supervisors. Besides this it should be stable and user interfaces are needed. A lot of things can go wrong.

1. Inappropriate numerical methods often cause approximation errors. Even if a program may run under normal conditions, errors under extreme conditions may occur. In very long source codes one can never be sure that there is no bug that causes an incorrect output.

2. For methods like the Monte Carlo algorithm that uses random sampling it is very important to do enough simulations that the output can converge. To find the right number of simulations is very important. Too many simulations would only lead to a longer runtime.

3. Programs getting more and more complex use a lot of data feeds. The assumption that the data for all assets was taken at exactly the same point of time does not always fulfill the requirement since it comes from different agencies and sources.

Wrong Calibration of the Model

While implementing the model the choice of statistical methods has to be made and the power of the estimates has to be estimated.

1. The wide range of statistical techniques for the same problems and estimations makes it difficult to choose the best one, since different methods can lead to different estimations for the demanded parameter.

2. Statistical methods usually have an uncertainty in their estimations. This uncertainty depends on the input. Even if statistics can help with information like confidence intervals it makes it more difficult. Often the input is estimated itself what makes things even worse.

3. The problem of handling outliers in the data can have severe consequences. Data points that differ a lot from the others may distort the real parameters if the outliers were just a mistake (e.g. typing error, measuring error), otherwise correct outliers that are neglected cause that some important information gets lost.

4. Each model parameter has to be calibrated, reevaluated and adjusted. The question is how often the input parameters should be refreshed and if assumptions like constant parameters can be holded to.

5. Personal judgment can be considered or just statistical methods relying on historical data. The first forward looking method has advantages e.g. when firm announcements will be made and a change is easy to predict.

Marked Data Processing

A model is always build on input parameters. The quality of the model so is highly connected with the quality of the input parameters - another weak point of models.

1. For many statistical methods a longer sampling period is better for more significant output. However the longer the period the more old observations get weighted and they might be out-of-date in changing markets.

2. Errors in the database are very hard to find and sometimes it is impossible to check the data for correctness.

3. Many securities are rarely traded and the price observations are not equally spaced. So the model can fail for this fragmentary input and produce an unreliable output.

Mis-Application

1. Even if a model is good and mathematically accurate it might be really bad under current market circumstances or if the assumptions are no longer valid.

2. Having one good model for a derivative might mislead to use it for a similar derivative ignoring that the similar one includes more or slightly different features.

4 Historical Examples

The list of failures due to model risk is very long since so many issues have to be considered and often these failures are followed by big financial losses. We will give a very short excerpt of selected examples taken from [1] and [x].

The wrong model

In 1997, after a heavy loss of US $83,000,000, the bank of Tokyo-Mitsubishi realized that they had used a wrong model to trade swaptions. The Black-Derman-Toy model, which was initially designed for the purpose of calibrating to market at-the-money swaptions prices, is found to be too simple to price out-of-the-money swaptions and Bermuda swaptions, which require multi-factor models [6].

The wrong numerical method

In 1982 the Vancouver stock exchange established a new index initialized at the level of 1000.000. Twenty-two months later the index was constantly decreasing to about 520 even though the exchange was setting records in value and volume [7]. A team of investigators found out that the index which was updated after every transaction just dropped the digits after the third digit instead of rounding. The "true" (rounded) value would have been 1098.892 [8].

The forgotten factor

The financial institution UBS took advantage of a benefit in British tax laws to have lower dividend tax credit. When the British government in 1997 just changed the tax laws UBS suffered huge losses. UBS was not the only bank that was taken by surprise with this change but the one that suffered the most. A possible change in this laws was just neglected in the models [2].

5 Conclusion

No matter how proud we may be of the accuracy of a model that is employed in hedging and valuing financial securities, we can never have one hundred percent confidence in any model - every model has its own limitation and inaccuracy. One should always bear in mind that a model, no matter how complex or how accurate it is, is the simplification of phenomena and can never include all mechanisms behind the phenomenal data (if there are mechanisms).One should also keep in mind that markets in developing countries are sometimes neither perfect nor efficient. Regulations and new laws can change everything. A missing or neglected factor may have superior influence. It's an endless list of what can go wrong.

So what do we think one should do to avoid the model risk (as far as it's possible) and how one can prepare for it?

First of all it is of very high importance to be aware of the model risk. As long as you ignore it consequences can only be worse. Knowledge of where and when model risk appears can help to minimize it. Hiring only the best qualified people to work on the model might help. Sometimes it is not enough to build the best statistical (backward looking) model if personal judgment is needed.During the modeling process the model building team and the model risk management should communicate a lot. Detailed documentations, discussions and tests can help to scale the risks down. Hiring only the best qualified people to work on the model might help too. Sometimes it is not enough to build the best statistical (backward looking) model if personal judgment is needed. After the model itself is finished one should never blindly trust it. Simulations, evaluations, stress-tests, adjustments are needed. To make it short: Never stop working on the model. It also might help that people using the models know how it works to avoid errors in application. Once such an error is found it should be easy to report someone in charge and should not be ignored or underestimated.
A company that is aware of model risk should do their best to avoid it and prepare for that case. For example the DAB bank group in Germany and Austria does so by adding 10% of the total calculated risk to this amount due to model risk [9].

In the end even if you are aware of model risk, errors in a model often are firstly discovered when the model goes really wrong and this comes with big financial losses. On November 28th this year, an order in the Swedish future market that was 131 times higher than the country's GDP [10] closed the exchange for several hours. This order due to a software bug had luckily no serious consequences (still a slight impact), since the order was annulated immediately because of the unrealisticly high ammount. However this recent example illustrates how fast model risk can appear and how it can affect a market any day.

6 Reading Guide

Here we provide a list for the reader who is interested in this topics.

For an introductory level, we recommend [1] which is a good starting point though incomplete (this literature focuses on insurance industry). It is easy to understand and shows what a consulting group worked out. After reading this literature, one can try [3], which is more comprehensive. For the individual who has some knowledge in finance, the overview article in the book [2] might be a good starting point. The structure of [2] is more comprehensive and stricter than [1] and [3].

For the people who are not satisfied with introductory level knowledge in this area, An Introduction to Market Risk Measurement [6] written by Kevin Dowd is a good choice. The book has 281 pages and introduces some mathematical techniques together with examples.

For an advanced reader or researcher, the comprehensive book Model Risk, Concepts, Calibration and Pricing [2] edited by Rajna Gibson might be a good choice. Some topics in this book are hard and require prerequisite in finance, statistics and calculus.

Literature

[1]   http://www.ey.com/Publication/vwLUAssets/The_importance_of_model_risk _management/$FILE/1110-1302246_Model_Risk.pdf

[2]   Model Risk - Concepts, Calibration and Pricing , Risk Books, 2000

[3]   Derman E., Quantitative Strategies and Research Notes - Model Risk, Goldman, Sachs & Co., 1996

[4]   Qian Y. & Weingas B. R., The Journal of Policy Reform: China's transition to markets: market-preserving federalism, chinese style, OPA, 1996

[5]   The Economist January 24, 1998

[6]   Dowd K., An Introduction to Market Risk Measurement, John Wiley & Sons Ltd, 2002, p.182

[7]   The Wall Street Journal November 8, 1983, p. 37

[8]   The Toronto Star, Tuesday November 29, 1983

[9]   http://www.dab-bank.de/servicenavigation/investor- relations/veroeffentlichungen/geschaeftsberichte.-ContentSlot- 42061-ContentSlottablist-50452-ContentSlottablisttab-000100- ContentSlottablisttabdownloadlist-9971-File.File.FileRef.pdf/ dabbank_jahr_2011_(d).pdf, p. 71

[10]   http://www.businessweek.com/articles/2012-11-29/software-bug-made-swedish- exchange-go-bork-bork-bork