Financial Carto- graphy

Building ALM models is a little like being a cartographer; we try to map the (financial) terrain a traveler needs to cross in order to get from point A to B in as much detail as possible. Depending on the desired goal and one's familiarity with the terrain, trying to get from A to B can get you into serious trouble when not equipped with a proper map.

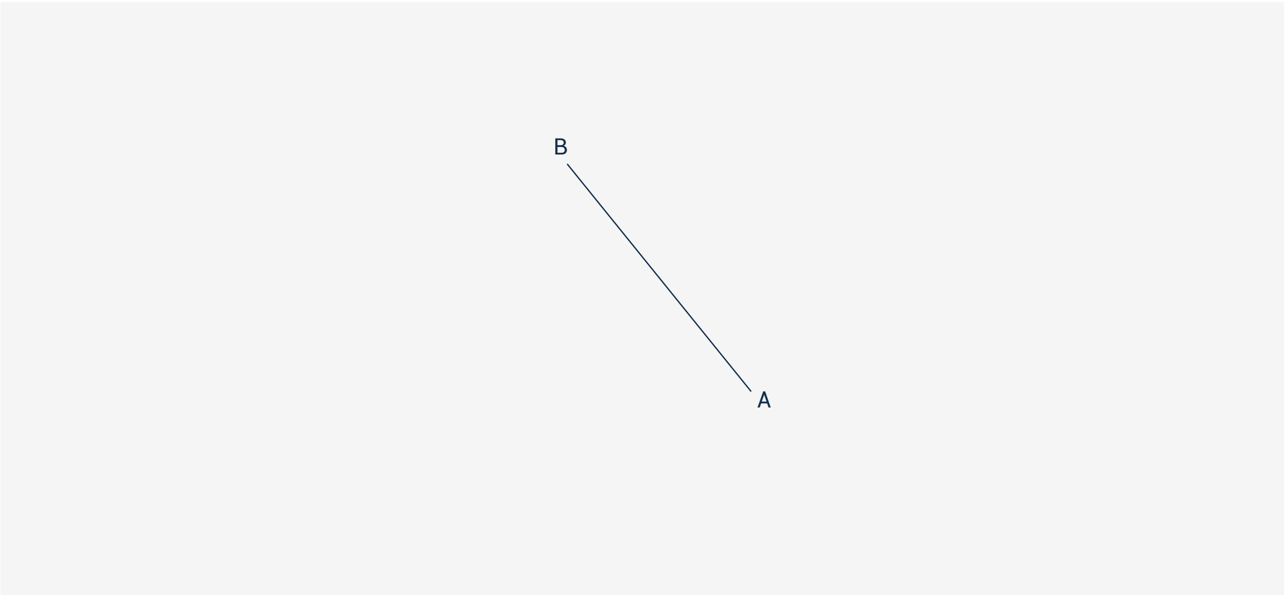


Figure 1: *Deterministic Modeling: Showing the goal but not the road; navigating in the blind*

In financial services, clients are all too often sent into unfamiliar and often rough terrain without a map. This has led to many casualties in the past, especially when the market's weather took a turn for the worse. New pension regulations in The Netherlands now require institutions which offer investment linked pension products, to show 3 scenarios: an average weather, a bad weather and a good weather scenario. Although this still doesn't tell you what the road towards these outcomes looks like, it at least shows you, in a somewhat simplified manner, whether or not you can end up in a ravine or what the highest peak you could possibly reach would be.

Some providers of financial products take a step further from only showing three different values on their client portals. With the best of intentions, they introduce the concept of Monte Carlo Analysis in order to show various scenario paths to their client. The problem however, with most out-of-the-box Monte Carlo models, is that these models do a poor job in realistically modeling the observed behavior of financial markets. Often the behavior of financial markets is reduced to a standard deviation, expected return and correlation; hence assuming market returns are distributed conforming to a perfectly balanced bell shaped curve. Although they are easy to use, and cheap to implement, they do a poor job in showing realistic scenarios.

The Illusion of Normality

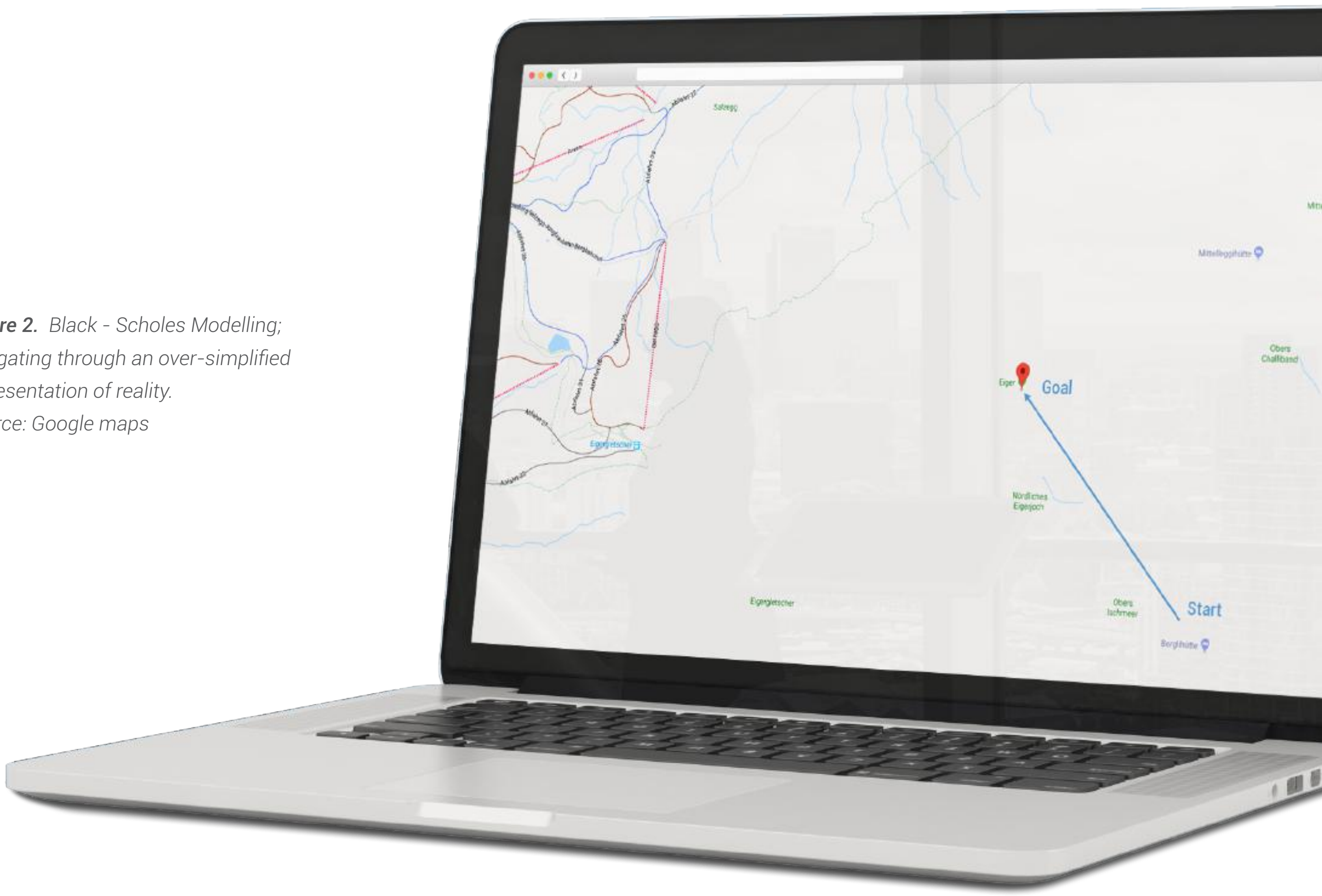


Figure 2. *Black - Scholes Modelling; navigating through an over-simplified representation of reality.*
Source: Google maps

Let's look at this normality assumption. Over the past decades, there have been countless academic studies pointing out skewness, kurtosis and tail-fatness in the distribution of financial returns. They unanimously reach the conclusion that financial returns are not normally distributed. From this observation it follows that when trying to model financial markets as realistically as possible, assuming normality is not such a good idea; it would be like drawing a map whilst ignoring crevices and ravines. So even though we can present clients with thousands of generated scenarios and fancy statistics, if the scenarios themselves are far from reality we are not actually helping clients to navigate unfamiliar terrain.

Unable to See The Wood for The Trees

Amongst the providers of scenario analyses tools for private individuals, we see a number who claim "superior modelling" due to the fact that they base their models on the characteristics of every individual security, flaunting databases with hundreds of thousands securities. Now, for an audience with no background in quantitative finance or investments, this might sound very appealing and convincing. However, one of the first lessons one learns in investment theory, is that:

- Long term returns are first and foremost driven by asset allocation, then regional or sector allocation, and last and with a very small contribution comes security selection. Add to this that:
- Although there is long term data available for asset classes, this is not the case for the vast majority of individual securities).
- Investors rarely hold individual securities forever whereas asset allocations tend to remain pretty much stable (life cycles can be applied)
- Individual risk return characteristics of securities are highly unstable over time; for indices less so The model cannot be calibrated anymore; it would be impossible to properly assure that the models projected paths, and how they behave relative to each other are in line with reality. For 20 risk factors this is already stretching it; for thousands this is plain utopia.

Although it makes for a nice sales pitch to non-investment professionals; applying forward scenario generation on individual securities claiming it enhances the quality of the projection has no academic basis.

Real World Modeling

Figure 3. *Real World Modelling; an as close as possible representation of observed reality: Swiss Topography. Source:SwisToppo*

The term used for models that try to closely replicate observed market behavior is "Real World Models". One popular version of these are Vector Autoregressive models. The main advantages of these models are that they are intuitive and capture long-term dynamics. However the downside of the basic form of this model is that it is still based on normality assumptions and it requires a large number of parameters to be estimated outside this model. Needless to say, the more parameters one needs to estimate, the bigger the chance that estimation errors accumulate. This limits the number of actual asset classes which can be used without ending in an over-parameterized hence error prone model.

Mean Reversion; does it exist?

Another assumption of the Vector Autoregressive models is the existence of mean reversion in asset prices. Academic economic opinion differs on whether or not mean reversion is actually present. Presence of mean reversion would lead to higher chances of a higher return after a (period of) below average returns, which would imply less downside risk compared to models that do not assume mean reversion. Without conclusive evidence as to its existence, assuming no mean reversion is more prudent as it would not underestimate portfolio risk, and therefore in our view more suitable for wealth management applications.

" The literature has found little evidence for long-run mean reversion in stock prices while the evidence for mean reversion in stock returns is also thin…. it seems prudent for a risk-averse investor to base investment decisions on conservative assumptions regarding the mean-reverting behavior of stocks"

Dutch Central Bank (DNB) Working Paper "Mean Reversion in Stock Prices", April 2012

Most importantly, we believe that ALM models should not enforce tactical market views and should provide an objective observation of past behavior. Financial intermediaries usually have their own tactical as well as strategic views on market returns which need be fed in the ALM model. It would be most undesirable if the model could embed opposing views to the tactical calls of the asset manager. Market timing and making return predictions is quite a different job from modeling historical market behavior. Mixing the two up would be like a cartographer trying to do a meteorologist's job.

For example see the Dutch Central Bank (DNB) Working Paper "Mean Reversion in Stock Prices", April 2012, which lists opposing views of several authors

Cobbler Stick to Your Last

The Finbotx model focuses on two undisputed phenomena which can be observed in financial markets:

- Periodic correlated crashes of different asset classes
- Volatility clustering

By using stochastic volatility to capture Volatility clustering and embedding a jump diffusion process to capture periodic market crashes, we are able to generate economic scenarios which can be calibrated to the actual behavior of asset classes, with a limited number of parameters.

An example to model a European High Yield, an asset class particularly prone to market shocks, can be seen in figure 4 which shows the outcomes of a simple Brownian motion. This is a simple Monte Carlo process also used in the well know Black and Scholes option pricing models. We compare this with the outcomes of the FinBotx model and an actual European High Yield index. Basically, what we are doing here is comparing the different maps with a satellite image and see how they match. As can be seen in this figure, the Finbotx model is a far closer representation of the actual observed market behavior than the simple model.

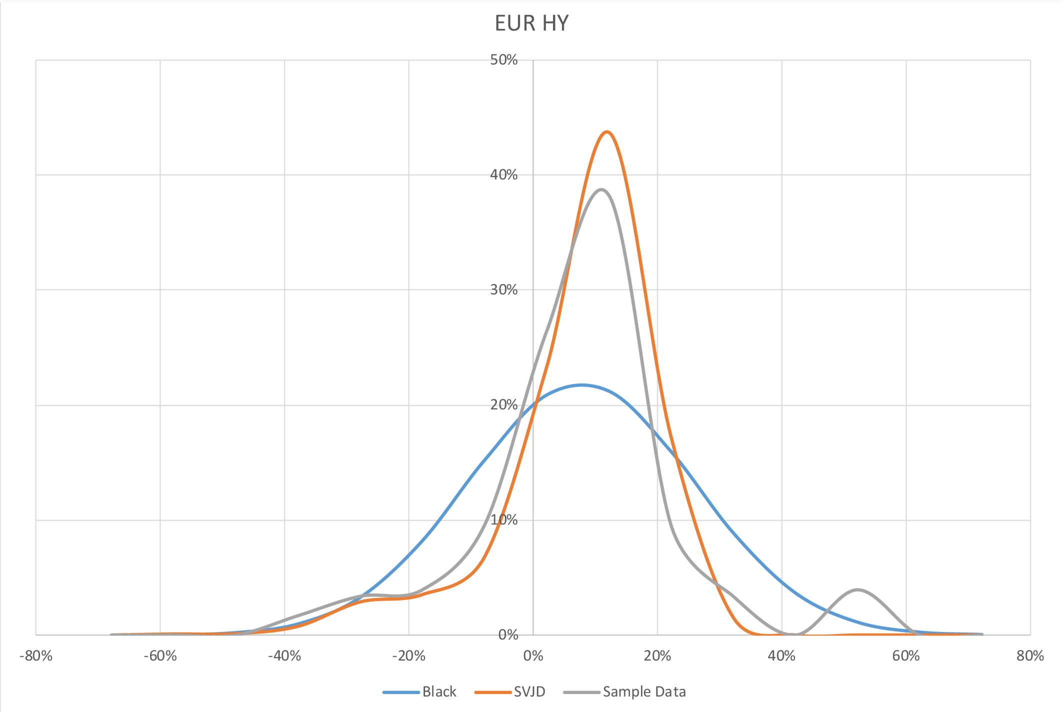


Figure 4. *Annual returns European High Yield, actual versus projected Black versus projected Finbotx*

Modelling Crashes

One doesn't need to be an investment professional in order to know that financial markets can crash sometimes, yet the most common known shortfall of the normality assumption is that the probability of a market crash is substantially underestimated. The inability to capture these so called "fat-tails" in asset price distributions has a direct impact on correctly modeling the price behavior of stocks. As market crashes in general are observed across asset classes, also the benefits by diversification of an investment portfolio are overestimated. If market crash correlations tend to move to +1 or -1 between asset classes, not correctly modeling for this behavior can substantially deteriorate the quality of the insights provided to wealth management clients regarding the risk and return characteristics of their portfolio.

Finbotx models market crashes with a so called Jump Diffusion process which takes into account the probability of a crash and a distribution of the actual crash with a given average (for example -15% down on average). Next to this, we also model the relationship of a crash across asset classes, addressing the "break" in correlations during a crisis.

An example of the Finbotx approach for Japanese and Emerging market equities and a regular Brownian Motions approach is shown below:

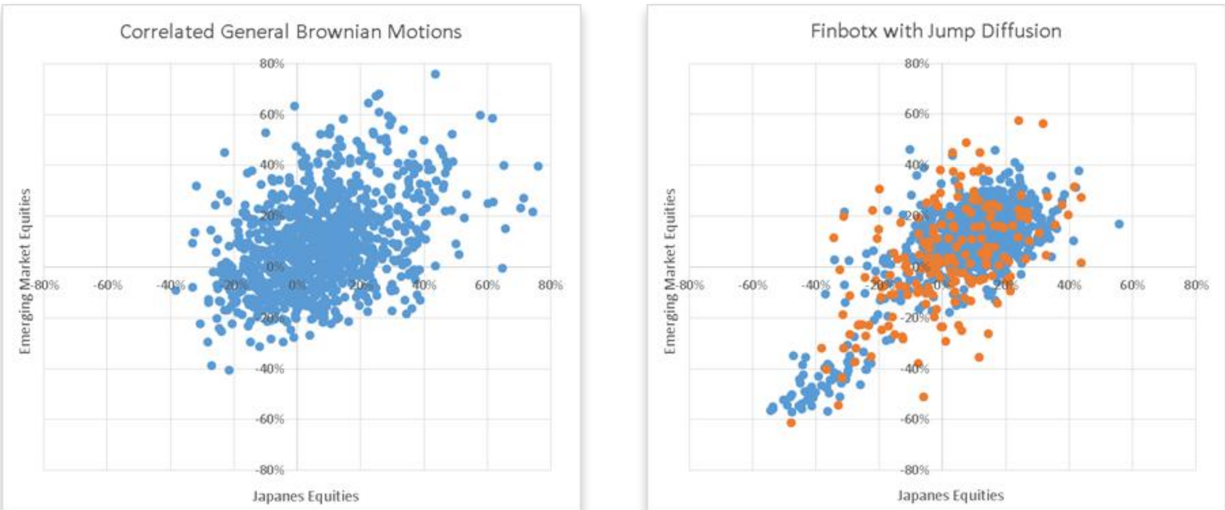


Figure (s) 5. *Comparison between outcomes of a regular correlated Brownian Motion and FinBotx Model with Jump Diffusion for 100 scenarios – yearly returns. Orange data points are the actual (monthly annualized) moves during 2001 and 2017*

Again both samples have the same mean and volatility, but the Finbotx graph clearly shows a correlated market crash impact. The actual moves – as per the orange data points – do reflect a similar behavior as the simulated numbers, confirming that the Finbotx produced mapping offers a closer representation of reality

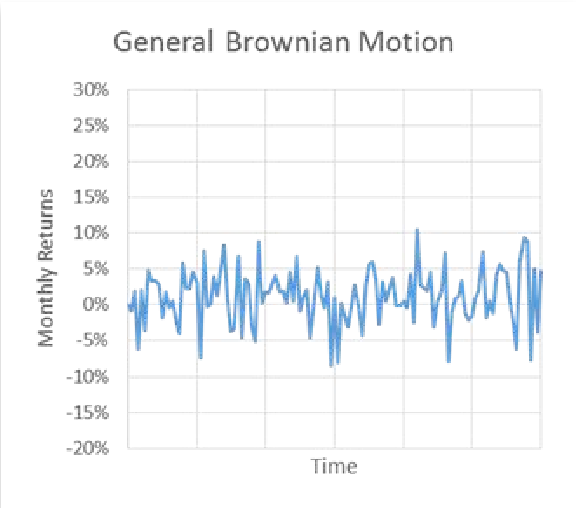
Embedding Volatility Clustering

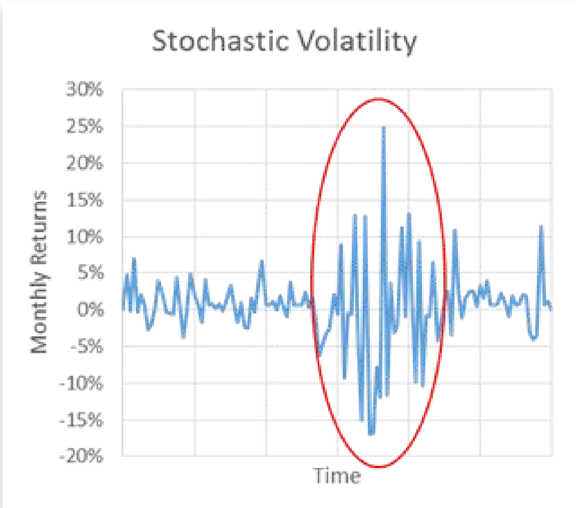
As mentioned before, volatility is observed to not be constant over time: very often we see periods where high levels of volatilities are clustered, as shown in figure 6 for the Standard and Poor's 500 (SPX) Index. For investors this implies that the actual downside risk of an investment might be bigger as what its average volatiliy suggests.

Figure 6. *Volatility clustering patterns in SPX daily movements*
Source: bloomberg

To model this behavior the Finbotx model incorporates stochastic volatility by means of a Heston Model. The Heston model is widely used in the financial industry and introduces a volatility of the volatility, a mean reversion parameter on volatility and long and short terms variance levels. These parameters are calibrated on long term historical data series like for example the SPX and its corresponding CBOE Volatility Index (VIX).

An example of single economic scenario using a simplistic Brownian motion versus Finbotx's stochastic volatility is presented in figure 7:





Figure(s) 7. *Volatility clustering patterns in SPX daily movements*
Source: Bloomberg and Finbotx

Although both samples have the same mean and volatility, the clustering is clearly present in Finbotx's stochastic volatility scenario, realistically showing the actual downside risk of the asset class. Like it is often said in statistics classes: *"one can still drown when crossing a river with an average depth of half a meter."*

The Proof is in the Pudding

So lets have a look at how the projected time-series of the model compares to the actual observed historical time series. When we did a good job as financial cartographers, the model should resemble the observed reality as closely as possible.

In the graph in figure 8, we have plotted the forward projected time series for the S&P 500 using the Black model and the Finbotx model versus the historical time series. Here one can clearly see that the Finbotx model replicates the behavior of the index much more accurately than the Black model.

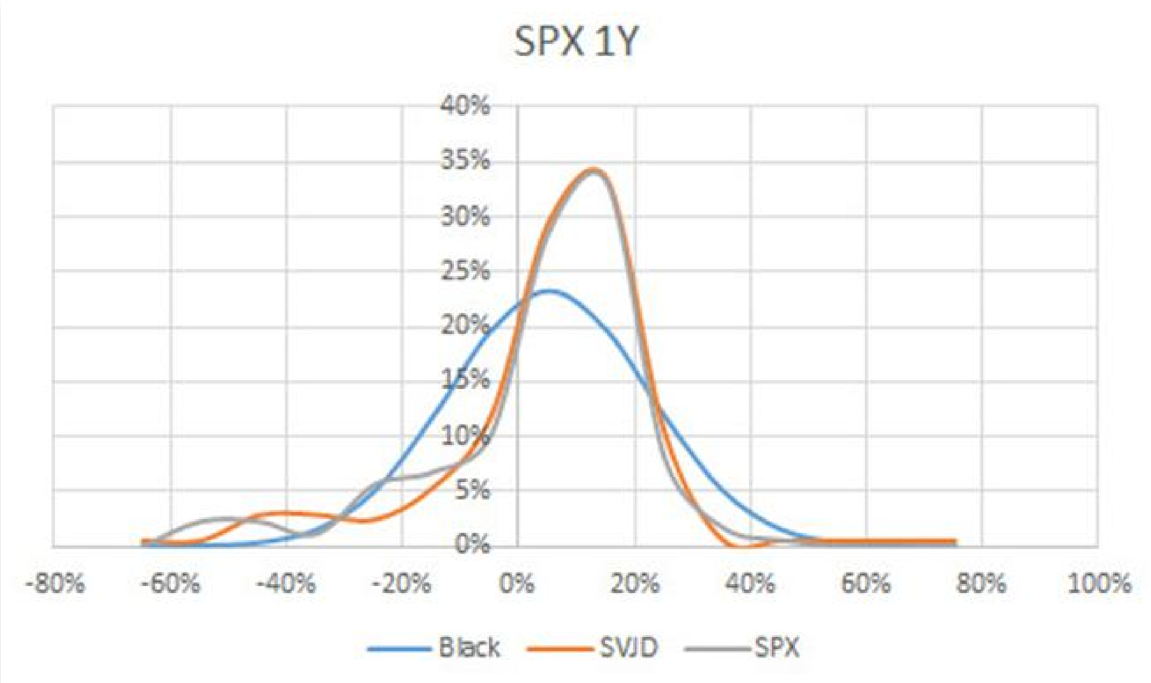


Figure 8. *Projection Black versus Finbotx (SVJD) and S&P500 returns*

So how does the above show in the actual advice to the client?

The below table shows a projection made with a simple Black model, calculating the chances of preserving capital corrected for inflation over a 10 years horizon:

	Savings	Income	Defensive	Neutral	Growth	Aggressive	Very Aggressive
Chance	38%	93%	89%	85%	84%	82%	81%
Shortfall	3%	0%	1%	1%	2%	3%	4%
Average scenario	598	692	760	794	851	914	982
Good scenario	604	846	1040	1.177	1.358	1.593	1.908
Bad scenario	592	569	541	519	499	458	431

x EUR 1.000

Then the same analysis done with the Finbotx model will yield the following results:

	Savings	Income	Defensive	Neutral	Growth	Aggressive	Very Aggressive
Chance	39%	83%	82%	80%	80%	78%	75%
Shortfall	3%	2%	3%	4%	5%	7%	9%
Average scenario	598	692	760	794	851	914	982
Good scenario	604	845	1.013	1.122	1.291	1.526	1.812
Bad scenario	592	533	489	437	396	323	264

x EUR 1.000

As expected, the Finbotx model, with it's fatter tail due to the inclusion of stochastic volatility and a jump process, will give significantly lower "bad scenario" capital values at the end of the horizon compared to the Black model. The same fatter tail also translates into lower probabilities of reaching a goal, despite the same mean.

Conclusion

From the above we can conclude that by embedding characteristics such as a jump diffusion process and stochastic volatility into its models, Finbotx has indeed been able to capture the main undisputed characteristics in financial market returns whilst navigating away from the many pitfalls of Vector Autoregressive models. As such, we have created a realistic map for those who want to venture into the world of investments. Applying these realistic scenarios in financial planning leads to a more conservative yet realistic outcome of calculating goal probabilities and projected portfolio outcomes. Combined with a powerful and flexible API, any front-end application can be used to tailor this information in a way suitable for the intended target audience.

About the Authors

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Years of Experience: 20

Bart has spent over 20 years in the world of international private banking and asset management.

He frequently authored articles and provided training on various investment related subjects. He has led the product development efforts of leading Dutch Private Banks both in Asia as in Switzerland, where he was responsible for the implementation of MIFID I and II throughout the bank.

Bart is passionate in translating highly complex investment problems and concepts into easy to understand articles, tooling and solutions for clients.
He co-founded Finbotx in 2016.

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Years of Experience: 10

Alexander is Assistant Professor of Finance and Risk Management at the Vrije Universiteit Amsterdam. He holds a MSc Econometrics from the Vrije Universiteit and a PhD in Financial Mathematics from the University of Amsterdam. Next to this, Alexander is the owner of Risk at Work consultancy, which aims to come up with state-of-the-art solutions for complex risk management matters.

He combines several years of practical experience in risk management with comprehensive academic knowledge. This enables him to quickly come up with suitable solutions for complex risk management issues.

His research has been published in high-ranked actuarial and financial mathematics journals such as the International Journal of Theoretical and Applied Finance, Insurance: Mathematics and Economics, and Quantitative Finance.

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Jacco has spent close to 20 years as a financial risk professional at various parts of the financial industry around the globe; including Private Banking, Wholesale Banking and Insurance. During his career he developed several in-house systems for the valuation and risk management of complex products as well as to fulfil regulatory requirements. This experience provides him with a good insight in customer needs and the skill-set to provide practical IT solutions for risk management issues.

He holds a MSc in Econometrics, a MSc in Actuarial Sciences and Mathematical Finance as well as a Certificate of Quantitative Finance.

Finbotx

Finbotx was founded with the aim to offer superior, flexible and cost efficient financial modeling services.

It currently offers the most advanced economic scenario generator for personal financial planning available; latest state of the art academic insights are incorporated in close collaboration with the VU University in Amsterdam

Contact us!

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