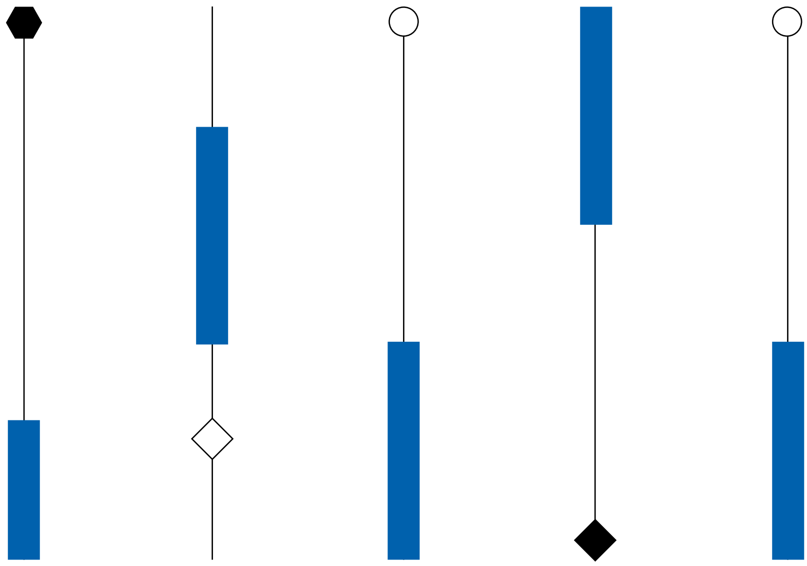


Synthetic Reality: Synthetic market data generation at scale using agent based modeling

By Natraj Raman, Jochen L. Leidner, Krishnen Vytelingum and Geoffrey Horrell

Simudyne

REFINITIV™ LABS

REFINITIV™ DATA IS JUST THE BEGINNING

Contents

1. Executive summary

Agent Based Modeling (ABM) offers advances over traditional model testing applications in the financial markets. This paper introduces the topic of Agent Based Modeling and illustrates its application in a number of scenarios.

Why simulations?

Trading strategies are evaluated traditionally against historical financial market data. The ability to forecast is largely based on events that occurred in the past. Simulations can explore what might happen outside of historical bounds and provide a powerful mechanism to analyze trading performance against a wide variety of market conditions and unforeseen scenarios.

Agent-based modeling

Complex systems such as financial markets are not amenable to a top-down modeling approach. ABMs observe the collective behavior that emerges out of the interactions between large numbers of autonomous trading agents. This bottom-up approach can simulate the outcomes of financial markets in a realistic manner. Perhaps with some artificially created stress tests and to an extent the modeling creativity of the tester.

Simulation models

This article outlines mechanisms to generate synthetic market prices. Agents that trade with varying behaviors are used to simulate alternative price paths of assets to create a variety of 'what-if' scenarios. The synthetic market prices are then compared to the real market prices using statistical techniques.

Refinitiv Tick History and Simudyne

The models are calibrated using the Refinitiv Tick history is an historical archive of tick by tick real-time pricing data, covering OTC and exchange-traded instruments, from more than 500 trading venues and third-party contributors.

2. Overview

History rhyming or repeating?

Financial professionals extensively use historical market data in order to gain insight into the effectiveness of their trading strategies. The presumption here is that the market comprises recurring patterns and by studying these patterns in the past, one can predict future price movements. There are several limitations with this approach. Relying on the belief (Davidson, 2009) that future events can be calculated with actuarial certainty from past data is deeply flawed. It is important to consider all possible outcomes, including those that are outside of historical bounds for efficient modeling of uncertainty and to avoid the danger of overfitting.

Computational simulations are an effective mechanism to augment historical data. They can model a wide variety of market conditions and explore what might happen under extreme situations. Classical simulation techniques that take a topdown modeling approach are not suitable because the dynamics of financial markets are just too complicated to be represented by structural models.

Modeling complexity

An agent-based model (ABM) (Bonabeau, 2002), which takes a bottom-up approach, may more realistically capture the complex dynamics of financial markets. ABMs study the interactions between large numbers of individuals termed **agents**, which possess independent decision-making capabilities. The key idea being these complex adaptive systems cannot be reduced to a sum of their constituent parts and capturing what happens when they interact is essential to model features such as non-linearity, adaptation and feedback.

In the real world, the market comprises different types of traders and the price evolution of an asset is governed by the buy and sell orders placed by these traders. Similarly, a financial ABM consists of autonomous trading agents who place orders to an artificial stock market. The collective behavior that emerges out of the interactions between these trading agents governs the movement of prices.

Simple building blocks

Using ABMs for market simulation offers several advantages (Turrell, 2016). We can encode the agents with a range of behaviors, starting from a simple agent that makes trading decisions without any strategy to an expert agent that adaptively decide whether to sell, to hold or to buy based on prevailing conditions. By simply altering the behavior and composition of the trading agents, we can generate different price paths that represent different situations. For example, by setting the number of agents that place a sell order to be significantly greater than the number of agents that suggests to buy an asset, a pessimistic market condition can be modeled. It is also easy to capture contagion and feedback effects that can magnify a distress situation into a crisis far beyond an initial price move by interconnecting correlated assets into the structure of the ABM.

Challenges

What makes agent-based simulations challenging?

1. We need to define the structure and behavior of the agents that can adequately represent the scenarios we wish to design.
2. The models must be calibrated to be close to observed market phenomena. ABMs often contain a large number of parameters and it is computationally expensive to identify parameters that reflect empirical data.
3. It is important to ensure that the simulated price paths produced by an ABM have the same statistical properties of the price dynamics in real financial markets. To gain confidence in the model.
4. The platform used for performing simulations must be flexible enough to represent complex models and scale well with the number of agents and the link structure between the agents.

Prototype

We have developed four prototype agent-based simulation models that can generate synthetic market prices under both steady-state conditions and stress situations. The what-if scenarios proposed here can help in assessing the impact of shocks on asset prices and the extent to which such shocks might propagate to other assets. The procedure to initialize the models with empirically observed historical prices is outlined. In addition, the ability of the models to replicate well-known statistical properties of the financial markets is illustrated.

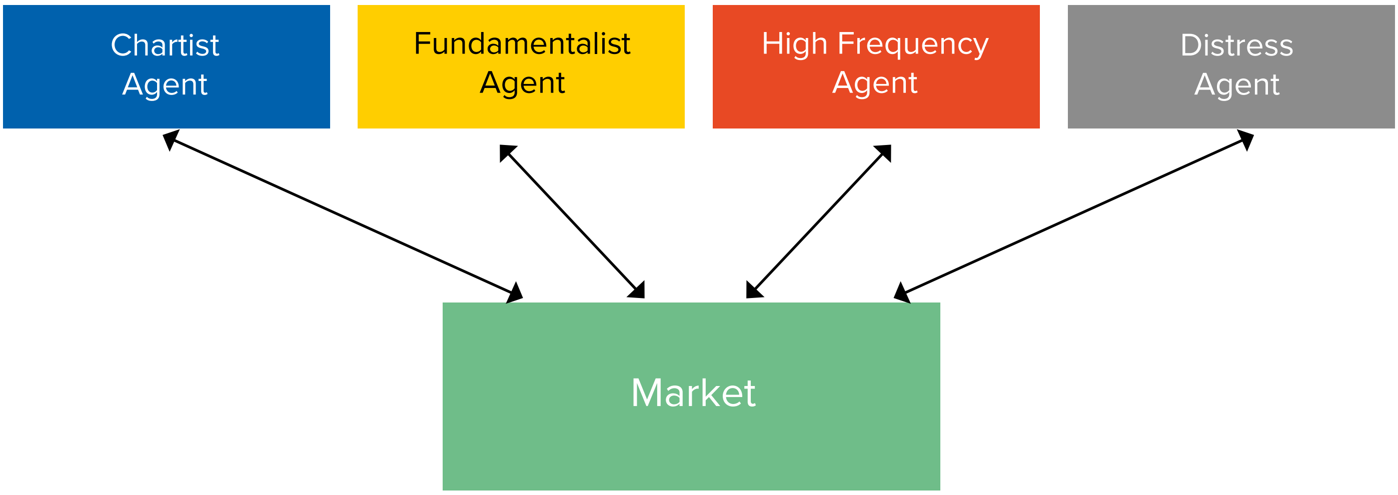
The models are developed using the simulation platform provided by Simudyne (Harmon and Lyon, 2017). The Java-based software development kit (SDK) from Simudyne offers a flexible interface to define the ABM structure and encode the behavior of various trading agents. Simudyne's technology enables concurrent execution of Monte Carlo simulation runs and agent computations. This distributed parallelization scales well even for enterprise-class applications. Both ABM calibration and validation needs access to historical time series of prices. The high fidelity tick history database (refinitiv.com/en/financial-data/market-data/tickhistory) from Refinitiv is used for this purpose.

3. Models

Can we define a single universal ABM topology that captures all market dynamics? Considering the dauntingly complex nature of the markets, the diversity in asset classes and the wide variety of scenarios one might want to investigate, the answer to this question is a resounding “no.” A pragmatic approach would be to develop a library of models, with each model addressing a specific use case of interest. Following this view, we introduce four different models: Heterogeneous, Semi Synthetic, Asset Interactions and Bond Pricing. Despite taking a simplified view of the real world, these models are powerful enough to produce markets in equilibrium and perform what-if scenario analysis. The agent types and behaviors of these models are adapted from the academic literature (Leal et al., 2016; Platt and Gebbie, 2016; Paulin et al., 2018; Panayi et al., 2012; Braun-Munzinger et al., 2016).

Heterogeneous

Heterogeneous model structure:



Price evolution over a short period of time is simulated in this model using a heterogeneous mixture of trading agents that interact with a stock market by posting orders at each time step to a limit order book (LOB). The market matches the orders according to the prices and reports the price at which orders have been fulfilled. By the end of a time step, the market also publishes bid, ask and volume of outstanding orders at various levels of the book. There are three main types of trading agents:

Chartist agents: These agents adopt a trend-following strategy. Their activation frequency is constant over time and is drawn from a truncated exponential distribution. The order quantity is a function of the difference between the closing prices at two preceding trading sessions and the order direction is determined from the sign of the quantity. The order price evolves using a simple geometric random walk.

Fundamentalist agents: This group of agents follow a mean-reverting strategy. Their behavior is similar to chartist agents for determining activation frequency and order price. However, the order quantity is a function of the difference between the fundamental value of an asset and the closing price at a previous trading session.

High frequency agents: Directional strategies that anticipate price movements are employed by these agents. Unlike the above two agents, they are activated endogenously based on the extent of price fluctuations. They also exploit the order information released by chartist and fundamentalist agents. The order size is based on the volume available in the opposite side of the LOB and the order price is close to the best bid and ask prices.

Heterogeneous model price dynamics

CHARTIST

$$A_i \sim [\text{Exp }(\theta)]_{\theta_{min}}^{\theta_{max}}$$

$$Q_{it} = \alpha\,(\bar{P}_{t-1} - \bar{P}_{t-2}) + \varepsilon_{it}$$

$$D_{it} = \begin{cases} sell, & Q_{it} < 0 \\ buy, & Q_{it} \geq 0 \end{cases}$$

$$P_{it} = \bar{P}_{t-1}(1+\delta)(1+Z_{it})$$

$$Z_{it} \sim \mathcal{N}(0, \sigma^z)$$

$$\varepsilon_{it} \sim \mathcal{N}(0, \sigma^q)$$

FUNDAMENTALIST

$$A_i \sim [\text{Exp }(\theta)]_{\theta_{min}}^{\theta_{max}}$$

$$Q_{it} = \alpha\,(F_t - \bar{P}_{t-1}) + \varepsilon_{it}$$

$$D_{it} = \begin{cases} sell, & Q_{it} < 0 \\ buy, & Q_{it} \geq 0 \end{cases}$$

$$P_{it} = \bar{P}_{t-1}(1+\delta)(1+Z_{it})$$

$$Z_{it} \sim \mathcal{N}(0, \sigma^z)$$

$$\varepsilon_{it} \sim \mathcal{N}(0, \sigma^q)$$

HIGH FREQUENCY

$$A_{it} = \left|\frac{\bar{P}_{t-1} - \bar{P}_{t-2}}{\bar{P}_{t-2}}\right| > \Delta_i$$

$$Q_{it} \sim [\text{Exp }(\lambda Q)]_{Q_{min}}^{Q_{max}}$$

$$D_{it} = \begin{cases} sell, & \mathbb{U}(0,1) < 0.5 \\ buy, & otherwise \end{cases}$$

$$P_{it} = P_t^{best}(1 \pm \kappa_i)$$

$$\Delta_i \sim \mathbb{U}(\eta_{min}, \eta_{max})$$

$$\kappa_i \sim \mathbb{U}(\upsilon_{min}, \upsilon_{max})$$

LEGEND

A_i	Activation Frequency of agent i
Q_{it}	Order Quantity of agent i at time t
D_{it}	Order Direction of agent i at time t
P_{it}	Order Price of agent i at time t
$\bar{P}_t$	Mid-Price at time t
$Z, \varepsilon, \Delta, \kappa$	Interim agent specific variables
$\theta, \alpha, \sigma, \delta, \eta, \upsilon, \lambda$	Parameters

In addition to these stochastically behaved agents, there is a rule-based distress agent which (when enabled) places an aggressive sell market order for a specified duration. The above table summarizes the behavior of the agents. The model contains various parameters such as the number of agents, frequency at which the agents get activated, order cancellation rate, extent of price drift, relative importance to the strategy, noise strength etc. By tweaking these parameters, one can generate different price paths and create alternative scenarios.

Semi Synthetic

What happens when we mix real-world orders with artificially generated orders? The Semi Synthetic model explores this interesting possibility and provides an opportunity for agents to interact with a live order book. By encoding their particular strategy into an agent behavior, traders can assess the short-term effect of their strategy on the market prices. The model uses two types of agents:

Real-world agents: This type of agent places an order as it occurred in the historical real world. While the order quantity and direction is exactly the same as a real order, the order price is adjusted relative to the prevailing market prices. Such a relative pricing method provides a simple mechanism to allow the real data set to react to price changes in the simulated environment.

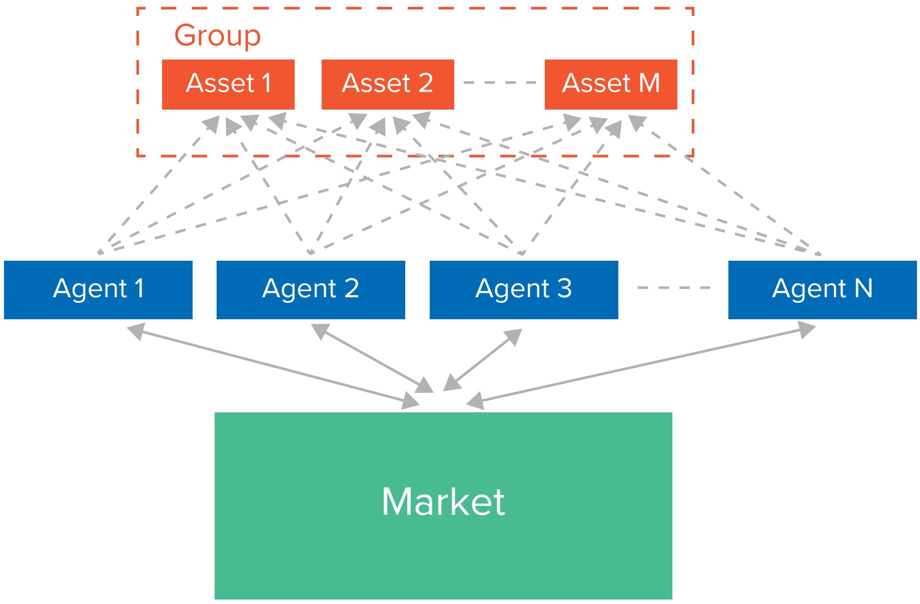
Synthetic agents: These agents make a stochastic decision to buy or sell based on a Bernoulli random variable. The order prices are uniformly distributed within a small range above or below the previous closing price. The order quantities are drawn randomly from a uniform distribution on a bounded interval.

Asset Interactions

The Heterogeneous and Semi Synthetic models consider one asset at a time. Instead of treating the assets in isolation, investors typically trade multiple correlated assets together. The Asset Interactions model deals with this workflow and examines the interaction between multiple assets grouped into a portfolio. The model comprises of agents who trade assets.

The agents get activated chronologically based on a frequency drawn from a truncated exponential distribution. The order quantity and direction is computed from a weighted combination of the expected returns of all assets in the group. The order prices follow a random walk as before. The model parameters allow scaling the number of agents with the assets and varying the portfolio level strength. The main advantage with this model is that we can gain insight into the different aspects of shock propagation between related assets.

Asset Interactions model structure



Bond Pricing

While the above models focus on short-term behavior of prices on liquid markets such as equities, the Bond Pricing model studies a fixed income market which has slower trading speed.

In particular, the model explores the sensitivity of bond prices induced by different trading strategies and exposure to exogenous shocks. The model comprises of three types of trading agents:

Momentum trading agents: These agents believe that short-term trends in yield will persist. Hence they buy or sell a bond depending on whether the current market yield is below or above the average yield over a time window.

Value trading agents: This group of agents associate a fixed yield value to a bond and buy or sell the bond when they believe the asset is undervalued or overvalued. Both momentum and value trading agents incorporate a loss rate that captures the probability of default.

Market marker agent: The momentum and value agents submit their orders to an over-the-counter market maker. The market maker sets the prices depending on the demand. The market maker also becomes increasingly risk averse if the prices become volatile.

Bond Pricing dynamics

$$R_{it} = (1-L)\left(1+Y_{t-1}+\phi^{m}(\bar{Y}-Y_{t-1})\right)-1$$

$$D_{it} = h_i R_{it} \qquad h_i \sim Exp(\gamma)$$

MOMENTUM

$$R_{it} = (1-L)\left(1+Y_{t-1}+\phi^{v}(Y_{t-1}-Y^{*})\right)-1$$

$$D_{it} = h_i R_{it} \qquad h_i \sim Exp(\gamma)$$

VALUE

$$log(P_{t+1}) = log(P_t) + (\lambda + vV_t)\left(\sum_i D_{it} + \varepsilon\right)$$

$$\varepsilon \sim \mathcal{N}(0, \sigma^2)$$

MARKET MAKER

R_{it}	Expected Returns of agent i at time t
$Y, \bar{Y}, Y^{*}$	Current Yield, Average Yield, Fundamental Yield
D_{it}	Demand of agent i at time t
h_i	Holdings of agent i
P_t, V_t	Price and volatility at time t
$L, \phi, \gamma, \sigma, \lambda, v$	Parameters

LEGEND

The dynamics of bond pricing is illustrated n the Bond Pricing dynamics table. The market maker adjusts the prices as a log-linear function of excess demand or supply and past volatility. The model parameters include the loss rate L, strength of the trading strategy ϕ, mean holdings percent γ, speed with which the market maker changes the prices λ, volatility coefficient v and standard deviation of the noise σ.

4. Simulations

How do the price paths generated using these simulation models look like? What scenarios do the models consider? How were the model parameters initialized? Do the simulations relate to real-market data? Are the empirical statistical properties replicated? Answers to these questions are provided in this section.

Results

Exhibit 1 illustrates the simulated prices generated by the Heterogeneous model using over 10,000 agents. The model was calibrated to emulate the prices for Vodafone Group on July 10, 2018 for a half-hour period between 11:00 and 11:30. The thick blue line shows the simulated prices obtained after averaging the prices over a number of Monte Carlo runs. Owing to the stochastic nature of the model, every time a simulation is executed, different price paths are generated. The thin blue lines display such alternative price paths. Note that the prices here correspond to the mid-price obtained from the bid and ask prices.

Exhibit 1: Real and simulated price paths for Vodafone Group over a 30-minute period under Heterogeneous model.

The Heterogeneous model supports simulating a scenario in which the asset prices drop suddenly. This is achieved by activating a distress trading agent who aggressively places sell orders. The agent is parameterized by the activation time, quantity of stocks that must be liquidated and the pace at which the sell orders are placed. The simulation results from this scenario is illustrated in Exhibit 2, where a distress agent becomes active around the 500th tick. The drop in prices causes other chartist agents to react negatively to the asset and consequently there is a sudden sharp drop in the prices, akin to a flash crash, followed by eventual recovery.

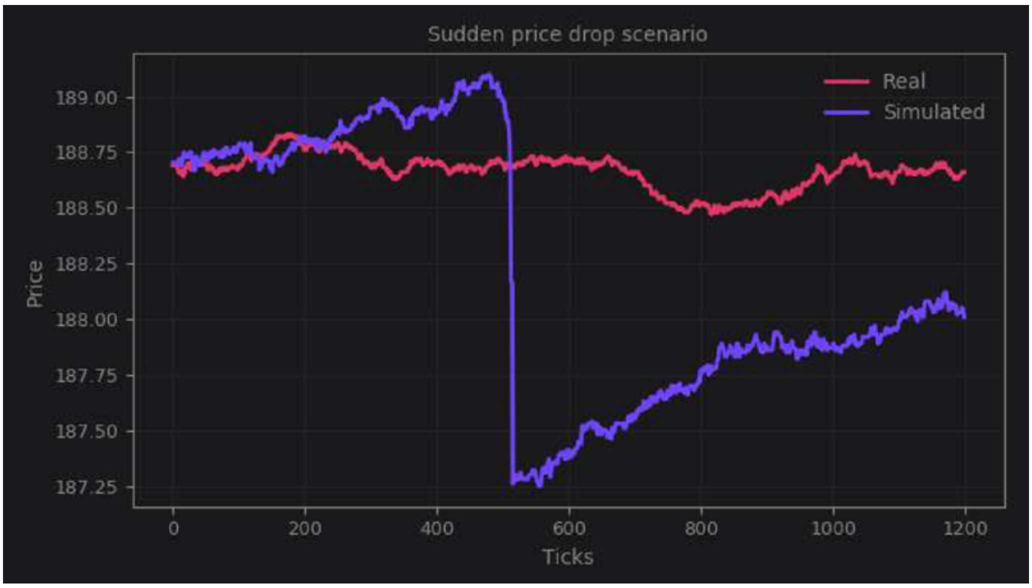


Exhibit 2: Simulation results when a distress agent causes sudden drop in prices.

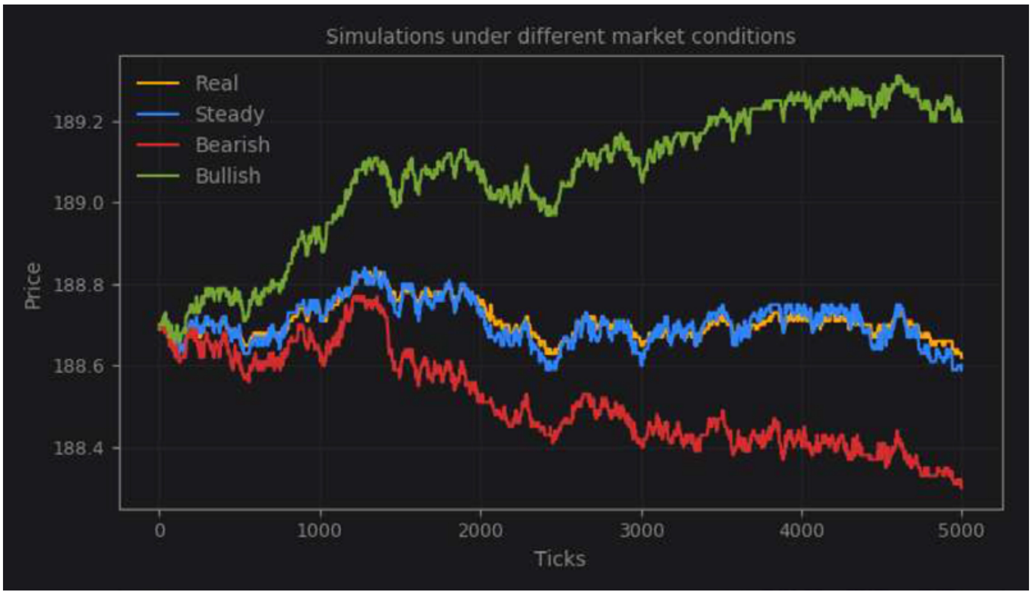


Exhibit 3: Prices generated using Semi Synthetic model for various market conditions.

Exhibit 4 displays the simulated prices under equilibrium conditions using the Asset Interactions model. A synthetic portfolio comprising of five assets from the financial sector, namely Wells Fargo & Co (WFC.N), US Bancorp (USB.N), CIT Group (CIT.N), American International Group (AIG.N) and Stifel Financial Corp (SF.N) was created, and these assets were traded together. The model parameters were initialized to emulate the real world prices on September 20, 2018 for a six-hour period. A total of 10,000 trading agents were used with the number of agents depending on the number of assets in the portfolio.

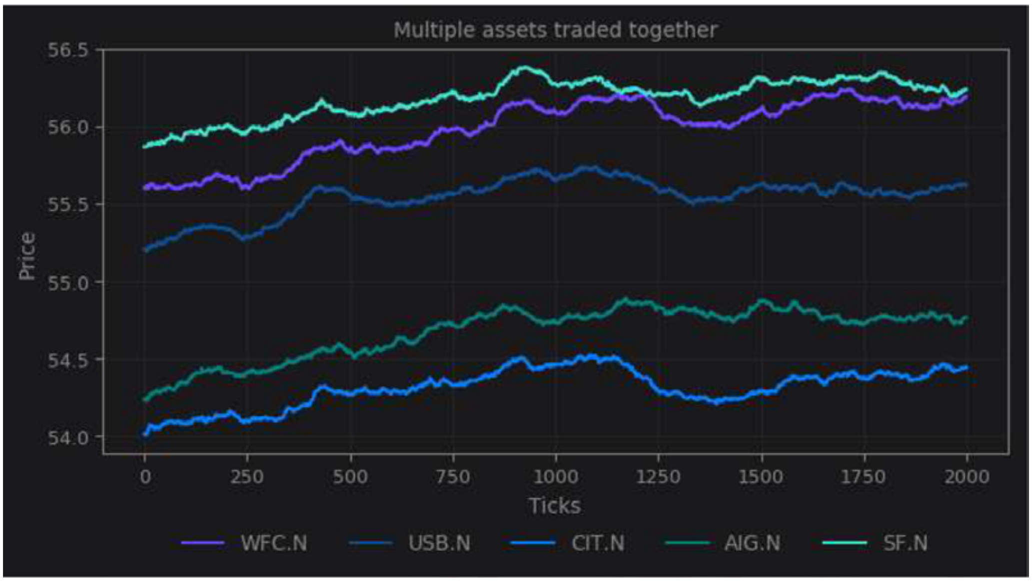


Exhibit 4: Simulation results for five assets trading together under Asset Interactions model.

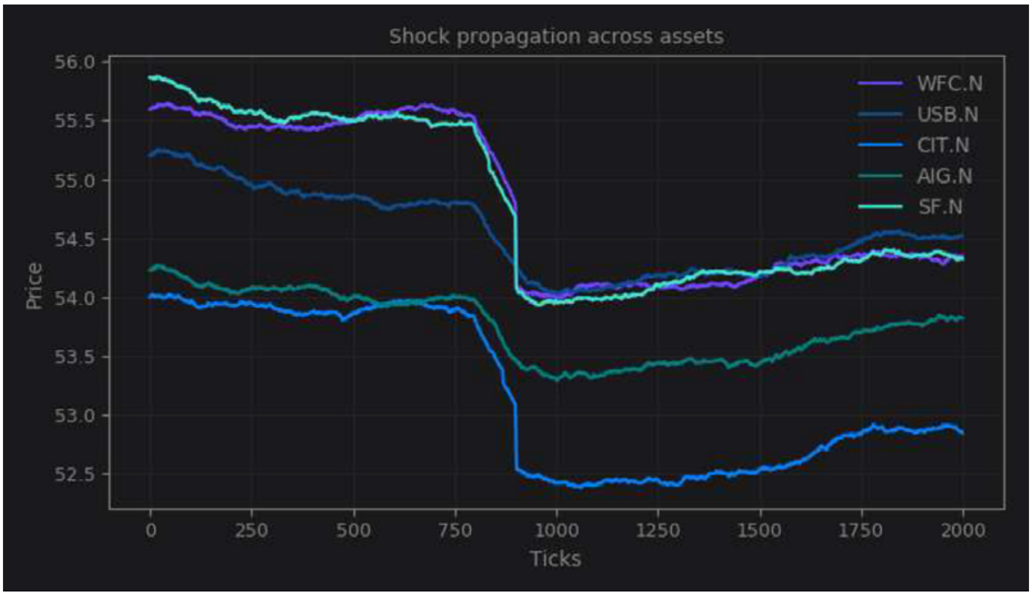


Exhibit 5: Response to shocks applied to a subset of assets.

In order to model a stress scenario, an exogenous shock was applied to WFC.N, CIT.N and SF.N. This was achieved by introducing a bias to the likelihood of selling these assets at a specific point in time for a configurable duration. Consequently, there is a visible drop in prices of these assets near the 800th tick as shown in Exhibit 5. What makes the scenario interesting is the effect of this shock on the other two assets in the group namely USB.N and AIG.N. Since the decision to buy or sell depends on the expected returns of all the assets in the portfolio, these two assets see a drop in the prices as well. By varying the parameters that control the extent of shock and the importance at portfolio level, the stress impact of one asset on the rest of the assets in a group can be investigated.

Finally, the simulated prices of a corporate bond under a steady state condition and a crisis scenario can be seen in Exhibit 6. The real prices correspond to the end of day prices between September 20, 2017 and 2018 for a 3.75% coupon, 29-year maturity Apple Inc. bond. Nearly 200 agents were used in this model, a number far smaller than the equity models. In order to capture the impact of a credit event scenario, the loss-rate parameter that represents the likelihood of a bond defaulting was altered. This changes the demand for the bond causing the market maker to react negatively to excess demand and volatility and resulting in a fall in the prices.

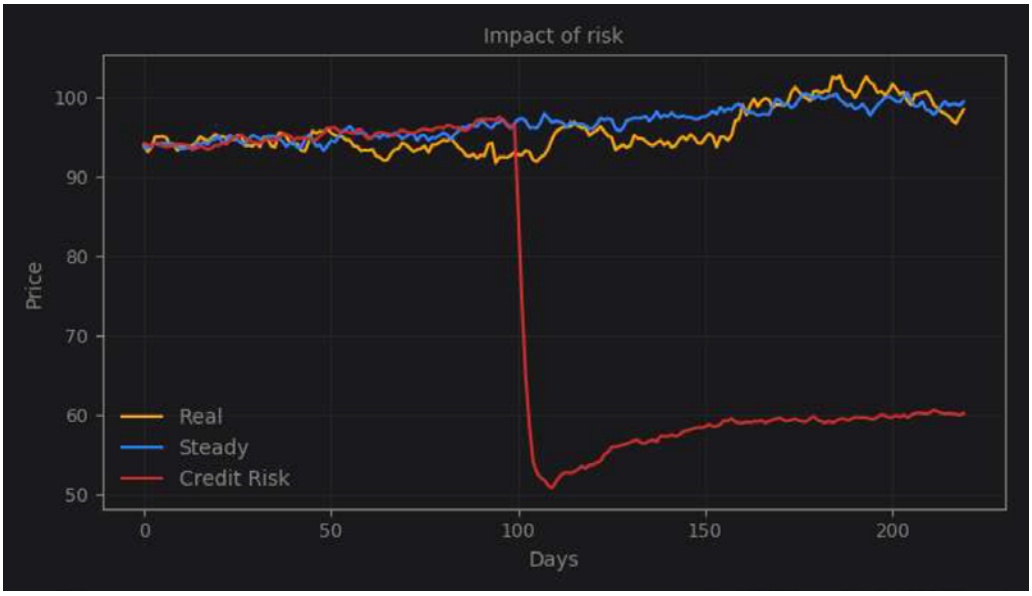


Exhibit 6: Bond price simulations under steady state and stress situation.

Stylized facts

It is essential to check that the simulated prices produced by the model resembles real empirical prices. The seemingly random variations of asset prices in the real world do share some statistical properties called stylized facts (Cont, 2011) that are common across many instruments, markets and time periods. By verifying whether the simulated time series of prices reproduces these stylized facts, one can validate the ABM output. The below exhibits provide evidence that the proposed models successfully replicate the empirical stylized facts.

The left section of Exhibit 7 shows the autocorrelation values of returns for the simulated prices against various lag periods. The price returns were calculated as logarithmic differences. The autocorrelation values do not reveal any pattern and are insignificant. This zero autocorrelation of price returns is consistent with the well-known fact that in liquid markets, significant linear correlations of price movements are generally absent owing to efficient market hypothesis. Exhibit 8 plots the autocorrelation in absolute returns, often used as a measure of volatility clustering, to visualize the similarity in autocorrelation values between real and simulated prices. The right section of Exhibit 7 contains a histogram of the simulated price returns pooled over different Monte Carlo runs. The density plot clearly illustrates that the distribution is leptokurtic with sharp peaks and heavy tails. This non-Gaussian character of the returns distribution has been repeatedly observed in real market prices and the fat-tailed slow asymptotic decay of the distribution with excess positive kurtosis confirms that the simulated prices are realistic.

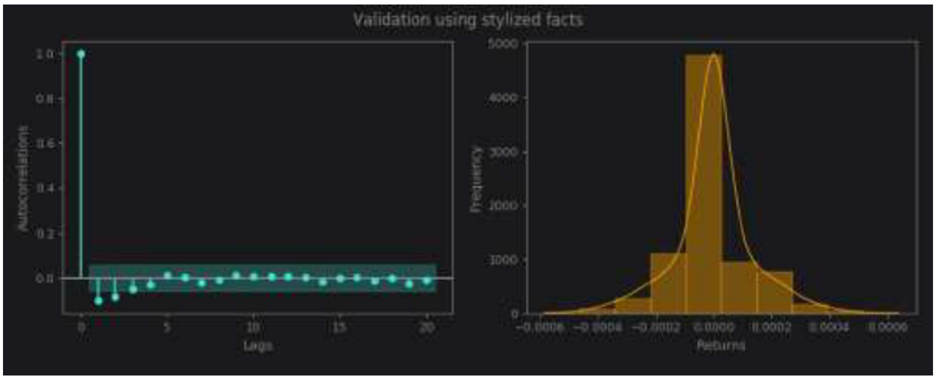


Exhibit 7: Autocorrelation of returns (left) and histogram of returns (right).

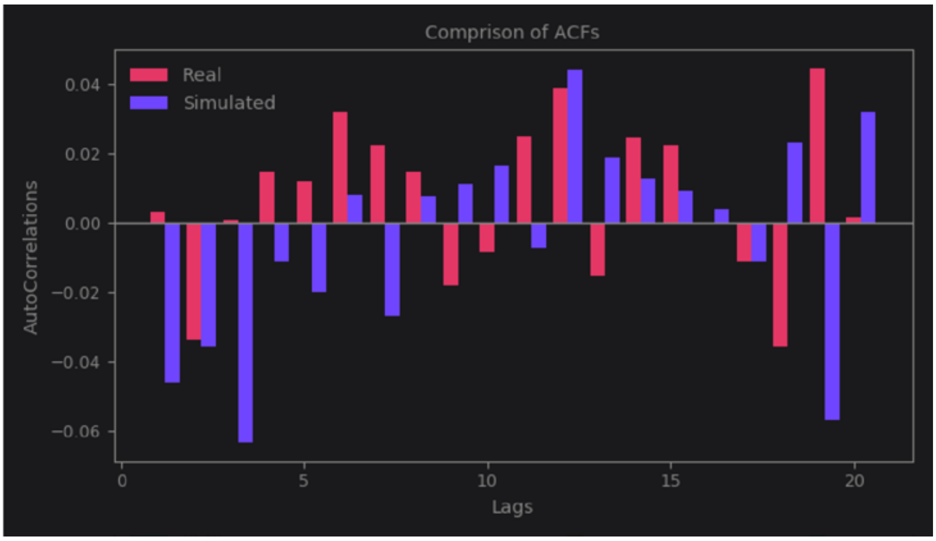


Exhibit 8: Real and simulated autocorrelation factors of absolute returns.

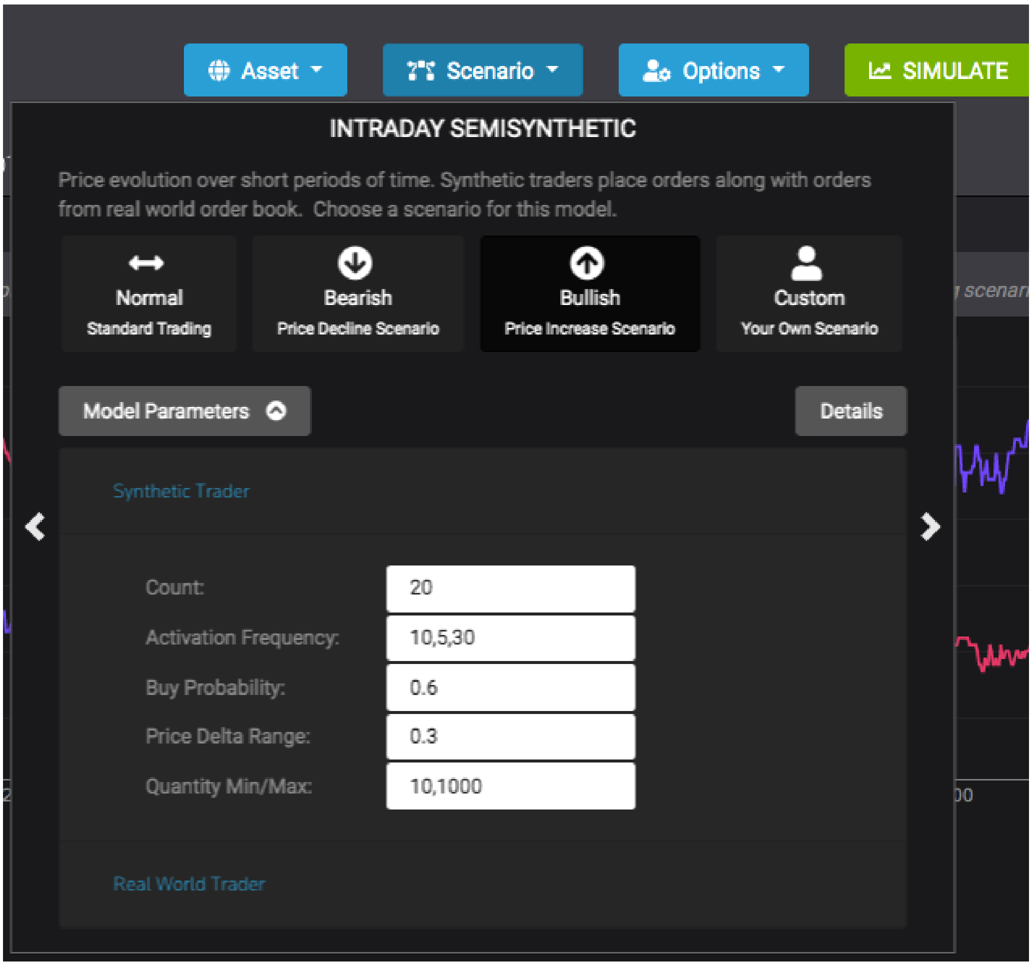
Surrogate assisted calibration

The model parameters must be initialized such that the simulated outputs replicate the stylized facts and are close to empirical prices. It is not feasible to manually try every parameter value or perform classical grid search because of the combinatorial explosion of parameters and computational burden of ABMs. Hence we construct an objective function that takes a set of model parameters as input, executes an ABM run and returns a real valued score that rates the quality of the parameters set. The score value is calculated by introducing a penalty if the simulated prices produced from an ABM run is not conformant with the stylized facts or deviates from the empirical distribution statistics. The major challenge with ABM calibration is that the objective function is costly to evaluate and the overall number of function evaluations must be reduced. We pursue a call-efficient Bayesian optimization approach (Bergstra et al., 2011) which takes probability distributions as parameter configuration space and replaces the objective function with a surrogate function that is cheaper to evaluate. Such an approach uses information from past evaluations to narrow the search space, thereby exploring the parameter space in a much more efficient manner.

Application

The above simulation models are initial prototypes intended to elicit customer feedback. As part of the Refinitiv Labs research and innovation process we create prototype applications to valide new ideas with customers. Consumers can gain access to new augmented content by specifying their preferred simulation scenario, the assets they are interested in, the historical reference time period and can even alter the model parameters to create new custom scenarios.

Choosing scenarios and tweaking parameters



One of the most important applications of simulated content is algorithmic backtesting. New trading strategies are typically evaluated against some reference time series from the past and several performance metrics that rate the utility of the strategies are collected. With the availability of simulated time series corresponding to various what-if scenarios, we can now expand the scope of testing to include new synthetic market data and analyze how the strategies perform in a broader sense. Such a testing process becomes qualitatively and quantitatively more robust. The below exhibit highlights this workflow where the returns generated for a particular strategy is compared both against a historical point in time and a simulated scenario.

Backtesting algorithms using simulated data

5. Conclusion

Simulations provide a meaningful framework to account for known unknown events. Conventional modeling methods cannot generate realistic simulations owing to the complex dynamics of financial markets. The microscopic modeling approach of agent-based models are an effective supplement. The ability of ABMs to capture emergent phenomena that are not explicitly programmed is a key distinguishing feature. We presented a few ABM-based simulation models built on Simudyne and highlighted their ability to generate price paths for various what-if scenarios. These models are by no means exhaustive and they will evolve incorporating new agent types and scenario designs. Simulated market data provides a compelling edge be it for training and evaluating algorithms, risk assessment or experimenting regulatory policies. We look forward to further developments in the adoption of ABM within the financial markets working with Simudyne's capability.

6. Collaboration between Refinitiv and Simudyne

Why we collaborated

In the project that this white paper resulted from, Refinitiv collaborated with Simudyne. This collaboration was a natural fit, as Simudyne is a leader in agent-based modeling in the finance domain, and Refinitiv is a leader in financial data services and technology.

What we did

We carried out a joint project to investigate how synthetic market data can be used in agent-based models, for two reasons:

- on the one hand, to explore user-defined scenario analysis
- on the other hand, to try out large-scale random simulations for stress testing under the widest possible outcomes

We were interested in emergent systemic behavior that could lead to flash crashes by sweeping through millions of parameter constellations scanning for risk.

Outcomes

This project demonstrated the feasibility of applying agent-based modeling for risk stress testing of markets and also the use of synthetic data to go beyond historic data. We developed a number of models (including Raman & Leidner, 2019), software for financial market simulations, which leverages Simudyne's platform, and a capability for generating synthetic but plausible data.

Business benefits

There are a number of business benefits resulting from leveraging agent-based modeling. Particularly for sell-side execution desks competing for client order flow, benefits can be achieved in:

- Creating differentiation in a crowded broker algorithm market
- Algorithm optimization to help win and retain client order flow
- Meeting regulatory requirements (MIFID II)

Refinitiv Labs Innovation Process

Geoff Horrell
Director of Innovation
Refinitiv Labs London

"Refinitiv Labs identifies new business opportunities through agile collaboration and experimentation with our customers and partners. This project allowed us to validate with customers the evolving market for advanced simulations."

Jochen L. Leidner (Ph.D.)
Director of Research,
R&D at Refinitiv Labs

"This project allowed us to tackle the technical challenges and begin a dialogue around this emerging field of synthetic data and ABM with the financial modeling community."

Justin Lyon,
Founder and CEO,
Simudyne

"Backtesting against historic data has been the primary tool for validating trading algorithms, leveraging high quality historical tick data from firms such as Refinitiv, along with data storage and replay tools," Justin Lyon, Founder and CEO at Simudyne, pointed out. "But as the term suggests, it's 'back' in time, and if we think the future may deviate from the past then we need a more sophisticated way of testing algorithm performance under multiple scenarios. The good news is that we now have the capability to do that, using Simudyne we can supplement traditional backtesting with 'possible future-testing': the mix of agent-based modeling and plausible synthetic data permits you to run parameter scans of large numbers of possible scenarios and identify risks that have not historically been encountered."

7. References

Davidson, P., 2009, Can future systemic financial risks be quantified?: ergodic vs. nonergodic stochastic processes. Brazilian Journal of Political Economy, 29(4), 324-340.

Bonabeau, E., 2002, Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the National Academy of Sciences, 99 (suppl 3), 7280-7287.

Turrell, A., 2016, Agent-based models: understanding the economy from the bottom up. Bank of England Quarterly Bulletin, 56(4), 173-188.

Harmon, R., Lyon, J., 2017, Computational Simulation – The next frontier for better decision-making. Technical Report. doi: 10.13140/RG.2.2.29926.01601

Refinitiv Tick History, refinitiv.com/en/financial-data/market-data/tickhistory. Last accessed January 4, 2019.

Leal, S. J., Napoletano, M., Roventini, A. and Fagiolo, G., 2016, Rock around the clock: An agent-based model of low-and high-frequency trading. Journal of Evolutionary Economics, 26(1), 49-76.

Platt, D. and Gebbie, T., 2016, The Problem of Calibrating an Agent-Based Model of High-Frequency Trading. arXiv preprint arXiv:1606.01495.

Paulin, J., Calinescu, A. and Wooldridge, M., 2018, Understanding Flash Crash Contagion and Systemic Risk: A Micro-Macro Agent-Based Approach. arXiv preprint arXiv:1805.08454.

Panayi, E., Harman, M. and Wetherilt, A., 2012, Agent-based modelling of stock markets using existing order book data. International Workshop on Multi-Agent Systems and Agent-Based Simulation, Springer, Berlin, Heidelberg, 101-114.

Braun-Munzinger, K., Liu, Z., & Turrell, A., 2016, An agent-based model of dynamics in corporate bond trading. Bank of England Staff Working Paper, 592.

Cont, R., 2001, Empirical properties of asset returns: stylized facts and statistical issues. Quantitative Finance, 223-236.

Bergstra, J. S., Bardenet, R., Bengio, Y. and Kégl, B., 2011, Algorithms for hyperparameter optimization. Advances in neural information processing systems, 2546-2554.

Vytelingum, Perukrishnen, Sarvapali D. Ramchurn, Thomas D. Voice, Alex Rogers and Nicholas R. Jennings, 2010, “Trading agents for the smart electricity grid”, Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2010), Toronto, Canada — May 10-14, 2010, volume 1, International Foundation for Autonomous Agents and Multiagent Systems Richland, ISBN: 978-0-9826571-1-9, pages 897-904.

Raman, Natraj and Jochen L. Leidner (2019, to appear), “Financial Market Data Simulation using Deep Intelligence Agents” Proceedings of the 17th International Conference on Practical Applications of Agents and Multi-Agent Systems (PAAMS 2019), Ávila, Spain, June 26-28, 2019.

ABOUT REFINITIV AND REFINITIV LABS

Refinitiv Labs is the innovation and research team that is part of Refinitiv. Refinitiv is a leader in financial information services and risk/regulatory/compliance solutions. At Refinitiv, we have a bold vision for the future of the financial community. Formerly the Financial and Risk business of Thomson Reuters, we’re now a new company built on a unique open platform, high performance products and best-in-class data In the face of unparalleled industry change, we’re drawing on our deep knowledge and heritage of objectivity to drive performance and innovation with our customers and partners.

ABOUT SIMUDYNE

Simudyne believes that computational simulation is the key to radically better decisions. Simudyne was founded with the goal of improving decision making across both private and public sectors by leveraging advances in computational power and complexity science. Simudyne trains intelligence in high-fidelity simulated environments to make better decisions, with the belief that simulation is the bedrock for training both human and artificial intelligence.

Visit **refinitiv.com**

Simudyne

REFINITIV™ LABS

REFINITIV™

DATA IS JUST THE BEGINNING

RE952889-Simulated/6-19