Betting on Dark Horses: Tools from Macroeconomics for Model Trading in hybrid crypto-assets portfolios

Abstract: The advent of blockchain technology, tokens, and crypto assets, combined with sufficient computing power to simulate interacting heterogeneous economic agents in realistic scenarios, has opened novel possibilities for management of new types of assets.

This paper presents a simplified methodology for either proprietary traders or bank trading floor strategists, to design small, transparent models based on macroeconomics that can explore potentially profitable situations through predictive analysis.

After a statement of motivations, and a brief review of macroeconomic modeling literature, come the description of this hybrid DSGE ISLM model architecture, the set of equations at its core, and details of its construction: The process of building this model use specific Excel features to simulate and generate scenarios as sample paths of macroeconomic variables. Chosen examples of numerical results are graphically shown and commented.

Finally, some remarks and ideas of extension for this model in future works conclude this paper.

Introduction

The banking and financial sectors are teeming with new, unexplored opportunities, driven by the marriage of financial innovations and technological breakthroughs. The advent of blockchain technology, tokens, and crypto assets, combined with sufficient computing power to simulate interacting heterogeneous economic agents in realistic scenarios, has opened novel possibilities for management of new types of assets. This paper presents a simplified methodology for either proprietary traders or bank trading floor strategists, to design small, transparent models based on macroeconomics that can explore potentially profitable situations through predictive analysis.

The structure of this paper is as follows: First, we provide a brief motivation, outlining the interest in trading specific combinations of uncorrelated, novel assets. From this interest, we discuss the requirements for the models to be built, based on the characteristics and variables of the products. A literature survey then shows how the integration of Agent-Based Models (ABM) and Dynamic Stochastic General Equilibrium (DSGE) models, embedded in a IS-LM framework, can achieve this goal. We then describe the construction process of such models and derive the set of equations at its core. We present the process of building models using advanced Excel modeling features. From these, we simulate and generate scenarios and show numerical results. Finally, we offer work-in-progress conclusions from this stage, its limitations and a perspective on future work.

1 Motivation

New opportunities arise from new assets. It is well documented that Asian and young urban professionals in Western countries now prefer holding crypto assets over traditional assets. The increasing use of crypto in portfolios is notable, with some populations, particularly Gen Z, even exclusively holding crypto assets.

We are not dealing with pure speculative trading on purely crypto assets. The behavior of these traders can probably be best modeled as agents not acting following macroeconomic situational context. Their collective behavior has been studied by numerous authors, including this author, in a different setting.

The portfolios considered here are of a new, hybrid type that requires a different kind of portfolio management. These portfolios, containing crypto assets, lack the arbitrage between stocks and bonds seen in traditional management due to the absence of classic correlation behavior between these new assets. These correlations can be highly variable, sometimes very correlated and other times anti-correlated. Thus, portfolio optimization for these assets requires different tools.

Firstly, the customer base is evolving. Banks aiming to provide more services and develop high-margin offerings must meet higher requirements:

- Relevance: Macro-economic theories specific to crypto assets are still in their infancy.
- Timeliness: Real-time interventions are necessary because the price evolution of these assets can be much shorter than the usual weekly or monthly scales.
- Insightfulness: The new customers, being highly educated and technologically savvy, expect more transparency and understanding of the investment rationale.

Secondly, portfolio optimization, conditional on accurate crypto assets ecosystem forecasts, requires a more intensive macroeconomic analysis than traditional portfolio management.

In parallel, providing counseling and advice may require more human expertise. Even advanced AI chatbots struggle to offer comprehensible explanations when the underlying decision-making models involve complex theories like DSGE or ABM.

Thirdly, the investment spirit has shifted with the advent of new customers and assets. Traditional metrics like the Sharpe ratio are less relevant. With crypto assets, especially smaller coins, the focus is on betting on high-risk, high-reward opportunities, rather than seeking gains from statistical averages. This shift necessitates new mathematical approaches and strategies in portfolio management, focusing on the tails of distributions rather than the entire probability spectrum.

2 Literature on markets and model trading

2.1 Trading with machine learning based approaches

In this study, the focus is on building macroeconomics-based models which provide rational and insightful decision making. Therefore, we will not use new “black box” tools such as machine learning or other artificial intelligence-based technologies.

The reader interested in these fields can refer to a vast amount of recent literature, such as:

- Optimizing Automated Trading Systems with Deep Reinforcement Learning by M. Tran, D. Pham-Hi, M. Bui (Algorithms 2023, 16(1), 23; https://doi.org/10.3390/a16010023)
- [MA5] Tran M., Duong T., Pham-Hi D. , Bui M., (2020), Detecting the proportion of Traders in the Stock Market: An Agent-Based Approach, Journal of Mathematics MDPI, 8(2), p.198 , special issue Supercomputing and Mathematics, Feb 2020.

2.2 Macroeconomics based exploratory models

2.2.1 Dynamic Stochastic General Equilibrium (DSGE) Models

DSGE models are pivotal in macroeconomic analysis as they facilitate the understanding of economic agents' optimizing behavior under uncertainty. They integrate microeconomic foundations with macroeconomic outcomes, making them highly suitable for analyzing crypto assets, which exhibit significant volatility and speculative behavior.

Christiano and Eichenbaum have early on shown the dynamic side of shocks and their impacts on monetary policy. Smets and Wouters then elaborated estimation methodologies and applied them to Eurozone.

Most DSGE model papers present results in the form of IRF's (impulse Response Functions): they show how the Economy's log linearized variations generally follow smooth amortized curves, bringing the variables gradually back to equilibrium levels. As such, they are designed to help monetary policy makers and Central Bankers engineer stimuli to regulate the economy, but they are not of a great help to asset managers and proprietary traders on specific markets and in more turbulent circumstances. These latter users need more flexible, lighter, smaller tools allowing them to inject imagined situations and elicit more turbulent, dynamic and interactive responses.

As it were, DSGE users generally look at one large shock (from Supply side, or from Demand side, or in interest rates …) and watch the economy snap back elastically, smoothly to its equilibrium (as reference, or normative values). New (crypto) assets portfolio and traders need a type of model where the Economy, instead of passively going back to equilibrium, either adjusts by displacing to a new equilibrium, or over-reacts and oscillates, or goes into dynamic, permanently shifting, equilibrium.

For that, the hybrid model in this paper uses another set of equations independent from DSGE to calculate a new "potential" equilibrium at each moment. The gap between the potential and the former equilibrium creates the force that prevents the Economy to snap back to its old state. These other equations come from dynamic IS-LM as proposed by Hall and augmented with the Taylor rule.

2.2.2 Neo Keynesian ISLM frameworks in Hall & Taylor spirit.

The IS-LM model, while considered outdated by some, provides an explicit and easy-to-understand framework that can be adapted to the new dynamics introduced by crypto assets. The flexibility of the IS-LM model allows for the incorporation of the new forms of money represented by crypto assets, which align interestingly with the original Keynesian concept of money, with a slightly different meaning of "speculative motive".

Woodford analyzed not only monetary policies but also their influence in shaping and structuring the banking industry. Hierarchies of lender, intermediary and borrower banks, and specialization among banks are modelled, and explain the dynamics of the many interest rates. The departure from the uniform landscape of 19th and early 20th century banking communities enriches the representation of interest rates in the financial sector.

2.2.3 A new type of knowledge representation with topographic maps for hybrid models

The integration of navigational maps in economic modeling provides a visual and predictive tool for understanding the complex interactions between hybrid assets like crypto assets. These models need to incorporate behavioral aspects to capture the erratic and speculative nature of crypto markets.

More human and irrational than Homo Oeconomicus, heterogeneous Agents have more liberties and are much more interesting to watch. Tesfatsion and Judd among others have pioneered ABM, “agent based modeling”. Dwayne Farmer of the Santa Fe Institute is also a great contributor to this field.

There is a very dynamic community of ABM practitioners. More and more computer based tools for animating Agents are created. However when it comes to finance, the complex psychologies are much more difficult to animate then aggregate than in other fields of physics or computer manufacturing where agents are used to represent electronic or software components.

2.3 Practical tools

Building practical models for trading opportunities in crypto assets involves leveraging accessible tools like Excel while incorporating advanced techniques from Agent-Based Models (ABM) and Stock-Flow Consistent (SFC) models.

2.3.1 Excel VBA for white box modelling

Excel's transparency and flexibility make it a suitable tool for building white-box models, which allow for clear visibility into the assumptions and calculations involved. This is crucial for gaining insights and ensuring the models are easily interpretable by human experts. Excel VBA is also very popular in the Trader-programmers' communities because proprietary traders who create models can “hack” and develop their own software without having to go through steps of specifying, explaining, to a professional programmer, therefore risking have their original exposed ideas stolen.

2.3.2 Agent-Based Models (ABM)

ABM are particularly useful for simulating the interactions of heterogeneous agents in a market, making them ideal for exploring the dynamics of crypto assets. These models can capture the emergent behaviors that arise from individual agents' actions and interactions.

2.3.3 Stock-Flow Consistent (SFC) Models

SFC models are valuable for integrating financial and real economy interactions, providing a comprehensive view of the economic system. They ensure consistency between stocks and flows, making them robust tools for macroeconomic modeling. Godley and Lavoie naturally introduce Stock Flow consistency from approaches of Balance sheets and accounting. Key concepts are potential connectedness of every accounts of all agents in an economy.

By integrating these theoretical and practical approaches, we can develop robust models to explore and capitalize on trading opportunities in the evolving landscape of crypto assets.

3 Construction of the simulation tool

3.1 Architecture of the modeling tool

We want to be able to project into the near future and make trading decisions based on the outcomes of scenarios. Scenarios start from a general equilibrium in phase space (e.g. GDP-Return rate plane), then small perturbations (calculated by dynamic recurrent variables) occur and accumulate, displacing the system state farther and farther in phase space, until a threshold is crossed and an abrupt market adjustment makes the equilibrium point "jump" over to a new phase state equilibrium position.

Therefore, there are 3 elements at play:

1. An IS-LM bloc, designed to set the long-term equilibrium level for such Stock variables as GDP, economic return on investment, … and from which we derive a time-variant sub model, typically a Hall & Taylor model, where time-dependent variables are introduced via Price index. This introduces inflation and connect it in a natural way to the DSGE part, both at the New Phillips Curve equation level, and the Consumption perturbation equation level via the Taylor Rule.
2. A DSGE bloc which allows the computation of consecutive, autocorrelated increments of the above Stock variables. These increments per unit time period can be seen as variations fluctuating around equilibrium points of the corresponding Stock variables. Though they do not exactly represent the differential, (because they refer to a “normative”, referential value, and not the previous period variable), they stand in nonetheless as a “flow”, in or out, around the

central value of a Stock, almost a “derivative” (if the reference were the last period value, and not the normative value).

3. A dynamic transmission mechanism, where the actions of the perturbations, representing the “Flow” values, incrementally push the "Stock" values farther and farther away from the multi-equilibrium point. A test is made at each period sequentially on the value of the gap as a distance between the current state position and the equilibrium position. When this gap crosses a threshold, a new equilibrium position is calculated in the IS-LM block and fed into the DSGE equations bloc as the central, normative, reference position.

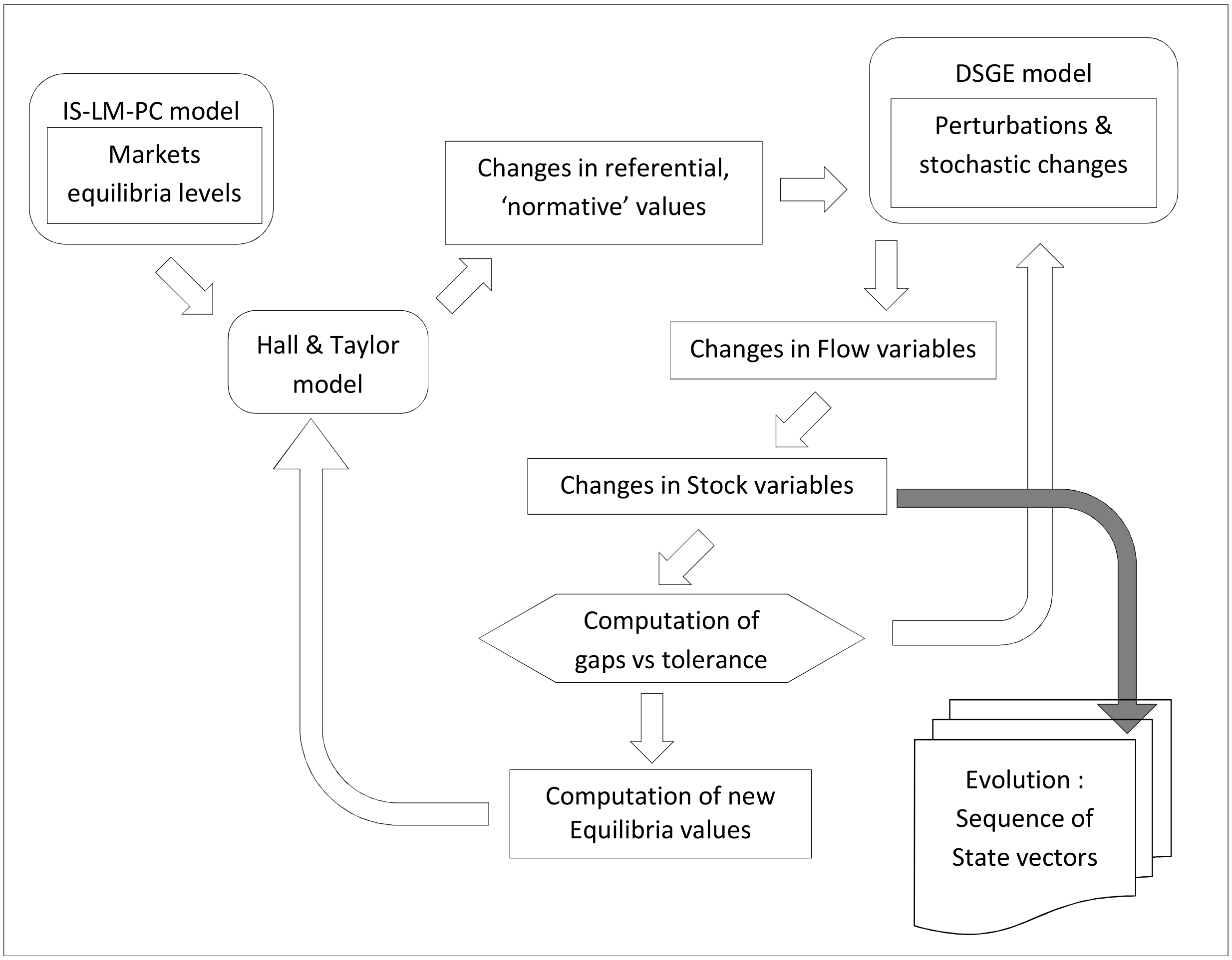


Figure 1. The architecture of this hybrid model derives macroevolutions from main theoretical frameworks.

3.2 The model's equations

3.2.1 Stochastic dynamic equations in New Keynesian context.

We use here the simpler New Keynesian equations for illustration. These already implicitly incorporate considerations of microstructure optimizations, price setting policies, Calvo-type lagging and other more realistic features of the DSGE framework.

The first equation is the dynamic IS curve, a log linearization of the Euler equation of intertemporal allocation of consumption of agents in the economy. In the following notation, as there is no possible confusion, we have dropped the usual "hat" used for log linearized variables. Current output gap y_t results from expected future output gap, less the risky part of real financial return (i.e. dis-inflated from future expected inflation gap). An auto correlated perturbation term is attached to the demand side.

We note $\varepsilon = 1/\sigma$ where σ is the usual relative risk aversion coefficient.

$$y_t = E_t(y_{t+1}) - \varepsilon\big(r_t - E_t(\pi_{t+1})\big) + w_t^D \qquad (1)$$

The second equation is the New Keynesian Philips Curve linking current inflation to discounted expected future inflation and to current output gap, with an autocorrelated perturbation term added on the supply side.

$$\pi_t = \beta E_t(\pi_{t+1}) + \kappa y_t + w_t^S \qquad (2)$$

Finally, we have the "Taylor Rule" summing the contributions from the output gap and the inflation gap terms. Such "rule" is generally considered to be empirical, and econometrically confirmed; however, it also has strong theoretical foundations: this equation comes naturally from annulling the first derivative of a quadratic penalty function accounting for antagonistic objectives of production and inflation, in the minimization process.

$$r_t = \phi y_t + \psi \pi_t + w_t^R \qquad (3)$$

We derive the more convenient matrix formulation

$$\begin{pmatrix} E y_{t+1} \\ E\pi_{t+1} \end{pmatrix} = \boldsymbol{P}.\begin{pmatrix} y_t \\ \pi_t \end{pmatrix} + \boldsymbol{Q}.\vec{\xi}_t \qquad (4)$$

where

$$\boldsymbol{P} = \frac{\mathbf{1}}{\boldsymbol{\beta}}\begin{pmatrix} \beta + \epsilon(\kappa + \beta\varphi) & -\epsilon(1-\beta\psi) \\ -\kappa & 1 \end{pmatrix}$$

$$\boldsymbol{Q} = \frac{\mathbf{1}}{\boldsymbol{\beta}}\begin{pmatrix} \beta & -\epsilon & -\epsilon\beta \\ 0 & 1 & 0 \end{pmatrix}$$ and the perturbations vector,

$$\vec{\xi}_t = \begin{pmatrix} w_t^D \\ w_t^S \\ w_t^R \end{pmatrix} \quad w_t^K = \rho^K w_{t-1}^K + (1-\rho^K)\omega_t^K \qquad (5)$$

with $w_t^K \sim \mathcal{N}(0, \sigma^K)$, $K \epsilon \{D, S, R\}$

To solve this system, we must choose one of two modeling approaches:

- either a Rational Expectations route, with solutions via Blanchard-Kahn conditions, more elegant but not always feasible depending on the values of the parameters,
- or a non-Rational Expectations route, for instance via a behavioral finance model. Closed form solutions are generally not available for recursive equations, because Expectations functions may vary through time (hence the "non-rational" characterization) so that one must posit hypotheses for anticipations mechanisms by agents to conduct simulations. These may be behavioral equations, representing investor psychology speculating about market dynamics, and prone to subjectivity from each trader. This type of modeling can allow everyone to have his own brand of model. Another branch is Adaptive expectations where agents process data like a physical electronic filter (e.g. Kalman) sieving through noise to get trends.

In the following we consider the Rational Expectations hypothesis and will leave exploration of the Behavioral finance branch for an ulterior study.

We next find eigenvalues (and eigenvectors) of matrix P to diagonalize (or trigonalize) the system. The idea is to break down the system into subsystems and to start solving the easier subsystems first and use these as steppingstones progressively towards more intricated subsystems.

If we take the usual parameters values found in the literature, for example in [Poutineau] or [De Grauwe] or [Liu & Zhang], in Table 1 below, we find that Blanchard-Kahn's conditions are met: the characteristic equation is quadratic, its discriminant is strictly positive, both roots are real, one root is smaller than 1, the other is larger than 1. We have one predetermined variable and one un-predetermined variable.

β	0.97
ε	0.1666
κ	0.13
ϕ	0.125
ψ	0.50
ρ^K	0.85
σ^K	0.05

The characteristic equation is:

$$\text{Det}\,(\boldsymbol{P} - \lambda I_2) = 0 \quad => \quad \lambda^2 - s\lambda + p = 0 \qquad (6)$$

where s = Trace ($\boldsymbol{P}$) and p = Det ($\boldsymbol{P}$).

The above values of parameters give $\lambda_1 = 1.14612$ and $\lambda_2 = 0.92798$

Next, using Jordan decomposition in this favorable case with 2 real roots, we make the following variables change to variables noted with tildes:

$$\begin{pmatrix}\tilde{y}_t\\ \tilde{\pi}_t\end{pmatrix} = U^{-1}.\begin{pmatrix}y_t\\ \pi_t\end{pmatrix} \text{ with } \mathrm{U}^{-1} = \begin{pmatrix}1 & 1\\ -1.16343 & 1.30179\end{pmatrix}^{-1} = (\mathrm{u_{i,j}}) \quad (7)$$

Matrix $\boldsymbol{U}$ is such that $\boldsymbol{P} = \boldsymbol{U}.\begin{pmatrix}\lambda_1 & 0\\ 0 & \lambda_2\end{pmatrix}.\boldsymbol{U}^{-1}$ and can be calculated with several techniques (or ready-made software). In the 2-dimensional (or even 3-dimensional) case, it is interesting in a "white box" approach (both for the Trader-modeler and for students) to simply use Excel and minimize the norms of the 2 vectors $(P - \lambda_j.I).\begin{pmatrix}1\\ x\end{pmatrix}$ down to zero by changing x with the Solver.

With the values of u_{jk} given in equation (7) , we get :

$$\tilde{y}_t = u_{11}y_t + u_{12}\pi_t \quad (8)$$

$$\tilde{\pi}_t = u_{21}y_t + u_{22}\pi_t \quad (9)$$

With that change of variables, the system is now separated into 2 independent equations:

$$E_t\tilde{y}_{t+1} = \lambda_1\tilde{y}_t + W_{1,t} \quad (10)$$

$$E_t\tilde{\pi}_{t+1} = \lambda_2\tilde{\pi}_t + W_{2,t} \quad (11)$$

where the W_j are linear combinations of the autocorrelated perturbations on supply and demand, explicated below.

Since $\lambda_1 > 1$, we have all $\tilde{y}_t = 0 \ \forall t$, and equation (8) allows to substitute one non-tilde variables y_t for the other π_t . Hence, equation (11) can now be turned into a one-variable recursive stochastic equation and solved in π_t.

$$u_{21}E_ty_{t+1} + u_{22}E_t\pi_{t+1} = \lambda_2(u_{21}y_t + u_{22}\pi_t) + u_{21}\left(w_t^S - \frac{\varepsilon}{\beta}w_t^D\right) + \frac{u_{22}}{\beta}w_t^D \quad (12)$$

Using equation (8) and $\forall t,\ \tilde{y}_t = 0$ we finally get the 2 recursive equations describing the increments of movements of the state of the Economy in IS-LM phase space Income ⊗ Return, through output gaps and inflation gaps :

$$\begin{cases} E_t\pi_{t+1}(u_{22} - u_{21}\frac{u_{12}}{u_{11}}) = \lambda_2\pi_t(u_{22} - u_{21}\frac{u_{12}}{u_{11}}) + \frac{u_{21}}{u_{22}-u_{21}}w_t^S + \frac{1}{\beta}\frac{u_{22}-\varepsilon u_{21}}{u_{22}-u_{21}}w_t^D & (13)\\ E_ty_{t+1} = -\frac{u_{12}}{u_{11}}E_t\pi_{t+1} & (14)\end{cases}$$

If the perturbations are small enough, the suite of output gaps is increasing, and that of inflation gaps is decreasing on average. They are the sequence of *flows* affecting the *stock* variables Income and Inflation.

To see how they influence the way things evolve, we turn to an IS-LM classic economy in equilibrium at macroscopic level, then let these incremental (or marginal) flows affect the initial stock variables.

3.2.2 Macroscopic and static equilibrium equations in IS – LM context.

We use IS-LM as a basic consensual macroeconomic framework to model equilibrium states, but any other stock variables model providing a stable set of equilibrium points can be used instead to provide stock variables more relevant to the trader-modeler.

This minimalist version of IS-LM equations can be enriched with those describing international trade through Imports-Exports equations (Mundell-Fleming-Tinbergen); or with those that describe the banking sector's behavior (following Bernanke or Woodford or Groth). These latter equations, detailing the different credit rates (borrower or lender) or detailing the bank's optimized balance sheet *vis-à-vis* Reserves versus the Risk adjusted Profit & Loss of banks, or financial frictions, should be used advantageously in specific contexts when the modeler desires to highlight certain specific variables (on interest rate markets or real estate markets or securities markets etc.).

Let us model the economy of a fictitious country, characterized by the following set of equations. Y is the domestic income, r is rate of return of the economy.

Consumption $$C_t = \alpha_0 Y^{disp} + \alpha_1 \qquad (15)$$

Tax $$Y^{disp} = Y - Tax = Y(1-\tau) \qquad (16)$$

Investment supply $$I = I_0 \exp(-\delta r) \qquad (17)$$

Liquidity demand $$L = L_1 + L_2 = k_p Y + L_O \exp(-\eta r) \qquad (18)$$

Government spending $G = G_0$; Money supply $M_s = mm$

Government spending is supposed to be exogenous, as is the Monetary supply. Investment supply and speculative liquidity demand are represented by exponentials and not linear functions because of 2 advantages: this prevents negative values for some critical stock variables, and furthermore, helps modeling liquidity trap and decreasing attractiveness of savings as income decrease.

α_0	0.7
α_1	300
τ	0.19
I_O	1040
δ	9.0
G_0	800
mm	1000
k_p	0.33
L_0	600
η	9.5

As a result, we have the initial equilibrium point for the Economy at Y = 4485.71 and R = 2.34%.

3.2.3 Embedding recurrent evolutions to make transitions between equilibria

We implement the following algorithm.

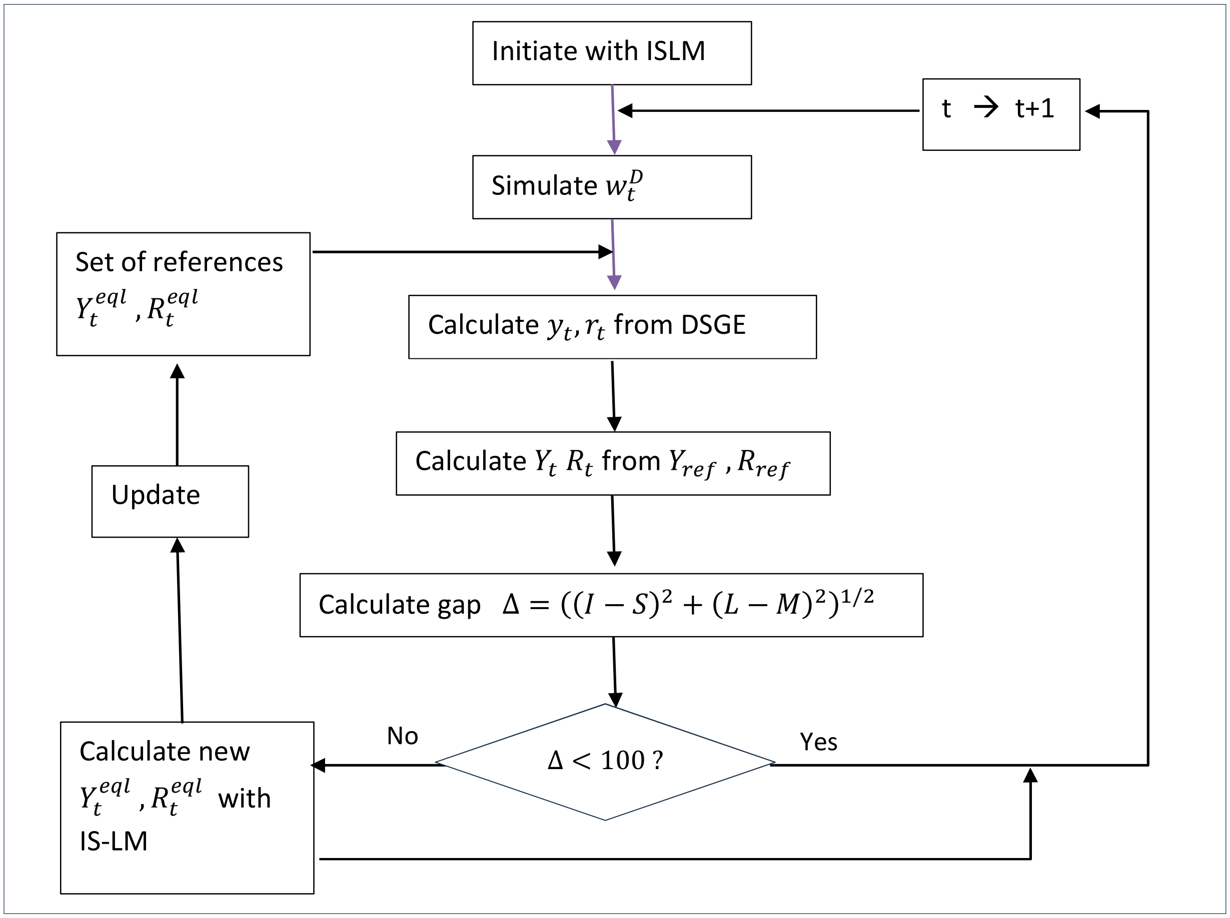


Figure 2. Structure of the software.

For the sake of clarity of illustration, we introduced only one set of perturbations, $\{w_t^D\}$

Calculations are carried out in Excel spreadsheet. For example, implement of Equation (5) is:

w_t^D = rho* w_{t-1}^D + (1-rho)*ampli*LOI.NORMALE.STANDARD.INVERSE.N(ALEA()) (19)

where *rho* and *ampli* are parameters.

4 Results

Just a few of the generated sample paths for Y_t, y_t, π_t and R_t will be presented and commented for the sake of illustration of the methodology. The practical work on trading floors consists in doing tens of thousands sample paths, aggregating at each time t the statistics on variable values into probabilities, and then choosing a path with the corresponding "dark horses betting" strategies.

4.1 Interpretation of sample paths

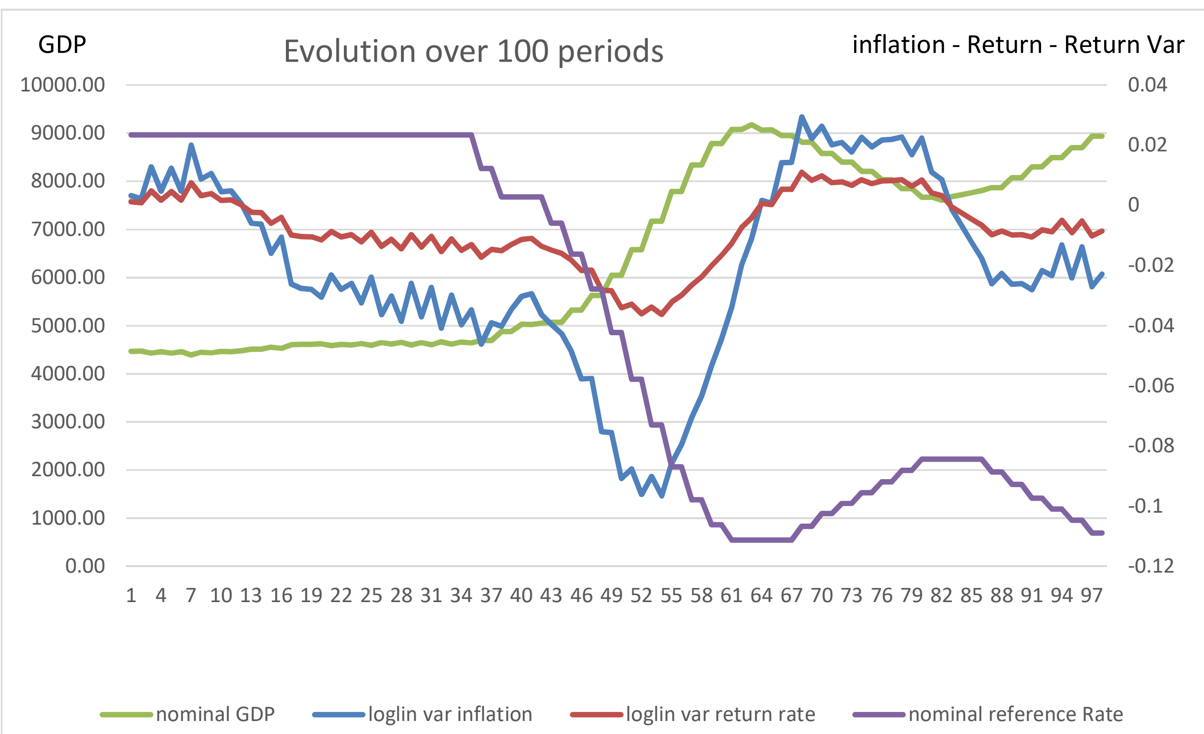
Each time we draw a series of 100 random, gaussian distributed, numbers, we generate a sequence of 100 points in time for the auto correlated perturbations $\{w_t^K\}$. This in turn create a path of 100 steps for trajectories of the log linearized variables $\{y_t\}$ and $\{\pi_t\}$. The nominal values of the IS-LM model are deduced from these "growth" increments, except when their growth diverge too much and do not follow an equilibrium path. At such point in time, an adjustment occurs, and the gap, calculated as the sum of the squared differences between supply and demand, on both the physical (IS) market and the financial market (LM) , is abruptly closed, aligning again the Economy on an equilibrium.

We thus obtain for each set of 100 sequential draws of perturbations, the trajectories for the log linearized inflation gap, the log linearized change in Return rate, the nominal income (GDP) and the nominal Return rate on investment.

In Excel, each press on the F9 button generates a new, different 100-steps scenario.

We have selected to comment on 3 scenarios represented by the following charts.

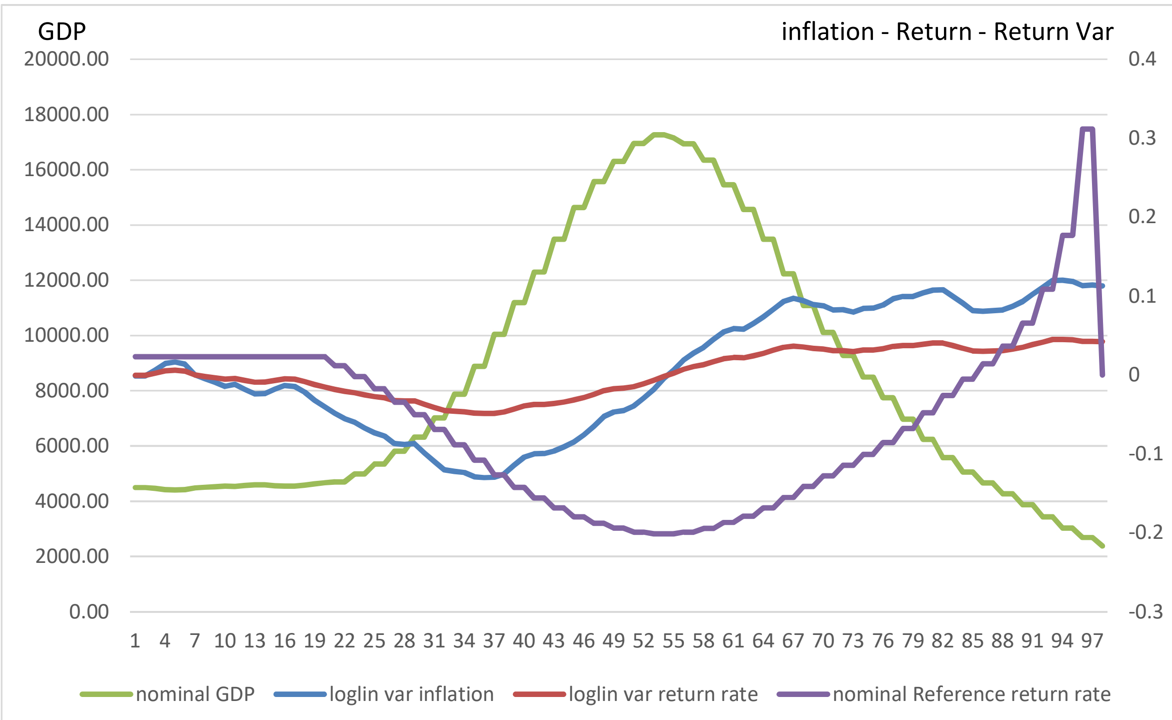
Figure 3. Moderate expansion thanks to falling interest rate.



In this scenario, we see nominal GDP (green) as well as other variables remain at a static level for almost half of the time, before growing hesitantly starting from the moment the nominal rate falls. Increments of inflation had burst upwards strongly when growth pick up.

From a crypto assets management perspective, falling interest rates and rising inflation are good motivations to protect cash by buying outside the circuit assets.

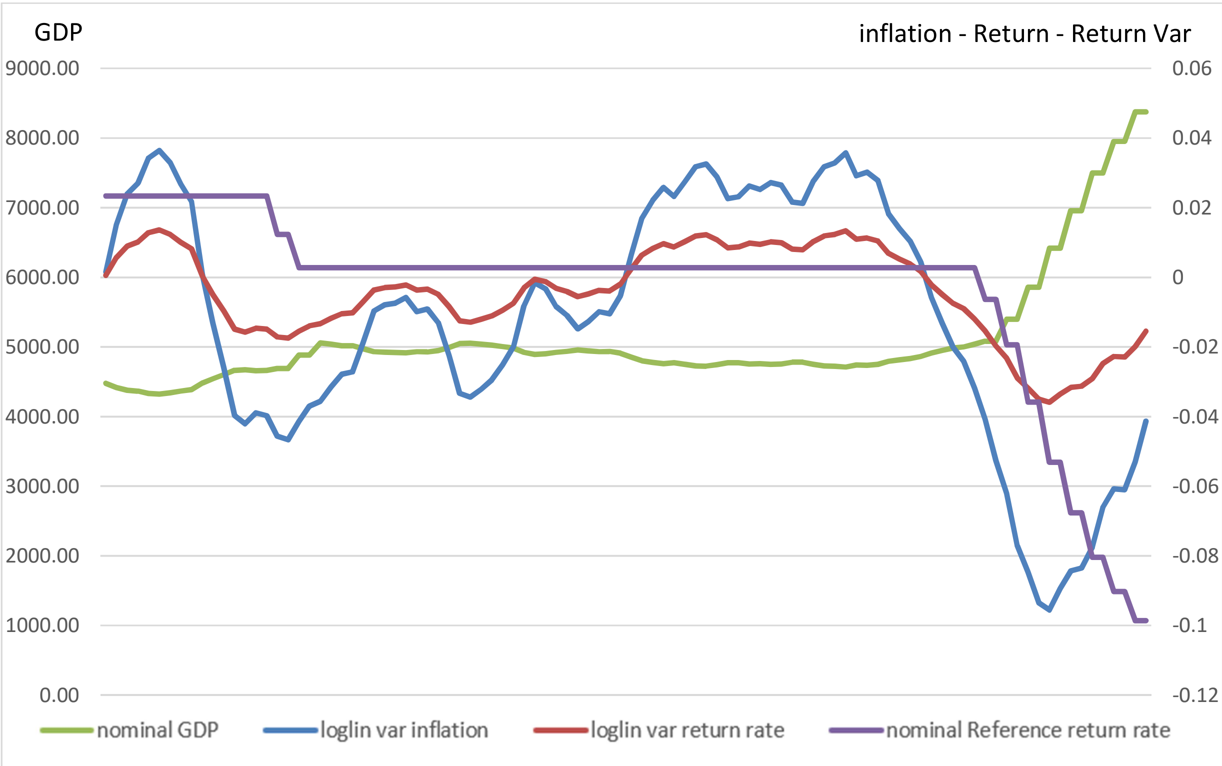
Figure 4. Impulsed growth falling back as Rate rises



In this scenario, nominal GDP has softly peaked then waned in the middle part of the whole period. Both inflation increments and return rate increments have stayed close to zero, so that the shallow trough in nominal Return rate did not prop up the growth in GDP for a long time.

From a crypto assets portfolio perspective, the situation does not strongly call for a decisive buy or sell action. The moderate rise in inflation increments has yet to be confirmed, so the push to buy crypto as a safe haven from inflation is not yet a strong case.

Figure 5. Stability with a start of growth at the end.



In this scenario, a long period of nominal Rate stability is observed, even though almost parallel increments of inflation and increments of return rate periodically fluctuate. Their actions did not touch the threshold of gap that triggers a re-alignment of equilibrium of IS-LM stock variables.

From a crypto assets portfolio management perspective, this is a case where not much could be done in the first 75% of the period. As increments of inflation finally fall, and almost immediately go back up again, time is too short to have a clear view of opportunities. Falling rates and soaring growth, both nominally, are classically "good" situations for business on the whole.

Concluding remarks and future works

It must be emphasized again, that though a few scenarios have been extracted and analyzed to show the meaningful, and insightful observations on economic short term evolutions this type of modelling brings, this is not the main objective.

As stated in the motivation section, crypto assets in hybrid portfolios are *Not* for people who aim at "*middle of the road driving*". The goal here is to seek and single out not-too-rare (but definitely not-average) circumstances that will allow hundred-fold or thousand-fold gains. Therefore, it is insufficient to analyze individual scenarios.

This is modelling for proprietary traders, trading floor and portfolio strategists, not for mainstream economists.

The correct approach to "bet on dark horses" is to do enormous quantities of simulations to generate statistics on the very rare occurrences. Implementing Monte Carlo and its more sophisticated variants to do automatic and large-scale tally of rare events is the next step which comes closer to the goal. This is somewhat reminiscent of the approach used in Basel III prescribe for Advanced Measurement Approach (AMA) of Operational Risks.

Nonetheless, as a didactic interest for students of macroeconomics, even in this first phase, we have demonstrated how to embed a New Keynesian DSGE at the core of an IS-LM neo keynesian equilibrium. This is a first step to create a comprehensive, dynamic methodology mapping both the stock and flow consistent variables and prove it much more advantageous and sharp over pointwise analyses in Portfolio management.

It is also much richer than just the Impulse Response Functions which are the only things, beside calibration, coming out from traditional DSGE studies.

Future work includes applying field theory concepts and path integrals for probability measurement and Monte Carlo simulations, enhancing the robustness of predictive models. This cannot be done in Excel, and it will be implemented in Python.

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Appendix : Excel formulae