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Lecture Quantitative Finance Spring Term 2015

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Today:

Model Validation explained - a practitioner's view

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Disclaimer: The views and opinions expressed in this presentation are those of the author and may not reflect the views and opinions of UBS AG.

Literature for today

- Office of the Comptroller of the Currency (OCC) / Board of Governors of the Federal Reserve System (FED),
Supervisory Guidance on Model Risk Management,
<http://www.federalreserve.gov/bankinfo/reg/srletters/sr1107.htm>
- M. Morini, Understanding and Managing Model Risk, 2011
- P. Quell, Ch. Meyer, Risk Model Validation, 2011

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Why you should listen today

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Summary

- As you are students of the MA in Banking & Finance and MSc in Quantitative Finance, it is likely that you will

- consume model validation results
- perform own model validations
- interact with model validation teams
- or organize or lead model validation teams

once you start working. Therefore you should know, what to expect and what to require from model validation.

- Additionally, model validation is an exciting job within the banking industry for somebody who is interested in quantitative topics, since he will see many models, work with different quantitative technics, get a good overview and see many parts of the bank.
- The downside is, that the existence and necessity and added value of model validation is not well accepted within some banks, and only seen as a regulatory requirement that needs to be fulfilled to keep the banking license without added value for the bank.
- I'm mainly working with models for credit risk measurements (like rating models (probability of default), loss given default models, exposure at default models, price distribution models (haircuts), economic capital models, liquidity models, deposit replication models, fair value models, incremental risk charge models). Besides quantitative finance, one uses there a lot of statistical methods: I intend to give you a flavor of these methods too.

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Summary

- Banks have between 10 to a around 1'000 models in production (probability of default, loss given default, exposure at default, option pricing, interest rates, future potential exposure, asset liability management, suitability, liquidity, market risk, operational risk, credit risk, fair value, backtesting, stress testing, economic capital, deposit replication, real estate valuation, ...)
- How do you make sure that these models work properly? You hire good model developers and you hire good model validators!
- In model validation, you independently check if the model has been designed properly and is working properly (effective challenge)
- Model validation = a) evaluation of conceptual soundness + b) ongoing monitoring + c) outcome analysis
- Ratio model developers to model validators: 6 to 1, 5 to 1, 4 to 1
- Why do we have it?
 - Internal requirement: 4 eyes principle, quality assurance
 - Regulatory requirement: OCC/FED, Basel II, FINMA
 - FINMA requires the model's validation report before they decide to accept a model

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- Derman 1996: One of the first articles to discuss how to validate (valuation) models under the title "Model Risk". Model validation is performed by some pioneering banks.
- "Watershed": OCC 2001: The OCC issued its bulletin OCC 2000-16 outlining key model validation principles. This started model validation for market risk/valuation models for the banking industry.
- Rebonato 2003: Introduces a new way of looking at model validation: Price vs. value approach: Market consensus price can deviate for years from a true fundamental value.
- Basel II 2006: Requires model validation in particular for credit risk models. This started model validation also for credit risk models for the banking industry.
- OCC/FED 2011:
 - Model validation is largely expanded into model risk management, which includes a) model development, b) model validation, c) model implementation, d) model use, and e) governance, policies and controls.
 - Model risk should be managed like any other kind of risk (e.g. market risk, credit risk, operational risk).

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OCC/FED definition of a model

- The term model refers to a
 - quantitative method, system, or approach that applies
 - statistical, economic, financial, or mathematical theories, techniques, and assumptions
 - to process input data into quantitative estimates.
- A model consists of three components
 - information input component: delivers assumptions and data to the model
 - processing component: transforms inputs into estimates
 - reporting component: translates estimates into business information

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Example: Black Scholes model

- is a quantitative method
- applies economic and mathematical theories (markets are arbitrage free, existence of a martingale measure, and assumptions (no trading costs, continues trading)
- to process stock price, interest rate and volatility inputs into European call option price.

So the Black Scholes model is a model in the OCC/FED sense.

- information input component: e.g. continues trading assumption plus Stock price
- processing component: Black Scholes formula, calculates price and sensitivities
- reporting component: Trader Screen, Sensitivities

OCC/FED: Three key elements of comprehensive model validation

- Evaluation of conceptual soundness
 - assess quality of model design and construction
 - review documentation and empirical evidence of methods and variables selected
 - check that model is consistent with published research and industry best practice
- Ongoing monitoring
 - to confirm that the model is a) appropriately implemented, b) being used as intended, c) performing as intended
 - to check if adjustment or full redevelopment needed
 - to check that extensions of scope of the model are valid
 - Benchmarking can be used (e.g. compare internal ratings with external ratings, if available)
- Outcomes analysis
 - Comparing model output to corresponding actual outcomes, e.g. comparing interest rate forecasts with actual interest rates, GDP forecast with actual GDP after the fact, internal ratings with default rates in the rating buckets (so-called backtesting)

What to do in validation

Conceptual soundness

- Understand proposed model and issues/risks to be addressed and write understanding down
- Reproduce (some of) the results
- Search academic literature
- Search industry best practice
- Build benchmark model and/ or use alternative data
- Assess assumptions and provided evidence for the assumptions
- Check mathematical derivations
- Assess proposed ongoing monitoring and outcome analysis (e.g. back testing)
- Assess model risk
- Assess documentation
- Write report and obtain feed back from model developers

What to do in validation Ongoing monitoring

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- Compare model output with other models, e.g.
 - compare internal ratings with external ratings,
 - pricing for illiquid derivatives: There are data providers, that gather derivative model prices from different banks, discard the most extreme ones and feed back the mean price to the participating banks. In this way, banks know, if they are off the market with their models.
- Be warned, that having a good running option desk, may not mean that you have hit a gold mine or have a superior model. More often than not, it means that your model is pricing off the market and if you do not have a very good reason for being off the market, this means a big loss for you, since your model is wrong.
- User feed back, may be one-sided though
- Have there any changes happened, that would require changes in the model? Changes like changes in products, exposures, activities, clients, or market conditions?

What To Do in Validation

Outcome analysis

- **Backtesting:** E.g. compare predicted probability of default with the number of defaults that have happened. Does it match?

What to do in a validation I

Working techniques

- Ask simple questions, because that's where models fail mostly.
- Always get a look at the implementation, because that's the truth. And it is precise.
- A small error may be a signal for a much bigger issue.
- After you have detected an error, think if the same error could have happened elsewhere as well.
- Check formulas, check references. You would not believe how much is wrongly copied and for how long.
- Look at the raw data.
- Good presentation of data is very important. Simple descriptives of data are important. What does that data measure? Returns of profit?
- Identify assumptions, discuss assumptions, evidence provided for assumptions by model developers?
- Test model at its boundaries: we saw once a model that did allow for default probabilities bigger than 1 at its boundaries, another did not allow for zero default probabilities, the smallest default probability was a magical constant.
- Stress assumptions, analyze sensitivities:
 - What would happen if the assumptions were slightly wrong, wrong, very wrong?

What to do in a validation II

Working techniques

- What would happen if the parameters were slightly different, different, very different?
- This gets quickly difficult and muddy, because what is a very wrong assumption, but still reasonable very wrong? What is a reasonable very different parameter? In addition, there are many sensitivities to check: If you have 5 parameters, then you have to check 5 changes of only one parameter, 20 combinations of 2 changed parameters, 60 combinations of 3 changed parameters, ...
- Is the documentation complete? Can you reproduce the results of the model developer, based on the documentation?
- Search for cliff effects.
- Does the model deliver reasonable results for all possible input values? Or are there regions in the input space, where the model must not be used? Is this documented? Is it made sure in the implementation, that the model is not used in this area?
- Numerical issues? Which numerical optimizers has been chosen?
- Do approximations break? Are we extrapolating too far? Does the Taylor formula hold in this particular application?

What to do in a validation III

Working techniques

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Taylor approximation to $\sin(x)$ in $x=1$

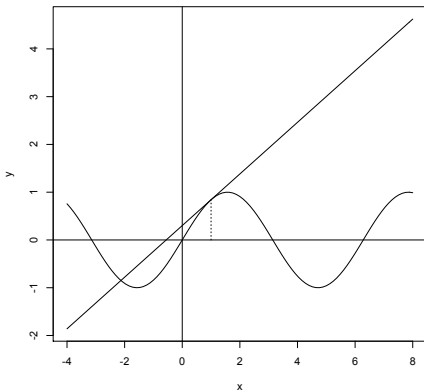


Figure: Taylor approximation is valid in a small interval around 1. Further out it becomes silly.

What to do in a validation IV

Working techniques

- Is the purpose of the model clear? Has the use of the model been extended over its initial purpose? Is this admissible?
- Have the right statistical estimators been chosen? Are they unbiased, efficient, consistent?
- Does the application of some text book knowledge fulfill the requirements as stated in the text book? Are assumptions (reasonably) met?
- Do we understand what the model is doing?

Building of benchmark models

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- For important models, is it advisable to build a benchmark model in the initial validation
- To grow up, to get a sense for the issues, what does the author want to say?
- To assess shortcuts taken in the proposed model
- No constraints as runtime, data availability, system environment need to be considered
- The process of building is more important than the result. It sharpens the understanding of the problem and solution space.
- Comparison of the models may be difficult, if the models are not nested. Statistical concept of generalization error may help.

There are four areas where models can go wrong:

- Design / methodology
- Implementation / coding
- Use (misunderstanding of output, using the model outside the original scope)
- Data (garbage in, garbage out)

We will concentrate in this presentation on the first item, **Method(ology)**:

- Regressing non-stationary (e.g. trending) time series onto each other. One should use concept of co-integration, error correction models/regress first differences. Co-integration: Drunken man with a dog on a leash. You have no idea where the man and his dog are going, you only now they will remain close to each other.
- Linear regression, $Y = a + bX + \epsilon$, when the dependent variable Y has bounded range but the independent variable X does not, i.e. $Y \in [0, 1]$, X in the real numbers. Use generalized linear models instead.
- Unidentified parameters. Simplify the model, if you can. E.g, you are modeling Y as follows: $Y = abX + \epsilon$ with ϵ a noise term. Then there is no way that you can determine a and b from observations from Y and X .
- Observations are outside of allowed range, e.g. LGD model allows only for LGDs in $[0, 1]$, but some observed LGDs are bigger 100%.

Where models can go wrong II

- Errors in statistical models are not always additive. In this case you cannot use least squares to fit a model, you have to use Maximum Likelihood methods. E.g logistic regression.
- Gamma distribution for observations which include the value zero with probability > 0 . Gamma has zero probability and zero density for the value 0. Use Tweedie distribution instead.
- Gamma distribution for observations which take values only in $(0, 1)$. Gamma takes values bigger 1.
- Ignore panel data structure (cross correlations, serial correlations), e.g. stock price time series for 15 stocks.
- Use of standard t - test in an explorative setting to select variables / multiple testing issue
- Confidence intervals widen considerably, if you have more than one parameter to test. Use Bonferroni intervals.
- Wrong estimators for the parameters in a Gauss copula
- Mixing real world data with risk neutral data
- Interest rate model allows / does not allow for negative interest rates
- Pricing products on interest rate spreads (say 5 year interest rate vs. 3 month interest rate) with a one factor interest rate model. Since there is only one factor, the spread is completely deterministic in the model, where in reality it is stochastic.

- Assuming a factor is constant and deterministic, when in fact it changes through time and/or is random. E.g. Black Scholes, where interest rate is assumed constant and stock is random.
- Assuming factors are independent, when in fact they are dependent or correlated.

Now some mistakes in the next two areas

- Model implementation / coding
 - Due to an index error in coding, a predictor for an extreme quantile was calibrated on the future data, for which it was supposed to forecast, instead of on past data. This estimate was remarkably good in forecasting the quantile. This is no surprise, since it was cheating. E.g., he was comparing $\frac{1}{n} \sum_{i=1}^n X_i$ with X_1, \dots, X_n instead of comparing $\frac{1}{n} \sum_{i=-1}^{-n} X_i$ with X_1, \dots, X_n .
- Model use, misunderstanding of model output:
 - 1%-VaR is not the worst ever possible loss, but only the 1% worst possible loss. I.e. it is always possible that a loss which is bigger than the 1%VaR can happen. It is just unlikely.
 - Recall the definition of 1%-VaR: $P[X \leq -VaR] = 1\%$

Where models can go wrong IV

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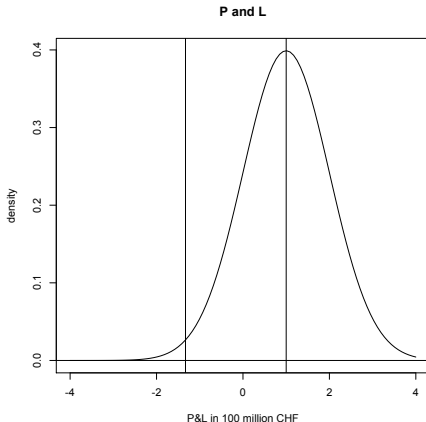


Figure: Company with normally distributed profit and loss, 100 million CHF average profit, 100 million CHF standard deviation and a 1% VaR of 133 million CHF. Obviously, losses bigger 133 million CHF are possible.

Where models can go wrong V

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- A once in a 1000 years loss it not a loss that will happen for the first time in a 1000 years from now, it can happen tomorrow, it is just very unlikely.

Toy validation Black Scholes model I

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- Information input component:
 - Assumptions: continues trading (in time, in amounts); no transaction costs; constant, deterministic volatility; constant, deterministic risk free rate; market completeness; no arbitrage holds; borrowing and lending at the risk free rate; stock price moves as geometrical Brownian motion (stock cannot default!); unlimited liquidity; unlimited credit; no delta limits
 - Assessment: None of these assumptions is true, but only the constant, deterministic volatility seems to be an issue: Smile/volatility surface
 - Data: Prices as quoted in the stock exchange, volatility is estimated on the historical prices of the last 120 days, government bond yield used as risk free rate, all data comes from Bloomberg,
 - Assessment: 120 days may be too long to react quickly to sudden changes in volatility, Bloomberg is a good data provider
- Processing component:
 - Formula: BS as in text books
 - Assessment: Formula is ok.
 - Recalculations: OK.
 - Literature research: Benchmark model:local volatility models, stochastic volatility models, ...

Toy validation Black Scholes model II

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Summary

- Industry best practice: BS, implied volatility surface (strike/ maturity), own refinancing rate as risk free rate
- Building a benchmark model: Heston: no clear picture emerges, different pros and cons
- Reporting component:
 - Prices and sensitivities are shown on the trader screen
 - Assessment: This is unproblematic from a model validation point of view.
- Conclusion: The model has to be amended. The smile cannot be accounted for in the model. Current best industry practice is to price plain vanilla European call with BS, implied volatility surface (strike/maturity), own refinancing rate as risk free rate.
- Ongoing monitoring: Results of the model will be compared real time with observed prices or quotes from competitors.
- Outcome analysis: After some time, say three months, one can compare the prices from the model from the last three months with the traded prices of the same period and analyze if there is a pattern.

- How do I backtest a VaR model?

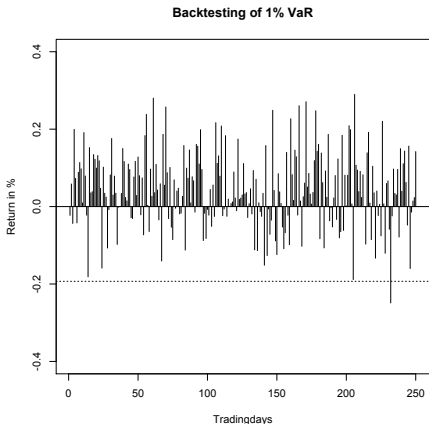


Figure: Daily returns for 250 trading days with a mean of 4% , a standard deviation of 10% and a 1%-VaR of 19.3% (dotted line). The VaR has been estimated correctly as long as there are not statistically significantly more or less than 1% observations (i.e. 2.5 observations) below the dotted line.

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- How do I backtest a VaR model?
- 1%-VaR: My loss should only be bigger than VaR in 1% of all trading days.
- What is the chance that I have 0, 1, 2, 3, ... trading days out of 250 trading days, where my loss is bigger than VaR (so called exceptions)?
- This is Binomially distributed and with the figure below, we see that the probability to have zero to four (five) exceptions is 89% (95.8%).
- Put differently, as long as I have not more than four exceptions, I have no reason to doubt the VaR model (on the 95% confidence level).

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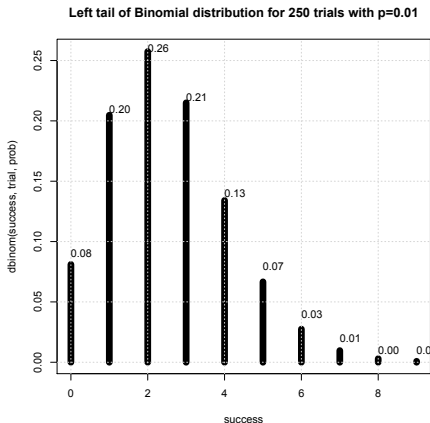


Figure: Left tail of the Binomial distribution of 250 trials with success probability of 1%. Zero to five (four) successes cover 95.8% (89%) of the total probability mass. The VaR model is fine (on the 95% level) as long as there are not more than 4 trading days out of 250 with losses bigger than the 1% VaR.

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- Works exactly like the VaR back testing
- What is the chance that I have 0, 1, 2, 3, ... defaults out of 250 clients, when their default probability is 1%?
- This is Binomially distributed and with the figure above, we see that the probability to have zero to four (five) defaults is 89% (95.8%).
- Put differently, as long as I have not more than four defaults, I have no reason to doubt the rating model (on the 95% confidence level).

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- Some models forecast densities, not only one value.
- E.g. forecasts of a distribution/density of the 3 month LIBOR interest rate tomorrow, say log normally distributed with a mean of 3% and some standard deviation
- How do you backtest them?
- Use the fact that $F(X)$ is uniform distributed, where X is a random variable and F is its cumulative distribution function, i.e. $F(x) := P[X \leq x]$.
- From the model, we get forecasts F_1, F_2, \dots, F_t of the cumulative distribution functions, from reality we will observe realizations x_1, x_2, \dots, x_t .
- If the forecasts are correct, then $F_1(x_1), F_2(x_2), \dots, F_t(x_t)$ are uniformly distributed, i.e. the histogram is flat.
- These F_i need not be the same! They can change, e.g. based on new observations.

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Some caveats

- If the forecasts are overlapping, then the forecasts are not independent anymore and the statistical tests need to be adapted.
- E.g. forecast of the 3 month LIBOR interest rate in 10 days from today, forecast tomorrow in 11 days from today, we see we have an overlap of 9 days. This means, if the first forecast was wrong, it is likely that the next forecast is also wrong, since both forecasts share 9 days of forecast
- If overlapping information is used for the forecasts, then the forecasts are not independent anymore and the statistical tests need to be adapted.
- E.g. forecast is based on the last 120 days observed LIBOR. We see that the forecast of today and the one of tomorrow share 119 days of observations. Therefore, we can expect quite similar forecasts. Again, this means, if the first forecast was wrong, it is likely that the next forecast is also wrong, since both forecasts share 119 days of observations.

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- Validation of vendor models is difficult due to lack of detailed knowledge of the inner working of the model.
 - Evaluation of conceptual soundness may not be possible
 - Ongoing monitoring can still be performed
 - Outcome analysis / back testing can still be performed
- Evaluation of conceptual soundness may be approximated by
 - Maybe the conceptual soundness of the vendor model is validated by an independent third party, e.g. a professor from an university, paid by the vendor / paid by you.
 - Maybe the vendor has an internal validation unit to your standards.
 - Maybe the vendor gives you more details, such that you can perform the validation.
 - Vendor model may be industry standard, therefore, no evaluation of conceptual soundness is necessary.

Periodic revisions and valid models

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- Periodic revisions: Models should be periodically re-validated, since
 - one has gained new experiences with the model,
 - there might be changes in the market (e.g. introduction of negative interest rates, short sales have been banned, currency pegs have been introduced/removed),
 - there might be advances in academia,
 - there might be changes in industry best practice (e.g. switch from one factor interest rate models to multi factor interest rate models)
- There are no valid models, there are only models that have survived model validation.
 - People usually expect from model validation, that it proves the fitness of a model for its purpose. In reality, model validation can only show, that the model validator was not able to find any (material) evidence against the model. There is always the chance that further inquiries would have revealed a major issue with the model. Due to time and cost constraints usually only a sample of all possible tests of the model is performed, commensurate with the importance and the model risk of the model.

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- Ph.Ds or MAs with experience or equivalent
- Statisticians, Econometricians, Mathematicians, Physicist, Quant finance people or equivalent
- Banking know how vs. modeling know how?

Effective challenge, independence

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- OCC/ FED key requirement: effective challenge of the model. Effective challenge depends on incentives, competence, influence.
- OCC/FED expects, that generally, people doing validations, are independent from model development and use. Independence can be achieved in different ways and degrees. In general, it helps if validators do not share
 - the bonus pool
 - the salary increase pool,
 - the promotion pool,
 - the line manager(s)

with the model developers and model users, if the model developers and users do not assess their performance.

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Organizational set up

- People that do the ground work
- People that sign off on models
- Escalation channels/procedures
- Reporting to the board of directors?
- Relationship to internal audit?

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- Controlling vs. coaching
- Second line of defense / validation will fix it
- Model validation is performed by model developers or by a separate organizational unit
- Your boss has no clue about mathematics, quantitative finance, econometrics, statistics
- SAS/R/MATLAB always computes a number for you, but does the model really fit? Use simulations.
- Switch from quantitative to qualitative statements: What is a big, medium, small, acceptable error?
- Lack of data, small sample statistics
- Validation around (regular) parameter updates needed? (Some parameter updates may require heavy judgement, others can be quite mechanistic.)
- Model validation is (very) costly. So you may be well advised to somehow decide upfront as part of your annual planning perhaps, on which models to concentrate your efforts. Cluster models into three (or four) groups:
 - a) models you want to spend a lot of effort,
 - b) models you want to spend a normal amount of effort and
 - c) (d) models you want to spend reduced (or no effort).

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This classification may be driven by different considerations, but a) importance/materiality of the model and b) model risk of the model should be key ingredients into that decision.

- Make it clear to your users where the limits are of what can be done quantitatively. This is very hard and not rewarded.
- There are no valid models, there are only models that have survived model validation.
- There is a tendency that regulators and senior management expect the model validators to be able to validate anything, to put a stamp of approval on anything, e.g. a business strategy. In reality, the expertise of a model validator lies in methodological questions, not in business strategy.

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Tools to use Quant finance

- Quantitative Finance

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- Use software like R, MATLAB, SAS



MathWorks®



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TO KNOW.

- Use their hotline
- Be aware that also those programs have bugs

- Linear regression: $Y = a + bX_1 + cX_2 + \epsilon$

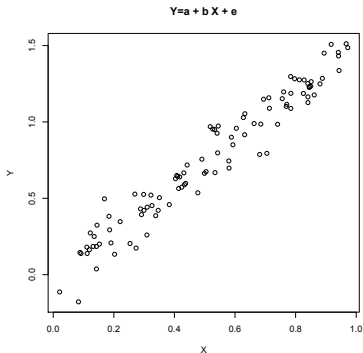


Figure: Data that follows a linear model $Y = a + bX + \epsilon$

- Logistic regression, probit regression, generalized linear models (GLM):
 $E[Y|X_1, X_2] = f(a + bX_1 + cX_2)$

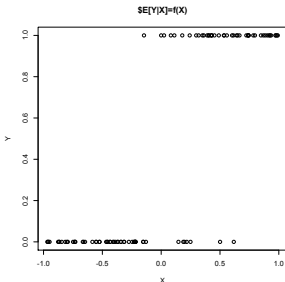


Figure: Data that follows a logistic model, i.e. Y takes only the values 0 and 1, and the probability of doing so depends on X . ($E[Y|X] = f(a + bX)$ with $f(x) = 1/(1 + \exp(-x))$, with $E[Y|X]=P[Y=1|X]=p(X)=1/(1+\exp(-(a+bX)))$ and $P[Y=0|X]=1-p(X)$, i.e Y is Bernoulli-distributed)

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- Generalized additive models: $Y = a + f(X_1) + g(X_2) + \epsilon$

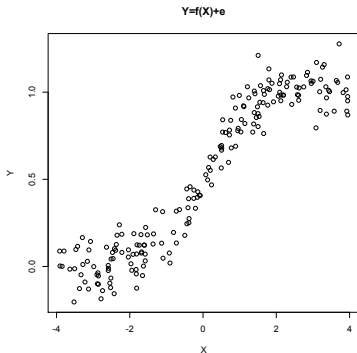


Figure: Data that follows a (generalized) additive model, $Y = a + f(X) + \epsilon$

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- Mixed models, random effects models $Y = A + BX_1 + CX_2 + \epsilon$, so A, B, and C are random variables too, usually assumed to be normally distributed

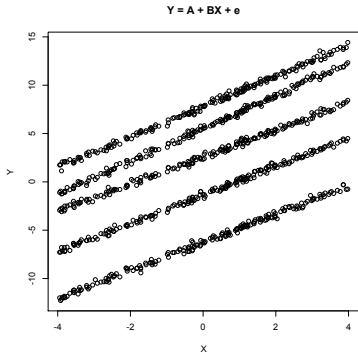


Figure: Data that follows a mixed or random model $Y = A + BX + \epsilon$, where coefficients are also random.

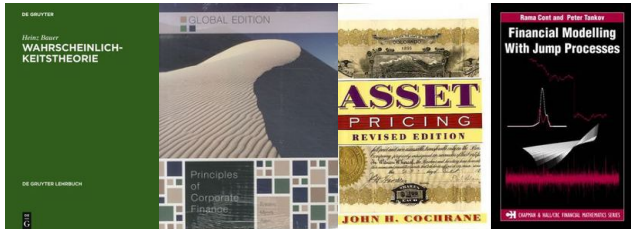
Tools to use Methods

- Use simulations. They are very helpful
- Machine learning, statistical learning: E.g., can help you select factors
- Bootstrapping: Sampling with replacement. This is very helpful.
- Maximum likelihood: Choose the parameters of your model in such a way, that the observations receive the highest possible probability in your model.
- Conditional expectations, filtrations
- Common sense
- Stochastic, probability theory

An example on how to use simulations. Excel simulation in class.

- To generate random draws according to a distribution: General method: Use the inverse cumulative distribution function F and apply it to random draws from a uniform distribution. E.g. in Excel for normal draws with mean m and volatility s : `NORMINV(RAND());m;s`
- Strict white noise process: $x_t := \mu + \sigma \epsilon_t$, μ observed mean
- MA(4) $x_t := \mu + \sigma \epsilon_t + q_1 \epsilon_{t-1} + q_2 \epsilon_{t-2} + q_3 \epsilon_{t-3} + q_4 \epsilon_{t-4}$,
- Random walk: $x_t := x_{t-1} + \sigma \epsilon_t$, $x_0 :=$ observed first value
- AR(1) $x_t := \mu + \sigma \epsilon_t + (x_{t-1} - \mu)\rho$, x_0 first observation
- Vasicek / Ornstein-Uhlenbeck: $x_t := x_{t-1} + k(\mu - x_{t-1}) + \sigma \epsilon_t$, x_0 first observation
- Cox, Ingersoll, Ross: $x_t := x_{t-1} + k(\mu - x_{t-1}) + \sigma \sqrt{x_{t-1}} \epsilon_t$, x_0 first observation
- AR-GARCH: $x_t := c + \phi x_{t-1} + \epsilon_t \sqrt{h_t}$, $h_t := \omega + \alpha \epsilon_{t-1}^2 + \beta h_{t-1}$, x_0 first observation, $h_0 := 0$
- logistic transformation: $y = \frac{1}{1 + \exp(-x)}$ to be in the open interval $(0, 1)$

Books that help you in validation.



- Introduction
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Model risk management I

- Model risk management, the new hot topic since 2011, the new much broader perspective on model validation (in fact it started much earlier)
- Comprises a) Model development, b) Model implementation, c) Model use, d) Model validation, e) Governance, Policies, and Controls
- Model risk (according to OCC/FED) defined as: The potential for adverse consequences from decisions based on incorrect or misused model outputs and reports.
 - Derman 1996: Does not give a definition but can be summarized as: Model risk is the risk, that a model does not get the value of a derivative right. (Value approach)
 - Rebonato 2003: Model risk is the risk of occurrence of a significant difference between the mark-to-model value of a complex and/or illiquid instrument, and the price at which the same instrument is revealed to have traded in the market. (Price approach)
 - Morini 2011: Model risk is the possibility that a financial institution suffers losses due to mistakes in the development and application of valuation models.
- Very helpful to understand validation in a broader context
- Very helpful because models don't have to be perfect anymore
- Key challenge: Model risk should be managed like any other risk (e.g. market risk, credit risk, operational risk). Identify, measure, report, control, underpin with capital.

Model risk management II

- How to quantify model risk, how much capital to put aside for model risk
- Model risk classification (quantification?): expert based, score cards (i.e. rankings)
- What's the model risk in the model that is used to quantify the model risk?
Vicious circle
- Some model risk can be quantified, other is hard or even impossible to quantify, so use a mixed model risk classification based on quantitative and qualitative criteria
- Techniques from statistics: bootstrapping, confidence bounds (if you believe that the model is right, but you may not have sufficient data to estimate the parameter)
- Is there no model risk, if we do not have a model? Before we had a model, there was no model risk. Now we have a model and we have model risk. Should we not dispense with the model altogether?
- Model risk management in fact is quite an old and natural topic (outside of the banking industry):
 - Ship masts are built with a safety factor of 4 (more recently 2.5), i.e. first we have a model to calculate the needed strength of the mast, then we multiply the result by 4 to be on the save side
 - Buildings are built with a safety factor of 2
 - Maximal allowable concentrations in food are estimated with a safety factor of 100

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Knight's distinction of risks, 1921:

- certainty
- quantifiable risk
- unquantifiable risk (uncertainty)

Taxonomy of uncertainty of Lo and Mueller, 2010

- Level 1: Complete certainty
- Level 2: Risk without uncertainty: distribution and its parameters are known
- Level 3: Risk with fully reducible uncertainty: distribution type is known and its parameters can be estimated statistically
- Level 4: Risk with partially reducible uncertainty: distribution type is known but its parameters cannot be estimated statistically
- Level 5: Risk with irreducible uncertainty: distribution type is not known

Physics is usually level 1 to 3, quantitative risk modeling level 4 (or even 5), e.g. CAPM, risk premium, volatility, ...

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- OCC/FED: Three key elements of comprehensive model validation
 - Evaluation of conceptual soundness
 - Ongoing monitoring
 - Outcomes analysis
- Periodic revisions
- There are no valid models, there are only models that have survived model validation.



K. Dowd

Chap. 16 in *Measuring Market Risk, 2nd Edition*.
John Wiley &, Sons Ltd., 2005.



M. Morini

Understanding and Managing Model Risk .
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Risk Model Validation.
Risk Books, 2011.



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April, 2009.



E. Derman.

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Quantitative Strategies Research Notes, Goldman Sachs April 1996, 1996.



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The Complete History of Model Risk-Abridged
October, 2011.

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Model Validation,

OCC Bulletin 2000-16, May, 2000.

For Further Reading III



Office of the Comptroller of the Currency (OCC) / Board of Governors of the Federal Reserve System (FED).
Supervisory Guidance on Model Risk Management,
OCC bulletin 2011-12 / SR 11-7 / SR 11-7a1, April, 2011.



R. Rebonato.
Theory and Practice of Model Risk Management
Quantitative Research Centre (QUARC) of the Royal Bank of Scotland, Oxford Financial Research Centre-Oxford University, not dated (2003).