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Computational Simulation

The Next Frontier for Better Decision Making

A Bluepaper from Simudyne and Cloudera

Dr. Richard Harmon

Director, EMEA Financial Services, Cloudera

Justin Lyon

CEO, Simudyne

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Introduction

With recent advances in technology and the explosion in the availability of data, the world is becoming much more interconnected and immensely more complex.

Today, society faces a wide range of challenges on an unprecedented global scale. These challenges span financial instability, economic inequality, disease, healthcare, climate change, sustainability, an aging population, migration, pervasive web and information technology, transnational governance, and security.[1]

While there have been advances in analytics in the past decade, we have not seen a step change in our analytical capabilities. On the contrary, a ground-breaking approach that will provide new tools and insights to help society address these challenges comes from complexity science. This field is designed to study emergent properties in complex systems. Emergence is observed in nature through the flocking of birds in the absence of any central coordination. Schools of fish, colonies of ants, and life itself are all examples of emergence. The utility of complexity science to humans becomes immediately apparent when it is applied to study large systems such as the stock market and the banking system.

This paper addresses the challenges faced by the financial services industry and shows how new analytical tools can be used to gain greater insight and produce better decision-making capabilities. We show how platforms, such as those developed by Simudyne, can be combined with the power of the Cloudera modern data platform to provide policy makers, regulators, and other key players in the financial services sector with the necessary tool kit to understand the modern financial sector.

Computational Simulation in Financial Services

The current Basel-mandated risk management metrics, most notably Value-at-Risk (VaR), and the forthcoming Expected Shortfall (ES) measures, are based on historical data.

Current standard risk metrics are inadequate due to the fact that they depend upon history and thus are only useful if the future looks like this past. As noted by Bookstaber, Paddrik, Tivnan (2017):

> "This is because a crisis is not similar to the past; it is not just a bad draw from the day-today workings of the financial system, and it is not a repeat of previous crises. Rather, it comes from the unleashing of a new dynamic, where shocks to markets and funding lead to a cycle of forced selling and to a reduction in liquidity that both magnifies the initial shocks and spreads the crisis to other markets and institutions. Each crisis is different, emanating from different shocks, affecting institutions that have different exposures to markets and to funding, often with financial instruments and sources of funding that did not even exist the last time around."

In this context, the ability to discover vulnerabilities to any crisis requires behavioral specification: this is where complexity science provides a foundation.

1 See Gilbert & Bullock (2014) for an elegant introduction to the role that complexity science will play in this increasingly interdependent and complex world.

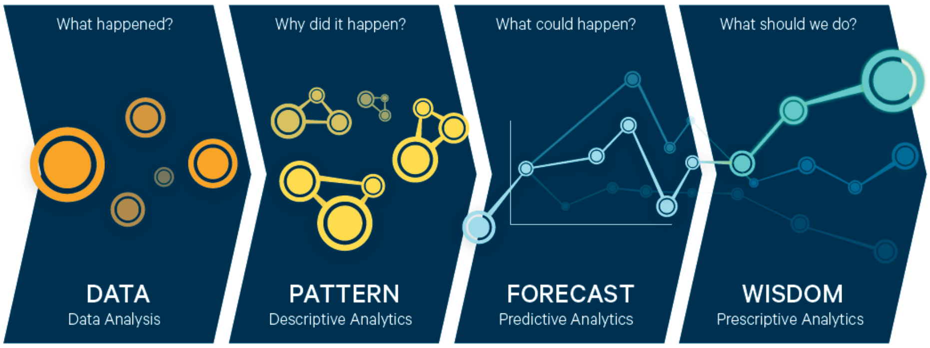


Figure 1: Condition-Based Monitoring

How to Predict the Future and Improve Decision-Making

Big data analytics has produced significant advancements over the past decade by enabling access to connected data sources with diverse data structures. One can view analytics within four analytic categories or phases, each building upon the prior's capabilities, as depicted in Figure 1.

_**Data Analysis:** Involves exploring data to identify, what happened. This is where deep understanding of the data is created, allowing for vast amounts of data to be aggregated to identify important trends, outliers, and other data-driven insights.

_**Descriptive Analytics:** The purpose of descriptive analytics is to summarize what happened, to identify historical patterns, and to provide insights into past events as to why they occurred.

_**Predictive Analytics:** Predictive analytics utilizes a variety of statistical and machine learning techniques to model historical data to estimate predictions about the future. Predictive analytics provides estimates about the likelihood of a future outcome.

_**Prescriptive Analytics:** Prescriptive analytics attempts to quantify the effect of future decisions to advise on possible outcomes before the decisions are made. At their best, prescriptive analytics predicts not only what will happen, but also why it will happen providing recommendations regarding proper actions to be taken.

When combined, this provides decision makers with not only possible future outcomes but also recommendations on possible actions to be taken to mitigate harmful results as well as to identify new insights and opportunities.

Building robust predictive and prescriptive analytic capabilities requires you to weave together three disciplines:

1. Machine learning
2. Computational simulation
3. Network modelling

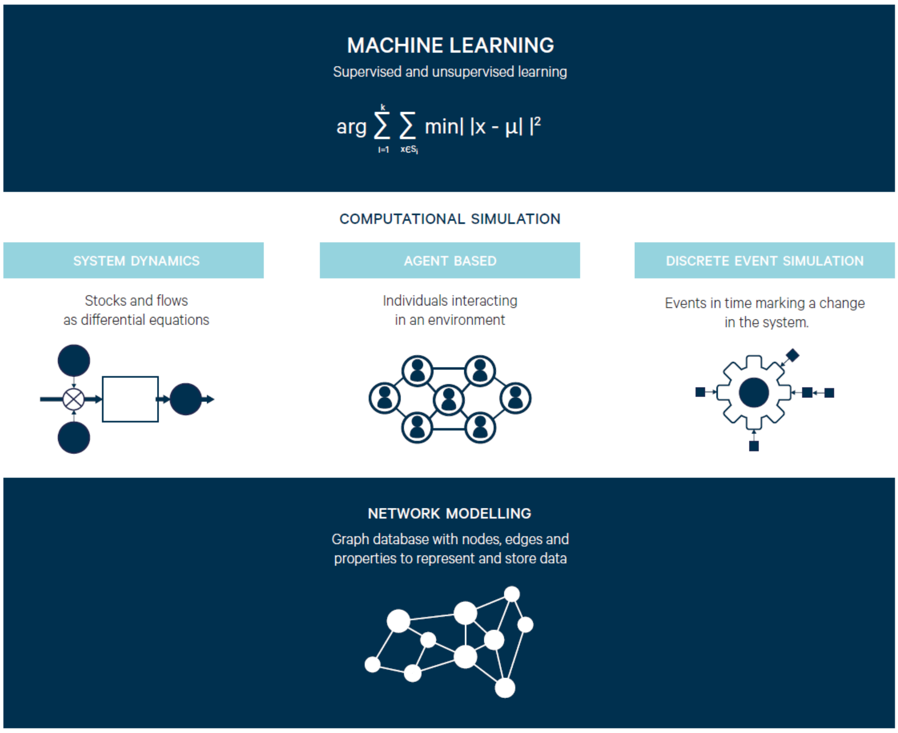


Figure 2

Machine Learning

Machine learning and statistical algorithms make it possible to identify relationships between variables and to understand how variables, working on their own and together, influence an overall system. They also allows us to make predictions and assess their uncertainty.

Machine learning and statistical algorithms are usually presented as a family of equations that describe how some, or all, aspects of the data might have been generated. Typically, these equations describe probability distributions, which can often be separated into components that can be specified in terms of unknown model parameters that need to be estimated from the data.

Because machine learning and statistical algorithms depend upon historical data and provide forecasts, they are especially useful when the number of data points is large and the data is disorganized. This means that the precision of the forecast improves with data, if the variables are disorganized. However, when the variables are not random, statistical modelling is not the right tool. If the variables are large and organized, then machine learning alone is insufficient, you need to combine it with computational simulation.

Computational Simulation

The advent of modern computing has enabled us to solve problems that involve dealing with a sizeable number of variables that also integrate into an organic whole. Many of today's problems are just too complicated to yield to simple structural models. They cannot be handled with the machine learning and statistical techniques that are so effective in describing average behavior in disorganized complex systems.[2]

2 Science and complexity by Warren Weaver in American Scientist, 36: 536-–544 in 1948.

Computational simulation refers to “methods for studying a wide variety of models of real-world systems by numerical evaluation using software designed to imitate the system’s operations or characteristics, often over time”.[3] Computer simulation fully supports the scientific method, allowing for experimentation on a system when experimental conditions include cases that cannot, and should not, be performed on real systems. All simulations share the common feature of encompassing the notion of a model, or some model-based activity.

Models of financial markets, if they are to be useful for real decision-making, require many interacting variables and components. Furthermore, decision makers require the output to be visualized as a web-based application to make the models suitable for real-time decision-making. None of this is possible without a computer simulation. With simulation, a uniform execution of a model can be used to solve a large variety of systems, irrespective of difficulty. The models are specified to recreate the actual system to a suitable level of granularity, avoiding overly simplistic or twisted alternatives that make the model fit an analytically solvable set of elegant equations that are divorced from reality, as has been done with some of the closed-form mathematical modelling to date. [4]

Simudyne’s SDK, as a foundational technology, supports all the modelling formalisms required to build enterprise computer simulations. While a review of the different modelling paradigms is outside the scope of this whitepaper, we will briefly address system dynamics (a continuous approach) and agent based modelling (a discrete-event approach) as these are the most commonly used.

System Dynamics

System dynamics is incredibly easy to learn, but frightfully difficult to master. It is a computer-aided approach to policy analysis and design. It applies to dynamic problems arising in complex social, managerial, economic, or ecological systems—literally any dynamic systems characterized by interdependence, mutual interaction, information feedback, and circular causality. Mathematically, the basic structure of a system dynamics computer simulation model is a system of coupled, non-linear, first-order differential (or integral) equations.

Illustratively, we can define the economy or a specific complex financial market in terms of coupled ordinary differential equations. Simulation of such systems is easily accomplished by partitioning simulated time into discrete intervals and stepping through the system, one interval at a time. [5]

Agent-Based Modelling

Over the past few decades, scientists identified opportunities to use another advanced modelling technique to understand complex markets. It’s called agent-based modelling. An agent-based model (ABM) are is a computer models in which the behavior of agents and their interactions are explicitly represented as decision rules that map agents’ observations onto actions. Agents are virtual copies of people, banks, companies, and any other autonomous entity. For a comprehensive review of the benefits of agent-based modelling, the reader is referred to Turrel (2016). There are two benefits of agent-based models that are of relevance to the financial services sector:

1. You can create highly accurate recreations of humans, companies, banks, and other entities.
2. You can embed agents with AI that allows them to learn and suggest the best course of action.

3 Kelton, W. D., Sadowski, R. P., and Sturrock, D. T., “Simulation with Arena (3 ed.)”, Boston, USA: McGraw-Hill, 2003.

4 Ören, T.I., “Body of Knowledge of Modeling and Simulation (M&SBOK): Pragmatic Aspects.” Proc. EMSS 2006 - —2nd European Modeling and Simulation Symposium, October 4-–6, Barcelona, Spain, 2006.

5 System Dynamic Society

Agent-based modelling generates results by studying the interactions of multiple types of agents in a simulation space rather than a single agent in a closed system. Because of the power of agent-based modelling, Simudyne's platform has built this capability on top of the Cloudera Enterprise Data Hub so that one can now scale agent-based model simulations to manage billions of interacting agents. Simudyne's SDK leverages the unique capabilities of Spark to distribute agent-based simulations by performing calculations in parallel across large numbers of machines. To manage the communication between the agents, they are represented as vertices in a distributed graph with edges connecting agents that communicate.

Agents-based models have three major components:

Agents

Traditional economic approaches to agent design usually focus on the role of intelligent (i.e., rational) agents that seek to maximize a utility function (e.g., profit). However, this approach relies heavily on agents having perfect information and proper knowledge of the long- and short-term implications of their decisions. In the real world, agents are often less than rational—an area of some interest for behavioral economics. Agents can only optimize over a subset of the information available to them or rely on a selection of heuristics that has worked for them in the past.

The Topology

The topology of an ABM is the mechanism through which agents can interact with one another in the model. It can be viewed as having two aspects: the rules and the link structure. The topology rules determine the communication forms that the agents can have with one another. The topology structure reflects the links that connect agents together to form a network.

The Environment

Environmental factors can generally be thought of as exogenous shocks that occur to the model. These shocks can come in various forms that affect agent behavior and topology rules. Though the set of possible environmental factors can be infinitely large in variety, the number to be tested is normally finite and often predefined by the set of objectives used in the model's initial construction, such as stress tests or policies being evaluated by regulators or risk management groups.

Network Modelling

The inability to capture, robustly, the interconnections between elements in traditional models has caused numerous failures for corporations and entire economies. For example, before the financial crisis, regulators only looked at financial institutions in isolation and not how they are related to each other.[6] During the 2008–2009 financial crisis, the Federal Reserve had no effective tools to assess the impact on other firms of letting Lehman Brothers default, nor the benefit of proposed rescue packages to other institutions.

For value chains, the failure of one critical company can lead to the bankruptcy of many other companies in a way that is counter intuitive due to effects such as contagion and feedback. In addition to answering enormously complex financial stability questions, we can also look at how various shocks might impact the financial markets. For example, we can simulate cyber attacks to identify which institutions are most likely to trigger a cascading failure in order to highlight the vulnerabilities which must be addressed to enhance resilience. We can now monitor liquidity and credit risk in interbank networks. We can also identify escalating risks and contagion in global financial markets. The approach is proven. It's recently been used to detect early warning signals for the 2015 Chinese stock market bubble and last year's energy sector meltdown.[7]

6 Hüser, Anne-Caroline. "Too interconnected to fail: a survey of the interbank networks literature," Journal of Network Theory in Finance, Volume 1, Number 3 (September 2015).

The Simudyne Platform

Simudyne's core technology incorporates machine learning, computational simulation, and network modelling. With this, you can explore millions of different plausible futures. In doing so, you can identify strategies and tactics that work under the widest range of possible outcomes.

Bias in human decision-making has always reduced our ability to decide the best course of action. To create the right environment for humans to make rational decisions, you need to think carefully about how you expose the results of the model and interpret them. Often the modeler and the decision maker are not the same person. This means you'll need to connect a computer simulation to a user interface that can be interpreted by the decision maker regardless of their technical capability. They should be able to easily ask questions within this interface and experiment safely by exploring various what-if questions.

The Simudyne platform was designed and built as a next-generation simulation platform for modern enterprise. It was built to comply with the needs of global organizations, particularly when it comes to security, ease of integration, and scalability.

Key capabilities include: Automated work-load distribution

1. Flexibility: On-premises or cloud-based and elastic
2. Models and data remain proprietary to the firm
3. Run infinite what-if scenarios
4. Many users running secure, parallel simulations
5. Interactive visual dashboards with fully customizable user interfaces
6. Financial institutions can create high-fidelity models of complex markets
7. An open source and open API approach
8. No specialized programming: uses standard enterprise developer skill sets (Java / Scala)

These enable financial institutions to:

1. Examine the impact on liquidity, capital, and asset pricing by stress testing key business drivers
2. Examine the impact of financial regulation
3. Identify contagion effects, particularly in credit and liquidity markets
4. War-game competitive bidding strategies
5. Quantify potential insurance losses from pandemics
6. Forecast prices to inform trading strategies
7. Model the impact of geopolitical shifts on assets
8. Evaluate the likelihood and impact of extreme tail events
9. Ultimately, to model any complex system

7 Financial Network Analysis: https://maps.fna.fi/2016/04/18/oil-plunge-impact-on-global-markets/

Simudyne's software approach for distributed computation (Spark and low-cost VMs), as opposed to a hardware approach (MPI and HPC clusters), makes the solution affordable to use on a daily basis without the need for expensive hardware and highly specialized programming skills.

In addition, Simudyne offers a ready built simulation console for visualisation and debugging. Developers can create fully customizable user interfaces that can be viewed in any browser. Simudyne provides libraries for charting, graphing, animations, maps, and other jQuery UI elements that provide an easy and adaptable framework to display data from models loaded onto the platform.

A Selection of Agent-Based Modelling Examples

In this section, we briefly illustrate a range of use cases where computational simulation is being used to help institutions, policy makers, and other leaders to more effectively address key business challenges faced by the financial services industry.

I. Simulating the UK Housing and Mortgage Market[8]

The Bank of England and the University of Oxford's Institute for New Economic Thinking (INET), led by Professor J. Doyne Farmer, have developed an agent-based model of the UK housing market to study the impact of macroprudential policies on key housing market indicators.

Their ABM approach allows them to properly capture the heterogeneity that exists in the housing and mortgage markets by modelling individual behavior and interactions of first-time buyers, homeowners, buy-to-let investors, and renters from the bottom up. The resulting aggregate dynamics in the property and credit markets are then observed. The model is calibrated using a large selection of micro-data, mostly from household surveys and housing market data sources. This helps ensure agents in the model have characteristics, and exhibit behaviors, which match those of the population at large.

Figure 3 illustrates the key agents and the market dynamics being addressed with this model. They find that an increase in the size of the buy-to-let sector may amplify house price cycles and increase house price volatility. Furthermore, to illustrate the effects of macroprudential policies on several housing market indicators, they implement a loan-to-income portfolio limit. Using this structure, they find that the imposing loan-to-income limits attenuates the house price cycle.

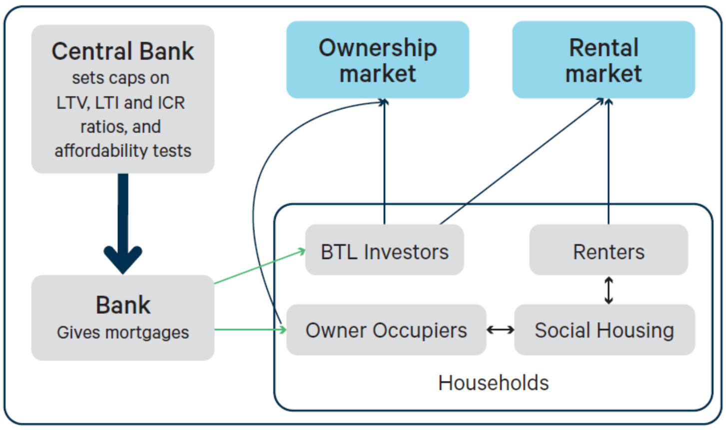


Figure 3

One of the key features of an agent-based model is that it can generate complex housing market dynamics, without the need for exogenous shocks. In other words, within-system interactions are sufficient to generate booms and busts in the housing market. Cycles in house prices and in mortgage lending are, in that sense, an “emergent” property of the model.[9]

One of the restrictions of the original Bank of England / University of Oxford work was the computational limitation of only being able to run simulations with 10,000 agents. This forces aggregation among households (approximately 2,700 per representative agent) which potentially reduces the impact of heterogeneity on the market dynamics—much like RMBS and CDOs hide their risk through only having access to aggregated information.

Simudyne imported this model into their platform running on a 15-node Cloudera Hadoop cluster. The Simudyne API forces you to write your own models in a scalable way so you don’t run into computational limits.

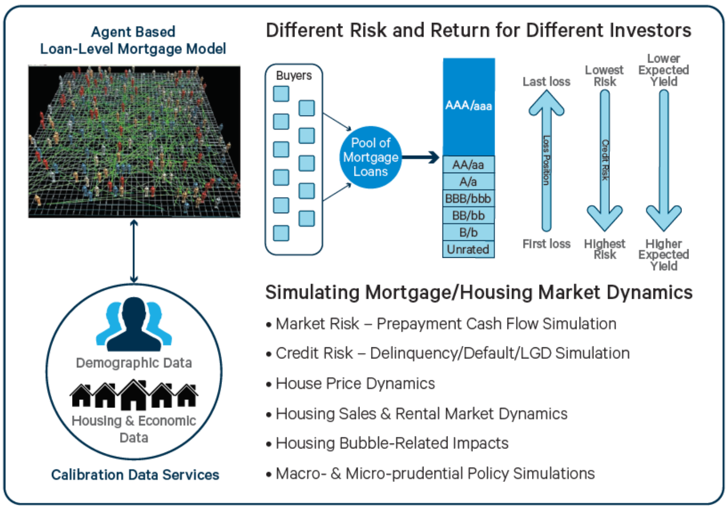


Figure 4

This housing model can be used to evaluate various aspects of mortgage market characteristics. Figure 4 illustrates the application for Residential MBS and the range of use cases that can be addressed.

II. Simulating Dynamics in the Corporate Bond Market [10, 11]

As noted by Andy Haldane, Chief Economist at the Bank of England, “The dynamics of financial markets are also an area of active policy interest, not least in the light of the recent financial crisis. During the crisis, there were sharp swings in asset prices and liquidity premiums in many financial markets. Since the crisis, there have been concerns about market -makers’ willingness to make markets, potentially impairing liquidity. These are policy questions which are not easily amenable to existing asset pricing models.”[12]

8 Baptista, Farmer, Hinterschweiger, Low, Tang and Uluc. (2016).

9 This short summary is from Haldane (2016)

10 Braun-Munzinger, et al. (2016)

11 Berndt, et al. (2016)

The Bank of England Corporate Bond Market ABM

The researchers at the Bank of England chose the agent-based modelling approach due to its ability to intuitively model complex non-linear feedback effects. The Bank of England team constructed a heterogeneous agent-based model of the US corporate bond market by capturing the interaction of market maker behavior, fund trading strategies, and cash allocation by end investors in funds to study feedback effects and the impact of market changes.

Funds are assumed to be one of three types:

Value Traders who assume yields converge over time to some equilibrium value, buying/selling when the asset is under-/over-valued;

Momentum Traders who follow short-term trends on the assumption they persist;

Passive Funds who only trade in response to in-flows and out-flows from end investors.

These interactions are shown in figure 5 below:

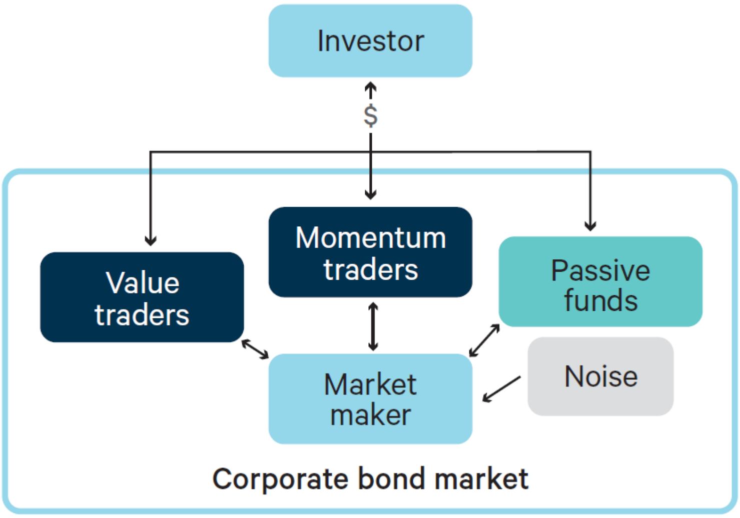


Figure 5

The interactions between these agents drove various emergent dynamics. For example, a shock to the expected loss on a bond reduces its demand for the funds holding it, and causes a re-pricing by the market -maker and momentum selling by funds, generating a further fall in the bond's price and in the wealth of the funds holding it. This is illustrated in figure 6.

12 Haldane (2016)

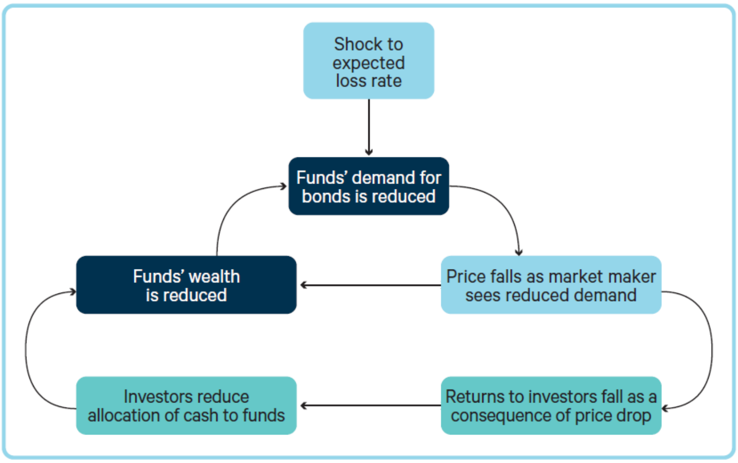


Figure 6

Braun-Munzinger, K., Liu, Z. and Turrell, A. (2016) find that:

1. The sensitivity of the market maker to demand, and the degree to which momentum traders are active, strongly influences the overshooting and undershooting of yields in response to a shock.
2. This suggests that correlation in funds' trading strategies can exacerbate extreme price movements and contribute to the procyclicality of financial markets.
3. While the behavior of investors in funds based on past experience plays a comparatively smaller role in model dynamics, it represents another source of amplification which could be particularly problematic if investors respond to a shock with greater risk aversion.

The Multi-layered Corporate Bond ABM

A multi-layered Corporate Bond Market model is developed by Berndt, Booger & McCart (2016). Their focus is on the analysis of liquidity dynamics under stress.

The financial system they develop is a bit more extensive and is structured as a multilayered network incorporating an asset layer, a funding layer, and a collateral layer. This is illustrated in figure 7.

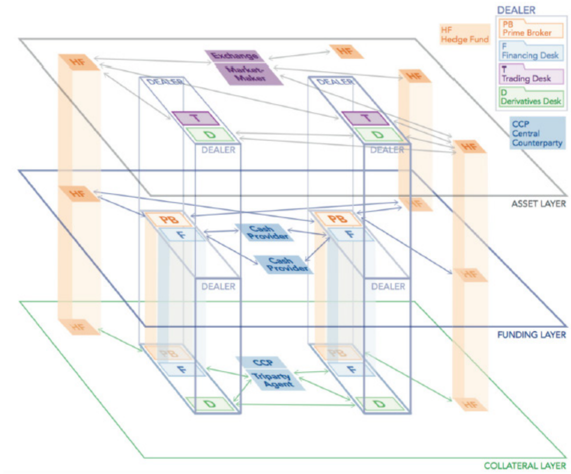


Figure 7

The agents consist of broker-dealers, hedge funds, mutual funds, and insurance companies. In this second agent-based model, funds are managed towards different investment horizons as highlighted in Figure 8.

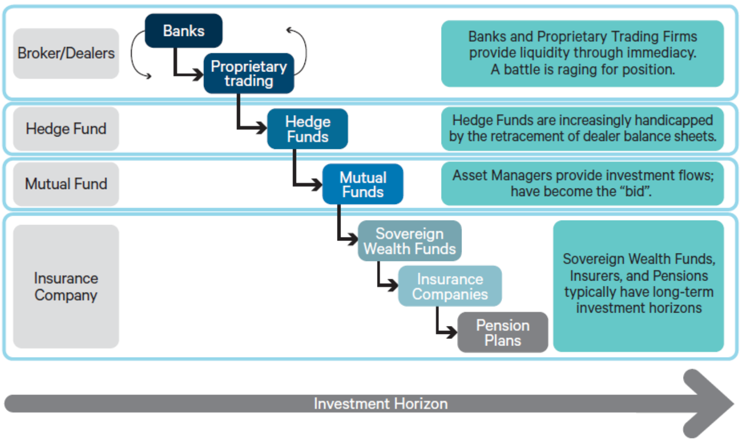


Figure 8

The corporate bond market dynamics is driven by five tradable corporate bonds which differ by size, maturity, and yield. This agent-based model is exposed to two types of shocks:

1. Parallel shifts of the entire yield curve (by 25, 50, and 100 basis points)

2. Point moves such as a 50-basis point move in the 10-year yield

The results are shown to generally replicate prior market dynamics with similar market dynamics that include fat-tailed pricing distributions.

III. Simulating Systemic Risk Exposures

The financial crisis of 2008, which led to the Great Recession, threw in sharp relief serious problems in the banking system. They included, among others, inadequate capital buffers and heightened vulnerability to liquidity risk, which, compounded with the high degree of interconnectedness in the financial system, brought systemic risk to the forefront.[13]

The systemic relevance of an institution is decisively determined by the potential impact of its failure on other institutions. It is therefore crucial to analyze such stressful situations in the market by taking into account the interdependence among the institutions.

The research effort on building more realistic and accurate models of systemic risk within the global financial system has grown enormously since 2008. While there are too many to even cite, our illustrative example will highlight a recent work that looks at a multilayered agent-based model developed by the research staff from the ECB.[14]

The Montagna and Kok (2016) approach involves developing an agent-based multilayered interbank network model based on a sample of 26 large EU banks representing 53 percent of assets.

The main finding is that looking at segments of banks' interconnections in isolation, without considering the interactions with other layers of banks' interrelationships, can lead to a serious underestimation of interbank contagion risk.

13 Haldane (2009)

14 Montagna and Kok. (2016). This was selected since they reflect many academic and central banking work- around systemic risks and the power of ABMs as a tool for analysis from a policy, regulatory, and institutional perspective.

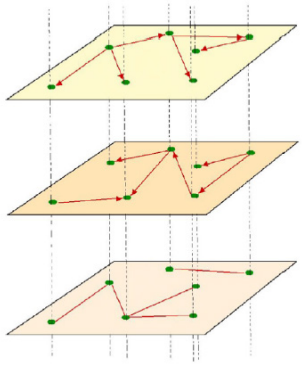


Figure 9

Figure 9 is a graphical example of a triple-layered network, with the same set of nodes belong to each of the three layers, characterized by its own topology. By modelling the various layers of interbank relations and the interactions between them, the contagion effects of a shock to one layer can be significantly amplified, compared to the situation where contagion risks are assumed to be confined within the specific layer where the initial shock arose.

The model also finds that capturing both direct bilateral exposures and a bank's common exposures (through their securities holdings) demonstrates an unexpected trade-off between risk diversification decisions and financial stability. This occurs when banks diversify their investment in securities, which may be optimal at the individual bank level, but the system-wide impact can result in higher contagion risk.

IV. Simulating Financial Stress Testing[15]

Stress testing is an important tool for the assessment and classification of a range of risk exposures. After the 2008 crisis, stress tests were buttressed by regulators by adding more severe scenarios and using more detailed data. Although stress tests currently being structured by the regulators take a step in the right direction by creating scenarios that are not fully dependent upon historical events, they are not able to incorporate the dynamics, feedback, and related complexities that are the real-world aspects of each stress scenario as well as any real future financial crisis.

A BIS study[16] issued in 2015 recommended that supervisory authorities should focus on "developing integrated liquidity and solvency stress tests (as opposed to standalone liquidity stress test exercises)". They argue that a key lesson from the 2008 financial crisis involved the underestimation of credit risk in structured credit products as well as substantial maturity transformation by banks in off-balance-sheet structured investment vehicles (SIV) was the benefits of considering both liquidity and solvency risks in an integrated manner.

15 Bookstaber, Paddrik, and Tivnan (2017)

16 Extracted from BIS (2015) study.

The BIS have categorized four key intermediation functions that banks are engaged in: [17]

- Credit transformation
- Maturity transformation
- Liquidity transformation
- Collateral transformation

Each of these intermediation functions creates potential channels of stress—a credit channel, a funding channel, a liquidity channel, and a collateral channel—through which stress can be transmitted to the bank.

Figure 10 provides a nice summary of the shocks to these four channels of stress and the relevant regulatory ratios under Basel III.

Typology of shocks and key regulatory constraints which can become binding

Shocks	Credit	Funding	Liquidity	Collateral
	Risk-weight migration, Credit loss hits capital, Increase in	Maturities shorten, mix changes, funding run-off or "run-in"	Commitments drawn, securitisation backup, liquidity puts exercised	Securities prices fall
Regulatory ratio constraints affected	Risk-based capital ratio		Risk-based capital ratio	Risk-based capital ratio
	Leverage ratio	Leverage ratio	Leverage ratio	
		Liquidity coverage ratio	Liquidity coverage ratio	Liquidity coverage ratio
	Net stable funding ratio	Net stable funding ratio	Net stable funding ratio	Net stable funding ratio

Figure 10

Agent-based models are designed to be applied in a wide range of stress scenarios beyond price shocks, such as reductions in funding by cash providers, a downgrade of banks'/dealers' credit rating, or a redemption shock to hedge funds.

17 Extracted from BIS (2015) study.

Network View of Initial Shock Propagation[16]

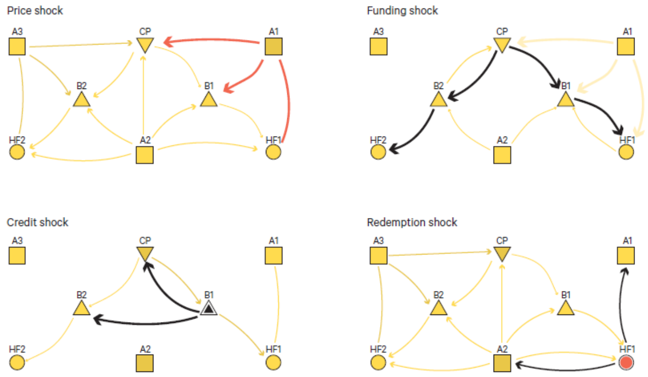


Figure 11

Figure 11 maps shock propagations based upon a simplified setup with two banks/dealers, two hedge funds, three types of assets, and one cash provider (denoted in the graph as CP). In this agent-based model, Bank/Dealer 1 (B1) and Hedge Fund 1 (HF1) hold equal weights in Asset 1 (A1) and Asset 2 (A2).

Bank/Dealer 2 (B2) and Hedge Fund 2 (HF2) hold equal weights in Asset 2 (A2) and Asset 3 (A3). For each channel of stress the origination point of an initial shock is shown in the network diagram with clearly marked impacts of stress across the relevant market players. This flexibility makes the agent-based modelling approach an ideal platform for creative stress testing and for exploring the weakest links and bottlenecks in funding flows.

V. Simulating Counterparty Credit Risk and Contagion Effects

Traditional Basel-mandated risk measures cannot assess crisis events such as:

- The progressive failure of the market for collateralized debt obligations
- The successive failures of Bear Stearns, Fannie Mae, Freddie Mac, and Lehman Brothers
- The path of counterparty exposures laid bare by the near- bankruptcy of AIG
- The more recent exposure of European banks to the risk of sovereign default

The application of agent-based models with respect to counterparty credit risk follows the general discussion above on systemic risk and stress testing but with a more detailed focus on credit exposures over time. The key advantage that an agent-based modelling approach provides is the ability not to be limited to one cycle of a credit-related event but rather to capture the dynamics and full feedback effects across a firm's entire counterparty credit exposures. This provides risk managers with an ability to examine many possible future states in the process of evaluating credit risk exposures.

Matteo, Caldarelli, and Cimini (2016) developed an agent-based model of bilateral exposures between banks (the agents of their model), which use micro-optimal rules to interact with each other and with the rest of the financial system. They explicitly model various categories of spillover effects arising during financial crises, such as fire sales and interest rate jumps due to leverage targeting and liquidity hoarding behavior of banks.

18 Extracted from BIS (2015) study.

The modelled dynamics of pro-cyclical policies are shown to spread financial losses via credit and liquidity interconnections, and may result in cascades of defaults. They show that this ABM can be used to stress- test the robustness of the financial system to an external shock, which can be either absorbed or cause an avalanche of failures eventually leading to the market freezing.[19]

Similarly, Co-Pierre Georg (2013) analyzes various ABM network structures of bilateral interbank loans, which form a simulated money market. Georg is evaluating if interbank networks exhibit what Haldane (2009) described as a "knife-edge" or "robust-yet fragile" property whereby in normal times the connections between banks lead to an enhanced liquidity allocation and increased risk sharing. Yet, when in a times of crisis, these same interconnections can amplify an initial shock into severe system-wide impacts.20

This implies that there are two different regimes of financial stability:

- A stable regime in which initial shocks are contained
- A fragile regime in which initial shocks are transmitted via interbank linkages to a substantial part of the financial system

This "knife-edge" property of interbank markets is attributed to a counterparty risk externality, which is characteristic of over-the-counter markets. This occurs as a result of limited information on the credit linkages across the system. When a bank lends to a number of other banks, it is oblivious to any links between those banks and might underestimate its portfolio correlation.

A comparable effect, which Georg calls correlation externality, can arise when a bank is oblivious to the asset holdings of other banks. The counterparty risk externality can lead to interbank contagion (sometimes called cascading defaults), while the correlation externality can lead to common and amplified shocks.

These are but two of dozens of examples on how an agent-based modelling framework is ideally suited for studying the relationship between the structure of financial networks and the extent of contagion and cascading failures. This is very relevant to risk management applications across the banking and insurance sectors.

VI. Simulating Endogenous Risk[21]

A Risk.Net article highlighted recent market turbulence demonstrating the shortcomings of conventional factor models used across the asset management industry. They are found to lose effectiveness when asset prices and correlations are driven by forces inside the market—called "endogenous risk."

19 Serri, Matteo, Guido Caldarelli and Giulio Cimini. "How the interbank market becomes systemically dangerous: an agent-based network model of financial distress propagation", arXiv preprint: 1611.04311, Nov, 2016.

20 Georg, Co-Pierre. ""The effect of the interbank network structure on contagion and common shocks". Journal of Banking & Finance, 37 (2013).

21 Mannix, Rob. "Avoiding crowds: BlackRock leads push to model ''endogenous'' risk", in Risk.Net – Asset Management, February 8, 2016.

Endogenous risk in this context refers to the risk that comes from market participants reacting to each other rather than reacting to outside forces. This impacts asset managers' ability to properly manage risk. As Mannix (2016) notes:

> For some the adjustment means tracking what competitors are doing. A few are thinking about borrowing ideas from game theory or using machine-learning technology to help them understand how markets are behaving. Others lag behind – still relying on models that take little account of endogenous risk at all.

An agent-based modelling approach is one approach for properly capturing and simulating the potential impacts of endogenous risk.

In one example, per Mannix (2016), Jean-Philippe Bouchaud of Capital Fund Management (CFM), points to work in recent years to quantify feedback loops from trading activity. This work showed how even small trades could have disproportionate effects on pricing.

> "In the past the view was that markets were huge and anybody trading in the market was small by comparison—that you could neglect the impact of what the firm was doing," Bouchaud says. "That view was completely wrong." CFM thinks investors with even relatively small positions can be trapped in a feedback loop where they cause asset prices to fall by selling, and are forced to liquidate more assets as a result. The logic here is that firms should look at holdings relative to securities available in the market, rather than compared with the whole universe of issued securities.[22]

To address this, CFM developed a mechanical agent-based model in which firms make assumptions about how different agents will act in different scenarios. CFM uses its insights gained from the agent-based model simulations to judge the size of holdings and to ensure they are well below the tipping point at which they risk creating their own de-leveraging vortex.

VII. Simulating Cybersecurity Threat Prevention

Kotenko (2016) is one of several examples of using agent-based models to simulate cyber-attacks and cyber-protection mechanisms. The Kotenko approach combines discrete-event simulation, multi-agent models, and packet-level simulation of network protocols. This is used to analyze various methods of counteraction against cyberattacks by representing attack and defense components as agent teams using the simulation environment.[23]

Simudyne's platform was used by a major central bank to stress test security with virtual attacks. Attack models of various threat actors were built using probabilistic algorithms with preference and graph theory. The bank used a private cloud framework to accelerate algorithmic processing with an encrypted web-based tool for secure access via web browsers. An example dashboard is displayed in Figure 12.

22 Taken from Mannix (2016).

23 Kotenko (2016).

Figure 12

The Simudyne solution dynamically updated the attack models as new threat intelligence arrived. This work helped define detailed InfoSec policies.

VIII. Simulating Equity Market Dynamics

NASDAQ ABM Simulation Model[24]

Darley & Outkin (2007) describe a multi-year agent-based modelling project that began in 1999 with a goal to explore the effects of the Nasdaq market microstructure, market rules, changes to them, behavior of participants such as market makers and traders, and on the dynamics and behavior of the market as a whole.

This model was used by Nasdaq to evaluate the potential impacts of a switch to a decimal-based trading structure. Counter to general assumptions at the time, the model correctly predicted that parasitic strategies may become more prominent after tick size is reduced and that the spread, or quote clustering patterns, are likely to appear more often. Both of those predictions are strongly supported by the available data.

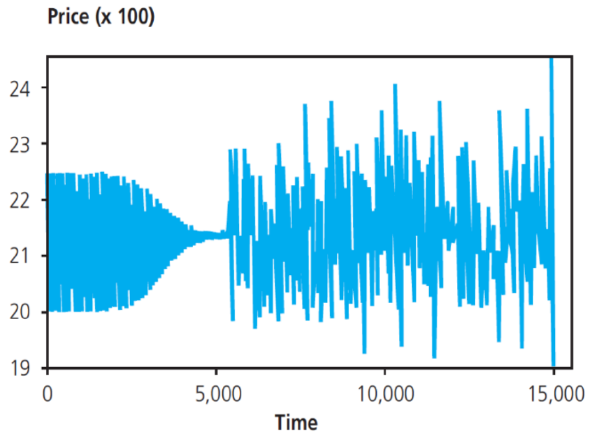
J. Doyne Farmer's Agent-Based Model of Equity Market Dynamics[25]

One of the most important contributions to equity market dynamics was J. Doyne Farmer's pioneering study on agent-based modelling of financial markets. Farmer used four types of agents: value investors, technical traders, liquidity traders, and market makers, to model the financial market using traditional economic assumptions such as random-walk behavior.

By repeating the agent-based behavior over a long period of time, he discovered that initially, the market behavior was as predicted by traditional economics. Prices converged and bid-ask spreads narrowed. At some point in time, when the market became very stable, traders began to make larger and larger trades and bets, and the market looked as if it were rapidly approaching perfect efficiency. But then, volatility suddenly exploded, and prices began to move chaotically. (See Figure 13.)

24 Darley and Outkin (2007)

25 Farmer, J. Doyne . "Toward Agent-based Models for Investments", Benchmarks and Attribution Analysis, Association for Investment Management and Research:



Source: Farmer (2001).

Figure 13

This turned out to be a unique view into an unexpected market dynamic. As the technical traders became richer, their trades became larger, and the large trades started introducing their own movements into the price. These movements created opportunities for other technical traders to try to arbitrage the patterns created by their fellow technical traders. When the technical traders had finished lunching on the seasonal traders, they began feeding off each other. This scenario happened in the absence of noisy inputs or external shocks.

This provided early key evidence that agent-based models as an approach could yield new insights on financial market dynamics that did not impose the standard economic restrictions, which required rational expectations and market equilibrium.

IX. Simulating New Product Launch with Dynamic Competitor Responses

Big data, from a marketing perspective, refers to the integration of multiple data sets to create a more comprehensive picture of an individual.26 Christopher Meyer outlines future vision for marketing that takes into account five transformative trends. This is illustrated in Figure 14.

Figure 14

1. Connected Consumers—consumers have begun to continually describe their own behavior in media observable to marketers.
2. Data Fusion—additional information about consumers is being collected through their clickstreams, cell phones, and credit cards.
3. Cognitive Science—is providing insights into how the mind makes choices.
4. Behavioral Science—scientists (including behavioral economists) were able to test these insights experimentally.
5. Agent-Based Models—the use of agent-based modelling enables marketing teams to simulate the interaction of heterogeneous individuals in the real world to validate these hypotheses and test marketing programs.

Corporate Banking: Marketing and Risk Management

Corporate banking needed to significantly grow the asset base while seeking to optimize the marketing strategy to help ensure that the bank hits its targets. Tied to this growth was the need to improve risk management practices to ensure that credit risk exposures were being properly measured in a timely manner.

Simudyne developed a simulation environment to stress test the Corporate Bank’s growth options under many scenarios. This simulation of the corporate banking business allows for a detailed analysis of the impact of various policy changes as well as impact on revenue targets. The modelling effort included conducting extensive executive level interviews, reviewed all internal risk processes, and observed risk committee meetings.

Figure 15 provides an illustration of the stress testing dashboard that was created for senior management to explore the impact of various changes in policies, risk standards, and external shocks.

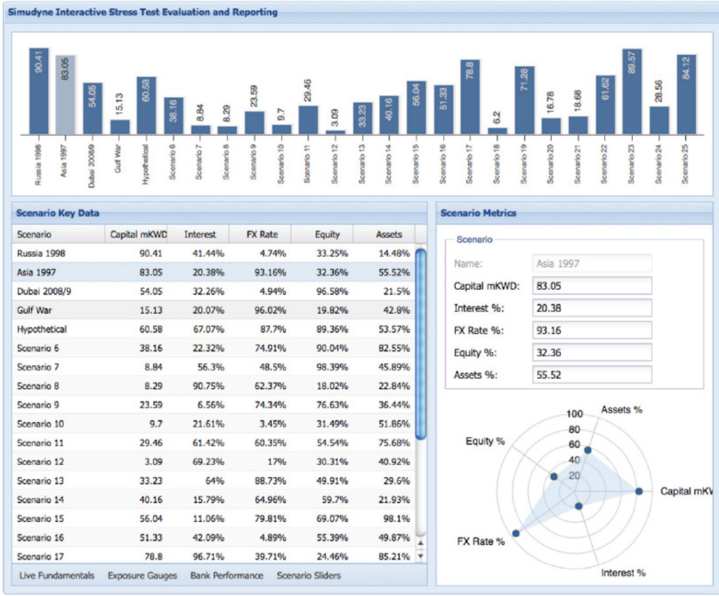


Figure 15

Outcomes of the configured Simudyne platform:

- Analysis of simulation findings and recommendations provided for CEO.
- Bi-monthly risk report of events.
- Net profit for the corporate bank was £43M; 40 percent above plan; optimized pricing policy generated £2.6M additional revenue.
- Achieved 30 percent growth in corporate demand deposits over two quarters.
- Stress test simulation provided near-instant calculation of the impact of various events on the balance sheet, profit and loss, and key ratios such as capital adequacy ratio (CAR), ROA, ROE, etc.

X. Simulation Commodity Markets—Predicting Crop Yields

Predictive Analytics for Crop Yield Forecasting

This firm had challenges in bringing together various models and data to generate timely forecasts and to identify potential new trading strategies. Their existing commodity trading processes are labor intensive and time consuming. Research relied heavily on “hacked together solution of COTS and niche modelling software” to create trading strategies. The original siloed environment prevented the analytics from being run in a secure environment to allow for coordination of the simulations between researchers and traders.

Simudyne converted their models to Java and linked them together via their platform.

This allows the models to be run with the right data at the right time using near realtime data processing engines to dramatically speed up the entire analytics process— from data ingest, processing to model application and simulation output. The simulation models generated mission-critical projections on a number of key metrics and forecasts, as shown in Figure 16.

The resulting forecasts were directly accessible at all times by the traders via an interactive web application that runs on their laptops and iPads.

Figure 16

The work resulted in the following operational benefits:

1. A simplified architecture that reduced the time to link and execute models from weeks to days
2. Reduction of time from days to seconds to get the right data ingested, validated, and executed
3. Reduction of the computation time by a factor of more than 10
4. Move from manual to automated processes, reducing errors significantly
5. An agile, interactive mobile interface for traders, that allowed rapid re-evaluation of model-driven forecasts as new events and data became available

Simudyne's Platform

Real-Time Decision-Making with a Hadoop-Based Architecture

Simudyne's platform runs on the Cloudera Enterprise Data Hub (EDH) and provides a highly scalable and cost-effective environment to address a wide range of complex business challenges.

Their platform adds enhanced decision-making capabilities to Hadoop via the simulation techniques outlined above. Simudyne enables the simulation processes to utilize all of the data within HDFS, HBASE, or KUDU and at scale to enable models to be truly developed from the micro-foundation level.

Data comes from internal and external sources, and for IoT applications from devices through a gateway. This data flows into the Hadoop cluster via Batch or Spark Streaming, which places that information directly into the Cloudera Enterprise Data Hub (EDH).

Once the data is on the cluster, using standard tools such as Impala or Hive, you can enrich your data and extract what you need for a simulation. When it comes to learning and prediction, Spark and its machine learning library can be used separately and directly with Simudyne's platform.

Spark plays an important role in the platform. Spark is used to distribute calculations across multiple machines. This technology allows the user to run models and simulations at pace and scale by putting agents, models, networks, and other calculations into a long-running Spark context. The user can then trigger Spark jobs via a UI built with our platform or directly via the Shell. These Spark jobs enable extraordinary simulation capabilities and performance. The consumer of the simulation has the power to run the model as many times as they wish under a range of different scenarios.

The Modern Data Platform—Powering the Next Generation of Analytics

Cloudera delivers the modern platform for data management and analytics. The world's leading organizations trust Cloudera to help solve their most challenging business problems with Cloudera Enterprise, the fastest, easiest, and most secure data platform built on Apache Hadoop. Our customers can efficiently capture, store, process, and analyze vast amounts of data, empowering them to use advanced analytics to drive business decisions quickly, flexibly, and at lower cost than has been possible before.

- The modern data platform:
- One place for unlimited data
- Unified data access

Cloudera makes it:

- Fast for business
- Easy to manage
- Secure without compromise

Cloudera Enterprise is available in the cloud, on-premises, or as a hybrid deployment.

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Contact

A: St Michael's Alley, London, EC3V 9DS

E: info@simudyne.com

W: simudyne.com

TW: twitter.com/simudyne

LI: linkedin.com/company/simudyne

Simudyne is a rapidly growing technology business, harnessing the power of advanced simulation, to help organisations make radically better decisions. Our efficient and scalable simulation platform allows enterprises to create a virtual environment where they can test drive their decisions, fail fast without consequences and create solutions that drive growth.