Investing through the lens of complexity economics

How to enrich the investor tool kit

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Chapter 1. Introduction

Every couple of years a new "**once in a** hundred year economic event" occurs. **Yesterday it was a real estate bubble; tomorrow it will be another market. Maybe even the same. The models said it was improbable; most investors thought so too. Why do we keep getting surprised?**

What was the world view that got us here last time?

According to neoclassical economics, the economy tends towards a stable equilibrium, behaviour is rational and risk is measurable. This was the generally accepted view in mainstream economics before the 2008 Financial Crisis. Consequently, the finance community relied extensively on ideas consistent with this neoclassical worldview. This widespread belief resulted in the underestimation of tail events; moreover, the type of out of equilibrium dynamics that often characterize crises were largely ignored. Instead, models postulated economic movements based on statistical patterns observed over a short and calm period. Investors projected everlasting price appreciations based on simple sample extrapolations. Academics, central bankers and regulators were too cautious in using the word "bubble"; after all, investors are rational and markets are efficient. At least, that is what the theory said.

A brief look at financial history will reveal a recognizable repetitive pattern. The pre-crisis environment is reminiscent of a textbook setup for a ``this time is different`` attitude to investing. As ever, strong consensus on the likely direction of a particular asset resulted: after all, housing prices can only go up in the long run they said. As has been the case, many times before in history, the investment community before 2008 was completely blind to the elevated probability of a crash. The memory of the dot-com crisis was quickly fading away.

Much to the surprise of those who believed in the neoclassical view, the once in a hundred year event happened again in the same decade. So, this leads us to ask the question: "Are the models wrong or is nature wrong"? So, what is going on here? Why are we always caught off guard when a crisis unfolds? Why do we keep using the same models to quantify risks when they fail us when we need them the most? And what should we do?

Complexity Economics, an increasingly popular rediscovered branch of economics, lends us a helping hand. By using ideas from biology, physics and network theories it steps away from the equilibrium dynamics of neoclassical theory and incorporates uncertainty into the investment process. It will not solve all our problems; but it is definitely a step in the right direction.

So let's summarize the three main chapters presented in this article.

1.1. "I got this!" – says the model

In stable times, quantitative economic models provide reasonable estimates of risk. As with most models, they are simplification of reality and for a good reason. Simplification has its merits. Primarily, it helps investors better understand the intuition of economic forces when the economy goes through a stable period. However, during extreme events, risks that are not captured by traditional models, such as systemic risk and uncertainty, come to light. And they have the tendency to catch us off guard. This is where the field of Complexity Economics can help us gain better insights.

Complexity Economics uncovers different dimensions of the economy. It typically considers the economy as a dynamic non-linear system made up of many interconnected elements. Uncertainty and instability are part of its central fabric. The economy can seem stable, but due to its chaotic movements and investor interactions that lead to uncertainty, it is inherently fragile. With time, imbalances build up and systemic risk rises. With each step, the system becomes increasingly fragile. Inevitably, the economy reaches a tipping point where a small shock throws it into the unknown. This leads to bubbles appearing and bursting. In such a system, investors' expectations and biases, together with strategic responses to financial innovation and central bank policy, can largely describe the type of tail events we see in reality.

Making complete predictions for a complex economy is difficult – if not impossible - due to the constant feedback loops created by investors in the market. Investors are influenced by market developments and the course of events is influenced by investors' views. This is what George Soros calls reflexivity. This feedback loop is self-reinforcing and causes the underlying uncertainty in markets. It also creates far-from-equilibrium dynamics where extreme events appear more often than expected. All these aspects of the economy, which unfortunately are overlooked by neoclassical economics, can be captured by Complexity Economics.

1.2. The devil is in the (de)tail

Mis-assessment of risk by relying exclusively on traditional models, contributed considerably to losses during the 2008 Financial Crisis. With the use of advanced quantitative models, qualitative assessments of the occurrence of financial events was largely omitted. Assuming normality of returns and neglecting consideration of tail risk was the standard approach. In this approach, uncertainty (unexpected risk) is not detected. When we take uncertainty into account, we realize that normality should not be the norm; skewness and kurtosis (fat tails) are empirical regularities that shouldn't be easily discarded.

Fortunately, Complexity Economics has a long tradition of including concepts such as tipping points, discontinuities and fat tails as a consequence of the feedback loops observed in the ever changing dynamics of the economy. Rather than focusing on better approximating the exact probabilities of extreme events, investors can first consider the underlying economic processes that may lead to stable or unstable outcomes. From here, we can observe possible states of the world and analyse their effect on the performance of different types of investments. These insights can easily be incorporated in risk management and investment frameworks using tools such as Economic Scenarios and Stress Events. Qualitative frameworks can provide a helping hand by simplifying the probabilities of events in terms of ranking and attributing them to Stress Events.

In terms of forecasting, Complexity Economics offers an explanation as to why economic behaviour cannot be accurately predicted. Making exact predictions for the economy can be difficult - if not impossible - due to market reflexivity (feedback loops that create uncertainty and instability). Having said that, we also need to acknowledge that certain patterns do emerge over time. So, qualitative predictions in terms of possible states of the economy can be made. A good example is the way the economy passes through credit cycles (e.g. the business and the debt cycle). Investing, for example, according to where the economy is in the credit cycle allows investors to take up risk when it is rewarded the most. More broadly, understanding when the financial system is fragile, can allow investors to better manage risk and strategically take risk when the financial system is close to a tipping point.

1.3. When your problems are my problems

The financial crisis in 2008 highlighted the extent to which markets are interconnected. Shocks can propagate rapidly and have the potential to impact financial stability across markets. This type of domino effect, which we call systemic risk, is hard to detect using traditional risk management models. For example, neoclassical models fail to capture the potential cascading effects created by interconnectivity and overlapping portfolios of financial institutions. The traditional approach focuses solely on one's balance sheet and overlooks the interconnectivity within the financial system. This can lead to substantial mis-assessment of underlying exposures. Is there a way we can reliably account for these hidden cascading affects? Looking at the interconnected links between investors is a powerful complement to the mainstream statistical models used in the industry. Complexity Economics sheds light on these type of domino effects using network theory.

In terms of interconnectedness, once the most interconnected institutions are identified, investors can try to measure their exposure to cascading effect in terms of overlapping portfolios or counterparty risk. Assessing the risk of the system and understanding the underlying process can give market participants important clues on how to manage risk exposure dynamically over time. That is why understanding economic fragility is the best tool for identifying risk build-up in the market. A fragile economy exhibits symptoms similar to a sick heart. We cannot predict when or what will create the heart attack. However, building a tool that can tell investors when to take preventive measures will be desirable. This measurement tool can simply encapsulate the increasing fragility of the financial system that arises from financial institutions' interactions. Constructing such a measurement tool will allow investors to reap the benefits of changes in the risk premia: take more risk when the economy is robust and de-risk when fragility is high.

Complexity's tools are complementary to neoclassical models

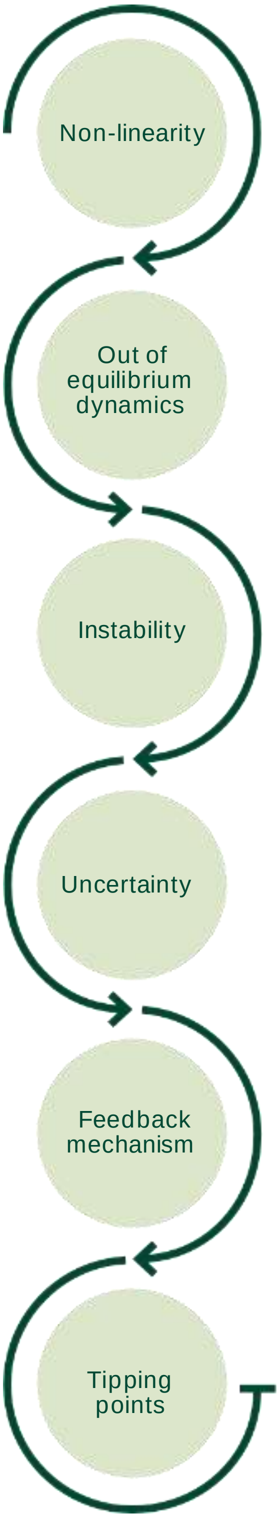
At the end of the day, Complexity's tools complement mainstream models. They present a diversity in methodology that investors can take advantage of. Perhaps even more importantly, by considering an additional world view, we are bound to grasp the limitations of mainstream reasoning. We can use mainstream models when we try to assess stable economic periods and rely on complexity's methods were economic regimes are about to shift. In this respect, we begin by expanding the ideas summarized in the previous paragraphs; and we start this endeavour by explaining the different perspective Complexity Economics takes when trying to capture the observed dynamics of the economy.

Chapter 2. **“I got this!” –** says the model

Why is it crucial for investors to understand the underlying dynamics of the economy instead of focussing on the statistics of output variables such as volatility and correlations of assets? This is a question we will try to answer by exploring the differences between Mainstream Economics and Complexity Economics. Starting with the most central concept in Mainstream Economics – equilibrium – we delve into the field of complexity. The main idea in Complexity Economics is that the economy is in perpetual motion and does not move towards a long term equilibrium. Investors strategically respond to the changes they mutually create in the market. This type of dynamics creates a non-equilibrium motion which is not captured by the more traditional economic models.

The economy is in perpetual motion and not moving towards a long term equilibrium.

What are the central characteristics of complex systems and how do they differ from mainstream economics?



2.1. Equilibrium

So, how did the concept of equilibrium come into place? Moreover, how did this idea become predominant in economics? Economic theory begun as a set of philosophical concepts with the work of Adam Smith. From there, the field progressed to a more formal science by relying extensively on mathematical linear models due to their simplicity where the economy has to be in a state of (or is moving towards) equilibrium. In other words, there exists some "ideal" price towards which the market price tends to converge as demand meets supply. This theory fits the observed market data in times of stable markets. For example, in near equilibrium markets, we observe every day similar events that give rise to statistical generalizations. In this case statistical generalizations are our view of what the norm is in the markets. However, movements during crises are out of equilibrium. These give rise to unique, historical events which break out of the everyday statistical generalizations.

Physics, through the theory of complex systems, teaches us that complex systems (such as the economy) are systems in a perpetual non-linear movement where multiple equilibria can exist. There is an inherent instability that can be observed in such systems that arises due to the interaction and the dynamics of the underlying components.

To illustrate this lets take an example where we consider a pile of sand with new grains being continuously added on top. In physics the sand particles are "behaving" strictly under the law of physics and yet still the interaction leads to complex systems. As the new grains are added, mini cascades can begin, signalling that the system might be under pressure. More grains are added and the sand pile gets closer to a critical point. When that point is reached (called a tipping point), an avalanche begins and the pile switches to a new equilibrium.

What if we apply this thinking to economic systems where humans are the equivalent of the sand particle and where humans interact based on emotions instead of the law of physics? Doing so provides an insight that allows us to understand why we mostly observe financial markets as self-destabilizing and tending towards disequilibrium. The crash comes as a result of a shock given to an already fragile financial market.

Complexity Economics uses a bottom-up approach and allocates specific behavioural rules to each individual.

2.2. Investors

Modern finance theory is based on shaky assumptions. A normative set of preferences, focused exclusively on means (returns) and variances (as a measure of risk) of assets, is at the core of (theoretical) asset pricing research. Investors were assumed to be rational and maximizing a constant predetermined utility function to gain maximum "happiness". In the process, investors choose portfolios that maximize their utility function given their risk aversion level.

However as introspection may reveal, we often find ourselves failing to make the rational choices that are predicted by "normative" economic models. In practice, individuals have to take decisions under uncertainty. Similarly, investors need to anticipate the future, but how the future unfolds depends on choices yet to be taken. Forecasting those choices accurately and anticipating their effect on markets is difficult in a complex system - making even weather forecasting seem trivial. Therefore, investors' decisions are often found (with hindsight) to be biased. This is one of the generic causes of price distortions.

In contrast to mainstream economic modelling, Complexity Economics employs a bottom-up approach and allocates specific behavioural rules (heuristics) to each individual. There is no representative rational investor. The heuristics describe the essential traits of heterogonous agents which are conducive to the group behaviour we observe in markets. Examples of such traits are: herding behaviour, loss aversion, over optimism etc. This theory helps to explain many of the empirical puzzles we observe in the financial markets.

2.3. Markets

In traditional models, interaction happens only indirectly through the market mechanism (the prices). However our understanding of the economic system can be hindered by only observing market dynamics without considering how individuals form this complex web of interactions (networks) at the level of financial institutions. Omitting the risk of cascading effects throughout the system due to interconnectivity can underestimate system wide risk.

Network theory provides tools that will help capture this interconnectivity. Interactions are key in understanding how markets can respond to certain shocks. With time, investors learn from previous interactions, adapt and switch their strategic choices. These particularities are extremely hard to incorporate in conventional economic models. Complexity Economics provides some of the tools such as network theory and agent based modelling to model the interconnectivity and feedback mechanisms. With the help of agent based models, a computer simulation enables us to observe emergent group behaviour (or reflexivity of the market) without making any top-down assumptions about market equilibrium.

2.4. Emergence/Reflexivity

The most important characteristic of a complex financial system is the concept of emergence or reflexivity. This concept is absent in conventional economic thinking. Micro and macroeconomic patterns are treated separately in traditional economics. In contrast, in complex systems, macro-patterns emerge from the interaction of individuals at the micro-level. There is no central command that dictates what market demand and supply should be. This "bottom-up" characteristic of modelling is at the core of the complex system. Individuals do not only respond to changes in the environment, but they also try to affect the environment in their own interest. As a result, the economy is in a constant flux. In this respect, reflexivity fosters uncertainty and creates non-linear dynamics in the system.

The idea of market reflexivity, proposed by George Soros, can be easily explained by feedback loops. Feedback loops can either be positive, which are self-reinforcing and build up the momentum during bubbles, or negative, which are self-correcting and allow the beliefs of participants to converge to a certain outcome for some period of time. In this sense, one can argue that equilibrium is a special case of a negative feedback mechanism. In addition, the impact of feedback loops changes in intensity over time due to the exuberant behaviour of market participants. So, behavioural economics plays an important role by amplifying the inherent fragility of the market.

The *boom bust boom dynamic* in the financial markets is a representative example of market reflexivity at play. Bubbles arise when an underlying trend gets mixed with a misconception concerning the trend. The two forces join strength and positively reinforce each other in the bubble formation period. Often this process is amplified by more private debt creation that comes with euphoric trends. Sooner or later prices become so decoupled from fundamentals that investors are forced to realize the existence of a misconception.

Before the crash, a ´twilight´ period is typical in which investors' doubts grow but the trend is still driven onward by the already accumulated momentum. These type of characteristics can be hard to capture with conventional Economic theory; however, Complexity Economics can help in this respect.

2.5. Agent Based Models

Until the advent of computers, nonlinear systems could not be solved. After their invention, a whole new level of phenomena analysis was enabled. The ability to create computer simulations has become central to investigations in a wide variety of fields, such as traffic, weather, earthquakes, and ecological systems. Simulations are especially useful in complexity theory as they allow the testing of simple rules to study complex systems. Stated formally, complexity studies the emergent phenomenon resulting from interactions of low level building blocks. More specifically, agent based modelling (ABM) utilizes simulations and heuristics to allow interactions between agents to resemble the real economy. ABM framework can be used to explain several economic phenomena especially the concept of emergence. For example if you see a higher percentage around you buying stocks after stocks have risen for a while, your probability of buying stocks increases. This change of view and of many others around you will lead to more investors buying stocks and may impact even more the probability of you buying stocks. Small changes in the individual behaviour (in this case probabilities) can create huge changes at a macro level. That's the essence of emergent behaviour. This way positive feedback loops can be modelled.

2.6. Dynamics of the system

As we have seen, the financial system is a complex system and making point estimate predictions is difficult – if not impossible - given the reflexivity of markets. The reality is more multifaceted than what mainstream economics teaches us. Financial systems do not merely converge towards an ideal equilibrium price. On the contrary, we frequently experience booms and busts. It creates far-from-equilibrium dynamics where extreme events can appear that are generally uncertain in terms of probability distribution and depart from the statistical regularities observed during calm periods. Understanding the dynamics of the economy is key to understanding the fragility of the financial system.

Patterns

Nevertheless, the system is not completely random and chaotic. Complex systems also contain patterns. If one looks only from one period to another, order cannot be seen. Order is an emergent phenomenon in complex systems as it is not constructed by a central authority. Rather, it is an inherited attribute that arises from the interaction of individuals with dissimilar preferences. Given past patterns, order shows how much we can know about the type of patterns that can appear in the future.

We could think of these observed patterns as the behaviour that certain asset classes have during certain economic scenarios, such as a deflationary spiral or a recovery. These patterns that emerge over time are the different states that the economy can take: recession, growth, stagflation etc. The well-known credit cycles - business and financial cycles - are also examples of such emerging patterns. This is a key insight. It teaches us that complete prediction of long term risk premia cannot be made. However, if we consider that returns are driven by fundamental macroeconomic drivers, then investing according to where the economy is in the financial cycle (selecting assets) allows investors to take up risk only when they can get the best reward.

Keeping these facts in mind, market players can adapt to ever emergent uncertainty by using scenarios analysis. We must depart from the comfortable mainstream models and also consider qualitative models in which the patterns observed over time are described. If investments are made such that no matter what economic scenario materializes, cumulative losses will not take the investor out of the market, than robustness is achieved. The goal for each investor and financial institution alike, is to become resilient to extreme movements in the markets.

Concluding remarks

Complexity's foundation is better aligned than mainstream models to our current understanding of economic forces in periods of transition. Reflexivity, non-equilibrium dynamics and networks are just some of the many intuitive concepts in Complexity Economics that are both theoretically appealing and accurately descriptive of real world developments. Overall, Complexity Economics represents a valid comprehensive complement to mainstream modelling that helps us better understand the uncertain world that we are living in.

Uncertainty of human behaviour coupled with the chaotic dynamics of the economy make precise prediction difficult. However, all is not lost, as economic patterns emerge over time and can be used as clues

Chapter 3. The devil is in the (de)tail

3.1. Risk vs. Uncertainty

Neoclassical economics has long assumed that perfect rational individuals can fully assess the probability of all possible events at any point in time. However, in complex adaptive systems the environment impacts the behaviour of individuals which in turn affects the environment itself. This back and forth creates uncertainty. As a result, uncertainty is a central characteristic of a complex system. Not accounting for uncertainty in the tail of the distribution can result in much larger than expected portfolio drawdowns during turbulent markets.

The main idea in complexity economics is that no one can fully predict when a crisis will happen or what would cause the next crisis, because of market uncertainty. Complexity economics is a tool that helps us understand and make sense of the unpredictable nature of markets. There are several aspects that lead to market uncertainty which in turn results in unpredictability:

- **Feedback effects and behavioural biases:** The way investors strategically interact and respond to market movements which will impact future market movements.
- **Path dependence:** The chaotic nature of the economy where even small changes can lead to significant differences in final outcomes. The idea that a chain reaction of tiny effects can reverberate through the economy.
- **Structural breaks:** Financial market relationships that lasted for a while can often transform. The past does not necessary equal the future. This added randomness coming from instability, complicates our understanding of financial markets. It is a straight forward idea when one thinks about innovation of computers, for example, and how the emergence of the PC has completely changed many aspects of the modern economy.
- **Evolution and adaptability:** We 'evolve' different behaviours in our own lives as we try to successfully adjust to the things around us. As investors, we try to adapt to the new environment, and thus innovation becomes the dominant trait. Evolution brings novelty within the

economic system which allows for the creation of order and further levels of complexity.

Since the 2008 crisis, research has made substantial progress in terms of our understanding of how financial markets function and how risk can be mitigated or insured. However, uncertainty or what we call unexpected risk, has been largely overlooked. Perhaps the most important feature of the real world that challenges traditional economic models is uncertainty, or what we call unexpected risk. We all have heard about the concept of risk which is widely used in the risk management world. However, it is important to disentangle the differences between
unexpected risk (uncertainty) and expected risk (the widely known concept of risk). In both instances we are talking about risk. In the expected case, you can measure the loss given a certain event happening. Whereas when you have unexpected risk, you can only assess the losses via qualitative tools such as scenario analysis.

The laws of statistics are useful when trying to deal with expected risk, but unexpected risk (uncertainty) is another animal altogether

But now, let's delve more into the topics. The more traditional risk models like VaR (Value at Risk) only try to address the expected risk, the part of the probability distribution that can be calculated given historic data and an assumption of the distribution itself. The idea of expected risk refers to measurable probabilities. Even though we are not sure which outcome will happen, we can know which outcomes can happen and with what probability. The classical example is rolling a dice. Defined in this way, expected risk can be measured and used for risk management. However, modelling the probabilities of investment opportunities by only taking into account historical data (known probabilities) is one way to quantify the future, but it inevitably falls short and can be quite detrimental when it comes to assess what are the effect of tail events on the portfolio.

The unexpected risk (uncertainty) cannot be completely captured by using classical statistical models based on historical data. Using VaR methodology, a risk manager tries to measure a potential loss over the next year, with, say, 95% confidence. But how about the 5%? Unexpected risk lies precisely in those 5% of outcomes that cannot be measured by quantitative models. It is actually more likely that the tail of the distribution is for example more skewed or that the distribution even is bimodal. Basing judgements only on quantitative measures can leave investors exposed to disruptions in the market and provide a false impression that they can fully insure against a particular risk by paying an appropriate insurance premium.

In order to better understand the implications and the difference between unexpected and expected risk let's look at an example. Imagine that you are trying to predict what would be the next number that a 6 face die will show. However, you don't know whether each time you are throwing a good die or a tampered one. In this case, we can address expected risk by constructing the probability distribution based on a volatility and mean for each type of die. However, even though we can manage to capture the true distribution of the two events, it is useless if you do not know what type of die you are throwing. This is unexpected risk. The risk that you are throwing the tampered die when you believe is a good die. In this respect, in order to describe the distribution of that each die face can appear if you throw either a good or a tampered die, we need to take into account that both events happen and not pretend that we only play with a normal die. Similarly, as investors we should not expect that we are only investor in normal, calm times. We should be able to protect our portfolio in case of severe downturns that we have seen during recessions. Thus, qualitative models such as scenario analysis should complement the quantitative framework.

The best way to address unexpected risk (uncertainty), according to Keynes is to construct scenarios and attach rankings to these possible states. Keynes looks at probabilities in two forms: a cardinal form in which the probability can be mathematically quantified (which is what basically expected risk is) and an ordinal form where the only information we have about an event is its relative position to another event (ranking). For instance, a market participant has the intuition that a state of the economy in which economic growth is expected is more likely than one in which a rise in inflation is expected. It implicitly ranks the two events. However, it does not know the exact probability of each state occurring. Therefore, each state of the economy receives a ranking in terms of the likelihood of each event occurring. The confidence level can be provided as a weight to the argument. The more information we can get about that event, the more confident we are in our view.

Consequently, the market participant can construct a scenario analysis for the tail of the distribution and for the rest of the distribution still employ the more traditional risk measurement techniques. When trying to address extreme events in our portfolio, namely unexpected risk (uncertainty), the framework proposed by Keynes can provide a qualitative way to manage the tail of the distribution. Ranking the possible states of the world and attaching confidence levels to these ranks can allow informed decisions around portfolio risk management. If the risk budget is not exceeded across the scenarios with their attached ranks and probabilities, then you can relax in your seat and enjoy the journey.

3.2. Forecasting

First and foremost, we need to recognize that financial markets are not stable all the time. On the contrary, the abnormal frequency of improbable outcomes under historically estimated returns is a clear characteristic of an instable system. As Feynman famously said: "If it disagrees with the observation it is wrong…it does not matter how beautiful the guess is, who said it, what his name is… if it disagrees with the observation it is wrong!" If unlikely events happen too often, it means that there might be something wrong with the model. So we need to start searching for alternatives ideas that can explain the phenomenon observed in the financial market.

Before the financial crisis in 2008, the majority of investors believed that all risk could be measured, computed and managed at all times. Moreover, the common misperception of mainstream models is that normality is the norm. As explained above, given the dynamics of the financial market and the unexpected risk (uncertainty) that is interwoven in the economy, point predictions are difficult. The dynamics of complex systems result in non-normal distributions. Fat tails are more common in such systems as feedback mechanisms can create abrupt shifts (instability) in the system and thus generate a much higher likelihood of disastrous events then the mainstream models (using Gaussian distribution) would predict. The same ideas hold also in the world of football, for example, where 22 individuals are interacting on the pitch under very specific rules. Even so, guessing the exact result of a match is difficult as the profits of sports betting agencies show.

Uncertainty impedes predictability. In this respect, one way to deal with uncertainty is to use economic scenarios

So if we cannot predict how the economy will behave, then what can we do to protect our investments in times of uncertainty? The easy answer: using economic scenario analysis.

It is important to recognize that the economy is a complex system that can switch abruptly from one economic regime to another. In such a system, it is not possible to accurately predict how the economy will develop in the long run, but one can recognise repeating economic patterns that emerge over time. So qualitative prediction in terms of possible states of the economy can be made. Examples of such patterns are the leverage cycles that seem to describe the dynamics of different states of the economy as it passes through the cycle. For known economic regimes, one can construct deterministic economic scenarios as we previously mentioned, in order to observe how their respective investments are likely to perform in each regime.

So what are Economic Scenarios? Economic Scenarios are our manifestations of possible future states of the economy and the impact they will have on financial markets. This is not an exact science, a scenario is based on our understanding of the current state of the economy within the business cycle and how this position is influenced by cyclical growth and inflationary pressures as well as by the long term debt cycle and investor behaviour. It needs to be understood that risk is driven by fundamental economic and behavioural drivers and one should attempt to assess these fundamental drivers rather than rely on historical statistical measures such as volatility and asset correlations. Here is where economic scenarios help us better understand how the relations between risk and fundamental economic drivers will change over time and affect the expected risk-return trade-offs. Better understanding of how the economy could evolve and how this will affect the key drivers of expected risk and return for different investments, is instrumental in strategic risk allocation. This way we can make better informed decisions and take those risks that are sufficiently rewarded.

Concluding remarks

The economy is a complex eco-system, where markets are reflexive and feedback loops are present. This makes it difficult to predict the future but it does create recurring patterns over time. In this respect, one way to deal with unexpected risk (uncertainty) is to use economic scenarios in order to overcome the reliance on statistical measures and focus the attention on the fundamental economic drivers of assets.

Chapter 4. When your problems are my problems

A system that seems stable under traditional risk measures (such as stress tests and Value at Risk) can all of a sudden become fragile as the last financial crisis has shown. The interlinkages within financial systems functioned as shock-amplifiers rather than absorbers. We have seen that the failure of one institution can lead to sequential insolvency of other connected parties and can reverberate throughout the whole system. In this respect, complexity theory provides us with some insights on the domino effects. It proposes a new way of assessing systemic risk, namely using network theory, by looking at interconnectivity between financial institutions throughout the financial system.

Network theory is inspired by epidemiology and helps us examine contagion and systemic risk. The terminology used is a clear example. By analysing the architecture of the financial system, we can gain insights into the way risks propagate through the network which will help us identify the "super spreaders". Super spreaders are highly interconnected institutions or systemically important financial institutions. Understanding what makes the financial system fragile, can allow investors to quantify risk and uncertainty in the market by getting a better understanding of the hidden, intertwined risks in the market.

To be more specific, Network theory allows investors to understand the systemic nature of financial fragility of the economy. It provides an indication of the level of fragility of the financial system that arises from financial institutions' interactions. Once the most interconnected institutions are identified, investors can try to measure their exposure to a cascading effect in terms of overlapping portfolios across the system or counterparty risk. Understanding the systemic nature of risk can help investors take informed decisions in terms of active risk budgeting across different potential states of the economy. Assessing the risk of the system can give market participants clues on how to manage risk exposure over time. Therefore, assesing the health of the economy can be a great tool for managing market uncertainty. A consequence is that investors can take more risk when the economy is robust and de-risk when it is fragile.

In his key note address during the research conference on financial network organized by IMF (2014), Nobel prize winner Joseph Stiglitz highlighted these lessons "In addition to being too big to fail, financial institutions can be too interconnected, too central, and too correlated to fail. Focusing on the "too big to fail problem" is not sufficient for designing a resilient financial systems".

4.1. So what is a *network*?

The notion of network is fairly intuitive. A network is composed of nodes and the links among them. The relationship among entities in the network is called a link. The Linkedin network is an example of such architecture. We can think of nodes as being individuals in a society or banks in a financial market. The balance sheet of a financial institution can be characterized by the nodes (assets) and the links among the nodes (asset covariance). In a similar manner, the entire financial system can be thought of as a network.

Recent research in network theory has highlighted several useful tools for analysing the banking system.

4.2. Role of interconnectivity in risk transmission

An important aspect when analysing systemic risk is that a seemingly robust system may in fact be quite fragile. There are several dimensions of financial network fragility that can be explored. The first is related to the fact that a high number of interconnections within the network will serve as shock-amplifiers rather than as absorbers depending on the position of the central hubs. This is the direct way of looking at the role of interconnectivity in risk transmission. By observing the structure of the ecosystem, we can understand whether the links facilitate the propagation of shocks and how we are exposed with our portfolio to these shocks.

Interconnectivity matters because it serves as a conduit for contagion

Direct interconnectivity: Counterparty transmission mechanism

Credit exposures between banks are among the most basic types of direct interconnectivity for example. As investors, we need to make sure we understand to what extent our counterparties are too central to fail. The propagation mechanism can be considered an amplifier and can be incorporated in the more traditional measures of risk like VaR, as a simpler scalar. This idea was introduced by Battiston et al. (2012).

Since Too Big To Fail another phrase has emerged; Too (Inter) Connected To Fail. This new phrase marks the shift of view of researchers and investors from TBTF to TCTF. The realization is that not the size of the bank is what matters but its connections to other banks and non-banks.

These connections can be direct or indirect and some of them are strong and others are weak. This idea can be generalized to other financial players like hedge funds or mutual funds.

Figure 1
Financial interconnectedness

More central = more systemically important
Source: Battiston et al. (2012)

In Figure 1. we can observe the level of interconnectivity by the intensity of the colour, where intensely connected, which in this case the biggest borrower (the credit exposure between banks), get an ever increasing darker green. Moreover, not only colour intensity but also the position in the figure is relevant. More central located institution have higher DebtRank measure and are able to put under distress the entire system. Debt rank is an indicator that tells you how much loss would cause the distress of that institution for the economy (Battiston et al. 2012). This is inspired by measures in network theory. In this manner, the "super spreaders" (highly interconnected institutions) can be detected. In several contexts, we will use the banking system as illustration since most of the research has been done in this area.

The above example represents a tool, which is applied in this specific case within the interbank market. Naturally, an investor can reuse the same tool to assess systemic risk in other markets depending on your interests. For example it has also been used in the CDS market (Rama et al. 2014), or assessing sovereign debt (Glover et al. 2014).

Indirect interconnectivity: Common asset holdings (feedback effects)

It is often the case that financial institutions mimic the business strategies and exposure of rivals in order to deliver performance comparable to peers. Crowded trades should be avoided by investors as they expose themselves to sell offs. Stocks overweighed by hedge funds are good examples — predominantly hyper-growth, high-multiple equities —. Moreover, financial institutions aim to reduce risk by holding "different" assets. Even if the system seems robust, as the financial institutions are diversified at the individual level, the system itself can become fragile. By holding similar asset structures the system becomes homogenous and each individual institution becomes exposed to feedback mechanisms. A fire sell can trigger cascading fire sells across institutions as they struggle to maintain leverage and capital requirements. Naturally, this will further depress the price of seemingly "uncorrelated" assets.

To illustrate this, take a shock to an illiquid asset in held by one financial institution. This shock is transmitted via a selling of liquid assets. This mechanism could get amplified by portfolio constraints such as leverage, capital requirements, liquidity ratios etc. and result in a fire sale.

From an investor's perspective, it can be useful to examine the exposure of portfolio assets to potential fire sales from systemically important institutions. This parameter can be of great use for risk management in order to better understand the potential for disruptive market movements in specific asset price increases driven by fire-sales.

4.3. Too connected to fail institutions

A valid approach in tackling "super spreader" institutions is determining hubs (banks, asset managers etc), that are highly interconnected within the network, and subsequently assigning tailored risk management policies. An example of a super spreader in the great financial crisis was Lehman Brothers. Lehman Brothers was an average sized institution in terms of assets. Nevertheless, its prime role as a broker gave it a distinct position in the market. Financial institutions may have enough capital to satisfy regulatory requirements. However, this capital can quickly prove to be inadequate if the cascading effects of system-wide losses are taken into account. Complexity has made advancements into better understanding these fragilities. For example, epidemiological models can be calibrated to post-crisis regulatory capital standards for the most interconnected banks (Craig et al, 2014). The impact of central clearing of derivatives contracts, instabilities in payments systems and policies which set minimum collateral haircuts on securities financing transactions are also being researched (Haldane, 2009). A better understanding of interconnectivity can provide information to investors of which parties are the "too central to fail". The investor can then take adequate measures to protect against a potential contagion effect.

4.4. Early warning systems

Network based measures of interconnectivity also have the potential to be used as early warning systems of financial crises or at least as a measurement tool for fragility. Devising early warning indicators that signal sharp increases in risk or a deterioration of liquidity conditions, could be very informative for investors. The literature has developed several indicators influenced by emerging market crises. Examples include: high credit growth, low international reserves, real exchange rate overvaluation and excessive (short-term) foreign debt. Evidently, focus has been placed primarily on indicators that signal currency or debt crisis. The great financial crisis has shown that even financial institution's interconnectivity (an aspect previously ignored by early warning signals literature) can exacerbate shocks and enable contagion across borders. Research in the area of financial interconnectivity as early warning signals thorough the use of networks, was conducted by researches such as Minoiu et al. (2015) who have paid particular attention to the probability of systemic banking crisis. Their investigation suggests that a country's interconnectivity rises before crisis and flattens out subsequently. The models constructed with the inclusion of financial interconnectivity in addition to macroeconomic indicators, seem to show symptoms of crisis long before the market realizes it is sick.
Another approach to determine fragility is to focus on these "too interconnected to fail institutions". In this respect, an early warning system can constitute the maximum fire sale loss on assets that would not create a cascading effect within the system. When that maximum level is passed, the probability that a crisis will unfold is high and the system becomes fragile. As we already mentioned, overlapping portfolios across financial institutions can be a major source of systemic risk if a fire sale is triggered and in highly connected networks, even a relatively small fire sale can induce a huge systemic crisis.

Concluding remarks

There is still much to be learned about financial fragility from network theory. However, it is crucial to understand that it promotes a holistic thinking about the risks observed in the financial markets. For example, the exposure investors have to super spreaders can be captured by observing the direct and indirect interconnectivity that arises through either holding assets that are exposed to fire sells or directly being involve in transactions with super spreaders. Understanding the fragility of the financial network can provide us with early warning signals that can point out potential symptoms before the illness becomes apparent to the market. It can allow investors to construct an fragility tool to assess the level of build-up of risks in the financial market. Understanding how fragile an economy is, provides the best tool for an investor who wants to know in advance when there is build-up of risk in the market. In short, complexity economics can reveal an array of valuable connections that had previously been ignored.

Chapter 5. Conclusion

Complexity Economics has the potential to enrich our understanding about financial markets and to improve investor's assessment of their risk exposures. It allows for investor expectations, out of the equilibrium dynamics, uncertainty and interconnectivity in modelling. The dominance by traditional models resulted in unnecessary losses for investors that blindly followed traditional model output. Complexity Economics enriches the existing toolkit of investors because instability and irrationality is part of the fabric of the framework. In this respect qualitative tools such as scenario analysis and network theory can provide a complementary view on financial markets and capture the hidden dimensionalities of the economy that quantitative mainstream models miss.

There are several take-aways put forward in this document:

Miss-assessing risk was a key issue during the 2008 financial crisis. The problem arises when investors take into account only expected risk, assuming a certain distribution, and do not account for unexpected risk (uncertainty) that characterizes complex systems. Unexpected risk results from the particular dynamics of complex systems such as behavioural responses of the investors. As a result, uncertainty impedes predictability, since economic busts are mostly out of equilibrium movements. Nevertheless, the system is not completely random and chaotic. Complex systems also contain patterns. This can help us deal with fragility by understanding which the possible states of the economy are and how the drivers of risk change across states.

One should try to assess fundamental imbalances from the perspective of the underlying economic process, rather than rely on historical statistical measures such as volatility and asset correlations. In this respect, qualitative models and scenario analysis are readily available and can allow sophisticated investors, who comprehend the validity of complexity's claims, to try and capture parts of unexpected risk. The qualitative nature of these approaches does not make them dispensable for decision makers; on the contrary, they are a convenient tool to supplement mainstream model output and to corroborate decision maker's economic intuition.

Interconnectivity is key in constructing an assessment of systemic risk and market disruptions in the economy.

Having established that the economy has many dimensionalities that create complexity, we need to recognize that interconnectivity is key. By taking interconnectivity into account we can enrich the common risk measurement tools and address the hidden risks that stem from cascading effects. Network theory provides investors with the necessary methodology to detect the fragility of the financial system. A high number of interconnections within a network can serve as a shock-amplifier rather than an absorber. The shock can also be transmitted through a fire sell, if investors hold overlapping portfolios. Looking at a maximum fire sell loss on assets that such "super spreaders" hold, can provide investors with early warning signals.

To conclude, the economic reality that we observe cannot be suitably addressed by staying only within the mainstream framework. Taking into account the reflexivity of markets that stems from the interconnectivity of agents is vital for constructing both a more resilient financial system and a more appropriate investment process. Complexity Economics can help us achieve that exactly. The next step for investors is to use this information and complexity's insights to construct economic barometers that approximate economic health. The end goal is to use fragility tools to take more risk when the economy is robust and to de-risk when fragility is high.

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Cardano Insights is the educational arm of Cardano. The team translate academic insights into practical ways to manage pensions and long-term savings in a robust way, creating stability in the financial world and to households. Our work includes the study of pension design, behavioural finance, investments and complexity. We work closely with our colleagues in Cardano to help our clients meet the financial goals of their stakeholders.

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