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ADVANCING A HEBB-HAYEK FRAMEWORK TO ADDRESS ECONOMIC COMPLEXITY

An application to monetary policy

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“I am well aware that not all economists believe our subject is a science. I leave it to the philosophers of science to adjudicate which side has the stronger arguments today. But perhaps we can all agree to entertain the hypothesis that economists can strive to be scientific, and that someday the profession might develop to such an extent that it could reasonably be considered a science.”

Robert Axtell

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Introduction

Background

What mainstream economics lacks today, as many lament,[1] is an approach to solving its inherent complexity in order for us to trust our models more than we do now and turn it into science. This is evident in many fields, including monetary policy, where the current body of evidence lacks an important heterodox line, that is, to unpack complexity through truly reductionist approaches.

This thesis argues in favor of a temporary framework for modelling agents in the economy, with the goal of improving the degree to which economics can be scientific, and I use monetary policy as a ground in which to show how so.

I address the issue of complexity, with particular reference to the transmission of monetary policy, by developing a model guidance based on the Hebb-Hayek framework.

A Hebb-Hayek framework is a method of interpretation of the human brain that lets us model individuals in a different way than is done today by economists and that hence allows us to avoid more aggregation than is necessary. Its name comes from two contributors in the field of cognitive science, Donald O. Hebb and Friedrich A. von Hayek, who provided the theoretical baselines that allowed neuroscientists to develop a so-

1. As an example, the highly cited paper by J. Doyne Farmer and Duncan Foley "The economy needs agent-based modelling," *Nature* 460 (2009): 685-686, underscores the need for a different approach to economic analysis through agent-based simulations.

called "Hebb-Hayek framework", and as a consequence allowed me to theorize a modelling approach based on it.

This approach could help us give birth to a different methodology of macroeconomics, and hence a different view on policies, including monetary policies.

Given its main general goals, this thesis aims to:

1. Provide an overview of the mainstream evidence on macroeconomics, with a particular focus on monetary policy and its transmission;
2. Present current complexity economics as a generally appropriate approach;
3. Formulate an epistemological argument and a baseline framework in favor of some special cases of such approach;
4. Briefly review the shown mainstream and heterodox literature on monetary policy according to the previously established epistemology;
5. Propose a step-by-step, very general modelling pathway to be followed by future research, offering examples on how to treat entities such as money and the central bank.

Respectively, there are five chapters.

In the first chapter I present money, monetary policy and the current challenges in the field. Then, I list and briefly describe an array of the most popular models that we currently considers as staples both in research and policymaking.

In the second chapter I introduce the concept of complexity in the subject of economics, why it is crucial, and how we currently try to solve it, with a modest appendix on monetary policy.

In the third chapter I develop an argument for cognitivism, which is both a neuro-psychological theory and a guide on modelling. I then develop an argument for the Hebb-Hayek principles to be used as the best, new modellable basis for individuals in a social science setting. Finally, I explore on why simulational models are the current most appreciable tools to apply it.

The fourth chapter is then dedicated to a quick review of the mainstream and complexity economics literature in accordance with the arguments developed in the third chapter.

In the fifth chapter I formulate a broad-spectrum proposal that advances the implementation of the Hebb-Hayek principles through a cognitive architecture called Clarion and subsequently guides the reader through how to create a monetary model that utilizes it. A gist of the limitations of the model follows.

Chapter 1
Monetary Policy: an Overview

1.1 Monetary Policy: Questions and Challenges

Along the history of economic thought monetary bodies like the money supply or interest rates have been argued to be connected to variables such as price levels[2] or economic growth.[3] As a consequence, it did not take long before monetary policy became a consistent instrument of governments and supra-national institutions. The most straightforward examples are central banks, many of which employ interest rates as operational to other economic variables.[4]

Central banks are financial institutions that are responsible for overseeing and regulating the monetary policy of a country or region. They

2. Milton Friedman and Anna J. Schwartz, *A Monetary History of the United States, 1867-1960* (Princeton: Princeton University Press, 1963) used U.S. evidence to argue that the money supply is strongly correlated with price levels because increases in money supply meant more money available to purchase goods and services, thus increasing demand and driving prices up. Similarly, a decrease in money supply reduces the amount of money available to purchase goods and services, thus decreasing demand and driving prices down.

3. James Tobin, "Money and Economic Growth," *Econometrica* 33, no. 4 (1965): 671-684. Eminent economists such as Tobin and Keynes (J.M. Keynes 1936) argued for the recognition of money as a direct and indirect influence on output and suggested policy proposals based on the finding that money supply was positively proportional to investment.

4. John B. Taylor, *Monetary Policy Rules* (Chicago: University of Chicago Press, 2007), 319 – 348.

have control over the money supply, can influence interest rates, and are responsible for issuing currency, managing foreign exchange reserves, and supervising the commercial banking system. But what do they actually do with respect to monetary policy?

Questions and Challenges

Monetary policy is one of the most challenging areas of economics, and many questions still remain unanswered. Monetary policy encompasses almost all corners of the economic science. It is of course a macroeconomic phenomenon in and of itself, as its focal point lays in its transmission to the economy, and hence in asking how the variation of an indicator propagates in the sectors of an economic system, but it can also involve the micro side of economic analysis,[5] by including in the assessment microeconomic findings regarding the single agents' behavior.

What are, then, the big questions of monetary policy?

The first and fundamental question that is about its transmission: what are the factors, the sectors and the channels through which the actions of policymakers pass through the economy and affect the set objectives? Which is the direction that they take?

As it turns out by a brief look at the evidence, this fundamental question is at the same time the most widely answered and the most debated

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5. Norberto Montani Martins et al., "The transmission mechanism of monetary policy: Microeconomic aspects of macroeconomic issues," *Journal of Post Keynesian Economics* 40, no. 3 (2017): 300-326. This article is an example of how the push towards micro-foundation of macroeconomics can be detected even inside anti-individualist, post-Keynesian circles. In the article the authors argue for a micro-macro integrated approach to analyzing the transmission mechanism of monetary policy in order to account for heterogeneity in policy responses across sectors and present a critique of New Consensus Macroeconomics (NCM) models with respect to their effectiveness in influencing prices and inflation. Furthermore, it suggests that alternative income policies and price regulation, taxation, qualitative restrictions, and antitrust policies should be used to address the microeconomic issues involved in determining inflation.

one. The explanation proposals are miscellaneous, with each one offering a different and complex causal chain and a subsequent policy suggestion.[6]

This question, of course, also touches on the effectiveness of such pass-through: poor policy implementation and market "imperfections" are usually thought to hamper how smoothly the interest rate passes through the economy. There also may be asymmetries affecting interest rate changes: they may have different effects on different economic sectors, depending on their varying levels of financial inclusion and market access.[7]

A second question concerns speed and time lags: assuming a given macroeconomic chain is true, how fast does the interest rate reach the end of the chain?[8] If I change the MRO rate from one percent to two percent, when will I see the economy's response?

A third question interrogates the researcher with the universalizability of the results that they obtain. If institutions, consumer and producer habits, and all factors that could differ across populations and regions vary, would the effects be the same? And if the effects are not negligible,

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6. Frederic S. Mishkin, "The Channels of Monetary Transmission: Lessons for Monetary Policy," *National Bureau of Economic Research* working paper no. 5464, (1996).

7. Iris Claus and Arthur Grimes, "Asymmetric Information, Financial Intermediation and the Monetary Transmission Mechanism: A Critical Review," *New Zealand Treasury*, working paper no. 03/19 (2003) reviews transmission models used by policymakers and argues that modelling transmission assuming perfect information in financial markets through the Modigliani-Miller theorem is a vastly limiting presumption.

8. The first academically successful inquiry was posed by Milton Friedman in "The Lag in Effect of Monetary Policy," *Journal of Political Economy* 69, no. 5 (1961): 447-466, but there happens to be consistent empirical evidence on the existence of time delays in monetary policy: a recent meta-analysis by Tomas Havranek and Marek Rusnak, "Transmission Lags of Monetary Policy: A Meta-Analysis," *International Journal of Central Banking* 9, no. 4 (2013) found an average time lag of 29 months after enactment.

how much complexity will the appropriate model have to incorporate for it to be sufficiently predictive?

These questions accompany the formulation of the theories necessary to explain interest rate transmission. Those are the most overpowering ones, because a failure in answering even one of them is very likely to imply that we are dealing with an incomplete expression of the issue we want to describe. At the same time, they are almost impossible to solve with absolute accuracy.

There are many more questions that researchers and policymakers are charged with examining,[9] but they are beyond the objective of this thesis, which aims instead at advancing a nascent approach in computational economics. Nonetheless, there is an important missing piece to the puzzle. A piece that represents the criteria upon which a model is to be deemed valid or invalid, regardless of the issue that it embarks on or that it ignores. That is, the methodology via which the model is constructed. What are the current models of monetary policy – and consequently of macroeconomics –, what is the methodology that lies behind them?

1.2 Monetary Policy and the ECB

Let us take the European Central Bank as an example. The ECB, but virtually all western central banks, have a monetary policy design: the bank will achieve its *goals* by implementing certain *instruments* according to a determined *strategy*.

9. For example, another common challenge faced in interest rate transmission is the one of inflation, which often constitutes on of the main objectives of monetary policy. In this sense, monetary policy must aim at a condition in which "price levels sufficiently stable so that expectations of change do not become major factors in key economic decisions" (Alan Greenspan, 1989): estimating such levels and the expectations' impact constitutes a hard challenge for the policymakers. One further drawback may come from downward nominal rigidities, especially sticky wages, as they have been studied to affect the optimal inflation rate (George Akerlof, 1996) and have thus been a grip for condemning zero-percent inflation targeting.

Goals are usually defined in terms of macroeconomic welfare indicators like growth and stabilization. For the ECB, the bigger, long-run *goal* is price stability – to keep the inflation rate low. The inflation rate is set to be kept at two percent, because a deflationary shock is thought to potentially hamper the economy worse than a steady, small price level yearly increase.

To achieve so, the ECB performs three incentive-regulating measures in the interbank market, utilizing the interest rate as an *operational goal*, that is, a target variable that serves as a representation of the actual target (i.e., inflation):

1. It sets an interest rate at which banks can deposit their money in the central bank;[10]
2. It sets the interest rate at which banks can ask to borrow money from the central bank through overnight loans (money to be repaid with interest in one day);[11]
3. It sets the interest rate at which banks can ask to borrow money from the central bank through longer payment time loans, such as Main Refinancing Operations (MROs), which consists in a one-week maturity.[12]

The first two actions are called "standing facilities": the deposit facility and the marginal lending facility. They set the boundaries for the interest rate that banks set when trading with each other, the interbank rate. The deposit interest rate is lower than the marginal lending interest rate, and the MROs is usually in the middle. These interest rates are called "key" interest rates because they are the main policy instrument of the ECB: when the policymakers wish to stimulate the economy, contract it, or to

10. "What is the deposit facility rate?," *ECB*, 2022. https://www.ecb.europa.eu//educational/explainers/tell-me/html/what-is-the-deposit-facility-rate.en.html.

11. "What is the marginal lending facility rate?," *ECB*, 2018. https://www.ecb.europa.eu/ecb/educational/explainers/tell-me/html/marginal_lending_facility_rate.en.html.

12. "What is the main refinancing operations rate?," *ECB*, 2018. https://www.ecb.europa.eu/ecb/educational/explainers/tell-me/html/mro.en.html

reach a targeted inflation level, the interest rates are the first item that they refer to in their list. There are many other instruments that central banks use, such as asset purchase programs, but they constitute a less important instrument and are used in more special cases instead of being an ordinary tool.

The same applies to the Federal Reserve,[13] the Bank of England,[14] and many other central banks around the world that have different names but similar features.

The rationale works as follows: if a bank wants to borrow money from another bank it will never pay more than it would pay when borrowing from the central bank because it would lose money, and the same applies to the deposits. This means that the interbank rate will probably not exceed the corridor set by the central bank, and the central bank will be able to control it with a certain margin of accuracy.

From a purely empirical perspective this approach somewhat respected its intentions. In Europe, estimates of the interbank rate (e.g., EONIA, or the Euro Overnight Index Average)[15] rarely outstripped the corridor.[16]

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13. "Open Market Operations," *Board of Governors of the Federal Reserve System*, 2023; "The Discount Window and Discount Rate," *Board of Governors of the Federal Reserve System*, 2023. https://www.federalreserve.gov/monetarypolicy/openmarket.htm, https://www.federalreserve.gov/monetarypolicy/discountrate.htm

14. "Bank of England Market Operations Guide: Our tools," *Bank of England*, 2023. https://www.bankofengland.co.uk/markets/bank-of-england-market-operations-guide/our-tools

15. ECB – Statistics. It should be noted that EONIA was discontinued as a benchmark in January 2022 because it was deemed to be no longer representative of the underlying overnight lending market. The European Central Bank (ECB) and the European System of Central Banks (ESCB) determined that €STR better reflected the cost of unsecured overnight borrowing in the euro area. €STR also provides a more reliable reference rate for financial transactions, as it is based on actual transactions in the interbank market and is more transparent than EONIA.

16. ECB – Statistics. The interbank rate did not always stay within the ECB corridor. The ECB corridor is solely a range of interest rates that the European Central Bank (ECB) uses to influence the euro-area money market: the interbank rate may

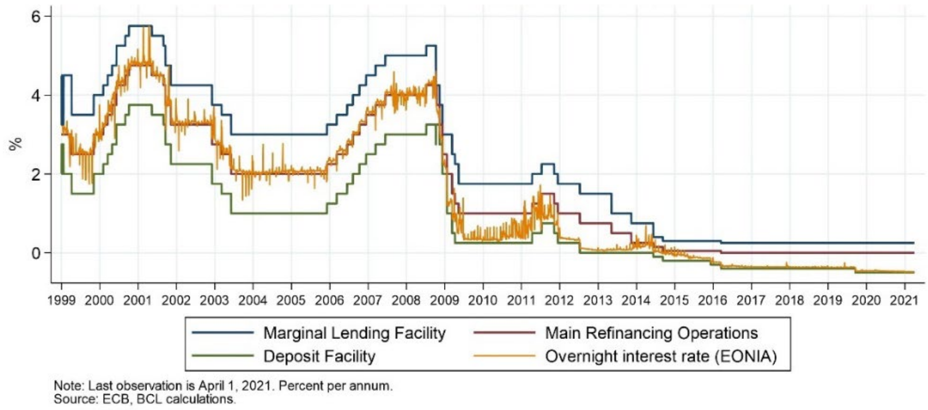

Figure 1.1.1: ECB Policy rates and EONIA overnight market rate.

The *strategy* of monetary policy is instead the modelling that the bank uses to understand how their instruments and their operational targets tie to the final goal. This both involves a model of the mechanism that explains how the instruments pass through the economy to influence the final goal and a macroeconomic model that serves as a quantitative updater of the operational goal based on new information. The strategy of a central bank includes communication too, because the information that agents get from the central bank about its plans shape their expectations and in turn the central bank's approach.

Whether the central bank is aiming to stimulate or contract the economy (or to stay neutral) based on how it mutates its instruments is called the monetary policy *stance*.

It is now evident how much modelling is involved in this process. It should also be evident that, being that the variables that the central bank must take into consideration when planning its monetary policies are

outstrip this range due to market forces such as changes in demand for funds, liquidity levels, and other economic factors. EONIA has breached the ECB corridor in the past. In May of 2020, EONIA was at -0.42%, which is below the corridor floor of -0.40%. In June of 2020, EONIA was at 0.09%, which is above the corridor ceiling of 0.00%. It bears mentioning that both breaches happened during a crisis and a new monetary policy experiment (PEPP), and at a quantitative level both entailed excesses of negligible scale.

several, the modelling process is not just monetary by itself, it is macreconomic.

1.3 Modelling Monetary Policy: Some Relevant Examples

Modelling in macroeconomics can be both theoretical and empirical. By theoretical I mean establishing relationships between economic variables based on assumptions, logical paths and modelling (be it more or less mathematical). For example, one may posit that low interest rates cause higher investment in a given economy not because one has observed so empirically, but because given that it makes borrowing money cheaper, they assume that people will then invest more (more common in early economic science). Empirical evidence, on the other hand, is the array of shared statistical methods that are used in many fields but applied to the analysis of economic phenomena (more common now).

The vast majority of mainstream macroeconomics uses empirical evidence as the very basis: it is used to derive theoretical economic relationships[17] in order to develop a unified model that puts them all together, and it is used to verify the descriptive and prescriptive power of such model through econometric analysis.

Empirical evidence has indeed been a staple of monetary policy research basically since its birth, and while there have been some exclusively theoretical models alive before the use of statistics, they have been either quickly replaced by it or augmented with it. Some other theoretical models which became very popular in the field of monetary policy, instead, such as the IS-LM model,[18] kept the possibility of being empirical (through the swap of their structural variables with real world data) since

17. For example, if a "mainstream" researcher observes in the data that capital and labor are used interchangeably, then would probably build a model in which capital and labor exhibit some sort of mathematical relationship of substitution.

18. John R. Hicks, "Mr. Keynes and the "Classics"; A Suggested Interpretation," *Econometrica* 5, no. 2 (1937): 147-159.

their development, but were not really meant to be, and have since been considered either as thought experiments for the training of economists or as general “guidelines” for macroeconomics.

Up next, a summary of the taxonomy of today’s mainstream literature on monetary policy. The literature can be divided into two broad categories: reduced-form evidence and structural models. The difference is very simple: the first explains how variables link by advanced statistical analyses alone while the latter establish theoretical relationships between the variables before applying statistical analysis.

Reduced-Form Evidence

As I said, reduced-form evidence is evidence that arises from the empirical relationship that a certain econometric method establishes between the input variable and the output variable, without a thorough theoretical structure in between. For example, an inference from the correlation between the money supply and the GDP alone would count as reduced-form evidence (and a primitive form at that, of course). In its most basic forms, i.e., as linear regressions, correlations et cetera, it remains the most elementary form of evidence, but there are more advanced methods which make it more valuable.

In our case – monetary policy – reduced-form evidence means the econometric relationship between the change in the key interest rates (input) and the change in economic and monetary factors such as the money supply, GDP inflation and so on (output).

Today, especially after the Lucas critique[19] and Christopher Sims’ contributions to the popularization of econometrics in the field of macroeconomics,[20] we notice a spike in the use of this kind of advanced statistics.

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19. Robert E. Lucas Jr, “Econometric policy evaluation: A critique,” *Carnegie-Rochester Conference Series on Public Policy* 1, no. 1 (1976): 19-46.

20. Christopher A. Sims, “Macroeconomics and Reality,” *Econometrica* 48, no. 1 (1980): 1-48.

Vector Autoregression Models

The most widespread category of advanced statistical tools that we use are Vector Autoregression (VAR) models.

We use VARs to capture the linear interdependencies among multiple time series. VAR models generalize the univariate autoregressive model (AR model) by allowing for more than one evolving variable, meaning that we can analyze the non-structural relationships among many different economic variables and "extend" our threshold of analysis for reduced-form evidence. All such variables in a VAR model are treated symmetrically, and each variable has an equation explaining its evolution based on its own lags and the lags of all other variables in the model.

In more formal terms, a VAR model describes a system of *n* variables (often endogenous variables, meaning that they can influence one another) and its evolution over the same set of time periods. The model describes each variable as a linear function of past lags of itself and of the past lags of the other variables.

In mathematical notation, a simple VAR model of order p, denoted VAR(p), can be written as:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + u_t$$

Where:

- Y_t is a k-vector of endogenous variables;
- A_i is a matrix of coefficients for the i-th lag (i = 1, ..., p);
- u_t is a k-vector of error terms, which is assumed to follow an uncorrelated distribution.[21]

Let us take monetary policy as an example. Assume there is a shock in monetary policy (e.g., a sudden change in interest rates) and we want to use a VAR model to see its effects on output and inflation.

21. Ibid.

We would then consider a three-variable (interest rate,[22] output and inflation) VAR model. This "shock" to the system obtained by the sharp change in interest rates by the central bank can be modelled as an error term u_t in the VAR. By running the model, we can trace the effects of this shock on inflation and output.

The VAR model will generate "impulse response functions" that show the reaction of all variables in the system to the shock. In this example, an increase in interest rates might initially reduce output and only affect inflation with a lag: the VAR model will show this response over time.

As it is evident, VAR models only consider "what we see" as evidence, and not really any background structure, which is instead a feature of structural models.[23]

Structural Models

Structural evidence is the evidence that also stems from empirical relationships between the input and the output variable but focuses on establishing it according to a structural basis that edifies an arithmetic relationship between the variables that the (change in) input influences and how they affect the (change in) output.

For example, one common web of reasoning is that a central bank's artificial injection of credit in the economy, which increases the money supply, negatively influences the interest rates, which influence positively the overall investment of the economy, which in turn increases GDP. As we see, it is not a statistical analysis between money supply and GDP; it is instead a combination of the factors that compound and "pass-through", from the input to the output. This "pass-through" is called transmission and – according to each model – can happen through many unique channels.

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22. Interest rates are set by the central bank and are hence given.

23. Lutz Kilian and Helmut Lütkepohl, *Structural Vector Autoregressive Analysis* (Cambridge University Press, 2017).

Indeed, on the theoretical side of macroeconomics, one of the main approaches to monetary policy transmission is to use DSGE (Dynamic Stochastic General Equilibrium models) models.

DSGE Models

The main structural model evidence, as of today, consists indeed of DSGE models.[24] DSGE models are an array of macro-econometric models that have adaptive characteristics with respect to time and that allow internal changes. DSGEs often engage (to some extent) in micro-foundation and hold general equilibrium principles in their assumptions. The acronym is there for a reason, because DSGEs are:

- Dynamic, as in they study how economic variables evolve over time (and include shocks);
- Stochastic, as in they incorporate randomness, reflecting uncertainty in economic decision-making;
- General Equilibrium, because they model the entire economy, considering all markets simultaneously and assuming that markets clear (demand equals supply) either in every period or in the long run.[25]

DSGEs are used both as general guidelines for explaining macro phenomena and as precise forecasting/policymaking methods. They come in very different shapes and sizes, but for the ends of this thesis this is not a concern, as the goal of the analysis is purely methodological.

DSGE models pretty much defined this era of macroeconomics (or at least the until the Great Recession), and they do provide many new advancements on monetary policy with respect to the traditional models,

24. In this chapter I only consider as DSGEs the DSGE models that include monetary policy, for obvious reasons. The most obvious exclusions are the Real Business Cycle (RCB) models that do not include money and financial frictions. The most obvious inclusion is Romer's inflation adjusted IS-MP model.

25. Barbara Annicchiarico, "Microfoundations of DSGE Models: I Lecture," *BBLM del Dipartimento del Tesoro* (2010).

that is, especially the most advanced ones, they include shocks, financial frictions and lags, economic growth, business cycles and/or many other variables.

Let us take monetary policy as an example again. A very famous early DSGE model is the IS-MP[26] model, which is very fitting in the case of macroeconomic policies like monetary policy. The model is composed by the below three fundamental equations.

1. **The Investment-Savings (IS) curve**: an output equilibrium equation which indicates that the level of output (y) depends on the gap between the natural level of output (y_N) and its responsiveness (φ_y) to the real interest rate gap (i_t - π_t - r^*), plus a random demand shock ($\varepsilon_{y,t}$).

$$y = y_N - \varphi_y\ (i_t - \pi_t - r^*) + \varepsilon_{y,t} \text{ with } \varphi_y > 0$$

where:

- **y**: the level of output (real output) at a point in time;
- **y_N**: the natural level of output (or potential output), a level of gdp attained when the economy is at full employment;
- **φ_y**: a positive parameter that determines the responsiveness of output to the interest rate gap;
- **i_t**: nominal interest rate at a point in time;
- **π_t**: inflation rate at a point in time;
- **r^***: the natural real rate of interest, which is the interest rate that would exist in an economy if it were at full employment;
- **$\varepsilon_{y,t}$**: a stochastic error term in the is equation, represents shocks to the demand for goods and services.

2. **Monetary Policy (MP) curve**: a monetary policy rule that illustrates the determination of the nominal interest rate (i_t) by the

26. David Romer, "Keynesian Macroeconomics without the LM Curve," *Journal of Economic Perspectives* 14, no. 2 (2000): 149-169.

central bank based on its target nominal interest rate (i^*) and its responsiveness (φ_π) to the inflation gap (π_t - π^*).

$$i_t = i^* + \varphi_\pi (\pi_t - \pi^*) \quad \text{with} \quad \varphi_\pi > 1$$

where:

- **i_t**: nominal interest rate at a point in time (same as in the is equation);
- **i^***: the target nominal interest rate set by the central bank;
- **φ_π**: a parameter that determines the nominal interest rate's responsiveness to the inflation rate;
- **π_t**: inflation rate at a point in time (same as in the is equation);
- **π^***: the target inflation rate, set by the central bank.

3. **Inflation Adjustment (IA) curve**: a dynamic inflation (π_{t+1}) curve based on the current inflation rate (π_t), its responsiveness (φ_P) to the output gap (y_t - y_N), and a random inflation shock ($\varepsilon_{\pi,t}$).

$$\pi_{t+1} = \pi_t + \varphi_P(y_t - y_N) + \varepsilon_{\pi,t} \quad \text{with} \quad \varphi_P > 0$$

where:

- **π_{t+1}**: inflation rate at the next period;
- **π_t**: inflation rate at a point in time (same as in the is and mp equations);
- **φ_P**: a positive parameter that determines the responsiveness of inflation to the output gap;
- **y_t**: the level of output (real output) at a point in time;
- **y_N**: the natural level of output (or potential output) at a point in time (same as in the is equation);
- **$\varepsilon_{\pi,t}$**: a stochastic error term in the inflation equation, represents shocks to the inflation rate.

To see this model at work, let us consider an economy, for example, hit by a negative demand shock due to a sudden drop in consumer confidence, leading to decreased consumer spending. Monetary policy in the IS-MP-IA model would respond as below:

1. Demand shock hits (IS): due to the sudden drop in consumer confidence, consumer spending falls. this decreases aggregate demand in the economy, shifting the IS curve to the left. as a result, real output decreases.

2. Output falls below potential (MP): the fall in real output means the economy is now producing below its potential level. on the MP curve, the economy moves to a point corresponding to a lower level of output.

3. Inflation decreases (IA): with output falling below potential, there's less pressure on prices, and inflation starts to decrease. This is represented by a downward shift in the IA curve.

4. Central bank lowers interest rate (MP): in response to the fall in output and inflation, the central bank decides to lower the policy interest rate. This is an example of countercyclical monetary policy, which aims to boost the economy during downturns. On the MP curve, the economy moves to a lower interest rate.

5. Aggregate demand increases (IS): the lower interest rate makes borrowing cheaper for businesses and households, stimulating investment and consumer spending. This increases aggregate demand, shifting the IS curve to the right.

6. Output recovers (MP & IA): with the increase in aggregate demand, firms produce more to meet the higher demand, and the output starts to recover, moving back towards the potential level. This leads to a rightward movement along the MP curve and could potentially lead to a rise in inflation, moving the IA curve upwards.

This example illustrates how monetary policy should be used to stabilize the economy in response to shocks according to the IS-MP-IA framework. The exact outcomes would depend on a variety of factors, including the size and duration of the shock, the speed and magnitude of the policy response, and the responsiveness of households and businesses to changes in interest rates. Still, as a general rule, the aforementioned steps apply.

Now, as I mentioned just a couple paragraphs ago, DSGE models are a blend of theory and empiricism. There are indeed other firmly theoretical ways of describing monetary policy and how it passes through the economy. The most assessed among economists are enunciated in a paper by Frederic Mishkin,[27] which explains many "channels" through which various monetary policies transmit to the economy: to provide a snapshot of this kind of evidence, some examples are displayed below.

1. **Interest Rate Channel:** the primary monetary transmission channel. As policy rates change, so do interest rates for consumers and businesses, affecting borrowing costs and investment, consequently impacting overall economic activity. This channel is the most classical and derives from Keynesian trends, in particular from the IS-LM model.[28]
    - M ↑ => i ↓ => I ↑ => Y ↑
    - An expansionary monetary policy M ↑ leads to a decrease in nominal interest rates i ↓, which are negatively correlated with investment in the economy, meaning that they will stimulate it I ↑ and, of course, increase the output Y ↑.

2. **Exchange Rate Channel:** changes in domestic interest rates affect exchange rates. Higher interest rates tend to strengthen the domestic currency, reducing exports and increasing imports, affecting aggregate demand.
    - M ↑ => i ↓ => E ↓ => NX ↑ => Y ↑

27. Frederic S. Mishkin, "The Channels of Monetary Transmission: Lessons for Monetary Policy," National Bureau of Economic Research working paper no. 5464, (1996).

28. John R. Hicks, "Mr. Keynes and the "Classics"; A Suggested Interpretation," *Econometrica* 5, no. 2 (1937): 147-159.

- Here, the expansionary monetary policy's low rates are thought to influence exchange rates directly, hence affecting the current account of a nation, which is part of the GDP accounting equation.

3. **Credit Channels:** changes in monetary policy can influence the credit availability in an economy. Lower interest rates might encourage more lending, impacting consumption and investment. For example, consider the bank lending channel:
   - M ↑ => bank deposits ↑ => bank loans ↑ => I ↑ => Y ↑
   - An expansion in credit availability will increase the deposits of the banks in an economy, which will drive them to lend more, hence stimulate firms to invest more and in turn increase output.

Many more channels are mentioned in the cited paper, but use this as a pattern to understand what is meant by purely "theoretical" models.

Now, at first, these models may seem to be very complex, and they for sure are. But they are complex in the sense that they use very complex tools of mathematics and very complex economic relationships to establish a linear prototype of an economy. They are not, however, complex in the sense that they treat the economy as a complex system, because, while their tools are very intricate, the generalizations they commit while analyzing the economy are all but complex in a scientific sense.

Indeed, the "economics of complexity", or "complexity economics", is a relatively recent field of science which tries to offer new methods of description of the system in which we live, very different with respect to reduced-form evidence or structural models.

Chapter 2
Complexity and Economics

2.1 What Is Complexity?

Economics studies intricate and adaptive systems where multiple elements interact simultaneously and in which changes in any one component can have an impact on the whole system, the structure of which is quite unpredictable just by looking at the components.

Complexity, in social science, refers to the study of phenomena that emerge from a collection of interacting objects. It is a framework or perspective that views social systems as complex adaptive systems, characterized by elements that are not only diverse and multiple but also interdependent and interconnected. The Santa Fe Institute, a pioneer center on the matter, provides a colorful description:

"There are, however, on this planet, phenomena that we study as complex systems: the convoluted exhibitions of the adaptive world – from cells to societies. Examples of these complex systems include cities, economies, civilizations, the nervous system, the Internet, and ecosystems. Paradoxically, the complex world is one that we can, in many senses, perceive and measure directly. Unlike distant stars or nearby minerals that require a significant increase in optical capability to arrive at insights into their elementary properties, behavior – both individual and collective – seems to present itself in ways that can be investigated rather modestly through observation or experiment. But the way in which complex phenomena are hidden, beyond masking by space and time, is through nonlinearity, randomness, collective dynamics, hierarchy, and emergence – a deck of attributes that have proved ill-suited to our intuitive and augmented abilities to grasp and to comprehend."[29]

The object of study of economics is indeed a complex system as defined in many other sciences and needs to be approached as such, because individuals act dynamically, simultaneously, and adaptively, very often with unexpected outcomes, outcomes that present differently from the mere deterministic sum of their elements.

But the individuals themselves – as organisms – are complex systems of many interacting elements too, as are their brains with respect to the neurons. It is then arguable that the most important complex sub-system that economics has to disentangle, second only its own subjects of analysis, i.e., social emergences such as markets or firms and the entire economy, is indeed the human brain. Of course, to do so, it must absorb other pieces of established science from different fields, like psychology, neuroscience, artificial intelligence, and so on.

With regard to the academia, it is undeniable that there is a growing consensus that traditional economic models have strong limitations in grappling with the complexity and dynamism of real-world economic systems: mainstream economic theories often rely on assumptions of rationality, equilibrium, and linearity, but these assumptions can be overly simplistic, while people do not always behave rationally, economies are rarely in equilibrium, economic phenomena are often nonlinear and discontinuous, and so on.[30]

To capture the complexity and dynamism of economic systems, we need to move beyond such assumptions. For instance, we could incorporate insights from miscellaneous branches of psychology, or we could draw upon the insights of evolutionary economics, which sees the

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29. "What is complex systems science?," *Santa Fe Institute*. www.santafe.edu.

30. J. Doyne Farmer and Duncan Foley "The economy needs agent-based modelling," *Nature* 460 (2009): 685-686.

economy as a continually evolving system shaped by processes of variation, selection, and replication.[31]

But most of all, complexity economics departs from the equilibrium-centric view of classical economics and instead sees the economy as a network of interacting agents that constantly adapt to each other's behavior.[32]

2.2 How We Try to Solve Complexity

The complexity approach was born in the fields of physics and mathematics and its integration with economics is relatively new. Nonetheless, there is some recent research to refer to when trying to connect the two.

Network Models

Network models are frameworks that depict relationships between multiple entities. They are particularly useful for representing complex systems where the interactions between components are as important as the components themselves. In a network model, the components of the system are represented as *nodes*, and the interactions between them are represented as *edges* or *links*.[33]

Network models can be used in many different fields, from computer science (where they represent connections between servers or websites) to biology (where they can represent interactions between species in an

31. Richard R. Nelson and Sidney G. Winter, *An Evolutionary Theory of Economic Change* (Harvard University Press, 1982).

32. W. Brian Arthur "Complexity Economics: A Different Framework for Economic Thought," *Santa Fe Institute* working paper 2013-04-012.

33. Albert-László Barabási and Márton Pósfai, *Network Science* (Cambridge University Press, 2016).

ecosystem or proteins in a cell). In economics, an example of a network model can be a Financial Network Model.[34]

This model is used to represent the interconnections within the financial system, where nodes can represent individual financial institutions (like banks or investment firms), and edges can represent financial relationships (like loans or investment links). The scope of the model includes analyzing systemic risk, contagion effects, and the impact of the failure of a single institution on the entire system.

Regarding monetary policy, network models can be very useful, especially in the case of monetary policy transmission, in which the connections of the agents are key and, most of all, are non-linear. The impact of a change at one node can propagate through the network in a non-linear fashion, meaning that small changes can have disproportionately large impacts. For instance, if a bank fails, it does not just affect that bank's direct lenders and borrowers; the impact can spread through the network, affecting institutions that had no direct connection with the failing bank. This leads to a complex cascade of effects that are really no match for the traditional causal chains of linear macroeconomic models.

Furthermore, network models allow for the inclusion of feedback loops: for example, a change in interest rates could affect the default rates of borrowers, which in turn influences the risk perception of banks, which could then affect lending rates, and so on. The emergent phenomena that "grow" from these loops are exclusive to complex modelling, because the traditional structural model causal chains (variable "x" influences variable "y", which influences variable "z", which in turn influences variable "x") only tell us that the connections between the looping variables exist but cannot quantify them nor derive emergent properties from them.

34. Fabio Caccioli et al., "Network models of financial systemic risk: a review," *Journal of Computational Social Science* 1, no. 1 (2018): 81-114.

Agent-Based Models

In the subject of economic simulations, agent-based models (ABMs) are computational models that simulate the actions and interactions of autonomous entities or "agents" in a network to analyze their effects on the whole system, with each agent displaying given characteristics and following specific rules.

ABMs are capable of representing a heterogeneous population and variegated interactions among individuals, making them suitable for studying complex adaptive systems. They allow for the inclusion of more realistic features of decision-making behavior than conventional models, which often assume homogeneity and rationality (which is bounded in the case of ABMs). In economics, they can incorporate evolving behaviors and rules that individuals follow in a market or in their spending trends, and can incorporate interaction effects among agents, which are often omitted in traditional economic models.

ABMs are stochastic, meaning that they display random probability patterns – this is because the "emergent" outcomes from the interactions of agents are infinite –, and are often iterated many times under different initial conditions to explore the range of possible outcomes. The kind of evidence that they produce is in terms of emergent patterns, i.e., system-level patterns that arise from interactions among individual-level behaviors, that are descriptive of a real-world correspondence, according to the specific ABM we are considering.

In the agent-based macroeconomic literature, ABMs capture emergences from the interaction of agents like households, firms and banks that lead to markers such as inflation, economic growth, and unemployment.

More specifically, designing an ABM for macroeconomic analysis involves some version of the steps below:

- Define the agents - identify who the key agents are (e.g., households, firms, banks) and define their properties and characteristics;

- Set the rules - define the behaviors, the decision-making processes, and interactions among the agents. These kinds of rules can be based on empirical data, on theoretical assumptions, or even on past ABMs from other fields of science;
- Set the initial conditions - set the initial state of the system, including the initial states of the agents and the environment;
- Design the environment - program the environment in which the agents operate: markets, institutions, and any external factors that affect the agents' behaviors can be inclusions;
- Run the simulation - let the agents interact over time in the program that was designed beforehand. Then, collect and analyze data on the emergent phenomena.

Let us take monetary policy as an example again. For instance, an ABM can describe a diverse set of households and firms that have different income levels, preferences, expectations, and borrowing constraints. It can include banks that set interest rates based on their market power and risk assessments, and a central bank that adjusts the policy rate based on macroeconomic indicators and could follow rules such as a Taylor rule. We could then simulate the effects of a change in the policy rate on individual behaviors (e.g., spending, saving, investment, price-setting) and aggregate outcomes (e.g., inflation, output, employment).

Are today's ABMs the end of it? The answer is most definitely no, and more and more sophisticated models are coming into existence as research progresses – remember, this is a new field. As a matter of fact, I do point out how modern models, even the ones from complexity economics, do not genuinely adopt a correct heuristic approach in the third chapter.

Concerning this chapter, though, I wish to conclude by mentioning what the “mainstream” complexity literature says on the subject of monetary policy.

2.3 Complexity and Monetary Policy

Given that "complexity" defines not a single model but a tendency of considering economics as a complex system, the results of this kind of evidence are very polychromatic, but it is still interesting to see how they arise. Let us consider three examples.

One study on the euro area[35] found that the primary ECB policy rate aligns well with a straightforward rule based on the projected near-term deviation of inflation from the ECB's price stability definition and the deviation of near-term output growth from its trend, which has the advantage of not requiring real-time estimates for the output gap, which the paper argues to have been mismeasured before the crisis.

The study goes on to analyze unconventional policy rules in eleven other Eurozone models and validates the fragility of policy analysis tailored to any specific model, supporting instead the advantage of averaging models in policy creation: policies derived by averaging across all 11 Eurozone models tend to perform better when using current results instead of future projections for output and inflation. The paper, hence, proposes that the "averaging rules" serve as valuable standards for assessing the robustness of other policy proposals. While this study does not stem from complexity economics, it can be interpreted as a critique of complex models used as policy-setting instruments for the central banks' strategies.

Another study,[36] instead, considers economic policy through complexity science and argues that, while complexity economics exists as a subfield of economics, it does not exhibit enough differences in policy proposals with respect to mainstream science and instead only complements it.

35. Athanasios Orphanides and Volker Wieland, "Complexity and Monetary Policy," CFS Working Paper No. 2012/11.

36. Steven N. Durlauf, "Complexity, economics, and public policy," *Politics, Philosophy & Economics* 11, no. 1 (2012): 45–75.

This paper has countless flaws. For instance, it universalizes the conclusions of a solely mathematical model to all complexity economics (zero consideration for network models or ABMs), or, for instance, it assumes rational expectations in demonstrating how complexity science only augments the current economic science, transparently falling into circular reasoning. Still, part of its model construction resembles the modelling of a complex system and can provide a nice insight on how to avoid too high of a similarity with the mainstream academic opinion.

We can use this as a warning for other pieces of science as well. When we see the word "complexity" used, we must make sure that it is not misinterpreted or reduced to other sub-meanings of the field.

Another paper[37] advances an alternative approach to the conventional surplus approach to value and distribution theories based on modern physics and mathematics. In capitalist economies, it argues, the production of commodities is primarily for exchange and not for direct use, which enlightens the necessity for alternative approaches to understanding and managing such economies. To do so effectively means to move past the traditional informal methods which have limitations in defining and addressing complexity analytically.

The paper proposes system dynamics as promise in this regard. The application of a computer-based mathematical approach in system dynamics heralds a shift in our economic perspective, enabling us to account for structural interdependence and feedback causal loops – features fundamental to understanding complex systems.

Then, the author delves into the possible relationship between economic complexity and statistical physics and quantum theory. He argues that both physics and quantum theory deal with non-linear dynamical systems that are extremely sensitive to initial conditions, similar to our complex economic systems, which clearly points to the possibility of economics evolving as a science of social physics. He also mentions the differences between complexity theory and connecting mathematical fields

37. Duccio Cavalieri, "Complexity In Economics: System Dynamics And Policy Implications," *History of Economic Ideas* 25, no. 3 (2017):101-136.

such as chaos theory when analyzing non-linear dynamical systems. Complexity, as the name suggests, is a broad, qualitative term that opposes simplicity while chaos is a more specific term denoting an unpredictable system with sensitive dependence on initial conditions. These terms, though used interchangeably, have distinct (negative) implications.

Critiquing the current mainstream, he says that in dealing with unstable economies linear frameworks have shown to introduce distortions in the analysis and hence they should not be employed to approximate non-linear (economic) relationships. Then, explorations into the realms of complexity and chaos in macroeconomic models marked by significant non-linearities result in important insights regarding monetary policy too.

Now, deviating from the existing evidence and getting into what this thesis offers, in this next chapter I seek to establish a theoretical background that will serve as an epistemological justification for the proposal of a different application of agent-based modelling in order to solve complexity in a more proficient way.

Chapter 3
Modelling Complexity: Cognitivism and the Hebb-Hayek Framework

3.1 Introduction

Economists have used modelling since the dawn of social science. While during the earliest developments of the field they may not have used mathematics, econometrics, or computer simulations, it's still easy to notice that in their words there is some kind of modelling involved.

In their minds there was no statement of absolute, ontological truths on humanity as an economically driven species. There was instead their own interpretation of who the agents in the economy were and which pattern of action they took; there were assumptions on the nature of wealth, on which aggregate variables caused it to increase or decrease,[38] and their relative conclusions and policy proposals. In other words, they modelled conceptually.

They applied the natural tools of pattern recognition and sensory observations and used them to fabricate the representations of the economic system that they thought were the most accurate. When new quantitative

38. Alessandro Roncaglia, *The Wealth of Ideas – A History of Economic Thought*, (Cambridge: Cambridge University Press 2001), 11-17.

tools started making their way into economics, the model-oriented nature of social science research simply became more apparent.

In our case, monetary policy is reasonably recent when we think about quantitative modelling. Indeed, the first statistical explanations date to its birth.[39] That being said, the more rigorous and narrow literature on monetary policy is to be found from the 1980s onwards.

Economists have tried to provide answers on monetary policy, and most of them have consisted in employing either theoretical (be it with or without mathematics) models, empirical data, or a mix of the two,[40] which also reflects the traditional modelling routes of economics.

Given this state of the academia and given that I also seek to review it, I therefore must interrogate myself: are the conventional modelling

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39. Alessandro Roncaglia, *The Wealth of Ideas – A History of Economic Thought*, (Cambridge: Cambridge University Press 2001), 285-291; 326-341; 366-367. Although money control existed since 600 BCE when the first minting attempts were ordered in Lydia by the governing authority and although the Bank of England had the power to print money since its establishment in 1694, this thesis refers to monetary policy in relationship to interest rates and their spreading patterns, which have only rose to prominence as monetary policy variables in 1914 with the first policies of the Federal Reserve. At that time, mathematical applications to economics had already become a major voice in the economic debate because of the influence of new neo-classical models.

40. This classification is justified with context in Chapter 1. Respective instances of theoretical, empirical and mixed models: *John M. Keynes, The General Theory of Employment, Interest and Money* (Palgrave Macmillan, 1936); Carlo A. Favero, Massimiliano Marcellino and Francesca Neglia, "Principal components at work: the empirical analysis of monetary policy with large data sets," *Journal of Applied Econometrics* 20, no. 5 (2005): 603-620; Ben S. Bernanke and Alan S. Blinder, "The Federal Funds Rate and the Channels of Monetary Transmission," *The American Economic Review* 82, no. 4 (1992): 901-921. The first instance is pure theory of society and economics. Data can be added to the theory, but it's not its main purpose, as even with data entries, the results are not supposed to be quantitatively accurate and are rather supposed to broadly indicate the way to pursue. The second one, instead, is pure econometrics: it does not mean much without data and when applied its results are to be considered an accurate assessment. A mixed model like the last one, instead, usually possesses the universality of deductive theory and some of the predictive accuracy of econometrical models.

strategies valid, do they preserve accuracy and are they down to earth? And to further expand, are the currently explored unconventional modelling strategies useful and do they fit reality? In order to come up with the answer, we must first unravel the epistemological nature of economics and start from the roots.

In this thesis, I make use of two notions frame the analysis of economic methodology: holism and reductionism. Both are strictly related to the complexity.

Holism is a doctrine that assumes that reality can be described as an indivisible whole. In other words, it is the understanding that individual elements of reality cannot be comprehended separately and exist only as part of a greater whole that comprises them all together.

Reductionism is instead the scientific effort to explain phenomena by breaking them down into ever-smaller components. Reductionism assumes that by studying the components of a system or phenomenon, one can gain a better understanding of how it functions as an integrated whole instead of studying the system assuming it as a unity in itself.[41]

These concepts are self-evidently opposites, at least for what concerns the field of methodology of social science.

Now, one may be tempted to classify models according to their purpose and relationship with data, or their scope, meaning whether they are descriptive instead of prescriptive. One may classify them according to the quantitative or qualitative nature of its foundations. One may classify models with regard to their agents' characteristics or their heterogeneity.

41. The two concepts of holism and reductionism are common in philosophy of science and they are debated also with regard to complexity in economics, with many agreeing that complexity does refute reductionism in that it rejects an explanation of a system through the mere. However, I use the term "reductionism" to intend the research to reduce to the smallest elements, but not necessarily the assumption that one can explain science only by themselves. Indeed, I include in the definition of reductionism the phenomena of emergence that the interaction between them create, not considering them as "wholes", but rather as orders, or outcomes.

Such a taxonomy does prove useful in many cases but can miss the acknowledgement of the level of generality of the model, which is provided by a categorization within the spectrum that exists between holism and reductionism.[42] The more a model is holistic, the less it "goes into detail", and as such is less general. Conversely, the more a model is reductionist, the more it deconstructs the elements of the subject, and hence has wider applicability.

When a modeler has no regard for their models' generality, the threat of the produced research being unscientific comes up. Therefore, it is necessary to make a heuristic digression in order to generate a coherent setting for evaluating and advancing research.

Cognitivism[43] is a *composite*, or *synthetic* way of conceiving economics: there is no drawing conclusions for the mere empirical observations and there is no axiomatic deduction of them. The experienceable wholes of society (institutions, like firms or households, and other emergent orders, like markets) are to be de-constructed in their complexity and descriptively re-constructed with the smallest known elements at our disposal as to represent them[44] with the least error *while still being able to model it*. Its tie to the Hebb-Hayek framework lies in the fact that the framework allows us to model individuals in a reductionist way (the smallest conceivable element are the learning processes of the individuals) and thus re-construct social orders from the individuals themselves, instead of assuming their existence and behaviors within the definitions of rationality, utility maximization, et cetera.

42. As is usually necessary to distinguish the two, since both idioms often contain moral and political facets when applied to social science, this thesis only takes into consideration the methodological meaning that is associated to them.

43. Not to be confused with cognitivism as a branch of psychology.

44. Samuel Bowles et al., "Retrospectives: Friedrich Hayek and the Market Algorithm," *Journal of Economic Perspectives* 31, no. 3 (2017): 215–230.

3.2 Cognitivism

The Methodology

"[…] to reduce the complex phenomena of human economic activity to the simplest elements that can still be subjected to accurate observation, to apply to these elements the measure corresponding to their nature, and constantly adhering to this measure, to investigate the manner in which the more complex economic phenomena evolve from their elements to definite principles."

Carl Menger, *Principles of Economics* (1871), 46-47.

Reductionism is the epistemological structure upon which modern natural science is based,[45] and if we wish to be scientific in the social sciences, we must at least try to adopt the same outline in that field too, unless we wish to separate them from the natural sciences not only in the object but in the underlying approach and provide proof of how their definitionally unscientific methodology is still a reliable way to obtain knowledge.[46] In this sense, the traditional difference between social and natural sciences would vanish in the long run, being replaced by the difference between "science" and "non-science", with some models pertaining to the first and the other to the latter categorization.

So, how can reductionism be applied to economics?

A typological scheme published in the late 1990s comes in handy in explaining the modelling process (see *Figure 3.2.1)*.

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45. Joseph L. McCauley, *Dynamics of Markets: The New Financial Economics* (Cambridge University Press, 2004), 185-196.

46. Robert Axtell, "Hayek Enriched by Complexity Enriched by Hayek," *Advances in Austrian Economics* 21 (2017): 63-121.

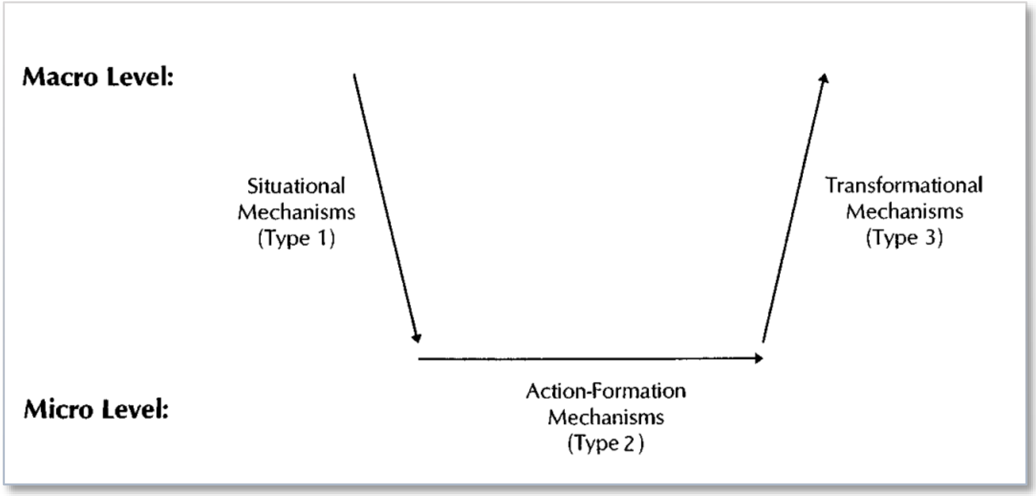

Figure 3.2.1: Hedström-Swedberg adjusted Coleman boat.[47]

The scheme helps to visualize the de-composition and re-composition demanded by cognitivism. We observe an empirical emergence, like a market or a firm (1), we try to "grow" it through action-formation mechanisms, for example by simulating an interaction among individuals (2), and we observe whether our artificial emergence is appreciably descriptive of the empirical observation (3).

Now, if it was possible to construct a methodology for economics based on the single actions of the cells or based on the most minute influences of physical particles on everything in the world, economics would be solved. However, since a theory of everything has not been successfully developed even in the field of physics, and since we as a society still have no access to perfectly accurate connections between physiological mechanisms and human action, we have to limit our reductionism to the "smallest modellable logical leap" in order for our models to still be as truthful to nature as possible within the confines of being useful.[48] An answer may be the Hebb-Hayek framework, which is discussed later in the chapter.

47. Peter Hedström and Richard Swedberg, *Social Mechanisms: An Analytical Approach to Social Theory* (Cambridge University Press: 1998), 13.

48. Another chapter may have been dedicated to pondering on the difference between modelling and useful modelling but would ultimately end up being either a sum of tautological arguments or a merely semantic juxtaposition. For now, I

"This is all the theories of the social sciences aim to do. They are not *about* the social wholes as wholes; they do not pretend to discover by empirical observation laws of behavior or change of these wholes. Their task is rather, if I may so call it, to *constitute* these wholes, to provide schemes of structural relationships […]."

Friedrich A. von Hayek, *Individualism and Economic Order* (1948), 72-73.

It must be clear that I do not hold in any way that traditional or complexity economics are of no use in practical circumstances. Conversely, I hold that their methodology does not allow for a process of truly scientific discovery in the field.[49] Indeed, since such a methodology has not yet been modeled successfully yet,[50] we want to (preferentially) resort to modern complexity economics both for our understanding of economics and for policy.

Now, a true process of scientific discovery in economics cannot but give significance to the cognitive aspects of the human action. In particular, it has to deal with the problem of interpretation by the individual.[51] In fact, though in its earlier years cognitivism (read: Hayek) had a very much axiomatic approach similar to the Kantian one on human action when dissecting the individuals' link to non-social elements,[52] in its later

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define useful model (or up to modern standards) as a model that can be formalized through mathematics or computation and that provides at least one of the following: description, prediction. For example, most classical and pre-classical models were of verbal nature and descriptive. They provided the reader with descriptive power, but lacked formalization (meaning strong applicability), and are thus not useful within the modern standards.

49. Friedrich A. von Hayek, "Scientism and the Study of Society. Part I," *Economica* 9, no. 35 (1942): 267-291.

50. See chapters 2 and 3.

51. Friedrich A. von Hayek, "The Facts of the Social Sciences" *Ethics* 54, no. 1 (1943): 1-13.

52. Agnès Festré, "Knowledge and Individual Behaviour in the Austrian Tradition of Business Cycles: von Mises vs. Hayek" *History of Economic Ideas* 11, no. 1

years it detached itself from apriorism in that manner too, when it was augmented with a neuropsychological grounding.

But what do we actually mean by "interpretation"? The existence of the problem of interpretation means that a social theoretician cannot jump from the assumptions on human action to the actual actions of the individual in a universalistic way but has to first explain how individuals interpret the information that is given to them and only then assess how they act. Of course, the information to which individuals have access is not the total information of society, but their own localized set of discoverable elements,[53] which constitutes another obstacle to easy modelling.

Another consideration to make is the issue with social interactions and their development: they are very different from individual-to-object interactions. In this sense, given that the Hayekian methodology is scientific in the sense that it's reductionist and synthetic, we may very well refute methodological individualism insofar as we can substitute it with a more accurately composite theory, the constituents of which are more elementary than individuals themselves, when science will allow us to do so.

(2003): 13-45. Mises shared a view on the axioms of human actions ascribable to the Kantian tradition of gnoseology, which Hayek shared in his earlier years as an economist. Individuals and social orders deduced "mathematically" from the axioms of human action

53. Friedrich A. von Hayek, "The Use of Knowledge in Society," *The American Economic Review* 35, no. 4 (1945): 519-530.

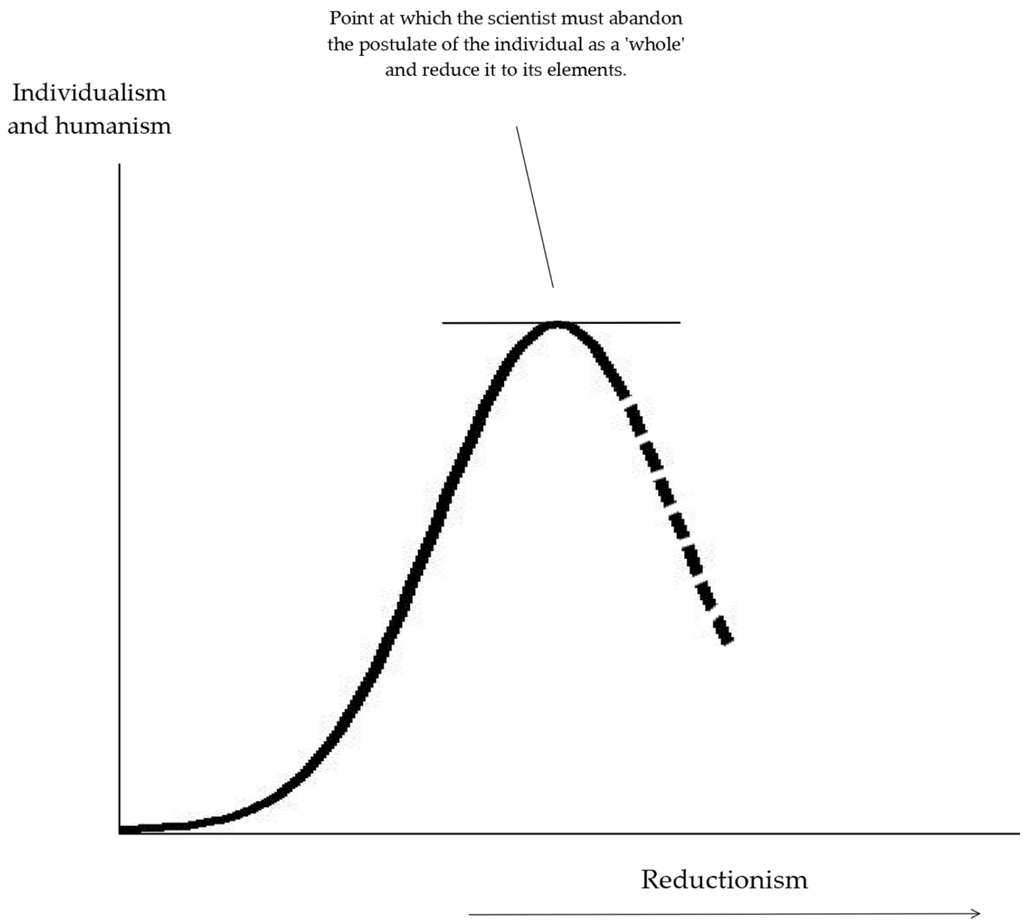

Figure 3.2.2: A representation of the relationship between individualism and reductionism as of today.

Note that the vertical axis measures individualism in both cases of elimination through ascription to wholes (holism) and elimination through ascription to sub-elements (reductionism). Furthermore, the continuous line represents today, and the dotted line represents the likely outcome of future research.

This graph can apply to any element, such as social wholes if we aggregate or cells if we reduce. In this case I use individuals because I wish to strongly mark the increasing scientificalness of individualism when we stray from holism, but, at the same time, the likely un-scientificalness of postulating the individual when the science on sub-elements is established. Cognitivism parts from apriorism exactly in this kind of situations; the spontaneous order is not aprioristic but empirical, and its structure is not posited, but *re-constructed through the most-reducible elements possible, in order to best reproduce how it is empirically observed.*[54]

The unknown, rightwards section of this curve will determine the appropriate length of the first arrow in Figure 3.1.1

Of course, this is a point in science that lies very far from our timeline, but it is worth noting.

Now, getting back to the argument, we can see how cognitivism clashes with traditional economic science. In the eyes of a cognitivist, these non-empirical experiments must still be falsifiable in order to be scientific and constantly improving, with a foremost example provided by the concept of equilibrium. In neoclassical models, equilibrium is – indirectly – assumed. We know the economy *must* tend to equilibrium (from other theorems which are proven on the basis of ex-ante principles), thus, if excess supply or demand manifest, *then* they will re-balance. The example from partial equilibrium theory is even more blatant in Walras' general equilibrium proof.[55] Again, maybe useful, but unfalsifiable hence unscientific.

Now, another crucial distinction must be made, one that concerns the formation of the analyzed social structures and their origin with respect to intentionality and unintentionality. Hayek politically and ethically criticized rationalism in its pretense to change societal norms to impose new ones based on reason, but he did so methodologically too, targeting their pretense to know how social constructs formed.

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54. Friedrich A. von Hayek, *The Counter-Revolution of Science: Studies on the Abuse of Reason* (Glencole, Illinois, The Free Press, 1952), 36-43.

55. Léon Walras, *Éléments d'économie politique pure* (1874). Indeed, a cognitivist genesis of equilibrium may only appear after the analysis has taken place. Clearly, the word "equilibrium" would have very little association with its conventional meaing in mainstream economics. The answer to the question about how one can abandon equilibrium and at the same time not fall into analytical anarchy is analyzed by Steve Fleetwood in "Order without equilibrium: a critical realist interpretation of Hayek's notion of spontaneous order," *Cambridge Journal of Economics* 20, no. 6 (1996): 729-747.

Rationalist thought, more specifically the rationalism of cartesian legacy, advocated that people had built social norms and institutions through the use of reason, meaning intentionally and with planning. Such an analysis, says Hayek, is highly fallacious. It is sure that reason plays a part, but it's not given that it is the determinant of the creation of the social norms and institutions.[56] It is of extreme importance to consider the unintentional consequences of intentional actions.

Given these facts about cognitivism, we can stylize more specifically what a scientific model is. A scientific model of economics is a model that:

- Acknowledges complexity and tries to untangle it in its most elementary usable elements;
- Simulates its re-composition with such elements with the least "jumps";
- Successfully mirrors the observed complex system;
- Makes use of as many proven and modellable natural science phenomena as it can;
- Contains as many sub-systems and parallelly influencing systems as it can.

Now, postulated in this format, this model accomplishes scientificness regardless of the modelling tool it uses. As a matter of fact, technology has perhaps more to do with the model's *capacity* and *precision*[57]: on one hand, a small and imprecise model may have a scientific soul, while on the other it would likely also not have wide-ranging descriptive power.

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56. Norms, as in: private property, language, law, education, cultural customs, et cetera. Institutions, as in: organizations, the government, firms, households, et cetera.

57. For example, one might try to use game theory, and similar attempts have been made, namely, in the form of evolutionary games. They are, though, extremely simple and have not been able to encapsule complexity. Other technologies are available nowadays that help us with this. The foremost example is computer simulation, which is discussed later on.

In terms of epistemological classification, a cognitivist-reductionist methodology, respectively:

- Tolerates methodological individualism as a temporary epistemology while science makes its course in explaining the 'individual person' in more elementary pieces successfully;
- Deals with theoretical vs. empirical proofs in relationship to the available information as follows:
    - If the most reduced elements at our observable disposal have strong empirical evidence, it shall be used;
    - If it is weak, it shall be augmented with a theoretical-hypothetical skeleton;
    - If there is none and their existence and functioning is only hypothesized, it may be useful to try and model them too with a simulation of the smaller complex system to which they pertain. If they do not fit and the simulation does not improve the model, then they are to be excluded.

Next, a figure to complement what I displayed with this methodology with historically established economic schools.

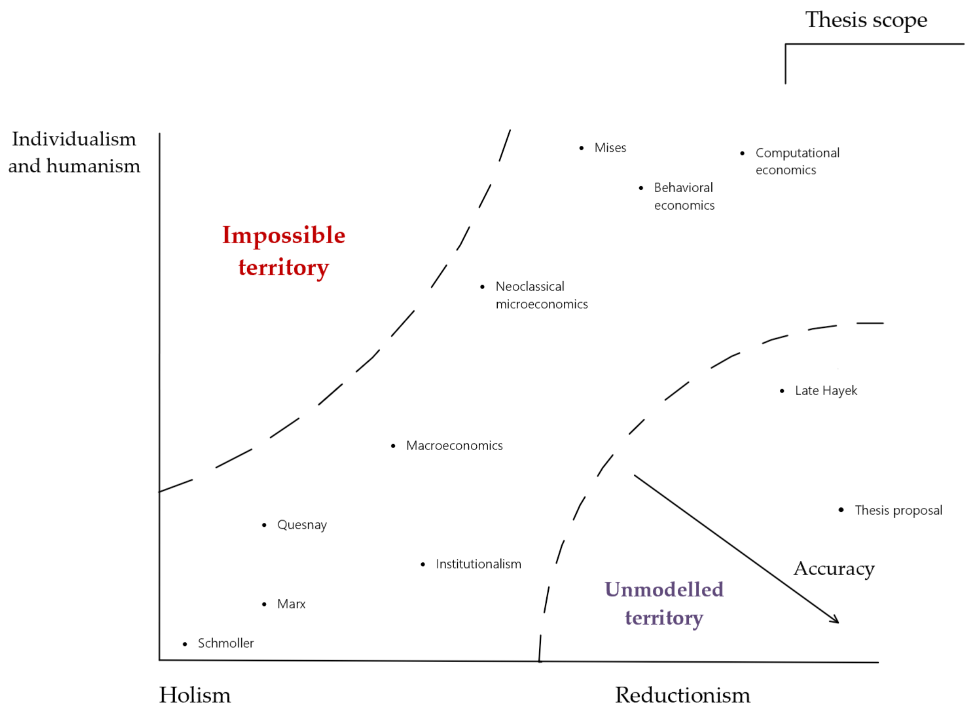

Figure 3.2.3: The relationship between reductionism and individualism as a classification for economic schools.

High aggregation (as conceived today) prevents individualist methodology. At the same time, high reductionism detached from the concept of the individual as the irreducible unit is somewhat explored in other sciences but is unmodelled with regards to economics. The unmodelled territory represents the dotted line of Figure 3.1.2 and rightwards from there.

Now, cognitivism is only the very base foundation that stems from an attempt to translate reductionism into social science, but does not tell us the *how*. Then, how can we model – today – in a cognitivist fashion?

3.3 The Hebb-Hayek Framework

The human brain is a complex system.[58] The empirical evidence on the sub-elements that make up its structure is enough to have coherent understanding on many sub-mechanisms, but it is somewhat insufficient

58. Danielle S. Bassett and Michael S. Gazzaniga, "Understanding complexity in the human brain," *Trends in Cognitive Sciences* 15, no. 5 (2011): 200-209.

when we try to map it precisely as a whole.[59] We must then resort to a representative framework that allows us to translate it into an actual model.

The Hebb-Hayek framework[60] is a neurological framework that is comprised of a set of principles which explain how neurons form cognits, units of memory constituted by a number of synaptically associated neurons. This framework is at par with modern neuroscience and proves itself rather modellable when trying to simulate the learning process of the brain, and hence is an important piece for the modelling of human action. This is particularly important in social sciences because the single agents are adaptive, meaning that their actions change depending on their environment, and are based upon previous experiences. In this section I argue in favor of this framework to be used as a guiding principle to model economics according to cognitivism.

This framework is built around two main works and their – arguably even more important – scientific legacy in the field of neurology: *The Organization of Behavior*[61] by Hebb and *The Sensory Order by* Hayek,[62] and goes as follows.

> "This central contention may also be expressed more briefly by saying that 'we do not first have sensations which are then preserved by

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59. This may seem as a malicious oversimplification of science in order to develop an easier theory. However, we really don't know much about learning and human action *at the core*. A prime example of this is how neural networks are developed in machine learning algorithms: they mimic the structure of the brain and are indeed based on Hebbian neuropsychology, but do not perfectly represent a brain because there are large research gaps.

60. Joaquín M. Fuster and Steven L. Bressler, "Cognit activation: a mechanism ena-bling temporal integration in working memory," *Trends in Cognitive Sciences* 16, no. 4 (2012): 207-218.

61. Donald O. Hebb, The Organization of Behavior: A Neuropsychological Theory (New York: John Wiley& Sons, Inc., 1949).

62. Friedrich A. von Hayek, The Sensory Order: An Inquiry into the Foundations of Theoretical Psychology (Chicago: The University of Chicago Press, 1952).

memory, but it is as a result of physiological memory that the physiological impulses are converted into sensations. The connexions between the physiological elements are thus the primary phenomenon which creates the mental phenomena.'"

Friedrich A. von Hayek, *The Sensory Order* (1952), 53.

In other words, an individual obtains sensory inputs which are translated through the brain – a complex system – and are *organized* in the mind. This organization becomes an order in the individual's mind, the sensory order, which is subjective to the individual and to the experience.

In this thesis I do not elaborate on the computationalism vs connectionism debate, since it is ongoing among the scientific community. For the sake of honesty, I state that the Hebb-Hayek framework is a connectionist network model that I chose for its adaptivity and ease in modelling and is hence not necessarily future-proof.

Now, according to Hayek, the brain is composed of a hierarchy of interconnected neurons, each with its own specialized function. The sensory input is processed through a series of stages, beginning with the primary sensory neurons and ending with the higher-level cognitive neurons. At each stage, the neurons are organized into the sensory order which is based on the similarity of the inputs. This order is then used to create an internal representation of the world. Thereafter, when the individual experiences a stimulus, the experience will cause them to associate it with a particular emotional or behavioral response.

Thus, the framework allows for agents to be *adaptive* and for the model to avoid randomizations of the actions of the agents with respect to time.

The sensory order obviously does not correspond to the physical order, or namely, the objective one, the one that is external to the mind and the one from which the mind catches the sensory inputs.

Now, it appears evident that if the brain can organize sensory inputs before they were already registered, then the sensory order is organized by a principle that precedes the empirical stimulus, which means that individuals associate the empirical stimulus to connected past experiences in their brain (associative learning). Hence, a Hebb-Hayek framework creates a heuristic environment thanks to which we can work on the problems of interpretation and intentionality in social science.[63]

On a side note, although Hayek uttered that his theory is not really concerned by the debate on whether sensory effects and their mental organization impact the anatomical structure of the brain,[64] but is merely made more complicated (or at most less consistent over time), I disagree with his convenient sweeping statement and furnish some of the anatomical evidence of the Hebb-Hayek framework in order to measure the extent to which it can be universalized.

Since Hebb's book is more connectable to the neuroscientific terminology than Hayek's, which remains more abstract, and since both are almost overlapping in the expressed concepts, an assessment of Hebb's work as how it is perceived by the scientific literature guides us on the validity of both.

The fundamental truth that subserves the Hebb-Hayek framework was established by the branch of psychology that originated from them. That is, cognitive psychology.

What is generally agreed in the literature is that prior beliefs and understanding are a crucial determinant of general behavior of individuals, especially in the process of framing a problem.[65]

Some intermediate-size discoveries prove the theory, while some others advocate for the recognition of exceptions. They are not be debated in this thesis, but a shortlist of the most significant goes as follows.

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63. Joaquín M. Fuster and Steven L. Bressler, "Cognit activation: a mechanism enabling temporal integration in working memory," *Trends in Cognitive Sciences 16*, no. 4 (2012): 207-218.

64. Friedrich A. von Hayek, *The Sensory Order: An Inquiry into the Foundations of Theoretical Psychology* (Chicago: The University of Chicago Press, 1952), 52-53.

65. Michael W. Eysenck and Mark T. Keane, *Cognitive Psychology: A Student's Handbook* (London: Psychology Press, 2015); Richard E. Mayer, "Cognition and instruction: Their historic meeting within educational psychology," *Journal of Educational Psychology* 84, no. 4 (1992): 405–412.

Favorable:

- The Hebbian framework is widely used in cognitive psychology to explain how people learn and remember information. It is also used to explain how people develop cognitive biases, how they respond to different types of stimuli, and how they form memories.
- The most widely accepted mechanism behind learning can be observed empirically to follow the synaptic strength increase suggested by Hebb;[66]
- A major adjusting process of neuronal connections abides by the Hebbian rule;[67]

Contrary:

- There is evidence of anti-Hebbian learning (learning can also occur through changes in the structure of synapses);[68]
- In some networks, other learning rules work better than the Hebbian rule;[69]
- The original Hebbian model is incomplete.[70]

66. Uwe Frey and Richard G. M. Morris, "Synaptic tagging and long-term potentiation," Nature 385, (1997): 533–536.

67. Natalia Caporale and Yang Dan, "Spike timing-dependent plasticity: a Hebbian learning rule," *Annual Review of Neuroscience* 31, no. (2008): 25–46.

68. Scott J. Cruikshank and Norman M. Weinberger, "Evidence for the Hebbian hypothesis in experience-dependent physiological plasticity of neocortex: a critical review," *Brain Research Reviews* 22, no. 3 (1996): 191-228.

69. Amos Storkey, "Increasing the capacity of a Hopfield network without sacrificing functionality," *Springer Berlin Heidelberg* 1327, (1997): 451–456 (Lecture Notes in Computer Science).

70. Graeme J. Mitchison and Nicholas V. Swindale, "Can Hebbian Volume Learning Explain Discontinuities in Cortical Maps?," *Neural Computation* 11, no. 7 (1997): 1519–1526.

It may be beneficial to reinstate the epistemological nature of the framework. The framework is *theoretical* but with many fundamental empirical proofs and it works in many simulations. It's not empirical; if it was empirical, it would be like describing the physiology of the lungs, or of the hamstring, of which we know most things about, but the same cannot be said for the brain. Hence, it's like an educated hypothesis that works in most cases, a hypothesis educated enough to consider useful to model adopting it.

It also appears crystal clear that this framework postulates the individual, which is limiting, but it does not postulate it as a 'whole', because the individual is influenced by the brain's learning process, that is detached from the concept of individual itself and as such is more reductionist than traditional economic modelling.

Furthermore, another limit is constituted by the fact that it's really just a theoretical framework on which we have *some* empirical evidence, which, if augmented with it, can expand it only within the limits of its theoretical-ness and, as of today, is not sufficient to substitute it. As mentioned previously, where the methodology is discussed, reductionism must be applied as much as possible, and this framework has empirical gaps when confronted with such an expectation.

If we were to apply the most extreme reductionism with the knowledge and tools of today, we would accomplish nothing, especially in the case of the brain. This appears true in other fields too, for example ethology:

"Trying to describe the nest-building behaviour of a bird in terms of the actions of individual nerve cells would be like trying to read a page of a book with a high-powered microscope. Not only would it be incredibly laborious to discern the boundaries and make out the identity of each printed letter, we might miss out completely on the grouping of letters first into words, then sentences, then paragraphs and so on."

Aubrey Manning and Marian S. Dawkins,
An Introduction to Animal Behaviour (2012), 4.

The next section discusses how simulations can help to work out complex systems. The applications of the Hebb-Hayek framework are instead mentioned in the fifth chapter, along with the proposal.

3.4 Simulations as Solutions

So far, I have discussed what to model and why. I did not, however, delve into which the most appropriate tools are for that goal and why.

As I stated before, the reductionist-cognitivist approach requires reconstructing society and its elements by their smallest components' interaction. In order to do so, one would of course apply some degree of approximation, which is fine as long as there is a desire to reduce it in the long run. Nonetheless, the approximation which we use today in non-simulational models is very anachronistic and we see it in traditional game theory, behavioral psychology, et cetera. These "fail" in the moment when they have to *simulate* the re-construction, because they do not have access to "simulative power" other than the one that the intelligence of the researchers can afford, which is usually circumscribed to a multi-faceted elaboration of simple axioms.

The natural consequence of this is that the models are usually very limited with respect to heterogeneity, they are static,[71] and they cannot confront large numbers of simulations in order to see if they actually can mirror the real world (best-ofs). In other words, they are unsuitable means when meeting complexity.

Then again, it is important to understand that if the models *do not* mirror the empirical reality and are thus not strictly scientific in the terms I introduced before, it does not mean that they are useless. On the contrary, "artificial" social models can contribute to understanding alternatives, implicit but unknown effects in interaction, more narrow social phenomena, and many other things which do refine the actual scientific,

71. Meaning that there usually is a "standard" situation in which some agents interact and a couple of particular cases dependent on the variation of one or two of the few variables included.

reality-oriented models.[72] Still, we need to limit approximation to the least we can for accurate modelling, and modern-day computer science offers us some solutions.

Computation

Today we have technology that can solve enormous amounts of calculation with relatively minimal input. Namely, we have powerful computers. Recent computers especially allow us to simulate complex systems with extreme power and endless possibilities, and at the same time to compare the simulations with graphical and numerical outputs.

The key to simulations is, of course, programming. Programming involves not just creating the model itself, but the software that runs it. The field is relatively new and the first complete software came out around 30 years ago. Since then, computational complexity has gained more and more traction.

This traction allowed for different types of computational models to be constructed. Not surprisingly, many are holistic and many are not.

Reductionism and ABMs

The most common type of early computer model in the field of economics was essentially just the pre-existing computational mathematics but applied to the fields of statistics and econometrics.

When we jump to actual economic modelling, as in modelling of society, we see that historically there have been two main paths: equation-based simulations and agent-based modelling (ABM).

Equation-based simulations "describe the dynamics of a target system with the help of equations that capture the deterministic features of the whole system. Typical examples of such equation-based simulations are

72. Nigel Gilbert and Rosaria Conte, *Artificial Societies: The Computer Simulation Of Social Life* (Taylor & Francis, 1995), 1-14.

system dynamics simulations, which use a set of difference or differential equations that derive the future state of the target system from its present state. System dynamics simulations are restricted to the macro level: they model the target system as an undifferentiated whole."[73]

Agent-based models, on the other hand, do not describe a-priori the dynamics of a system, simply because it is assumed that they are unknown. They instead describe single agents (and their features) and only then simulate their interaction with the environment and other agents in order to derive the whole system. Agents can be anything, from neurons to trees to individuals to firms.[74]

The parallelism between the two modelling strategies and the two polars of epistemology is quite unmistakable, as is the consequent route of this subchapter. Still, I want to specify a bit on agent-based models and reductionism.

As per the methodology established beforehand, ABMs are, currently, the only kind of models that *can* be a reductionist model.[75] That does not mean that they all are. As a matter of fact, most of them are not.

In order for an ABM to be as representing of reality as it can be, the agents cannot be firms and households. They ideally should be individuals, and, if possible, maybe in the future, be cognitive units that make up the individual action. Such a model would generate a cutting-edge model for economics and society. Still, it may not be the only way that a reductionist agent-based model can be worked through: neurons may be better represented (fitting) by an equation-based model, and only then shall be merged into cognits and then individuals. This is however too big of a leap forward.

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73. Till Grüne-Yanoff and Paul Weirich, "The Philosophy and Epistemology of Simulation: A Review," *Simulation & Gaming* 4, no. 1 (2010): 20–50.

74. Joshua M. Epstein and Robert Axtell, *Growing Artificial Societies: Social Science from the Bottom Up* (MIT Press, 1996).

75. Robert Axtell, "Why agents? On the varied motivations for agent computing in the social sciences," *Center on Social and Economic Dynamics* working paper no. 17, (2000).

As of today, we do not have any model that simulates the whole society and at the same time is reductionist. We have deeper theoretical neural frameworks and we have societal simulations with simple agents. We also have linkage proposals by some, but we don't have actual models that comprise the two, and for sure not at the level of simple neurons.

In any case, the ultimate agents in the contemporary frameworks, i.e., the individuals, are best represented only in ABMs and not in equation-based simulations, meaning that, as of today, the ultimate representation of a comprehensive model would correspond to an individual-agent-based simulation.

This is because of a variety of reasons that make ABMs just superior:

1. **Heterogeneity**: ABMs have the capacity to represent diversity among agents. Each agent can have unique characteristics and behaviors, reflecting a truer variety in populations than just differences in income or propensity to spend. Equation-based models, on the other hand, often assume homogeneous agents for the sake of simplification.

2. **Autonomy**: in ABMs, agents are autonomous entities that make their own decisions based on their individual states and local information. This stands in stark contrast (and advantage) to equation-based models, which typically assume either a centralized, omniscient decision-maker or perfectly rational agents following pre-determined behaviors.

3. **Local Interactions**: ABMs allow for direct interactions between neighboring agents, capturing local dynamics and emergent behaviors that are often missed by equation-based models that typically assume global interactions.

4. **Adaptation and Learning**: ABMs allow agents to adapt their behaviors over time in response to changes in their environment or interactions with other agents, capturing complex dynamics such as learning, evolution, or innovation. Equation-based models generally lack this adaptability, assuming static behaviors and fixed decision rules.

5. **Emergent Phenomena**: the patterns that arise from the interactions of many individual agents, which cannot be predicted by looking at the agents in isolation, are the core of ABMs.

Equation-based models, which instead focus on the aggregate level, cannot attain this feature.

Limitations

While ABMs are probably the best tool we have, it does not mean that they are the best tool we will ever have. They indeed have some faults.

The most obvious problem of multi-agent simulations is tied to their ambition: to solve complexity. Population-wide agent-based models are extremely difficult to model, especially if they incorporate non-linear and dynamic behaviors. Such models not only require efforts in initial development but are very energy consuming in error correction and multi-run confrontations.

Also, as computer simulations, they require computational power to be run and need time to show results, which raises issues with regard to the funding for the model.

The results of ABMs are not easy to interpret either and can offer an apparently skewed version of the causality of an event emerged in the artificial society.

The biggest adversity, though, is the potential mis-inclusion of a variable the importance of which was overlooked or the existence of which was not acknowledged. These kinds of errors in an agent-based simulation can very well cause domino effects and damage the integrity of all the results.

Still, agent-based models' faults must be compared to the ones of traditional modelling. Monetary policy, with its wide range of covered areas and with its characteristic of needing both descriptive and predictive models, makes a good ground of comparison.

Based on the principles established by this chapter, the next chapter undertakes a review of the mainstream and complexity literature. The chapter is optional and can be skipped to get to the proposal, which has a more direct connection to the concepts of chapters two to three .

Chapter 4
Addressing complexity: a review of the cited literature

The body of evidence on monetary policy has only opened to simulations in the recent decades thanks to the progress in the science of large-scale agent-based simulations, usually comprising a structure of modelling not dissimilar to the traditional macroeconomic ones with regards to the single agents (each agent usually follows an equation-based pattern, or has an associated production or consumption function), but with the exception of them interacting in an agent-based simulation and the sporadic insertion of systematic tendencies.

The review will consider theoretical models as subsets of empirical models and instead make a distinction with complexity-oriented models congruously with the first chapter.

Here, I separately revise and evaluate empirical and complexity evidence in accordance with the epistemological principles established beforehand, mostly pointing out the problems of each type of evidence.

4.1 Reviewing Mainstream Evidence

Vector Autoregression Models

Vector Autoregression (VAR) models exhibit three main problems: their assumptions (linearity and stationarity), the exogeneity of shocks, and the historical dependency of the variables they analyze.

We can break down the problems of their assumptions separately.

The linearity assumption in VAR models implies that the impact of a one-unit change in a given time series on another time series is constant, regardless of the level or previous changes of the time series, which is an extremely restrictive assumption, especially when dealing with complex phenomena. Many relationships are indeed better described by an asymmetric pattern. For instance, in financial economics, it is often observed that market variables respond differently to positive and negative shocks (leverage effects).[76]

Moreover, in many economic phenomena, certain thresholds or "tipping points" exist. These are points beyond which the relationship between variables changes.[77] For example, the relationship between pollution and economic growth may be different above a certain level of pollution.

Another big problem with linearity is pointed out by empirical evidence on volatility clustering and fat tails: financial data often show the phenomenon of volatility clustering, where large changes tend to be followed by large changes (of either sign) and/or small changes tend to be followed by small changes. VAR models assume homoskedastic errors, which *cannot* capture this pattern. Furthermore, financial data often have heavy-tailed distributions, implying a higher probability of extreme events than the Gaussian distribution assumed by VAR models.[78]

Of course, these issues with the linearity assumption map into every other model that uses it too, and the same applies to stationarity.

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76. Robert A. Haugen et al., "The Effect of Volatility Changes on the Level of Stock Prices and Subsequent Expected Returns," *The Journal of Finance* 46, no. 3 (1991): 985-1007.

77. Bruce E. Hansen, "Threshold effects in non-dynamic panels: Estimation, testing, and inference," *Journal of Econometrics* 93, no. 2 (1999): 345-368.

78. Tim Bollerslev, "Generalized autoregressive conditional heteroskedasticity," *Journal of Econometrics* 31, no. 3 (1986): 307-327.

Stationarity in VAR models means that the "properties"[79] of the time series don't change over time. However, a lot of empirical evidence contradicts this assumption.

For example, many economic and financial time series exhibit trends (both deterministic and stochastic) and/or seasonality. The presence of a unit root, representing a stochastic trend, is a form of non-stationarity where the series can wander far away from its starting point and shocks have permanent effects.[80] Additionally, real-world data often face sudden changes due to significant events like policy changes, wars, financial crises, or technological breakthroughs, events that can very well cause a structural break in the data, meaning that the parameters of the model suddenly change at a certain point in time. A VAR model with constant parameters cannot capture this kind of change, leading to biased and inconsistent estimates.[81]

Now, many of these issues have been contained if not fixed by the latest VAR-inspired models. The same, however, cannot be said for the next two.

The exogeneity of shocks in VAR models is an often unrealistic assumption because it disregards potential correlation structures and causal mechanisms inherent in the shocks themselves. Shocks, in reality, can come from common sources and have lasting impacts that spread through time, violating the assumption of a noise error. Structural Vector Autoregressive (SVAR)[82] models were developed to overcome some of

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79. The mean, variance and autocorrelation structure.

80. David A. Dickey and Wayne A. Fuller, "Distribution of the Estimators for Autoregressive Time Series With a Unit Root," *Journal of the American Statistical Association* 74, no. 366 (1979): 427-431. I cited this paper because it is one of the foundational works on unit roots in time series data, which is a common form of non-stationarity that violates the assumptions of VAR models.

81. There are many examples of this. One of the most famous was given by Pierre Perron, "The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis," *Econometrica* 57, no. 6 (1989): 1361-1401.

82. Lutz Kilian and Helmut Lütkepohl, *Structural vector autoregressive analysis* (Cambridge University Press, 2017).

these limitations by incorporating economic theory into the identification of shocks.

However, they do not fully solve the issue of exogenous shocks. The main reason for that is that SVAR models *impose* a structure on the contemporaneous relationships between variables based on a certain set of assumptions. These assumptions are necessary to identify the model (i.e., to be able to estimate it). For instance, a common method is to use a causal ordering of the variables, implying that a shock to one variable can contemporaneously affect others that come later in the order, but not those that come earlier. This assumption might be acceptable in certain circumstances, but it is arbitrary and can be unsatisfactory in many cases. Another method is the use of economic assumptions to incorporate some endogeneity of shocks, but they remain arbitrary and based in not much else than logic.

Likewise, while the SVAR approach enables the estimation of impulse response functions, which trace out the response of the system to shocks, it still assumes that the shocks are uncorrelated, unless a specific correlation structure is imposed. This allows for a very high dispersion of potentially incisive modellable effects.

Lastly, VAR models are unreliable because of their own autoregressive nature: the values of the analyzed variables are assumed to depend on their previous values (historical dependency). Historical dependency implicitly assumes that "the past is a good predictor of the future",[83] which could be highly misleading in situations where the data-generating processes change over time, such as in the case of structural breaks. Structural breaks can arise from changes in policy, technology, economic crises, or other large-scale disruptions. If these breaks are not properly accounted for, they can lead to biased parameter estimates and poor forecast performance.

83. Ibid.

DSGE Models

DSGEs models, which do represent the structural models of today's macroeconomic standard, possibly have even more issues that remain unsolved with respect to VARs.

Firstly, the representative agent assumption in DSGE models overlooks heterogeneity in economic agents. The key idea is to treat the economy as if it were being driven by a single, unitary individual or firm. This "representative" agent is supposed to embody the *average* behavior of all individuals or firms in the economy, which brings a degree of tractability to models, enabling economists to build elegant mathematical functions that deliver analytical results that are easy to interpret. However, this simplicity comes at the cost of overlooking a significant reality of economies: heterogeneity.[84] In real-world economies, agents vary their behaviors so much that this noise shapes aggregate outcomes significantly.[85] Moreover, by postulating a representative agent, we rule out any actually meaningful role for economic interactions among different agents of the same class.

Secondly, the hypothesis of rational expectations, which supposes that the agents in the economy can predict future variables given the current information set. This "fatal conceit" on rationality demands a certain level of internal coherence to economic models, capturing the intuition that economic agents utilize all accessible information to inform their decision-making processes. However, upon examining the broad implications of this concept, several critical challenges and limitations arise.

The rational expectations hypothesis predicates its premise on another assumption, the one that posits that all agents possess access to the same set of information and interpret this information identically. In the real world, information is frequently imperfect and asymmetrically distributed among agents, and different agents interpret the same piece of

84. Alan P. Kirman, "Whom or What Does the Representative Individual Represent?," *Journal of Economic Perspectives* 6, no. 2 (1992): 117–136.

85. W. Brian Arthur "Complexity Economics: A Different Framework for Economic Thought," *Santa Fe Institute* working paper 2013-04-012.

information in a myriad of ways based on their unique experiences, contexts, and cognitive frameworks.

The hypothesis also assumes that agents can forecast – more or less accurately – future economic variables, disregarding the inherent complexity and unpredictability of economic systems, which are especially nowadays characterized by dynamic interdependencies and are continually influenced by a multitude of factors such as policy changes, technological advancements, and global events. Consequently, formulating accurate predictions becomes an insurmountable task, even for professional forecasters equipped with sophisticated econometric models, not to mention the cognitive biases that come with that.[86]

On a side note, the first issue also compounds with this second one, because expectations are not homogenous just like agents.

The third and last "standard" issue is probably the most critical and concerns the idea of equilibrium, which is central in these models. The analysis of the behavior of economic variables over time is done under the assumption that the economy perpetually maintains or reverts to a state of equilibrium, where demand equals supply in every market. Again, this simplification provides mathematical tractability and allows for the formulation of elegant theoretical results but is heavily problematic, because equilibrium cannot be proven. Unfortunately, there is not much to say either, because equilibrium[87] is a concept that has no theoretical justification, it is an *assumption* that requires mathematical verification all along the specific model in which it appears, and *all* the theorems associated with it are its consequences, but not its proofs.[88]

An additional critique is that DSGE models often rely on a linearization process around a steady state for their practical solutions and

86. J. Doyne Farmer and Duncan Foley "The economy needs agent-based modelling," *Nature* 460 (2009): 685-686.

87. Here, I refer to both local/partial and general Walrasian equilibrium.

88. Alan P. Kirman, "The Intrinsic Limits of Modern Economic-Theory - the Emperor Has No Clothes," *The Economic Journal* 99, no. 395 (1989): 126–139.

estimations, but I already made an argument against it in the context of VARs.

More specifically in accordance with the methodology I established beforehand, I wish to make some comments on the appreciability of the micro-foundations and on whether the problems that come with aggregation are solved by the new methods that the DSGEs bring to macroeconomics.

In short, both issues are welcomed with a refusal. According to a reductionist framework, the micro-foundations of DSGE models are simply not considerable micro, as they are more holistic than the already unappreciable methodological individualism. The micro-foundation of DSGEs usually consists in applying microeconomic principles in order to build larger-scale equations. For example, the goods market equations often rise from models such as the one of perfectly competitive markets, which in itself considers firms as units (wholes) and is not – actually – micro-founded, and the same level of aggregation is utilized in New Keynesian DSGEs, in which markets are not perfectly competitive but monopolistically competitive. General equilibrium too, for example, excludes any chance of micro-foundation: partial equilibria in themselves are a non-micro-founded social phenomenon simply *assumed to happen* by economists (instead of emerging from a simulation), and cancel out in a Walrasian fashion when considering a multitude of markets.[89]

At the same time, the problems of aggregation that rose during the early development of macroeconomics are not solved, because the level of aggregation that DSGE models agree upon is the same as the old-time General Theory. Still, they are to be considered an advancement and more than just a more complicated version of a traditionally wrong route.

As I am sure is clear, I am very critical of mainstream empirical evidence, both statistical and structural, and do not consider it scientific. Next up an evaluation of complexity economics, which fills some of the gaps of mainstream modelling but could use a lot of improvement.

89. Argia M. Sbordone et al., "Policy Analysis Using DSGE Models: An Introduction," *FRBNY Economic Policy Review* (2010): 1-43.

4.2 Reviewing Evidence From Complexity Economics

Network Models

One of the bigger merits of network models with respect to statistics is that they allow us to visualize individual agents or variables as nodes and to represent relationships or interactions among them as edges, because this kind of structure can effectively deal with high-dimensional data and capture complex interconnectedness in the system, overcoming the dimensionality issue[90] in VAR models.

The big advantage of network models is indeed the clear and multifaceted representation of the connections between variables and agents, and they do not suffer from as many problems because their scope is usually limited to a very small scope. They do not usually display the general-purpose characteristics of DSGEs, and as such do not fall into similar methodological dangers.

Indeed, they are often used as smaller scale tools that can encompass complex subsystems inside a bigger model. Namely, if we are trying to progress in reductionist modelling, agent-based models.

Agent-Based Models

Despite their strengths, there are significant critiques against the use of ABMs in economics. One of the most pronounced criticisms pertains to their lack of analytic tractability. In contrast to equilibrium models,

90. VAR models are very flexible in describing the dynamic interrelationships among multiple time series but can suffer from the "curse of dimensionality": as the number of variables increases, the number of parameters to estimate grows exponentially. Thus, VARs often limit the number of variables included in the model, potentially ignoring important connections and interdependencies in a complex system.

where outcomes can be calculated analytically, ABMs are simulation-based. While this allows them to capture complex dynamics, it also makes it difficult to assemble generalizable insights. ABMs are also heavily dependent on specific parameters and initial conditions, there is a risk of overfitting to particular datasets.[91]

Another significant critique is the black-box nature of ABMs. Despite the detailed micro-specifications, the link between the micro-rules and the macro-outcomes can often be opaque. It may be difficult to trace out why a particular outcome occurred or to understand the underlying mechanisms driving the dynamics. This opacity can limit the interpretability of ABMs and their usefulness for policy recommendations.[92]

With regards to macroeconomics and monetary policy, there have been developments in MABMs, or Macroeconomic Agent-Based Models, which are a subset of agent-based models that engage in economic aggregation. They are comprised of many sub-families and have just as many applications as non-computational and non-simulational models. All the current sub-families treat households, firms, governments, banks et cetera as agents, therefore as wholes, and generate a simulation with a number of them interacting with each other.[93] Nonetheless, certain sub-families, such as the JAMEL,[94] present some adaptive properties of agents that make them more consistent with a framework that considers important to "grow" the economy.

---

91. Blake LeBaron and Leigh Tesfatsion, "Modeling Macroeconomies as Open-Ended Dynamic Systems of Interacting Agents," *American Economic Review* 98, no. 2 (2008): 246-50.

92. Herbert Gintis, "The Dynamics of General Equilibrium," *The Economic Journal* 117, no. 523 (2007): 1280-1309.

93. Herbert Dawid and Domenico Delli Gatti, "Agent-Based Macroeconomics," working paper no. 02-2018 – chapter 1 from Cars Hommes and Blake LeBaron, *Handbook of Computational Economics Vo. IV* (Amsterdam: Elsevier, 2018).

94. Pascal Seppecher, "Flexibility of wages and macroeconomic instability in an agent-based computational model with endogenous money," *Macroeconomic Dynamics* 16 supplement S2 (2012): 284-297.

These models work as follows.

- Firstly, agents and their relationships are defined. For example, banks lend money to firms, and firms produce goods. Then, consumers buy goods.
- Secondly, their specific behaviors and actions are dictated. They usually are microeconomics-based equations with a time element. For example, a consumer that maximizes their spending according to their budget constraint, or a firm that maximizes profits according to their factors and cost constraints.
- Then, the simulation is programmed and ran through a program many times, which prints some tracked variables such as GDP, investment and inflation over time.

Two main problems are inherent to this approach. Firstly, agents in a reductionist framework, even if heterogeneous, should not be entities as aggregated as banks or firms, but individuals that merge into bigger entities as displayed beforehand. Secondly, equations cannot describe the agent's actions as a whole based on a behavioral assumption. They must firstly model the individual as a complex system in itself, extract a rule from such model and only then implement it into a larger-scale simulation or, even better, include the simulation of the individual in the larger model itself. Unfortunately, simulations that both are this complex and do contribute to the study of macroeconomics – let alone monetary policy – do not exist yet, and that is what this thesis' proposal is about.

Now, it may seem impossible to model in such a way, but today's instruments allow it and what we need is guidance and brilliance. In the next chapter I offer a new, general guidance for this kind of modelling.

Chapter 5
Modelling Monetary Policy in a Hebb-Hayek Framework: a Proposal

This proposal articulates the general set-up and rules of the modelling strategy that allows a temporarily reductionist strategy to represent as accurately as possible the dynamics of individuals, markets and the economy, with special consideration for money and monetary policy.

5.1 Translating Theory Into Practice

The First Layer: the Brain

As said before, the brain is still not completely mapped out. As such, we must approximate it to the most accurate but modellable form in order to include it in the bigger simulation. This layer of modelling takes the name of *cognitive architecture* modelling.

In our case, since the proposal concerns an economic model, this layer of the agent-based simulation will be devoted only to the parts that produce a pertinent outcome, in order to simplify as much as possible its use. Then again, in our case, probably, the most important brain process that has implications for economics and policy is, apart from action and choice, adaptive learning.

The Hebb-Hayek principles explain to us that the brain abstracts from its experience because it engages in a process of synaptic modulations as a consequence of multiple, separate experiences that it tries to universalize. Take the example of two actions that fire two different cognits (units of memory): viewing a key and touching a key. Viewing a key ignites the memory of viewing it, and the same goes for touching it. However, after the brain abstracts, a new cognit is created by the assembly of synapses, the "key" cognit. Now, when we either view or touch the key, our brain activates the new cognit "key" that originated from abstraction, that is however separate from the other two.

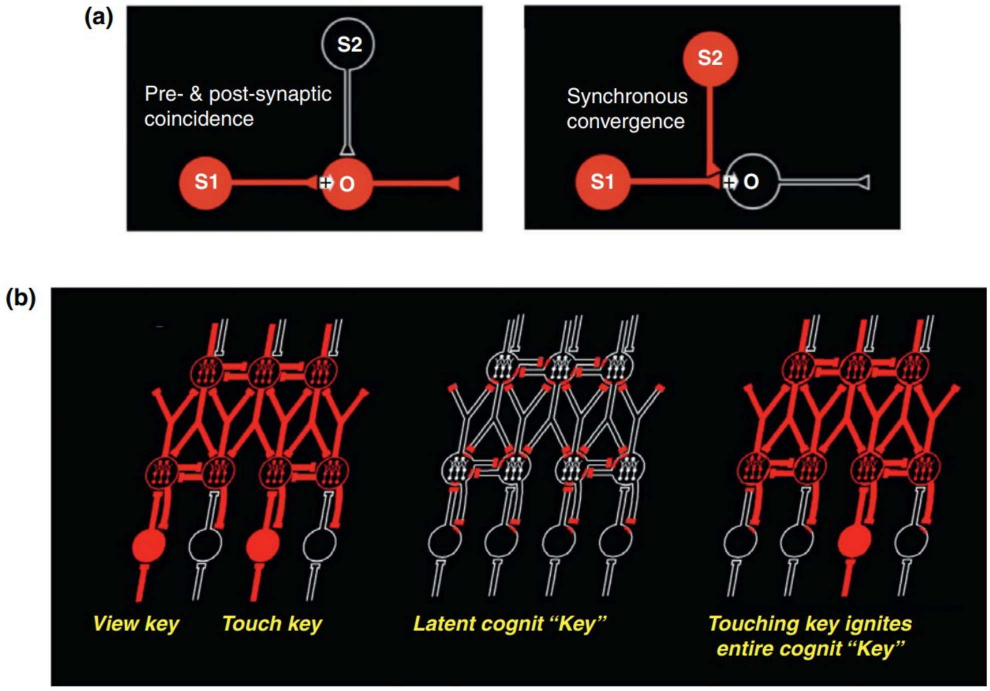

Figure 5.1.1: The Hebb-Hayek principles. [95]

"(a) The two principles of synaptic modulation in memory formation, as enunciated by Hebb. On the right, the principle of 'sensori-sensory' association, considered paramount by Hayek […]. (b) Schema of formation and activation of cognits in cortical networks that possess the essential types of connectivity (feed-forward, feedback, and collateral), allowing bottom-up as well as top-down processing and activation. By the synchronous convergence of stimuli from the sight and touch of an object, my key, a cognit ('key') is formed in a network of my association cortex. In the latent state, the bimodal cognit 'key' is defined in that cortex by a spatial pattern of facilitated synapses. The touch of the key in my pocket activates its entire cognit, with its visual image." [96]

95. Joaquín M. Fuster and Steven L. Bressler, "Cognit activation: a mechanism enabling temporal integration in working memory," *Trends in Cognitive Sciences* 16, no. 4 (2012): 207-218.

96. Ibid.

If we hold this process to be true for all the information and the experiences that the brain is subject to, then we can develop a model of cognitive architecture that stems from it. As stated in the first chapter, the current state of the science does not allow the development of a full-fledged agent-based model for the brain. We cannot simulate the neurons as single agents to print a superbly accurate picture of our cognition. At the same time, we cannot throw away the baby with the bathwater: within this layer, simulation still has a place.

What do we do, then? We compromise, but we do so with elegance. But how so? The answer is simple: we take what we know from our established principles and our partial simulations and we apply it to the modelling of the individuals' mind patterns without modelling the brain itself as a separate object.

Perhaps an example can clarify: the model would not include the neurons that connect with each other when the individual views and touches the key as agents themselves, the model would not include the cognit as a "spontaneous emergence" from the simulation of the brain. The model, in this example, would only include the individual, its action array, and the key. The individual views the key, then touches the key, than "unlocks" many actions that feature the key thanks to its abstraction process, which we know to happen and to be true, but we do not include as a simulation itself, we just "put" it in the model.

It is the range of behaviors, actions and memory-storing processes that the individual holds, practically, what would constitute the *cognitive architecture.* To summarize, we model the mind but not the brain. There is already literature regarding this kind of halfway simulation, and even though it is young, it is very promising and does prove operational to this proposal.

Indeed, various cognitive architectures have been developed, with some being more prone than others to approaching the simulation of the economy via the Hebb-Hayek principles. The best cognitive architecture that matches our case is called Clarion.

Clarion, or Connectionist Learning with Adaptive Rule Induction On-line,[97] is a computational cognitive architecture designed to provide the computational social science and psychology literature with a model that simulates cognition, with special applicability to adaptive learning. This architecture is not a direct bi-product of the Hebb-Hayek principles but also stems from other pieces of literature on psychology and the brain, which means that it does not only contain the memory processes that the principles define but augments them with specifications and categorizations stemming from the recent literature on memory and learning. It is still the most straightforward connection that one can stray for if looking to model such principles.

Next up is a summary of how the Clarion architecture works.

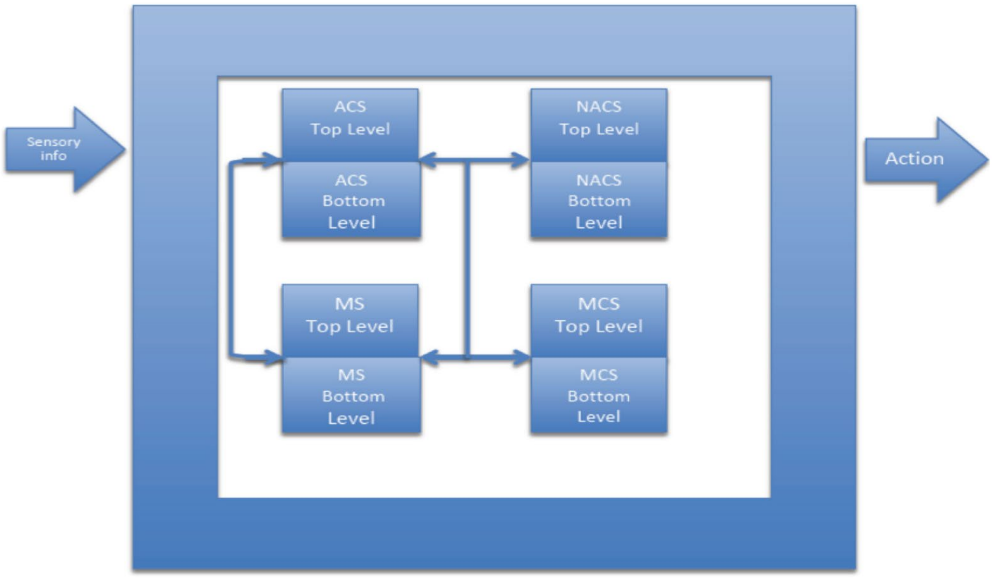

Figure 5.1.2: The Clarion cognitive architecture.[98]

The top floors are where the explicit, or conscious, processes happen. The bottom floors are where the implicit, or subconscious, processes happen. In each component, the top and bottom floors work together. The bottom floor learns from the top floor and can

97. Ron sun et al., "From implicit skills to explicit knowledge: a bottom-up model of skill learning," *Cognitive Science* 25, no. 2 (2001): 203-244.

98. Ron Sun, *Anatomy of the Mind: Exploring Psychological Mechanisms and Processes with the Clarion Cognitive Architecture* (Oxford University Press, 2016), 38.

influence it: for example, picking up a key might involve the automatic action of unoccupying one's hands.

1. *The Action-Centered Subsystem (ACS) is like the doer or the action-taker. When you decide to do something, like touch key that lays on a table, it's the ACS that's responsible. It learns from the actions taken and their results, helping to make better decisions in the future. The top floor might contain explicit rules for what to do in certain situations. The bottom floor learns from experience and forms automatic responses.*[99]
2. *The Non-Action-Centered Subsystem (NACS) is like the big-picture thinker. Instead of focusing on specific actions, the NACS deals with broader concepts and ideas. It's the part of the mind that understands what a "key" is, regardless of its size, color, or material. The top floor deals with explicit concepts and relationships ("this key is akin to the idea of the 'key'"). The bottom floor learns and recognizes patterns without conscious thought.*[100]
3. *The Motivational Subsystem (MS) is the goal-maker. It's the part of the mind that gives the agent a reason to do things. It might motivate it to pick up the key because the agent needs to access a locked door, or maybe just because, in a certain model, the agent is simply programmed to be curios. The top floor houses explicit goals ("I want to open the door"), while the bottom floor deals with implicit drives and feelings, like hunger or love.*[101]
4. *The Meta-Cognitive Subsystem (MCS) is like a supervisor. It keeps track of what the other systems are doing and makes them work together effectively. It is also what regulates the "thought" process of the agent. The top floor involves explicit monitoring and control of "thought" processes, while the bottom floor regulates these processes automatically.*[102]

The ACS and NACS are connected to each other, sharing information and learning from each other. The MS provides motivations that can guide the actions of the ACS. The MCS oversees all other systems, making sure they're working well together and making adjustments as necessary.[103]

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99. Ibid., 51-120.

100. Ibid.

101. Ibid., 121-154.

102. Ibid.

103. Ron Sun, *Cognition and Multi-Agent Interaction: From Cognitive Modelling to Social Simulation* (Cambridge University Press, 2005), 79-97.

The reason why the Clarion architecture makes the best tool for modelling according to the Hebb-Hayek principles is that it is a connectionist model that emphasizes the importance of learning from experience and suggests that the environment provides information to the organisms, which they use to form new abstract concepts and make associations. Both Hebb in *The Organization of Behavior* and Hayek in *The Sensory Order* (the theory) agree with the Clarion architecture (the practice) in explaining abstraction as the main process that makes learning possible. Clarion allows the modeler to let the agents generate new rules after they have experiences that universalize what they have learned from the single encounters both with inanimate objects and other agents.

Moreover, both the theory and the practice collude in approach cognition and the mind as dual complex adaptive systems. For example, in *The Sensory Order*, Hayek posits that the mind is a complex structure of mental models and classifications, continually adapting to new inputs, and producing implicit and explicit outputs.[104] Similarly, Clarion recognizes the mind as a complex system, integrating various cognitive processes and continually learning and adapting from experience, both in an explicit and implicit way.

On the other hand, Clarion is not the only computational cognitive architecture that allows for adaptive learning, but it is the best one because it allows for many newly discovered processes of memory and rule creation, making it the most accurate – as "accurate" as a non-prescriptive model can be. For example, one can include emotions, personality, tastes and many other variables with much less error with respect to a linear model, and hence produce a much better model of, for example, consumer choice or of the labor market's supply side.

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104. Friedrich A. von Hayek, *The Sensory Order: An Inquiry into the Foundations of Theoretical Psychology* (Chicago: The University of Chicago Press, 1952), 79-101.

The Second Layer: the Individuals

The individuals can be modelled in all kinds of programming languages. As of today, Clarion has libraries in C# and Java. However, I advocate for the theoretical architecture to be translated into an easier and more concise programming language such as Python, for which there are experimental attempts.[105] In this subchapter I explore what a Clarion structure for defining agents could be in an agent-based model, using a very simple Python code to demonstration the various categorizations of the cognitive architecture.

Let us take a step back, though. How do we model individuals in the first place? In order to model individuals and their interactions, in general, we first need to *define* them. We usually define them through classes, as "objects", according to the programming language we are utilizing. Then, we assign attributes to each class of agents that we want to model. For example, size, shape, color, speed, but also mental characteristics such as the Clarion model. We then define the rules of the game: how agents interact, how they respond to stimuli and so on.[106]

Afterwards, we define the environment in which the agents act. This could include the physical environment such as terrain, climate, and resources, the social environment such as culture, norms, and institutions, and the economic environment such as markets and prices depending on the scope and topic of the model.[107] Usually, economic models assume that 'wholes' such as banks, firms or governments are agents, and proceed to model holistically, for which I provide a primitive explanatory code.

In order to better clarify what it means to practically build an agent-based model, here is a rudimental example of a simulated money market

105. "Ongoing experimental Python implementation of Clarion: PyClarion, PyClarion dev," *Can Serif Mekik*, 2018. https://sites.google.com/site/drronsun/clarion/clarion-project.

106. Nigel Gilbert and Pietro Terna, "How to Build and Use Agent-Based Models in Social Science," *Mind & Society* 1, no. 1 (2000): 57-72.

107. Ibid.

with just banks and the central bank as agents. I utilize Python because of its general simplicity with regard to object-oriented programming.

First, I import the random module, which I use to randomize the initial amount of money each bank has, and to select banks for lending and borrowing operations.

```
import random
```

Then, I define the classes. I define the central bank, which sets the base interest rates and lends money to the ordinary banks. For each class, we define a function or multiple functions. These are the actions that the agents perform.

In this case, I define *__init__()* as the initializer method for the central bank class, which sets the base interest rate for the central bank. I set it to a fixed value (0.02 or 2%) in this simulation, but of course in a more complex simulation it could be adjusted over time based on economic conditions and monetary policy stance. The function *lend()*, instead, allows the central bank to lend money to a bank. The amount of money is added to the borrower-bank's account at the base interest rate. Then, I command to print the action.

```
class CentralBank:
    def __init__(self, base_interest_rate):
        self.base_interest_rate = base_interest_rate

    def lend(self, bank, amount):
        bank.money += amount
        print(f"The central bank lent {amount} to Bank {bank.id} at an
interest rate of {self.base_interest_rate}")
```

I define the ordinary banks. This class represents a commercial bank in our simulation. Each bank has an id (as there are multiple), an amount of money, and an interest rate, which I set at 0.05 or 5%. I again use the *__init__()* function as the initializer.

```
class Bank:
    def __init__(self, id, initial_money):
        self.id = id
        self.money = initial_money
        self.interest_rate = 0.05
```

Then, I define an adjustment mechanism for the banks based on their account of money. If the bank has a deficit (negative money), it increases its interest rate, hoping to attract more lenders. If the bank has a surplus (positive money), it decreases its interest rate, making it cheaper for others to borrow from it. The adjustment works as a linear modification (plus or minus 1%) of the base rate set by the central bank.

```
 def adjust_interest_rate(self, base_interest_rate):
        if self.money < 0:
            self.interest_rate = base_interest_rate + 0.01
        else:
            self.interest_rate -= 0.01
        self.interest_rate = max(0.01, min(0.1, self.interest_rate))
```

Finally, for each bank, I define the lending function *lend()* just like I did for the central bank, but I also define the *borrow()* function, which is simply the lending function but for the other banks. Then, I define the *__str__()* function, which simply returns a string which gives you info about each banks' final money.

```
def lend(self, other_bank, amount):
        self.money -= amount
        other_bank.money += amount
        print(f"Bank {self.id} lent {amount} to Bank {other_bank.id}
at an interest rate of {self.interest_rate}")

 def borrow(self, other_bank, amount):
        other_bank.lend(self, amount)

    def __str__(self):
        return f"Bank {self.id} now has {self.money} money"
```

After defining the classes and the actions of the agents, I set the central bank's base interest rate, in this case at 2%, and I set a random amount of initial money in integer terms for the commercial banks through the *random.randint()* prompt. In this case, from minus fifty units of money (debt, such that the bank will borrow) to 100 units of money (such that the bank will probably lend).

I also set an arbitrary number of banks (in this case there are 5) for which the randomization of the assigned money is assigned for each bank through a for loop.

```
central_bank = CentralBank(0.02)

banks = [Bank(i, random.randint(-50, 100)) for i in range(1,6)]
```

Finally, I use a for loop to run the simulation. In this example I make it run ten thousand times, but the numbers in actual models are usually much higher and can take hours to process. Notice that each bank chooses randomly among all the other banks through the *random.choice()* command.

Now Let us say that the central bank only lends money to a bank if the bank has less than minus twenty-five units of money. Then, if the bank has positive money and finds a bank in debt, it lends money; if the bank has between minus twenty-five and zero units of money, then it can borrow from the other banks; if the bank has less than minus twenty-five units of money, then it borrows money from the central bank.

```
for _ in range(10000):
    for bank in banks:
        bank.adjust_interest_rate(central_bank.base_interest_rate)
        if bank.money > 0:
            other_bank = random.choice(banks)
            if other_bank != bank and other_bank.money < 0:
                bank.lend(other_bank, min(bank.money, -
other_bank.money))
```

```
        elif bank.money > -25 and bank.money < 0:
            other_bank = random.choice(banks)
            if other_bank != bank and other_bank.money > 0:
                bank.borrow(other_bank, min(-bank.money,
other_bank.money))
            else:
                central_bank.lend(bank, min(-bank.money, 100))
```

Then, I command to print the state of each bank, which will display the output of the simulation in the console of the compiler.

```
for bank in banks:
    print(bank)
```

Below, a typical output of the simulation.

```
The central bank lent 15 to Bank 1 at an interest rate of 0.02
Bank 2 lent 20 to Bank 5 at an interest rate of 0.04
The central bank lent 12 to Bank 4 at an interest rate of 0.02
The central bank lent 1 to Bank 5 at an interest rate of 0.02
Bank 1 has 0 money
Bank 2 has 0 money
Bank 3 has 16 money
Bank 4 has 0 money
Bank 5 has 0 money
```

This simulation helps to understand how agent-based models are written and how individuals – in the place of banks – can be modelled. It also helps to clarify the difficulty of modelling reductionistically, as:

1. What we might see as reductionist may very easily be not. Often, when we see something happening and we give ourselves an explanation, there are instead ten underlying more which we did not and perhaps could not notice, maybe even all contributing at once;

2. We are prone to just type the general rule of behavior, which is difficult to amend and complexify later without rebuilding it from zero.

Indeed, this is then not just a very simple simulation, but also a very anti-reductionist one, even though it is a small-scale micro-founded model. Banks do not exist in the real world as "thinking" entities, they only exist as legal and economic structures that emerged from the interaction of individuals. And even if they were individuals, this modelling strategy would not be reductionist. This is because the actions prescribed are simply too gross. A bank (or an individual, for that reason) does not just lend or borrow based on their quantity of money, nor does it participate in any other economic activity according to such simple rules as the ones defined in the previous code. Unfortunately, adding more variables, agents, or making the rules of action more credible through profit-maximization or other traditionally used economic equations of behavior does not increase the level of reductionism of the simulation significantly enough.

Instead, in order to solve this kind of complexity, we can utilize the aforementioned Clarion, which stems from the theoretical ground inspired by the Hebb-Hayek principles to display a computer-modellable cognitive architecture and lets us create a sound framework of action for the agents.

Recall, my proposal is an insight on how the cutting-edge level of reductionism in economics could be extended by future research through the computational application of the Hebb-Hayek principles.

In order to show a practical example of this, I built a Python code to serve as the most crude structure for generating a reductionist agent-based model, founded upon the categorizations of the mind that Clarion suggests. I did not make use of any imported library, which made the code very simple and repetitive.

I wrote the code according to the following very broad descriptions of the architecture.

- Action-Centered Subsystem (ACS): implementation of a decision-making algorithm that factors in the current state of the environment and the agent's goals.
- Explicit Non-Action-Centered Subsystem (NACS) as to store of symbolic and declarative knowledge, which the agent could access as needed. Implicit NACS to be implemented through a neural network, which can learn representations of concepts from data.
- Motivational Subsystem (MS): representation of the offset of the goals of the agent, which may be modelled with a function that generates them based on the individual's current state and needs. For example, if the individual is hungry, the MS may generate a goal of finding food.
- Meta-Cognitive Subsystem (MCS): to activate only in some circumstances. For example, a supervisory function that manages the other subsystems, which might include an algorithm to determine which subsystem's output to follow when there's a conflict, and another to monitor the agent's performance and adjust its strategies as needed.

In the following code, the blue background represents the structure, the red background represents an example of a container for implementable algorithms in each of the subsystems. I only wrote more specific code for the first subsystem, in order to exemplify how to augment the framework.

First of all, I defined the agent with the *class* prompt and assigned it an *__init__()* initialization method just like the one from the simulation before, which contained the initialization of the four subsystems, all pertaining to the function argument *self*, which is the agent itself.

```
class Agent:
    def __init__(self):
        self.ACS = ActionCenteredSubsystem()
        self.NACS = NonActionCenteredSubsystem()
        self.MS = MotivationalSubsystem()
        self.MCS = MetaCognitiveSubsystem()
```

Then, I defined the subsystems as separate classes, each with an initialization process and the two levels, implicit and explicit.

In the case of ACS, I defined it as the subset "action" of the function *perceive_and_act*, with *state* as the argument: the agent performs the action in the environment, update *state* based on the action results, then return the updated state.

After defining *__init__()* as the initializer method, I defined the implicit process as a process including *state*, which serves as the reference of the state of the agent.

```
def perceive_and_act(self, state):
        action = self.ACS.decide(state)
        return state

class ActionCenteredSubsystem:
    def __init__(self):
```

Here, *rule_base* would store the explicit rules. The Q-table[108] *q_table* records the reward and punishment history, that would appear later in the modelling process.

```
        self.rule_base = {}
```

108. Christopher J. C. H. Watkins and Peter Dayan, "Q-learning," *Machine Learning* 8, no. 3-4 (1992): 279-292. Q-learning is a type of machine learning that involves an agent trying to learn how to behave in a certain environment to maximize its rewards. It basically works as follows. The agent finds itself in a certain state => The agent can perform various actions => Each action leads to a new state and provides a certain reward => The agent wants to learn the best action to take in each state to maximize its total reward. The agent keeps track of the expected reward for each action in each state (Q-table). At first, it doesn't know anything, so it makes random decisions, but after each time it gets a reward, it updates its expected reward function with this new information. Over time, the agent learns which actions tend to give the best rewards in each state. This process is the "learning" in Q-learning. So a Q-learning decision is basically the agent consulting its Q-table and choosing the action that it expects will lead to the highest reward. It's all about learning from experience to make better decisions in the future.

```
        self.q_table = {}
```

```
    def implicit_process(self, state):
```

An implicit process could indeed be a simplified Q-learning[109] decision, like in this case, to connect to the previous *q_table*. It is a very simple rule-based decision-making process that works through dictionary.

```
        if state in self.q_table:
            return self.q_table[state]
        else:
            return None
```

```
        pass

    def explicit_process(self, state):
```

Repeat the entries for the explicit process:

```
        if state in self.rule_base:
            return self.rule_base[state]
        else:
            return None
```

```
        pass
```

109. Ibid.

Below, a decision method that uses a decision-making function which primarily relies on the results of two other processes (*explicit_process* and *implicit_process*) and returns a default action if neither of those methods provide a decision.

```
def decide(self, state):
        explicit_decision = self.explicit_process(state)
        implicit_decision = self.implicit_process(state)

        if explicit_decision is not None:
            return explicit_decision
        elif implicit_decision is not None:
            return implicit_decision
        else:
            return 'default_action'
```

The rest of the structure is displayed below. Again, I did not develop an experimental code (red tabs) for the rest of the structure, because I am not developing a model but providing a practical example of a Clarion architecture. I limited my commented explanations to be in-text, starting with a "#".

```
class NonActionCenteredSubsystem:
    def __init__(self):
# Initialize the non-action-centered subsystem
        pass

    def implicit_process(self, concept):
# Implement a neural network or any other distributed representation
learning
        pass

    def explicit_process(self, concept):
# Implement a symbolic concept retrieval
        pass
```

```
class MotivationalSubsystem:
    def __init__(self):
```

```
# Initialize the motivational subsystem
        pass

    def implicit_process(self, state):
# Implement the fundamental drives and needs the implicit motivations could be more fundamental needs or drives, which could be modeled as stochastic variables

        pass

    def explicit_process(self, state):
# Implement a goal generation in which the explicit motivations could be coded as specific tasks to achieve
        pass
```

```
class MetaCognitiveSubsystem:
    def __init__(self):
# Initialize the meta-cognitive subsystem
        pass

    def implicit_process(self):
# Implement a basic activity regulation - the implicit MCS could be a more basic mechanism for regulating their activity
        pass

    def explicit_process(self):
# Implement a rule-based or strategy-based subsystem management - the explicit MCS might involve certain rules or strategies for managing the other subsystems
        pass
```

Now, this code could serve as a skeleton for further augmentation, but not necessarily so, as the structure of a Clarion framework for the agents can vary by a large margin. It is, again, a practical example of the generalized concepts that Clarion proposes.

After this expansion on the grade of reductionism that this thesis promotes at the agent level, it is necessary to contextualize it and transpose it to the (entire) model level.

5.2 Climbing the Steps

Let us broaden the picture, then: how do we turn this "horizon" of a modelling strategy for the agents into a large-scale monetary model?

What comes next is a step-by-step modelling proposal which I advocate to be followed by future research in the field of economics as a complex system.

Step 1: Define the Agents

Assume all the agents are individual humans, and that the individual humans are the irreducible element of the simulation: that is, that if the simulation is to be conceived as a recursive agent-based model,[110] then the most irreducible layer of agent is the individual. Recall the third chapter: we cannot yet model the brain because we cannot input the neurons as agent for a comprehensive subsystem in the system that is the individual, such that we only model the individuals.

Assume that each agent follows some kind of Clarion cognitive architecture, and that each agent will have their own implementation of the Clarion cognitive architecture based on its environment, allowing for diverse behaviors and decisions based on the four subsystems enunciated along the previous subchapter.

Adopt cognitivism in social orders. That is, assume the existence of the empirically observed social institutions and greater interactions, such as corporations, banks, families and markets, the internet, economic sectors respectively. These must be deconstructed, simulated, and then inserted into the larger simulation, but must be assumed to exists prior to the running of the simulation, and not as agents.

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110. Ron Sun, Cognition and Multi-Agent Interaction (Cambridge University Press, 2006).

Step 1.1: Define the Characteristics of the Agents

Describe each agent with certain characteristics that define them. In the context of a monetary model looking to expand on monetary policy transmission, this will contain:

- Arbitrary variables, necessary to any social model. These include income, wealth, employment status, household conditions, geography et cetera.
- Attitudinal variables, necessary specifically to monetary models. These include risk tolerance, personality traits that predict job orientation, interests and industriousness, propensity to invest and consume, and other variables that have impactful effects on the agent's environment from the psychometric literature.

Step 1.2: Implement the Clarion Architecture for Each Agent

Each agent will be equipped with an implementation of the Clarion cognitive architecture, hence implementing the four subsystems (ACS, NACS, MS, MCS) for each agent, which will guide the agent's behavior and decision-making process. This task would involve writing code or using a software package that supports Clarion to build the agents.

The implementation of the four subsystems could include both reinforcement learning and supervised learning. In the ACS, actions may be selected based on their expected utility, and reinforcement learning could be used to update these expectations based on the outcomes of taken actions. In the NACS, supervised learning is used to learn from explicit feedback.

The extent of each layer can be modified according to the needs of the specific research, involving that the researcher may simplify the Clarion model. They can do so, but as long as Clarion keeps the adaptive learning properties from the Hebb-Hayek principles.

Only then the choice of the rule-based system can happen. This will depend heavily on psychological research – remember the assumption that all agents are individual humans – and on equations or response or reward functions that fit the empirical findings.

Step 1.3: Define the Initial State of the Agents

The initial state of the agents is the state at which they start the simulation. By "state" I indicate the set of variables that the researcher has put into each agent's code.

Defining the initial state may involve both assigning absolute values to some characteristics (such as income) or may involve assigning functions that respond to other agents' behavior or the environment's features.

A way to assign absolute values is, obviously, to just input a value, but also to randomly assign a number within a certain range, or setting up a predefined distribution that matches with empirical data on the population that the agent-based simulation wants to replicate.

The initial state will likely have a major influence on the behavior of the agents and the overall simulation. Hence, randomization and functions instead of single number inputs prove useful when trying to universalize one's findings.

Step 1.4: Create a Method for Generating Agents

This step is optional, as it is probably only required for very large simulations, which are intended to be run for in-simulation years, in which births produce a significant effect.

Indeed, depending on the size and complexity of the simulation, it may reach hundreds of millions of agents, meaning that the births and the existence of children cannot be ruled out.

Step 1.5: Define How Agents Perceive Their Environment

In relationship with the established code in the four subsystems, the researcher must define what information each individual can perceive from their environment (talk, watch the news, read on-line et cetera) based on their knowledge and status: are they financially educated, do they know about monetary policy, and do they have expectations on inflation? The actions and perceptions must of course not be in contradiction with respect to the subsystems and layers that were previously built.

Note that the environment, for an agent, is all that is not itself or other agents. This means that, in a monetary model, money, the interest rate, the markets – if not accessed through p2p interaction – constitute the environment.

Then, the researcher must implement how this information is processed through the cognition of the agent and review the base code structure to apply the connection.

In the context of a monetary model, this is crucial to simulate the process of interest rate transmission: a stockbroker or a CFO of a firm, but also the individuals in the household will respond to the signals that the markets emits about the changing monetary conditions of the economy, and they will amend their choices accordingly. Then, the researcher can observe how the transmission mechanism works in different contexts and verify the accuracy of the previously established channels of transmission in the literature.

Step 1.6: Define How Agents Interact with Each Other

Agents will need to interact with each other in various ways, such as through small-scale trade and lending, or through collaboration and competition. The rules for these interactions, and how they are influenced by the agents' characteristics and perceptions, should be defined according to the type of model one wants to generate.

For instance, if the model wants to simulate a hunt, which is not our case, the agent *human* may interact with the *prey* through an action "approach", after which the prey will respond with either "attack" or "escape", and the human will continue the interaction accordingly.

In monetary models a direct application might include hot tips from peers who work in the financial sector.

Step 1.7: Fine-Tune the Agents

Once agents and all their functions have been defined, it is important to test them to ensure they behave as expected. And by "expected" I do not mean "as I wish them to behave", but rather "their actions do grant a flow to the simulation". In other words, it is important to go through a debugging process that fixes any threats to the iteration of the simulation.

This might involve taking out smaller sections of the simulations and running them separately, or do unit tests to check that the Clarion subsystems are working correctly and the agents are making realistic decisions based on their characteristics and perceptions, both by analyzing the data output from the agents as a whole, but also by inputting markers in the code that print the functioning of the single subsystems.

Remember that this process might require a number of iterations to fine-tune the agents. Developing an agent-based model is an exploratory process, and it often requires several iterations to get the model to behave as desired.

Step 2: Define the Environment

A necessary note: the environment has to be modelled after the agents, but the research project must at the same time have a very precise idea of what the environment will be while defining the agents, because the agent's functions' complexity must be relative to the complexity of the environment: if we define the agents to have cultural and geographically derived features just for the sake of including as much stuff as we can, we may very well end up stuck in defining the environment, which could become too hard if we did not plan to assign the appropriate amount of workload to it.

Step 2.1: Identify the Environment

The environment in this case involves a monetary economy, so Let us take a very large-scale simulation as an example. If we were modelling in a context of a MABM, we would need to model the different aspects of the economy, such as interest rates, money supply, goods and services, labor, and so forth separately and according to neoclassical, New Keynesian or any other kind of other non-reductionist evidence.

Instead, a reductionist simulation would work with only the single agents being modelled and with no aggregate concepts (except for “factual” ones, like the money supply or the employment rate) being inserted. Each agent will have their characteristic, such as being a participant in the labor force and investing a certain amount of money, and will participate in the simulation as a whole, with the data and theory on the models of labor, macroeconomics, money, et cetera being extracted afterwards, when the simulation has been run and there have been spontaneous social emergences.

What place do social institutions such as firms or governmental agencies take, within this method? Well, since they cannot be agent in a reductionist framework, they must be modelled as the environment,[111] and take the form of “situations” in which agents interact with each other and are affected by exogenous (to each agent) factors, such as the labor relationships.

Several operations of fine-tuning and debugging in each of those internal institutions are needed for the larger simulation to work, because

111. As long as we try to model a very complex economic environment, this is the best compromise possible. The alternative would involve modelling social institutions as agents, which I criticized earlier on. On the other hand, when a simulation is simple, such as the simulation of a single market, social institutions may not be included at all.

they must *emerge* (and fall) as spontaneous orders of agent interaction, both voluntary and unintentional. One must "grow" the institutions by themselves and fine-tune them, then insert them in the larger simulation. Keep in mind this is an assumption: the researcher assumes the existence of firms with certain, general characteristics and tries to replicate them according to a cognitivist approach in the simulation.

Given the difficulty of unifying all the smaller components of the agent-based model, one may assume the presence of some general macroeconomic relationships too, such as the market for goods and services, the labor market and the money market, but must at the same time simulate and fine-tune them separately just like in the case of the social orders.

Step 2.2: Model the Central Bank

This aspect is of course optional to a monetary model simulating a modern country with a central bank. Just like the other social orders, modelling the central bank is done at optimum with a separate simulation and with fine-tuning. However, since the mechanisms of the central bank are well-known (it is suggested to model according to one exemplary central bank), the central bank may be completely exogenous, and coded as pure environment.

Especially on the topic of monetary policy transmission, where we try to find and quantify the economic channels of pass-through of the instruments of the policymakers, the central bank being exogenous is a very useful simplification which does not impose threats to the validity or to the level of reductionism of the simulation.

A central bank might be exogenously modelled as a rule-based actor. For example, raising interest rates when it predicts that inflation is high according to the model it is using. In case of the European Central Bank, the simulation may include a rule-based algorithm which implements some variation of the IS-MP-IA model,[112] used to interpret macroeconomic data at a general level.

A more complex model could be based on real-world central bank behavior, could involve also asset purchase programmes and unconventional monetary policy instruments, such as interest rate programmes of miscellaneous maturity.

In the case of a model analyzing transmission, I advocate for an extremely simple rule-based approach based on a simplified IS-MP equation for which the central bank:

- Collects macroeconomic data. This data will coincide with the data we observe in the model as researchers.
- Compute a policy interest rate based on a primitive inflation targeting equation, only long-run based:
- $i = r + \pi \;\Rightarrow\; i^* = r^* + \pi^{TGT}$
- where:
    - i = nominal interest rate;
      i^* = policy nominal interest rate
    - r = real interest rate
      r^* = policy-adjusted real interest rate
    - π = inflation rate
      π^{TGT} = the inflation level targeted by the central bank, usually 0.02 (2%).
- When the inflation rate is too high or too low, the central bank will adjust the policy nominal interest rate (increase and decrease, respectively) in order to recuperate the "golden rule" inflation level.

112. David Romer, "Keynesian Macroeconomics without the LM Curve," *Journal of Economic Perspectives* 14, no. 2 (2000): 149-169.

Step 2.3: Define the Initial State of the Environment

Just like we did for the single agents, we must define an initial state of the environment once we have defined its everlasting characteristics. Some sections of this process will result easier, some will result harder.

For example, a setting of the initial state of the consumer side of a generalized goods market, after the fine-tuning process may be easier. A researcher may use real-world data to input into the price levels for the selected goods, in order to then look at the fluctuations given a monetary policy.

On the contrary, a setting of the producer side of the same market may be a lot harder, as the agents in the supply process are firms, which are emergent social orders and collaborative aggregates of multitudes of agents.

Step 2.4: Test the Environment Implementation

Just like with the agents, it's important to test the environment implementation to ensure it behaves as expected. This could involve running smaller-scale simulations (like the interaction between two firms) or specific (unit) tests to check the behavior and dynamics of the environment.

Remember, the environment is a crucial part of any agent-based model, and getting it right is key to producing a realistic and useful simulation.

Step 3: Set Complementary Rules for Agents

Step 3.1: Set Rules for Changing of Economic Stances

Economic behavior and conditions can change over time, so the rules of interaction should account for these changes. This could involve rules for how agents update their expectations on prices according to the central bank's target rate, how they adjust their behavior in response to new media information, or how their economic conditions evolve over time (for example, adjust spending according to changes in income).

Step 3.2: Set Rules for Opinion Formation and Spreading

Opinion spreading is the diffusion of stances and opinions (relevant to the model) between agents in a defined network. This is an optional step but adds a lot when modelling a model in which the monetary policy has to take into consideration the agents' expectations, or in which there is a political system which has effects on the economics of the model.

Notice that this section of the proposal includes network science as a tool for this model, but not as a basis for the whole model itself, which is instead given by an agent-based computational framework.

The computational literature concerning opinion spreading in network science is well established, but there is also some literature that works out models where both opinion spreading and complex interaction rules are present.[113]

This kind of modelling can be done as I now present.

1. **Set initial opinion.** Initially, every agent will have an opinion about different topics or issues, possibly resembling data from a real-world correspondence (if we want to simulate something approximating Italy, we take into consideration surveys from Italy);
2. **Build an influence system**. Define how agents will interact and influence each other. Some agents might be more influential than others (think of politicians, or even more so social media influencers). Also, the influence could be dependent on other factors like the similarity of opinions, proximity, the credibility of the agent,

113. Damián H. Zanette and Santiago Gil, "Opinion spreading and agent segregation on evolving networks," *Physica D: Nonlinear Phenomena* 224, no. 1–2, (2006): 156-165.

or the social status of the agent.[114] For example, it has been shown in the network science literature that fake news spread to individuals who are already inclined to believe their implicit message.[115]

3. **Opinion update rule**. According to the level of influence, we need to implement a rule to update agents' opinions after each interaction. For instance, a basic rule might be that an agent moves their opinion closer to the average opinion of their five closest friend or toward the opinion of a more influential agent that they follow on social media.
4. **Network Topology**. The structure of the social network also plays an important role. Depending on the connection patterns between agents, different kinds of topologies can be defined like fully connected, small-world, scale-free networks, etc.
5. **Define the threshold**. Define the threshold for when an agent's opinion changes and the threshold for when the change in opinion causes a change in action. For example, in a political spectrum, absorbing and processing one new unfavourable political information will shift the agent's opinion by one point; after fifty points towards a direction, the agent's opinion is amended. After an predetermined amount of amendments, the agent will change its stance.

Step 4: Run the Simulation and Collect the Data

The running of the simulation can work in two ways:

1. Letting the simulation run for a long period of time;

114. Laura Burbach et al., "Opinion Formation on the Internet: The Influence of Personality, Network Structure, and Content on Sharing Messages Online," *Frontiers in Artificial Intelligence* 3 (2020): 45.

115. Michela Del Vicario et al., "Echo Chambers: Emotional Contagion and Group Polarization on Facebook," *Scientific Reports* 6, no. 37825 (2016).

2. Running the simulation for a short amount of time, for multiple runs.

A way to collect results effectively would be to compare the two types of simulation data and confront their similarities. Bumping into bugs is very common in these cases, hence it is crucial that, before running multiple instances of the mode, the researcher tries to spot errors in smaller scale test runs.

In a monetary model, of course, the data to collect would include the money supply level, plotting the interest rates, inflation, et cetera, but also indicators such as GDP, unemployment rate, wage levels, and so on. At the same time, as it is a thoroughly micro-founded model, it is also useful to insert trackers for the social orders (institutions), their evolution, behaviors and unit effects on the economy.

This would meet the current micro and macro literature in its own terms, by presenting data in the same form, but stemming from another perspective.

5.3 The Limitations

The limitations of this kind of modelling are many, but are not, like most of other macroeconomic models, on the explanatory side, as this kind of modelling route would probably encapsulate much of what is already contained in most other general-purpose models. They would likely be instead on the funding and on the difficulty of merging all the different sections of the code to create a unified model.

Still, even the most outstanding version of the model that I described in this proposal would have some theoretical limitations. One would be in relationship to the other fields of science connected to the topic, which are mainly two:

- **Neuroscience**. The field of neuroscience puts the biggest constraint to this modelling strategy, as its advance would make the Clarion architecture obsolete, and maybe even the Hebb-

Hayek principles. This would imply that methodological reductionism will require further research on brain modelling to produce something appliable to social science.

- **Psychometrics**. The field of psychometrics, meaning the field of "quantitative psychology", gives us the rules of behavior to implement into the agents' definitions. New psychometric research would require updates to the model, but not its total restructuring. Hence, psychometrics constitutes a limitation to the model, but not as much as a threat.

Nonetheless, there are some limitations separate from the ties with the other fields of science. To start with, a big one is the computational power that is available today, especially in modelling the environment. Most programs are just not detailed enough to implement all the rules and characteristics necessary to a comprehensive simulation of the economic system, and most advanced computers are not powerful enough to simulate in a reasonable timeframe so many iterations of such a complex simulation.

The model itself is not the ultimate model either, even if we had the most powerful computational tools, a Clarion agent-based economy would not be totally future-proof. The field of cognitive architectures is young and flourishing, which means that more detailed ones will come out in the near future, and this proposal will be more and more obsolete. But it is not only a matter of modelling a cognitive architecture, but also what stands behind it: the background of the agents' actions, the brain. It is a matter of "when", not if, new models for learning and cognition will come out and surpass the Hebb-Hayek simplification.

Moreover, there are some characteristics of the model that make it complicated to monitor. That is, the fact that it is so based on adaptive learning rules can very easily lead it to compound on unlikely outcomes, such as groups of individuals or institutions deviating too harshly from the majority of the existent rules of the model's population, which would probably not have any real-world correspondence. Since its scale is medium to very large and its nature requires it to iterate the simulations in order to come up with consistent results, it is also unlikely that the monitoring would happen intra-simulations and would simply mean to remove the highly variating iterations from the array of printed results. As of today, we have not yet developed software applications for agent-based models that focus on the accessibility of the programmer to each simulation's iteration *while running*, maybe with the exception of NetLogo,[116] a program in Java that allows for imagery and graphs that display the data's variation during the running process. NetLogo is however mostly used for small-scale simulations and would hardly find applications for cognitive architectures and/or whole economic systems.

116. "NetLogo," Uri Wilensky, 1999. http://ccl.northwestern.edu/netlogo/.

Concluding Remarks

Today, there is a void in mainstream economic research, a void in the methodology used by economists when they build models: the complexity of the economy is underestimated and answered with aggregation. This issue is particularly present in the field of macroeconomics and, as a consequence, monetary policy.

I used the literature on monetary policy as a proxy to introduce the problems with today's state of the art models and I exhibited how today's mainstream macro evidence does not encapsulate complexity at all, and why its more heterodox, complexity-oriented ramification does encompass it, but in a fashion that could use several improvements.

The main necessity is to update its degree of aggregation, which complexity economics does improve from the mainstream, but not by an appreciable amount, and proposed an easily modellable cognitive framework – the Hebb-Hayek framework – to advocate for an individual-based model instead of an institution or aggregation-based model.

I then transported the framework into the cognitive architecture Clarion, which agrees with it and which tells us how to model individual minds more specifically in a multi-agent system. Finally, I described how to use this architecture to create a bottom-up macroeconomic model, specifying the particularities of including the central bank's policies.

From the needed research and the elaboration of this thesis it emerged that the scientific community is partially heading to the "right" direction and that being that complexity economics and agent-based economics are young fields, we do not need a shock in the academia to solicit change, but it can use some guidance and can experiment with models such as the example in this thesis' proposal section to expand its confines.

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