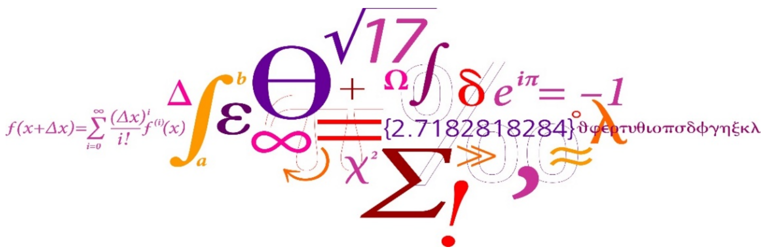
Thesis Title

Author Name

PhD Thesis
Month 20??

Department of Technology, Management and Economics
Technical University of Denmark



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Summary

The goal of the thesis is to ...

Resumé (Danish)

Målet for denne afhandling er at ...

Preface

This thesis was prepared at... in fulfilment of the requirements for acquiring...

The thesis deals with ...

The thesis consists of ...

Kgs. Lyngby, Month 20??

Author Name

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I would like to thank...

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Chapter 1

Introduction

In this Chapter...

1.1 A Section

Counterparty credit risk refers to the risk that a counterparty to a bilateral financial derivative contract may fail to fulfill its contractual obligation causing financial loss to the non-defaulting party. Only over-the-counter (OTC) derivatives and financial security transactions (FSTs) (e.g., repos) are subject to counterparty risk. If one party of a contract defaults, the non-defaulting party will find a similar contract with another counterparty in the market to replace the default one. That is why counterparty credit risk sometimes is referred to as replacement risk. The replacement cost is the MTM value of a counterparty portfolio at the time of the counterparty default. In order to forecast the future market to market values of the deals that belongs to a counterparty portfolio it is essential to realistically simulate the future scenarios of the underlying risk factors. Equity derivatives is only one of the many asset classes and its main underlygin risk factor is the equity prices, equity volatility surfaces and interest rates. In this work equity price dynamics are investigated.

Some of the qeustions that this work tries to answers are as following,

- What kind of model is suitable for realistically forecast the future price distributions of an equity?
- How to estimate the parameters of the chosen model?
- How do we assess if the chosen model and its parameter estimation technique is suitable with regards to the observed realized historical prices?

Hello	World
1	2
3.14	2.78

Table 1.1: Example Table.

Figure 1.1: Example Figure.

link to file

Chapter 2

Methodology

2.1 Credit Exposure Modelling

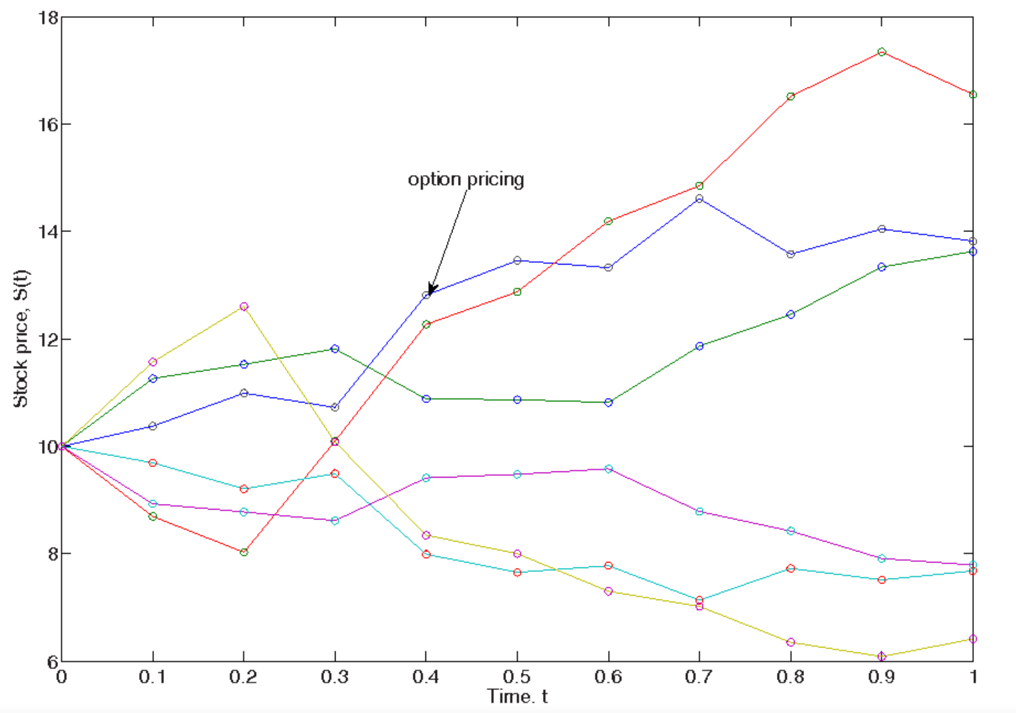

Figure 2.1: Example simulation of credit exposure modelling.

2.2 Preliminary model selection

The standard model for equities is a geometric Brownian motion as defined by the volatility and dWt is a standard Brownian motion. The approach assumes that the equity returns are normally distributed. The drift may be chosen to be positive or negative to reflect a conservative assumption based on the transactions involved or it may be set to the risk-free rate plus some risk premium (as defined by the capital asset pricing model). The volatility could also be either market-implied or determined from historical analysis. For practical purposes, it may not be advisable to attempt to simulate every *single underlying stock. Not only is this highly time-consuming but it also leads to a large correlation matrix that may not be of the appropriate form.6 Rather, one may choose to simulate all major indices and then estimate the change in the individual stock price by using the beta7 of that stock, assuming a correlation of 100index (this may often represent a conservative approximation).* says [Can09].

When simulating the evolution of a risk factor the correlation to other risk factors should also be considered. There are some potential obstacles while simulaitng the equity prices. i) there are many equities in a bank's portfolio from all around the world. Not all of these equities are moving independent. Most of them correlated with each other in clusters. For example it is probable to observe for a stock in certain country to be correlated with other equities in the same country. In this case a multi factor model which has significantly less risk drivers than the number of equities in that country might be useful. This is because the correlation matrix will be too big to handle if one would simulate the all equities seperately with a correlation to the other equities, FX rates or interest rates. Therefore, one of the models that are going to be used in this work is GBM and multifactor GBM. Another method is to simulate the relevant indices and using the CAPM to obtain the future state of the equities. Both multifactor and CAPM approach will help us reduce the dimension of the correlation matrix. However, they will make us lose small amount of information since we will be working with a lower number of risk drivers than the number of equities.

In [Cap12], author gives 3 other alternatives to the conventional GBM process for equity and FX rates. i) local volatility ii) stochastic volatility model such as Heston. iii) Jump diffusion model.

2.3 Risk factor models

The models below are usually used for the underlying process of the equity or FX derivatives. They are mosty used for pricing and hedging in no arbitrage framework. Therefore, the equity prices are martingale for pricing and hedging purposes. However, in this work they are meant to be used for counterparty risk modelling which means that the intention is to forecast the future distributions in real world P measure rather than the risk neutral measure.

2.3.1 Geometric Brownian Motion Process

$$dS_t = \mu S_t dt + \sigma S_t dW_t \tag{2.1}$$

$$S(t) = S(0)e^{\mu t + \sigma W} \tag{2.2}$$

2.3.2 Multi factor Geometric Brownian Motion Process

$$S_i(t) = S_i(0)\exp((\mu_i - \frac{1}{2}\sigma_i^2)t + \frac{\sigma_i}{\omega_i}(\sum_{k=1}^{m} \omega_{ik} W_k(t) + \epsilon_i \tilde{W}_i(t))) \tag{2.3}$$

$$\omega_i^2 = \epsilon_i^2 + \sum_{k,l=1}^{m} \omega_{ik}\omega_{il}\rho_{kl} \tag{2.4}$$

2.3.3 Heston stochastic volatility process

We again use the GBM as the main dynamics of the stock prices as following:

$$dS_t = \mu S_t dt + \sigma S_t dW_t \tag{2.5}$$

We introduce another variable $v_t = \sigma_t^2$, which is the variance and another variable $r_t = ln(S_t/S_0)$ as log-return. Then our process can be rewritten as:

$$dS_t = \mu S_t dt + \sigma S_t dW_t \tag{2.6}$$

$$dS(t) = \mu S(t)dt + \sqrt{V(t)}S(t)d\widetilde{W}_1(t) \tag{2.7}$$

$$dV(t) = \kappa(\theta - V(t))dt + \sigma\sqrt{V(t)}d\widetilde{W}_2(t) \tag{2.8}$$

Estimation

In [WHZZ17], it is explained that ...

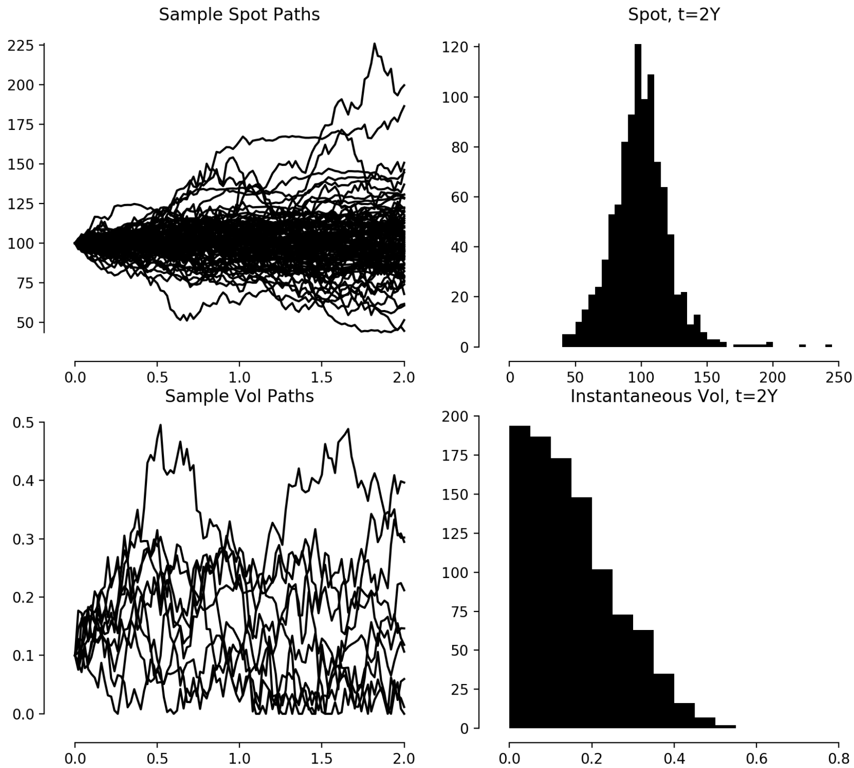

Figure 2.2: Example simulation of heston process.

2.4 Pricing models

2.5 Equity swap

2.6 European Option

2.6.1 Black-Scholes

2.6.2 Heston stochastic volatility model

2.7 American Option

2.8 Barrier Option

$$\frac{1}{N}\sum_{t,k} w_{t,k}(P_{t,k} - P^{\Theta}_{t,k})^2 \tag{2.9}$$

2.9.3 Deep Learning Approach for historical simulation

2.10 Backtesting

The Basel regulatory capital framework specifies that IMM banks backtest their expected positive exposure (EPE) models, where backtesting is defined as the quantitative comparison of the IMM model's forecasts against realised values. Backtesting is only one element of the validation process, but recent experience with IMM banks has shown it to be an area where additional instruction is needed. Backtesting of IMM models is an evolving process and a definitive methodology, as exists for market risk, has yet to be determined. It is not the intention of this paper to prescribe specific methodologies or statistical tests, nor to constrain banks' ability to develop their own validation techniques. Rather, it outlines areas of methodological consideration and potential improvements of the existing backtesting framework in banks, and attempts to clarify terms and concepts

According to regulation there is no strict must-do approach on the backtesting whereas in market risk there are well defined rules on how to label a model good or bad. Therefore, there are some variations among the industry practices.

The backtesting methodology in this section is based on [Rui].

further sampling of data from, for example, a number of counterparties or risk factors, can be used to increase the amount of data

2.10.1 Autocorrelations of the p-values

[Rui], indicates that *As said, this methodology automatically incorporates a way to deal with the autocor- relation induced in the algorithm when $<$. That automatism comes from the fact that the same autocorrelation is also induced in the calculation of (D). Given that the procedure scores a model based on a benchmark probability distribution which takes the autocorrelation eects into account, the outcome is neutral to that eect.*

Chapter 3

Experiment and results

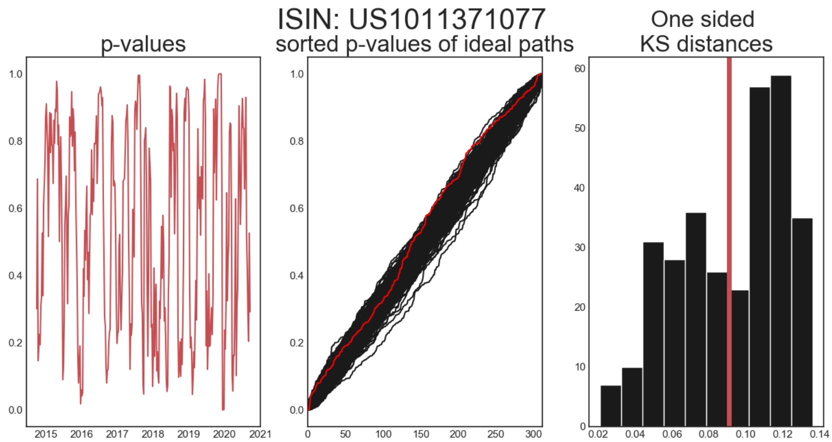

Figure 3.1: Backtesting results for one equity for 1 month horizon (ISIN:US1011371077).

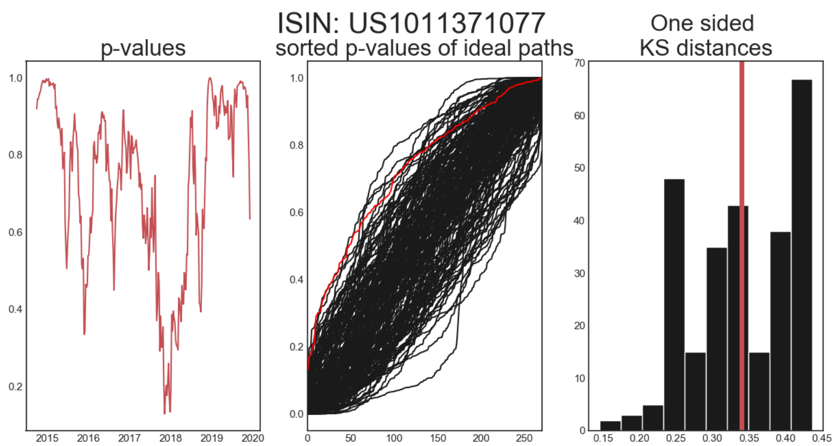

Figure 3.2: Backtesting results for one equity for 1 year horizon(ISIN:US1011371077).

ISINs/horizons	4w	8w	24w	52w
US78378X1072	GREEN	GREEN	GREEN	GREEN
EU0009658145	GREEN	GREEN	GREEN	GREEN
US9839191015	GREEN	GREEN	GREEN	GREEN
US0718131099	GREEN	GREEN	GREEN	GREEN
US0865161014	GREEN	GREEN	GREEN	GREEN
US0970231058	GREEN	GREEN	GREEN	GREEN
JP3906000009	GREEN	GREEN	GREEN	GREEN
JP3122400009	GREEN	GREEN	GREEN	GREEN
US1011371077	GREEN	GREEN	GREEN	GREEN
US1101221083	GREEN	GREEN	GREEN	GREEN
DE0007100000	GREEN	GREEN	GREEN	GREEN
DE0007164600	GREEN	GREEN	GREEN	GREEN
DE0007236101	GREEN	GREEN	GREEN	GREEN
DE0008404005	GREEN	GREEN	GREEN	GREEN
DE000BASF111	GREEN	GREEN	GREEN	GREEN
DE000BAY0017	GREEN	GREEN	GREEN	GREEN
DE000ENAG999	GREEN	GREEN	GREEN	GREEN
DE000ZAL1111	GREEN	GREEN	GREEN	GREEN
DK0010268606	GREEN	GREEN	GREEN	GREEN
DK0010272202	GREEN	GREEN	GREEN	RED

References

[Can09] E. Canabarro. *Counterparty Credit Risk*. Wiley Finance, London, 2009.

[Cap12] Agostino Capponi. Modelling, pricing and hedging counterparty credit exposure: A technical guide, by g. cesari, j. aquilina, n. charpillon, z. filipovic, g. lee and i. manda. *Quantitative Finance*, 12(3):341–342, 2012.

[Rui] Ignacio Ruiz. Backtesting counterparty risk: How good is your model?

[WHZZ17] Ximei Wang, Xingkang He, Yanlong Zhao, and Zhiqiang Zuo. Parameter estimations of heston model based on consistent extended kalman filter. *IFAC-PapersOnLine*, 50(1):14100–14105, 2017. 20th IFAC World Congress.

Appendix A

Stuff

More stuff...