



Putting Economics Back in Economic Scenarios

Rising complexity in the world and structural breaks across markets require new non-stochastic approaches to scenario generation. The world is also too complex for simplistic ad-hoc assessment. We demonstrate the insights gained by implementing a supply chain agent-based model (LINKS Mira) and run the “China hard landing” scenario with curious conclusions.



As the world goes through a significant economic and political transformation, the number and complexity of risks and opportunities for institutional portfolios increase considerably. Gone are the days when the direction of globalization and integration was unquestionable, the question was just the differences in pace.

Increasing complexity creates additional problems for investment management. **How does one manage risk and return in an environment where history is no longer a fair guide?** Typically, economic scenario analysis and stress testing are the tools of choice. The common approach is statistical: basic models rely on stochastic processes with a random variable drawn from normal distribution, while more complex approaches involve multiple distributions, decomposition into multiple trend patterns and regime switches. A less common approach is designing ad-hoc descriptive scenarios in the context of the growth-inflation framework. Both approaches fail to deliver actionable results.

Please get in touch with us on +3170 8919282 or info@linksanalytics.com to discuss this report with a partner of LINKS Analytics in your city:

London
Geneva

Stockholm
Zurich

Toronto
Amsterdam



Failings of Conventional Scenario Generation

Having statistical science behind economic scenario generation is, among other things, extremely comforting: abundance of random scenarios reassures investors that all possible scenarios are taken into account. But most importantly, as the scenario exercises typically generate ranges of outcomes with certain statistical significance (e.g. in 95% of cases returns will be between A% and B%), the greatest contribution of the method is to reassure investors that even the worst outcomes are still acceptable.

Unfortunately, there is still very little economics in most of today's accepted economic scenario generation techniques. Many of the approaches are statistically sound and have the "scientific rigour" on their side. But when it comes to producing reliable and actionable intelligence, the statistical methods fail in most instances. We can count at least four major reasons for this failure:

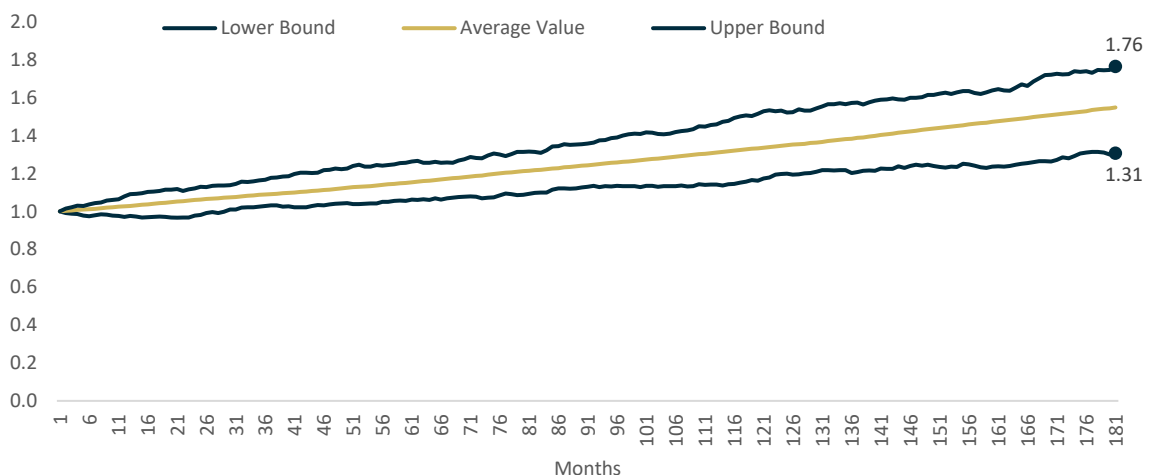
- i. The problem of defining the problem
- ii. History not repeating
- iii. Asset price behaviour assumptions
- iv. Incompleteness

In this paper, we cast a critical glance at stochastic and ad-hoc techniques and propose a practical and methodologically sound alternative – an agent-based model for scenario analysis.

Defining the problem

In a typical case a random process (e.g. Wiener process) is used to generate forward returns. In case of a portfolio of assets, random variables are generated based on historical covariance of assets, so the future returns of assets are correlated (Cholesky decomposition). In a hypothetical example, a balanced portfolio of bonds and equities (60 x 40) will generate a return of ~52% over 15 years based on today's equity risk premium and bond yields (Figure 1). Of course, there is no certainty about this, but the range is not unappealing either: 31% to 76% (this is an asset-only example).

Figure 1: Monte-Carlo simulation results, data source: S&P, Barclays Indexes, LINKS calculations





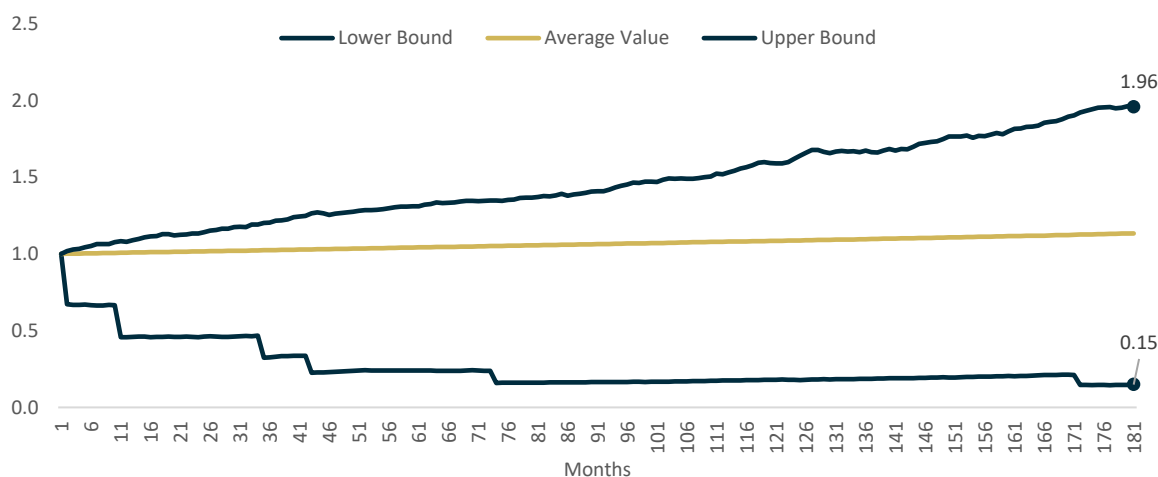
Plenty has been said about the degree to which this estimate is unrealistic. Most criticism focuses on the normal distribution – actual observed extreme returns are of course far greater than implied by the normal distribution. But the problem with this approach is far bigger than just the distribution.

Even before we run the analysis, we make implicit assumptions that the asset classes continue to behave as they did in the past, and that the underlying economic entities (the businesses and governments) remain as healthy and profitable as they did in the past. Needless to say, there is an implicit assumption that the country in which these assets are based, remains intact (so how does one go about analysing disintegration of the EU?)

The layers of unrealistic assumptions even before getting to the asset return distribution are staggering. Let us relax at least two of the assumptions and make realistic assessments: most countries experience wars and hyperinflations. Instead of altering the normal distribution let us assume that in case of war or a hyperinflation the equity portfolio loses instantly 60% of its value, while bonds lose 30%.

There were 55 hyperinflation events in the last 100 years in the world¹, and about 55 major wars. Since at any given point there are 200-odd countries, we will have $200 \times 100 \times 12 = 240,000$ available country-months and the probability of a cataclysmic event in any given month is 0.046%. By incorporating this likelihood into the calculation, we get an entirely different picture (Figure 2).

Figure 2: Simulation results including wars and hyperinflation, Data source: S&P, Barclays Indexes, LINKS calculations



There are multiple takeaways from this exercise. First, one of the major problems with statistical approaches is the definition of the problem. It is in this stage that most relevant abstractions of the real life are made and often forgotten: a simple assumption that there may be wars and hyperinflation cases wipes out all the “confidence” interval – these are not extreme events, rather

¹ S. Hanke, N. Krus, “World Hyperinflations”, CATO working paper, August 15, 2012 and http://www.historyguy.com/major_wars_20th_century.htm for a non-exhaustive tally of major wars.



events that are very likely to occur. In fact, assuming our 0.046% estimate is correct, over 15 years an average country is likely to experience those events with a probability of 7.9%.

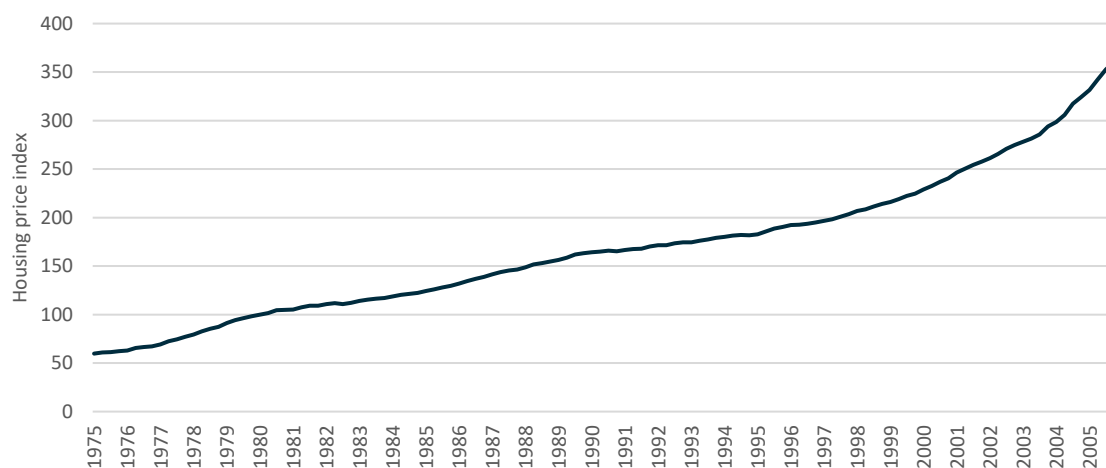
The second problem is the creation of false certainties: the range in Figure 1 gives the mandate to managers to afford the luxury of having no views. Since all the expected range is acceptable, there is no need to try to assess the real-world relationships, impacts and risks. Statistical economic scenario generation creates an inaccurate vision of the world.

Of course, wars and hyperinflations are not the only two cataclysmic events. Countries may change the social structures (Russia), nationalise (France), impose prohibitive taxes (EU), go bankrupt (Argentina, Turkey). All the above may not be (and most probably is not) part of the parameter estimation for an ESG. Unfortunately, if the problem is defined correctly, the solution may not be practical or usable in any way due to the range of outcomes that is just too wide.

History does not repeat

Perhaps the most damaging recent example of history not repeating is the US housing price index. Figure 3 shows how the index looked in October 2010. A statistical scenario generation with trend decomposition (isolating the long- and short-term trends) would at best suggest an index reverting to the long term average pace of increase in house prices.

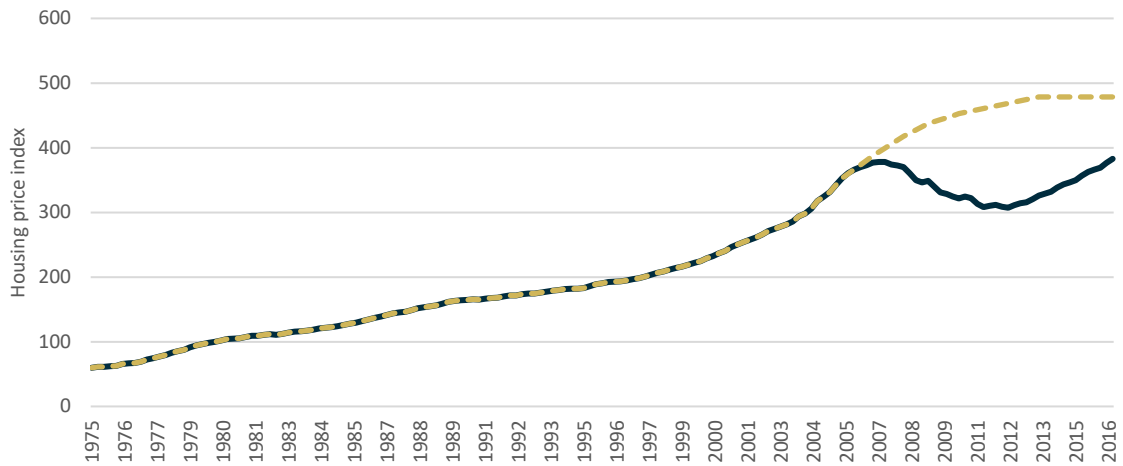
Figure 3: US housing price index 1975 - 2005, Source: FRED



The actual development of house prices followed, of course, a pattern that cannot be tackled with statistical methods: an extremely tough adjustment period of 4 years followed by recovery, however, nowhere near the levels implied by the long-term trend. The nature of the underlying economic asset had changed considerably: mass-scale securitization, moral hazard problems, significant growth rates of sub-prime segment were all hallmarks of the housing market only in the last few years. Understanding the nature and behaviour of the underlying economic asset is essential.



Figure 4: Actual and forecast (dotted line) housing price index, Source: FRED, LINKS calculations

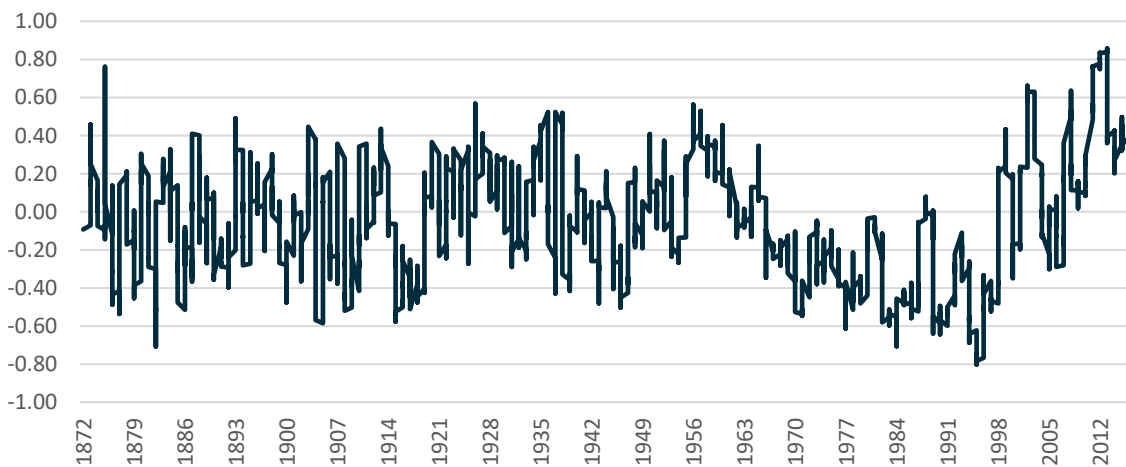


Asset price behaviour assumptions

Most investors instinctively realise the inherent problems with these methods, which is why there are continuous attempts to draw scenarios outside the “comfort zone” of the traditional scenario generation: Eurozone breakup, Brexit, hard-landing in China or the election of far-right parties in OECD countries are all examples of structural breaks. To design such a scenario, however, the long-term economic behaviour of asset prices has to be understood. However, often overly simplistic or outright incorrect assumptions are customarily used to draw conclusions.

The most common framework of translating hypothetical events into asset returns is based on the typical growth-inflation paradigm. Performance of equities and bonds is linked with high and low growth/inflation environments directly: high GDP growth will result in good equity and poor bond performance; high inflation will be reflected in yields (Figure 5). Unfortunately, if this were the case, the correlation between equity and bond returns would be stable and negative. In practice, the correlation is not only volatile, but also directionally unstable: there are extended periods of both high positive and high negative correlation.

Figure 5: Correlation coefficient of change in 10-year yield and S&P 500 return, Source: Shiller dataset





Academic studies are in broad agreement: GDP growth and inflation rates have no clear relationship with asset returns (Tables 1 & 2).

Table 1: Selected research publications on relationship between inflation and equity returns

Study	Conclusion
Lintner, J. (1975). "Inflation and Security Returns," <i>Journal of Finance</i> 30(2), 259-280.	"Recent statistical analyses, however, have shown stock prices and returns are negatively rather than positively related to inflation as standard economic models presume."
Jaffe, J. F., and G. Mandelker. (1976). "The 'Fisher Effect' for Risky Assets: An Empirical Investigation," <i>Journal of Finance</i> 31(2), 447-458.	"For the period of 1953-1971, the returns on stocks appear to be significantly negatively related to the anticipated rate of inflation..."
Nelson, C. R. (1976). "Inflation and Rates of Return on Common Stocks," <i>Journal of Finance</i> 31(2), 471-483.	"The evidence presented... suggests that a negative relation between returns and both anticipated rates of inflation and unanticipated changes in the rate of inflation has prevailed in the post-war period"
Fama E. F., and G. W. Schwert. (1977). "Asset Returns and Inflation," <i>Journal of Financial Economics</i> 5(2), 115-146.	"The most anomalous result is that common stock returns were negatively related to the expected component of the inflation rate, and probably also to the unexpected component".

Table 2: Selected research publications on relationship between GDP growth and equity returns

Study	Conclusion
Dimson, Elroy, Paul Marsh, and Mike Staunton, 2002, <i>Triumph of the Optimists: 101 Years of Global Investment Returns</i> Princeton: Princeton University Press.	"...the correlation between the compound real rate of return on equities and the compound growth rate of real per capita GDP is minus 0.39"
Inc., MSCI, <i>Is There a Link between GDP Growth and Equity Returns?</i> (May 13, 2010). MSCI Barra Research Paper No. 2010-18.	"Although this relationship seems quite intuitive, historically long-run stock price growth has fallen short of GDP growth in many countries."
Jay R. Ritter, <i>Economic growth and equity returns</i> , <i>Pacific-Basin Finance Journal</i> 13 (2005) 489 – 503	"...the cross-country correlation of real stock returns and per capita GDP growth over 1900-2002 is negative"

Despite these conclusions most non-statistical scenario generation focuses on translating scenarios into GDP growth and inflation forecast, followed by explicit assumption on asset class returns. This approach builds two layers of error into the estimates: the translation of any given scenario into GDP/inflation forecasts and translation of growth forecasts into asset returns.

Completeness

Completeness refers to the importance of considering all major impacts of a given scenario – positive and negative. Although most instances require assessment of negative scenarios, any assumption of drastic change yields both negative and positive effects. These effects can be across time and across sectors or parts of the supply chain.

In a simple example of a hard landing in China (which in itself requires elaboration), it is plausible to assume that commodity prices will fall. Although detrimental to energy and mining companies, this may well be very positive for energy and base metal consumers: aluminium smelters, automotive companies.

The oversimplified vision of the world economy in an ad-hoc scenario will yield a result that is arbitrary and wrong not only in terms of the scale but also direction.

Timing of the events is also significant. A negative price shock on commodities may result in multiple set of actions and reactions in the economy: falling prices limit supply but increase demand, thus



setting the scene for higher prices going forward. The total impact is impossible to assess without explicitly modelling the supply chains.

Scenario Analysis: An Agent-Based Model

The problems with developing scenarios using conventional statistical and analytic methods prompts the use of alternative techniques. Agent-based models (ABM) are uniquely suitable for the type of scenario generation and analysis required by institutional investors. An ABM is a class of models that enables simulation of the actions and reactions of autonomous agents. LINKS Mira is an implementation of such a model, whereby agents are industries-country pairs, governments and companies.

ABMs enable non-linear analysis at a more granular level. Depending on the quality of data and modelling ABMs have also disadvantages (Table 3).

Table 3: Comparison of ABM and stochastic models

Model	Advantages	Disadvantages
Stochastic model	simple to implement, results aligned with history	no context (scenario is hypothetical), cannot account for structural breaks in the real context, incomplete
ABM	can be based on context, can highlight potential structural breaks,	Difficult to accurately explain the history, does not generate “realistic” pricing patterns aligned with history, complex to build and validate

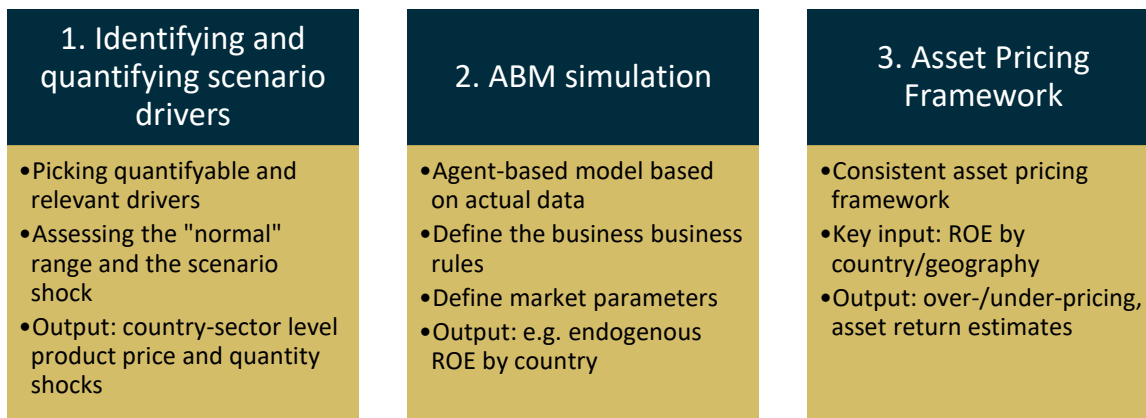
In this report, we will describe a generic approach to building and testing economic scenarios based on ABM. LINKS have developed and tested several critical scenarios based on LINKS Mira:

1. China hard landing
2. EU Break-up
3. EM debt defaults
4. Globalization stopping/trade war
5. Hard Brexit
6. Oil shock

Although this report uses hard landing in China as an example, the results of all scenarios will be made available to institutions. Scenario generation process can be broken down into three stages (Figure 6).



Figure 6: Generic ABM modelling process



Identifying scenario drivers

This is unavoidably the most arbitrary “art” part of scenario generation. Although colloquially it is acceptable to mention “China hard landing” without specifically mentioning the drivers and the magnitude, in practice it is impossible to model an event without these specifics. The specific drivers should also be economically relevant.

What are likely drivers of “China hard landing”? Real GDP would be one such metric: a base growth rate of 5-6% is a norm for China. A hard landing would be considered growth rates of under 1-2%. Although this could be sufficient to build a scenario, we do have more specific information about the Chinese economy that can yield better outcomes: mining and metals related industries are the ones with greatest overcapacity and are likely to suffer the greatest cuts. This gives us a combined set of quantifiable drivers that we can use as an input into LINKS Mira (ABM) – Table 4.

Table 4: "China hard landing" drivers

Agent	Volume impact	Price impact
China real GDP	-5%	-
Mining and quarrying	-	-20%
Manufacture of basic metals	-	-30%
Manufacture of fabricated metal products	-	-10%

ABM Simulation

Although preparing and maintaining data for an ABM framework is labour intensive, the model itself is relatively simple. Agents in an ABM are specific industries in a country, while the relationship between the agents are the annual turnover of an industry of a country generating from other industries globally. Once we know the initial shock – for instance a 5% volume decline in all industries in China, we can trace the impact of such a decline across all other countries and industries: the result would be lower purchases of materials for suppliers, which then would translate into falling prices due to lower demand. New prices are then used as a new shock to assess what happens in the second period. In each period, we can calculate the revenues and profits of all industries in all countries, government spending and taxes, consumer income and spending. A more formal description of the model is presented in the information box.



In case of the “China hard landing” scenario, our initial shocks (p and q vectors) are given by Table 4. Simulating the ABM for 6 calendar quarters generates the behaviour of all regional commodity prices and markets. Instead of deriving the USD value of profits, we require the percentage change in profits, or ROEs, which is a more appropriate input for the next stage.

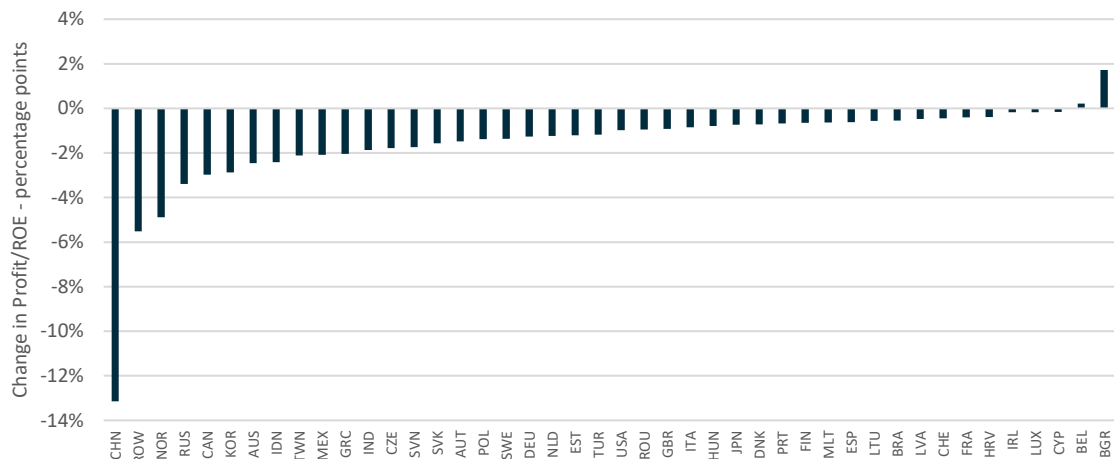
Provided the network of countries/industries includes all major counterparties in the global economy, ABM yields as nearly complete impact assessment as possible. All action-reaction feedback loops are taken into account in the result. The results are interesting in more than one way: for instance, Norway, Russia, Canada and Korea are among the biggest losers of a China hard landing, while the US is relatively insulated (Figure 7).

Infobox 1: ABM Model Description

We can define an ABM model by means of adjacency matrix:

- $A_t = \begin{pmatrix} a_{11t} & \dots & a_{1nt} \\ \vdots & \ddots & \vdots \\ a_{n1t} & \dots & a_{nnt} \end{pmatrix}$, where a_{ijt} is the annual USD-denominated sales volume of i -th country-industry pair to the j -th country-industry pair in period t
- The scenario vectors are represented by p_0 and q_0 – the expected percentage changes in prices and quantities of products produced by industry-country pairs.
- The dynamic process is described by: $A_{t+1} = \begin{bmatrix} (1+q'_t) \\ \dots \\ (1+q'_t) \end{bmatrix} [(1+p_t) \dots (1+p_t)] A_t$
- Finally, p and q vectors are governed by business rules: $q_{t+1} = q_t \times PES$, $p_{t+1} = p_t \times iPED$, where PES is the price elasticity of supply vector and $iPED$ is the inverse of price elasticity of demand vector.
- The output of our ABM is the profit vector: $\pi_t = p_t q_t - \hat{u} A_t$

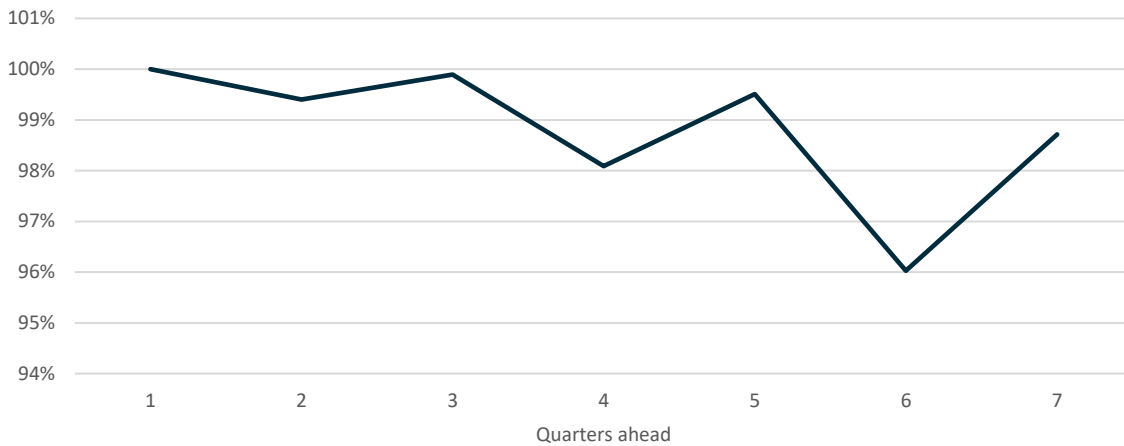
Figure 7: ABM simulation results - impact on country ROEs



ABM also yields results for the behaviour of product/commodity prices. These results are not linear and are in no way driven by historic pricing: structural breaks will be implicitly modelled if conditions are appropriate. Prices for oil products in the US for instance are likely to fall and become more volatile (Figure 8). The single run of ABM has in fact generated forecast price series for hundreds of commodities and products.



Figure 8: Oil product price forecast in case of China hard landing, ABM



Just like traditional stochastic models, agent-based models can be appropriately verified and validated.

Asset Pricing Framework

An appropriate asset pricing framework is crucial for valid scenario analysis: it is at this stage that economic variables, such as ROEs, are translated into asset prices and return estimates. Simple deterministic models can be used (such as a DCF), so long as asset pricing of multiple assets is carried out simultaneously (bond and stock prices are based on the same assumptions) and consistently (the direction of impacts is plausible).

Assessment of changes in Returns on Equity (ROEs) have direct effect not only on equity pricing, but also on bonds. Country ROEs are of course the key drivers of equity pricing: the value of equities depends on the economic spread, i.e. ROE – Cost of Equity. At the country level, however, ROEs are also drivers of growth, as higher ROEs mean more retained earnings and reinvestment for future growth, which in turn defines long-term interest rates.

More formally, we use LINKS Graham Risk framework – see the information box for details.

Infobox 2: Graham Risk Asset Pricing

RP is the solution to the following regional model (dividend discount model):

$$MV = \sum_{t=1}^3 \frac{D_0(1+g)^t}{(1+r+ERP)^t} + \frac{E_0(1+g)^4(1-PR)}{(r+ERP-g)(1+r+ERP)^3}, \text{ where}$$

$MV = \sum_{i=1}^N P_i S_i$ - is the market value (price * shares outstanding) of all N companies in the region, $D_0 = \sum_{i=1}^N D_i$ - is the total trailing 12-month dividends for the region, $E_0 = \sum_{i=1}^N E_i$ - total trailing 12-month earnings for the region, r is the yield on ten-year sovereign bonds for the region $g = ROE_0 \times (1 - \frac{D_0}{E_0})$ level of internally funded growth in the near-term.

The actual fair level of ERP is derived using the following empirical time-series model and the most recent readings of the respective variables:

$$ERP_{Fair} = \beta_0 + \beta_1 s + \beta_2 \sigma_{GDP} + \beta_3 i + \beta_4 d + \varepsilon, \text{ where}$$

s is the ratio of net savings to GDP for the country/region, σ_{GDP} is the volatility of GDP, i is the level of dispersion of inflation expectations, d is the debt to total asset base. Combining II and III yields GR for equities:

$$GR_{Equities} = ERP_{Fair} - ERP$$

Graham risk for sovereign bonds is given by:

$GR_{Sovereign} = Yield_{Fair} - Yield$, fair yield is driven by the following empirical model:

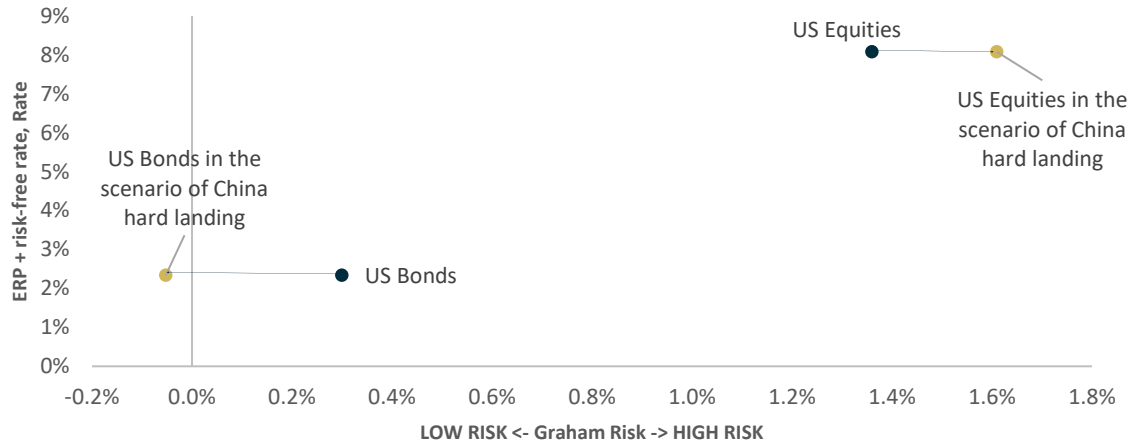
$$Yield_{Fair} = \beta_0 + \beta_1 s + \beta_2 ROE + \beta_3 g_{GDP} + \beta_4 I + \varepsilon, \text{ where}$$

s is the net savings, g_{GDP} is trend growth of GDP, I is the rate of inflation.



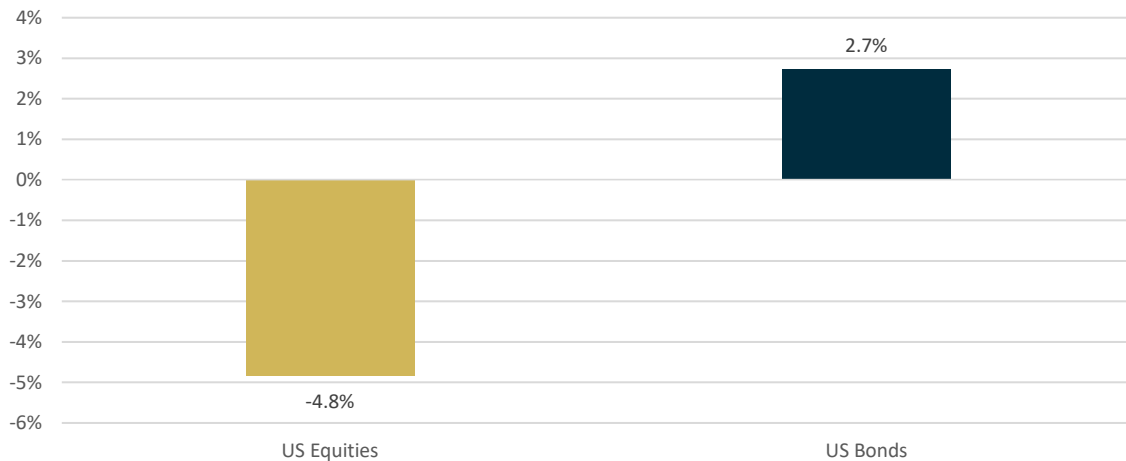
Based on the ABM simulation we have a change of US ROE of 0.97%, which drives fair yields down by 35 basis points and equity risk premium up by 25 basis points (Figure 9).

Figure 9: Scenario impact on valuation - Graham Risk framework



These changes combined with the duration indicate a 4.8% downside for equities and 2.7% for bonds. Note that the moves are not symmetric: bonds are usually 5-10 times more volatile than equities, stochastic models would match a 2.7% change in bond prices with 15-20% change in equity prices. In real life, however, relative volatilities seldom hold true.

Figure 10: ABM simulation impact on asset pricing – China hard landing



Finally, it is somewhat surprising to find that such a widely feared and publicized negative scenario as “China hard landing” could result in only a mild change in asset prices. Of course, ABM allows assessment of all impacts: both negative and positive. The multiple period positive effects help balance the negative impacts and result in only mild change. After all, growth in China has been deteriorating for a while now, with so far very minor impact on major economies (other than Australia and Canada).



Conclusions

Traditional economic scenario generation based on stochastic modelling suffers from several shortfalls: problem definition, inability to foresee structural breaks, myopic model of asset price behaviour and incomplete modelling. Agent-based models address these issues and enable more complete and realistic analysis of the global economy and asset prices. Although developing an ABM from scratch requires new skillset and data, the benefits are too many not to dedicate time and resources.



About LINKS:

LINKS Analytics B.V. has a focused offering of industry leading systemic risk management solutions for institutional investors. Our unique and proven methodology of estimating the degree of systemic risk is based on the assessment of asset valuation dislocations globally (Graham Risk) and the degree of interconnectedness and concentration.

Contact:

LINKS Analytics B.V.
Kluizenaarsbocht 6, 2614 GT Delft
The Netherlands
Tel: + 31 (0) 70 891 9282

E-mail: info@linksanalytics.com
www.linksanalytics.com

© LINKS Analytics B.V.

Limitations:

This document is provided for information purposes only. The information contained in this document is subject to change without notice and does not constitute any form of warranty, representation or undertaking. Nothing herein should in any way be deemed to alter the legal rights and obligations contained in agreements between LINKS Analytics and its clients relating to any of the products or services described herein.

LINKS Analytics makes no warranties whatsoever, either express or implied, as to merchantability, fitness for a particular purpose, or any other matter. Without limiting the foregoing, LINKS Analytics makes no representation or warranty that any data or information supplied to or by it are complete, or free from errors, omissions or defects.

LINKSSM, LINKS AnalyticsSM, BIPSSSM, LINKS Risk PlatformSM, Graham RiskSM are service marks of LINKS Analytics B.V. Other products, services, or company names mentioned herein are the property of, and may be the service mark or trademark of, their respective owners.