# Prospective Hindsight

using system dynamics and exploratory modelling & analysis to find a new methodology for scenario building in financial institutions

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# Preface

What you see on the cover is a combination of two paintings: 'Heraclitus' and 'Democritus', both by Johannes Moreelse. Democritus (the right side of the image) is one of the favourite paintings of the Dutch astronaut, André Kuipers. When I met him for the second time at the Future Force Conference 2017, he challenged me to go see the painting.  Coincidentally, NN is the main sponsor of the Mauritshuis museum (and this thesis), home to Democritus. When I went on a guided tour of the Mauritshuis, organised by NN, I saw the painting with my own eyes and immediately fell in love with it.

The painting Democritus is that of the laughing philosopher and contrasts the second painting and character of Heraclitus, the weeping philosopher (the left side of the image). Both philosophers address the condition of man as being unknowing, insecure and frail. Democritus and Heraclitus can both be considered as rationalists; Democritus as scientific rationalist philosopher and the Heraclitus as a stoic. The way they both approach human follies is different however. One bursts out into tears, having pity and compassion for we are all in the same condition. The other approach is that of humour, not because it is pleasanter to laugh than to weep, but because it is more disdainful and condemns us more than the other[1]. To me, the paintings represent the topics I am trying to write about as well as the scientific discourse in the System Dynamics community; uncertainty and how to approach it.

In this thesis, one of the core components is performing Exploratory Modelling & Analysis. Described briefly, Exploratory Modelling & Analysis is a research methodology that uses computational experiments to analyse complex and uncertain systems (Bankes, 1993). This approach stands for rejecting the idea we can model or fully understand reality. Rather, it is our ignorance, biases and uncertainty that we explicitly try to model. By taking this approach, we set ourselves up to having a broad definition, understanding and scope of reality, if it can exist at all. We do not laugh or cry away our frailty, but rather embrace it – a third approach and balance between Democritus and Heraclitus. Unfortunately, this approach is sometimes difficult to combine with System Dynamics community. Due to the different philosophical nature of the methods, Exploratory Modelling & Analysis provides classical system dynamicists less information instead of more. Maybe this is because of the different goals of the approaches, or maybe due to misunderstanding of the relatively new scientific field of data science. Whatever the case, we will argue for integration; benefitting from the modelling techniques of System Dynamics, while expanding our analytical capabilities in the field of data science.

With this philosophical explanation, the title of this thesis can also become clear. We try to model uncertainty explicitly so that we can consider possible changing realities when making decisions. We try to evoke hindsight before events have happened and think carefully about the future: Prospective Hindsight.

[1] Findings from poet Lucretius in 'De Rerum Natura', translated by Cyril Bailey.

Prospective Hindsight, owns its existence to many different people and institutions. In no specific order, I would first like to thank prof.dr.ir. V.A.W.J. (Vincent) Marchau for being thesis supervisor. It has been very difficult to find someone to supervise this thesis in the System Dynamics community or associated universities, but prof.dr.ir. V.A.W.J. Marchau proved to be the perfect link with the Radboud University and TU Delft – the university where the author is from and where the research was conducted, respectively. Prof.dr.ir. V.A.W.J. Marchau knows both universities, the other professors involved in this research and is an expert on Robust Decision Making himself. Many important articles used for this research were partially written by prof.dr.ir. V.A.W.J. Marchau and his involvement has greatly increased the quality of this thesis.

With regard to the analysis of this thesis, I would like to thank Dr. E. Pruyt for introducing me to Exploratory Modelling and Analysis, allowing me to follow his lectures and participate in class. We first met during the System Dynamics conference of 2016 where he was enthusiastically encouraging me to be a guest student at the TU Delft. The second main contributor to Exploratory Modelling & Analysis (and the creator of the workbench used in this thesis) is Dr.ir. J.H. Kwakkel. His lectures and setup of the course Model-Based Decision Making provided me with enough footing to perform a multitude of analyses on my own. Finally, from the TU Delft, I would like to thank all the students in the MSc Engineering and Policy Analysis programme. We have worked on projects together, had a lot of fun and helped each other out. As my background is not based in mathematics or programming, many students helped me by sharing code and explaining things outside of class. I am thankful for their open, hard-working and enthusiastic attitude.

Last but not least, I want to thank the team of Risk Integration of Nationale-Nederlanden Bank; Remco Bloemkolk, Harald de Bruijn and Coen Ribbens. Remco Bloemkolk, as the manager of Risk Integration, trusted me to let me follow my instincts, design my own path and come up with an approach for the thesis. Harald de Bruijn has worked closely with me by explaining the banking system, operations, legislation and proofreading the thesis many times. Finally, Coen Ribbens helped me gain an intuitive understanding of the macroeconomy by lecturing me on a diverse range of economic theorems. I owe them a lot and am very grateful.

# Executive summary

Since the economic crisis of 2008, the economic system has been under ever more scrutiny. To assess the financial health of the system and its participants, the central banks of European countries demand a yearly stress test from financial institutions. A stress test is a procedure for calculating the effects of economic changes on a financial institution, testing the limits of economic pressure institutions can handle. Performing this test is also a requirement to continue operations. To develop input for a stress test, scenarios are generated that describe possible (negative) future configurations of the economic system. These scenarios are generated (i.e. thought of) by institutions themselves and then used as input for the stress test. The results are reported to the financial authorities that use this information to monitor the economic system. However, current practice shows huge flaws and vulnerabilities around the development of scenarios in financial institutions.

Institutions currently build scenarios according to a traditional approach. In short, scenarios are based on expert knowledge and produce a singular storyline (one per scenario). As scenarios of the economic system are dealing with high uncertainty, this becomes a major problem: because there are no experts in the face of uncertainty, yet experts come up with these scenarios. In a situation of uncertainty, relying on expert prediction for making scenarios is an outdated approach. Another problem is in how scenarios are presented. Producing and visualizing a singular storyline in the face of uncertainty is wrong and misleading: output should be presented as a range of possible outcomes (per scenario). When focussing on a range of outcomes, decision makers are better equipped to design policies that perform well in a diverse environment. Finally, the traditional scenario building approach is not able to standardise it outcomes. This makes it easy to steer scenarios and makes it infeasible for the auditor to assess the quality of scenarios. Our critique on traditional scenario building as a methodology for designing input for stress tests can be summarised as follows:

1. Relying on expert knowledge for uncertainty projections is faulty because:
    - Experts are intrinsically biased;
    - Due to limited cognitive capacity, one person cannot take into account all variables at play when developing a scenario;
    - The values assigned to cases are chosen arbitrarily and unlikely dynamics can be left out of the picture;
2. Scenario design should focus on a range of forces because:
    - Decision makers (humans) have limited cognitive capabilities and therefore can only focus on a limited number of scenarios;
        - Certain scenarios will thus be neglected;
        - The amount of uncertainty in an analysis is therefore also limited;
3. The production of scenarios should be well-traceable because:
    - When offered too much freedom, it is possible to pick scenarios that have a beneficial outcome for the financial institution;
    - Regulators should be able to accurately compare institutions and thus design fitting measures for the future.

The goal of this thesis is to design a new methodology to deal with the critique of the current approach. We will addresses the shortcomings of scenario design in financial institutions and introduce Robust Decision Making as a solution to better decision making in the face of uncertainty. The product of this research will be better input for stress tests which in turn produce a more robust and stable financial system. Robust Decision Making plays a central role in this thesis and forms the theoretical base of this research. This method combines computational and quantitative analysis with scenario-planning to help decisionmakers choose strategies that perform well over a variety of potential futures. We will follow some steps in the Robust Decision Making process, but will make a few adjustments.

The first step in Robust Decision Making is to structure the goals, uncertainties, and choices of the decisionmakers. The second step is to use computer models to generate a large database of plausible futures – that in our case will represent the macroeconomy. The third step is identifying clusters of scenarios in the output space. We identify clusters by setting criteria for the output and can then calculate backwards what the input(s) of the model had to be to arrive at that outcome. The last step is to make a trade-off analysis of the policy options and then choose/implement a policy, or repeat the cycle if no desired/robust policies are found. Our implementation of Robust Decision Making stops around the third step, but this thesis is set up to also support future implementation of the full methodology.

This thesis thus implements a custom form of Robust Decision Making; these changes are made due to time and resource constraints. The first change is that we are not going to test policies in our Robust Decision Making cycle. In our case, a Robust Decision Making approach can still be valuable, because there already is a model that can describe policies: the existing stress test model. This is an internal model of the financial institution we are collaborating with. Consequently, if there are no policies, there is no trade-off analysis (step 4). Our Robust Decision Making cycle is therefore focussed on finding scenarios in a generated dataset and later use those scenarios for the stress test model. In the future, it might be possible to implement Robust Decision Making fully, with the inclusion of policy analysis.

Following our custom Robust Decision Making design, our research consist of the following steps:

1. Build multiple economic models that explain system behaviour

Instead of one source or expert knowledge, we will use a variety of economic theorems that explain macroeconomic behaviour. We use multiple theorems to explore the whole possible range of economic configurations; because there is no one singular and/or agreed upon theoretical lens to view the world. Our models are built with System Dynamics methodology. This is a differential equation-based computer simulation that is well equipped to explain dynamic behaviour and cycles – which we often see in economics. These models will serve as our engine for the generation of datasets. The second step will therefore be:

2. Run the model(s) thousands of times with different input for the uncertain, external parameters to generate datasets

We will generate these datasets by translating the earlier described System Dynamics model to Python 3.6 computer language. Converting the model into code allows us to write custom programs to do analysis not possible in basic System Dynamics software packages. When we have generated the dataset, we move to the last step:

3. Analyse and cluster the outcome space of the datasets to generate possible scenario input for a stress test

To analyse the dataset, we make use of computer algorithms that look for patterns based on a binary classification of our cases of interest. Simply put, the scenarios generated by this approach are those instances in which the economy changes so that the financial institution cannot continue operations as normal. Those outcomes are then translated into input scenarios for a stress test by giving the ranges of input that the uncertain parameters had. Scenarios are also generated based on the value of key indicator values that activate emergency policies. Finally, scenarios are generated based on other outcomes of interest as specified by the financial institution.

Keep in mind that the three steps described are merely part of the custom Robust Decision Making approach. As for our goal to implement new methodology, we will reflect on our outcomes and compare them with current practice. Since we are building a System Dynamics model with stakeholders, as well as adopt datamining techniques, we are building more than a scenario generator – we challenge current methodology and try to set a new standard. Individual parts of the thesis can certainly be used as only a scenario generator or a dynamic model of the Dutch macroeconomy, but it is not the purpose of the thesis. The purpose of the thesis is to contribute to the robustness of the macroeconomic system. One method of achieving this is dealing with criticism of current scenario building methodology. A second is leaving the way open for further implementation for Robust Decision Making. Our first step in this endeavour is increasing the analytical impact that stress tests have by producing better input. When in the future it becomes possible to expand this methodology and let multiple financial institutions adopt this approach, it will strengthen the financial system as a whole and make candidate policies more robust in an uncertain environment.

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# 1 – Introduction

## 1.1 Context

Stress tests are a valuable tool for the banking sector to calculate financial risks. Nowadays, there are a lot of legal requirements considering these stress tests. This legislation is to protect citizens from collapsing financial institutions, because the damage they can cause is immense. In a stress test, banks are tested on how much economic volatility they can take before needing support or even collapsing. The European Banking Authority (EBA) initiates and coordinates a EU-wide stress test to test individual financial institutions and consequently the economy as a whole (European Banking Authority, 2011). This test is done by giving banks a baseline stress scenario and look at the performance of those banks. The EBA requires banks to present their performance during the change of economic factors such as GDP, inflation, unemployment and interest rates (European Banking Authority & European Systemic Risk Board, 2016). What is important to note when considering the yearly EU-wide stress test, is that only Global Systemically Important Banks (G-SIBs) have to participate in this test – or in laymen terms, the banks that are 'too big to fail' (BCBS, 2013). Only the G-SIB have to follow the exact scenario and settings set by the EBA. Also, G-SIB are under the direct supervision of the European Central Bank (ECB), the central bank of the 19 European Union countries which have adopted the euro. Most financial institutions however do not fall under the category of global importance. Financial institutions that are not of global importance do not have to follow the scenario set by the EBA and are not under the direct supervision of the ECB. Luckily, every institution is monitored by their respective national central bank under the Sigle Supervisory Mechanism (SSM). The SSM regulations states that every active bank on the European market is supervised under the same rules, so both G-SIB and other institutions should follow roughly the same reporting standards and calculate stress tests the same way. Thus, the list of G-SIBs for the European wide stress test has been specifically designed to include the banks that are most important to the financial system and all institutions are tested with the same framework of rules – the only difference being the supervisors. The SSM is important to minimize reporting differences to make a better comparison across nations or between institutions so something meaningful can be said about the state of economy.

The construction of G-SIB and the other financial institutions under the SSM might not strike as an immediate problem. However, the amount of credit institutions that are marked as G-BIS is 30, while the total amount of credit institutions active in Europe is 5,897 (European Central Bank, 2017). This means that 5,847 credit institutions (that is 5,897 institutions in total minus the G-SIBs and minus the respective central banks) are left out in this EU-wide test (BCBS, 2013; European Central Bank, 2017). Looking at the cumulative power of those institutions, it becomes apparent the picture of the EBA may be incomplete. Furthermore, the SSM is not specific enough to give accurate comparative power between financial institutions, as we will see now.

To compare financial institutions, all non-GSIBs have to preform stress tests for their national central bank (European Banking Authority, 2015). They execute these tests based on macro-financial scenarios developed internally. This however poses two problems: 1) never is there a moment where all credit institutions in the EU follow the same tests (methodology and/or scenario) and 2) the scenarios and the way they come about differ significantly between financial institutions, so no real comparison can ever be made between institutions (Borio, Drehmann, & Tsatsaronis, 2014). In conclusion, there is a common supervisory framework in principle, but no common or accepted method to specify scenarios – and every institution can create their own standards. The European Parliament and the European Council had the following to say in legislative regulation (EU) No 575/2013, article 177, clause 2:

'[] the test shall be one chosen by the institution, subject to supervisory review. The test to be employed shall be meaningful and consider the effects of severe, but plausible, recession scenarios []' (European Parliament, 2013).

An important takeaway from this legislation is that there are notable flexibilities that credit institutions have been given. They can thus choose the tests they want to perform, the scenarios developed and the allocation of financial variability to those scenarios. This flexibility is reason to critically analyse what methods are currently used and see if there are improvements. Also, this allows us to develop new methods, if the requirements of the supervisor are met.

## 1.2 Problem definition

The methods when setting stress testing scenarios can vary broadly. Knowing this, we can zoom in on the process of how stress testing scenarios are developed and see if there are improvements to be made. Here we find that a typical model to simulate economic shocks (the input for a stress test) is based on four steps, as described by Borio (Borio et al., 2014):

1. Choose the set of risk exposures subjected to stress;
2. Set the scenarios that defines the (exogenous[2]) shocks that stress the exposures;
3. Developing the model that maps those shocks onto an outcome (or impact), tracing their propagation through the system[3];
4. Measure the outcome(s).

From this framework, we can make numerous interesting conclusions. If we start to analyse the first step, we see that exposures should be identified first. This is not the most difficult step, as financial institutions continuously monitor the macroeconomic factors that are relevant to them. For example: a mortgage bank already monitors housing prices, as a shift in these prices will directly affect their balance sheet. Disregarding these factors would lead to inaccurate reporting and to the institutions economic downfall. What causes un-comparability here, is that every institution will likely choose/have different exposures.  In the second step, scenarios for the possible exposures are developed. This is where even more variability is created in between

[2] Exogenous (shocks) are influencing factors from outside that are not determined by that system. For example; a flower grows by getting sunlight. The sun is an exogenous factor that influences the growth of a flower. The sun is not affected by the flower.

[3] Here, the system can refer to either to a real system (linked events or objects) or a simulation of the system.

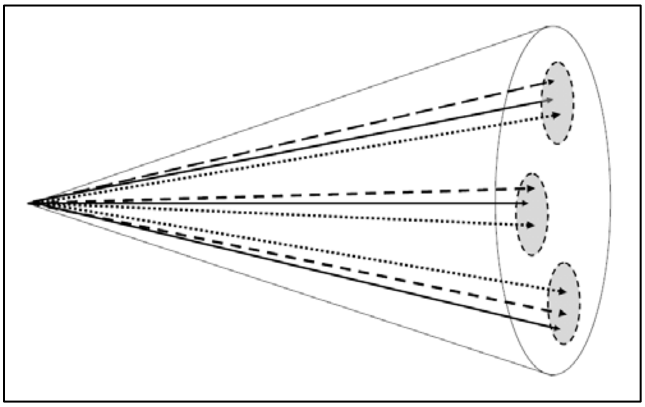
financial institutions. As defined so far, scenarios must be severe enough to be meaningful, yet plausible enough to be taken seriously (European Parliament, 2013). This open space on the interpretation of how economic scenarios can and will develop or what scenarios are relevant or not.  Our first point of critique thus becomes the varying choices for scenarios – a methodological critique.

Within the third step, a new problem arises; when mapping economic shocks, how should their values in the model be allocated? Even if two financial institutions have the same scenario (and exposures), the map of shocks will most likely be different. For example: at the time of writing, a reasonable stress scenario is the possible installation of an anti-Europe government in France (Shaffer, 2017). The fear is that if Marine Le Pen of the party National Front would be president, she would try to undo the euro and break up the euro-zone – as that is one of her main points during the campaign. Recognizing this threat in a stress test, values need to be assigned to economic indicators as described in step 1. As there is no authority or consensus on the economic developments that would come out of this scenario, people will likely give different values for the economic indicators. Hence, we end up with another factor that distorts the comparison of financial institutions.

When reviewing the last step, we can argue that comparatively, financial institutions will almost certainly have inconsistent outcomes of their tests, based on the different scenarios chosen and the different impacts they generate. This situation does not allow for accurate comparison between financial institutions. Even when the calculations themselves are flawless, results from stress tests are arguably inaccurate if used to assess the health of a financial sector in detail.

Besides the logical errors in the pursuit of a stress test, literature points our more critiques about the use of scenarios. One of the main critiques is that when executing stress tests based on a scenario, they only give one single projected outcome rather than a distribution of potential outcomes (Borio et al., 2014; Papadopoulos, 2017; Quagliariello, 2009). This is a paradox, because there is not one single scenario in the face of uncertainty. Even when developing multiple scenarios, not showing a range can pose a problem. For example, when we have multitude of outcomes, we do not know if they cover (for example) 80% or 95% of all possible futures (Walker, Marchau, & Kwakkel, 2013). This practice fixes humans  to a defined position – albeit conscious or unintentional - rather than a position of inherent uncertainty (Quagliariello, 2009).

*Figure 1: Visualisation of 3 Scenarios*



Visually we can think about it as presented in Figure 1: Visualisation of 3 Scenarios (Kosow & Gassner, 2008). In this figure, we see three scenarios. The three scenarios are interpreted multiple times; shown by the three arrows hitting the three marked areas. However, these scenarios only take up a part of the total spectrum of possibilities and thereby neglect a many potential futures. Literature therefore suggests to use a range to not miss the input or output space of models so that unexpected behaviour of the system can be better accounted for explored (Walker, 2000; Walker et al., 2003).

More critique still exists about methods in practice. Currently, scenarios are developed with the help of expert knowledge, combined with supporting models – having models is not always the case however, as models require expert knowledge and do not always exist or are simply not used. In best practice, expert knowledge can be used for extracting trends and assigning values to parameters in scenario outcomes. Models (or modelling) can then be used to then generate the input required for a stress test (Quagliariello, 2009; Walker et al., 2013). This approach again poses a problem, because in the face of uncertainty, no person (expert) can make reliable judgements about the future. Relying on expert knowledge for uncertainty analysis is another paradox and using experts for scenario development is partially arbitrary (Walker et al., 2013).

Everything taken together: there is a lot of variability between institutions' methodology and outcomes because of legislative flexibility. This flexibility also allows us to think of and implement better solutions. Ways of improving standards in current methods would include solving the incomparability issue between financial institutions by adopting a standard practice, keeping into account the input and output distributions of scenarios, assess role of experts in modelling and reliably construct economic scenarios.

## 1.3 Proposed solution

A well-tested way to simulate systems and develop scenarios is System Dynamics (Derbyshire & Wright, 2014; Suryani, Chou, Hartono, & Chen, 2010). This approach allows us to manage user input, make implicit assumptions explicit and test different hypotheses. Besides that, System Dynamics models are especially well equipped to deal with mid to long-term dynamic phenomena (Kapadia, Drehmann, Elliott, & Sterne, 2012; Wheat, 2007). This is a very convenient timeframe for scenarios used in the banking sector. Additionally, System Dynamics has three other advantages that can be useful when making scenarios. First, overview-models can be constructed fast and still be able to show basic dynamics (Pruyt & Hamarat, 2010). Secondly, the wishes, underlying assumptions and/or information of the stakeholders can easily be considered when constructing a model. This advantage is often understated as other approaches (e.g. econometrics, agent based models, etc.) generally take a lot more time to set up for simulation, are not transparent enough to communicate said wishes from and to the stakeholder or have methodological constraints (Homer, 1996; Meadows, 1980; Scott, Cavana, & Cameron, 2016; Sterman, 2000). A third advantage is that models can be recycled to extend the use beyond the original purpose: a System Dynamics model can for example be developed to analyse policy decisions in one situation and re-purposed to serve learning or facilitation in the next (Ford & Sterman, 1998; Hovmand et al., 2008; Rouwette & Vennix, 2006; Vennix, Andersen, Richardson, & Rohrbaugh, 1992; Vennix & Forrester, 1999).

Although System Dynamics has many benefits, none of the attributes just mentioned solve the problems of traditional scenario planning in uncertainty that were previously mentioned. Thus, we are back where we started and could just as well propose the use of tarot cards to develop scenarios. To address all criteria, we need to extend our toolbox further, beyond System

Dynamics. This is where Robust Decision Making (RDM) comes into play; the answer to our critique. The field of RDM tries to overcome uncertainty conditions by using computational tools to calculate and reason with multiple scenarios simultaneously and help decisionmakers using a quantitative framework (Bankes, 2002; Lempert, 2002; Lempert, Groves, Popper, Bankes, & Popper, 2006). To run these calculations, we also need quantified data as input. This is where the link with System Dynamics can be found. System Dynamics can be used as a base model with all its inherit benefits. Then, rigorous quantitative measures can be applied to the System Dynamics model to view the range and boundaries of results (Bryant & Lempert, 2010; Cariboni, Gatelli, Liska, & Saltelli, 2007).

However, we are not there yet. Every method proposed in this study should align with current legislation and pass the judgement of the supervisor. If not, the proposed methods cannot be applied in practice and the application is rendered useless. As the main topics of this thesis are not of legal nature, a separate part in appendix A is devoted to the legislative situation. What is important to note right away, is that financial institutions are free to develop methods for generating scenarios. Only the scenarios themselves are under heavy scrutiny of the financial supervisor (European Banking Authority, 2015, 2016a; European Parliament, 2013). Any method of developing scenarios is thus fair game, the key is to provide financial institutions with more insights to make them better. Please refer to the appendix A on 'legal framework and the stress test' for a more in-depth analysis.

## 1.4 Research objective and questions

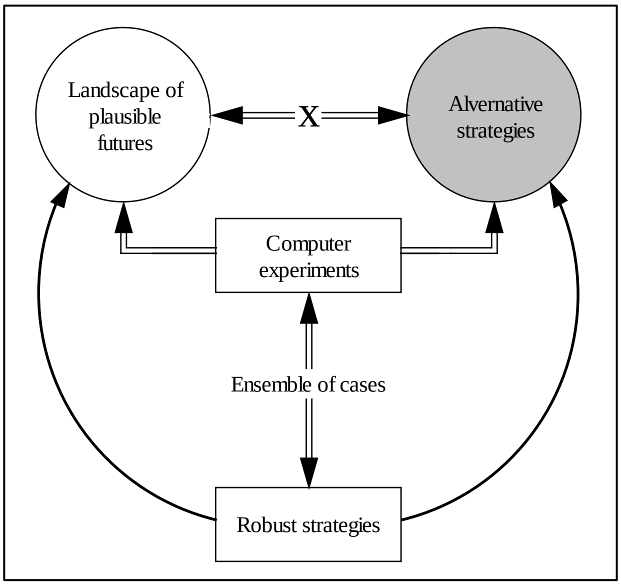
The goal of this research is to systematically develop relevant economic scenarios that can be used as input for financial institutions' stress tests. Instead of doing this in a traditional manner, we are going to look at alternative methodologies. This is done by using the theoretical framework of Robust Decision Making. The economic system - and partially some scenarios - will be developed using a System Dynamics approach. We will use the modelling software Vensim DSS to accommodate this. To calculate the range of inputs, outcomes and evaluate the results, we will use Exploratory Modelling Analysis. Concretely, this entails translating the System Dynamics model into a Python 3.6 (a programming language) interpretable model and run a variation of computational tests and algorithms. Python is used to expand the range, speed and analytical toolset of the System Dynamics model. This setup aims to solve the most important critiques of uncertainty management in the banking system, stress testing and scenario planning. At the same time, the approach should be able to comply with the demands of the supervisor – comply with legislation of financial institutions. The thesis can be considered a success when the demonstrated approach is in line with current legislation, the approach is realistic to apply in practice and is at least more useful than current techniques and standards. These criteria will be judged by the end user, a financial institution.

To guide and focus the research goal, the following main question will be answered:

*How can we design scenario building methodology to improve the quality and reliability of scenarios used for stress testing in financial institutions?*

We will answer the question by first going over the traditional scenario planning approach and its criticism. After that, we will introduce Robust Decision Making as an alternative method which we will partially apply to a case. We will not be able to design a full Robust Decision Making approach and thus will follow a custom design. However, we will still go over the full theory to leave the way open to future application and further exploration on how Robust Decision Making can improve the scenario building practices within financial institutions. To explain this visually, please refer to Figure 2: Visualisation Robust Decision Making[4]. Normally in Robust Decision Making, the goal is to explore the landscape of plausible futures and find alternative (robust) strategies. In this thesis, we will focus on the creation of a landscape of futures – the grey area of developing alternative strategies is left out. With the help of internal models of the financial institution we are working with, we can test the extreme ranges and thereby increase robustness. We will not yet implement a full Robust Decision Making design, but use the framework for the setup of this research.

*Figure 2: Visualisation Robust Decision Making*




This thesis consists of topics in System Dynamics and Robust Decision Making. We will build a System Dynamics model and perform the analysis within a RDM framework. We also need to make sure our methodology complies with regulations. To see if we can fit within the legislative framework of financial institutions, we quickly explore the legal context and environment of NN Bank (more can be found in appendix C). This is done in appendix A. Merely pointing out the framework and understanding the environment is enough for this research; we should know we are able to implement our approach, which we can.

To design more reliable scenarios and improve the process, we will engage in scenario building ourselves. The first step is to define the environment of the economic system and lay it out. This we will do in a System Dynamics model. The sub-questions that will help us assist in building a System Dynamics model are:

1. How can we translate macroeconomic theorems to a working model of the Dutch economy?

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[4] Figure based on Lempert, R.J., S.W. Popper, and S.C. Bankes (2003). Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis, Report MR-1626-RPC, The RAND Corporation, Santa Monica, CA.

2. What are the drivers forces and interaction of variables in the Dutch economy that connect to the performance of financial institutions?

With these two questions, we can build a model of the Dutch macroeconomy that contains drivers for performance of financial institutions. As such, we can translate the dynamics and possible configurations in the model to outcomes of interest.

Sub-questions that address explorative modelling are:

3. What are the main uncertainties in our model of the Dutch macroeconomy?
4. What patterns can be discovered in this range of uncertainty?
5. How can we structure the output of these analyses to usable input for the scenario building process and stress tests?

The answers for our sub-questions in the domain of System Dynamics are found in economic theories. By constructing a System Dynamics model based on the most important economic theorems and integrating them, we hope to come up with a dynamic understanding of macroeconomic processes. The sub-questions about explorative modelling are found in doing analysis in the domain of Robust Decision Making. The analysis is done with the help of tools, lectures and information provided by the TU Delft.

To summarize, the sub-questions help us with developing a model and performing the analysis. When the analysis is complete, we should be able to tell if RDM (even if it is a partial application) can improve the scenario building process in financial institutions. Our goal is to improve the decision-making in financial institutions and improve reports about the health of the financial system to the central bank by improving current methodology. The practical part of the goal consists of building such tools for financial institutions to use. Our theoretical part of the goal is to propose new methodology to apply in high uncertainty situations.

### 1.4.1 Scientific relevance

In this thesis, we will test new methodology as opposed to traditional scenario building. We challenge the status quo and critically look at the consequences and applicability of traditional approaches. This thesis' agenda is a partial push for Robust Decision Making in financial institutions. Although a full application is not possible because of resource- and time constraints, the design of our approach is such that the full features of Robust Decision Making require little more than model adjustments. We will thus test if we can improve the current scenario building approach and also open the door for more Robust Decision Making in financial institutions by examination the reactions of financial institutions.

This thesis will also add to the general progression of integrating Robust Decision Making (RDM), Exploratory Modelling & Analysis (EMA) and System Dynamics. Although there are a lot of advantages to be listed on why to construct stress test scenarios with a System Dynamics approach, there is almost no literature or applications available to use in the banking industry thus far. The reason for a lack of literature could be due to a combination of factors. First, this lack could stem from business secrecy. There might already be multiple System Dynamics models existing within banks, but due to the confidential nature of these models, details are not disclosed - even the details on how to design them. As second reason that examples are missing could be due to the pressure between theoretical coherence in science and desired empirical granularity for (commercial) clients. To illustrate: economic computer simulations are used to predict economic phenomena like growth, business cycles or fiscal policies. The theoretical applicability for these models is very broad since the models are often quite aggregated, as are the phenomena the models try to explain (Burrows, Learmonth, Mckeown, & Williams, 2012). As we increase the scope of research and thereby the number of monitored units, the role of an individual organization compared to the overall results is decreased. Due to this logical process, there is a trade-off when building computer simulations: have a granular model with practical applicability for one specific organization or be able to generalize and generate scientific theory with lessened accuracy for single organisations. It would then make sense for (publishing) scientists to go with the latter option, as the former would be less likely to generate new novel theoretical insights.

Besides the missing literature in the System Dynamics field, there also is a lack of literature on how to connect modelbuilding to statistical analysis. Most scientific literature discusses either model building or quantitative analysis, not both. The reason for this missing piece is because explorative modelling with uncertainty is a small branch in the system dynamics community or model building community. The University of Technology in Delft deserves a special mention, as they are current pioneering in this field and offer academic courses to deal with these topics (Islam, Vasilopoulos, & Pruyt, 2013; Kwakkel & Pruyt, 2013; Pruyt & Hamarat, 2010). Still, this literature most often focusses on either model building or analysis, leaning towards explaining methodology.

A focus on methodology is very understandable in this early stage of the research field in datamining. However, this leaves the eager system modeler or business analyst with almost no practical guidelines when going to the process from start to finish. This is a real loss when taking into account the body of literature describing the benefits of using System Dynamics when modelling economic or abstract systems (Forrester, 1992; Sterman, 2000; Wheat, 2007), the solutions System Dynamics can offer to critiques in current practice (Papadopoulos, 2017; Quagliariello, 2009; Walker et al., 2013) and the benefits of Exploratory Modelling & Analysis (Hamarat, Kwakkel, & Pruyt, 2013; Hamarat, Kwakkel, Pruyt, & Loonen, 2014; Kwakkel & Jaxa-Rozen, 2016; Maier et al., 2016; Walker et al., 2013). Therefore, the approach of this thesis is to apply all these scientific fields into one unique case study – describing the process from model building to analysis.

### 1.4.2 Practical relevance

To assess the practical relevance of this thesis, we can consider the projected outcomes and interpret the possible impacts from the perspective of a financial institution. From a financial institutions' point of view, we can ask ourselves why we would do a stress test and what the benefit of an improved scenario would be. In short, stress tests can be used for balance sheet optimisation, external credit-safety ratings and to adjust and monitor the risk appetite (the amount of risk acceptable to an organisation). Improving the input for the tests could yield more representative results and thus would help in the aforementioned goals. Adding to that, more trust can be gained from the supervisor and public when multiple models and methods are being applied. Especially the supervisor contributes great value to techniques that can validate or test (mental) models. Finally, the outcomes of stress tests are used in policy- and decision making. Any improvement in those fields can lead to systematically improved choices in the financial sector. This in turn will increase the robustness of the entire sector.

If the goals of this thesis are met, there are also possible gains for the ECB or national central bank. If a multitude of financial institutions would adopt the same method, a better assessment of the economy can be made. On top of that, if the developed model would be publicly shared, all financial institutions on the market could use the same scenario generator. This can help financial institutions that have not developed advanced models that monitor economic parameters as well as standardize scenario planning. There is a small caveat however, as multiple models should be in circulation to keep the economy safe: just as one cannot rely on one person or expert in the face of uncertainty, so should one not trust one single model. This is however something to easy overcome. If made publicly available, everyone could make their own adjustments, which would automatically lead to different models.

## 1.5 Research object

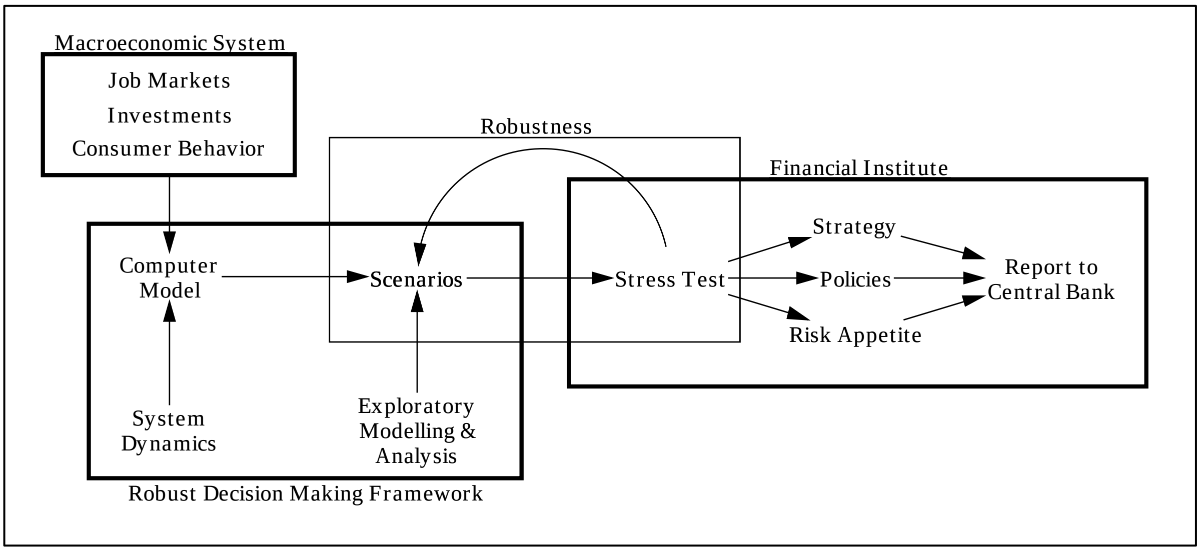
This thesis was partially motivated by and performed in cooperation with NN Bank (NNB). NNB is a part of NN Group, an insurance and asset management company that operates in numerous European countries and Japan (more can be found in appendix C). Contact between NNB and the author was made through an acquaintance working at the bank who knew about the study of the author; System Dynamics. NNB is currently working on automating stress tests by translating them into System Dynamics software. On top of the already existing models, they had need for a module that would connect the macroeconomy with the bank. The outcomes of interest from a macroeconomic model in the initial request were: unemployment rates, gross domestic product (GDP), inflation and interest rates.

Initial motivation for cooperation was the mutual benefit in this project. NNB will receive a System Dynamics scenario generating module that can connect the bank to the macroeconomy. The author in turn can work with likeminded system-dynamists in practice on a problem with real-life implications. NNB has therefore made their resources available to the author: experts, corporate data, laptops, software packages and more. Experts within NNB were especially made use of as they knew the banking sector, macroeconomy and could help with problem definitions. NNB always has lend a hand if needed and were always sincere. The author would therefore like to thank NNB for this opportunity and pleasant cooperation.

## 1.6 Conceptual map

This paragraph tries to give a general overview of how this research is setup. Not all the definitions, methodologies and approaches will be made clear here. This will be done in a step-by-step manner in later chapters. To keep track of our progress however, we can use the conceptual model as a map to see where we are in the process. Also, some interlinkages between theories will become clearer.

*Figure 3: Conceptual Map*




In this overview, the most essential elements of the thesis are shown. Our goal is to improve the decision-making in financial institutions and improve reports about the health of the financial system to the central bank by improving current methodology, but how do we get there? We do this by first considering the already existing macroeconomic system and financial institute. Then, we try to connect the two with our research.

If we read from left to right, we first see there is a macroeconomic system. This system consists of many different elements like job markets, investments and consumer behaviour. Of this macroeconomic system, we are trying to build a computer model. This model represents the macroeconomic system - to make it tangible for our research. Simulating this model allows us to run tests, explore linkages and overall understand the macroeconomic system/behaviour better. We build this model by using System Dynamics. Thus, when we combine the macroeconomic system and System Dynamics, we can build a computerized representation.

As has been made clear before, experimenting with one computer model, or simulation, is not a good practice when facing uncertainty. To get robust decisions in a complex environment, we can apply analytical tools that help us make sense of the possibilities. One of the (possible) components in Robust Decision Making is Exploratory Modelling & Analysis. Without using technical terms, we use EMA to (de)activate various parts of the computer model and run many simulations – one single simulation represents one full run of the computer model with fixed parameters. The reason this step is so important is because our model is wrong. Yes, we assume our model is incorrect beforehand. Admitting this might seem strange, but it allows us to openly face the fact that we need to test different configurations of the model to understand system behaviour. With EMA, we can create variance in the system and (de)activate policies and feedback in the system. Even though it is impossible to accurately copy the complete system, –

especially when projecting in the future – this method can make our endeavours worthwhile. Patterns of simulations can be gathered to make well estimated ranges and consider worst-case scenarios (Halim, Kwakkel, & Tavasszya, 2016).

When we can generate scenarios, we have completed our custom RDM setup. We can now go back to our System Dynamics model and reflect on our scenario results or use results to adjust previously made scenarios. It is important to remember that even though the execution of the stress test is not discussed in this research, the generated scenarios should be able to be used further in the process. With the results and goals of the stress test, we can again go back to exploring alternative configurations of the macroeconomy. The generated scenarios should be delivered in a format such that a financial institution can use them as input for their stress tests.

Finally, it is interesting too consider the arrow from the stress test, back to the scenarios. In a normal Robust Decision Making design, it would be possible to connect performance with scenarios. Here, we iterate from scenario to stress test and back. We thus operate with a Robust Decision Making mindset, but do not complete the full analysis. The reason this thesis is set up as a partial Robust Decision Making project instead of only a scenario generating one, is the future wish to implement the full design.

# 2 - Theoretical framework
## 2.1 Scenario Planning
In this section, we will first discuss the theory of scenario planning to explain what the current methodology in practice is. Later, we will go over the critiques and why those exist. Finally, we will move to introducing an alternative approach.

The concept of scenario planning is built up from the words 'scenario' and 'planning'. A scenario can be considered as an imagination of what the future holds – a story. As Michael Porter defined it (Porter & Millar, 1985):

> 'A scenario is an internally consistent view of what the future might turn out to be – not a forecast, but one possible future outcome.'

We can have one scenario, but it is common to develop multiple or an assemblage: scenarios. If we combine the definition of scenario(s) with planning for the future, we arrive at the following definition for scenario planning (Ringland & Schwartz, 1998):

> 'That part of strategic planning which relates to the tools and technologies for managing the uncertainties of the future.'

Tools and technologies have always played a big role in scenario planning. Mathematical and computer models can be used to simulate an environment with the same constraints as in real life. Adding to that, we can allocate resources differently to create and test multiple scenarios (Ringland & Schwartz, 1998). What is important to note is that the tools and technologies for scenario planning should have the same rules and constraints as in real life. It is therefore desirable that the model can incorporate a potential large set of rules to accommodate this. A model can be considered successful when it has (Ringland & Schwartz, 1998):

- the ability to anticipate real world behaviour - which may be unexpected - through exploring the constraints or changes in the external environment, or the relationships between forces;
- the creation of a mental model which allows the user to look for early confirming or disconfirming evidence.

Within the first point that Ringland & Schwarts (1998) make, the definition of scenarios is once again uncovered: 'constraints or changes in the external environment'. Relationships point to forces generated endogenously – within the system. Thus, a model should be able to calculate the effects of scenarios - created somewhere outside the model (external) – and relationships between forces – behaviour generated within a system (possibly a feedback loop). The second point that is made refers to decision structures and with what information choices are made.

The reason to conduct scenario planning is that the exercise explicitly shows linkages and reasoning between activities, now and in the future. This can be exploited and lead to competitive advantages (Porter & Millar, 1985). This future oriented aspect can also help when dealing with high levels of uncertainty. Scenarios can tell us what could possibly happen in the future, without adding probabilities (Hamarat et al., 2013). This makes scenario planning a qualitative focussed approach, even though quantitative data and analysis may be used to design the scenarios.

A policy is fit for level 4 uncertainty when it is ‘robust’. In the context of scenario planning, robust can be defined as: a policy that produces the most favourable outcomes across all the scenarios (Walker et al., 2013). This does mean that multiple scenarios should be generated. Schwarz (1988) gives additional criteria for best practices scenario planning (Ringland & Schwartz, 1998; Walker et al., 2013):

- Consistency: the assumptions made are not self-contradictory; a sequence of events could be constructed leading from the present world to the future world;
- Plausibility: the posited chain of events can happen;
- Credibility: each change in the chain can be explained (causality);
- Relevance: changes in the values of each of the scenario variables is likely to have a large effect on at least one outcome of interest.

Looking at this list, it again becomes clear why by definition we need multiple scenarios: multiple sequences of events are possible and multiple chains of events can happen. Walker et al. (2013) then structured these criteria together with literature from Schwartz (1996), RAND Europe (1997), Thissen (1999) and van der Heijden et al. (2002) to summarise how most decision makers traditionally deal with uncertainty. By assuming that the future can be specified enough to produce favourable scenarios, decision makers tend to follow these steps when building scenarios (RAND Corporation, 1997; Schwartz, 1996; Thissen, Weijnen, & ten Heuvelhof, 1988; Van der Heijden, Bradfield, Burt, Cairns, & Wright, 2002):

<u>Step 1</u> – Specify system, outcomes of interest and time horizon;
<u>Step 2</u> – Identify external factors that drive change for the system and outcomes of interest;
<u>Step 3</u> – Categorize factors from (fairly) certain to uncertain;
<u>Step 4</u> – Assess the respective impact of the uncertain factors on the system;
<u>Step 5</u> – Design scenarios based on different configurations of the external factors.

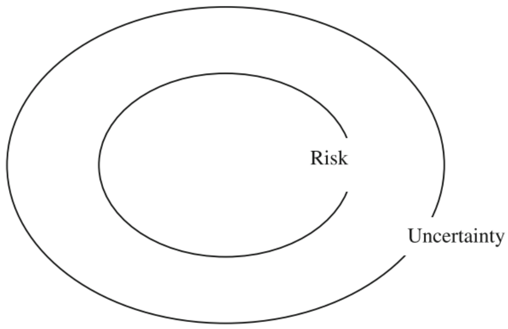
According to Ringland et al. (1998), Walker et al. (2003, 2013) there are benefits for policy analysis when using this approach. First, following these steps can give you an overview of the sources of uncertainty and help categorize them. Secondly, this approach allows decisionmakers to explicitly think of ways in which the future can change and what the implications of those changes are. Lastly, this approach continuously faces the decisionmaker with uncertainty and thus reduces the effect of surprise in the case of a bad outcome. When all pathways have been thought of before, action can be taken fast and appropriate (Ringland & Schwartz, 1998; Walker et al., 2003, 2013).

There are also significant downsides to using a scenario planning approach in a situation of uncertainty. We have mentioned these downsides in the chapter ‘Problem statement’, but will go over them again. Every scenario only gives one single projected outcome rather than a distribution of potential outcomes (Borio et al., 2014; Papadopoulos, 2017; Quagliariello, 2009). Analysing a scenario in this manner is inappropriate, because uncertainty implies a range of outcomes. This has two significant consequences (Quagliariello, 2009; Walker et al., 2013). First, decisionmakers are nudged to think of one single outcome (at a time), which leads to a loss of focus of the bigger picture. Second, decisionmaker can become enfranchised with one particular scenario (good or bad), which leads to a more narrowed view – this would achieve the exact opposite from our original goal. The final critique that we touched upon was on how scenarios are generated. Scenarios are designed with experts and stakeholders. However, in the face of uncertainty, no expert or other person can make reliable judgements. Relying on experts to design scenarios for uncertainty analysis is an arbitrary, paradoxical practice (Walker et al., 2013). Thus, when moving towards suggesting an analytical approach for this thesis, these critiques should be addressed.

## 2.2 Uncertainty

To develop a way to deal with uncertainty (in scenario planning), we first need to define uncertainty. We need to categorize it and study its components to know the effects on decision making, because when it comes to decision making, the only certainty is the existence of uncertainty. Due to uncertainties – in the present or future - decision makers open themselves up to risk. Risk and uncertainty should not be confused as they mean two different things. Uncertainty represents the incalculable, uncontrollable and unknowable. Within uncertainty, risk is a calculable sub-space. It is a space where we are unsure of exact outcomes, but since we can make calculations, the uncertainties thus become controllable (Knight, 1921). We can represent the concept visually in Figure 4: Risk and Uncertainty**Error! Reference source not found.**[5]:

*Figure 4: Risk and Uncertainty*




Intuitively we can think of it as the following: if you go to a casino and play blackjack, you are dealing with risk. The amount of money you put on the table is controlled (by yourself) and the expected value of a bargain can be calculated beforehand. Risk represents the probability of an

[5] Based on (Walker et al., 2013)

event times the loss of when that event occurs. If you would go to work the next day – after the casino adventure – and present a marketing proposal to a client; whether they will like it or not is uncertain. There is no expert (or theoretical agreed lens) that can inform you about probability distributions. Uncertainty in absence of knowledge on probability distributions and outcomes is also referred to as deep uncertainty (Lempert et al., 2006). This does not mean you cannot mitigate or decrease the likelihood of certain outcomes happening. In the marketing example, uncertainty about client agreement on a proposal can be reduced by having regular meetings. Even though we can say this increases the success rate, this increase does not have a numerical value.

We have already seen that there can be different kind of uncertainties and have used risk as an example to explain the principle. Next, we consider a framework combining uncertainty with decision making. Walker proposes a framework to classify uncertainty based on nature, location and level (Walker et al., 2013). First, the nature of uncertainty describes the character. Are we dealing with epistemic uncertainty (imperfect knowledge), ontic uncertainty (natural variability) or ambiguity (multiple interpretations of the problem by the involved actors)? Distinguishing these seemingly minor differences can make a significant impact when coming up with solutions. Ontic uncertainty can for example be replicated in a model, – by replicating variance or introducing random effects - but ambiguity cannot. Ambiguity can for example be dealt with by involving stakeholders in the process and leaving future pathways open for shifting preferences. In short, depending on the nature of uncertainty, we need different approaches to deal with them.

As a next step, Walker et al. (2010) defines four levels and locations of uncertainties (Kwakkel, Walker, & Marchau, 2010; Walker, Marchau, & Swanson, 2010). Defining these levels helps us determine what kind of approach to use for dealing with uncertainty. If there is a (very) low level of uncertainty, we may not need a Robust Decision Making approach as the scale of what we don't know is controllable. The four levels are distinguished in Table 1: Uncertainty Framework (Walker et al., 2003):

*Table 1: Uncertainty Framework*

| Location | Level-1 | Level-2 | Level-3 | Level-4 |
|---|---|---|---|---|
| | | | (deep uncertainty) | |
| Context | A clear enough future | Alternative futures (with probabilities) | Multiple plausible future outcomes | Unknown future |
| System Model | Single system model | Single system model with probabilistic parameterization | Several system models, with different structures | Unknown system model |
| System outcomes | Point estimate and confidence | Several sets of point estimates and confidence | A known range of outcomes | Unknown outcomes |

| | | | | |
|---|---|---|---|---|
| | interval for outcomes | intervals, with probabilities on each set of outcomes | | |
| Weights on outcomes | Single estimate of weights | Several sets of weights with probability | A range of weights | Unknown weights |

This framework provides great insight when mapping the levels of uncertainty. It can tell us where to pay attention to when mapping uncertainty in a space. Also, parts of a research can have different levels of uncertainty. The location of uncertainty describes where the uncertainty occurs in the (conceptual) model of the system. Location of uncertainty can also be thought of as asking the question: 'what can be uncertain?' Locations of uncertainty predict the existence of uncertainty in external factors, objectives and preferences, policy variables and outcome indicators (Walker et al., 2013). Knowing in where uncertainty resides, we know what to be careful off when making decisions based on information. It can tell us more about prediction errors and where they are coming from (Walker et al., 2013).

The framework of uncertainty presented thus far has a great emphasis on model-based decision support. There are more frameworks of uncertainty that focus more on simulation models in general, without specific model-based decision support (Kwakkel et al., 2010; Petersen, 2012). Kwakkel et al. (2010) has integrated these models into one synthesised framework which we will use for this thesis. The components of location uncertainty we recognize are (Kwakkel et al., 2010; Petersen, 2012; Walker et al., 2000):

- System boundary;
- Conceptual model;
- Computer model;
  - Model structure;
  - Model parameters;
    - Fixed parameters;
    - Parameters as input for the model to simulate change or policy;
- Input data;
- Model implementation;
- Processed output data.

First, system boundary determines the topic of research and what will be or not be researched. This boundary is often set by the context of the problem and the framing of the research question (Kwakkel et al., 2010). A demarcation of what is included or not, is necessary in research and there are a lot of tools to visualise this (Sterman, 2000). The second location is the conceptual model. When making a map of a problem, it is almost impossible to include all the possible views and theories to integrate them. The conceptual model specifies the theoretical lens and gives the computer model meaning. The third location of uncertainty is in the translation of the conceptual model to a computer model – how the concepts form in the code. This in turn can be divided in the model structure and parameters. The parameters are subdivided in the fixed parameters in the model and the changing parameters in the model that simulate eternal developments (Kwakkel et al., 2010). Input data uncertainty, the fourth location, is the uncertainty about how to choose the data to put in the model. It is not the uncertainty about the parameters in the model, but about the choice of what values to use. Fifth, model implementation is the uncertainty about the model – if the model has bugs, errors or other issues that make it perform as not intended. The sixth and last location is processed output data. This location questions if the information shown to the decision makers, is being communicated correctly (Kwakkel et al., 2010).

All the levels, locations and natures can be integrated in one framework (Kwakkel et al., 2010; Walker et al., 2000). We can use this new framework to determine uncertainty and communicate it explicitly to the audience of this paper and stakeholders. Here, we have an integrated view that makes us understand and capture uncertainty as seen in Table 2: Integrated Uncertainty Framework:

*Table 2: Integrated Uncertainty Framework*

| | | Level 1 to 4 | Nature | | |
|---|---|---|---|---|---|
| Location | | Level | Ambiguity | Epistemology | Ontology |
| System boundary | | | | | |
| Conceptual model | | | | | |
| Computer model: | structure | | | | |
| | Parameters in model | | | | |
| | Input parameters | | | | |
| Input data | | | | | |
| Model implementation | | | | | |
| Processed output data | | | | | |

We have dealt with the concept of uncertainty by starting with the nature of what uncertainty means, to where it can be located during a decision-making process. Finally, we arrived at a framework that categorizes uncertainty in four levels. With this knowledge, we can now approach decision-making obstacles and categorize them to choose the best plan of action. There are several ways of dealing with uncertainty, depending on the nature, location and level of uncertainty. It is, for example, not necessarily to employ drastic robustness measures for level 1 uncertainty. For level 1, a simple 'predict and act' approach can suffice (Walker et al., 2013). Thus, we must always remember the goal of decision making to not over- or underreact with our strategy:

‘The ultimate goal of decision-making in the face of uncertainty should be to reduce the undesirable effects of negative surprises, rather than hoping or expecting to eliminate them, and to take advantage of positive surprises (Dewar, 2002; McDaniel & Driebe, 2005).’

With this goal mind, let us quickly go through the nature, location a level of uncertainty we face in this thesis. It is important to establish the correct form to devise a fitting approach. Making this quick distinction now allows us to focus on the most relevant theory and ignore approaches that do not fit this research. We will thus quickly prove the existence of uncertainty in our work and give examples. We will later focus more on how to deal with those uncertainties within the presented theoretical framework when we encounter them - especially during the model building process and executing of the analysis.

### 2.2.1 Nature of uncertainty

To choose the correct strategy for solving our business case, we must determine the nature, locations and levels of uncertainty we can encounter. Starting out with determining the nature, there is little ambiguity (ambiguity as nature of uncertainty) in our business case. This is mostly since we are working for a stakeholder that has one model of interpretation of results – financial statements or numbers rather than personal interpretation. The bank has one calculative model that interprets the information from our model as either good (increasing the overall financial stability or revenues) or bad (decreasing financial stability or costs). Besides that, our work stops when we have generated scenarios. Remember that ambiguity is not about the weights stakeholders put on the outcomes, but how they view the reality: if they acknowledge a similar problem/solution or view something as a problem/solution – also known as wicked or messy problems (Vennix et al., 1992; Vennix & Forrester, 1999). However, there is much ambiguity when it comes to views about the macroeconomy. We might not have to deal with many stakeholders who have different views, but we do have to deal with integrating economic theorem in a holistic way. In that regard, there are many different schools and views. As we can only pick a limited number of frames and should make modelling decisions, ambiguity lies in the interpretation of the macroeconomy.

Ontic uncertainty in this research can stem from the natural variability in the economic system. A way we can put this in an example is by describing the Goodwin model or Goodwin Cycle. It is an older economic theorem about economic growth cycles, but still in use today. Its assumptions are constant and steady growth of technology, labour, wages and capital-output ratio’s, but the model produces a cycle (oscillating behaviour) through expansion, peaks, contractions and troughs of the economic system (Goodwin, 1965). It does this by explaining that markets should adjust to one another. This is what we call adjustment times in System Dynamics; it defines the speed of a change to take hold in the system. To give an example: the demand for labour has a different adjustment time for adjusting to new circumstances than the supply of labour. Put into practice, when there is an economic crisis, a lot of people working in the construction sector will be laid off – there is no longer need of them. All the people who have been fired still want to have jobs, but it takes time to find work in a different sector. Put into reverse: if the general economy is rising again, it takes time to hire or train construction workers. This produces endogenous economic fluctuations in the system, even when assuming overall stable growth (Goodwin, 1965). Besides the Goodwin Cycles, there are more economic cycles or economic variances in play, but we will go over these later.

Epistemic uncertainty stems from unexpected developments in the economy – a lack of knowledge. When we look at the historic development of productivity, nobody predicted a rise in productivity due to computers before they existed. This is an unexpected event with major consequences. Macroeconomic models try to account for epistemic uncertainty – by adding corrective variances (that have no good theoretical background) in formulas to connect with reality. For example, the European Central Bank makes economic forecasts based on the Dynamic Stochastic General Equilibrium (DSGE) theorem – more specifically, the ECB uses the Smets-Wouters DSGE variant (Smets & Wouters, 2007). Ignoring model intricacies for now, there is a random variance factor to account for technological changes and its unexpected outcomes. Technological change is an economic disturbance, affecting the efficiency of an economy (Edge, Kiley, & Laforte, 2008; Gertler, Sala, Trigari, & Wiley, 2014) and can be categorised as an epistemic uncertainty. However, you can also view the addition of technological change to the DSGE theorem as a weakness, because there is no good theoretical basis to explain this growth-disturbance factor (Naastepad, 2002). Technological change thus becomes the unexplained epistemic uncertainty.

### 2.2.2 Level of uncertainty

In basis, we have seen 4 levels of uncertainty. We do not tread in level 1 or 2 territory; we cannot adequately forecast our outcomes with probabilities (Walker et al., 2013). Level 3 is the situation where we (sometimes can) rank alternatives with a wide set of ranges/weights. Level 4 is complete uncertainty where we only know we don't know. In this thesis, we are mainly operating in level 3 uncertainty. Even though macroeconomic theorem can be inconsistent, we can still deduce usable information from the system. The reasons we thus tread in level 3 territory is due to the context of the case, the system models and outcomes. In our modelling context, there are many competing views on how to explain macroeconomic phenomena. There are predictive models which achieve moderate accuracy and are proven to have explanatory power (Bao Hong, 2008a, 2008b; Basu, Fernald, & Liu, 2012; Gertler et al., 2014; Goodwin, 1965; Smets & Wouters, 2007), but it is not always clear which are appropriate. Also, these models often are very aggregated and have difficulty going into detail about the development in specific countries. This means we must admit from the start that we will be unlikely to replicate macroeconomic developments in a single model truthfully. We should thus use multiple models in our case. These models can then be combined to give ranges of outcomes. Outcomes that we produce cannot be ranked, since we do not know what model we use is the correct one. It is more likely that we do not foresee future policies becoming active then replicating the environment truthfully. Knowing this beforehand does enable us to be diligent when making decisions based on our work. We thus face multiple, equally possible futures (or unknow futures). These reasons accumulate to level 3 uncertainty in our research.

### 2.2.3 Locations of uncertainty

Our model would give an overview of the macroeconomic system and the potential configurations of that system. Our outcomes of interest are (amongst others) unemployment rates, consumer behaviour, interest rates and gross domestic product (GDP). We employ multiple economic theorems and different modelling tools to achieve this goal. Combining these findings yields us Table 3: Integrated Uncertainty Framework with Values:

*Table 3: Integrated Uncertainty Framework with Values*

| | | Level 1 to 4 | Nature | | |
|---|---|---|---|---|---|
| Location | | Level | Ambiguity | Epistemology | Ontology |
| System boundary | | 2 | | | |
| Conceptual model | | 3 | | | |
| Computer model: | structure | 3 | | | |
| | Parameters in model | 3 | | | |
| | Input parameters | 3 | | | |
| Input data | | 2 | | | |
| Model implementation | | 2 | | | |
| Processed output data | | | | | |

This new framework of thinking provides us with a map to view uncertainty. This can then be used for our own research – to assess if we apply appropriate solutions – and to communicate with stakeholders. There will always be uncertainty, but we can try communicating those concepts in a way that gives more understanding instead of less.

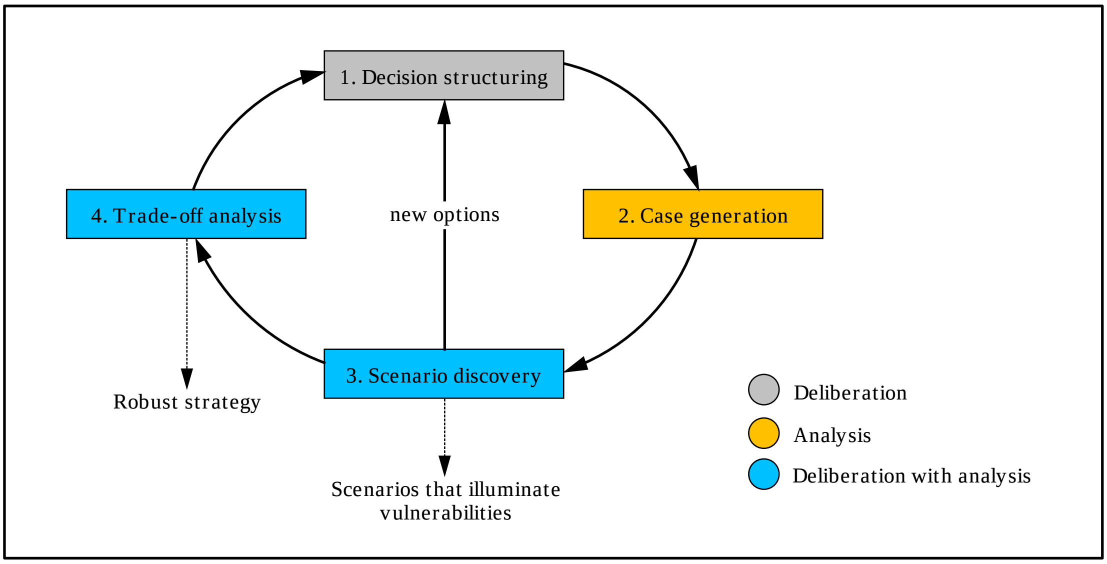
## 2.3 Robust Decision Making

Now that we have defined the problems with traditional scenario planning and what uncertainty is, we can move to introducing a new approach: Robust Decision Making (RDM). RDM combines computational and quantitative analysis with scenario-planning to help decisionmakers choose strategies that perform well over a variety of potential futures (Lempert et al., 2006). As put by Lempert et al. (2006):

'Robust Decision Making (RDM) is an analytic method that helps design robust strategies through an iterative process that first suggests candidate robust strategies, identifies clusters of future states of the world to which they are vulnerable, and then evaluates the trade-offs in hedging against these vulnerabilities (Lempert et al., 2006)'

In the past, decisionmakers relied on prediction-based analysis of a model and focussed on a set of alternatives. With RDM, we run a variety of model thousands to explore the range of possible futures (RAND Corporation, 2013). After a dataset is created, visualisation and statistical analysis can be applied to make the results tangible and useful for decision making. With RDM we can test and explore future conditions, policy decisions and changing environments (Giuliani & Castelletti, 2016; RAND Corporation, 2013). A very important novelty of RDM and the mindset is to 'run the model backwards' (RAND Corporation, 2013). We are looking for cases of interest in a large output space. When we found cases of interest, we are reasoning backwards to find out what input of the model led to that specific output. Only after that analysis we start to reason what the characteristics to paths of success might be, not before. This disables any biases or predictive thoughts of decision makers and forces those involved to look for broad and robust policies (RAND Corporation, 2013). Step by step, the RDM process is organised as seen in Figure 5: Robust Decision Making Process[6]:

*Figure 5: Robust Decision Making Process*




In step 1, we try to give the environment shape by defining the uncertainties (as we did in the previous paragraph). Further, we should consider the possible policy choices and environmental changes that could happen and translate them to a model. In step 2, we then try to run the model (and different model-structures) thousands of times. This dataset now contains all our cases which we need to extract and bundle in step 3. In this step 3 we can see the performance area's and effect of uncertain parameters. We can now choose to introduce new policy choices (go back to step 1) or adapt decisions by making a trade-off analysis of the pathways available (RAND Corporation, 2013). After the trade-off analysis, we can conclude that we have found a sufficient robust policy, or not. In the latter case, we can again go back to step 1 to think of new policies and introduce them in our model.

Before we move on, it is very important to know how Robust Decision Making relates to Exploratory Modelling & Analysis in this research. As we have seen, RDM consists of 4 steps which one should follow. Yet, we have also mentioned Exploratory Modelling & Analysis (EMA). Traditionally, EMA is a methodology that uses computational experiments to combine plausible models and other uncertainties in order to generate a large variety of scenarios – which partially

[6] The following overview is based on (RAND Corporation, 2013).

corresponds with our definition of RDM (Hamarat et al., 2013). It has existed since 1993, before large computer experiments could be performed on average pc's that would make this approach widely available (Bankes, 1993). Nowadays however, EMA can be seen as the convergence of step 2 and 3 (Hamarat et al., 2013). Furthermore, RDM should be viewed as a way to offer model-based decision support to policymakers and alike. RDM is therefore not the only way to apply computational and statistical analysis. Closely related are Dynamic Adaptive Policy Pathways and Robust Optimisation, which also require large datasets (Hamarat et al., 2014; Kwakkel, Haasnoot, & Walker, 2016). Those methods then can also use the analytical framework of EMA. The differences between, for example, RDM and Robust Optimisation – which both 'use' EMA – then becomes on what we want to achieve, sacrifice and our theoretical lens (Kwakkel et al., 2016). In this sense, EMA can be viewed as a tool of RDM.

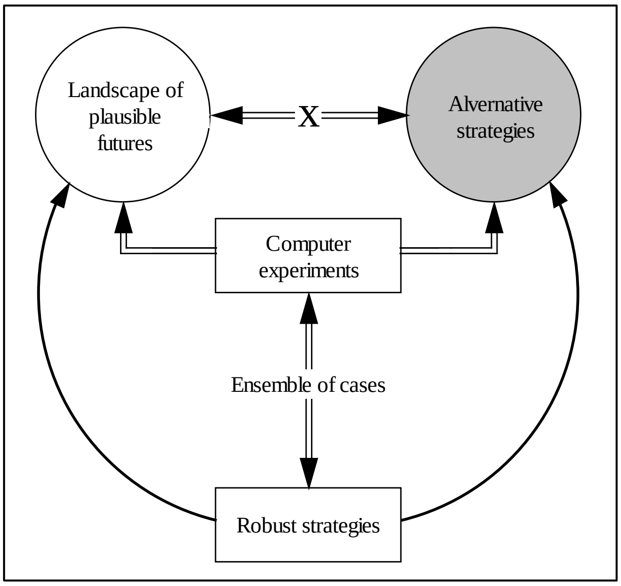
EMA can be a great addition to System Dynamics. Combining the two allows us to further explore the system that has been build. However, in basis, System Dynamics and EMA do not align philosophically. Philosophically, System Dynamics is based on Systems thinking: a school of thought that understands changes in the world by looking at the linkages and interactions between components of a system. The focus of System Dynamic therefore has become understanding and modelling that system, so that purposeful and controlled changes can be made to make a change (Ackoff, 1979). When a system is modelled, it can be understood. When it is understood, we can control changes mechanically. This goes against the philosophy of EMA; which lies in the domain of Robust Decision Making. In this school of thought, scientist claim that the world is insecure, unknow and that almost anything unexpected can happen. Here, it becomes not the most important to describe the system as accurately as possible, but to account for uncertainty by addressing system changes and unknowns (Bankes, 2002). This produces a vast amount of output as we do not have one single system-outcome, but a large range. With a System Dynamics philosophy, this is unhelpful and produces unusable data – we can no longer test single policy changes and impact. In the philosophical school of Exploratory Modelling and Analysis, this large dataset represents all possible outcomes a decision maker should keep into account when making policies for the future.

In this thesis, we can overcome philosophical differences by adopting a broader framework of RDM. System Dynamics and EMA are used as tools within our design. Secondly, we will try to fight the opaqueness of applying EMA to System Dynamics models by carefully explaining the steps and code we use. As the tools for performing EMA are quite experimental, this approach is necessarily to keep the thesis understandable for a broad audience. This will also help with interpreting the data and for other scientist to recreate the experiments.

### 2.3.1 Robust Decision Making approach

This thesis implements a custom form of Robust Decision Making. Most changes are made due to time and resource constraints. The first change is that we are not going to test policies in our Robust Decision Making cycle - as a part of step 1 in RDM. As stated, time and resources do not allow for building a model of the macroeconomic environment plus all possible policies of a financial institution and the impacts in the system. Building such a model requires not only detailed knowledge about macroeconomic factors, but also the specific portfolio of the

*Figure 6: Visualisation Robust Decision Making*




institution in question. Consequently, if there are no policies tested, there is no trade-off analysis (step 4). We can think back of the figure we used earlier in chapter 1, now seen in Figure 6: Visualisation Robust Decision Making. As seen in this overview, we will focus on uncovering the landscape of possibilities and will not design alternative strategies. There is feedback between the landscape of possibilities and strategies by using internal models of NN Bank, but there is no continuous connection between the models. We thus leave the grey area in Figure 6: Visualisation Robust Decision Making out of the analysis. This feature can (and should be) added in the future.

Even though we are not using the full potential of RDM by mapping the policies, we can still make an impactful research. This is because we can connect the outcomes of our custom RDM cycle to an existing stress test model. Doing this does not allow the financial institution to directly see the effect of their policies, but does allow them to explore the output space of possible future configurations of the macroeconomic system. We can thus come up with scenarios previously not thought of before. Our Robust Decision Making cycle is therefore focussed on finding scenarios in a generated dataset, rather than the direct consequences for policy.

Following our custom Robust Decision Making design, we are left with the following steps:

1. Build multiple economic models that explain system behaviour;
2. Run the model(s) thousands of times with different input for the uncertain, external parameters to generate a dataset;
3. Analyse and cluster the outcome space of the dataset to generate possible scenario input for a stress test.

For the first step, we will use a variety of economic theorems that explain macroeconomic behaviour. We use multiple theorems to explore the whole possible range of economic configurations; because there is no one singular and/or agreed upon theoretical lens to view the world. Multiple models are also a necessity in deep uncertainty, as we have seen in our uncertainty framework.

Our second step consists of running the models with a variety of parameter space. The space chosen for the parameters will consist of two things: what the financial institution wants to test and what experts in the field say. The selection of the institutions' wants is just asking for their input for the test. Regarding the experts: economic forecasts and predictions will be searched on websites of statistical bureaus and other organisations. Within their own confidence bounds, we can again adjust the predictions with our own confidence bounds. Depending on how certain sources are to be trusted, we can add a certain percentage on the upper and lower bounds.

In our third step, we run into a problem: we need to explicitly state our search criteria in the dataset. Usually we can look for performance (of the policies) directly, but now we have an intermediate step that disconnects the institutions' performance with the analysis. This means that the definition of a 'case' is also different in this custom design. In RDM, a case is where the outcomes of a certain policy meet a numerical threshold (Bryant & Lempert, 2010). For example: a case when a plan is exceeding 20% of its budgeted costs. A set of cases where costs exceed 20% of budget can be called a scenario. Since our custom design approach case(s) and scenario do not have performance measures in our custom design, we will use the classification in conjunction of the existing stress test model. For example: we know that a policy will trigger when macroeconomic variables reach certain thresholds - key indicators in a financial institution that trigger certain (emergency) policies. This threshold thus becomes the boundary of our scenario (which contains cases). With close cooperation and the help of experts in the financial institution, the search criteria in that dataset could be defined by the value of key indicator values that activate (emergency) policies. Search criteria can also be defined on basis on the minimum requirements to continue operations as usual. Another viable option to define search criteria in our dataset is to test the dimensional value of traditional scenarios already generated by the financial institution. Thus, with this setup and cooperation of the financial institutions we can continue with our custom RDM design.

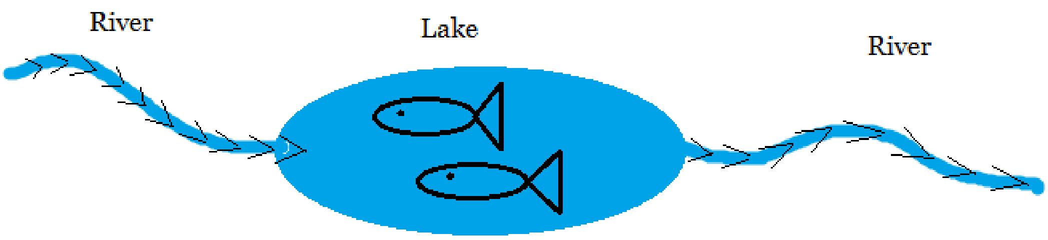
# 3 - Methodology
## 3.1 System Dynamics
If we want to condense System Dynamics in one single thought, we can summarize it as follows:

To know the behaviour of a system, either real (e.g. a river flowing into a lake) or abstract (e.g. economic systems), you need to know: 1) the layout of the system and 2) the initial state of the system.

If we try to imagine the following simple example of driving a car, both principles can easily be demonstrated: when driving a car, we need to know two things. The first thing we should know is how the road looks like. Is there a turn or is the road straight? Is it a highway or sand road we are driving on? These questions on how the road looks like might be considered as 'the state of the system'. Without this information, we cannot act as a driver.
Secondly, it is of vital importance to know where the car is. Is it in the middle or side of the road? Is it in a turn or roundabout? This final part of information needed can be considered as 'the state of a system'. Only with the combined information of these questions is it possible to get from point A to B (safely).

Let's consider a new real system to explain System Dynamics further: a river flowing into a lake, and the lake flowing into another river. A visual representation would be Figure 7: River/Lake Visualisation:

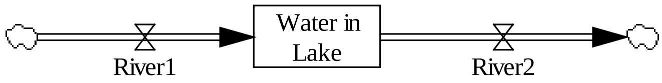
*Figure 7: River/Lake Visualisation*




If we look at Figure 7: River/Lake Visualisation, we see the river flowing from left to right. Also, water is accumulating in the lake. The amount of water that flows into the lake, determines the amount of water in the lake. Water is also lost in this system; the river on the right takes water away from the lake. The amount of water that flows out of the lake, also determines the amount of water in the lake. All thing taken together, the amount of water in the lake is affected by both rivers; the inflow and the outflow of water.

Now that we understand the workings of the lake and rivers, let us make a schematic overview in System Dynamics language. Such an overview is called a 'stock and flow diagram' (SFD). A 'stock' is where items (water, money, fish) can accumulate, a 'flow' determines how the stock is influenced (river, transactions, births). A SFD of the river system can be seen in Figure 8: SFD of River/Lake Case:

*Figure 8: SFD of River/Lake Case*




As we can see in Figure 8: SFD of River/Lake Case, the water still accumulates in the lake (the stock), represented by the box. The rivers in this picture are the flow and add water to the lake, represented by the arrows going in and out the box. It is important to note that nothing can be stored in a flow (river). Only in the stock (lake) can items accumulate over time. Examples of a Stock are: a storage magazine, animal populations, food on your plate (real systems) or money on a bank account, customers in a database and a mental count of sheep when going to bed (abstract systems). Respectively, a flow to the mentioned systems would be: items sold, births, food eaten (real systems) and transactions, database adjustments and new sheep counted (abstract systems).

Next, we will briefly consider the causality in the system. We do this by presenting a simple Causal Loop Diagram (CLD). To do that, we must draw arrows from the variables that have an influence on other variables. Doing that yields us Figure 9: CLD of River/Lake Case:

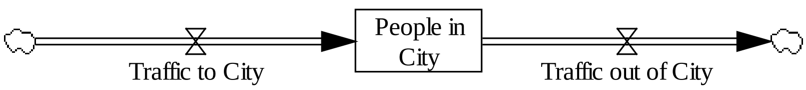
*Figure 9: CLD of River/Lake Case*

River 1 ⟶ Water in Lake ⟵ River 2

Although the flow of the river is from left to right, if you make connections on the causalities, the lake itself has no influence on the process. We see again that only the flow of the river influences the amount of water in the lake, not the lake itself. Don't be fooled by the arrow of "River 2" however! Although water flows out of the lake in River 2, it has nothing to do with the causality. A CLD therefore looks different from a SFD. A CLD views causality, in the SFD we could see the in- and outflows and accumulation. Both have a distinct purpose in System Dynamics.

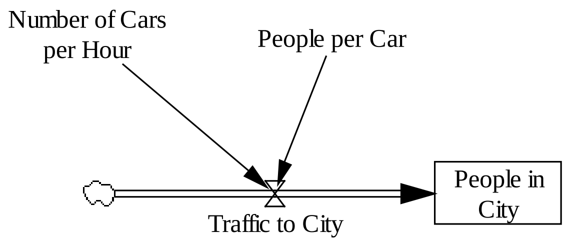
We have now learned what a Stock is (where items accumulate) and flow (how the stock is affected – filled or drained). Let's consider another example to see how we would run a computer simulation. We are therefore going to add variables and form differential equations. Our new example will be Figure 9: CLD of River/Lake Case:

*Figure 10: CLD of Traffic/City Case*



This is a great model to explain how many people are in the city. People traffic to the city and people traffic out of the city. However, if we want to make this model produce output, we need to consider the following: what does traffic mean? Is it cars? How many people are in cars? To answer those questions, we need to introduce the next symbol: the 'Converter'. A converter is nothing more than a mathematical equation acting upon the model. In our example of People in the City, the model with converters may look like Figure 11: SFD of Traffic/City Case(only the people going to the city are considered for simplicity sake):

*Figure 11: SFD of Traffic/City Case*




Our previous question on what "traffic to city" meant is answered. We are defining it by "Number of Cars per Hour" and "People per Car". In mathematical terms:

Traffic to City = Number of Cars per Hour * People per Car

We now can know the development of the stock (people in city). If we multiply "Number of Cars per Hour" with "People per Car", we know how many people go to the city per hour! Again, it is important to not what all signs mean. The square is a stock. We can store information here. Here, the stock (People in City) counts what is added or subtracted. The flow (Traffic to City) influences the stock by defining the change. It is similar to the river we saw earlier. Lastly, the converters ("Number of Cars per Hour" & "People per Car") are merely computations to define what "Traffic to City" means. If we were to put all the calculations in the flow itself (which is possible), we would lose track of what we are doing. Therefore, to be transparent and show what we are doing, we use converters.

Let's go to the last step and think of the output our model will produce. We will take the example from Figure 11: SFD of Traffic/City Case. To get output, we need to define the converters "Number of Cars per Hour" and "People per Car". Here, we set the values as follows:

| | |
|---|---|
| Number of Cars per Hour | = 5 |
| People per Car | = 2 |
| Traffic to City | = Number of Cars per Hour * People per Car = 5 * 2 |

The flow, "Traffic to City", thus becomes "Number of Cars per Hour" * "People per Car" or 5*2. Therefore, every hour, the stock "People in City" will rise with 10 (5*2). In 3 hours, the number of "People in City" will be: 3 hours * "Traffic to City" or 3*10 = 30.

The flow in "Traffic to City" is always going to remain 10 per hour. If we measure this in 5 hours, the flow is still going to be 10. However, if we measure the stock "People in City", it will have accumulated to 50: 5 hours * 10 = 50. Graphically, the stock and flow develop like seen in Figure 12: Traffic to City and Figure 13: People in City:

*Figure 12: Traffic to City*

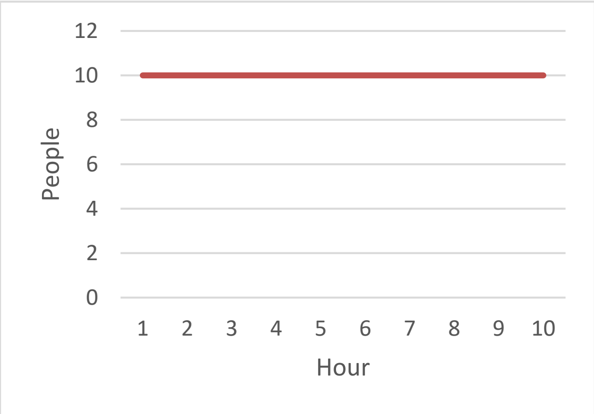
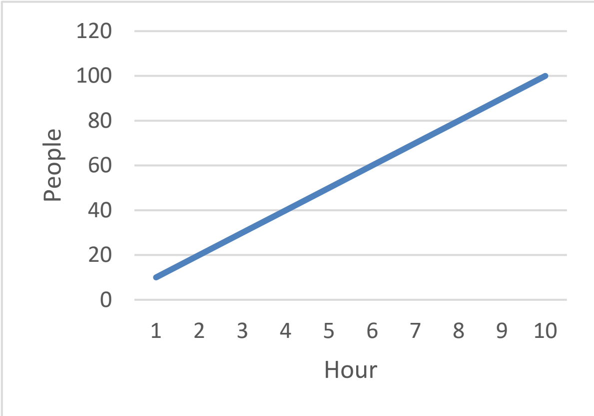



*Figure 13: People in City*




As seen here, the flow always stays 10, every time-step (from 1 hour to 10 hours). The stock on the other hand increases with 10 every time-step (from 10 at hour 1, to 100 in time 10). We have now seen the flow and accumulation effect of the stock in action!

### 3.1.1 Mathematical basis of System Dynamics

We have now explained System Dynamics in a rather intuitive language. Let us continue to explain further and dive into the calculations that make up System Dynamics models. As we have already seen, System Dynamics models are based on capturing an amount of stock at various points in time and the change that occurs. We will define the time-interval (the time between the measurements) as *t*. *t* can have any value, depending on the model specifications. It is important however to separate the unit "time" and 'time-interval'. A unit of time can (for example) be one month, year or decade. When we talk about the time-interval, we address the calculation from one point in time to the next. To illustrate: if the time unit of a model is "year" and the time-interval is 12, this means that every $1/12^{th}$ year, there is an update of the stocks and flows in the model. Thus, *t* stands for the point of measurement in time and not the unit. It should be noted that in our calculations, *t* always keeps the same value throughout – no matter what the value is.

Next, we define the value of a stock as *x* and the flow is as *f*. *f* is a function and represents the amount of change that would occur between *t* and *t*+1. The value of a stock at a time *t* can be described as $x(t)$. With this, we can note the following:

$$x(t+1) = x(t) + f(t) \tag{3.1}$$

This means that the stock, one time-interval from now, has the value of the previous interval plus the change over the interval. The value of the stock at the current interval therefore is:

$$x(t) = x(t-1) + f(t) \tag{3.2}$$

Here we see the usage of the time-interval $t$ in action. If we assume that $x(t)$ is the value of the stock from the initial time 0 to time $t$, we can rewrite the equations 3.2 as:

$$x(t) = x(0) + \sum_{i=0}^{t-1} f(i) \tag{3.3}$$

Equation 3.3 reads that the value of $x(t)$, the stock, has a value at any given time of the starting value $x(0)$ plus $f(t)$, which is the sum of change over time from $x(0)$ to $x(t)$. We have now integrated the stock and flow into a mathematical format.

To understand and translate macroeconomic concepts to System Dynamics language, something we will do later, we should also explain differential equations. The need for differential equations arises if we want to make calculations on a continuous basis – that means make $t$ as small as possible and keep calculating the value of our stocks. To do so, we need the derivative: the change in a function with $lim\, \Delta t \to 0$, where $\Delta$ is the change in $t$, and $t$ is approaching zero, but not zero. We have previously seen in equation 3.2 that:

$$x(t) = x(t-1) + f(t) \tag{3.2}$$

From equation 3.2 we can derive a new function when incorporating the derivative:

$$x(t) = x(t-\Delta t) + f(t-\Delta t)\Delta t \tag{3.4}$$

The change in time (derivative) is can be represented as:

$$\frac{x - x(t-\Delta t)}{\Delta t} = \frac{dx}{dt} \tag{3.5}$$

Our new knowledge combined in a function can be summed up as:

$$\frac{dx}{dt} = f(t) \tag{3.6}$$

In equation 3.6, we have replaced $\Delta$ with $d$, meaning the delta – the change in between time measurements. The flow of our model is now defined as the change in stock. Consequently, the change in stock (which is the same as the amount of flow) can be represented by:

$$dx = f(t)dt \tag{3.7}$$

A final important thing to note about differential equations is the following: the answer of a differential equation is a function, *f*. In normal algebraic equations, there are set answers. For example, $2y + 9 = 15$. This is not the case for differential equations: answers are defined in the form of functions and there is no real 'solution'. Every time a System Dynamics model gets the command to simulate, it is constantly updating the function to determine the values in the model.

## 3.2 Macroeconomics

In this part of the thesis, we will explain how to use System Dynamics reasoning to translate macroeconomic concepts and formulas to a workable model (Yamaguchi, 2013). We will try to consolidate a few traditional economic views with the help of the work of Yamaguchi (2013); all the models in this chapter are based on the work of Yamaguchi (2013) and later adjusted for the specific context of the Netherlands. The original work can be found on the online[7].

The basic model we use is built for a capitalist market economy – chapter 9 of Yamaguchi (2013). This means that all factors of production and goods and services are exchanged in the markets with money as medium for exchange (Yamaguchi, 2013). Sectors of the economy are interacting with each other and there is money, goods and financial products flowing between them. The interaction of economic actors is determined by a multiplicity of economic theorems. To get a wholistic idea of the macroeconomy, we need to define a model as such that it can show/generate wage, labour, inflation, production, demand. To achieve this, we need to combine and synthesise divergent functions in one model. We will now go over the most essential functions present in the model – some that we had to adjust for this thesis. This is important to get a feel of the theory we are basing this thesis on and the assumptions we make about the economy.

*3.2.1 Goodwin model*

Yamaguchi (2013) first begins with producing a business cycle in the economy, expressed in System Dynamics terms. Business cycles in the economy can be explained with a Goodwin model (sometimes also called Goodwin cycle). The Goodwin model combines aspects of the Harrod–Domar growth model (explains economic growth through level of saving and productivity of capital) with the Phillips curve (describes the inverse relationship between unemployment and inflation) to generate endogenous cycles in economic activity (Naastepad, 2002). The business cycle model is used as an example of how to translate economic formulas to System Dynamics formulas, but it is too simple to be used as a national macroeconomic model. We can however use some of its components and integrate them with other theories. This we will do in a later part of the thesis.

*3.2.2 Keynesian economics*

The Goodwin model – though adequate for showing dynamic behaviour – is not suitable to use for our macroeconomic model. This is because the Goodwin model assumes Say's law – a theorem that states that supply creates its own demand. However, output (GDP) is determined by the aggregate demand, not supply of economic goods. Say's law was rejected in the Keynesian view of the economy in the description of the circular flow of income. In short, economists do not agree about what consumers do with the money they do not consume (their savings). Neo-classicists assume all the savings are reinvested in the economy. Keynesians assume the same, but only if the return on investment exceeds the interest rate. On top of that, the rate of

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[7] http://www.muratopia.org/Yamaguchi/MacroBook.html

(consumer) investment is also dependent on the expectations of the future. Consumers can thus invest their savings, keep them in their household or make a deposit. Concluding: investment is exogenous – depending on future expectations – rather than endogenous. We can thus see that this view of the economy is demand driven: driving up the returns on investment will generate demand (more investments) and feed the economy.

Now that we have established the basics of our economic view, it is time to go over the basic equations of the Keynesian model (Naastepad, 2002). This overview can be seen in Table 4: Formulas in the Keynesian model. Note that these are by no means all the equations of the Keynesian system and that formulas have been simplified for better understanding. We will go into more detail of the formulas once we explain how the model is build. Also, this model excludes the money market – describing the pressure between money supply and money demand. These equations in the Keynesian model governs the market interest rate. However, as our System Dynamics model does not keep track of actual money of economic agents, this is impossible to calculate endogenously. Luckily, the market interest rate only has an influence over the amount of capital in the economy and can thus be easily replaced by a constant or dataset.

*Table 4: Formulas in the Keynesian model*[8]

| | | |
|---|---|---|
| ***Goods market*** | | |
| *Production (equilibrium)* | $y = y^d$ | (3.8) |
| *Aggregate demand* | $y^d = c + g + i^p + i^g$ | (3.9) |
| *Consumption* | $c = (1-\sigma)(1-\tau)y$ | (3.10) |
| *Private investment* | $i^p = i^p(y, r)$ | (3.11) |
| *Private saving* | $y = c + s^p + \tau y$ | (3.12) |
| *Price level* | $p = (1+\varphi)W\lambda^{-1}$ | (3.13) |
| *Mark-up rate* | $\varphi = \varphi(b)$ | (3.14) |
| *Capacity utilization* | $b = \dfrac{y}{(k * \kappa)}$ | (3.15) |
| ***Capital stock*** | | |
| *Capital stock* | $k = k_{t-1} + i^g + i^p$ | (3.16) |
| ***Labour market*** | | |
| *Labour demand* | $l^d = l^d(y)$ | (3.17) |
| *Unemployment* | $u = l^s - l^d$ | (3.18) |
| ***Technological progress*** | | |
| *Labour productivity* | $\lambda = \lambda(W\lambda, y)$ | (3.19) |

| ***Exogenous variables*** | |
|---|---|
| *Public expenditure* | $g$ |

[8] Partially based on lectures and work of Dr. C.W.M. Naastepad in the course Intermediate Economics at the TU Delft in 2017.

| | |
|---|---|
| *Public investment* | $i^g$ |
| *Autonomous consumption* | $a$ |
| *Capital stock previous period* | $k_{t-1}$ |
| *Labour supply* | $l^s$ |
| *Nominal rate of interest* | $r$ |
| *Output-capital ratio* | $\kappa$ |
| *Propensity to save* | $\sigma$ |
| *Income tax rate* | $\tau$ |
| *Wage rate* | $W$ |

When we want to translate this set of formulas to a Stock and Flow Diagram, we need to make some practical adjustments. We will explain the translation process with a few examples found later in the model. This adjustment process is a consequence of how the theories treat and deal with time. In economics, we know logical, mechanical and historical time. Logical time is when a when a logic set of relations links variables in a unique direction (causal relationship) (Biasco, Chick, Roncagia, & Rowthorn, 1981). Mechanical time is when time extends throughout a set of unchanging relations – the values of variables change and can be described at any point in time. Finally, historical time assumes that the future is qualitatively different from the past (Biasco et al., 1981). The last definition of time assumes possible structural changes. Keynesian theory assumes logic time and System Dynamics uses mechanical time (and Robust Decision Making subscribes to historical time).

We see logical time in Keynesian theory if we try to adapt the formulas: marginal propensity to consume $[1-\sigma]$ times income after tax $[(1-\tau)y]$ equals consumption. Also: at any equilibrium point, an increase in income and savings $[(1-\tau)y+s^p]$ leads to more investments – because the propensity to consumption $[1-\sigma]$ stays equal and $y^d = c + g + i^p + i^g$, thus $i^p$ and $i^g$ must rise. In any case, the calculations follow a set logical order to arrive at the answer. System Dynamics at the other hand has a delta of time in its equations expressed by $dt$ or $\Delta$ - in economics, the sign $\delta$ is used to express change. We have seen these multiple times in the previous part explaining System Dynamics. System Dynamics is made to account for variables at very timestep and therefore we should translate economic theory in a new format to account for mechanical time.

We can transform economic concepts to mechanical time by introducing a new variable Adjustment Time (AT). AT is a very common process in System Dynamics. It is the time it takes for a process or information to propagate through the system. For example, when we have a desired inventory of 50 widgets and raise it to 60, it takes time for those 10 extra widgets to be in our actual inventory. Adjustment Time can also be explained as a natural phenomenon: when you feel an itch, you want to scratch it. However, for the signals in your brain to make the decision to scratch and for you hand to actually move to the location of the itch takes time. Although we do not experience this consciously, this adjustment process can be found anywhere. In the Keynesian economic model, AT can be seen whenever a market or function is not in equilibrium. When that happens, a new equilibrium is sought – and this takes time. In that regard, we should redefine the formulas in terms of change. If we do not do this, the market cannot find a new equilibrium point – we should come up with a new formula to describe how the market can adjust itself. To give an example of how this works, let us look at the production function and add Adjustment Time to define the adjustment process.

We have seen that equation 3.8 ($y = y^d$) is the production function, but only in equilibrium conditions. Although we have rejected Say's law, there are still forces in the economic system that generate cycles. This means that the economic system always tries to satisfy the condition $y = y^d$, but that it does not have to be true. Whenever $y \neq y^d$ the economy should adjust. In logical time, this happens instantaneously, but in mechanical time that approach does not work – a real system does not instantaneously achieve new values. Therefore, we need to describe the adjustment process for when production (supply) is not equal to demand. This new equation becomes:

$$\frac{dy}{dt} = (y^d - y)/AT \tag{3.20}$$

In other words, the change in production over time is the aggregate demand minus the production, divided by the Adjustment Time. Now we can account for the formulas when the Keynesian equilibrium condition is not met. Equation 3.20 is now the representation of production as a flow with production as a stock. The same can be done with the other formulas. When for example the production changes - $y \neq c + s^p + \tau y$ (equation 3.12) - private savings would change to match a new equilibrium, ceteris paribus. We will give one additional example of a transformation of the consumption function to express change. The following represents the change in consumption:

$$\Delta c = a + (1 - \sigma)(1 - \tau)\Delta y \tag{3.21}$$

Equation 3.21 states that a change in income results in a change in consumption. There is no adjustment process added to this new definition. This is because consumption only changes because of income and does not seek an equilibrium with other functions in the system. To put it in terms of logical time: consumption is a consequence. This is of course when we assume the tax and consumption behaviour does not change.

### *3.3.3 Neoclassical economics*

We have seen how we can construct a System Dynamics system using economic theorem. However, Yamaguchi (2013) is not satisfied with the explanatory power of some of the functions. To give more explanatory power to the system, we can change the production function into the Cobb-Douglas production function. The added benefit to this function is the inclusion of labour. This new function allows us to add a labour market to the system. Synergizing the Cobb-Douglas production function with Keynesian economics is not common, as it is one of the cores of Neoclassical economics (Acemoglu, 2009). However, as we use System Dynamics we can connect economic concepts in a way they can be integrated. By combining the theorems, we can reduce the number of exogenous variables and increase explanatory power. The first step in this process is to change our production function:

$$Y = f(K, L, A) = AL^{\beta}K^{a} \tag{3.22}$$

Where:

Y is the total production (the real value of all goods produced in a year);
L is the labour input (the total number of person-hours worked in a year);
K is capital input (the real value of all machinery, equipment, and buildings);
A is total factor productivity;
α and β are the output elasticities of capital and labour, respectively. These values are constants determined by available technology.

With this new function 3.22, we can make a distinction between labour output and the output of capital. Formulating the function in this matter also allows us to draw up a new distinction: potential GDP (or potential production). The potential GDP will be achieved if we constitute the input of labour in our previous formula with the total labour force. Our potential GDP thus becomes:

$$y_{potential} = f(K, LF, A) \tag{3.23}$$

Where LF is the total labour force.

The difference between potential (equation 3.23) and actual GDP (equation 3.22) allows us to calculate 'gaps' of desired and actual production in the economy. We have seen in equation 3.13 that the price in the economy is determined by the mark-up rate, labour productivity and wages. With this additional information, we can endogenously set new formulas for functions we are missing. Since we know that (under equilibrium conditions) the labour demand is equal to the aggregate demand and that output is based on labour and capital, we can refer the wanted production from labour. We can deduce this by separating output elasticities for capital and labour (which we did with the Cobb-Douglas production function). Assuming wages raise with the growth factor in the economy plus inflation and actors in the economy want to have a buffer of capital, we can set desired labour to:

$$l^{*} = \frac{(1 - y/y_{potential}) * (\beta * (1 - \mathrm{R}) * p * y^{d})}{w\prime} \tag{3.24}$$

Where:

$l^{*}$ is the desired labour;
R is the tax rate for owners of capital;
$w'$ is the expected wage of employees.

Important to note here is that we introduced a new exogenous variable R and endogenous $w'$. The reason expected wage rate is used instead of the normal wage is due to the mechanical time we use in System Dynamics and how decisions of actors should be modelled. In real life, a decision to hire (or fire) labour depends on an estimation of future wage of employees, not the current wage. This reality is reflected in our formula as well. We multiplied the normal wage rate with inflation as to make an estimation what employees expect at minimum. It can also be argued the expected economic growth should be added, as we stated previously that wages are dependent on the inflation and economic growth rate. In this solution, we choose to let employees demand more wage after the fact of economic growth (or decline).

The creation of labour supply is still an exogenous function in the system. We can constitute this value by adding a population development module to the economic model. Working with System Dynamics and its software allows us to add modules (of exogenous values) we are missing to get to a holistic overview. By using a standard population development function and adapting it for the Dutch economy, we can endogenously determine future population and labour supply. An alternative would be to feed the model with a dataset. This approach is chosen with dynamics too difficult to simulate in the current circumstances. An example where this is done is in the development of interest rates. Building a model that would reflect this behaviour in a truthful manner would require another thesis.

Finally, we have stated previously that we can integrate Keynesian and Neoclassical economics. Now that we have given functions in both theorems, we will show an example of how this using our new production function 3.22: $Y = f(K, L, A) = AL^{\beta}K^{\alpha}$. To synthesize this with our Keynesian model, we need simply find the definitions as input. Capital input $K$ in Neoclassical theorem, can be interpreted as the capital stock $k$ within in Keynesian economics. Similarly, labour input $L$ is translated to employment $l^d$. Finally, there is a coherence with the productivity factor $A$ and productivity $\lambda$. We now can freely move between both functions:

$$Y = f(K, L, A) = AL^{\beta}K^{\alpha} \tag{3.22}$$

and

$$y = f(k, l^d, \lambda) = \lambda {l^d}^{\beta} k^{\alpha} \tag{3.25}$$

Potential production $y_{potential}$ can also be reinterpreted from:

$$y_{potential} = f(K, LF, A) \tag{3.23}$$

to

$$y_{potential} = f(k, l^s, \lambda) \tag{3.26}$$

Where the Neoclassical labour force has been switched for Keynesian labour supply. Repeating this process for numerous functions can increase the range of the system we build and our understanding of it.

## 3.3 Macroeconomic System Dynamics model

The macroeconomic model we use is divided in different modules. These modules are based on the work of Yamaguchi (2013). A modular design is chosen because it offers better clarity, it is easier to test individual effects and it is less effortful to later edit or add modules. There are modules describing the GDP (demand, supply and production in the economy), consumer behaviour, governmental expenditure, labour market and housing market. We will go over each of the modules to explain their workings to understand the 'engine' of our dataset. Remember that all the modules are built upon macroeconomic theorems and this approach does not follow a traditional System Dynamics pathway - more on this can be found in the description of model limitations. Another thing we should keep in mind is that the model we will explain in this chapter is the model used for EMA. Because of translating a System Dynamics model to Python, we cannot use certain functions that are embedded within System Dynamics software. Therefore, delays are modelled as stocks and minimum- maximum functions are transformed to represent If, Then, Else functions. More on this can also be found in the description of model limitations.

Before we go into the model, we should first explain the colours variables have. In order to make modelling and reading easier, we have adapted colours for certain variables to quickly see what is what. In Table 5: System Dynamics Colour Codes, the colouring is explained.

*Table 5: System Dynamics Colour Codes*

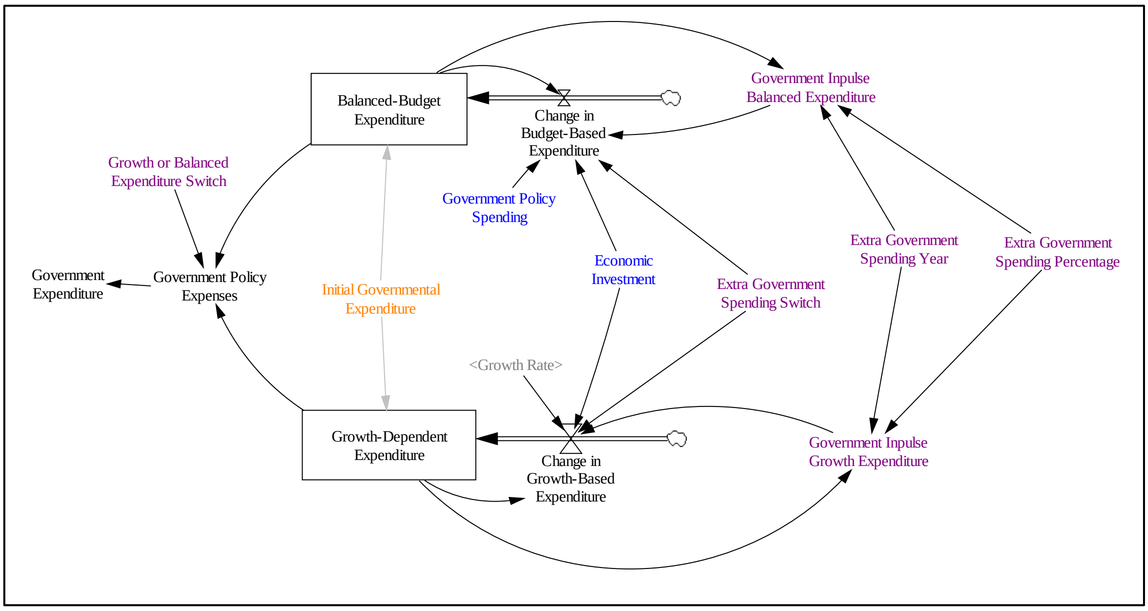
| Colour | Type | Definition |
|---|---|---|
| Turquoise | Constant | Uncertain variables within economic theorem. Either due to lack of knowledge (about the future) or the system. |
| Blue | Parameter | Uncertain variables within economic theorem, some of which can change over time. Changes might occur due to natural developments or changes can represent shifting uncertainties. |
| Orange | Initials | Initial values of the model. Some are calculated with use of system variables and some represent numbers from an outside source. |
| Green | Parameter | Adjustment times used in translation process from economic theorem to System Dynamics. Some of the values are able to change due to system changes. |
| Purple | Lever | Policies in the model. These policies represent either uncertainty about the layout of the economic system or are introduced due to stakeholder wishes. |
| Black | Calculations | Black variables contain formulas and serve as auxiliary values, stocks and flows. |
| Grey | Reference | Grey represents a variable that is calculated elsewhere in the model. In System Dynamics terms, the name for this variable is a 'shadow variable'. Shadow variables allow us to reference parts of the model already built. |
| Black arrows | Relations | Black arrows tell us there is a relation between the variables connected. The point of the arrow indicates direction of causality. |
| Grey arrows | Calculation of initials | Some initial values are generated endogenously – within the model itself. The grey arrows show us how initial values are calculated that do not require input from outside the model. |

Besides these colours there are also hidden variables that are invisible. The hidden variables are "Initial Time", "Time" and "Year". Sometimes "Year" is used to calculate flows that have no delay time (delay time = 1). The variables "Initial Time" and "Time" are used to initialize values and activate certain switches. As they only serve a supporting role or are used in unit calculations they are often left out. These variables are only used a minimum amount of times. Although hidden in this chapter, they can be found in the model documentation in appendix J of the thesis.

### *3.3.1 Government Expenditures*

Now that we have introduced our colour scheme, we can go on exploring the model. The first module we will explain is about how the government decides to spend money. There are two possibilities: Growth-Dependent Expenditure (GDE) or Balanced-Budget Expenditure (BBE). With GDE, the government consumes a standard amount of goods/services that is increased by the growth rate of the economy (marked grey). This shadow variable is calculated elsewhere. Besides economic growth, governmental expenditures with GDE can also rise with economic investments (marked blue). Since the government module is simplified, we can simulate the government being a continuous investor in the economy.

*Figure 14: Government Expenditures*




With BBE, the primary governmental expenditures due to policy. As is, the value of that policy is zero. When we want to test hypothesis and potential futures, we can insert a dataset of predictions in this variable to simulate different government behaviour. Additionally, it is possible for the Government to invest in the economy like seen with GDE, but anticyclical. This means that when economic growth is increasing 1%, expenditures will decrease with 1%. If the opposite happens and economic growth decreases, expenditures increase with the same amount. Whether BBE or GDE is used depends on the switch “Growth or Balanced Expenditure Switch”. Turned to zero, the eventual government expenditure equals GDE and when the switch is one the model uses BBE.

One of the reasons the model of government expenditures is so simple is because the variables in the Keynesian model that describe it are both constant: $g$ for public expenditure and $i^g$ for public investment. Both are needed in our calculation for aggregate demand: $y^d = c + g + i^p + i^g$. However, simply including constants or inserting a dataset would underrepresent Keynesian theory and would be uninteresting to model. Therefore, when looking at literature and when observing political budget making ourselves, we can elicit two plausible paths for public expenditures $g$ (Yamaguchi, 2013). Though still a simple solution, GDE produces endogenous behaviour based on economic growth. BBE can also produce endogenous behaviour - when opting for anticyclical investments – or exogenous behaviour based on outside sources.

Public investment $i^g$ is represented by a standard economic investment and can be extra stimulated with shocks. This policy in the model allows the government to spend an extra percentage for one specific year. This policy is introduced to simulate extraordinary spending (in the case of an economic crisis) and to increase our knowledge about the effects that will propagate through the system when activating said policy. Finally, $g$ and $i^g$ are combined into one variable "Government Expenditure".

*3.3.2 Consumer Behaviour*

To accurately describe a Keynesian model, we need to include consumption. These are the expenditures of the people living in a country of which we are trying to simulate the economic system. As we have seen, consumption $c$ is calculated as the following: $c = (1 - \sigma)(1 - \tau)y$. Unfortunately, this model does not include income tax rate $\tau$. This is because there is no data available about collected taxes of wages and we thus cannot test if our simulations of the economy are correct. We therefore must exclude $\tau$ from the model and modify $c$ to become: $c = (1 - \sigma)y$. The constant savings rate $\sigma$ can be found in literature, although values for $\sigma$ differ between papers and research groups. This is because $\sigma$ represents a theoretical concept and we cannot observe this number directly. It would therefore be a good idea to let this value vary in our experiments.

We are going to make one final addition to the consumption function. This addition is best explained following logical reasoning. In our description of the economy, when people don't receive any income $y$, there is no consumption. In real life however, we know this is not the case. People will die if they do not consume goods (like food and water). Consuming, but not receiving income cannot be continued indefinitely, but will continue as long as there are savings. Savings in the model can be represented in the model by the cumulation of income that was not spend or was not paid in taxes: $y = c + s^p + \tau y$. We can therefore also simulate basic consumption when $y = 0$. We do this by introducing the autonomous consumption function $a$. This is a constant, exogenous function in the model. Thus, our final consumption function becomes:

$$c = a + (1 - \sigma)y \tag{3.27}$$

The starting value of $a$ is calculated by looking at historical data. As we know, our consumption function is $c = a + (1 - \sigma)y$ and therefore:

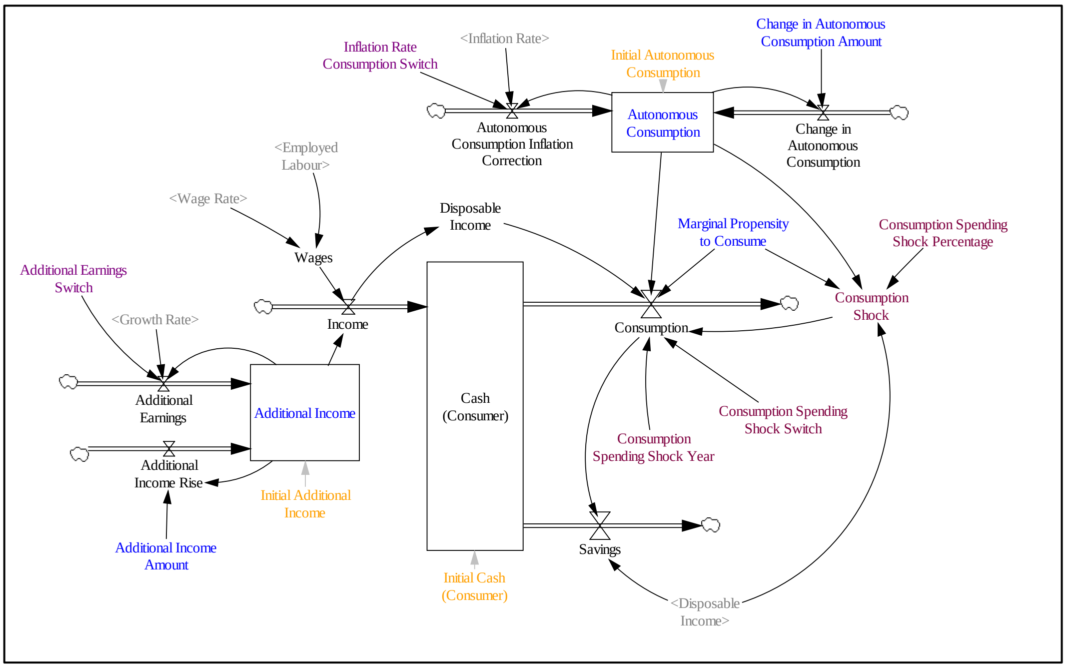
$$a = c - (1 - \sigma)y \tag{3.28}$$

Although we can calculate $a$, we can't plug equation 3.28 into our model. This is because $c$ must be known to calculate $a$. We therefore calculate function 3.28 once using historical data and assume autonomous consumption either rise naturally from themselves or change with inflation. We have done this in an Excel datasheet by performing a simple linear regression. This data can be viewed in the appendix. Change with inflation is a policy and can be switched off. This approach is the best we can do as in literature, autonomous consumption $a$ is the theoretical threshold that says even when people don't receive income, they must consume.

In the model, income $y$ is represented by multiplying wages with employed labour. This is not the whole story however, as people can gain income through other sources than labour. Alternative to working, people can be paid in dividends and lend money (Yamaguchi, 2013). To not let the module become too complex, historical behaviour between wages and alternative income has been studied to find initial values for both variables. Wages is represented endogenously and alternative income is based on a simple regression of historical data. This is by no means a loss as we can steer the amount of alternative income of consumers by variating the growth rate, which synergizes with our RDM approach.

We now have explained all the components to calculate consumption. What is left is the possibility to shock the system. Just as with extra governmental expenditures, consumers also can decide to go on a spending frenzy. What is more interesting is the opposite effect of when the consumption spending shock percentage is a negative number. This would enable us to simulate consumer uncertainty about the economy, increase our knowledge about the strength of effects in the system and experiment with finding new equilibrium points in the economy.

*Figure 15: Consumer Behaviour*




### *3.3.3 Gross Domestic Product*

To make explaining the Gross Domestic Product module easier and better understandable, we insert a visual cue when mentioning a variable in the model. We do this because there are a lot of variables and concepts that intertwine. Whenever we directly refer to a variable in the module, we mark them with double quotation marks like this: “variable”. When we mention for example “GDP”, we refer to the variable in the model. When mentioning GDP, we refer to the economic concept and representation, not a variable in the model directly. We have already done this throughout the thesis, but have not said this explicitly. Only now does noticing this visual cue become crucial for better understanding.

This module calculates gross domestic product, but also contains private investment $i^p$, represented by the variable “Investments”. For clarity reasons, “GDP” and “Investments” are marked with a hexagon as they are the main outputs of the module and sector, respectively. Furthermore, it should be noted that we make a distinction between real and relative values. If we take GDP as an example, we see that there is “GDP” (marked in the hexagon) and “GDP real” (shown as a flow). The distinction is that “GDP” is the yearly value of GDP and “GDP real” shows the actual GDP development with 2016 as starting year. The latter is adjusted for inflation by dividing it with the price development in the economy – price development is calculated in another module. The same applies to all variables containing ‘real’ behind the name. Making this distinction in the model allows us to honour Keynesian theorem without adding inflation to its core formulas and break down growth from relative growth. Price and inflation are calculated endogenously in another module.

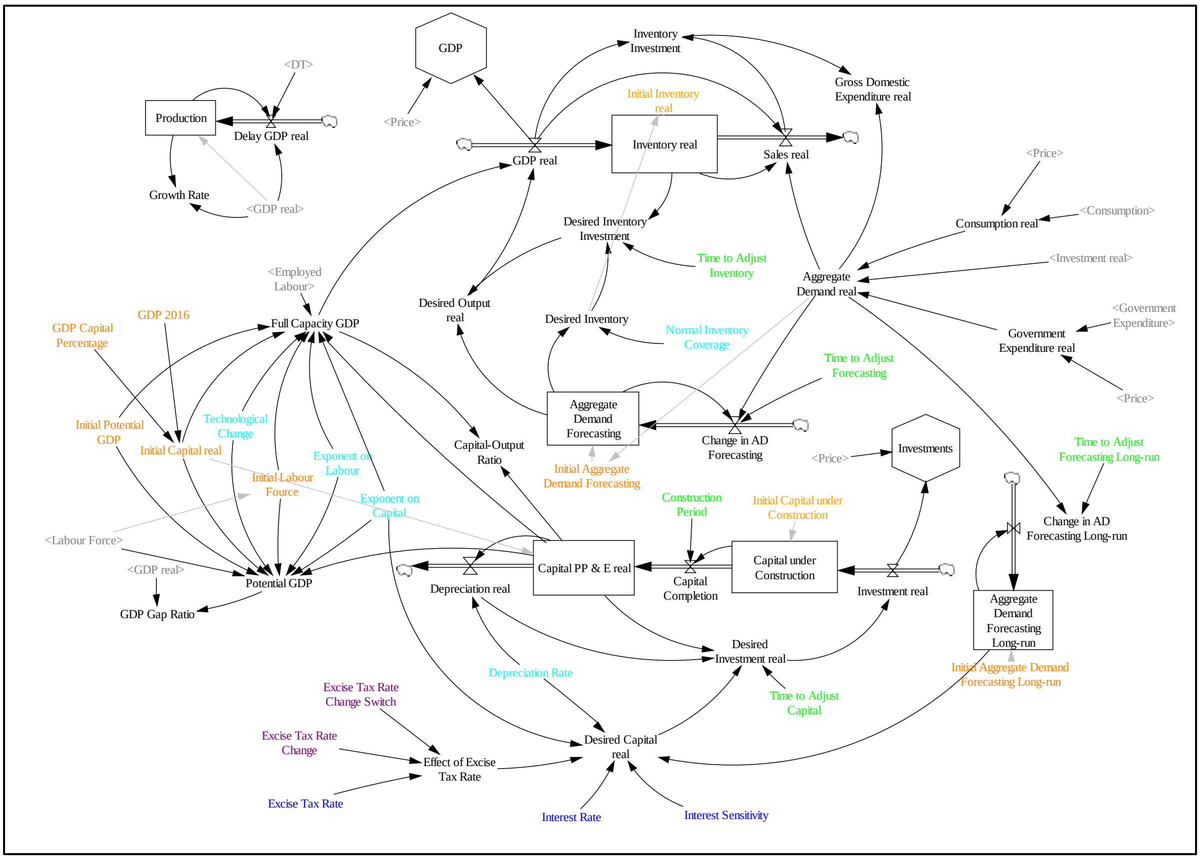
For the explanation of the model we will start with “GDP real”. GDP represents the production of an economy. Also, we have stated before that our economy is driven by demand (Naastepad, 2002; Yamaguchi, 2013). Therefore, GDP will equal the demand in the economy ("Aggregate Demand real"). However, producers cannot know what will be asked exactly, so they will make a forecast about what the demand will be ("Aggregate Demand Forecasting"). On top of the forecast of demand, producers will also want to produce a level of inventory to account for the building of new production capital or to absorb upward shocks in demand. Therefore, GDP will equal the "Desired Output real" which considers the aggregate demand and inventory investment. However, production cannot be higher than the maximum production capacity. When the desired output thus exceeds the maximum production capacity of the economy, the "Full Capacity GDP" becomes the new value of "GDP real" until enough production capacity is built.

Another feature of GDP in this module is the difference between full capacity and potential GDP. In short, "Potential GDP" calculates what a society could produce if all labour and capital were to be utilized. If "Aggregate Demand real" = "GDP real" = "Potential GDP", the market has obtained its equilibrium-point. The introduction of potential GDP therefore stands for value $y$ if $y = y^d$. The remainder of definitions describe the adjustment process of GDP in the market when $y \neq y^d$. We also need the distinction of potential GDP to calculate "GDP Gap Ratio". This variable gives an upward or downward pressure in the economy, influencing the price of goods – which we will see in the module about price, wage and inflation.

The development of "Full Capacity GDP" and "Potential GDP" is driven by dynamics in capital creation and the labour market and the constants "Technological Change", "Exponent on Labour" and "Exponent on Capital". We will first go over the constants. The exponents on labour and capital both explain whether the labour and capital have constant, diminishing or increasing returns to scale (Naastepad, 2002). In short, it determines the effectiveness of adding labour or capital and the returns of that extra quantity. When $\alpha + \beta = 1$, it means the retuns are contant. When $\alpha + \beta < 1$, the economiy returns less over time with extra capital and labour. As we do not observe increasing returns in the economy, we will limit $\alpha$ and $\beta$ both to 0.5 or lower.

Technological change is first and foremost a strange variable. It is an exogenous constant that influences productivity, but it has no clear real-world observability. Technological change was introduced by economists who found that output growth could not be explained by increases in $k$ and $l$ (Naastepad, 2002). This difference has now been captured by technological change. Although technological change makes Neoclassical theory fit better with reality, it could just as well represent the lack of knowledge about the true economic dynamics. Technological change affects the productivity of labour, which means the higher its value, the less employees are needed for the same production. More productive labour is rewarded with higher wages. If this economic growth is led by an increase in wages $W$, it raises aggregate demand and output. Now, $\lambda$ is stimulated both directly by the increase in labour costs, and indirectly by output growth (Naastepad, 2002). At the same time, increasing labour productivity $\lambda$ negatively impacts price. This process is caught within its own cycle and therefore will produce growth without inflation.

*Figure 16: Gross Domestic Product*




In our model, the process of non-inflationary growth does not completely unfold as in Keynesian theory. This is due to the integration of Neoclassical theory. Originally, as prices are formed as a mark-up over costs, with a lower mark-up rate $\varphi$, prices will be kept low to $\varphi = \varphi(b)$ and $p = (1+\varphi)W\lambda^{-1}$. When more production can be achieved with the same capital, capital utilization $b$ will be lower through its effect of $b = \frac{y}{(k * \kappa)}$. In our model (the Neoclassical framework), prices are set by the difference between potential output and what the output currently is. This is a new interpretation of capital utilisation - this can be seen in the module containing price (Yamaguchi, 2013). We also follow an adjusted development of labour due to the integration of supply and demand. The wage rate $W$ will initially rise as more productivity constitutes a greater reward, but later drop due to a constant stream of new labour and lessened demand for labour $l^d$ for the same output $y$. This decreased demand stems from having a more efficient labour force as a function of $y$ with $l^d = l^d(y)$. Private investments $i^p$ will fill the gap between what labour can produce and what is demanded in the economy $y^d$ trough the effect of $i^p = i^p(y, r)$, until production equals demand in equilibrium conditions $y = y^d$. Technological change still causes growth with a lesser degree of inflation, but less so than in original theory.

Demand $y^d$ in the economy is determined by "Aggregate Demand real". This variable is the cumulation of consumption (from government and consumers) and investments: $c + g + i^p + i^g$, written as the formula "Consumption real"+"Investment real"+"Government Expenditure real" in our System Dynamics model. Sales in the economy equal to the aggregate demand. Sales drain the stock of "Inventory real" as long as the stock is above zero and there is unsatisfied demand.

Investments in the model are calculated as a function of the current production stock of capital and the desire to attract more capital. Capital stock ($k = k_{t-1} + i^g + i^p$) is attracted based on the value of return on capital ($i^p = i^p(y, r)$), with interest and demand as drivers. We use "Aggregate Demand Forecasting Long- run" to illustrate long-term decisions when it comes to attracting capital. We do not use the variable "Aggregate Demand Forecasting", as it is reserved to calculate every-day production (Yamaguchi, 2013). For simplicity, we split the investment function into "Desired Capital real" and "Desired Investment real". "Desired Investment real" stands for:

$$i^p = \frac{k^*(r) - k}{Time\ to\ Adjust\ Capital} + \delta k \tag{3.29}$$

Where $k^*(r)$ represents the desired capital as a function of interest and $\delta k$ the depreciation on capital (Yamaguchi, 2013). $k^*$ is gained by

$$k^*(r) = \frac{\alpha(1-t) - y^*}{r + \delta k} \tag{3.30}$$

Where $t$ is the excise tax rate – also known as corporate tax rate.

In the model, the sensitivity to interest is also described in "Interest Sensitivity". This variable describes if investors are risk averse (if the number is high: >1), or risk seeking (when the number is low: <1).

### *3.3.4 Price, Wage and Inflation*

Price is formed from capital utilisation (our adjusted interpretation) and wage changes. Starting with capital utilisation, we calculate an effect on the price by calculating the gap between what is produced and what could be produced in an economy: "Desired Output real"/"Potential GDP" = "Production Ration". This production ratio stands for what could be achieved with full labour in an economy. As we follow the assumption that the economy will try to gain equilibrium

$y = y^d$, it will try to reach an employment rate of economic maximisation $l^d = l^d(y)$. On top of the labour ratio, we also consider the desired and actual inventory in the economy. This is a minor adjustment process that can ask for less or more production per year, depending on "GDP real" and "Sales real" – see Gross Domestic Product module. In short, when we can easily produce more than what is currently sold, the effect on price level is negative. If we cannot produce as much as we want to sell, prices in the economy will rise. On top of that, prices in the economy will change depending on the change in wages. This process is summarised as follows (Yamaguchi, 2013):

$$p^* = \frac{p}{\left((1-w)\frac{y_{potential}}{y^d} + w\frac{Inv}{Inv^*}\right)^e} + \psi * \delta W \tag{3.31}$$

Where:

$p$ is price;
$p^*$ is the desired price;
$Inv$ is the current inventory of the economy;
$Inv^*$ is the desired inventory;
$w$ is the weight between inventory or production;
$\delta W$ is the change in wages;
$e$ are is the power of the effect on price and;
$\psi$ is the cost-push force.

The cost-push force $\psi$ might require more explanation: as we want to adjust the prices in the economy to wage changes, we don't want to multiply the wage change with the current price $p * \delta W$. Instead, we use $\psi$ to represent the price where $\psi < p = \psi < 1$. If we would use $p$ instead, there would be no real wage change in the economy as every growth in wages would be countered by an equal growth in $p$.

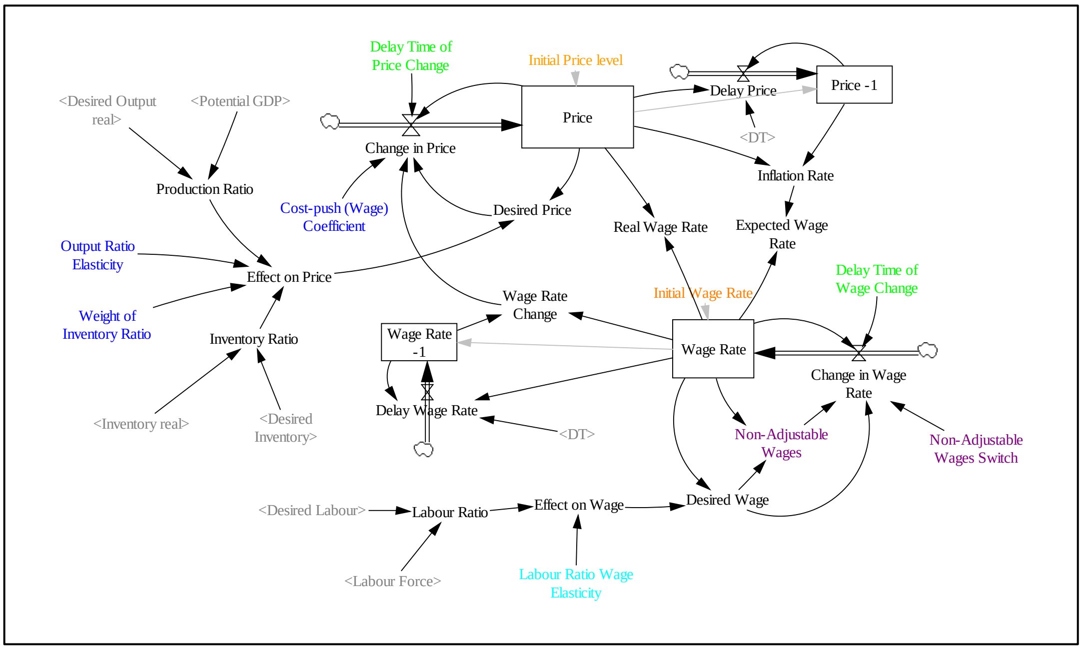
We would have liked to integrate a second definition of the Neoclassical system for price: $\frac{M^s}{p} = \frac{1}{v}y$. This equation tracks the development of price using the money supply $M^s$ and velocity of money $v$. In theory, we should be able to build it if we have a structure that can capture and track economic actors and their possessions. Yamaguchi (2013) is able to do this in his work, but this approach only works theoretically. We are already finding it hard to come up with reasonable and rational values for economic ratios; adding such a structure would add even more parameter uncertainty.

Wages is a very simple calculation that considers the desired for labour $l^d$ and compares it to the amount of labour available $l^s$. Based on market developments, elasticity rates and a wage rate in the starting year, we can track the developments very simply. We owe this simple method by taking the definition from Neoclassical economics: $l^s = l^s \frac{W}{p}$ and $l^d = \alpha y \left(\frac{W}{p}\right)^{-1}$. We will go over the intricacies of the labour market in the explanation of the next module.

The development of the wage rate in the economy also has a policy. This policy, if turned on, states that wages cannot drop. Reason for the invention of this policy, is that we almost never see a wage-cut in real life. The real wages can drop however; when price developments outpace those of wage. Theoretically, we can see that wages drop. Also in real life, one might argue that the base-wages of new workers will be lowered in certain economic conditions. However, as new labour is only a relative small amount of the total employed labour, it can be reasonably argued this effect is negatable. The policy therefore reflects what we see in real life, versus what one might expect in theory.  Both options of the model will be explored.

The last notable outcome of the module, inflation, is a simple calculation that takes the development of price over time. Neither the Keynesian or Neoclassical model defines the inflation rate explicitly, but uses the definition of price per time. We can thus substitute the inflation rate with price when modelling certain connections.

*Figure 17: Price, Wage and Inflation*




### *3.3.5 Population & Labour Force*

The final module containing traditional economic relations contains that of the labour market and population development. As the previous modules were based on Yamaguchi (2013) and contained only minor adjustments, - often not needing explicit mention – this module is different when it comes to population development. Yamaguchi (2013) used the 'World3' model[9] to calculate the changing population and labour population. In this thesis, we built an aging chain with a population total as a goal: "Population Goal". Simply put, the Dutch Central Bureau

[9] World3 is a standard population development module available from Ventana Systems, Inc.

for Statistics estimates there will be a total population of 18.1 million in 2060[10]. With this knowledge, we start out with the population in 2016 – as spread over age groups 0 to 15, 16 to 69 and 69 and above - and set a goal for the system to reach in 2060. This is still a very simplified version of looking at population development: we do not consider premature deaths or age-group specific characteristics. We have made available a population dynamics module in the appendix that was built to actively keep track of these variables, but we unfortunately could not use it due to integration problems with Python[11]. It works by hardcoding varying age-groups to include internal aging mechanisms and deaths per age-group. This method is the most accurate, reliable and modern to define age-groups in System Dynamics. We could implement this model in the future by neglecting the System Dynamics translation and just programming the module in Python directly. In this thesis, all models will be based on System Dynamics due to the simple nature of the models and graduation subject of the author. Fortunately, for our purpose which is a rough estimation of the working population, this method is acceptable.

In the Keynesian or Neoclassical model, population dynamics is not a feature. The reason for introducing this ourselves is to define the labour supply, "Labour Supply", endogenously. This is done by looking at the population between 16 and 67 years old and applying a participation rate. We currently assume this number is static and does not change. Reason for this is the high value for participation rate in the Netherlands, 79,6%[12]. This amount is the 4th highest in the worldwide economy. With this setting, labour supply $l^s$ has now been made endogenously.

Employed and unemployed labour are decided by two factors. First, new employment and unemployment (from the growing or retracting labour force) is added evenly depending on the current unemployment rate. The second factor that governs the labour market is the desire for labour. This definition is borrowed from the Neoclassical economic framework. This function is derived from the production function and the assumption of profit maximisation. As we know, our production function looked like:

$$Y = f(K, L, A) = AL^{\beta}K^{a} \tag{3.22}$$

Or similarly:

$$y = f(k, l^{d}, \lambda) = \lambda {l^{d}}^{\beta} k^{a} \tag{3.25}$$

We will stick with the equation 3.22 for now, since this definition contains the official characters of the Neoclassical system.

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[10]http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=7461BEV&D1=a&D2=0&D3=101-120&D4=66&HDR=G3,T&STB=G1,G2&VW=T

[11] This module can be found in appendix H and is based on the lectures of Advanced System Dynamics 2017 by Dr. E. Pruyt at the TU Delft.

[12] https://data.oecd.org/emp/labour-force-participation-rate.htm

If we reason from profit maximisation and the production function, profit $\Psi$ can be deduced from:

$$\Psi = \text{py} - \text{Wl} - \Pi\text{k} = \text{pa}l^{\alpha}k^{\beta} - \text{Wl} - \Pi\text{k} \qquad (3.32)$$

Where:

$\Psi$ are the profits (also known as 'supernormal' profits);
py is the price of output;
Wl is the price of labour and;
Πk is the price of capital.

Equation 3.32 is as simple as saying that profits equal revenue minus costs. Here, capital has costs and labour has costs. Both labour and capital also produce. The decision to add extra labour is taken when adding labour, creates more value than costs. This will be our maximizing function, when profits in respect to labour is zero:

$$\frac{\delta\Psi}{\delta l} = 0 \qquad (3.33)$$

Where the sign $\delta$ stands for a change in the factor behind it. For clarity: we have previously used $\delta$ to assign delta's and deprecation, thus it keeps the same definition. The profit maximisation function, when keeping inflation into account, is the same condition as:

$$\text{p}\frac{\delta y}{\delta l} - \text{W} = 0 \qquad (3.34)$$

Which leads to:

$$\frac{\delta y}{\delta l} = \frac{W}{p} \qquad (3.35)$$

Mathematically, profits can be maximised when the productivity of labour, equals the wage rate adjusted for inflation (the real wage rate). If we now equal our profit maximisation function with our production function of profits, we can calculate the optimal point for labour. When $\frac{\delta\Psi}{\delta l} = 0$ (the condition for profit maximisation – equation 3.33), no extra labour can be added to improve production so that $\alpha\text{pa}l^{\alpha-1}k^{\beta} = 0$. This leads to:

$$\alpha\text{pa}l^{\alpha-1}k^{\beta} - \text{Wl} - \Pi = \frac{\alpha y}{l} = \frac{W}{p} \qquad (3.36)$$

From equation 3.36, we can deduce that:

$$l^{\alpha-1} = \frac{W}{p}\alpha^{-1}\alpha^{-1}k^{-\beta} \qquad (3.37)$$

Multiplying equation 3.37 with $l^{-\alpha}$ is ridding us of $\alpha - 1$ so we can arrive at the labour function:

$$l^d = \left(\frac{W}{p}\right)^{-1} \alpha y \quad (3.38) \qquad \text{under the condition that} \qquad \frac{\delta l^d}{\delta(\frac{W}{p})} < 0$$

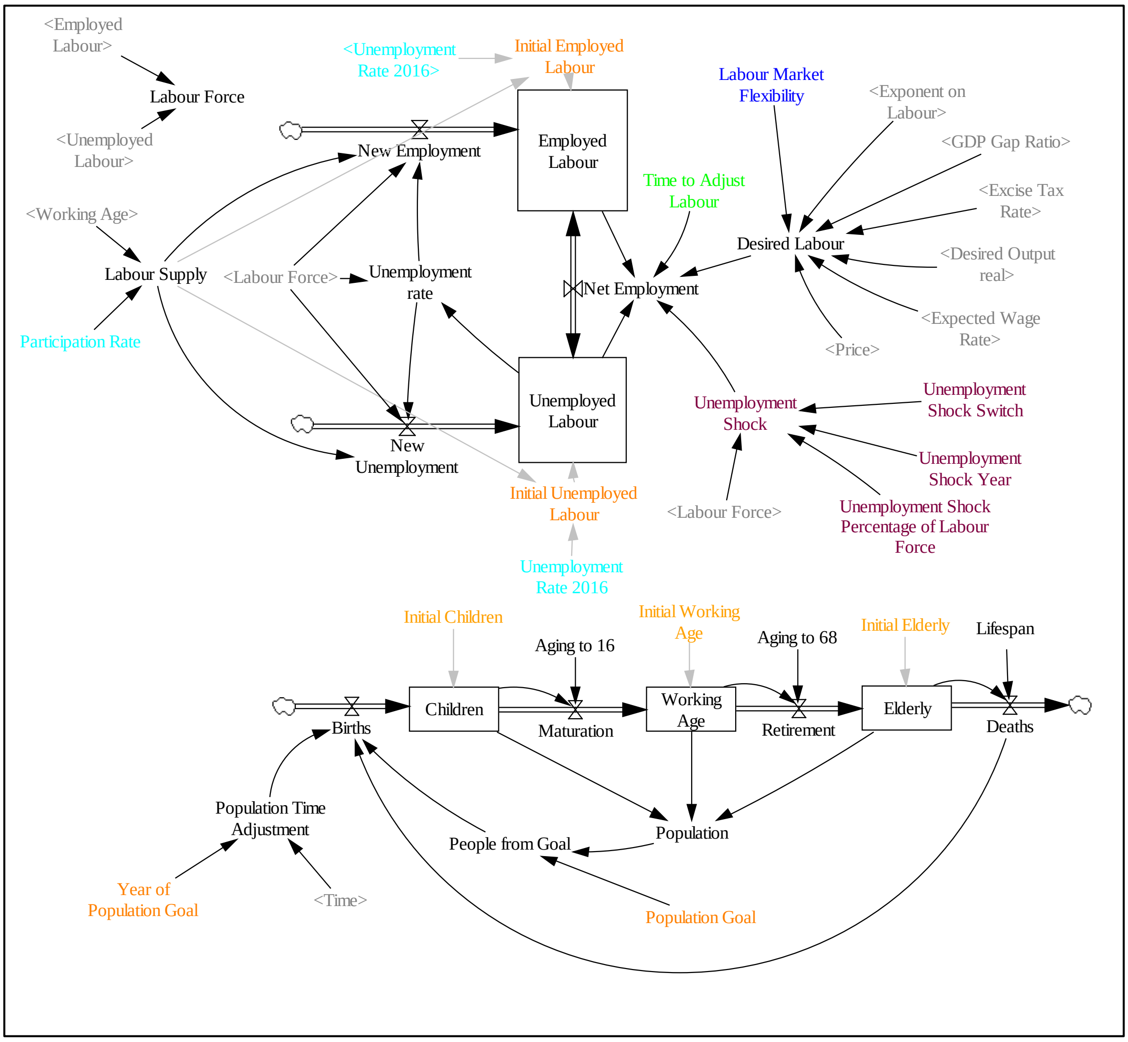
Equation 3.38 is the same formula in our variable "Desired Labour" (equation 3.24). We take $l^d$ and divide it by the expected wage. Thus, we end up with our new function which incorporates the condition standards for equation 3.38:

$$l^d = \frac{\left(\frac{W}{p}\right)^{-1} \alpha y}{\delta(\frac{W}{p})} \tag{3.39}$$

Yamaguchi (2013) made some adjustments to his model to account for effects like excise tax rate, as the Neoclassical formula does not adjust for taxes explicitly in its functions. Thus, demand and the productivity factor are lessened by the tax rate, so we get: "Exponent on Labour" * 1 - "Excise Tax Rate") * "Price" * "Desired Output real" to represent $\alpha y$. We have made a partial adjustment for price, but are not in a condition that produces maximum output such that $\frac{\delta l^d}{\delta(\frac{W}{p})} < 0$. Therefore, we adjust the function by lessening our desired output with the gap between the potential and realized GDP. We thus multiply our previous function with: 1 - "GDP Gap Ratio". So, when the gap between potential and realized GDP becomes 1 (no difference), the outcome of the function will be zero, adding no extra labour. Finally, Yamaguchi (2013) adds a labour market flexibility function that will increase of decrease the effect of the "GDP Gap Ratio". This is to represent economic theorem that states companies cannot freely hire or fire employees at any time – by for example the power of legislation and trade unions. Also, this flexibility can represent disequilibria in the labour market where production overshoots.

Finally, regarding policies, the model adds the option to shock the economy with a percentage of unemployment to study its effects. There is a year in which a total amount of the labour market can be made unemployed, on top of the already unemployed and unemployment rate. We could have built the model so that a percentage of the employed labour would get unemployed, but this would not have allowed us test when 'an x% of the labour force gets unemployed' – as percentages of employed labour and the total labour force would be different.

*Figure 18: Population & Labour Force*




### *3.3.6 Housing Market*

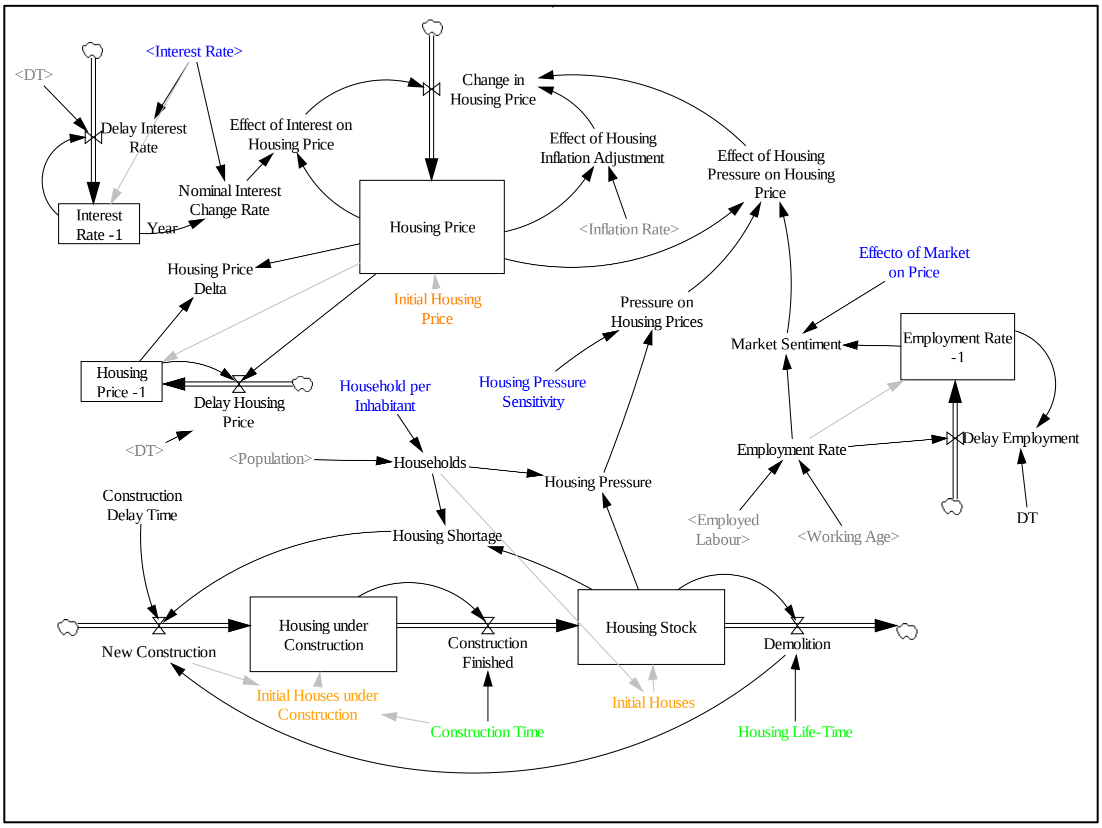
The module containing housing market is not build on economic theorem, but serves two purposes. First, it is the wish of the stakeholder to add a module to explain some dynamics in the housing market – only housing prices for now. The second purpose of this module is to demonstrate the ease in which modules can be added in a modular design of a System Dynamics project.

The following housing model is based on Eskinasi (2014) who has built multiple housing markets based on a four-quadrant model (4QM). In short, Eskinasi (2014) describes the relationships between housing property market, housing services, the construction market and stock adaption. This is where the name 4QM comes from. There are different ways of representing this structure and multiple System Dynamics representations have been build (Eskinasi, 2014). We pick the theoretical solution that has the most connection points with our other modules so far. The model we have chosen has connections with the labour market, population and interest rate. We further defined sensitivities and effects based on regressions and patternrecognition in our existing dataset – made from the simulations of the other modules. This module therefore is heavily susceptible to data fitting.

In short, this module works by tracking the available houses against the demand for houses. Demand is easily gathered by having a standard value for inhabitants per household, multiplied by the population. The building of houses follows a simple chain of steps: under construction and completed. Construction times and lifespans of households are copied from finding of Eskinasi (2014).

The price of houses is firstly adjusted for inflation. Secondly, interest rate dictates how expensive it is to borrow money to buy a house and thus indirectly governs the price of houses – as we assume houses are sold for a maximum price from the seller's perspective. Finally, the economy in general influences the housing market. When a lot of people lose their jobs, the attitude towards the economic state will decrease. Consumers are less likely to make large expenses in negative economic circumstances and thus the housing price will stagnate. The opposite is also true when we see economic revival. Reason for taking the employment rate as anchor to account for macroeconomic effects on the housing price, is that we are specifically looking for the market sentiment. It does not matter if the economy is actually growing or declining, the assumptions and beliefs of buyers and sellers is what makes the purchase or selling stagnate and grow.

*Figure 19: Housing Market*



# 3.4 Model validation

## 3.4.1 Reflection on model building

During the rest of this chapter, our main concern will be testing and validating the model shown in previous parts. This can be done with various tests, qualitative and quantitative. Before simulating and testing however, we will first reflect on what we have built so far. In this paragraph, we will try to validate our model. We should however note that truly 'validating' our model is impossible, as valid implies being correct. We can do nothing more than make representations of the real world and cannot make perfect simulations (Sterman, 2000). Knowing this, we will try the next best thing: have as many contact points with reality as possible. When talking about validation in this thesis, we thus refer to the effort of finding links between reality and our model.

To make our first steps toward validation, we will reflect on our model and critically question our assumptions. To help in the process, we will use a questionnaire to reflect on our System Dynamics model building (Sterman, 2000, pp. 852–853):

**Purpose, Suitability, and Boundary**

*Q - What is the purpose of the model?*

A - Our purpose is to reflect a relevant portion of the macroeconomy: those factors that can be used in a stress test scenario for financial institutions.

*Q - What is the boundary of the model? Are the issues important to the purpose treated endogenously? What important variables and issues are exogenous, or excluded? Are important variables excluded because there are no numerical data to quantify them?*

A - In our boundary lie macroeconomic theorems from Keynesian and Neoclassical economics. Furthermore, a representation of the housing market is also present. Important to the macroeconomy, but exogenously generated is the development of interest rates. Outside our boundary is the location and amount of transactions in the economy – we do not track each actor individually. Also, the model describes the domestic economy and international relations and trade are thus not in the model.

*Q- What is the time horizon relevant to the problem? Does the model include the factors that may change significantly over the time horizon as endogenous elements?*

A – The time horizon for our model will be from 2016 to 2035. This horizon is quite arbitrary, but fits our method later when we dive into RDM. Our time horizon for simulations when validating the model is from 1995 to 2013. This horizon is dependent on consistent datasets to allow for the construction of a historical reference.

**Physical and Decision-Making Structure**

Q - Does the model conform to basic physical laws such as conservation of matter? Are all equations dimensionally consistent without the use of fudge factors?

A – Our model conforms to macroeconomic theorems, to the extent that they can confirm in a System Dynamics framework. Sensitivities and effects are kept to a minimal, with the exclusion of our Housing Market module.

Q - Does the model represent disequilibrium dynamics or does it assume the system is in or near equilibrium all the time?

A – Economic theorem steers toward equilibrium, but the model assumes neither equilibrium nor disequilibrium. We set up the model with the most accurate values we can find from outside sources. Not all values can be directly observed (for example: "Initial Potential GDP"). Those values are based on estimates that let our model arrive at fitting values for the starting position.
Q - Are appropriate time delays, constraints, and possible bottlenecks taken into account?
A – Our usage of time is difficult to address. Time delays are a consequence of translating economic theory to System Dynamics. Furthermore, no actual data about delays can be discovered from reality. We have tried to solve this problem by making best estimates, based on economic processes we see. For example: the delay time to adjust inventory would be one or less, but not zero. We reason that adjusting inventory with production capital already in existence does not take more than a year. Also, this process cannot be instantaneous. A value higher than zero, but not higher than one fits that description.
Q - Are people assumed to act rationally and to optimize their performance? Does the model account for cognitive limitations, organizational realities, noneconomic motives, and political factors?
A – As our model tries to follow economic theorem, these questions should be redirected to our theory in use. However, we have built in different mechanisms that allow our model to represent different behaviour. Switching between those options would allow us to have both and reduce our model uncertainty.

**Robustness and Sensitivity to Alternative Assumptions**

*Q - Is the model robust in the face of extreme variations in input conditions or policies?*
A - Most of our exogenous parameters consist of sensitivities and effects, but none of them affect the model greatly. We have shifted all effects and sensitivities, but there is no clear set of variables that mostly govern the behaviour of the model. However, what is important to the behaviour of the model is the initial value of the variables that are not calculated endogenously. For example, when "Initial Potential GDP" is far above the desired output of the economy, we see a shrinkage in the economy as the economy is too efficient for its own good. This effect is paired with deflation and relative lessened consumption. When "Initial Potential GDP" is far below the desired output, we see heavy inflation and the desire to invest in the economy. Luckily, parameters such as these, although not fully observed, can be put inside a reasonable range. If we let the model run, we see there is a relation between the potential GDP and actual GDP. Tracing this relation backwards, we can estimate the parameter range. Furthermore, we also know from real life that it is not likely that with any state of unemployment, potential GDP lies much lower than the desired output. We would be able to observe this in developing nations, but it also does not fit with our model assumptions that the economy seeks equilibrium.
Q - *Are the policy recommendations sensitive to plausible variations in assumptions, including assumptions about parameters, aggregation, and model boundary?*
A – Our policies in the model mainly govern investment, consumption and government expenditure decisions. With a changing structure, the model finds a new equilibrium. For example, when the government spends more, this trickles down to a greater consumption and investment (as desired output increases and more capital and labour is needed). However,

within the reasonable limits of the model, policies do not drastically alter behaviour on their own.

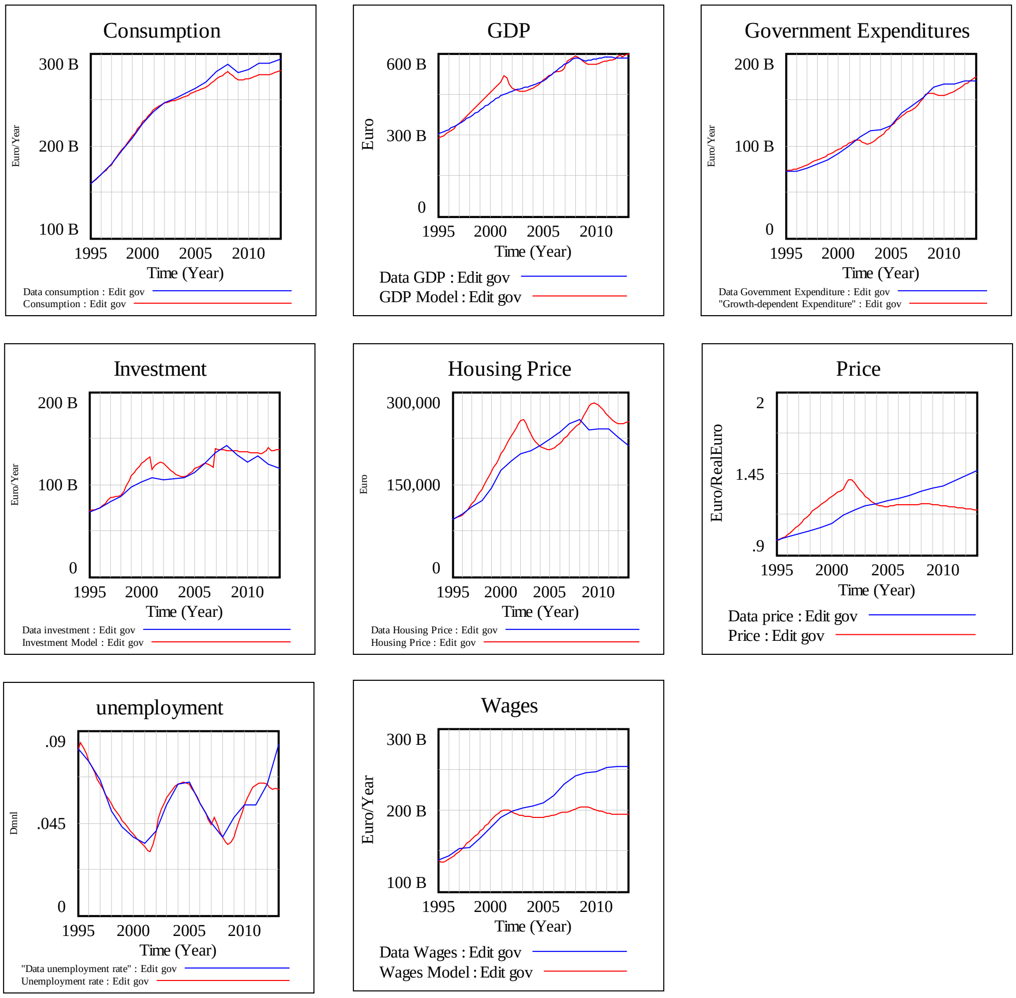
### 3.4.2 Simulating historical behaviour

After finishing the questionnaire, we have already shared some insight into the model. To test our model, a different version was created that includes historical datasets. Our goal to see if our model is accurate, is to simulate historical behaviour. We simulate historical data from 1995 to 2013. The full documentation of the model can be found in the appendix. There is a description of the initial values used and the datasets. The outcomes shown in Figure 20: Optimised Historical Simulation are consumption (consumers), investments (private sector), government expenditures, GDP, price, wages, unemployment rate and the housing prices. In all simulations, the blue line represents historical data while the red represents the model outcomes.

All reference modes (actual historical behaviour) are build up with data gathered from Statistics Netherlands (CBS), the statistical bureau of the Netherlands. Not all reference modes were directly available and had to be estimated. These reference modes are wages and price development. As they could be roughly estimated we decided to include them, but they are neither reliable nor does the model accurately simulate them. All the initial values that are not calculated internally are also gathered from Statistics Netherlands. In the appendix there is a list explaining economic variables, summarizing the data gathered and used from Statistics Netherlands.

We should keep in mind is that the model we have explained previously in this chapter is the model used for EMA. Because of translating a System Dynamics model to Python, we cannot use certain functions that are embedded within System Dynamics software. Therefore, delays are modelled as stocks and minimum- maximum functions are transformed to represent If, Then, Else functions. In the end, the only real difference between modelling with embedded System Dynamics functions and using the functions we used is aesthetic. Besides that, the model use for testing has preloaded historical data for simulation comparison.

*Figure 20: Optimised Historical Simulation*




These runs are produced with the help of the optimisation function in Vensim. More specifically, we use model calibration and let our model pick values for certain parameters to best fit a dataset. However, there are some dangers in using this function, as a model with unrealistic formulations could generate the correct behaviour by chance (Oliva, 2003). We can combat this problem by looking critical towards the optimizer definitions. In our case, we have specified realistic parameter spaces as explained before. Secondly, the parameters that are allowed to change during calibration process are mostly adjustment times. A few of the parameters are effects and sensitivities. On top of that, the sensitivities and effects that can change, are not overly sensitive to change. We used the list in Table 6: Optimisation Settings and Outcomes for calibration.

*Table 6: Optimisation Settings and Outcomes*

| Variable | Lower bound | Upper bound | Value from calibration |
|---|---|---|---|

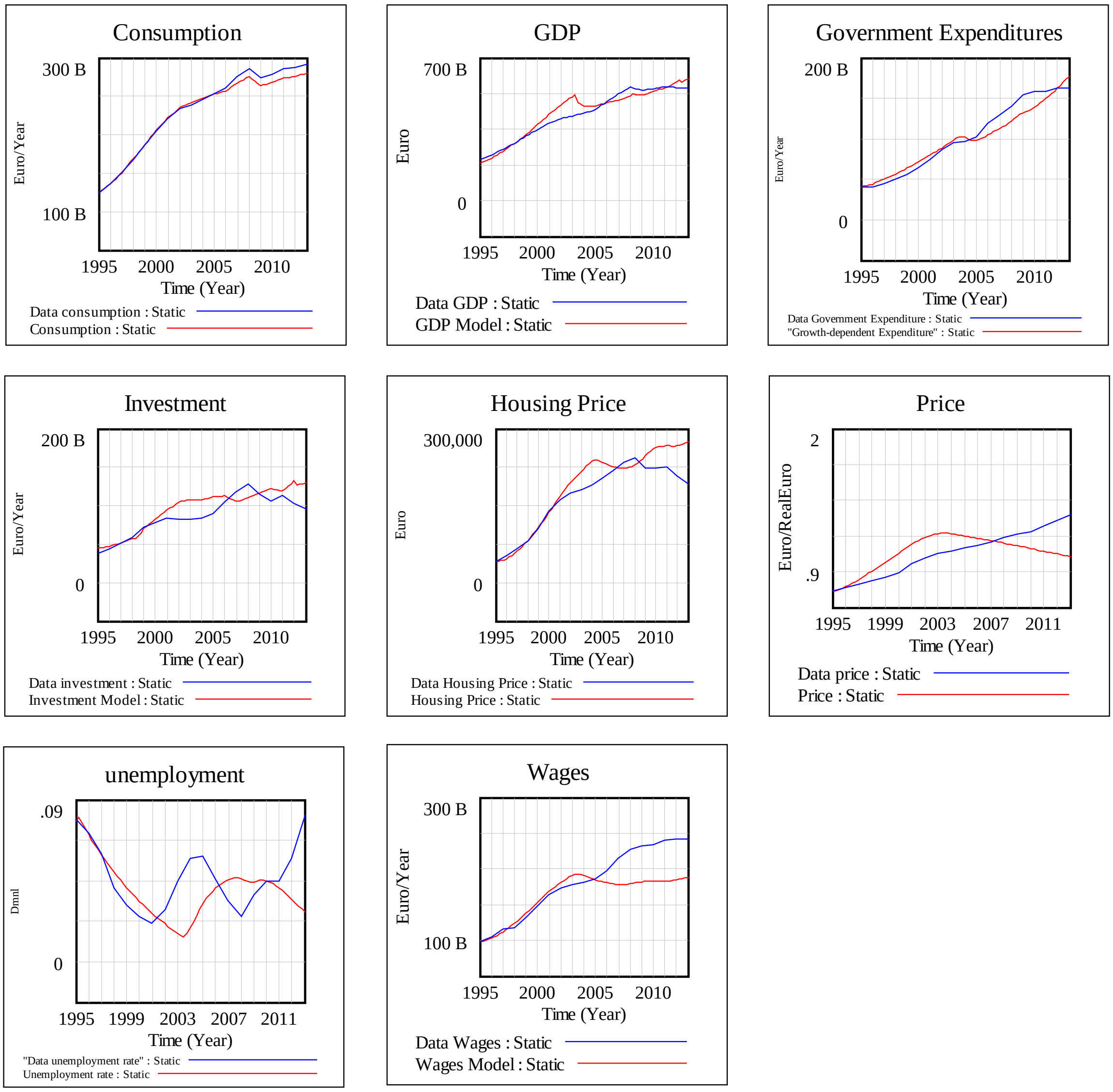
| | | | |
|---|---|---|---|
| Time to Adjust Labour | 1 | 8 | 5.96 – 4.81 – 3.88 |
| Labour Market Flexibility | .5 | 2 | .5 |
| Output Ratio Elasticity (Effect on Price) | .1 | 2 | .43 |
| Weight of Inventory Ratio | 0 | .5 | .26 |
| Delay Time of Price Change | 1 | 4 | 3.27 – 1 – 3.2 |
| Delay Time of Wage Change | 1 | 4 | 1 – 4 - 4 |
| Cost-push (Wage) Coefficient | 0 | .5 | 0 |
| Time to Adjust Inventory | .4 | 1 | .4 - .51 - .4 |
| Exponent on Capital | .35 | .5 | .37 |
| Exponent on Labour | .35 | .5 | .5 - .5 - .43 |
| Construction Period | 1 | 4 | 1.79 – 1.08 - 1 |
| Time to Adjust Forecasting (Long-run) | 3 | 8 | 8 – 4.79 - 8 |
| Time to Adjust Forecasting | .3 | 2 | .3 - 1.48 - .3 |
| Time to Adjust Capital | 2 | 6 | 6 |
| Depreciation Rate | .07 | .2 | .10 |
| Normal Inventory Coverage | .1 | .35 | .249 |
| Technological Change | 0 | .05 | .027 |
| Policy Spending | -.01 | .02 | .2 -.2 - 0 |
| Interest Sensitivity | .5 | 1.5 | .5 |
| Labour Ratio Elasticity | .5 | 1.5 | .5 |

We can see the upper and lower bound that we have given the model to work with. Within the column 'Value from calibration' we can read the value the model has picked. Be aware that some variables have 3 values that the model chose. This is because we allowed the model to change values at three points during the simulation. We did this for two reasons. First, it is very reasonable to assume that the system of the economy can change over time. Significant events or new insights might make it so that we make longer projections, change our inventory coverage or other. Allowing the model to self-adjust to new circumstances is a fair way to treat the economic theory. This adjustment process is not always justified however, which simulations is the second reason the model can adjust itself. We can for example generate a nonsensical sequence. An example would be the following sequence for the exponent on labour: .35 - .5 - .35. In this sequence, we see that the maximum is used in the beginning of calibration, the minimum value is picked afterwards and finally the highest value is used again. Although it would be reasonable to assume the exponent on labour can change, it is unrealistic for it to change to its maximum, minimum and back in the timespan of 18 years. Luckily, most values do not change – even though they can.

The numbers we do see change significantly is those of "Time to Adjust Labour". This sequence goes from 5.96 to 3.88. This change happens gradually however and in order. It is not unreasonable to assume this trend. The trends that are problematic are those of "Time to Adjust Forecasting (Long-run)", "Time to Adjust Forecasting" and "Delay Time of Price Change". The values used in calibration show shifting behaviour in a non-linear path. The reason for this change however becomes clear when we run the model without the option of changing. Doing this, we can see that our outcomes for unemployment have worsened while other outcomes have remained the same or even improved. Our assumption is that the model cannot keep up with changes in the labour market during the economic crisis, as it tries to find the best fit with the whole dataset. In our data, we have a huge spike of unemployment from 2008 and forward. This behaviour is arguably extraordinary as it is caused by the economic crisis. It is therefore not strange to assume that during extraordinary times, the aforementioned factors cannot shift drastically. The adjustment times are rattled as consumers and producers update their view on the current economy. The adjustment of price is fastened to account for the revaluation taken place in the economy.

In Figure 21: Simulation with Fixed Variables, there is no adjustment process of the previous values mentioned during the calibration process. As said before, unemployment is behaving worse, while the other model variables stay more or less the same. We even see an improvement in price, wages and investments. On top of supporting our previous assumption that the model cannot adjust itself fast enough during economic crisis, we can also say we are missing certain dynamics regarding the labour market. This is not entirely strange as both Keynesian and Neoclassical economics have many exogenous variables that we have made endogenous. Secondly, there are no external shocks given to the model to simulate a sudden change of behaviour – or change in the system. This is something we should however anticipate as we try to follow a RDM design.

*Figure 21: Simulation with Fixed Variables*




Finally, we can simulate much historical behaviour more accurately if do not try to optimize the unemployment rate. These results can be seen in Figure 22: Partial Optimisation Simulation. Reason this simulation performs partially better is because our model assumes the labour market should optimize itself, but historical data shows there is always a constant unemployment rate. Since the goods-market is driven by demand, production is also a function of labour and labour affects price, employment will try to reach zero:

$$Y = f(K, L, A) = AL^{\beta}K^{a} \tag{3.22}$$

$$y_{potential} = f(K, LF, A) \tag{3.23}$$

$$l^* = \frac{(1-y/y_{potential})*(\beta*(1-\mathrm{R})*p*y^d)}{w'} \quad (3.24)$$

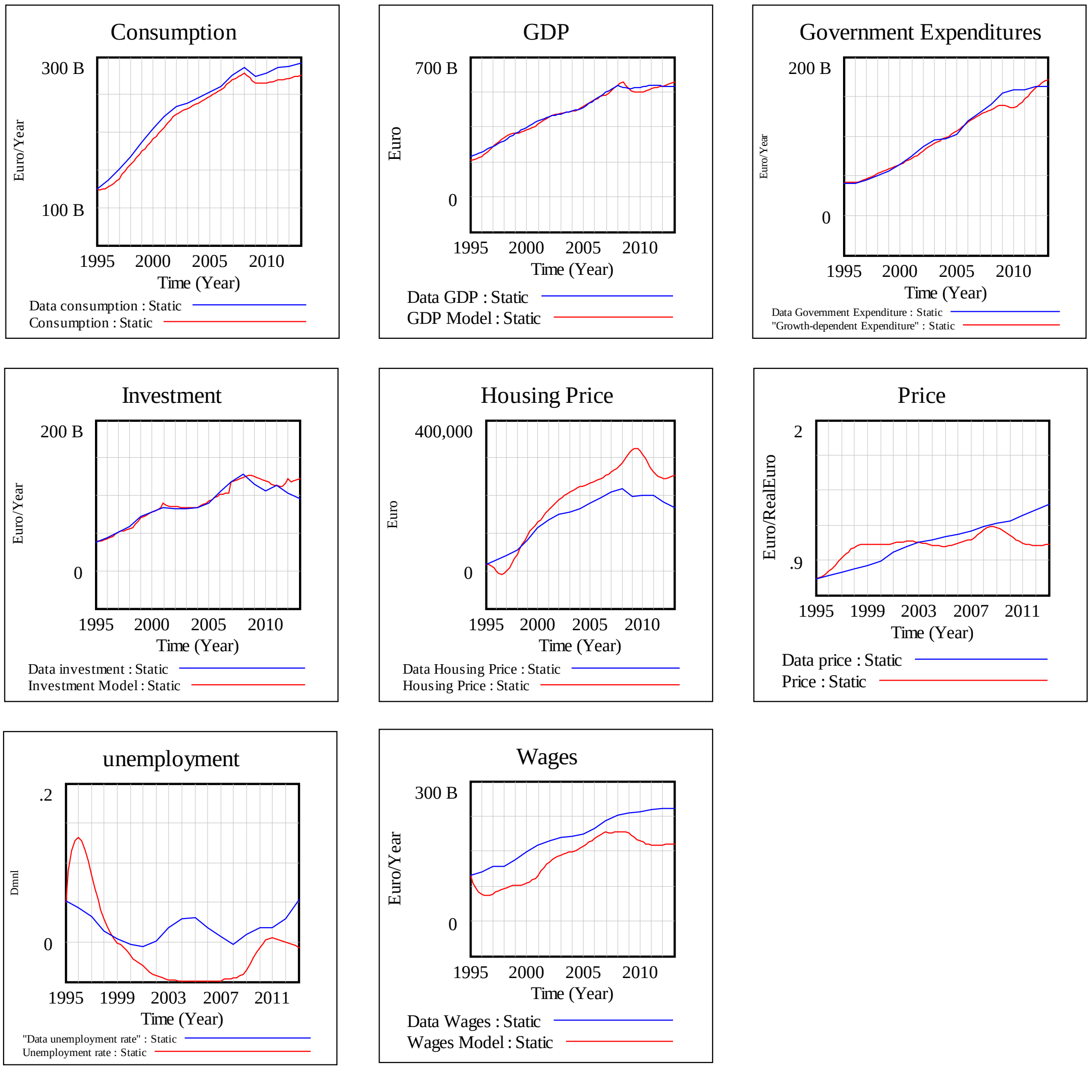
$$p^* = \frac{p}{\left((1-w)\frac{y_{potential}}{y^d}+w\frac{Inv}{Inv^*}\right)^e} + \psi * \delta W \quad (3.31)$$

To understand why unemployment rate is difficult to simulate accurately with Keynesian and Neoclassical macroeconomics, we can also think about it like the following: the economy as stated here will try to reach full potential. Full potential means that everybody is working and producing in the economy. Price and wages will influence each other until unemployment reaches zero – this is the point where most can be produced and consumed. This also is why, without outside fluctuating factors, the economy aims for total employment.

Theoretically, this can be solved by having a standard unemployment rate or a sticky labour mechanism (Naastepad, 2002). Having for example a ceiling of unemployment would be a solution, by not allowing the model to be in equilibrium[13]. Although this would solve our unemployment rate behaviour, it would fall in the domain of data fitting as there is not solid theoretical foundation to build this structure on (Oliva, 2003). Therefore, we have decided not to go down this road. Also, keep in mind that in all simulations, the housing price is not optimized in Figure 22: Partial Optimisation Simulation.

[13] The model not being able to achieve equilibrium is not a problem in itself. It is unlikely that in real life this ever happens.

*Figure 22: Partial Optimisation Simulation*




## 3.4.3 Structure assessment & behaviour reproduction

Another method to validate System Dynamics models is to perform a structural assessment (Sterman, 2000). In short, we ask the question if the model is structural consistent with relevant descriptive knowledge of the system. We can answer this question by directly inspecting the equations and causality in the model. In our case, we have set up to build a theoretical presentation of the macroeconomy using various economic theorems. For economic theorem to be accurately represented, it is key that we translated economic theory correctly. To test this, we can simply give input to the model, and see if the behaviour shown is consistent with theoretical expectations. Also, it is important that our stakeholder believes in the behaviour the model produces, if we want to have any chance to making model based decisions. To test both, we can test assumptions of the stakeholder and see what the model does with those assumptions. We do this by looking at behaviour in a base run and change one variable to see what the difference is. For example, when the interest rate is turned negative, we expect the housing price and investments to rise. This approach allows us to reproduce expected behaviour and have a structural assessment at the same time.

Our first test will be what happens when interest rates turn negative. We will run a basic simulation with positive 3.5% interest and second simulation with negative 3.5% interest and compare the results. The remainder of the variables do not change. We expect both investments and the housing price to rise. For investments; lending has become cheaper and it is easier to attract capital and thus make investments. For the housing price; with lower interest rates, it is relatively cheaper to get a loan. Sellers will know this and adjust their housing prices accordingly. The output of this test is the following, with the red line as our base case and the blue line with negative interest rate:

*Figure 24: Investment Behaviour*

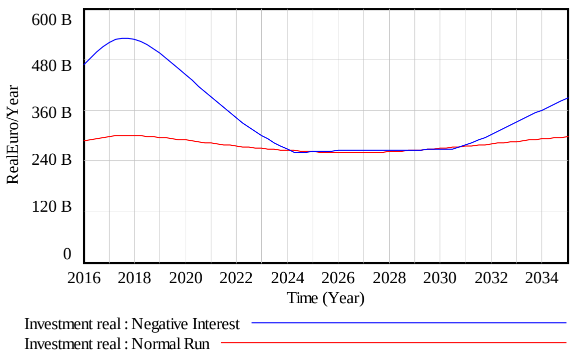
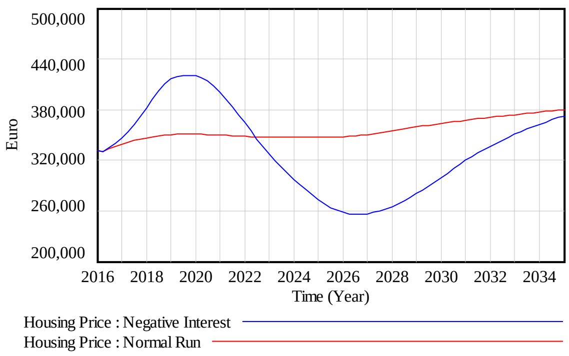
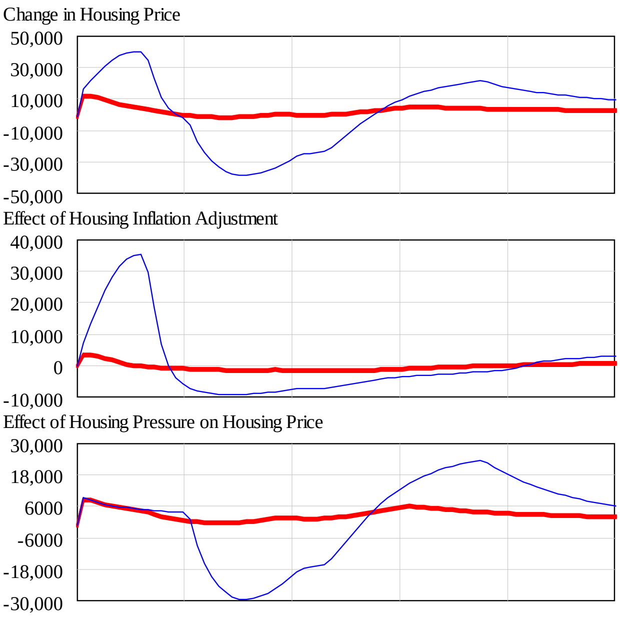



*Figure 23: Housing Price Behaviour*




As we can see, both investments and the housing price rise as we expected. Do note that our investments are represented as a flow and the housing price as a stock. This means that the amount of capital is far higher than the difference between the red and blue line at some points. For the housing price however, we see that the housing price while initially increasing, is lowered than expected later. Let’s explore why that is.

*Figure 25: Housing Price Behaviour*




In Figure 25: Housing Price Behaviour, we see all the effects on the housing price in one graph. Again, the red line represents the base case while the blue line represents the negative interest scenario. In the upmost graph, we can see the net change of the housing price. In the middle graph, we can see that the housing price rose initially by the rising inflation effect. This inflation happened due to the low interest rates. However, due to this large peak in demand, production of houses was put into overdrive. In the lowest graph, we can see the pressure on the housing market was relieved by a large number of houses available.

The story about the housing market is consistent with what the stakeholders would expect – although the oscillating behaviour due to extra houses being build was not immediately obvious. In our economic theorem, there is no way to confirm our housing market simulation, but the investment behaviour checks out. If we go back to our desired capital formula, we see that with a lower interest rate, we expect more capital being bought:

$$k^*(r) = \frac{\alpha(1-t)-y^*}{r+\delta k} \tag{3.30}$$

With a lower interest rate $r$, and everything else being equal, it is easy to see that we arrive at a larger outcome if we divide the sum by a smaller number. This story then checks out in theory and practice. Also, our model has no problems with simulating negative rates – something we have not yet mentioned.

We have done the test as described above with a multitude of factors, but chose interest rate to demonstrate the example. We chose interest rates, because it is the only main economic variable not created endogenously and we could demonstrate negative rates. Using this method, we were able to test the consistency of increasing/decreasing consumption, governmental expenditure, technological change, wage and unemployment. Although it must be said that our model tries to find full employment and maximum economic output. Also, we were unable to test the model outcome “Price”. Theoretically, the structure should replicate the mark-up effect and the development of wages. If not that, inflation (price development) could be considered a policy by the European Central Bank as they strive to grow the consumer index according to their vision (Naastepad, 2002). Finally, price development can be interpreted as pressures between money supply and money demand. In the end, it is difficult to prove or justify any narrative as many actors view inflation as a natural consequence, but do not ponder questions about causality.

### 3.4.4 Behaviour reproduction test

So far, we have looked at the reasoning behind the model, its historical reproduction and structure. All these tests are qualitative tests that are dependent entirely on interpretation. Our next test will be a more quantitative measure: the Theil inequality statistics test. The Theil inequality statistics measures bias, unequal variation and unequal covariation, based on the mean squared error (MSE). Bias (Um) arises when the model output and data have different means. Unequal variation (Us) indicates that the variances of the two series differ. Unequal covariation (Uc) is a behavioural phase shift or unexplained variability (Sterman, 2000). For the calculation of each of these three variables, we divide them by the mean square error so that Um+Us+Uc=1. So, what does this all mean? In short, Um, Us and Uc tell us what percentage of the MSE is due to bias, unequal variation and unequal covariation. For example, a bias of .50 means that 50% of the MSE is due to differences in means.

The bias $Um$ (unequal mean) is the square of the difference between the model mean $Xm$ and the historical data mean $Xd$, divided by the MSE (Morecroft, 2007):

$$Um = (Xm - Xd)^2/MSE$$

$Um$ will be the blue line in all the following figures.

The unequal variation $Us$ (stretch/shrinkage) is the square of the difference between the standard deviation of the model $Sm$ and the standard deviation of the data $Sd$, divided by the MSE (Morecroft, 2007):

$$Us = (Sm - Sd)^2/MSE$$

$Us$ will be the red line in all the following figures.

The unequal covariation $Uc$ is the product of the standard deviation of the model $Sm$ and data $Sd$, multiplied by twice the correlation coefficient $(1 - r)$, divided by the MSE (Morecroft, 2007):

$$Uc = (Sm * Sd) * 2(1 - r)/MSE$$

$Uc$ will be the green line in all the following figures.

The calculations of these three factors are per point in time. For our overall overview, we will show a development of Um, Us and Uc over time and assess the score based on the average value. That way, we can say something about the dataset overall.

In this paragraph, we will show the development of the bias, unequal variation and unequal covariation, together with the rooted mean squared error (RMSE) and mean absolute percentage error (MAPE). We will show the average Us, Um and Uc, while the RMSE and MAPE are a summation in the development. We use the RMSE to help with interpretation of our Theil inequality index. The MAPE is the average difference between sets of continuous variables, expressed as percentages. This tells us how much our predictions are on course with the historical set. This adds value besides only using RSME, since the RSME does not give information about relative error.

We now have a statistic that expresses the amount of error, and a statistic that can tell us the nature of deviation, so let's apply those on the objectives that we have previously tried to optimize: consumption, GDP, governmental expenditures, investments and unemployment.

### *3.4.4.1 Consumption*

*Figure 26: Theil Statistics Consumption*

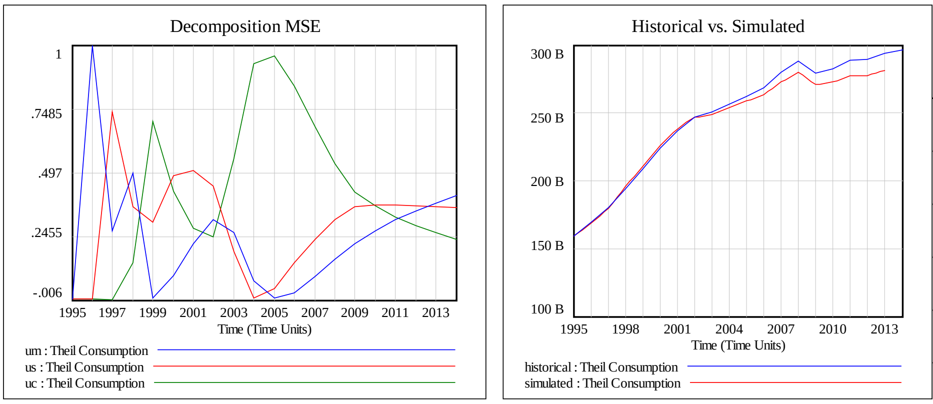



***Table 7: Theil Statistics Consumption***

| | |
|---|---|
| **RMSE** | 6.471B |
| **MAPE** | .01787 |
| **Uc** | .4401 |
| **Um** | .2496 |
| **Us** | .3103 |

As we can see in Figure 26: Theil Statistics Consumption and Table 7: Theil Statistics Consumption, the RMSE is very high in absolute terms, but not so much in relative terms. When the RMSE is lower, we have a better fit. What can be considered low or high depends on the dependent variable. In this case, our consumption function goes to somewhere around 300 billion. Compared to the overall values, a RMSE of 6 billion is thus not a large number. We can also be happy with a percentage error of 1.787%, which is very low – we should multiply the MAPE score with 100 to give a percentage error. As we can see, historical and simulated behaviour are very close. Now, we can prove this statistically.

There is also bad news: we have a rather high Um and Us. This unfortunate, as the optimal distribution of Theil inequality statistics is: Um=0, Us=0, Uc=1. This distribution would indicate that there is an overall bias due to some parameter setting. A high Us indicates systematic error and a high Uc would mean the model is possibly driven by historical data. In our case, we can also see evidence of a high Um when looking at historical data: the trend is the same, but our simulated behaviour stays precisely below the historical behaviour. There also appears to be some phase shifting, since our Theil inequality index indicates that around 31% of our RMSE is in Us.

In the end, we should still be quite happy with the results, Uc is still the largest from the three. Even though our Theil inequality index is far from perfect, our RMSE and MAPE are very small. When an error is small, the cause for that error becomes less relevant.

### *3.4.4.2 GDP*

*Figure 27: Theil Statistics GDP*

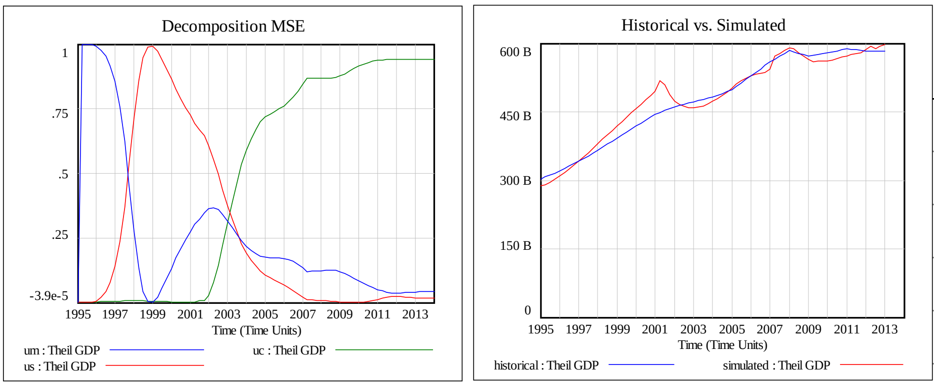



***Table 8: Theil Statistics GDP***

| | |
|---|---|
| **RMSE** | 20.39B |
| **MAPE** | .03368 |
| **Uc** | .5127 |
| **Um** | .2712 |
| **Us** | .2717 |

Figure 27: Theil Statistics GDP and Table 8: Theil Statistics GDP show the results for statistical screening for GDP. Relative to 600 billion, our RMSE is low and so is our MAPE. Secondly, the Theil inequality index tells us that more than half RMSE stems from variation as we have a Uc of 51%. Um and Us are divided almost perfectly. We can see signs of bias in our starting value. This is reflected in the decomposition of the MSE and can also be seen in the historical versus simulated behaviour. Around the ear 2000, there is a strange amplitude in our reference mode, reflected by a high Us. We can conclude that by the decomposition of the MSE, that our model has issues with initializing. As there are many uncertain values and a lot of values to optimize, it takes time for dynamic behaviour to take hold.

### *3.4.4.3 Government expenditures*

*Figure 28: Theil Statistics Government Expenditure*

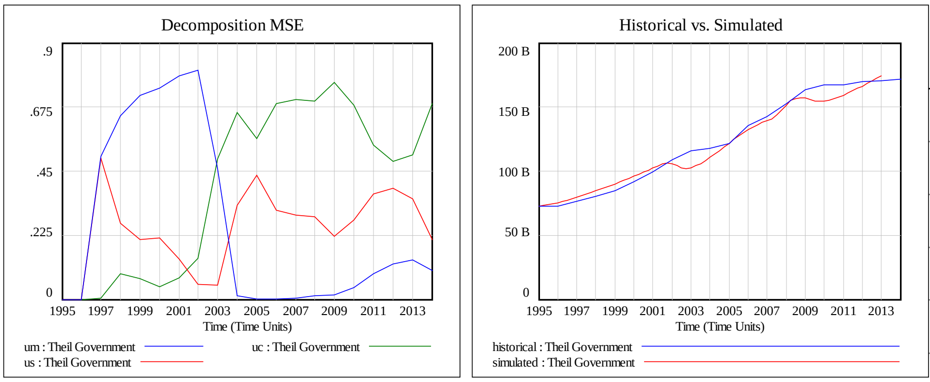



***Table 9: Theil Statistics Government Expenditure***

| | |
|---|---|
| **RMSE** | 5.818B |
| **MAPE** | .03856 |
| **Uc** | .4001 |
| **Um** | .2828 |
| **Us** | .2616 |

The scores on government expenditures are worse than GDP or consumption. Our RMSE is relatively larger, but luckily, we still have a smaller Uc compared to Um and Us. It appears that initialisation of the model affects the scores in a negative way. This is a trend we have seen in previous scores and is something we will continue experiencing. The end-score of Uc is .675, but in the overall run it was around .4. If we thus look at the overall run, we can't be very satisfied with the origin of error. If we look at the MAPE however, on average, the forecast is off by 3.856%. This is a very low score, though we should remember it is based on only our sample.

### *3.4.4.4 Investments*

*Figure 29: Theil Statistics Investments*

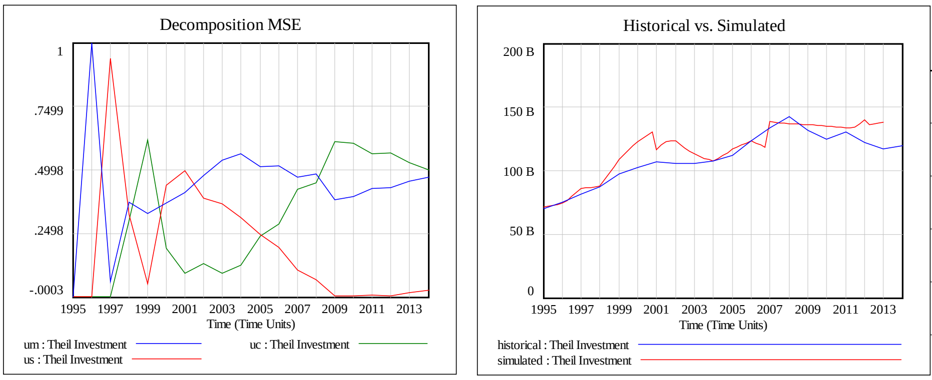



***Table 10: Theil Statistics Investments***

| | |
|---|---|
| **RMSE** | 10.3B |
| **MAPE** | .07 |
| **Uc** | .3239 |
| **Um** | .4552 |
| **Us** | .2209 |

Our investment historical behaviour versus simulated looks the worst from all the optimized simulations. This observation is confirmed in the actual scores of the Theil inequality statistic. Investments are first driven by historical behaviour, then is initialised with an incorrect amplitude and later is driven by historical behaviour again – according to our statistical outcomes. These scores are on average and investments suffer more for initialisation than our previous variables. The outcomes of the statistics, together with our reference behaviour, give us reason to believe that our investment function is incomplete. It appears our model cannot capture behaviour observed in the real world. If we want to make statements about investments based on this model, we should reconsider altering the model structure until we get a better fit. However, as this is a theoretical model and does seem to capture theoretical behaviour, such changes would likely include policy or behaviour typically/only observed in the Dutch economic system. It would therefore depart from being a theoretical model.

### *3.4.4.5 Unemployment rate*

*Figure 30: Theil Statistics Unemployment*

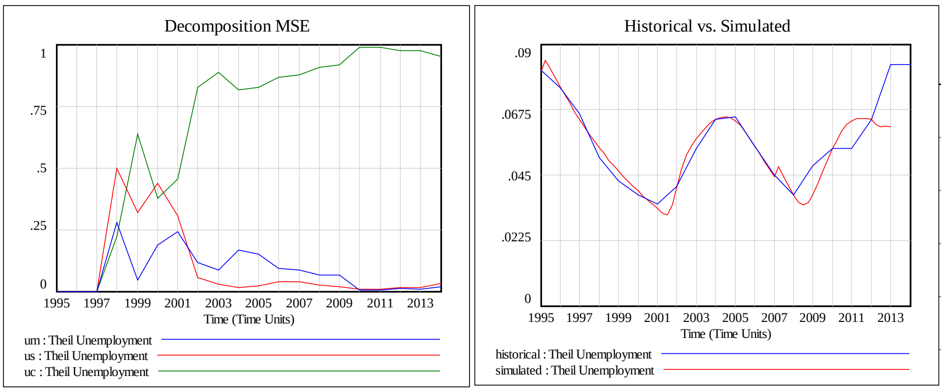



***Table 11: Theil Statistics Unemployment***

| | |
|---|---|
| **RMSE** | .00604 |
| **MAPE** | .05336 |
| **Uc** | .6963 |
| **Um** | .08967 |
| **Us** | .1029 |

Our statistical tests show very promising behaviour. As opposed to our previous errors, unemployment rate does not suffer from a lot of initialisation errors. In the beginning, unemployment rate is not particularly driven by data and has a goof fit. Besides that, the development of the MSE shows that most variation is caused by unequal covariance. We should take care in interpreting our RMSE, as here, a low number is a different number from before. We should interpret the RMSE of .006 on a scale of scores between .09 and .03 – the ranges of unemployment rate. In this perspective, we can still say that .006 is a small number compared to .03. Our MAPE tells us that on average, we are 5.336% off from historical behaviour, which is very acceptable.

### 3.4.5 Uncertainty

We also want to spend some time going back to uncertainty and where it resides in our model. Thinking back of chapter two, we introduced an uncertainty framework. Knowing how our model looks like, we will now try to fill in this framework for the whole model. Afterwards, we want to make certain nuances and explain how we got to that position.

*Table 12: Complete Integrated Uncertainty Framework*

| | | Level 1 to 4 | Nature | | |
|---|---|---|---|---|---|
| Location | | Level | Ambiguity | Epistemology | Ontology |
| System boundary | | 2 | X | | |
| Conceptual model | | 3 | X | | X |
| Computer model: | structure | 3 | | X | |
| | Parameters in model | 3 | | X | |
| | Input parameters | 3 | | X | |
| Input data | | 2 | | X | |
| Model implementation | | 2 | | X | |
| Processed output data | | | X | | |

As we know, epistemic uncertainty stems from unexpected developments – gaps in our knowledge. Ontic uncertainty is a natural variability of uncertainty: we know for example when a 6-headed dice is rolled 1000 times what the normal distribution would look like, but we can't predict individual throws. The level of uncertainty represents a framework of how well we can make judgements and how we should proceed with modelling.

As shown in Table 12: Complete Integrated Uncertainty Framework, our system boundary has a level 2 uncertainty with an ambiguous nature. We want to know what will or should not be researched, but this proves to be a difficult task. From a stakeholder perspective, there exists no macroeconomic framework or model. This means that we as researchers have translated and made decisions about what macroeconomic outlook to follow. We have gotten aid in the form that we knew what the outcomes of interest were, but everything in between was up for interpretation. Yet, we chose to go for one boundary of the problem.

Our conceptual model is the macroeconomy through Keynesian and Neoclassical lenses. Even though we have economic theorem to guide us, there is ambiguity about what theory to pick. Uncertainty arises from the macroeconomic theorems, which tell us that only certain outcomes and developments are possible, but not all relations are clear. We therefore have alternative futures, but most within boundaries. Our conceptual model is ambiguous, as we don't know for certain how to interpret the economy – we have to choose. This choice can be considered ontological: no matter how much more research we do, we may never know what a correct interpretation of the macroeconomy is.  Also within our models, there is no clear direction given, only a certain range. We therefore tread in level 3 uncertainty.

Regarding the computer model in general, there is insufficient data and methods to see if there is a truly valid model. Especially in the macroeconomy, there are many factors and effects influencing a multitude of outcomes. Furthermore, there may be systematic errors arising from the translation process of economic theorem. Also, we have multiple structures to explain differing policy behaviours and thus have level 3 uncertainty. It is important to not also that not all modules are created equal. There are more- and less complicated structures. Finally, the housing market module was added last as an extra component. It was not created by a rigorous macroeconomic theorem translation process.

We tried to reduce the input data uncertainty by using one source only when testing the model. This increases the chance that the model displays the correct behaviour, even when there is a systematic error in the dataset. This is possible, because even though we only used data from the statistical bureau of the Netherlands, their own databases also contain inconsistencies. Depending on the years of data retrieved from their site, calculation methods and definitions change. As it is not clear due to the unavailability of knowing if we used the correct data, we treat this is epistemic.

Our model has had many bugs, errors and wrong formulations during the building process. We have around 45 versions up to final validation and 20 models more before we could do EMA simulations. Sometimes, polarities were switched and other times a bracket was forgotten. Unfortunately, we cannot say with certainty that we have removed all errors. We did everything we could and have performed (and now passed) various validating techniques, but the possibility remains. This is epistemic uncertainty, as even more research would allow us to eventually find 100% of the possible errors in the model.

Finally, the question if the model outcomes are being communicated to the stakeholder correctly is ambiguous. It will largely depend on our skill to visualize and present the outcomes. This is what we will try to do in our custom Robust Decision Making approach. With statistical analysis and visualisation, we will try to convey the correct message to those involved.

### 3.4.6 Model limitations

The System Dynamics model used for this research does not follow a follow a traditional System Dynamics pathway. Normally in System Dynamics, scientist build a model from a problem based view (Sterman, 2000). This means that structure will be added to a model when it helps to better view, understand and/or simulate the problem behaviour. For example; when modelling cars entering a city, variables will be added to the model until the model can reliably represent reference behaviour of real cars entering a city. In our case, we did not follow such an approach. Although we did have a clear System Dynamics modelling challenge, – modelling Dutch Macroeconomic behaviour – we set out to translate macroeconomic theorem. We tried to model a system, not a problem and we did not add structure to a model until it had a fit with reality. This approach was taken for two reasons. First, it would be unfeasible to try to come up with a new System Dynamics or macroeconomic definition of (Dutch) macroeconomics. There are plenty System Dynamics descriptions and macroeconomic formulas already in existence, ready to be translated into a model for us to use. Building something from scratch would therefore be a less efficient method. Secondly, the lack of a macroeconomic background of the author does not forebode the constitution of a rigorous macroeconomic model. Also, when the focus of the thesis is partially the creation and analysis of large datasets, time should be spent wisely. Thus, to best use existing literature and to save time we translate macroeconomic theorem rather than coming up with new, novel ideas. This does not mean that we do not have to make our own adjustments to existing models. We must account for the Dutch economy, experimental setups and stakeholder preferences. The usage of existing models and theorems is for the building of a first, basic model.

The consequence of using macroeconomic theorem first and afterwards adjust, is that we have built a theoretical model of the Dutch macroeconomy, and not a necessarily a model of the Dutch macroeconomy. The distinction is that our model represents theoretical behaviour and is built with the assumption that macroeconomic theory is good enough to make accurate predictions of actual behaviour when applied to reality. If we were to build a macroeconomic model of the Dutch economy in a traditional way, we would have small iterations of models that would improve our reference behaviour. Macroeconomic theorem does not necessarily have to play a leading role in this approach. We could just as well observe quantitative shocks in the economy and link this to newspaper articles. In the approach of this thesis however, we have first build a large base-model of theory and later adjusted it to fit the Netherlands. We are concerned if (for example) our model fits with a Keynesian description of the economy. These two approaches do not have to lead to different results, but can due to the focus of model-building. In our case, we do not want to deviate from economic theorem, which could be a limiting factor when building a model that describes the Dutch economy as accurate as possible.

A place where we potentially have seen the divergence between a theoretical model and a macroeconomic model is in the outcomes of our Theil inequality statistics. In some runs, but especially investments, we did not change the model structure to better fit the historical behaviour. We have chosen to strictly follow macroeconomic theorem. This may seem stubborn, as we have seen the historical behaviour and model behaviour of investments have a bad fit. However, if we would opt for changing the model, we open a new pathway for uncertainty and validity problems: how should we change the model and according to who? As the world of macroeconomic theorem can be very fickle, the realm of human opinions is even more volatile. If we would want to change the investment function to have a better fit, we have to 1) open a new can of macroeconomic theorem aside from Neoclassical or Keynesian or 2) have economists make specific adjustments, not knowing if their solutions are well-proven or provide a good fit with our theoretical framework. Neither of these options seem very appealing, though we did talk to macroeconomist. The message we have gotten repeatedly is that no one should rely on a model, but merely use it as support – which is congruent with our approach. Yet a third option to change the investment function would be to adopt a whole new theoretical framework. An option would be the Smets and Wouters DSGE model the ECB uses (Smets & Wouters, 2007). In the end, adopting this new framework would come with its own limitations as this model has a heavy emphasis on the supply side – as one of the limitations.

Besides limitations due to the methodology, there are more things to consider. For example, we cannot say with certainty that we have removed all errors. We have performed various validating techniques, but the possibility of errors still remains. There can be mistakes in formulating the theorem or in the model itself. Both are epistemic uncertainty, as even more research would allow us to eventually find 100% of the possible errors in the model – although the trade-off of costs for 100% certainty might not be worth it. Something we can rely on for now are the Theil inequality statistics tests. In general, the tests showed the model has problems with initiation, but improves over time as dynamics start to play a dominant role. We hope to solve this problem when sampling many different starting points for the model. Setting up our experiments in a Robust Decision Making framework should shield us to such variations, theoretically.

# 4 – Analysis

## 4.1 Exploratory Modelling & Analysis

During our validation tests, we have said that true validation is not possible. Besides that, some of the validation tests do not show the entire picture. For example, when looking at the sensitivity of the variables in the model, we said not policy or parameter drastically alters model behaviour. But what about everything shifting all at once? This is possible within the spectrum of uncertainty and we should prepare for such an event. To test these possibilities, we move to Exploratory Modelling & Analysis. The analysis will be within a Python – we use Jupyter Notebook. Jupyter Notebook is the program in which we build model using Python computer language. The original and working workbook is made available in a digital file with the thesis and the output can also be found in the appendix. Jupyter Notebook is a free program that comes with Anaconda Navigator[14]. If the reader is interested in replicating the experiments, we recommend using the 32-bit version to ensure all libraries work. Further explanation about what libraries to use and documentation can be found within the Notebook. The notebook is also made available freely available with this thesis, so simulations can be made by the reader as well.

During the analysis, we will use the model as shown and explained throughout the thesis so far. There is one minor difference: for Python to read the code smoothly, we build some extra variables that can be easily read in and changed some names. This has not consequence for the reader or the names of the variables we will look at in this thesis. Nor was any code, formula or relation added or changed. This model can be found in the appendix. Also found in the appendix are the initial values the sources. We have tried to use only one source, the Dutch bureau for statistics, but not all needed information could be gathered there and therefore other sources had to be used. This search for information and question on how to quantify all variables is what is difficult in any System Dynamics research. For example, wage rate is a value that some sources describe as being 29000 (with tax correction) and others as 24000. Finding the correct value is especially made difficult if we consider that our model does not calculate taxes. To minimize inaccurate predictions or coming up with faulty values, we have the option to simulate the entire range between values. This is what we will do during the analysis.

Before we move on to Python, it is interesting to note again why we use Explorative Modelling & Analysis. As we have stated before, we have built a theoretical model of the economy, so what could such an assignment possibly tell us? First, in accordance with our stakeholder, we will mainly focus on relationships to create scenarios for the stress test. This means we will test for example what possible ranges of developments in unemployment are with both increasing housing prices and GDP growth. Secondly, by testing a range and possible development, we do not fool ourselves by claiming we can predict the future.

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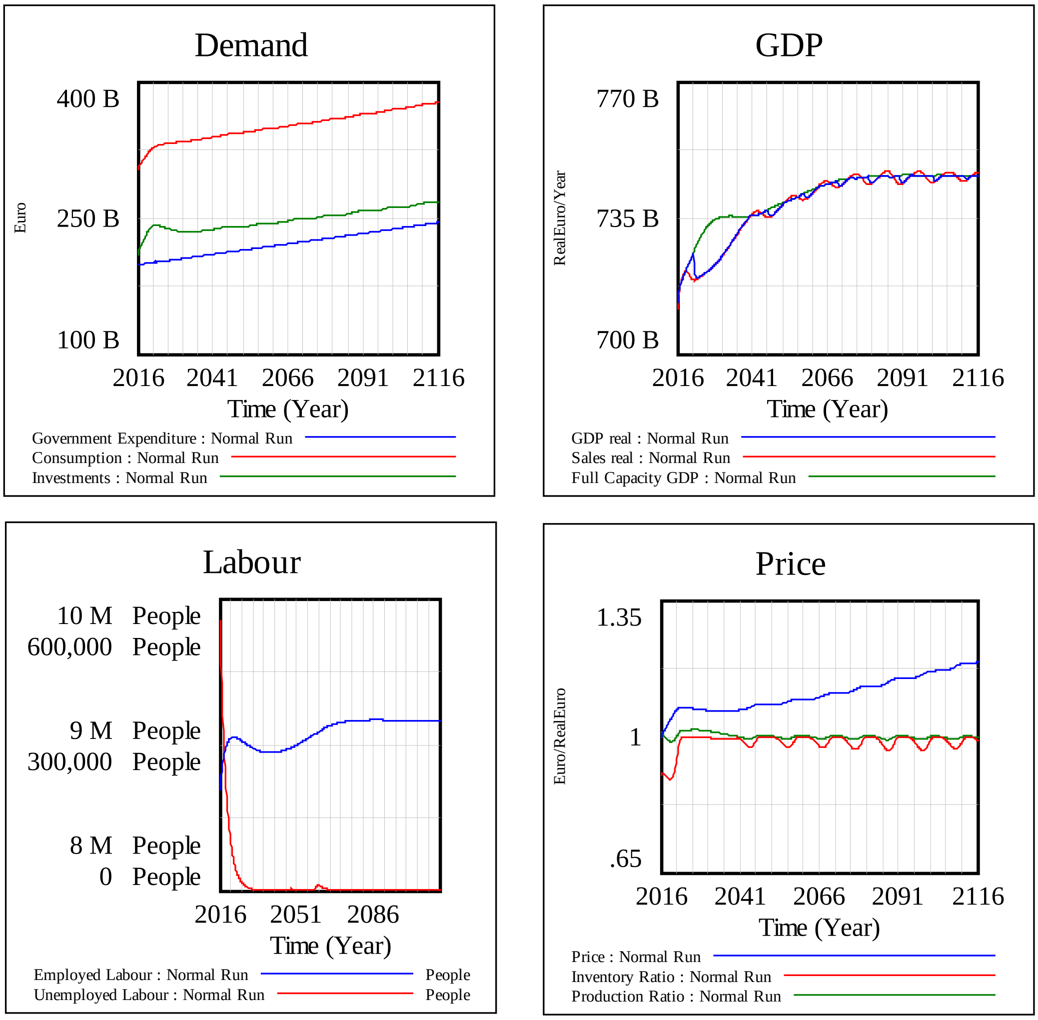
[14] Download for free at https://www.continuum.io/downloads.

Finally, to be as transparent as possible, we have made a 100-year simulation of the model as we are about to translate it to Python. The results can be seen in Figure 31: 100 Year Simulation. Keep in mind that this is not at all what we are after to show. We simply want to present current dynamics and equilibria as we are about to tread in new territory. During the analysis, we will use multiple parameter ranges and initial values, so the following cannot be interpreted as model outcomes for use. Model specifications for the parameters can be found in the appendix (BeforeEMArun.mdl).

*Figure 31: 100 Year Simulation*

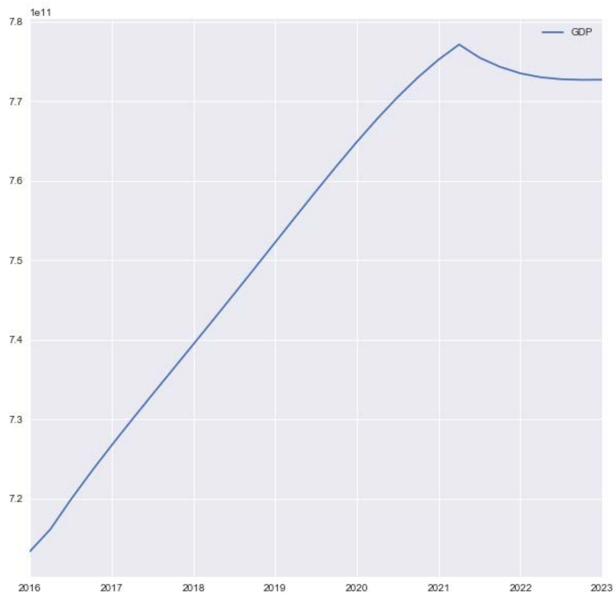



## *4.1.1 From SD to Python*

We start with testing if we can correctly import the model to Python by running a few tests. The document with these tests is called 'PySd.ipynb'. Before we can start with any kind of testing, we need to import certain libraries. The list of libraries and explanation can be found in the appendix. After importing the libraries, we first need to convert our Vensim model to a code that can be read by Python. Furthermore, we test a simple run to see if the import was successful. We do this with a Python package called PySD – hence the name for this module 'PySd'. This package can read in a Vensim model and let it run in Python. However, there are a few things we need to be aware of. First, it is not possible to have delay functions. Therefore, we model delays without special functions, but with a stock and flow structure. We have seen this before during the model explanation - we did not use typical System Dynamics functions. We also need to publish our Vensim models in a .vpm file before we can load them in. This is done within Vensim itself. Once published, Python can recognise the dataset and convert it. When replicating these experiments, be aware of the settings in Vensim DSS. In this case, the hard underbar setting is turned on (Settings, Sketch, Use hard underbar). This means that the sign '_' is not recognised as a space, but a separate symbol. In practice, this means that if we want to report variables that use a space - for example "Labour Force" - we can write "Labour Force" instead of "Labour_Force". Keep this in mind while replicating the experiments as the following functions are modelled without the underbar (so the Vensim setting is turned on).

After importing the model as described in more detail in the appendix, we can test if the import was a success. A simple replication of GDP can be seen in Figure 32: GDP Simulation in Python.

*Figure 32: GDP Simulation in Python*




This is only a simple run, but it appears our model is recognized. When in the base run, we compare the outcomes in Python and Vensim, we see a match of 775.4 Billion. This is not well represented by graphical output in Python as these are a simplification. When we return to test policy, we can repeat this test.

A second thing we will test on our import is if our switches work correctly. Normally, if we want to change policies or their effect, we do not need to return to the Vensim model. This is time-consuming and we can also make these changes in Python. We therefore derived a code in which we can activate, deactivate and set values to numerous policies in the model. Policies we can affect in the model are the growth- or balanced based expenditure of the government, government spending shocks, inflation adjustment for consumers, growth depended spending of consumers, excise tax change, unemployment shocks and random spending of consumers. The time when these changes take effect as well as their strength can be defined in Python by changing parts of the code that Python interprets. We now show two runs, one of which all policies and effects are zero. The second run switches the governmental expenditure behaviour and adds a consumption spending shock in 2020 of 5%. We will not redefine any other parts of the model and they will thus remain the same.

When running the model, the GDP in the first run ends up at 768.4184 billion in 2023. In the second case, GDP in 2023 is 767.5361. This is a difference of 882.3 million. This finding is 100%

accurate with what we find if we run the model in Vensim and compare the runs: 768.4184 billion and 767.5361 billion with a difference of 882.3 million. This experiment can be found in the Notebook and the Vensim model (EMA20.mdl in the Vensim folder).

*4.1.2 Setting up the experiments*

This paragraph contains the explanation the EMA experiments, found in 'EMA Notebook'. Now that we have tested and know our model has translated correctly, we can move to setting up the experiments. In the workbench, we can set constants, uncertainties, levers and more. We need to specify said values for the computer to know how to handle them. Defining values as constants mean they will not change. This means we can setup experiments with policies on or off that will not change. Changing the levers in the model to constants is a good way to create smaller datasets that represent specific outcomes: for example, when we want to only test a situation in which the consumers gain income through economic growth rate. However, it does not capture the design or purpose of RDM. We want to create a dataset containing all possibilities. This means we are going to disregard constants our EMA analysis, except for one. As we said before, it is not observed in the Dutch economy that wages actually decrease; they stagnate. Therefore, we do want to keep the "NonAdjustable Wages Switch" to zero. That way, wages do not decrease over time as the economy naturally develops. If we want to come back to this decision, we can simply redefine the switch from a constant, to an uncertainty.

Uncertainties in the model are variables that are sampled in our experiments for each run to create a dataset. Initial values in the model, not determined by formulas, can also be considered as uncertain. As we don't know the exact value of initial values, we can test behaviour of the model with different starting values. We will vary the initial values of those variables that have a lot of uncertainty and have a big impact on model runs. The initial values that are up to change are: "Initial Potential GDP", "Initial Capital Percentage", "Initial Wage Rate" and "Initial Housing Shortage". The value of these variables can be estimated within a range, but can't be reliably reduced to a single number. These values are very dangerous to vary, as they determine the starting position of the model and are sensitive to change. Luckily, we could calculate a lot of initial values using the model itself. Other exogenous initial variables sometimes had good and unambiguous data sources - like "Initial Employed Labour". Other cases still had initial values that were not important to the model if they were in an acceptable range of the desired value during model initiation - like "Initial Inventory (real)". For those values, we have initialized them as being a certain percentage of the desired value - between 90% and 100%. The percentage chosen stems from the standard development distance between the actual and desired value in a model run. Letting them vary between those ranges is a perfect solution to deal with this uncertainty.

We also cannot get exact real-world data form other uncertain variables as "Delay Time of Wage Change" or "Exponent on Labour". These values are either economic concepts or remnants of a translation process between economic theorem and System Dynamics. Luckily, there are logical boundaries to parameters. For example, it is unlikely that an exponent on labour or capital exceeds .5 (or 1 cumulative). If that were the case it would mean that for every extra capital or labour in the economy, relative output per extra unit would increase. This does not conform with what we see in the world and can thus be disregarded. So even though we cannot define all factors exactly, we can give an estimated range - if not that, we can ground it based on our cases of interest. Our "Exponent on Labour" can therefore be given a maximum value of .47 (almost near perfect constant gains) and a minimum of .37 (an inefficiency of 26% of output with added labour). Finally, not all the uncertain factors will be adjusted. Some factors, adjustment times and effects are left out of the picture for now – values that have a weak impact. This reduces the cluttering of cases not of interest and increases the simulation speed.

The next step is to set policies. This thesis does not support decision structures or outcomes of the stakeholder and therefore we define policies of the actors in the economic system. If we would have been in possession of a decision structure and outcome of party of interest, we would be able to find optimum strategies and policies. Now, the following policies are used to represent the possible realities and as a stand-in to show what we can do with EMA. Do keep in mind then that policies in this instance refers to using different models (realities). With decision and outcomes structures of the stakeholder present, we should both insert policies and use different models. Here, we can only use different models (called policies - as they refer to decision structures of economic actors). Future work should definitely include such a structure, but due to the limited time and resources of the author, such a feat was not yet possible. In our experiments, we will vary the government spending structure, growth rate influences on consumption and extra earnings with economic growth for consumers. Later, we can split these policies to see their individual effects.

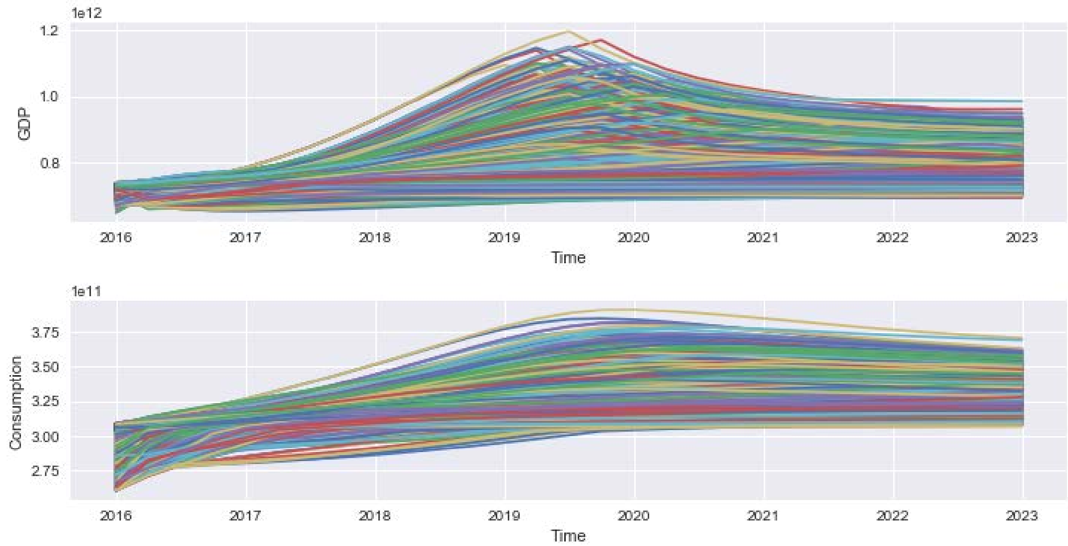
There also is a possibility to define the shocks by giving the levers values so they are activated at specific events (for example; more government spending when economic decline is -3% or more). Knowing such possibility exist greatly increases the possible output we can generate. However, since we have done little research about such interpretations of the economy, we will not implement these levers - as they do not enhance our true understanding. The levers were originally created to test model behaviour and we will not widen their use in this research.

*4.1.3 Output visualisation*

Regarding our experiments, we will look at either "GDP", "Consumption", "Investments", "Government Expenditure", "Growth Rate", "Inflation Rate", "Interest Rate", "Unemployment rate" and "Housing Price Delta" or a combination of those outcomes. This focus is chosen in accordance with the stakeholder. For the visualisation, we chose to only show GDP and Consumption. The full visualisation can be either found in appendix G (EMA output) or in the full description of the experiments in appendix H (Jupyter Notebook Python 3.6). Figure 33: EMA Raw Output GDP & Consumption is a visual representation of the ranges of our outcomes of interest[15]. We can clearly see the different starting values

[15] Full visualisation can be found in appendix G - Figure 49: Untransformed EMA Data, and also in appendix L - Jupyter Notebook Python 3.6.

*Figure 33: EMA Raw Output GDP & Consumption*

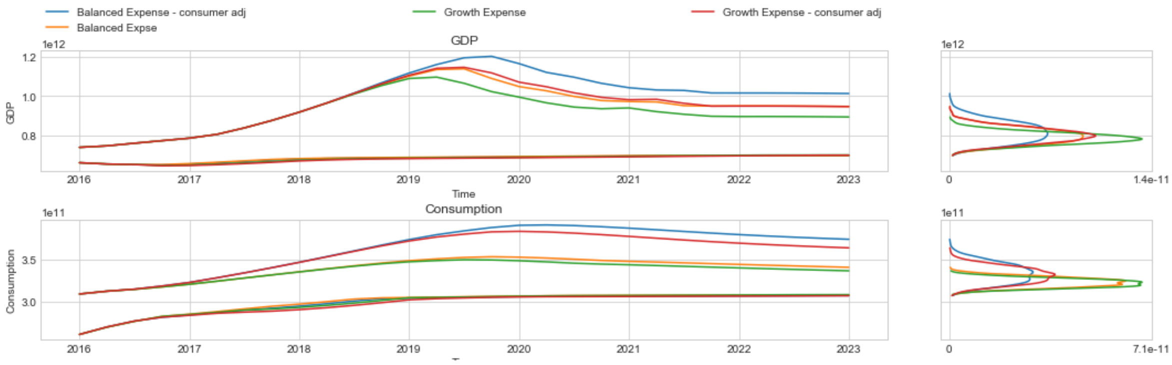



of variables that had initial values change or were affected by initial value change. We can also get a glimpse of the extreme ranges of the dataset. Besides those observations, not much can be derived from this overview. The data should thus be reordered to make it usable. To achieve this, we will organize the data such that we see the maximum development and the minimum development of each of the graphs. That way, we can visualize the uncertainty range of an outcome indicator over time between the minimum and maximum values at each time point. Next to showing upper and lower bounds, we will also add a Kernel Density Estimation (KDE) plot to the right. The KDE shows the probability distribution of density of the outcomes. It is something like a histogram, but in a smooth function. As presented here, the KDE graphs show the probable distribution over the y-axis.

Figure 34: EMA Policy Boundaries & KDE shows the extreme ranges for all our runs[16]. Besides showing the KDE, we will also organise the data such that we can distinguish between run and policies. We will thus give each policy its own KDE representation and upper and lower bound in different colour. This way, we can quickly organise the data and see discrepancies between the polies and the effects on the dataset.

[16] Full visualisation can be found in appendix G - Figure 50: EMA Policies and KDE, and also in appendix L - Jupyter Notebook Python 3.6.

*Figure 34: EMA Policy Boundaries & KDE*




As we can see with our first two decision structures about governmental expenditure, we see that adjusting governmental inflation leads to a higher government spending and greatly affects the outcomes GDP (the Red and Green line). When looking at governmental expenditure alone, we see no possible shrinkage in expenditures when also adjusting for inflation (in the Balanced Budget policy). We can also see this clearly in the distribution of the KDE plot.

The policies that govern if consumers spend more according to inflation and earn more with economic growth, we also see some interesting developments (the red and blue line). As expected, consumption tends to be higher as seen in the normal and KDE graph. Also, with more consumption, there is overall a smaller tendency for unemployment. Looking at the causal structure of our model, this effect is as follows: more consumption means higher GDP, leads to more need for investment capital and labour to produce goods. There are also effects to be noticed to the change in housing prices. Since they are rather small and the KDE densities of all four policies have an equal distribution, this difference is not worth taking into consideration.

With this setup, we can already see some relations and effects that the policies have. We can go further and build a scatterplot. In a scatterplot, variables are written in a diagonal line from top left to bottom right. Then each variable is plotted against each other. This means that some effects will cancel each other out while true effects will remain. Here, we have left out interest rate, since it is an exogenous input to the model. It is thus impossible for factors in the model to have an impact on the interest rate. No correlation is possible from a factor that is randomly sampled and is a constant.

We can see a part of our scatterplot in Figure 35: Scatterplot[17]. Not all behaviour shown here is very clear. First off, none of our rates have a very good correlation and we have thus left them out – this is also true for the full graph in appendix G. This is not strange as they move on very different axis. Expenditures and investments range in the billions, while rates are around the o

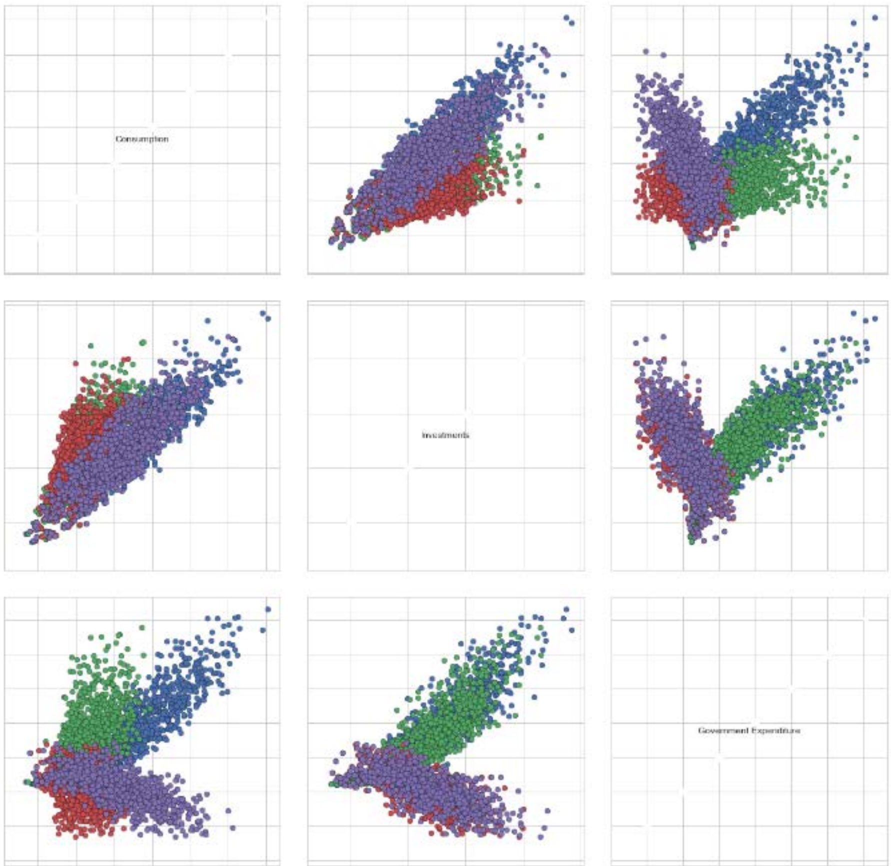
[17] Full visualisation can be found in appendix G - Figure 51: EMA Correlation Graph, and also in appendix L - Jupyter Notebook Python 3.6.

*Figure 35: Scatterplot*


and 1. More experiments can be found in the appendix where this phenomenon is explained. Another interesting feature we see is that it seems like government expenditures has different correlation paths. We can explore further by splitting the policies once again.

In Figure 36: Scatterplot with Policies, we see the same figure as before, but with the policies split from each other[18][19]. We can see that switching from government spending policy can have an effect on the overall correlation between variables. This is probably because when no policy is active, there is a standard growth rate in consumption behaviour and when policies are active, it can behave erratic. It is thus unwise to make too many assumptions based on this particular output.

*Figure 36: Scatterplot with Policies*



Finally, while it is great that we can extract policies and analyse them independently, it is not important to the end conclusions of our research. Since our policies represent not actual policies, but alternative methods

[18] Full visualisation can be found in appendix G - Figure 52: EMA Correlation with Policies (1/2), Figure 53: EMA Correlation with Policies (2/2), and also in appendix L - Jupyter Notebook Python 3.6.

[19] Green = Balance Based Budget; Blue = Balance Based Budget & consumer earning adjustment; Red = Growth Based Expenses; Purple = Growth Based Expenses & consumer earning adjustment.

to model the economy, we must analyse all simulations. Still, is good for our understanding to check the effect of the model structures and see if unexpected behaviour occurs. When for example extra consumer spending would lead to overall less consumption or a lower distribution of outcomes in the KDE graph, we would have reasons for concern. Luckily, there is no sign of such behaviour and the model behaves as expected.

*4.1.4 PRIM*

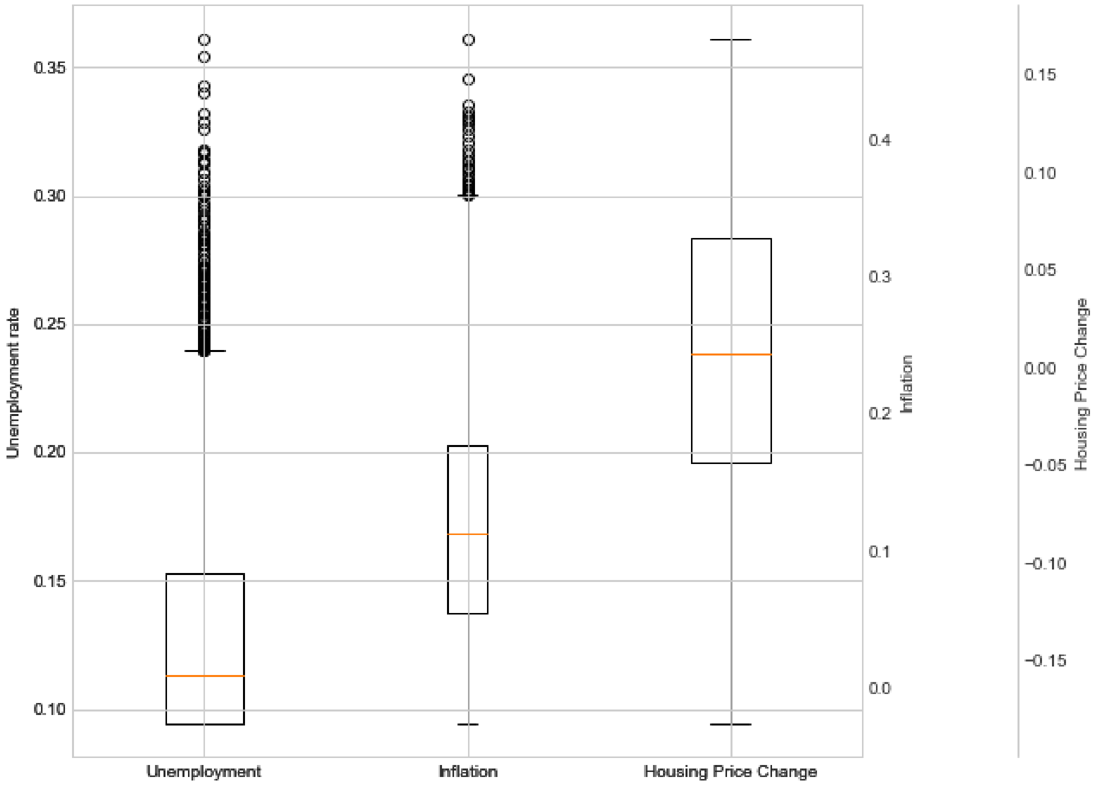
A vital part of RDM is that we can use computer algorithms to analyse big datasets. In this research, we can use the algorithm PRIM to see which factors have the most influence on our outcomes of interest. PRIM stands for Patient Rule Induction Method. This algorithm analyses the whole dataset and slices parts from that data that brings relative most improvement to the objective function, typically the mean of the data (Kwakkel & Cunningham, 2016). We can think about it visually by imagining a box of data. Each step of the algorithm, PRIM removes the upper, lower, right or left part of the data to improve the objection function. PRIM basically encloses the data in steps until an objective is met. This step-by-step procedure produces many different boxes between the starting point and the last box of data remaining. This enclosing process can be seen in a peeling trajectory - the trajectory of slices that were removed from the original data. We as analysts have to then select a box we want to explore further. Selection criteria for this are coverage, density, and interpretability (Bryant & Lempert, 2010; Kwakkel & Cunningham, 2016). Coverage is the fraction of the cases that are of interest fall within a box identified by the algorithm (Kwakkel & Cunningham, 2016). A score of 1 means that all of the cases of interest are contained in a given box. By definition, this always the first box where no data was removed. However, in such a box, the density will probably be very low. Density represents the fraction of cases of interest that are in the box, versus the cases that are not of interest, but also in the box. With a density of 1, all data-points in the box are cases of interest. The final criteria, interpretability, is not a numerical outcome but a choice of the analyst. In general, we want to have a high coverage, high density and a limited amount of dimensions (Bryant & Lempert, 2010).

We now know how PRIM operates, but when does it know exactly when to stop cutting data to its bare minimum? For this, we set a threshold for PRIM when to stop. This threshold is a number between zero and one and represents the of the last box on the peeling trajectory. Sometimes, PRIM cannot fulfil its objective function if the given threshold is too high - in that case the score of desired data-points is not available in the analysis. Unfortunately, this number cannot be known in advance, so the threshold set in experiments is found by trial and error. With all this set, we know how to set up the experiments.

Although PRIM is a simple but effective algorithm to sort through data, there are some downsides. First, if we want to analyse multiple objectives, we must re-do and repeat the PRIM process with new objectives. PRIM encloses an objective with a binary formulation of the objective function and so can only do one task at a time. Second, PRIM may slice off the end of a range for a parameter, which suggests that a policy may be sensitive. Its search method can also constrain useless parameters that do not predict cases of interest (Bryant & Lempert, 2010). For this purpose, Bryant and Lempert (2010) pose a quasi p-value test and resampling. The quasi p-value tests the likelihood that PRIM constrains some parameter by chance. With resampling, the PRIM algorithm is run different times on sub-sets of the original data. Doing this can compare the sub-sets of data and look for inconsistencies between the results to see how often the same definitions are chosen.

For our fist analysis with PRIM, we first should give it an objective. To set this objective, let's look at some of the outcomes in our dataset. We will present some of the runs in a boxplot so we can inspect the boundaries of values. We will first look at unemployment, the change in housing price and inflation.

*Figure 37: Boxplot Unemployment, Inflation, Housing Price*




In Figure 37: Boxplot Unemployment, Inflation, Housing Price, we can get an intuitive feeling for various variables[20]. Now we know the upper and lower bounds, we can direct better questions. The dots that appear outside the unemployment and inflation edge are outliers in the data. Also, we have made the graph so that unemployment shows the average value of unemployment, but inflation and the change in housing price is cumulative. This is because we can't interpret cumulative unemployment very well. At the same time, showing average

[20] The figure and configuration can also be found in in appendix L - Jupyter Notebook Python 3.6.

inflation or a housing price change does not say very much about the development of the economy in a timeseries (results will be clustered).

For our first PRIM experiment, let's look at unemployment and answer the question about what the conditions must be if unemployment is in the top 25% of all possible outcomes - around 15% or higher. As we can remember from our KDE graph, high unemployment has a flat tail in the upper values, meaning the top 25% values are pretty far from each other. It would be interesting to find out what causes that behaviour. To set this up, we tell the algorithm to look for instances in which average unemployment over the series is higher than .15 or 15%. We set a threshold of .75, meaning that PRIM will stop when a box mean is smaller than threshold or the box mass is less than the minimum mass (these values are not shown in the output). With this binary expression of the goal, we can ask the algorithm to look through the data. There will be three types of output presented: 1) raw output of the numerous boxes showing the coverage, density, mass, mean and number of dimensions, 2) peeling and pasting trajectory (trade-off graph) that shows the trajectories of mean, mass, coverage, density and dimensions over the simulations, and 3) the coverage vs. density overview. We will first go over the raw output that PRIM has calculated with our definitions. We will only show a small part of the output, as our experiment has produced 52 boxes. We will show 30 to demonstrate the point.

*Table 13: PRIM Raw Output Unemployment*

| | coverage | density | mass | mean | res dim |
|---|---|---|---|---|---|
| 0 | 1.000000 | 0.266750 | 1.00000 | 0.266750 | 0 |
| 1 | 0.987816 | 0.277368 | 0.95000 | 0.277368 | 1 |
| 2 | 0.974695 | 0.288248 | 0.90200 | 0.288248 | 2 |
| 3 | 0.955951 | 0.297897 | 0.85600 | 0.297897 | 2 |
| 4 | 0.933458 | 0.306273 | 0.81300 | 0.306273 | 3 |
| 5 | 0.930647 | 0.321567 | 0.77200 | 0.321567 | 3 |
| 6 | 0.912840 | 0.332196 | 0.73300 | 0.332196 | 3 |
| 7 | 0.900656 | 0.345187 | 0.69600 | 0.345187 | 3 |
| 8 | 0.876289 | 0.353631 | 0.66100 | 0.353631 | 3 |
| 9 | 0.868791 | 0.369617 | 0.62700 | 0.369617 | 3 |
| 10 | 0.852858 | 0.382353 | 0.59500 | 0.382353 | 3 |
| 11 | 0.841612 | 0.397345 | 0.56500 | 0.397345 | 3 |
| 12 | 0.826617 | 0.411381 | 0.53600 | 0.411381 | 3 |
| 13 | 0.818182 | 0.428782 | 0.50900 | 0.428782 | 3 |
| 14 | 0.797563 | 0.440476 | 0.48300 | 0.440476 | 3 |
| 15 | 0.776007 | 0.451965 | 0.45800 | 0.451965 | 3 |
| 16 | 0.761949 | 0.467241 | 0.43500 | 0.467241 | 3 |
| 17 | 0.739456 | 0.477603 | 0.41300 | 0.477603 | 3 |
| 18 | 0.724461 | 0.492985 | 0.39200 | 0.492985 | 3 |
| 19 | 0.717901 | 0.514785 | 0.37200 | 0.514785 | 3 |
| 20 | 0.701031 | 0.529745 | 0.35300 | 0.529745 | 3 |
| 21 | 0.677601 | 0.539552 | 0.33500 | 0.539552 | 4 |
| 22 | 0.658857 | 0.552673 | 0.31800 | 0.552673 | 4 |
| 23 | 0.639175 | 0.564570 | 0.30200 | 0.564570 | 5 |
| 24 | 0.618557 | 0.576923 | 0.28600 | 0.576923 | 5 |
| 25 | 0.597938 | 0.588561 | 0.27100 | 0.588561 | 6 |
| 26 | 0.580131 | 0.602140 | 0.25700 | 0.602140 | 6 |
| 27 | 0.560450 | 0.612705 | 0.24400 | 0.612705 | 6 |
| 28 | 0.545455 | 0.629870 | 0.23100 | 0.629870 | 6 |
| 29 | 0.524836 | 0.639269 | 0.21900 | 0.639269 | 6 |
| 30 | 0.507966 | 0.651442 | 0.20800 | 0.651442 | 6 |

In Table 13: PRIM Raw Output, we can see the scores of each box on numerous scores[21]. Coverage is the number of cases of interest in the box. Density is the cases of interest versus the remainder of the cases in each box. The mass is simply the number of data-points in the box, divided by the total amount of data-points (Kwakkel & Cunningham, 2016). Restricted dimensions are the number of variables that explain a certain behaviour with a given coverage and density. Naturally, we have a coverage of 100% when we do not slice any data (box 0). In box 1 after the first slice, there is only 1 restricted dimension and we see the coverage decrease. The box tells us that that .99 coverage of the cases with a .28 density can be explained from the behaviour of one variable in the model. Although we are very satisfied with a coverage of .98, a density of .28 is very poor: around 72% (1-.28) of the data-points in the box

[21] The complete table can be found in in appendix L - Jupyter Notebook Python 3.6.

are not of interest. We should therefore look for a box that has a high coverage paired with a high density. Before we go on our search however, we will first go over the other output the algorithm can give us.

The progression of the algorithm can be visually represented by a trade-off graph and peeling trajectory. In the Figure 39: Peeling and Pasting Trajectory[22], we can try to find obvious boxes to select. We could for example focus on the intersection of coverage and density. In the graph, we see that the intersection of coverage and density with explanatory power of 60% is restricted by 6 dimensions. 6 dimensions however is unwieldy to analyse a dataset with. Unluckily, our overall scores are not very good. If we for example look at Figure 38: PRIM Coverage & Density[23], we see that both a high coverage and density is not possible. The peeling trajectory is almost linear, meaning there are no obvious variables that are sensitive to our outcome. Ideally, we would like to see a half parabola from high density to high coverage. To salvage the dataset, we can transform the data when we have selected a box.

*Figure 39: Peeling and Pasting Trajectory Unemployment*

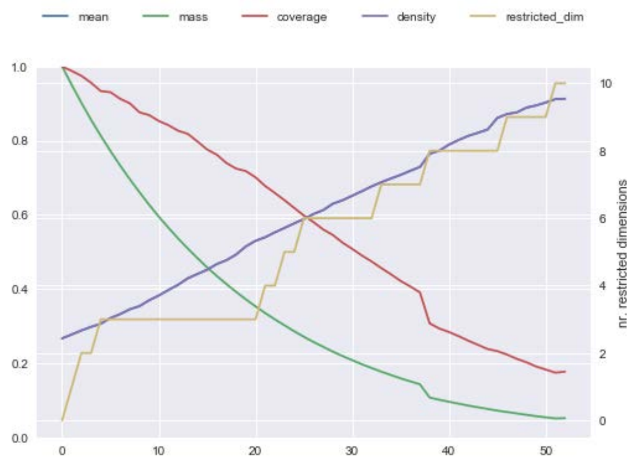
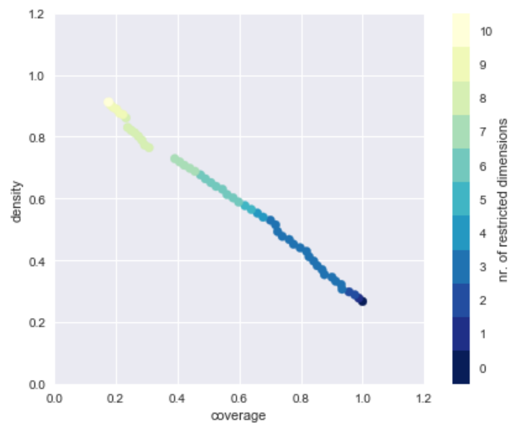



*Figure 38: PRIM Coverage & Density Unemployment*




PRIM does not tell us what to explore, so we have to pick one based on the interpretability of the box. This is one of the downsides of PRIM - that there is not always an obvious answer. Unlucky for us, we also do not high scores on both density and coverage at the same time. If we look at the trade-off between density and coverage, we can select box 14 for now, with around 80% of the cases of interest, but more than half that do not meet the requirement. Let's explore further and look at the distribution of the data.

Exploring box 14, PRIM gives us the following overview in Table 14: PRIM Box 14 Output:

*Table 14: PRIM Box 14 Output Unemployment*

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[22] The figure configuration can be found in in appendix L - Jupyter Notebook Python 3.6

[23] The figure configuration can be found in in appendix L - Jupyter Notebook Python 3.6.

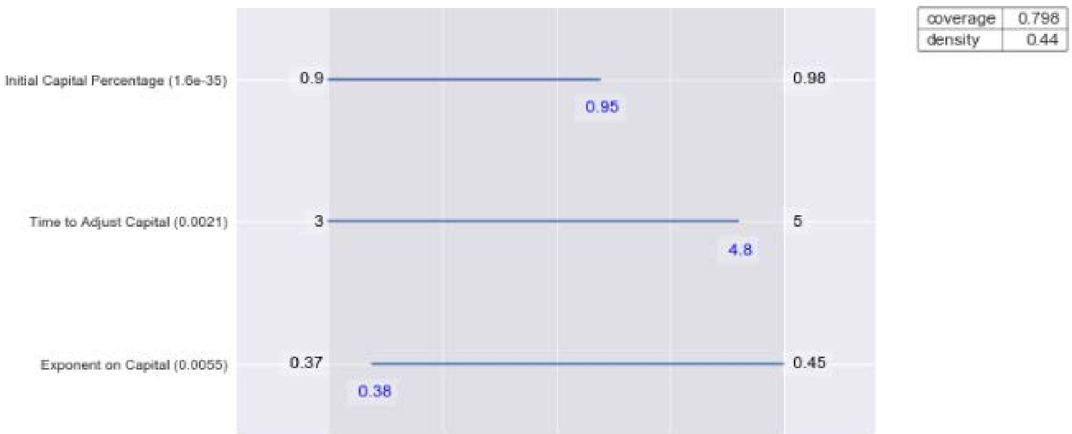
```
coverage    0.797563
density     0.440476
mass           0.483
mean        0.440476
res dim            3
Name: 14, dtype: object

                              box 14
                                 min       max     qp values
Initial Capital Percentage  0.900077  0.947759  1.575348e-35
Time to Adjust Capital      3.000780  4.798202  2.062917e-03
Exponent on Capital         0.377767  0.449979  5.514886e-03

                  Box status:
       coverage   density   mass  res_dim
box 1  0.797563  0.440476  0.483        3
                                Explanation:
                               box 1
                                 min       max
Initial Capital Percentage  0.900077  0.947759
Time to Adjust Capital       3.00078    4.7982
Exponent on Capital         0.377767  0.449979
```

This overview tells us that this box can be explained by "Initial Capital Percentage" with a value between 0.900077 and 0.947759, "Time to Adjust Capital" with a value between 3.000780 and 4.798202, and the "Exponent on Capital" with a value between 0.377767 and 0.449979. We also have been given quasi-p values. All the quasi-p values are large and we do not reject the null hypothesis that our values are significant. We can further explore the box by visualising the outcomes in Figure 40: PRIM Box 14 Results[24].

*Figure 40: PRIM Box 14 Results Unemployment*




This overview shows us in an easy manner what the conditions for this box are. Also, we see a visual representation of the data that has been sliced. With the slicing process, we see another

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[24] The full version of the figure can be found in appendix G - Figure 54: PRIM Box Selction & Outcomes, and the figure configuration can be found in in appendix L - Jupyter Notebook Python 3.6

downside of PRIM (or actually optimisation algorithms in general). When slicing data and selecting a new field, this happens with a square selection on a 2D plane. In the sliced boxes of "Exponent on Capital", we see that data points are centred in the top left when cross examining the data with "Initial Captial Percentage". We cannot select a smooth outline of the data, but can only select boxes. If we, in this case or others, thus see data that cannot be captured in a box, we should divide the data into multiple boxes. As such, we must repeat PRIM experiments until we have captured the data using multiple boxes (Kollat & Reed, 2006; Parker, Srinivasan, Lempert, & Berry, 2015). In our case, we will not resort to such methods due to the weighing between complexity of implementation and gained explanatory power (in our case). We can try to make assumptions based on box 14, but with a density of .44, we would not be accurate enough to make reliable statements. Therefore, let's pick a box that has a higher density. Box 22 might prove promising, with a mass of .318 corresponding with the box, we can try to make assumptions about 30% of the data (see raw output of PRIM). Finally, the box is restricted by only 4 dimensions - only one more. So, let's explore box 22 further. The scores of box 22 are as are presented in Table 15: PRIM Box 22 [25] and Figure 41: PRIM Box 22 Results[26]:

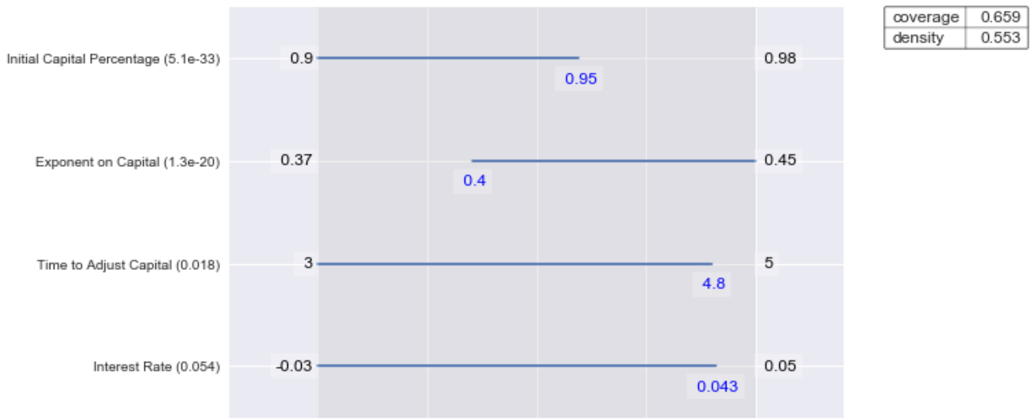
*Table 15: PRIM Box 22 Output Unemployment*

```
coverage    0.658857
density     0.552673
mass           0.318
mean        0.552673
res dim            4
Name: 22, dtype: object

                              box 22
                                 min       max     qp values
Initial Capital Percentage  0.900077  0.947759  5.131815e-33
Exponent on Capital         0.398263  0.449979  1.285766e-20
Time to Adjust Capital      3.000780  4.798202  1.773885e-02
Interest Rate              -0.029991  0.042689  5.355439e-02

                  Box status:
       coverage   density   mass  res_dim
box 1  0.658857  0.552673  0.318        4
                                Explanation:
                                box 1
                                  min        max
Initial Capital Percentage   0.900077   0.947759
Exponent on Capital          0.398263   0.449979
Time to Adjust Capital        3.00078     4.7982
Interest Rate              -0.0299913  0.0426894
```

[25] The table configuration can be found in in appendix L - Jupyter Notebook Python 3.6.

[26] The figure configuration can be found in in appendix L - Jupyter Notebook Python 3.6.

*Figure 41: PRIM Box 22 Results Unemployment*




The outcomes of box 22 are still very poor. If we look at the variables, coverage and density, we are able to find a box that has 66% of the cases of interest with a density of 55%. In other words, with initial capital being between 90% and 95% of what is required in the economy, an exponent of .4 or higher and almost any time to adjust capital and interest rate, we can arrive at 66% of the cases of interest - with 45% cases that do not meet the requirement of employment averaging above 15%. With low explanatory power, we are able to give a very wide range of factors that explain this behaviour. This still is a suboptimal outcome. However, instead of looking at new boxes, let's drop variables that we are not interested in. We can decrease the limited dimensions without altering the dataset by removing certain factors. Often, one would look for the variables with a low quasi-p values. In our case, we are going to remove variables based on our knowledge of the model and argumentation. For example, it is great that the time to adjust capital can be almost anything, but: 1) this tells us almost nothing and 2) this variable is the consequence of the translation process of macroeconomic theory. Based on this logic and unavailability to explain its validity, let's explore what happens when we drop this variable from the analysis in Table 16: PRIM Box 22 New Output[27] and Figure 42: PRIM Box 22 New Results[28].

*Table 16: PRIM Box 22 New Output Unemployment*

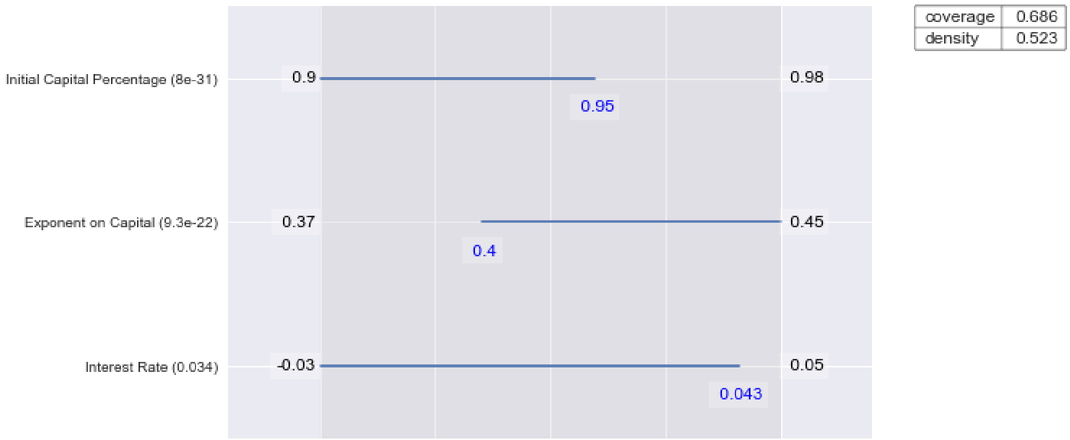
```
coverage    0.686036
density     0.522857
mass            0.35
mean        0.522857
res dim            3
Name: 58, dtype: object

                              box 58
                                 min       max     qp values
Initial Capital Percentage  0.900077  0.947759  7.979104e-31
Exponent on Capital         0.398263  0.449979  9.315609e-22
```

[27] The figure configuration can be found in in appendix L - Jupyter Notebook Python 3.6.

[28] The table configuration can be found in in appendix L - Jupyter Notebook Python 3.6.

```
Interest Rate                -0.029991  0.042689  3.427577e-02
```

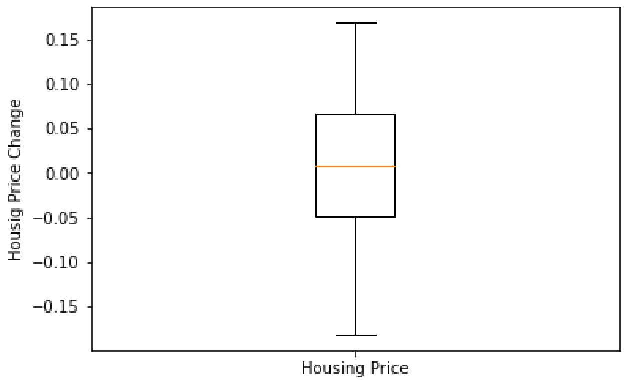
*Figure 42: PRIM Box 22 New Results Unemployment*




We see an increase of coverage, from 67 to 69 while keeping the same density. At the same time, we got rid of a variable that according to PRIM explained the behaviour of unemployment, but in fact was a variable used for the transition from economic theorem to System Dynamics. The box we are left with tells us that if there is an incentive to make up for capital and the payoff from capital is not too low, high unemployment is very likely. This happens under almost any circumstances of interest rates. In essence, this answer is pretty intuitive and agrees with general economic observations and theorem. Now, we are able to quantify the conditions in which such a thing is likely to happen, but with a rather average coverage and low density this explanation is not very satisfying. Nevertheless, knowledge about the difficulties about boxing in specific variables that determine unemployment is still knowledge.

To give a clearer picture of the explanatory power of PRIM, we will present a single dimensional case. For this, we will analyse the change in housing prices and repeat the previous process. The first step is thus to define an objective for the algorithm. We will take another look at the boxplot of housing price change in Figure 43: Boxplot Housing Price[29].

*Figure 43: Boxplot Housing Price*




As we can see in the boxplot, it is about as likely that prices will drop as they will rise. Let's try to find out in what conditions the price of houses may rise. Thus, we set our objective to outcomes that are larger than zero: housing price change > 0. The corresponding output of PRIM can be

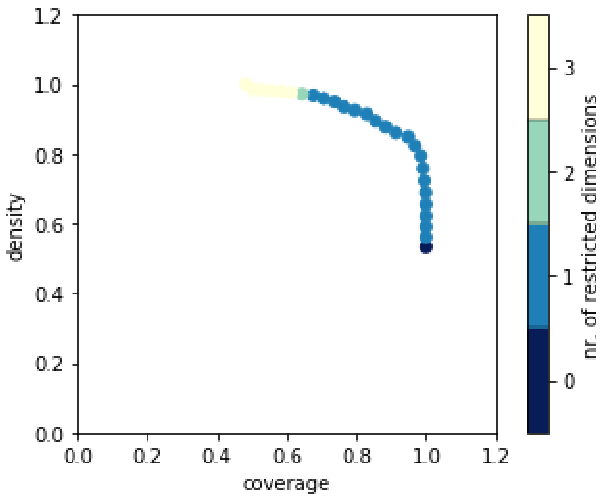
[29] The figure configuration can be found in in appendix L - Jupyter Notebook Python 3.6.

found in Table 17: PRIM Raw Output Housing Price[30] and Figure 44: PRIM Coverage & Density[31].

*Table 17: PRIM Raw Output Housing Price*

| | coverage | density | mass | mean | res dim |
|---|---|---|---|---|---|
| 0 | 1.000000 | 0.532500 | 1.000 | 0.532500 | 0 |
| 1 | 1.000000 | 0.560526 | 0.950 | 0.560526 | 1 |
| 2 | 1.000000 | 0.590355 | 0.902 | 0.590355 | 1 |
| 3 | 1.000000 | 0.622079 | 0.856 | 0.622079 | 1 |
| 4 | 1.000000 | 0.654982 | 0.813 | 0.654982 | 1 |
| 5 | 0.999061 | 0.689119 | 0.772 | 0.689119 | 1 |
| 6 | 0.995305 | 0.723056 | 0.733 | 0.723056 | 1 |
| 7 | 0.991080 | 0.758261 | 0.696 | 0.758261 | 1 |
| 8 | 0.984977 | 0.793495 | 0.661 | 0.793495 | 1 |
| 9 | 0.968545 | 0.822568 | 0.627 | 0.822568 | 1 |
| 10 | 0.948826 | 0.849160 | 0.595 | 0.849160 | 1 |
| 11 | 0.913146 | 0.860619 | 0.565 | 0.860619 | 1 |
| 12 | 0.883568 | 0.877799 | 0.536 | 0.877799 | 1 |
| 13 | 0.854930 | 0.894401 | 0.509 | 0.894401 | 1 |
| 14 | 0.829577 | 0.914596 | 0.483 | 0.914596 | 1 |
| 15 | 0.795775 | 0.925218 | 0.458 | 0.925218 | 1 |
| 16 | 0.763850 | 0.935057 | 0.435 | 0.935057 | 1 |
| 17 | 0.737089 | 0.950363 | 0.413 | 0.950363 | 1 |
| 18 | 0.706103 | 0.959184 | 0.392 | 0.959184 | 1 |
| 19 | 0.676056 | 0.967742 | 0.372 | 0.967742 | 1 |
| 20 | 0.644131 | 0.971671 | 0.353 | 0.971671 | 2 |

*Figure 44: PRIM Coverage & Density Housing Price*




The housing price is not affected by many dimensions. If we think back to our model, this is true. Only the market conditions, housing shortage and inflation has an effect. We gave a static number to interest change, so this variable has no effect in our current simulations. What is also nice is the half parabola shape of the peeling trajectory. Ideally, we can slice off data in our dataset and not lose density. This is well represented in our analysis. Going back to the raw output from PRIM, box 11 has a good coverage and density, 91% and 86% respectively. Let's see what the drivers are in this set in Figure 45: PRIM Box 11 Results[32].

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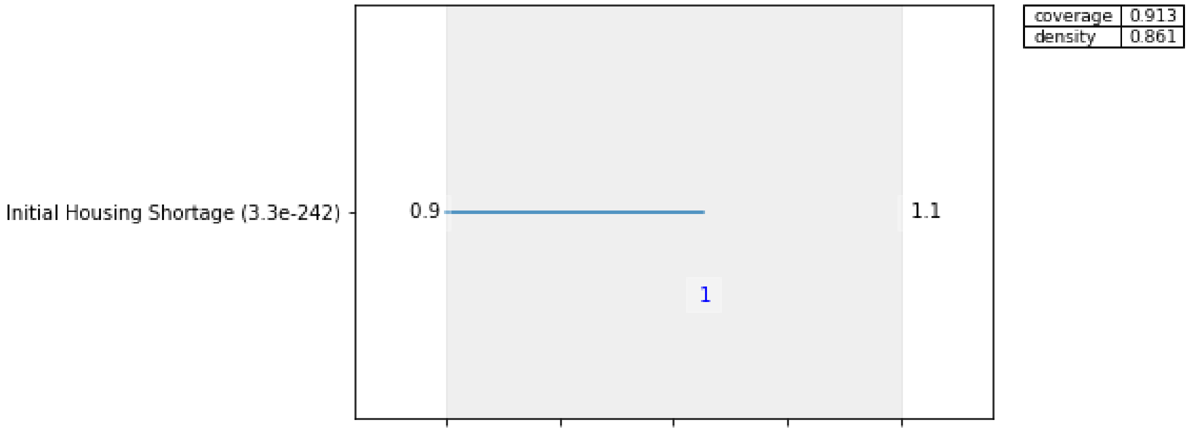
[30] The figure configuration can be found in in appendix L - Jupyter Notebook Python 3.6.
[31] The figure configuration can be found in in appendix L - Jupyter Notebook Python 3.6.
[32] The figure configuration can be found in in appendix L - Jupyter Notebook Python 3.6.

*Figure 45: PRIM Box 11 Results Housing Price*




From the remaining variables that can affect housing price, the housing pressure effect is strongest. This effect variable determines if the initial housing market conditions; if we have a housing shortage or abundance. Here, we see a rise in housing prices is imminent when the current state of the market is a shortage. Thus, without taking into account the effect of interest rate, a rise in housing price is likely when current conditions state a housing shortage. With a coverage of 95% of the cases and a very high density, we can be pretty sure of this event happening (if we assume the model is correct).

The previous statements about the outcome of our analysis represent one of the features that we have added to our System Dynamics model. Unfortunately, this is all we can so with the workbench as of now. With these results, we can assess the likelihood of scenarios with certain parameters, but we cannot assess the effect of interventions. A financial institution would thus be able to assess likelihood of scenarios and have key indicators to track in the economy, but cannot assess the effects of their policy. If in the future, we can also build interventions and choices for the institution in the System Dynamics model. With that extra information, we can optimize policy decisions and optimize decision paths. Regarding the optimisation of decision paths; optimisation does not mean 'highest payoff' or 'most revenue'. Optimisation can also be defined as the path with minimal regret, avoiding the truly worst outcomes. In that sense, our definition of optimisation determines our goal and can therefore also mean Robust.

## 4.2 Pilot current methodology versus new methodology

In the beginning of the thesis, we have made a case against financial institutions using only scenario planning in a traditional manner when using the outcomes as input for stress testing. We have previously established that traditional scenario planning 1) relies mostly on expert opinion, 2) produces singular outcomes and 3) outcomes of current methodology do not allow for comparison between institutions. It is important however that a methodology does not strengthen these three factors. We will structure the main arguments and their consequences in an overview displaying the causality of arguments:

1. Relying on expert knowledge for uncertainty projections is faulty because:

    - Experts are intrinsically biased;
    - Due to limited cognitive capacity, one person cannot take into account all variables at play when developing a scenario;
    - The values assigned to cases are chosen arbitrarily and unlikely dynamics can be left out of the picture;
2. Scenario design should focus on a range of forces because:
    - Decision makers (humans) have limited cognitive capabilities and therefore can only focus on a limited number of scenarios;
        - Certain scenarios will thus be neglected;
        - The amount of uncertainty in an analysis is therefore also limited;
3. The production of scenarios should be well-traceable because:
    - When offered too much freedom, it is possible to pick scenarios that have a beneficial outcome for the financial institution;
    - Regulators should be able to accurately compare institutions and thus design fitting measures for the future.

Solving these points would enhance the robustness of the economic system and we should create a scenario generator design that improves these points. It should be noted that Global Systematic Important Banks (G-SIB) are tested with a static scenario given by the European Central Bank (ECB) – this is further explained in the introduction of the thesis. Designing a new approach will therefore mostly enhance the robustness of a national economy. To test this, we have summarised the scenario building steps within NN – a financial institution (bank) and our partner in this research. After that, we will go through the same steps as the Exploratory Modelling & Analysis and see if we can contribute to the scenario generating process. We aim to improve the general process of scenario generation, but are aware that this thesis should be viewed as a proof of concept.

### 4.2.1 Traditional scenario planning

The following is a brief overview of the design process within financial institutions. We have summarised the main steps of scenario planning and defined the actions taken within the company within a previous discussed framework (RAND Corporation, 1997; Schwartz, 1996; Thissen et al., 1988; Van der Heijden et al., 2002):

Step 1 – Specify system, outcomes of interest and time horizon;
This first step is partially depended on financial jurisdiction and the financial institution, except for the time horizon. Rules about time horizon are set by the Dutch Central Bank (European Banking Authority, 2015). How the system is specified and what the outcomes of interest are, is set by the financial institution, but needs to be approved by the Dutch Central Bank (or ECB in the case of G-SIB). The outcomes of interest are those economic factors that would affect the performance of a financial institution when subjected to change. The specification of the system is how factors interact with each other. Since we rely on experts, this is done qualitatively.

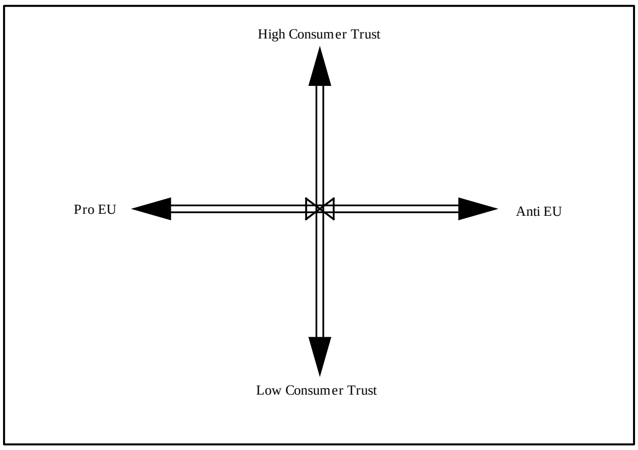
Step 2 – Identify external factors that drive change for the system and outcomes of interest;
From this step onward, the financial regulator will still be involved, but won't set any strict rules

anymore. There is a framework and data quality financial institutions must absolutely abide by, but a financial institution won't be explicitly told what choices to make (European Banking Authority, 2015; European Parliament, 2013).

To determine the external/uncertain factors, experts come together to think about potential exposures. This can be done by looking at economic outlooks, or by brainstorming about other general futures can potentially be harmful for the financial institution. In previous chapters, we have mentioned a scenario where anti-European Union parties would be elected to govern neighbouring countries. This would spell danger for financial institutions. However, one party winning or losing the elections would not be a key uncertainty, this is too simple and one-dimensional. An uncertainty would be phrases as 'Anti EU sentiment', containing numerous effects. If something is truly uncertain, EU sentiment can also flip the other way, giving use our second key uncertainty: 'Pro EU attitude'.

<u>Step 3</u> – Categorize factors from (fairly) certain to uncertain;
The uncertainties formulated in step 2 can be put on a grid from certain to uncertain. Visually, the process can be represented by Figure 46: Two Axes with Uncertainty.

*Figure 46: Two Axes with Uncertainty*

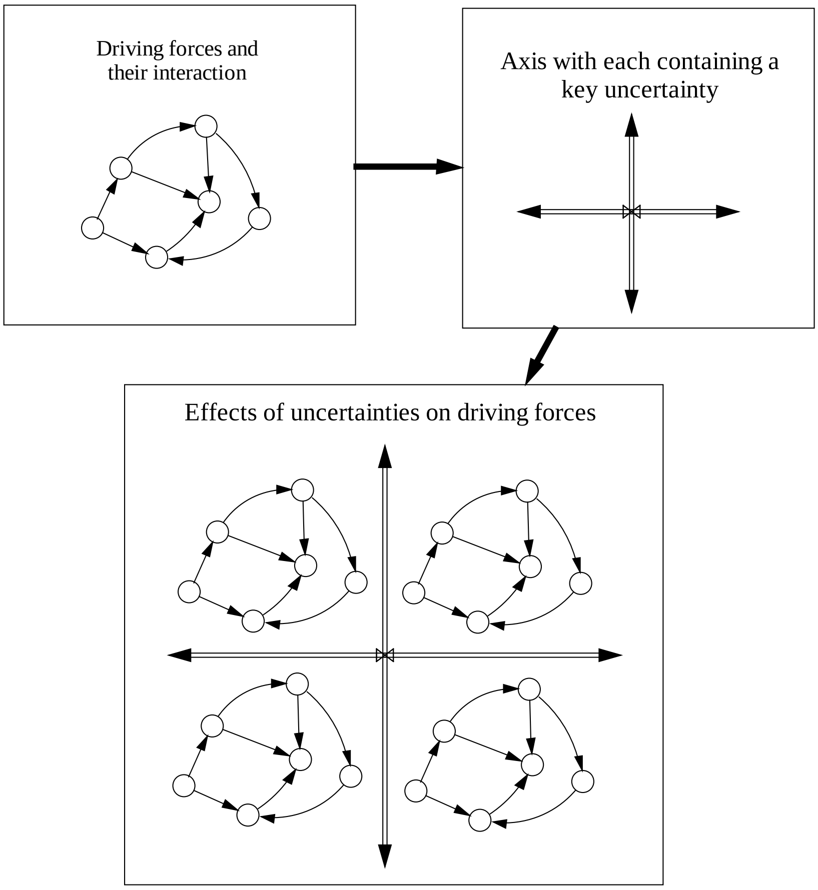



A grid is made, often containing two or three axes (in our case two). On each axis, an uncertainty is place. Here, we take 'consumer trust' and 'EU sentiment' as an example. What these two uncertainties for example could mean is that we are unsure if the labour market will adjust fast or slow, and if EU sentiment is positive or negative (the uncertainties on the axes are chosen arbitrarily to prove a point).

Do note that the extremes of the key uncertainties can be interpreted as a story about the potential future. Those stories will contain numerous effects.

<u>Step 4</u> – Assess the respective impact of the uncertain factors on the system;
In this step, we combine the axes containing uncertainty with the outcomes of interest. After that we can assess the multitude of potential system outcomes. This is best explained visually in Figure 47: Driving Forces and Uncertainties.

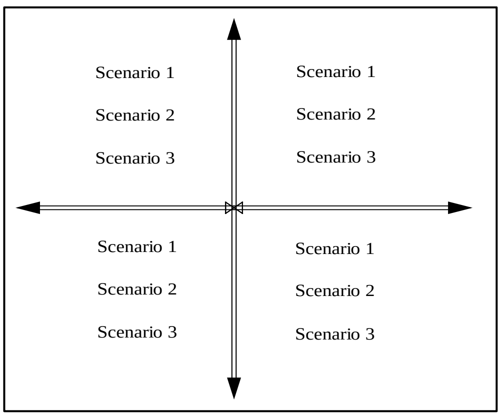
*Figure 47: Driving Forces and Uncertainties*




With a cluster of driving forces in a framework of uncertainties, we can not only create stories but also think about likely impacts.

Step 5 – Design scenarios based on different configurations of the external factors;
The last step consists of grouping the outcomes on the axes into coherent stories which we can use as scenarios. This is the final step in scenario production and after this, scenarios can be used as input for stress testing. We can best explain this visually:

*Figure 48: Scenario Development*




Here, we see the cluster of outcomes neatly ordered in coherent scenarios. We have organised three scenarios in each area, but we can choose any number of scenarios to produce.

Our work building the scenarios is now complete. In reality, this process is very complex as values have to be assigned to each value interest within an uncertain area. After this step, financial institutions can calculate the effects that each scenario can have on the performance. This process is done outside of scenario building. When calculations of the effects of scenarios are complete, a financial institution might opt to tweak the scenarios to be more or less severe – possibly depending on the outcome of the institutions' performance.

Reflection

As said before, in practice this process can be very complex. Still, the 5 (theoretical) steps we just demonstrated can be easily identified within institutions that build scenarios. Sadly, the downsides of this approach mentioned earlier are also clearly visible. First, in this process, the downsides of using only experts can be noticed throughout the steps. We are limiting the number of factors in our analysis and assign values to scenarios based on expert reasoning. Also, it is in the nature of experts (people in general) to have biases and outcomes will thus likely differ, based on who is asked the questions. There exist many possibilities to envision a world in which people are asked about their idea of (for example) a state of anti-EU sentiment. As our second main plea against traditional scenario planning, not being able to focus on a range limits the number of uncertain factors in the analysis. Traditional scenario planning has a focus on qualitative envisioning of outcomes. It is not easy to focus on ranges or outcomes spaces. Traditional scenario planning steers us towards a choice: in our example, we have made two choices (and therefore there are two key uncertainties). Thus, we have limited in the number of uncertain factors in our analysis. Finally, the production of these scenarios is not well-traceable. The scenarios will surely be documented by the experts and decision makers that have gone through the process, but as we have gone through the process ourselves, it is easy to see a lot of variability is possible in generating scenarios. This thus does not allow financial authorities to compare institutions. Also, this allows financial institutions to create narratives that perform best, when going back and forth between scenario development and stress testing.

### 4.2.2 Robust Decision Making design

In our pilot of our custom RDM design, let's go through the five steps again, see what is different and improve the process. For this pilot, we have sat down with the department of risk integration of NN Bank. This team is responsible for designing scenarios, managing the calculations in the stress test process and the final report that is audited by the Dutch Central Bank. Do sincerely note that this is a pilot and a proof of concept. The models and analysis are made by one person under supervision and there was not enough expert knowledge integrated to make definitive conclusions about the outcomes of the experiment. However, outcomes regarding the methodology are still valid. There is no reason we can't test a methodology with an imperfect model.

The outcomes below the five steps are the conclusions based on going through the whole System Dynamcis model and through the Exploratory Modelling & Analysis with NN Bank:

Step 1 – Specify system, outcomes of interest and time horizon;

The outcomes of interest and our time horizon are going to remain the same. No amount of simulations or methodology is going to affect legislation or macroeconomic factors that are connected to the balance sheet of NN Bank. However, the definition of the system is heavily under change. Instead of using qualitative measures, we use System Dynamcis to make our assumption about the macroeconomy explicit. We are forced by thinking about relations by noting them down. If we are unsure about the system, we can simply design multiple systems (multiple models for uncertain systems). We can collaborate with experts mentioned previously so they can help us with building the model, but the model can also help experts to think about their assumptions – possibly uncovering biases. Besides experts, we can use a more grounded theoretical approach when defining the system; the main approach chosen in this thesis. We are able to test our own assumptions, those of experts and theoretical assumptions by using validation tests on our System Dynamics model.

Step 2 – Identify external factors that drive change for the system and outcomes of interest;
Mainly, the outcomes of interest are defined by the exposures of the financial institution. For example, when a bank has no foreign stock, there is no need to define the factors of change for foreign stock – assuming there are no indirect effects to other variables from foreign stock change.

When following a traditional System Dynamics approach, we could also reverse step 1 and 2: we can define the system such that we can explain our outcomes of interest. In this approach, we took a traditional scenario planning approach, but used System Dynamics to define the system first.

Step 3 – Categorize factors from (fairly) certain to uncertain;
In our demonstration of the workbench, we made estimations about parameter ranges. Parameter we were uncertain off received a large range. Parameters we were fairly certain off or that did not have a lot of impact on the system received no or a very small range. We are free to have as many parameter ranges as we want. We are not restricted by our thinking as well. We are free to define stories and come up with axes of extremes, but there is no cognitive limit as we don't have to intuitively understand all consequences.

Step 4 – Assess the respective impact of the uncertain factors on the system;
In the traditional scenario approach, we would have to assign values to the different configurations we have designed for the system. Often this is done while simultaneously building the scenarios in step 5, as it is unfeasible to calculate a lot of configurations. In our workbench however, we have previously set the relations between variables and thus do not have to explicitly assess the impacts – this happens when we simulate. On top of that, key uncertainty factors as we have seen on the axes can be represented through policies or by using different models.

Step 5 – Design scenarios based on different configurations of the external factors;
Following step 5 with our custom RDM design deviates more from traditional scenario planning than our previous steps. Our new approach namely allows us to ask questions about scenarios in reverse: when is an outcome of interest (for example unemployment rate) above or below a certain level? As we have seen in our PRIM analysis, relevant factors to include in such a scenario are the capital in the economy, the efficiency of capital and interest rate.

Another method to approach scenario development using Exploratory Modelling & Analysis is by first defining the outcomes of interest and plotting them in a boxplot of KDE graph. It is likely we know beforehand which outcomes of interest are important to a financial institution and can therefore analyse variables that show an undesirable range. For example, when we put interest rate, unemployment rate and housing price in a boxplot, we can assess the ranges of our simulations. We also know that our financial institution will likely experience negative results in the case of (for example) interest rate of 5%, unemployment above 15% and housing price of 10% below current values. In our boxplot (or KDE graph), we can then look at the corresponding values and asses the severity of potential outcomes. The data in the boxplot of housing prices and interest rate might well be in the safe zone, but unemployment might indicate that the likelihood of rising above 15% is 25% of the simulations. In that case, it can be very valuable to explore the underlying factors further, reassess the scenario and test the results in a stress test.

<u>Reflection of practical application</u>

After going through and discussing all the steps with the employees of Risk Integration of NN Bank, it was clear this approach can add value. NN Bank was especially interested in 1) expanding upon expert judgement using a System Dynamics model to test assumptions, 2) being able to search for severe exposures of outcomes in the data and 3) future possibilities to optimise policy measures to counter negative scenarios. We were able to demonstrate and deliver on the first two points by building a macroeconomic scenario generator, but have not yet implemented the decision structure of the financial institution.

True Robust Decision Making should be able to assess the severity of scenarios. With this design, the stress test and the scenario are disjointed. However, moving between the analysis in this thesis and the stress test model of the financial institution does allow for RDM 'light'. We can develop scenarios, calculate their effects and move back to developing scenarios.

<u>Reflection of methodology</u>

By backtracking the steps in our custom RDM design, we can clearly see we have improved or solved our issues with merely traditional scenario planning. First, we eliminate the sole reliance on experts by designing a System Dynamics model. We can explore biases by explicitly noting down our assumptions, take our time to discover all relevant variables and not let ourselves be fooled by unlikely dynamics. We can simulate our assumptions and steer ourselves towards a better model. It must be said though that if this custom RDM design was to be applied again or applied elsewhere, other model than System Dynamics would also be appropriate as long as they are accessible.

Our second issue with traditional scenario building has been solved: we can now focus our attention on a range of outcomes rather than singular outcomes. There is no limit to the number of uncertain factors to attach to our model which also is a great advantage. Our workbench allows us to insert, structure and analyse a broad number of uncertain factors while keeping overview on the process. We now have the ability to work with a very broad number of uncertainties and add more value to uncertainty analysis. Also, it is not less likely we will see

Our new approach also deals with the lack of consistency in traditional scenario planning. Because we first define our assumption about the system in a model, we have a good documentation to present to the auditor. Also, we can support our decisions for choosing certain scenarios quantitatively. When a financial institution for example wants to test a certain scenario, we can assess quantitatively what the potential exposure is and what the driving forces are of that particular scenario.

<u>One step further</u>

To enable a true RDM design, new modules should be added to the System Dynamics model that can track financial institutions and their decisions. If we could complete such a project, we can not only ask questions about ranges of variables, but also incorporate performance of the financial institution. As of writing this, these new modules are being developed by people who know the financial institution. Even though we could not fully finish our RDM analysis at this time, we have already contributed to the current process.

The System Dynamics model, based on Yamaguchi (2013), that we have adopted for the Dutch macroeconomy has been used to assess theoretical links between key performance indicators. For example, what patterns occur in the economy with a shift in interest rates or shocks in unemployment? We have not shown the application in the thesis as this function is not our goal, but stakeholders have shown great interest in testing assumptions with the help of a model. Even when explained the theoretical nature of the model and the possible inaccuracies of prediction, the trends that could be deduced are helpful when accounting for variable change in scenario development. We are quite sure that the System Dynamics model cannot be used for accurate prediction, but at the same time it should display the theoretical relations correctly. It thus can be used for detecting trends.

The RDM module we build serves a different purpose. First, it is a step towards a true RDM approach in financial institutions – a proof of concept. It serves to let people become familiar with the types of questions and frames in RDM. When for example the stakeholders were asked to give input for the EMA simulations, questions where phrases based on causality and focussed on one variable. This is very typical when first coming into contact with RDM. When we see a model, we tend to think chronologically: 'what would happen to unemployment with negative interest rates?' In RDM however, questions should be phrased such that we inspect conditions for a certain outcome: 'in what conditions is unemployment high/low' or as a follow-up question 'what are the vulnerabilities of a driver, policy or outcome?' This line of reasoning is very different from typical System Dynamics reasoning and takes getting used to. This new way of thinking was not being helped by the custom RDM design. It is easier to overcome this hurdle when such questions can be phrased about policy decisions and impact rather than economic variables. With future expansions to the model in the making, this hopefully will not pose to be an obstacle for next iterations of RDM in financial institutions.

# 5 – Conclusion

The main question we set out to answer was the following:

*How can we design scenario building methodology to improve the quality and reliability of scenarios used for stress testing in financial institutions?*

We have answered this question by introducing a custom Robust Decision Making design of scenario generation. We have done this by first developing a System Dynamics model of the Dutch macroeconomy using the sub-questions:

1. How can we translate macroeconomic theorems to a working model of the Dutch economy?
2. What are the drivers forces and interaction of variables in the Dutch economy that connect to the performance of financial institutions?

We have answered these questions by developing a macroeconomic framework based on a mix of Keynesian and Neoclassical economics and with the help of our stakeholder. To answer the first question, have used the work of Naastepad (2002) and Yamaguchi (2013) to define macroeconomic concepts and translate them into a System Dynamics model (Naastepad, 2002; Yamaguchi, 2013). For the second question, we worked together with NN Bank to define the driving forces important to their performance.

The second part of the thesis contained the analysis. We used the following questions to guide us:

3. What are the main uncertainties in our model of the Dutch macroeconomy?
4. What patterns can be discovered in this range of uncertainty?
5. How can we structure the output of these analyses to usable input for the scenario building process and stress tests?

We have defined the main uncertainties in sub-question 3 as the ranges and values we could not accurately determine when simulating the economy. We have used the uncertainty framework of Kwakkel (2010) and Walker et al. (2013) to identify these uncertainties (Kwakkel et al., 2010; Walker et al., 2013). Sub-question 4 was answered by performing Exploratory Modelling & Analysis. We visualised the output and transformed the data to make quantitative decisions on what scenarios to explore. For the final sub-question, we applied the Prison Rule Induction Method algorithm to sort scenarios and discover sensitivities.

With this method introduced, we performed a pilot of traditional scenario building and compared it to our new custom RDM design. The issues and critiques of traditional scenario planning we set out to solve were the following:

1. Relying on expert knowledge for uncertainty projections is faulty because:
    - Experts are intrinsically biased;

    - Due to limited cognitive capacity, one person cannot take into account all variables at play when developing a scenario;
    - The values assigned to cases are chosen arbitrarily and unlikely dynamics can be left out of the picture;
2. Scenario design should focus on a range of forces because:
    - Decision makers (humans) have limited cognitive capabilities and therefore can only focus on a limited number of scenarios;
        - Certain scenarios will thus be neglected;
        - The amount of uncertainty in an analysis is therefore also limited;
3. The production of scenarios should be well-traceable because:
    - When offered too much freedom, it is possible to pick scenarios that have a beneficial outcome for the financial institution;
    - Regulators should be able to accurately compare institutions and thus design fitting measures for the future.

We found out that our new method could deal with all the criticism: 1) our custom RDM approach did not solely rely on expert judgement as we had a System Dynamics model to base our system on. By making assumptions explicitly we can test expert opinion and by defining the system before simulation we can assign sensible values to scenario outcomes. 2) the analysis and exploration of economic forces was performed in a range, not singular outcomes. We visualised the ranges and could see the ranges of our macroeconomic model. 3) finally, we could make qualitative decisions, based on quantitative data. We did not pick scenarios, but let the model present them to us based on performance and importance.

On a practical level, the new methodology also was embraced by the stakeholder, NN Bank. They rated the experiences with the custom Robust Decision Making design as positive and more insightful compared to using solely traditional scenario planning. NN Bank also showed interest to expand the model and analysis to include the performance of the financial institution, thereby becoming a full Robust Decision Making design. As of September 2017, this full application of is being designed.

This research serves as proof that we can solve the criticism about scenario planning in financial institutions by using this new approach in conjunction with current methodology. This thesis also can serve as a basis/template for macroeconomic model building and RDM analysis for financial institutions or other institutions that can be connected to the model. We have explained System Dynamics modelling, basic macroeconomics and the basic setup of the Exploratory Modelling & Analysis workbench in plain and simple language so that researchers in any field may understand it. By documenting all the steps on the way, we have explicably created a document to reflect and work for new researchers in the field.

# 6 - Discussion

With moderate certainty, we can say that this approach contributes to building scenarios for stress testing – as we only applied this approach to one organisation. We established previously this thesis would be considered a success when we can contribute or provide an improvement to the current method. After the pilot comparison, the stakeholders in NN Bank agreed the method contributed to the current design. They also expressed great interest to implement RDM further. As we cannot say this thesis contributes to strengthening the economic system directly, we can say that outcomes of this research can be used as discussion point for future legislation. With modules being added to the current model, we see the potential for contributing to stress testing growing. Also, we must strafe from our original position and idea to build/test financial institutions using this method. This is not because of the limitations of this approach, but due to the rules and establishment already in place. Seeing the stress testing procedures up close and inspecting the dialogue between the Dutch Central Bank and financial institutions, we think it is unlikely to insert new methodology easy – the part of the stress test itself. As stated before, we are able to adopt new methods. However, this does not mean that there are unspoken approaches and guides that financial institutions follow – and thus the Dutch Central Bank is used to seeing. Applying RDM methodology would serve as an addition to stress testing and the design of the scenarios themselves, but likely won't be accepted as stress tests on their own.

The position and goal that has not changed is the opportunity to create a general applicable and open RDM module for financial institutions. The application could be used and managed by the Dutch Central Bank. As we - as well as our stakeholders - believe in the addition of a RDM approach, there is chance to apply this method in a broader framework. When just one financial institution would adopt this approach, it can be considered a novelty. No doubt the financial authorities will applaud the effort, but that would hardly be worth the effort in the bigger picture of the economic system. If work, models and design of RDM schemes would be shared in the open, a public domain can be created. As said before, there are plenty of reasons why this would be a smart idea and that it would solve a lot of problems: 1) comparability of financial institutions, 2) data-fitting of stress test input/results, 3) inconsistent macroeconomic outlooks, 4) financial exposure flaws and 5) a restricted-dimensional view of the economy, risk and uncertainty. However, when a method proves to have theoretical benefits, it does not automatically mean it can or will be adapted.

As for the model building itself, there will always exist the chance of mistakes; in the formulation of relations, simulations, analysis and more. We tried to capture as many mistakes as possible by reviewing the model on many separate occasions and apply various testing methodologies. There is however one catch to using models in general when simulating crisis conditions. Even if our behaviour reproduction tests would have been perfect, the model cannot be expected to accurately capture crisis behaviour. It is the very nature of a crisis to go beyond normal relations and expectations, thereby changing correlations and causalities. This limitation does not take away the benefits of using this methodology, but does warn us about putting too much fate in modelling in general.

## 6.1 Ethics

To comply with thesis and reference standards, we should discuss the ethical standards and implications of this research. We will discuss the following subjects that may apply to the context of this thesis:

- Intellectual property
- Multiple roles of the researcher
- Confidentiality and privacy

By shortly covering these topics, the reader can get a nuanced insight about the research process. Also, this provides some reflection for the author.

### 6.1.1 Intellectual property

It is important to take credit for the work actually performed and not for the work of others. We have referenced the works of others in this thesis, but we can again spend extra time to explicitly state what we used. First, we in large parts used macroeconomic models developed by Yamaguchi (2013) to base our macroeconomic modules on. We have first removed much structure that was not relevant or could not be validated properly. Secondly, we added our own interpretation of the Dutch macroeconomy by changing decision structures and adding real values. With the help of the lectures of Naastepad (2002) we were able to find rational for the choices and structure in Yamaguchi (2013), as macroeconomic assumptions were not always explicit. In any case, we owe very much to the work of Yamaguchi (2013) and Naastepad (2002).

With regard to Robust Decision Making, our main inspiration was Walker et al. (2013) and Kwakkel & Pruyt (2013). We were immediately mesmerised by the application and implications of both articles. It can be said that those two articles propelled the author to write about Robust Decision Making. Also during the writing of the thesis, authors of both articles helped directly with the final product.

During the analysis in the thesis, we mainly used the EMA Workbench, developed by J.H. Kwakkel. We would advise everybody who reads this to go to the Github page of J.H. Kwakkel and find more about the EMA Workbench (link: [https://github.com/quaquel](https://github.com/quaquel)). The workbench is open source and can be freely downloaded, alongside Jupyter Notebook Python 3.6 or any other version.

Finally, when it comes to the use of this thesis, we would invite anyone to use, copy or modify the model, code or any other products and findings. We would happily share the results and source codes directly. It is the authors opinion that being protective about your work is a brake on academic progress and learning. We can see this when comparing scientific fields. If we for example compare System Dynamics to programming, we see stark differences in open platforms and learning. Test this for yourself and try to find free to use System Dynamics models about simple processes like fish in the sea or cars in a city – it is nowhere to be found. Also, when you ask authors directly if you can use their models, rejection often follows (we tried this numerous times). Instead of building upon each other, we had to recreate all System Dynamics models from papers instead of receiving the source code. This delayed the thesis for months. In programming, code is often shared in the open so people can learn from each other, but it also speeds up general progression. We would like to do the same thing and share the System Dynamics model with anyone who asks.

### 6.1.2 Multiple roles of the researcher

During the writing of this thesis, the author was both a student at the Radboud University Nijmegen and Delft University of Technology, but also an intern at NN Bank. In such a situation, it is possible that the interests of involved parties conflict. In this case however, this was not the case. This partially had to do with the nature of the thesis: 1) the method has never been executed in a financial institution in this manner and 2) the model did not require confidential information. Regarding the first point, there was no standard practice to follow and the author was left free to create a new design. There was thus no force upon the author to do things a certain way. About the second point, because there was no confidential or banking information used in the scenario design, results can be freely published. In summary, the professional performance of the author or scientific findings have not been impaired by any relationships with financial institution or university. All relations have positively impacted the thesis.

### 6.1.3 Confidentiality and privacy

As already touched upon in the multiple roles a researcher can have, this thesis does not contain any information of NN Bank. All information used was gathered from statistical bureaus. The information that was gathered from the bank was used to be able to generate the correct outcomes in the macroeconomic model. There are thus no confidentiality conflicts in sight. Regarding the code and workbench used in the thesis, all the code is open-source and can be used and distributed freely.

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Walker, W., Marchau, V. A. W. J., & Swanson, D. (2010). Addressing deep uncertainty using adaptive policies: Introduction to section 2. *Technological Forecasting and Social Change*, *77*(6), 917–923. https://doi.org/10.1016/j.techfore.2010.04.004

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# Appendix

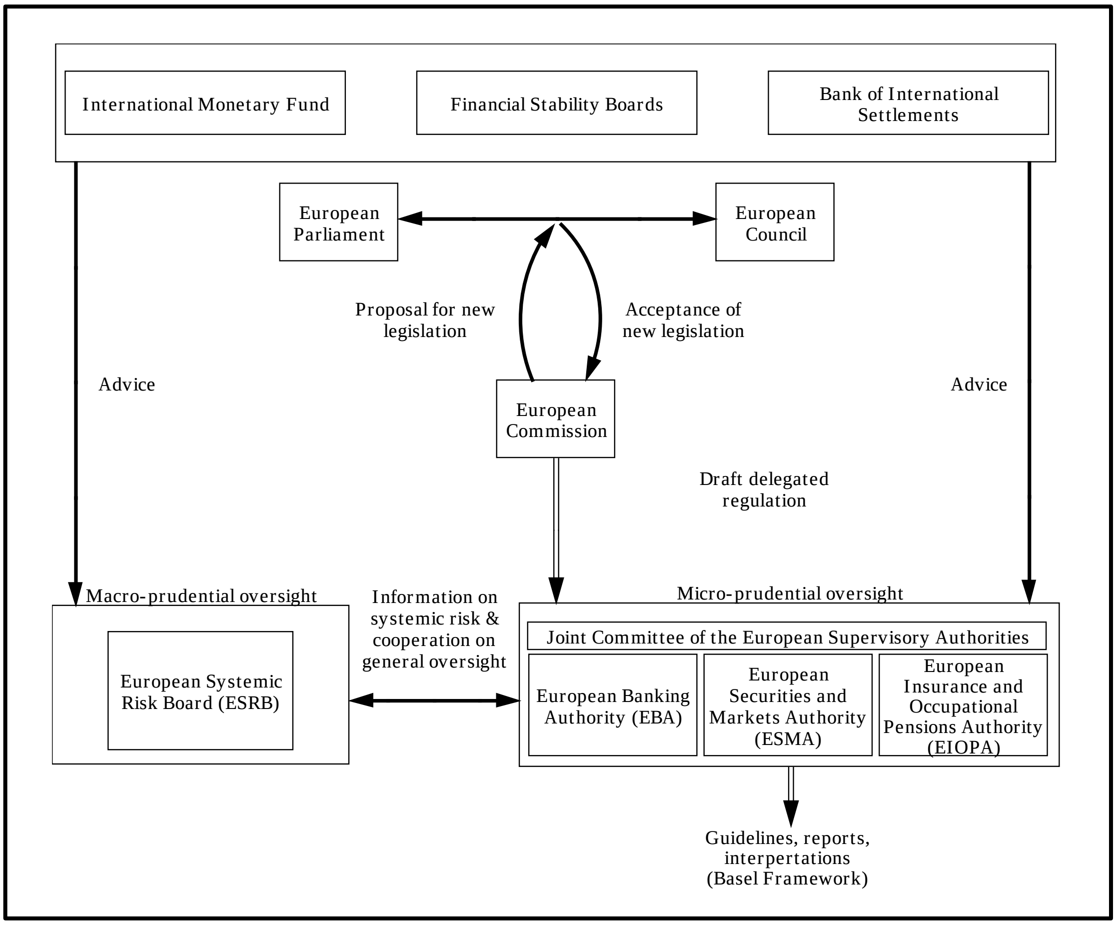
## A. Legal framework and the stress test

During and after the financial crisis, more rules and regulations were made so that banks have to meet stricter requirements to continue operations (Basel Committee on Banking Supervision, 2009; Burrows et al., 2012). To illustrate, banks must pass a multitude of stress tests to calculate how much economic volatility they can take. When the standards of passing these tests are (repeatedly) not met, the European Central Bank or government in question can take possession of assets owned by the offender in question or take other measures deemed appropriate (European Banking Authority, 2016).

The rules that the banking industry must abide by is received from the Bank of International Settlements (BIS). This framework for banking is called Basel – the name stems from the city in Switzerland where the BIS is located. The framework exists to (1) improve the banking sector's ability to absorb shocks arising from financial and economic stress, (2) improve risk management and governance of financial institutions and (3) strengthen banks' transparency and disclosures (BIS, 2011). The framework offered by the BIS is further specified by the European Banking Authority (EBA) and the European Commission in legislative format.

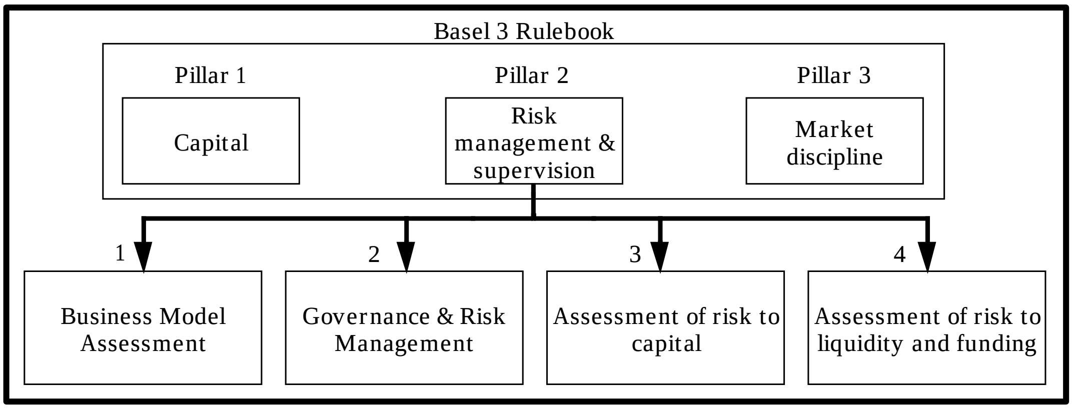
To get an intuitive feel of where new legislation and rules are being created and who supervises whom, we can use the following visual representation that gives an overview of the entire EU-wide financial legislative body[33]:

[33] Based on EY Prudential regulatory report.




The Basel framework, which banks must adhere to, is organized in three pillars: (1) capital, (2) risk management & supervision and (3) market discipline. The first pillar gives minimum capital requirements to continue operations and how to calculate the requirements. The second pillar is concerned with risk measures and is the focus field of this research. The final pillar consists of rules about what to disclose to consumers and transparency. For a visualization and better understanding pillar 2, please consider the following figure[34]:

[34] Based on EY Prudential regulatory report.




In the section of risk management & supervision, there are two main goals. The first and second component are aimed at the institutions and its management who should have governance control measures and a sound risk profile. The third and fourth component set the rules for measuring risk assessments, including stress testing and the risk an institution can pose to the financial system (EBA, 2014). Overall, the risk management & supervision control is done holistically in the Supervisory Review and Evaluation Process (SREP). The SREP is the assessment of the bank (within pillar 2 as in the previous figure), based on capital and liquidity planning, peer comparisons and the macro environment of the bank (European Banking Authority & European Systemic Risk Board, 2016). A holistic approach is chosen because the business model and governance cannot be separated from performance on liquidity or capital measures – how management structures the bank and sets the risk appetite will often determine performance on liquidity and capital robustness. The SREP has a principle based design and is applicable to all credit institutions.

## B. MSc programme Engineering and Policy Analysis: TU Delft

To gather the required knowledge and skill to do the analysis proposed in this thesis, the author will follow two courses at the technical university in Delft (TU Delft). Both courses are from the master program Engineering and Policy Analysis (EPA). The first course is Advanced System Dynamics, taught by Dr. E. Pruyt. This course is meant to deepen the knowledge with respect to System Dynamics. Special attention is given to data testing, formal model analysis and integrating simulation methods. This serves as a first step to learn the author how to connect System Dynamics models to databases and translate models to other computer programming languages. Model-Based Decision-Making is taught by Jan Kwakkel. This course is meant to strengthen the authors' understanding of Robust Decision making and perform statistical analyses with the datasets generated from a model.

## C. NN

The model will be from the perspective of NN Bank (previously known as Nationale-Nederlanden Bank). NN Bank is a part of NN Group; a financial service company active in the markets of insurance, reinsurance, mortgages and more. The business unit NN bank is concerned with savings, investment and mortgages and borrowing.

The reason for cooperation stems from an inside request to build a stress testing model in System Dynamics software. This is a perfect opportunity to research stress testing models and report to the System Dynamics community the lessons learned and potential guidelines found in this experience. NN Bank had already been preparing for this assignment; there is a System Dynamics-team already active within the bank. There will therefore be multiple specialists working on different parts of the model. Thus, some of the needed information to build a model will be readily available and the client/stakeholder (NN) knows the boundaries of the model. Having a team can greatly reduce the time needed to research the bank itself for relevant information in the model.

## D. Translation of economic to System Dynamics variables

**Exponents & Sensitivities**

| | |
|---|---|
| Exponent on labour | It shows the relation between two or more inputs in the economy. In the case of our model, the amount of output that can be produced by labour, capital and their relation on the initial status is given. Thus, the components act as output elasticities of labour and capital in our model. |
| Exponent on Capital | It shows the relation between two or more inputs in the economy. In the case of our model, the amount of output that can be produced by labour, capital and their relation on the initial status is given. Thus, the components act as output elasticities of labour and capital in our model. |
| Interest Sensitivity | Amount of desired capital for producers, based on interest rates |
| labour Market Flexibility | How desired labour is influenced by the GDP-gap ratio |
| labour Ratio Elasticity (Effect on Wage) | Wage development through labour rate |
| Money Ratio Elasticity (Effect on Interest Rate) | the level of output that an economy can produce at a constant inflation rate. Although an economy can temporarily produce more than its potential level of output, that comes at the cost of rising inflation. Potential output depends on the capital stock, the potential labour force, the non-accelerating inflation rate of unemployment (NAIRU), and the level of labour efficiency (exponent on labour). |
| Output Ratio Elasticity (Effect on Price) | strength of output gap on desired price |
| Price Elasticity of Consumption | how much consumption is added per price |
| Weight of Inventory Ratio | high number is production ratio more important, low inventory ratio. Determine desired price |

**Initials**

| | |
|---|---|
| Initial Potential GDP | GDP with full labour in economy |
| Initial Capital (real) | Production capital that producers can work with |
| Initial Discount Rate | interest rate applied to the loans of reserved fund at the central bank by commercial banks |
| Interest Rate | Cost of lending money. Also serves as threshold to invest |
| Initial Price level | Converts the physical units (Euro) to the nominal units for comparison in the economy (RealEuro). |
| Initial Wage Rate | Wages before development economic factors |
| Base Expenditure (Expenditure of Government) | Starting point of expenditures government (with revenue based expenditures) |

**Economic factors**

| | |
|---|---|
| Basic Consumption | AKA; Autonomous consumption. Consumption in economy when there is no production |
| Marginal Propensity to Consume | Consumption based on a relative price elasticity of consumption |
| Cost-push (Wage) Coefficient | Strength of price level change in the economy when wages rise. It is the change in price as effect of the delta in wages. |
| Depreciation Rate | How fast capital (for producer GDP creation) declines |
| Normal Inventory Coverage | To avoid shortage under equilibrium production or above sales, an inventory coverage ups the desired inventory next timestep |

# E. Parameters System Dynamics model for EMA

| Initials | value | | source | formula |
|---|---|---|---|---|
| **Initial Aggregate Demand Forecasting** | x | | | potential GDP |
| **Initial Aggregate Demand Forecasting (Long-run)** | x | | | potential GDP |
| **Initial Autonomous Consumption** | 2.39912E+11 | | | Consumption = basis+Y*margin >>>> Basis = consumptie-(margin*Y) |
| **Initial Capital (real)** | 1.58094E+12 | | CBS statline | GDP*(225/100) >> Because capital in the Dutch economy is 225% of the GDP |
| **Initial Capital under Construction** | x | | | Depreciation (real)*Construction Period |
| **Initial Cash (Consumer)** | 0 | | | |
| **Initial Deposits (Consumer)** | 0 | | | |
| **Initial Employed Labour** | 8461000 | | CBS statline | |
| **Initial Governmental Expenditure** | 1.9818E+11 | | CBS statline | |
| **Initial Houses** | 7641323 | | CBS statline | |
| **Initial Houses under Construction** | x | | | New Construction * Construction Time |
| **Initial Housing Price** | 330923 | | http://www.gemiddeldehuizenprijs.nl/gemiddeldehuizenprijs/index.php?do=NL&province=&city=&postalcode=&type=all | |
| **Initial Inventory (real)** | 78218000000 | | CBS statline | |
| **Initial Labour Fource** | 8966000 | | CBS statline | |
| **Initial Population** | 16979120 | | CBS statline | |
| **Initial Potential GDP** | 720000000000 760000000000 | - | Uncertain factor: added percentage rate on top of current GDP of 702 billion | |
| **Initial Price level** | 1 | | | Index value starts at 1 |
| **Initial Wage Rate** | 22000 - 30000 | 1st | http://www.minimumloon2017.com/gemiddeld-inkomen/ | |
| | | 2nd source | http://www.gemiddeld-inkomen.nl/modaal-inkomen-2017/ & | |
| **Initial Unemployed Labour** | 505000 | | CBS statline | |
| **Initial Additional Income** | 69331000000 | | | Income-wages |
| **Wages total** | 2.67717E+11 | | CBS statline | |
| **GDP** | 7.02641E+11 | | CBS statline | |
| **Consumption** | 3.10692E+11 | | CBS statline | |

| | | |
|---|---|---|
| **Income** | 3.37048E+11 | CBS statline |

# F. Data used for reference mode

All presented data comes from http://statline.cbs.nl/Statweb/?LA=nl. Some data is transformed for calculates, hence the difference between data from CBS and data used

## GDP

| **Data from CBS** | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Bbp vanuit | Waarde in | Nationale | Totaal | Totaal | mln euro | 303068 | 319952 | 341310 | 365474 | 392667 | 418785 | 444946 | 460919 | 472400 | 482425 | 498254 | 528635 | 559156 | 584025 | 572284 | 578699 | 588025 | 583218 | 582930 | 591123 | 603604 |
| Bbp vanuit | Waarde in | Nationale | Consumpti | Totaal | mln euro | 231972 | 242459 | 256837 | 275037 | 293851 | 315550 | 336117 | 355925 | 366956 | 374059 | 384184 | 404033 | 422671 | 441166 | 442934 | 449742 | 456097 | 459631 | 463903 | 468668 | 473221 |
| Bbp vanuit | Waarde in | Nationale | Consumpti | Huishoude | mln euro | 159182 | 169612 | 180577 | 194419 | 208979 | 223978 | 236585 | 246821 | 251045 | 256409 | 262462 | 268541 | 279921 | 288516 | 279579 | 282510 | 288939 | 289756 | 293645 | 296682 | 301839 |
| Bbp vanuit | Waarde in | Nationale | Consumpti | Overheid | mln euro | 72790 | 72847 | 76260 | 80618 | 84872 | 91572 | 99532 | 109104 | 115911 | 117650 | 121722 | 135492 | 142750 | 152650 | 163355 | 167232 | 167158 | 169875 | 170258 | 171986 | 171382 |
| Bbp vanuit | Waarde in | Nationale | Bruto inve | Totaal | mln euro | 70136 | 75223 | 81382 | 87457 | 97250 | 102708 | 107026 | 105570 | 105763 | 107466 | 112372 | 123170 | 133745 | 142414 | 131554 | 124649 | 130402 | 121928 | 117107 | 119530 | 131431 |
| Bbp vanuit | Waarde in | Nationale | Bruto inve | Bedrijven e | mln euro | 58180 | 62195 | 68217 | 73680 | 81598 | 85888 | 88420 | 85071 | 84413 | 87105 | 92025 | 100426 | 110027 | 116968 | 104976 | 98442 | 104688 | 97770 | 93350 | 96232 | 107521 |
| Bbp vanuit | Waarde in | Nationale | Bruto inve | Overheid | mln euro | 11956 | 13028 | 13165 | 13777 | 15652 | 16820 | 18606 | 20499 | 21350 | 20361 | 20347 | 22744 | 23718 | 25446 | 26578 | 26207 | 25714 | 24158 | 23757 | 23298 | 23910 |
| Bbp vanuit | Waarde in | Nationale | Veranderir | Veranderir | mln euro | 960 | 2270 | 3091 | 2980 | 1566 | 527 | 1803 | -576 | -319 | 900 | 1698 | 1432 | 2740 | 445 | -2204 | 4308 | 1526 | 1659 | 1920 | 2925 | -1048 |
| Bbp vanuit | Waarde in | Uitvoer va | Totaal | Totaal | mln euro | 187432 | 196551 | 221464 | 232555 | 249900 | 297929 | 304244 | 300413 | 302530 | 332889 | 363466 | 401272 | 430974 | 457913 | 390004 | 454398 | 497347 | 528623 | 535320 | 547415 | 557890 |
| Bbp vanuit | Waarde in | Uitvoer va | Goederen | Goederen | mln euro | 149960 | 156285 | 174871 | 182786 | 194580 | 237003 | 239991 | 234447 | 237033 | 263897 | 290071 | 324943 | 348357 | 367956 | 304198 | 360296 | 398744 | 425408 | 427390 | 429655 | 427415 |
| Bbp vanuit | Waarde in | Uitvoer va | Diensten | Diensten | mln euro | 37472 | 40266 | 46593 | 49769 | 55320 | 60926 | 64253 | 65966 | 65497 | 68992 | 73395 | 76329 | 82617 | 89957 | 85806 | 94102 | 98603 | 103215 | 107930 | 117760 | 130475 |
| Bbp vanuit | Waarde in | Invoer van | Totaal | Totaal | mln euro | 165159 | 175539 | 197813 | 208714 | 227729 | 268653 | 272494 | 266831 | 268259 | 291375 | 316111 | 350695 | 376850 | 402775 | 344748 | 401585 | 442443 | 466677 | 465502 | 475530 | 484963 |
| Bbp vanuit | Waarde in | Invoer van | Goederen | Goederen | mln euro | 127590 | 135047 | 150703 | 156867 | 169119 | 203270 | 202625 | 194164 | 195243 | 215851 | 236284 | 267349 | 288003 | 307119 | 250982 | 300067 | 333823 | 354312 | 352043 | 353737 | 351268 |
| Bbp vanuit | Waarde in | Invoer van | Diensten | Diensten | mln euro | 37569 | 40492 | 47110 | 51847 | 58610 | 65383 | 69869 | 72667 | 73016 | 75524 | 79827 | 83346 | 88847 | 95656 | 93766 | 101518 | 108620 | 112365 | 113459 | 121793 | 133695 |
| Bbp vanuit | Waarde in | Bruto binn | Bruto binn | Bruto binn | mln euro | 325341 | 340964 | 364961 | 389315 | 414838 | 448061 | 476696 | 494501 | 506671 | 523939 | 545609 | 579212 | 613280 | 639163 | 617540 | 631512 | 642929 | 645164 | 652748 | 663008 | 676531 |

| **Data used** | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Consumers | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 1.59E+11 | 1.7E+11 | 1.81E+11 | 1.94E+11 | 2.09E+11 | 2.24E+11 | 2.37E+11 | 2.47E+11 | 2.51E+11 | 2.56E+11 | 2.62E+11 | 2.69E+11 | 2.8E+11 | 2.89E+11 | 2.8E+11 | 2.83E+11 | 2.89E+11 | 2.9E+11 | 2.94E+11 | 2.97E+11 | 3.02E+11 |
| | | | | | | | | | | | | | | | | | | | | |
| Government | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 7.28E+10 | 7.28E+10 | 7.63E+10 | 8.06E+10 | 8.49E+10 | 9.16E+10 | 9.95E+10 | 1.09E+11 | 1.16E+11 | 1.18E+11 | 1.22E+11 | 1.35E+11 | 1.43E+11 | 1.53E+11 | 1.63E+11 | 1.67E+11 | 1.67E+11 | 1.7E+11 | 1.7E+11 | 1.72E+11 | 1.71E+11 |
| | | | | | | | | | | | | | | | | | | | | |
| Investements | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 7.01E+10 | 7.52E+10 | 8.14E+10 | 8.75E+10 | 9.73E+10 | 1.03E+11 | 1.07E+11 | 1.06E+11 | 1.06E+11 | 1.07E+11 | 1.12E+11 | 1.23E+11 | 1.34E+11 | 1.42E+11 | 1.32E+11 | 1.25E+11 | 1.3E+11 | 1.22E+11 | 1.17E+11 | 1.2E+11 | 1.31E+11 |
| | | | | | | | | | | | | | | | | | | | | |
| inventory change | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 9.6E+08 | 2.27E+09 | 3.09E+09 | 2.98E+09 | 1.57E+09 | 5.27E+08 | 1.8E+09 | -5.8E+08 | -3.2E+08 | 9E+08 | 1.7E+09 | 1.43E+09 | 2.74E+09 | 4.45E+08 | -2.2E+09 | 4.31E+09 | 1.53E+09 | 1.66E+09 | 1.92E+09 | 2.93E+09 | -1E+09 |
| | | | | | | | | | | | | | | | | | | | | |
| GDP | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 3.03E+11 | 3.2E+11 | 3.41E+11 | 3.65E+11 | 3.93E+11 | 4.19E+11 | 4.45E+11 | 4.61E+11 | 4.72E+11 | 4.82E+11 | 4.98E+11 | 5.29E+11 | 5.59E+11 | 5.84E+11 | 5.72E+11 | 5.79E+11 | 5.88E+11 | 5.83E+11 | 5.83E+11 | 5.91E+11 | 6.04E+11 |

# Consumption

| **Data from CBS** | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Huishoude | Alternatief | mln euro | 223568 | 231736 | 247467 | 261121 | 275209 | 292633 | 321579 | 336288 | 343375 | 349690 | 355529 | 376410 | 392595 | 403660 | 411055 | 416047 | 423737 | 427884 | 429960 | 431964 | 441418 |
| Huishoude | Vrije / indi | mln euro | 21309 | 19065 | 21369 | 18034 | 14799 | 12931 | 24169 | 21922 | 20008 | 18725 | 15793 | 18312 | 19252 | 15291 | 24239 | 22683 | 23139 | 23705 | 22797 | 20348 | 25389 |

| **Data used** | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Alternative income (bruto) | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 2.24E+11 | 2.32E+11 | 2.47E+11 | 2.61E+11 | 2.75E+11 | 2.93E+11 | 3.22E+11 | 3.36E+11 | 3.43E+11 | 3.5E+11 | 3.56E+11 | 3.76E+11 | 3.93E+11 | 4.04E+11 | 4.11E+11 | 4.16E+11 | 4.24E+11 | 4.28E+11 | 4.3E+11 | 4.32E+11 | 4.41E+11 |
| Consumption expenses (bruto) | | | | | | | | | | | | | | | | | | | | |
| 1.59E+11 | 1.7E+11 | 1.81E+11 | 1.94E+11 | 2.09E+11 | 2.24E+11 | 2.37E+11 | 2.47E+11 | 2.51E+11 | 2.56E+11 | 2.62E+11 | 2.69E+11 | 2.8E+11 | 2.89E+11 | 2.8E+11 | 2.83E+11 | 2.89E+11 | 2.9E+11 | 2.94E+11 | 2.97E+11 | 3.02E+11 |
| Savings | | | | | | | | | | | | | | | | | | | | |
| 2.13E+10 | 1.91E+10 | 2.14E+10 | 1.8E+10 | 1.48E+10 | 1.29E+10 | 2.42E+10 | 2.19E+10 | 2E+10 | 1.87E+10 | 1.58E+10 | 1.83E+10 | 1.93E+10 | 1.53E+10 | 2.42E+10 | 2.27E+10 | 2.31E+10 | 2.37E+10 | 2.28E+10 | 2.03E+10 | 2.54E+10 |
| | | | | | | | | | | | | | | | | | | | | |
| % income of consumption | | | | | | | | | | | | | | | | | | | | |
| 0.712007 | 0.731919 | 0.729701 | 0.744555 | 0.759347 | 0.765389 | 0.735698 | 0.733957 | 0.73111 | 0.733247 | 0.73823 | 0.713427 | 0.713002 | 0.71475 | 0.68015 | 0.679034 | 0.681883 | 0.677184 | 0.682959 | 0.686821 | 0.683794 |
| | | | | | | | | | | | | | | | | | | | | |
| Marg propensity to consume can be: | | | | | | | | | | | | | | | | | | | | |
| | Matching the Distribution of Liquid Financial and Retirement Assets | | | | | | | 19% | | | | | | | | | | | | |
| | or | | | | | | | | | | | | | | | | | | | |
| | Matching the Distribution of Net Wealth | | | | | | | 11% | | | | | | | | | | | | |
| | | | | | | | | | | | | | | | | | | | | |
| 11% | | Autonomic consumption | | | consumption=basis+Y*margin | | | Basis=consumption-(margin*Y) | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 1.35E+11 | 1.44E+11 | 1.53E+11 | 1.66E+11 | 1.79E+11 | 1.92E+11 | 2.01E+11 | 2.1E+11 | 2.13E+11 | 2.18E+11 | 2.23E+11 | 2.27E+11 | 2.37E+11 | 2.44E+11 | 2.34E+11 | 2.37E+11 | 2.42E+11 | 2.43E+11 | 2.46E+11 | 2.49E+11 | 2.53E+11 |
| | | | | | | | | | | | | | | | | | | | | |
| 19% | | autonomic consumption | | | consumption=basis+Y*margin | | | Basis=consumption/(margin*Y) | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 1.17E+11 | 1.26E+11 | 1.34E+11 | 1.45E+11 | 1.57E+11 | 1.68E+11 | 1.75E+11 | 1.83E+11 | 1.86E+11 | 1.9E+11 | 1.95E+11 | 1.97E+11 | 2.05E+11 | 2.12E+11 | 2.01E+11 | 2.03E+11 | 2.08E+11 | 2.08E+11 | 2.12E+11 | 2.15E+11 | 2.18E+11 |
| | | | | | | | | | | | | | | | | | | | | |
| Autonomous consumption delta & index | | | | | | | | | | | | | | | | | | | | |
| Delta | 7.764866 | 6.334562 | 8.533358 | 8.311521 | 7.500712 | 4.01682 | 4.227723 | 1.552623 | 2.256586 | 2.637974 | 0.902014 | 4.211802 | 3.175752 | -5.14851 | 0.974182 | 2.466996 | -0.02694 | 1.727381 | 1.286509 | 1.539868 |
| Index | 107.7649 | 114.5913 | 124.3698 | 134.7068 | 144.8108 | 150.6276 | 156.9957 | 159.4332 | 163.031 | 167.3317 | 168.841 | 175.9523 | 181.5401 | 172.1935 | 173.871 | 178.1604 | 178.1124 | 181.1891 | 183.5201 | 186.346 |
| | | | | | | | | | | | | | | | | | | | | |
| Article has 21%! | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 1.12E+11 | 1.21E+11 | 1.29E+11 | 1.4E+11 | 1.51E+11 | 1.63E+11 | 1.69E+11 | 1.76E+11 | 1.79E+11 | 1.83E+11 | 1.88E+11 | 1.89E+11 | 1.97E+11 | 2.04E+11 | 1.93E+11 | 1.95E+11 | 2E+11 | 2E+11 | 2.03E+11 | 2.06E+11 | 2.09E+11 |

# Wages

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Data from CBS** | | | | | | | | | | | | | | | | | | | | |
| Lonen | mln | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 138455 | 143731 | 152989 | 154596 | 166229 | 178225 | 190976 | 198430 | 202614 | 204707 | 208631 | 218250 | 231327 | 242160 | 245616 | 246542 | 251715 | 253193 | 254034 | 253880 | 261220 |
| | | | | | | | | | | | | | | | | | | | | |
| Real wages | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 1.38455E+11 | 1.43731E+11 | 1.53E+11 | 1.55E+11 | 1.66E+11 | 1.78E+11 | 1.91E+11 | 1.98E+11 | 2.03E+11 | 2.05E+11 | 2.09E+11 | 2.18E+11 | 2.31E+11 | 2.42E+11 | 2.46E+11 | 2.47E+11 | 2.52E+11 | 2.53E+11 | 2.54E+11 | 2.54E+11 | 2.61E+11 |
| | | | | | | | | | | | | | | | | | | | | |
| Income | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 2.23568E+11 | 2.31736E+11 | 2.47E+11 | 2.61E+11 | 2.75E+11 | 2.93E+11 | 3.22E+11 | 3.36E+11 | 3.43E+11 | 3.5E+11 | 3.56E+11 | 3.76E+11 | 3.93E+11 | 4.04E+11 | 4.11E+11 | 4.16E+11 | 4.24E+11 | 4.28E+11 | 4.3E+11 | 4.32E+11 | 4.41E+11 |

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Data used** | | | | | | | | | | | | | | | | | | | | |
| Additional Income | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 85113000000 | 88005000000 | 9.45E+10 | 1.07E+11 | 1.09E+11 | 1.14E+11 | 1.31E+11 | 1.38E+11 | 1.41E+11 | 1.45E+11 | 1.47E+11 | 1.58E+11 | 1.61E+11 | 1.62E+11 | 1.65E+11 | 1.7E+11 | 1.72E+11 | 1.75E+11 | 1.76E+11 | 1.78E+11 | 1.8E+11 |
| | | | | | | | | | | | | | | | | | | | | |
| Additional Income Delta & Index | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| Delta | 3.397835818 | 7.355264 | 12.75112 | 2.304623 | 4.98073 | 14.15548 | 5.555003 | 2.10579 | 2.99941 | 1.320845 | 7.666544 | 1.965099 | 0.14386 | 2.439009 | 2.457703 | 1.484912 | 1.551546 | 0.706963 | 1.226652 | 1.18708 |
| Index | 103.3978358 | 111.003 | 125.1571 | 128.0415 | 134.4189 | 153.4466 | 161.9706 | 165.3813 | 170.3418 | 172.5917 | 185.8236 | 189.4752 | 189.7477 | 194.3757 | 199.1529 | 202.1101 | 205.246 | 206.697 | 209.2324 | 211.7162 |
| | | | | | | | | | | | | | | | | | | | | |
| Inflation with new index | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 2 | 2.1 | 2.2 | 2 | 2.2 | 2.6 | 4.5 | 3.4 | 2.1 | 1.2 | 1.7 | 1.1 | 1.6 | 2.5 | 1.2 | 1.3 | 2.3 | 2.5 | 2.5 | 1 | 0.6 |
| index | 2.1 | 4.3 | 6.3 | 8.5 | 11.1 | 15.6 | 19 | 21.1 | 22.3 | 24 | 25.1 | 26.7 | 29.2 | 30.4 | 31.7 | 34 | 36.5 | 39 | 40 | 40.6 |
| negative idx | 0.979 | 0.957 | 0.937 | 0.915 | 0.889 | 0.844 | 0.81 | 0.789 | 0.777 | 0.76 | 0.749 | 0.733 | 0.708 | 0.696 | 0.683 | 0.66 | 0.635 | 0.61 | 0.6 | 0.594 |
| 85113000000 | 88005000000 | 9.45E+10 | 1.07E+11 | 1.09E+11 | 1.14E+11 | 1.31E+11 | 1.38E+11 | 1.41E+11 | 1.45E+11 | 1.47E+11 | 1.58E+11 | 1.61E+11 | 1.62E+11 | 1.65E+11 | 1.7E+11 | 1.72E+11 | 1.75E+11 | 1.76E+11 | 1.78E+11 | 1.8E+11 |
| 85113000000 | 86156895000 | 9.04E+10 | 9.98E+10 | 9.97E+10 | 1.02E+11 | 1.1E+11 | 1.12E+11 | 1.11E+11 | 1.13E+11 | 1.12E+11 | 1.18E+11 | 1.18E+11 | 1.14E+11 | 1.15E+11 | 1.16E+11 | 1.14E+11 | 1.11E+11 | 1.07E+11 | 1.07E+11 | 1.07E+11 |
| | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| New delta | 1.226481266 | 4.942786 | 10.39477 | -0.09741 | 1.997671 | 8.37708 | 1.302787 | -0.5414 | 1.432879 | -0.89596 | 6.108213 | -0.21306 | -3.27169 | 0.702755 | 0.543982 | -1.93259 | -2.2951 | -3.25788 | -0.4328 | 0.175209 |
| New index | 101.2264813 | 106.2299 | 117.2722 | 117.158 | 119.4984 | 129.5089 | 131.1962 | 130.4859 | 132.3556 | 131.1697 | 139.1818 | 138.8853 | 134.3414 | 135.2855 | 136.0214 | 133.3927 | 130.3312 | 126.0852 | 125.5395 | 125.7594 |
| | | | | | 2000 to 2001 transition euro | | | | | Growth US investements & international treaties | | | | | | | | | | |
| | | | | | | | | | | https://www.cpb.nl/persbericht/329092/economische-groei-trekt-stevig-aan | | | | | | | | | | |

## Housing

| | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Data CBS** | | | | | | | | | | | | | | | | | | | | | | |
| **Bestaande koopwoningen; gemiddelde verkoopprijzen, regio** | | | | | | | | | | | | | | | | | | | | | | |
| **Onderwerpe** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **Gemiddelde** | **verkoopprijs** |
| **Perioden** | **1995** | **1996** | **1997** | **1998** | **1999** | **2000** | **2001** | **2002** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** | |
| **Regio's** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | **euro** | |
| **Nederland** | 93750 | 102607 | 113163 | 124540 | 144778 | 172050 | 188397 | 199752 | 204829 | 212723 | 222706 | 235843 | 248325 | 254918 | 238259 | 239530 | 240059 | 226661 | 213353 | 222218 | 230194 | |
| **Totaal huish** | **x 1 000** | 6469 | 6518 | 6581 | 6656 | 6745 | 6801 | 6867 | 6934 | 6996 | 7049 | 7091 | 7146 | 7191 | 7242 | 7313 | 7386 | 7444 | 7513 | 7569 | 7590 | 7665 |

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Data used** | | | | | | | | | | | | | | | | | | | | |
| Housing price | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 93750 | 102607 | 113163 | 124540 | 144778 | 172050 | 188397 | 199752 | 204829 | 212723 | 222706 | 235843 | 248325 | 254918 | 238259 | 239530 | 240059 | 226661 | 213353 | 222218 | 230194 |
| | | | | | | | | | | | | | | | | | | | | |
| Delta | 2010=100 | | | | | | | | | | | | | | | | | | | |
| 39.13915 | 42.83681 | 47.24377 | 51.99349 | 60.44253 | 71.82816 | 78.65278 | 83.39331 | 85.51288 | 88.8085 | 92.97625 | 98.46074 | 103.6718 | 106.4242 | 99.46938 | 100 | 100.2208 | 94.6274 | 89.07152 | 92.77251 | 96.10237 |
| | | | | | | | | | | | | | | | | | | | | |
| % 1995 begin | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 8.447467 | 9.447467 | 10.2878 | 10.05364 | 16.2502 | 18.83712 | 9.501308 | 6.027166 | 2.541652 | 3.853946 | 4.692958 | 5.898808 | 5.292504 | 2.654988 | -6.53504 | 0.533453 | 0.220849 | -5.58113 | -5.87132 | 4.155086 | 3.589268 |
| | | | | | | | | | | | | | | | | | | | | |
| Households | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 6469000 | 6518000 | 6581000 | 6656000 | 6745000 | 6801000 | 6867000 | 6934000 | 6996000 | 7049000 | 7091000 | 7146000 | 7191000 | 7242000 | 7313000 | 7386000 | 7444000 | 7513000 | 7569000 | 7590000 | 7665000 |

# Population

| | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Data CBS** | | | | | | | | | | | | | | | | | | | | | | | | |
| **Bevolking; kerncijfers** | | | | | | | | | | | | | | | | | | | | | | | | |
| **Onderwerpe** | **Onderwerpe** | **Onderwerpe** | **Perioden** | **1995** | **1996** | **1997** | **1998** | **1999** | **2000** | **2001** | **2002** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** |
| **Bevolking n** | **Bevolking n** | **Totale bevol** | **aantal** | 15424122 | 15493889 | 15567107 | 15654192 | 15760225 | 15863950 | 15987075 | 16105285 | 16192572 | 16258032 | 16305526 | 16334210 | 16357992 | 16405399 | 16485787 | 16574989 | 16655799 | 16730348 | 16779575 | 16829289 | 16900726 |
| **Bevolking n** | **Bevolking n** | **Jonger dan** | **aantal** | 3760155 | 3771609 | 3787364 | 3809170 | 3839842 | 3873008 | 3908053 | 3940636 | 3968999 | 3987557 | 3987957 | 3975626 | 3957103 | 3940450 | 3933585 | 3928334 | 3913819 | 3894754 | 3870773 | 3846040 | 3828059 |
| **Bevolking n** | **Bevolking n** | **20 tot 40 jaa** | **aantal** | 4981153 | 4938040 | 4893195 | 4848625 | 4809644 | 4761504 | 4727104 | 4685727 | 4624170 | 4548566 | 4467783 | 4389840 | 4319136 | 4267063 | 4233861 | 4192772 | 4162599 | 4141893 | 4120358 | 4117652 | 4134447 |
| **Bevolking n** | **Bevolking n** | **40 tot 65 jaa** | **aantal** | 4649238 | 4723368 | 4802709 | 4886678 | 4979805 | 5076996 | 5177417 | 5280208 | 5378947 | 5470755 | 5561116 | 5638285 | 5713401 | 5783060 | 5846526 | 5915555 | 5984435 | 5977333 | 5964099 | 5946573 | 5930535 |
| **Bevolking n** | **Bevolking n** | **65 tot 80 jaa** | **aantal** | 1557819 | 1579397 | 1596420 | 1616527 | 1634782 | 1652103 | 1657864 | 1667107 | 1676486 | 1692856 | 1715097 | 1743443 | 1767510 | 1799337 | 1840607 | 1890334 | 1927399 | 2030353 | 2121525 | 2201935 | 2272709 |
| **Bevolking n** | **Bevolking n** | **80 jaar of ou** | **aantal** | 475757 | 481475 | 487419 | 493192 | 496152 | 500339 | 516637 | 531607 | 543970 | 558298 | 573573 | 587016 | 600842 | 615489 | 631208 | 647994 | 667547 | 686015 | 702820 | 717089 | 734976 |
| **Bevolking n** | **Bevolking n** | **Jonger dan** | **%** | 24.4 | 24.3 | 24.3 | 24.3 | 24.4 | 24.4 | 24.4 | 24.5 | 24.5 | 24.5 | 24.5 | 24.3 | 24.2 | 24 | 23.9 | 23.7 | 23.5 | 23.3 | 23.1 | 22.9 | 22.7 |
| **Bevolking n** | **Bevolking n** | **20 tot 40 jaa** | **%** | 32.3 | 31.9 | 31.4 | 31 | 30.5 | 30 | 29.6 | 29.1 | 28.6 | 28 | 27.4 | 26.9 | 26.4 | 26 | 25.7 | 25.3 | 25 | 24.8 | 24.6 | 24.5 | 24.5 |
| **Bevolking n** | **Bevolking n** | **40 tot 65 jaa** | **%** | 30.1 | 30.5 | 30.9 | 31.2 | 31.6 | 32 | 32.4 | 32.8 | 33.2 | 33.6 | 34.1 | 34.5 | 34.9 | 35.3 | 35.5 | 35.7 | 35.9 | 35.7 | 35.5 | 35.3 | 35.1 |
| **Bevolking n** | **Bevolking n** | **65 tot 80 jaa** | **%** | 10.1 | 10.2 | 10.3 | 10.3 | 10.4 | 10.4 | 10.4 | 10.4 | 10.4 | 10.4 | 10.5 | 10.7 | 10.8 | 11 | 11.2 | 11.4 | 11.6 | 12.1 | 12.6 | 13.1 | 13.4 |
| **Bevolking n** | **Bevolking n** | **80 jaar of ou** | **%** | 3.1 | 3.1 | 3.1 | 3.2 | 3.1 | 3.2 | 3.2 | 3.3 | 3.4 | 3.4 | 3.5 | 3.6 | 3.7 | 3.8 | 3.8 | 3.9 | 4 | 4.1 | 4.2 | 4.3 | 4.3 |
| **Bevolking n** | **Demografisc** | **Totale druk** | **%** | 60.2 | 60.4 | 60.6 | 60.8 | 61 | 61.2 | 61.4 | 61.6 | 61.9 | 62.3 | 62.6 | 62.9 | 63 | 63.2 | 63.5 | 64 | 64.1 | 65.3 | 66.4 | 67.2 | 67.9 |
| **Bevolking n** | **Demografisc** | **Groene druk** | **%** | 39 | 39 | 39.1 | 39.1 | 39.2 | 39.4 | 39.5 | 39.5 | 39.7 | 39.8 | 39.8 | 39.6 | 39.4 | 39.2 | 39 | 38.9 | 38.6 | 38.5 | 38.4 | 38.2 | 38 |
| **Bevolking n** | **Demografisc** | **Grijze druk** | **%** | 21.1 | 21.3 | 21.5 | 21.7 | 21.8 | 21.9 | 22 | 22.1 | 22.2 | 22.5 | 22.8 | 23.2 | 23.6 | 24 | 24.5 | 25.1 | 25.6 | 26.8 | 28 | 29 | 29.9 |
| **Bevolking n** | **Gemiddelde** | **Totale bevol** | **Jaar** | 37.4 | 37.6 | 37.7 | 37.9 | 38 | 38.2 | 38.3 | 38.4 | 38.6 | 38.7 | 39 | 39.2 | 39.5 | 39.7 | 39.9 | 40.1 | 40.3 | 40.6 | 40.8 | 41 | 41.3 |

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Data used** | | | | | | | | | | | | | | | | | | | | |
| **Population** | | | | | | | | | | | | | | | | | | | | |
| **1995** | **1996** | **1997** | **1998** | **1999** | **2000** | **2001** | **2002** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** |
| 15424122 | 15493889 | 15567107 | 15654192 | 15760225 | 15863950 | 15987075 | 16105285 | 16192572 | 16258032 | 16305526 | 16334210 | 16357992 | 16405399 | 16485787 | 16574989 | 16655799 | 16730348 | 16779575 | 16829289 | 16900726 |

# Inflation

| | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Data CBS** | | | | | | | | | | | | | | | | | | | | | | |
| **Inflatie; C** | **Onderwerpe** | **Perioden** | **1995** | **1996** | **1997** | **1998** | **1999** | **2000** | **2001** | **2002** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** |
| | **Inflatie** | **%** | 2 | 2.1 | 2.2 | 2 | 2.2 | 2.6 | 4.5 | 3.4 | 2.1 | 1.2 | 1.7 | 1.1 | 1.6 | 2.5 | 1.2 | 1.3 | 2.3 | 2.5 | 2.5 | 1 | 0.6 |
| | **Inflatie, afge** | **%** | 1.8 | 1.5 | 2 | 1.7 | 1.7 | 2.2 | 3.6 | 3.4 | 1.9 | 0.9 | 1.4 | 1.5 | 1.5 | 2.2 | 0.9 | 1.1 | 2.2 | 2.1 | 1.3 | 0.6 | 0.5 |

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Data used** | | | | | | | | | | | | | | | | | | | | |
| Yearly inflation | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 2 | 2.1 | 2.2 | 2 | 2.2 | 2.6 | 4.5 | 3.4 | 2.1 | 1.2 | 1.7 | 1.1 | 1.6 | 2.5 | 1.2 | 1.3 | 2.3 | 2.5 | 2.5 | 1 | 0.6 |
| | | | | | | | | | | | | | | | | | | | | |
| | | | | | | | | | | | | | | | | | | | | |
| Index | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 1.02 | 1.021 | 1.022 | 1.02 | 1.022 | 1.026 | 1.045 | 1.034 | 1.021 | 1.012 | 1.017 | 1.011 | 1.016 | 1.025 | 1.012 | 1.013 | 1.023 | 1.025 | 1.025 | 1.01 | 1.006 |
| 1 | 1.021 | 1.043462 | 1.064331 | 1.087747 | 1.116028 | 1.166249 | 1.205902 | 1.231226 | 1.246 | 1.267182 | 1.281121 | 1.301619 | 1.33416 | 1.35017 | 1.367722 | 1.399179 | 1.434159 | 1.470013 | 1.484713 | 1.493621 |

# Capital

| Perioden | Landen | % van bruto | % van de tot | % van bruto | % van de tot | % van ICT-in | % van ICT-in | % van ICT-in | % van bruto | % van bruto | % van bruto | % van bruto | % van bruto | % van bruto | % van bruto | % van bruto | % van bruto |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1995 | Nederland | 225 | 4.4 | 10.6 | 15.7 | 38.5 | 29.3 | 32.2 | 0.11 | 0.02 | 0.09 | 2.9 | 4.8 | 1.9 | 27.6 | 41.1 | 13.5 |
| 1996 | Nederland | 223 | 4.83 | 11.3 | 16.4 | 39 | 27.2 | 33.8 | . | 0.03 | . | 4 | 7.7 | 3.7 | 30.7 | 46.9 | 16.1 |
| 1997 | Nederland | 220 | 5.52 | 12.3 | 17.9 | 37.1 | 26.2 | 36.7 | 0.14 | 0.05 | 0.09 | 2.9 | 6.3 | 3.5 | 32 | 51.6 | 19.6 |
| 1998 | Nederland | 219 | 6.49 | 12.9 | 18.9 | 34.6 | 21.7 | 43.7 | 0.23 | 0.05 | 0.18 | 9.2 | 9.1 | -0.1 | 40.8 | 56.7 | 15.9 |
| 1999 | Nederland | 217 | 7.66 | 13.7 | 19.1 | 34.9 | 20.2 | 45 | 0.31 | 0.09 | 0.22 | 10 | 14 | 4 | 46.7 | 63.4 | 16.7 |
| 2000 | Nederland | 216 | 8.69 | 12.9 | 19.9 | 32.7 | 20.3 | 47 | 0.37 | 0.09 | 0.28 | 16.6 | 19.6 | 3.1 | 63.3 | 79.3 | 16 |
| 2001 | Nederland | 218 | 9.77 | 11 | 19.9 | 33 | 17.7 | 49.3 | 0.23 | 0.04 | 0.19 | 13 | 12.6 | -0.3 | 70.6 | 82.9 | 12.3 |
| 2002 | Nederland | 223 | 10.55 | 10.1 | 19.1 | 32.5 | 16.8 | 50.7 | 0.2 | 0.04 | 0.16 | 5.7 | 7.3 | 1.6 | 79.9 | 90.6 | 10.6 |
| 2003 | Nederland | 226 | 11.52 | 10 | 20 | 32.9 | 19.9 | 47.3 | 0.1 | 0.01 | 0.09 | 5.3 | 9.6 | 4.3 | 85.1 | 103.1 | 17.9 |
| 2004 | Nederland | 225 | 12.42 | 9.5 | 21.3 | 32.2 | 19.5 | 48.3 | 0.09 | 0.01 | 0.08 | 2 | 6.1 | 4 | 85.2 | 103.2 | 18 |
| 2005 | Nederland | 226 | 13.42 | 9.5 | 22 | 31.7 | 18.4 | 49.9 | 0.16 | 0 | 0.15 | 6.1 | 19.3 | 13.2 | 75.1 | 100.9 | 25.8 |
| 2006 | Nederland | . | . | 10.1 | 22.3 | 30.3 | 18.9 | 50.8 | 0.1 | 0.01 | 0.09 | 2.1 | 10.5 | 8.4 | 81.6 | 118.1 | 36.6 |
| 2007 | Nederland | . | . | 10.4 | 19.5 | 30.3 | 18.3 | 51.4 | 0.1 | 0.03 | 0.08 | 15.3 | 7.1 | -8.2 | 98 | 120.4 | 22.4 |
| 2008 | Nederland | . | . | 10.9 | . | . | . | . | 0.13 | 0.04 | 0.09 | 0.5 | 7.8 | 7.3 | 74.1 | 102.2 | 28.1 |
| 2009 | Nederland | . | . | 9.9 | . | . | . | . | 0.09 | 0.02 | 0.07 | 4.5 | 3.6 | -1 | 83.2 | 120.6 | 37.3 |
| 2010 | Nederland | . | . | 9.7 | . | . | . | . | 0.1 | 0.02 | 0.08 | . | 7.1 | . | 76.1 | 123.4 | 47.3 |
| 2011 | Nederland | . | . | 10.1 | . | . | . | . | 0.11 | 0.02 | 0.09 | 2 | 3.8 | 1.8 | 69.6 | 117 | 47.4 |

| Data used | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| As % of GDP | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 10.6 | 11.3 | 12.3 | 12.9 | 13.7 | 12.9 | 11 | 10.1 | 10 | 9.5 | 9.5 | 10.1 | 10.4 | 10.9 | 9.9 | 9.7 | 10.1 | 9.44705882 | 9.28823529 | 9.12941176 | 8.97058824 |

# Interest rates

| Data from CBS | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 4.647621 | 3.410236 | 4.355857 | 1.997879 | 1.134047 | 0.789172 | 0.319063 | 0.811404 | 1.381344 | 0.82112 | 0.966586 | 2.4472 | 2.073522 | 1.577408 | 0.894446 | 1.855471 | 0.202454 | 0.25 | 0.3 | 0.3 |
| | | | | | | | | | | | | | | | | | | | |
| Data used | | | | | | | | | | | | | | | | | | | |
| 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 4.647621 | 3.410236 | 4.355857 | 1.997879 | 1.134047 | 0.789172 | 0.319063 | 0.811404 | 1.381344 | 0.82112 | 0.966586 | 2.4472 | 2.073522 | 1.577408 | 0.894446 | 1.855471 | 0.202454 | 0.25 | 0.3 | 0.3 |

# Unemployment rate

| Data from CBS | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| workingpopulation; kerncijfers provincie 1987-2014 | | | | | | | | | | | | | | | | | | | | | | | |
| | | Perioden | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 voor | 2001 na re | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 |
| Onderwerpen | Onderwerpe | Regio's | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland | Nederland |
| population (15 tot 65 jaar) | population ( | x 1 000 | 10498 | 10534 | 10566 | 10606 | 10665 | 10729 | 10801 | 10800 | 10863 | 10903 | 10925 | 10940 | 10952 | 10968 | 10997 | 11014 | 11017 | 10994 | 10992 | 11013 | 10980 |
| workingpopulation | Totaal worki | x 1 000 | 6596 | 6686 | 6832 | 6941 | 7069 | 7187 | 7273 | 7187 | 7312 | 7364 | 7417 | 7455 | 7507 | 7653 | 7801 | 7846 | 7817 | 7811 | 7894 | 7939 | 7870 |
| workingpopulation | Werkzame v | x 1 000 | 6063 | 6185 | 6384 | 6587 | 6768 | 6917 | 7021 | 6935 | 7010 | 6968 | 6941 | 6973 | 7097 | 7309 | 7501 | 7469 | 7391 | 7392 | 7387 | 7283 | 7215 |
| workingpopulation | Werkloze w | x 1 000 | 533 | 501 | 448 | 354 | 301 | 270 | 252 | 252 | 302 | 396 | 476 | 482 | 410 | 344 | 300 | 377 | 426 | 419 | 507 | 656 | 656 |
| Niet workingpopulation | Niet working | x 1 000 | 3901 | 3848 | 3734 | 3665 | 3596 | 3542 | 3528 | 3613 | 3551 | 3539 | 3508 | 3485 | 3444 | 3315 | 3196 | 3167 | 3200 | 3183 | 3098 | 3074 | 3110 |
| Werkloosheidspercentage | Werkloshei | % | 8.1 | 7.5 | 6.6 | 5.1 | 4.3 | 3.8 | 3.5 | 3.5 | 4.1 | 5.4 | 6.4 | 6.5 | 5.5 | 4.5 | 3.8 | 4.8 | 5.4 | 5.4 | 6.4 | 8.3 | 8.3 |

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Data used** | | | | | | | | | | | | | | | | | | | | |
| population (15 - 65) | | | x1000 | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 10498000 | 10534000 | 10566000 | 10606000 | 10665000 | 10729000 | 10800000 | 10863000 | 10903000 | 10925000 | 10940000 | 10952000 | 10968000 | 10997000 | 11014000 | 11017000 | 10994000 | 10992000 | 11013000 | 10980000 | 10980000 |
| 0.35 | 0.341751 | 0.302858 | 0.377145 | 0.553211 | 0.596514 | 0.657407 | 0.57995 | 0.366872 | 0.201373 | 0.137112 | 0.109569 | 0.145879 | 0.263708 | 0.154349 | 0.027231 | -0.20921 | -0.0182 | 0.190684 | -0.30055 | 0 |
| no work | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 533000 | 501000 | 448000 | 354000 | 301000 | 270000 | 252000 | 302000 | 396000 | 476000 | 482000 | 410000 | 344000 | 300000 | 377000 | 426000 | 419000 | 507000 | 656000 | 656000 | 656000 |
| | | | | | | | | | | | | | | | | | | | | |
| working | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 6063000 | 6185000 | 6384000 | 6587000 | 6768000 | 6917000 | 6935000 | 7010000 | 6968000 | 6941000 | 6973000 | 7097000 | 7309000 | 7501000 | 7469000 | 7391000 | 7392000 | 7387000 | 7283000 | 7215000 | 7215000 |
| | | | | | | | | | | | | | | | | | | | | |
| workingpopulation | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 6596000 | 6686000 | 6832000 | 6941000 | 7069000 | 7187000 | 7187000 | 7312000 | 7364000 | 7417000 | 7455000 | 7507000 | 7653000 | 7801000 | 7846000 | 7817000 | 7811000 | 7894000 | 7939000 | 7870000 | 7870000 |
| | | | | | | | | | | | | | | | | | | | | |
| workingpopulation extra | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 0 | 90000 | 146000 | 109000 | 128000 | 118000 | 0 | 125000 | 52000 | 53000 | 38000 | 52000 | 146000 | 148000 | 45000 | -29000 | -6000 | 83000 | 45000 | -69000 | 0 |
| | | | | | | | | | | | | | | | | | | | | |
| Unemployment rate | | | | | | | | | | | | | | | | | | | | |
| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| 0.081 | 0.075 | 0.066 | 0.051 | 0.043 | 0.038 | 0.035 | 0.041 | 0.054 | 0.064 | 0.065 | 0.055 | 0.045 | 0.038 | 0.048 | 0.054 | 0.054 | 0.064 | 0.083 | 0.083 | 0.083355 |

# G. EMA output

*Figure 49: Untransformed EMA Data*

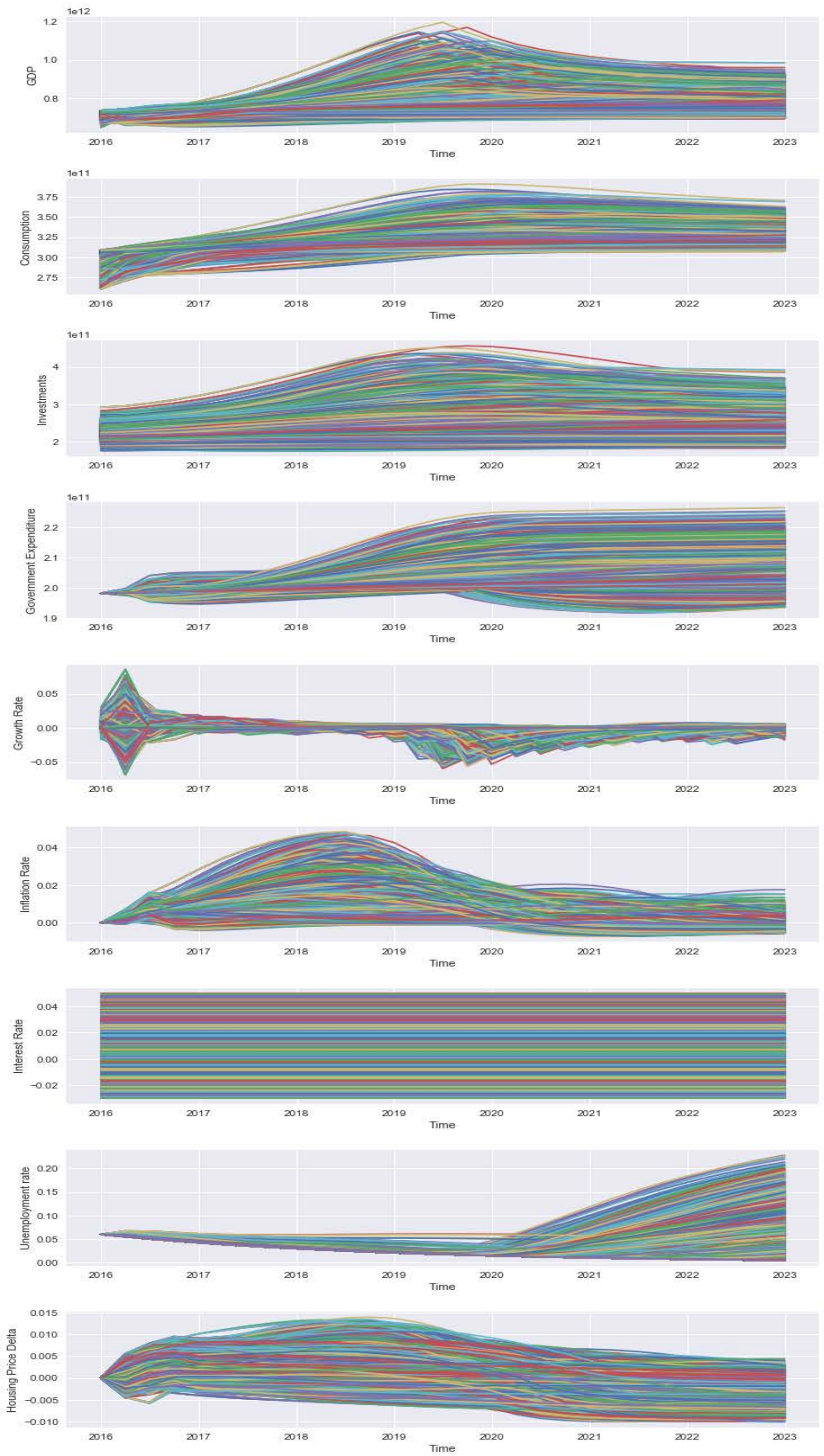


*Figure 50: EMA Policies and KDE*

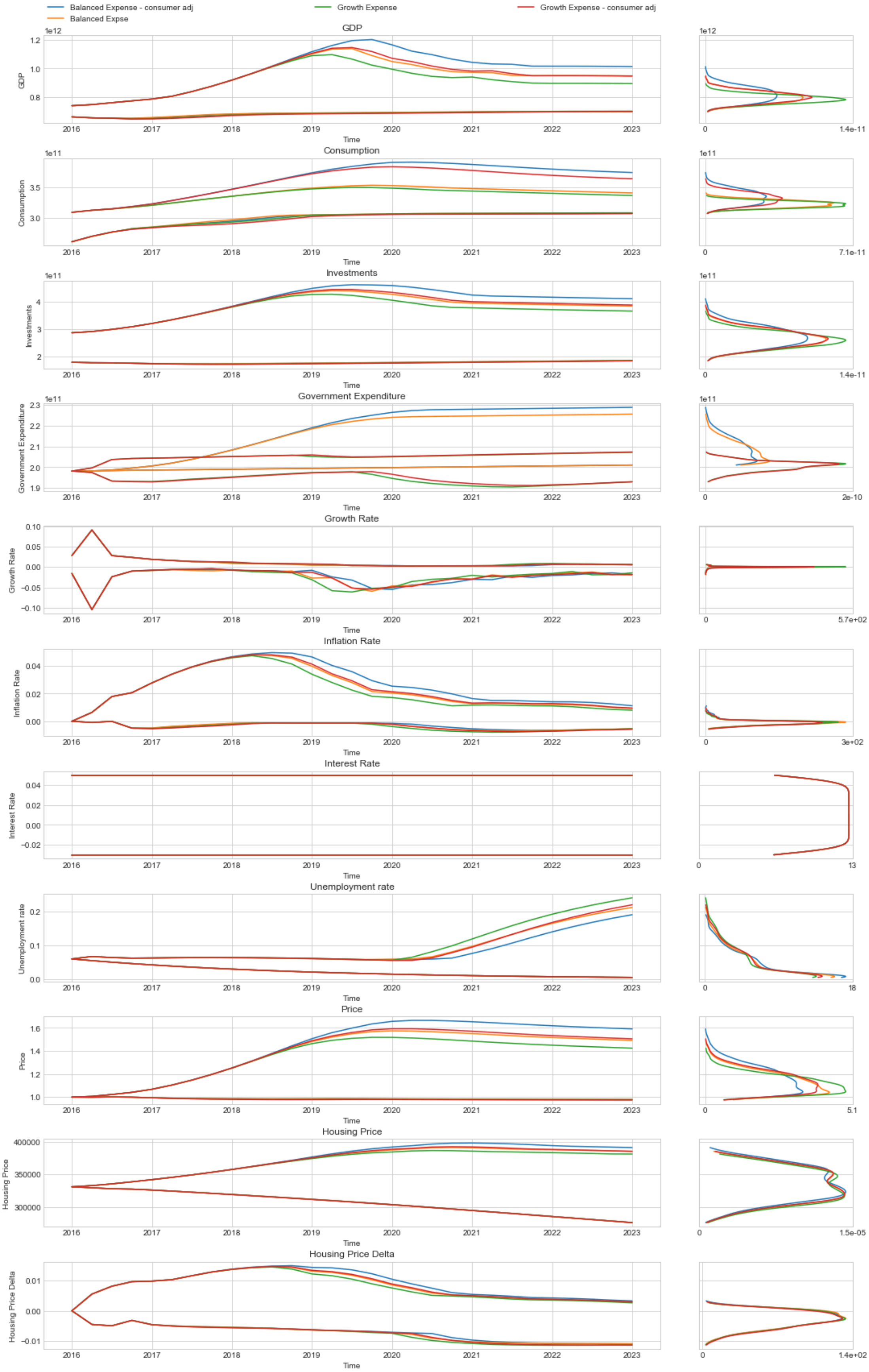


*Figure 51: EMA Correlation Graph*

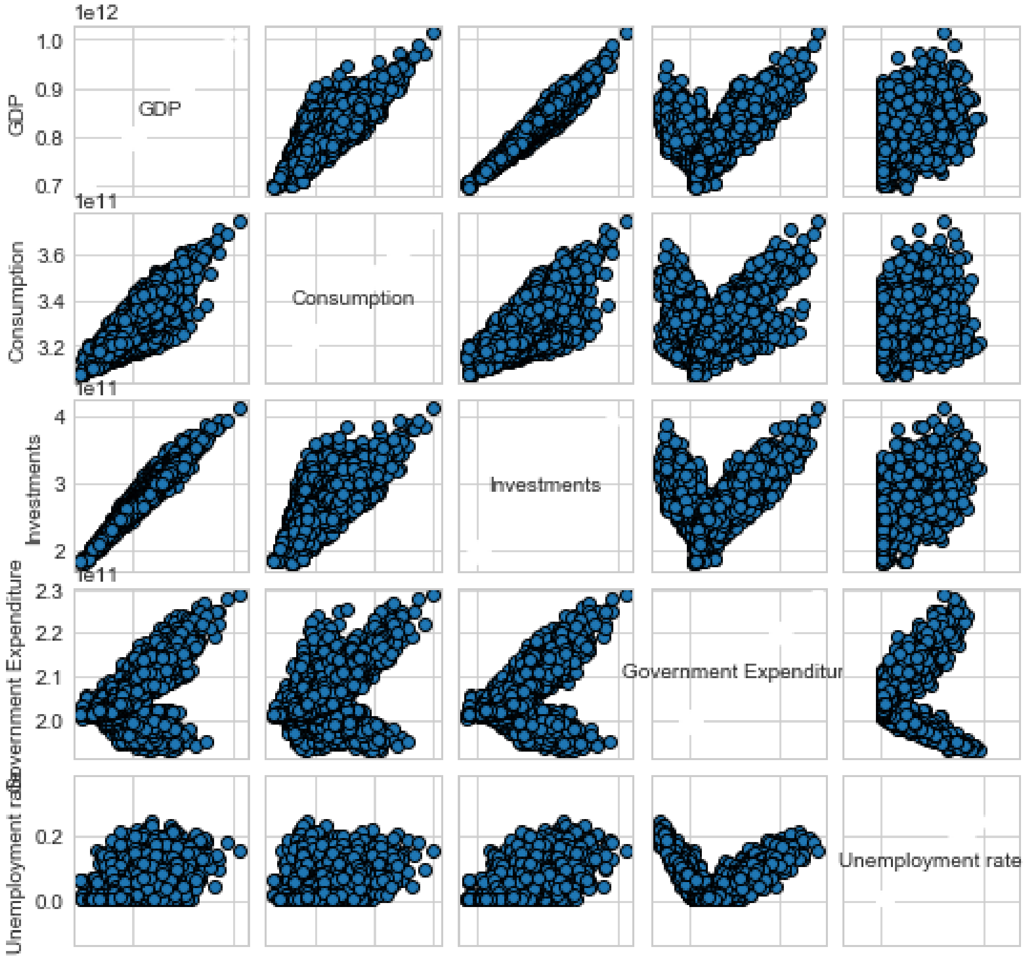
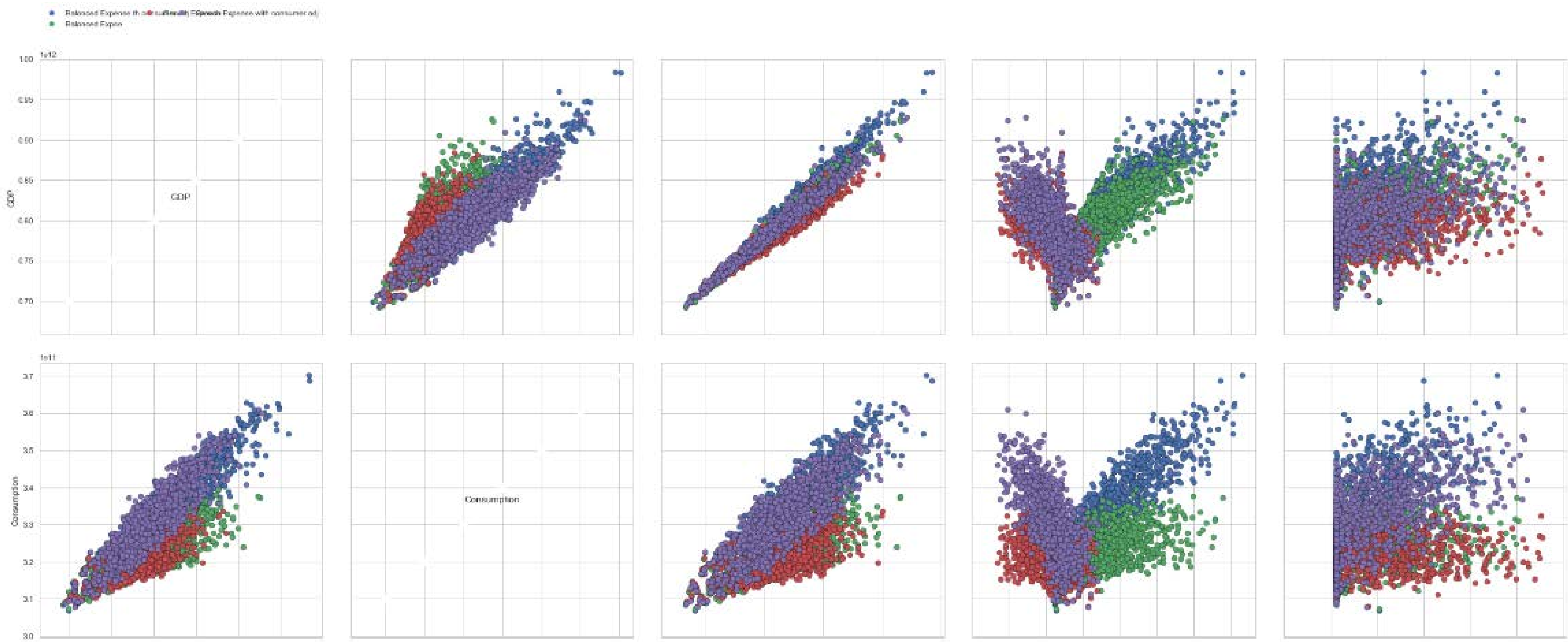


*Figure 52: EMA Correlation with Policies (1/2)*



Green = Balance Based Budget;
Blue = Balance Based Budget & consumer earning adjustment;
Red = Growth Based Expenses;
Purple = Growth Based Expenses & consumer earning adjustment

*Figure 53: EMA Correlation with Policies (2/2)*

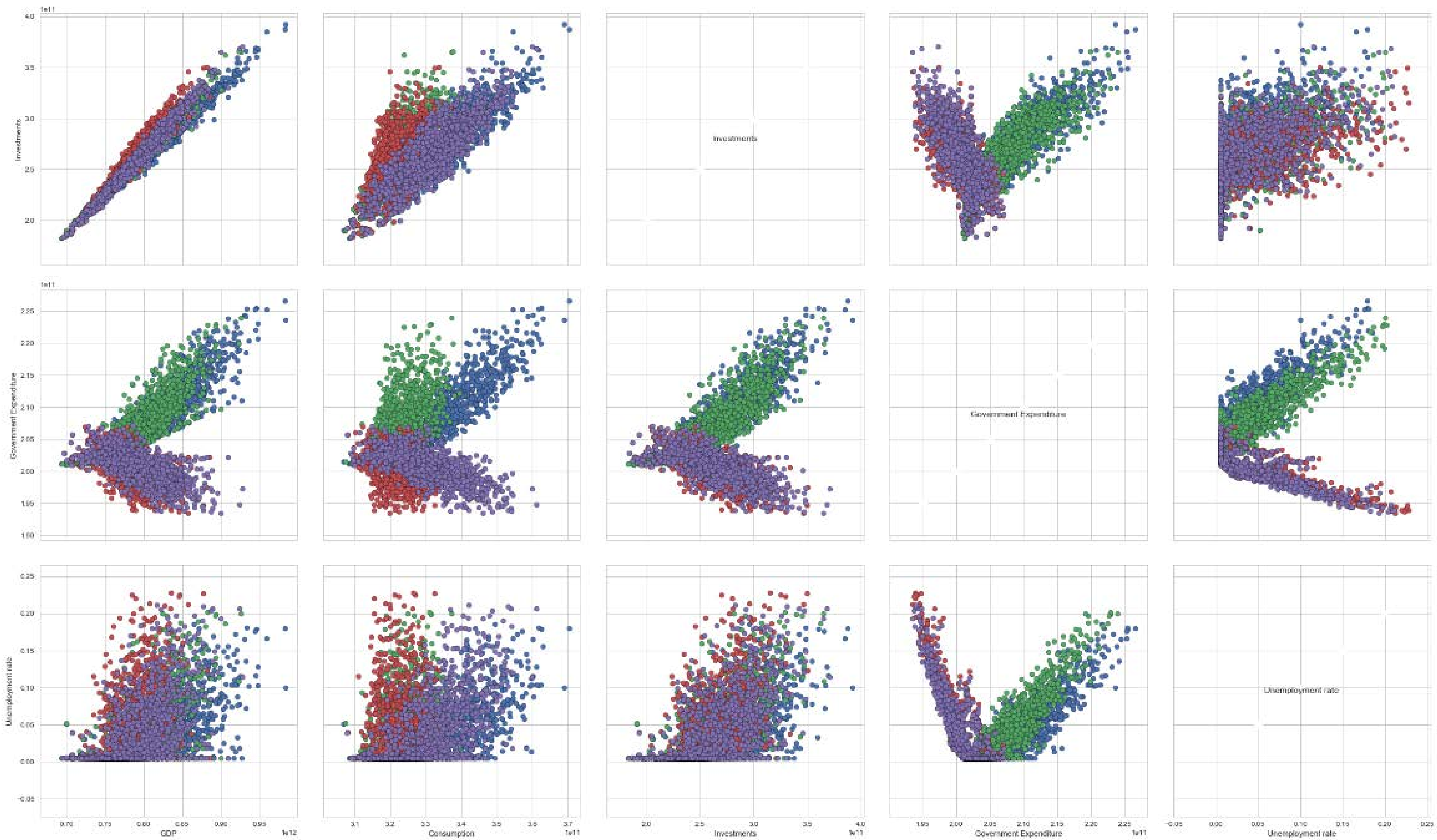
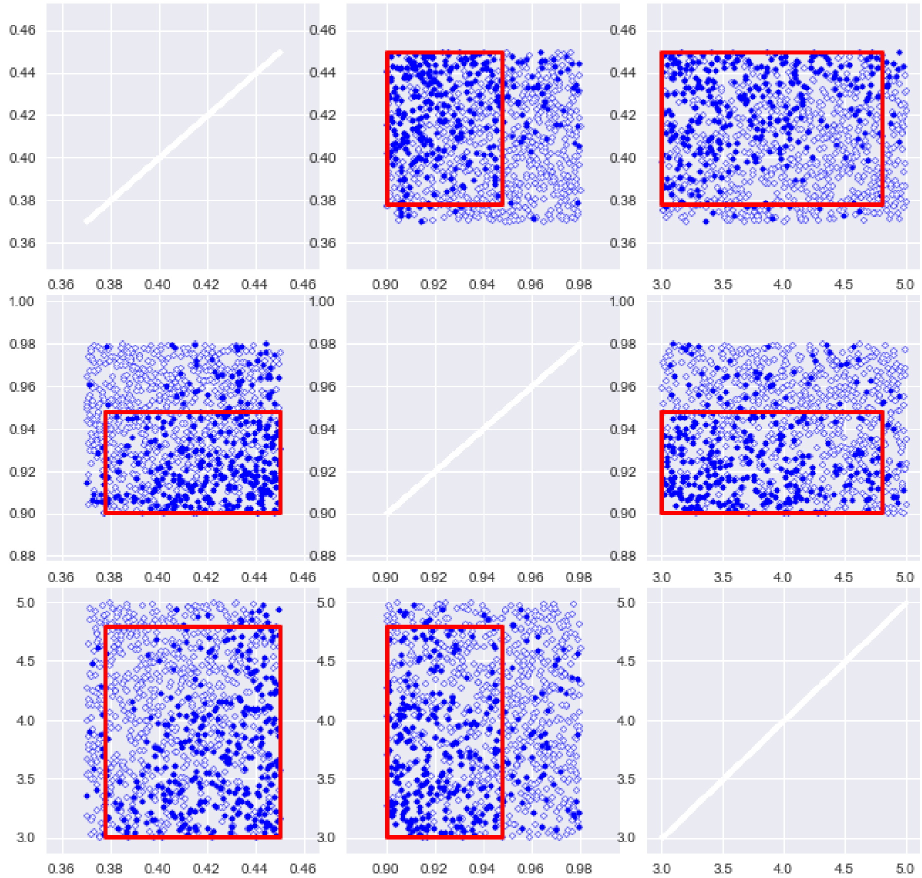
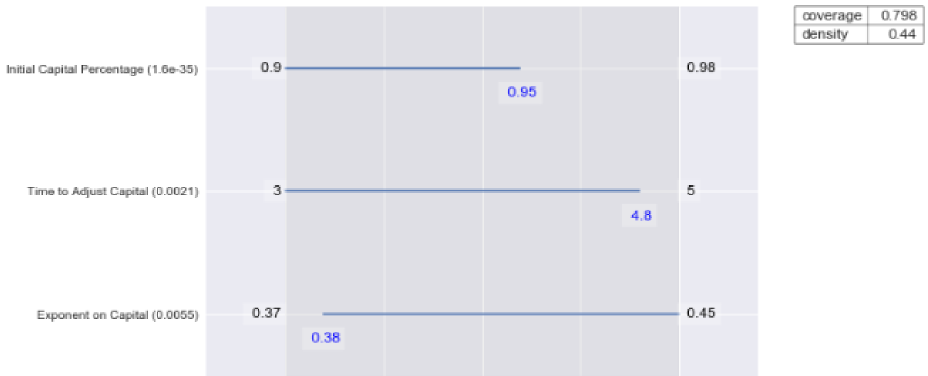


*Figure 54: PRIM Box Selction & Outcomes*





## H. Subscripted population model

Full documentation of the model can be found in the digital folder of the thesis.

Top

### (Type) Subscripts (4 Variables)

| Group | Type | *Variable Name And Description* |
|---|---|---|
| Population subscripted | #2 Sub | **AgeGroups** ()<br>AgeGroups:Age0to4,Age5to9,Age10to14,Age15to19,Age20to24,Age25to29,Age30to34,Age35to39,Age40to44,Age45to49,Age50to54,Age55to59,Age60to64,Age65to69,Age70to74,Age75to79,Age80plus<br>**Present In 1 View:**<br>• View 1<br>**Used By**<br>• Ageing<br>• Average age per age group<br>• Deaths<br>• Initial population http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=7461BEV<br>• Mortality rate<br>• Population Ageing[PreviousAgeGroups]-Ageing[AllButYoungestAndOldest]-Deaths[AllButYoungestAndOldest]<br>**Feedback Loops:** 0 (0.0%) (+) 0 [0,0] (-) 0 [0,0] |
| Population subscripted | #4 Sub | **AllButYoungestAndOldest** ()<br>AllButYoungestAndOldest:Age5to9,Age10to14,Age15to19,Age20to24,Age25to29,Age30to34,Age35to39,Age40to44,Age45to49,Age50to54,Age55to59,Age60to64,Age65to69,Age70to74,Age75to79<br>**Present In 1 View:**<br>• View 1<br>**Used By**<br>• Ageing<br>• Deaths<br>• Initial population http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=7461BEV<br>• Population Ageing[PreviousAgeGroups]-Ageing[AllButYoungestAndOldest]-Deaths[AllButYoungestAndOldest]<br>**Feedback Loops:** 0 (0.0%) (+) 0 [0,0] (-) 0 [0,0] |

| | | |
|---|---|---|
| Population subscripted | #16 Sub | **FertileAge** ()<br>FertileAge:Age15to19,Age20to24,Age25to29,Age30to34,Age35to39,Age40to44<br>**Present In 1 View:**<br>• View 1<br>**Used By**<br>• Population Ageing[PreviousAgeGroups]-Ageing[AllButYoungestAndOldest]-Deaths[AllButYoungestAndOldest]<br>**Feedback Loops:** 0 (0.0%) (+) 0 [0,0] (-) 0 [0,0] |
| Population subscripted | #32 Sub | **PreviousAgeGroups** ()<br>PreviousAgeGroups:Age0to4,Age5to9,Age10to14,Age15to19,Age20to24,Age25to29,Age30to34,Age35to39,Age40to44,Age45to49,Age50to54,Age55to59,Age60to64,Age65to69,Age70to74 -> AllButYoungestAndOldest<br>**Present In 1 View:**<br>• View 1<br>**Used By**<br>• Ageing<br>**Feedback Loops:** 0 (0.0%) (+) 0 [0,0] (-) 0 [0,0] |

## I. System Dynamics model for historical behaviour

Full documentation of the model can be found in the digital folder of the thesis.

| Model Information | Result |
|---|---|
| Total Number Of Variables | 241 |
| Total Number Of State Variables | 23 (9.5%) |
| Total Number Of Stocks | 18 (7.5%) |
| Total Number Of Feedback Loops No IVV (Maximum Length: 30) [2, 30] | 1,428 (721\|707\|0) |
| Total Number Of Feedback Loops With IVV (Maximum Length: 30) [0, 0] | 0 (0\|0\|0) |
| Total Number Of Causal Links | 390 (244\|73\|73) |
| Total Number of Rate-to-rate Links | 5 |
| Number Of Units Used In The Model (Basic/Combined) | 6/15 |

| | |
|---|---|
| Total Number Of Equations Using Macros | 0 (0.0%) |
| Variables With Source Information | 0 (0.0%) |
| Dimensionless Unit Variables | 52 (21.6%) |
| Variables without Predefined Min or Max Values | 237 (98.3%) |
| Function Sensitivity Parameters | 0 (0.0%) |
| Data Lookup Tables | 0 (0.0%) |
| Time Unit | Year |
| Initial Time | 1995 |
| Final Time | 2013 |
| Reported Time Interval | TIME STEP |
| Time Step | 0.25 |
| Model Is Fully Formulated | Yes |
| Model Defined Groups | No |

| Potential Omissions | Result |
|---|---|
| Unused Variables | 1 (0.4%) |
| Supplementary Variables | 29 (12.0%) |
| Supplementary Variables Being Used | 0 (0.0%) |
| Complex Variable | 53 (22.0%) |
| Complex Stock | 0 (0.0%) |

| Warnings | Result |
|---|---|
| Number Of Undocumented Variables | 220 (91.3%) |
| Equations With Embedded Data | 23 (9.5%) |
| Variables Not In Any View | 0 (0.0%) |
| Nonmonotonic Lookup Functions | 0 (0.0%) |
| Cascading Lookup Functions | 0 (0.0%) |
| Non-Zero End Sloped Lookup Functions | 0 (0.0%) |
| Equations With If Then Else Functions | 17 (7.1%) |
| Equations With Min Or Max Functions | 6 (2.5%) |
| Equations With Step Pulse Or Related Functions | 0 (0.0%) |
| Equations With Unit Errors Or Warnings | 5 (2.1%) |

## K. System Dynamics model for EMA

Full documentation of the model can be found in the digital folder of the thesis.

| Model Information | Result |
|---|---|
| Total Number Of Variables | 203 |
| Total Number Of State Variables | 26 (12.8%) |
| Total Number Of Stocks | 26 (12.8%) |
| Total Number Of Feedback Loops No IVV (Maximum Length: 30) [2, 30] | 3,836 (2,005\|1,831\|0) |
| Total Number Of Feedback Loops With IVV (Maximum Length: 30) [0, 0] | 0 (0\|0\|0) |
| Total Number Of Causal Links | 361 (248\|103\|10) |
| Total Number of Rate-to-rate Links | 5 |

| | |
|---|---|
| Number Of Units Used In The Model (Basic/Combined) | 8/11 |
| Total Number Of Equations Using Macros | 0 (0.0%) |
| Variables With Source Information | 0 (0.0%) |
| Dimensionless Unit Variables | 43 (21.2%) |
| Variables without Predefined Min or Max Values | 199 (98.0%) |
| Function Sensitivity Parameters | 0 (0.0%) |
| Data Lookup Tables | 0 (0.0%) |
| Time Unit | Year |
| Initial Time | 2016 |
| Final Time | 2023 |
| Reported Time Interval | TIME STEP |
| Time Step | 0.25 |
| Model Is Fully Formulated | Yes |
| Model Defined Groups | No |

| Potential Omissions | Result |
|---|---|
| Unused Variables | 0 (0.0%) |
| Supplementary Variables | 9 (4.4%) |
| Supplementary Variables Being Used | 0 (0.0%) |
| Complex Variable | 22 (10.8%) |
| Complex Stock | 0 (0.0%) |

| Warnings | Result |
|---|---|
| Number Of Undocumented Variables | 171 (84.2%) |
| Equations With Embedded Data | 4 (2.0%) |
| Variables Not In Any View | 0 (0.0%) |
| Nonmonotonic Lookup Functions | 0 (0.0%) |
| Cascading Lookup Functions | 0 (0.0%) |
| Non-Zero End Sloped Lookup Functions | 0 (0.0%) |
| Equations With If Then Else Functions | 17 (8.4%) |
| Equations With Min Or Max Functions | 0 (0.0%) |
| Equations With Step Pulse Or Related Functions | 0 (0.0%) |
| Equations With Unit Errors Or Warnings | 1 (0.5%) |

## L. Jupyter Notebook Python 3.6

# PySd

September 20, 2017

## 1 Introduction

This notebook is for better understanding the data analysis for the thesis 'Prospective Hindsight; using system dynamics with exploratory modelling & analysis to generate scenarios' by Niels van Rosmalen. First, we will setup the notebook and go over some packages necessary to perform the experiments. In this thesis, we will use the following packages:

- future
- numpy
- scipy
- pandas
- ipython
- ipyparallel
- JPype1
- jupyter
- mpld3
- scikit-learn
- seaborn
- matplotlib
- pyzmq
- pysd
- salib
- OS

We will explain the packages in more detail once we install them. It should also be noted that in order to use the ema_workbench with Vensim connectors, we need Vensim DSS 32-bit.

## 2 Importing libraries and functions

The underlining code does nothing more than import the necessary components for the run. Python runs in a way that we have to import functionality (if we do not want to code everything ourselves). As such, we import and can refer to code written by others.

```
In [1]: #Sub-library of matplotlib. We use the '%' sign to define the graphs we
        #want to call as we perform experiments.
        %matplotlib inline
```

```
#Provides a MATLAB-like plotting framework for data analytics and image
#processing to produce figures in the notebook.
import matplotlib.pyplot as plt

#Not necessary for analysis (as we use it), but it allows us to change
#colours in graphs.
import seaborn as sns

#Used to create and manage N-dimensional array objects and random number
#capabilities.
import numpy as np

#Used for data structures and data analysis to manage Microsoft Excel-like
#structures.
import pandas as pd

#Running System Dynamics models in python.
import pysd

#Use operating system dependent functionality to manipulate paths - to
#save/load files. This is important when copying this code or replicating
#the experiments so we don't have to develop new paths.
import os

#Used for designing experiments and the performing of experiments.
import ema_workbench

from ema_workbench import (Model,
                           IntegerParameter,
                           RealParameter,
                           ScalarOutcome,
                           Constant,
                           perform_experiments,
                           save_results,
                           load_results,
                           TimeSeriesOutcome,
                           Policy)

from ema_workbench.em_framework import samplers, util

from ema_workbench.connectors.vensim import VensimModel
```

It is possible to expierence an error about netlogo connectors and/or platypus based optimization. Both libraries are not used in this thesis and the error can thus be disregarded.

```
In [2]: #Import and turn on logging to view EMA process run. This is so that we
        #get updates during experiments.
        from ema_workbench import ema_logging
        ema_logging.log_to_stderr(ema_logging.INFO)
```

Out[2]: <Logger EMA (DEBUG)>

## 3 Translating the model to Python

Now that we have imported the libraries we need for setting up and perform the experiments, we move on to setting up the model. We first need to convert our Vensim model to a code readable in Python. Furthermore, we test a simple run to see if the import was successful. We do this with a Python package called PySD. This package can read in a Vensim model and let it run in Python. However, there are a few things we need to be aware of. First, it is not possible to have delay functions. Therefore, we model delays without special functions, but with a stock and flow structure. We have seen this before during the model explanation - we did not use typical System Dynamics functions. We also need to publish our models in Vensim before we can load them in. This is done within Vensim itself. Once published, Python can recognise the dataset and convert it.

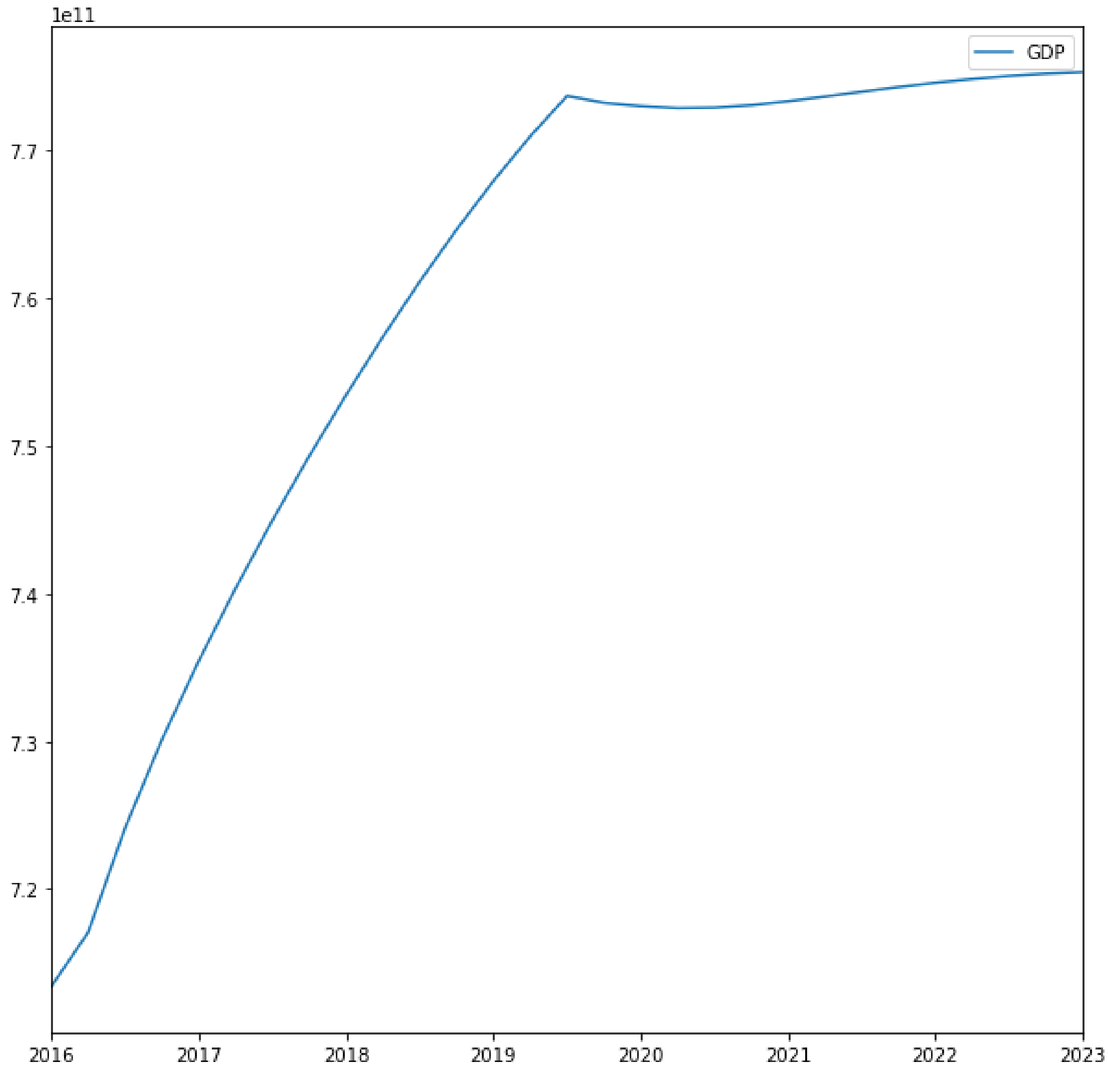
Finally, when replicating these experiments, be aware of the settings in Vensim DSS. In this case, the hard underbar setting is turned on (Settings, Sketch, Use hard underbar). This means that the sign '_' is not recognised as a space, but a separate symbol. In practice this means that if we want to report variables that use a space - for example "Labour Force" - we can write "Labour Force" instead of "Labour_Force". Keep this in mind while repeating the experiments as the following functions are modelled without the underbar (so the Vensim setting is turned on).

```
In [3]: #We first load the model in Python. In our case, the model is in the
        #folder labeled 'Vensim'. We simulate a range from 2016 to 2023. This
        #range is chosen in accordence with the length of stress scenarios.
        model = pysd.read_vensim(r'Vensim/EMA20.mdl')
        #Define the work drive and instantiate the model. Afterwards, we change
        #the name of the model to 'MacroModel'.
        MacroModel = VensimModel("MacroModel", model_file=r'Vensim/EMA20.vpm')
```

Let's also test if the import worked. We can try to call a graph to make sure we can read similar results. First, we need to run the model. Next, we call try to call a graph. As we can see from our test, Python can now read the Vensim model.

```
In [4]: #Here, we run the model and show output from GDP in a basic run.
        outcome = model.run(return_columns=['GDP'])
        outcome.plot(figsize=(10,10))
```

Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0xe4210d0>




## 4 Policies and levers

This part of the notebook allows us to modify policies and switches. Normally, if we want to change policies or their effect, we do not need to return to the Vensim model. This is time-consuming and thus we can also make these changes in Python. As it is, the values given below correspond to the model in Vensim. This means that this code does not change anything. It does give us an overview of how we could change the model. To test if everything is as we say, let us run the model with different levers and values. We will simulate GDP in the base case and next play with some levers.

```
In [5]: model.run(return_timestamps=[2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023],
                  params={
        #We use this to define the position of the levers and thus policies.
        #0=Growth-Expenditure, 1=Balanced Expenditure
```

```
                'Growth or Balanced Expenditure Switch': 0,
#0=Shock policy off, 1=Shock policy on
                'Extra Government Spending Switch':0,
#1=inflation influences consumer spending
                'Inflation Rate Consumption Switch': 0,
#1=consumer earnings based on economic growth
                'Additional Earnings Switch': 0,
#0=off, 1=on
                'Excise Tax Rate Change Switch': 0,
#0=off, 1=on
                'Unemployment Shock Switch': 0,
#0=off, 1=on
                'Consumption Spending Shock Switch': 0,

#We use these constants to define the strength in percentages to the
#shocks, if we want to shock the model.
#.01=1%
                'Extra Government Spending Percentage': 0,
#.01=1%
                'Excise Tax Rate Change': 0,
#.01=1%
                'Unemployment Shock Percentage of Labour Force': 0,
#.01=1%
                'Consumption Spending Shock Percentage': 0,

# Some of the policies require a specific year to take effect. These
#are the policies that contain pulses and we can let them vary when
#to take effect. The shocks won't work if the levers are turned off.
#This value defines the year the shock will take effect
                'Extra Government Spending Year':0,
#This value defines the year the shock will take effect
                'Unemployment Shock Year': 0,
#This values defines the year the shock will take effect
                'Consumption Spending Shock Year': 0
                },
         return_columns=['GDP'])
```

```
Out[5]:               GDP
        2016  7.126552e+11
        2017  7.348385e+11
        2018  7.413045e+11
        2019  7.494356e+11
        2020  7.561448e+11
        2021  7.614137e+11
        2022  7.654670e+11
        2023  7.684184e+11
```

Let's change the model by switching the governmental expenditure behavior and adding a consumption spending shock in 2020 of 5%. We will not redefine the parts of code we do not have to change in order for the changes to take effect - Python remembers our previous commands.

```
In [6]: model.run(return_timestamps=[2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023],
                   params={
                          'Growth or Balanced Expenditure Switch': 1,
                          'Consumption Spending Shock Switch': 1,

                          'Consumption Spending Shock Percentage': 0.05,

                          'Consumption Spending Shock Year': 2020
                          },
                  return_columns=['GDP']
                  )
```

```
Out[6]:                GDP
        2016  7.126571e+11
        2017  7.335886e+11
        2018  7.409193e+11
        2019  7.490915e+11
        2020  7.553987e+11
        2021  7.632606e+11
        2022  7.649383e+11
        2023  7.675361e+11
```

With this different output, we have proven we can adjust the model from Python.

# Setting up EMA experiments

In [1]:

```
#Sub-library of matplotlib. We use the '%' sign to define the graphs we
#want to call as we perform experiments.
%matplotlib inline

#Provides a MATLAB-like plotting framework for data analytics and image
#processing to produce figures in the notebook.
import matplotlib.pyplot as plt

#Not necessary for analysis (as we use it), but it allows us to change
#colours in graphs.
import seaborn as sns

#Used to create and manage N-dimensional array objects and random number
#capabilities.
import numpy as np

#Used for data structures and data analysis to manage Microsoft Excel-like
#structures.
import pandas as pd

#Running System Dynamics models in python.
import pysd

#Use operating system dependent functionality to manipulate paths - to
#save/load files. This is important when copying this code or replicating
#the experiments so we don't have to develop new paths.
import os

#Used for designing experiments and the performing of experiments.
import ema_workbench

from ema_workbench import (Model,
                           IntegerParameter,
                           RealParameter,
                           ScalarOutcome,
                           Constant,
                           perform_experiments,
                           save_results,
                           load_results,
                           TimeSeriesOutcome,
                           Policy
                           )

from ema_workbench.em_framework import samplers, util
from ema_workbench.connectors.vensim import VensimModel
from ema_workbench.connectors.pysd_connector import PysdModel

from ema_workbench.analysis.plotting import (lines, kde_over_time)
from ema_workbench.analysis.plotting_util import KDE, BOXPLOT
from ema_workbench.analysis.pairs_plotting import (pairs_lines,pairs_scatter,pairs_density)

import ema_workbench.analysis.prim as prim
```

In [2]:

```
#Import and turn on logging to view EMA process run. This is so that we
#get updates during experiments.
from ema_workbench import ema_logging
ema_logging.log_to_stderr(ema_logging.INFO)
```

Out[2]:

```
<Logger EMA (DEBUG)>
```

In [4]:

```
#We first load the model in Python. In our case, the model is in the
#folder labeled 'Vensim'.
MacroModel = PysdModel('MacroModel', mdl_file=r'Vensim/EMA20.mdl')
```

In [3]:

```
results = load_results(r'Runs/1000 with 4 pol')
experiments, outcomes = results
```

```
[MainProcess/INFO] results loaded succesfully from C:\Users\niels\Dropbox\Sy
stem Dynamics - European Master\NN\EMA\Runs\1000 with 4 pol
```

It is important to not that we previously worked in PySd and that we are now shifting to using the ema_workbench. The next code will look like what we did previously, but it has a different influence on the model. In the workbench, we can set constants, uncertainties, levers and more. We will first go over the constants. Defining values as constants mean they will not change. Thus we can do the same as we did previously with PySd to our dataset; make datasets with or without certain policies/decisions.

In [4]:

```
"""
#We use this to define the position of the levers and thus policies.
MacroModel.constants = [
         Constant('Growth or Balanced Expenditure Switch', 0),
         Constant('Extra Government Spending Switch', 0),
         Constant('Inflation Rate Consumption Switch', 0),
         Constant('Additional Earnings Switch', 0),
         Constant('Excise Tax Rate Change Switch', 0),
         Constant('Unemployment Shock Switch', 0),
         Constant('Consumption Spending Shock Switch', 0),


#We use these constants to define the strength in percentages to the
#shocks, if we want to shock the model.
         Constant('Extra Government Spending Percentage', 0),
         Constant('Excise Tax Rate Change', 0),
         Constant('Unemployment Shock Percentage of Labour Force', 0),
         Constant('Consumption Spending Shock Percentage', 0),


#Some of the policies require a specific year to take effect. These
#are the policies that contain pulses and we can let them vary of
#when to take effect. The shocks won't work if the levers are turned off.
         Constant('Extra Government Spending Year', 0),
         Constant('Unemployment Shock Year', 0),
         Constant('Consumption Spending Shock Year', 0)
         ]
"""
```

Out[4]:

```
"      \n#We use this to define the position of the levers and thus policie
s.\nMacroModel.constants = [\n         Constant('Growth or Balanced Expendit
ure Switch', 0),   \n         Constant('Extra Government Spending Switch',
 0),\n         Constant('Inflation Rate Consumption Switch', 0),     \n
    Constant('Additional Earnings Switch', 0),             \n         Consta
nt('Excise Tax Rate Change Switch', 0),          \n         Constant('Unempl
oyment Shock Switch', 0),               \n         Constant('Consumption Spe
nding Shock Switch', 0),      \n          \n\n#We use these constants to defi
ne the strength in percentages to the \n#shocks, if we want to shock the mod
el.\n         Constant('Extra Government Spending Percentage', 0),
    \n         Constant('Excise Tax Rate Change', 0),
  \n          Constant('Unemployment Shock Percentage of Labour Force', 0),
 \n          Constant('Consumption Spending Shock Percentage', 0),
 \n          \n\n#Some of the policies require a specific year to take effec
t. These \n#are the policies that contain pulses and we can let them vary of
\n#when to take effect. The shocks won't work if the levers are turned of
f.\n         Constant('Extra Government Spending Year', 0),\n         Consta
nt('Unemployment Shock Year', 0),             \n         Constant('Consumpti
on Spending Shock Year', 0)       \n         ]\n"
```

Changing the levers in the model to constants is a good way to create smaller datasets that represent specific outcomes. However, it does not capture the design or purpose of RDM. We want to create a dataset containing all possibilities. This means we are going to disregard the code that defines constants in our EMA analysis and change them to values that can change. The previous code is therefore blocked from running. Doing this means our dataset will represent all realities possible in the system we built. For now, we will introduce the different decision structures and not shock to the system. We do however want to set one policy: as we said before, it is not observed in the economy that wages actually decrease. Therefore, we do want to keep the "NonAdjustable Wages Switch" to zero. That way, wages do not decrease over time as the economy naturally develops. If we want to come back to this decision, we can either run all the code again without the part specifying constants or empty the constants by giving no values.

In [5]:

```
MacroModel.constants = [Constant('NonAdjustable Wages Switch', 1)]
```

Let's move on to setting policies. This thesis does not support decision structures or outcomes of the stakeholder and therefore we define policies of the actors in the economic system. If we would have been in possession of a decision structure and outcome of party of interest, we would be able to find optimum strategies and policies. Now, the following policies are used to represent the possible realities and as a stand-in to show what we can do with EMA. Do keep in mind then that policies in this instance refers to using different models (realities). With decision and outcomes structures of the stakeholder present, we should both insert policies and use different models. Here, we can only use different models (called policies - as they refer to decision structures of economic actors). Future work should definitely include such a structure, but due to the limited time and resources of the author, such a feat was not yet possible.

There also is a possibility to define the shocks as in our levers to go off at specific events (for example more government spending when economic decline is -3% or more). Knowing such possibility exist greatly increases the possible output we can generate. However, since we have done little research about such interpretations of the economy, we will not implement these levers - as they do not enhance our true understanding. The levers were originally created to test model behaviour and we will not widen their use in this research.

```
#We made up a policy where the government is spending through a Growth-
#or Balance Budget method. Later, we can compare the effects the
#government has on the economy by choosing one of the decison methods.
pol = [{'Growth or Balanced Expenditure Switch':0,
        'Inflation Rate Consumption Switch':0,
        'Additional Earnings Switch':0},

#As there is no data available at this time about possible future
#government spendings, we decided to let the goverment spend relative
#to the inflation growth, but without a decline in the case of deflation.
       {'Growth or Balanced Expenditure Switch':1,
        'Inflation Rate Consumption Switch':0,
        'Additional Earnings Switch':0},

#The following two policies are the same as before when it comes to
#government spending, but differ in that consumers spend more or less
#according to economic developments.
       {'Growth or Balanced Expenditure Switch':0,
        'Inflation Rate Consumption Switch':1,
        'Additional Earnings Switch':1},

       {'Growth or Balanced Expenditure Switch':1,
        'Inflation Rate Consumption Switch':1,
        'Additional Earnings Switch':1},

       ]

policy1 = Policy('Growth Expense',**pol[0])
policy2 = Policy('Balanced Expse',**pol[1])
policy3 = Policy('Growth Expense - consumer adj',**pol[2])
policy4 = Policy('Balanced Expense - consumer adj',**pol[3])
```

```
policies = [policy1,policy2, policy3, policy4]
```

Now it is time to set the uncertainties. These variables are sampled in our experiments for each run to create a dataset. Besides setting the uncertainties, we also modify the initial values of the model. As initial values are not all certain, we can test behaviour of the model with different starting values. We will vary the initial values of those variables that have a lot of uncertainty and also have a big impact on model runs.

In the first block of code, we are going to set the parameters in the model that make up sensitivities and exponents which we cannot get exactly from real-world data. Luckily, there are logical boundaries to parameters. For example, it is unlikely that an exponent on labour or capital exceeds .5 (or 1 cumulative). If that were the case it would mean that for every extra capital or labour, relative output per extra unit would increase. This is not conform to what we see in the world and can thus be disregarded. So even though we cannot define all factors exactly, we can give an estimated range - if not that, we can ground it based on our cases of interest. Finally, not all the uncertain factors are given here. Some factors, adjustment times and effects like are left out of the picture for now. This also reduces the cluttering of cases not of interest.

After that, we will define the uncertain components of the model that include adjustment times. In the model, these factors are light green. The factors are made up by the author to connect economic theorem and System Dynamics. Therefore, we estimate the parameter range by gathered information from natural cycles in time of the Dutch economy and use logic (in collaboration with the project-owner).

Finally, we set uncertainties for initial values the model has. These are very dangerous to vary, as they determine the starting position of the model. Luckily, we were able to calculate a lot of initial values using the model itself. Other exogenous initial variables sometimes had good and unambiguous data sources - like "Initial Employed Labour". Other cases still had initial values that were not important to the model as long as they were in an acceptable range of the desired value during model initiation - like "Initial Inventory (real)". For those values, we have initialized them as being a certain percentage of the desired value - between 90% and 100%. The percentage chosen stems from the standard development distance between the actual and desired value in a model run.

In [7]:

```
MacroModel.uncertainties = [RealParameter('Technological Change', 0, 0.005),
                            RealParameter('Exponent on Labour', .37, .47),
                            RealParameter('Exponent on Capital', .35, .45 ),
                            RealParameter('Interest Sensitivity', 0.7, 1),
                            RealParameter('Interest Rate', -0.03, 0.05),

                            RealParameter('Delay Time of Wage Change', 2, 4),
                            RealParameter('Time to Adjust Capital', 3, 5),

                            RealParameter('Initial Potential GDP', 720000000000, 760000000000
#Specifies the percentage of capital in the economy at the start of the
#model.
                            RealParameter('Initial Capital Percentage', .9, .98),
                            RealParameter('Initial Wage Rate', 22000, 30000),
#Specifies if the housing market is either short or has an abundance of
#houses relative to the desired housing.
                            RealParameter('Initial Housing Shortage', .9, 1.1)
                            ]
```

The final step before we can run the experiments is setting out outcomes of interest. We define the following list of effects that our stakeholder is interested in:

In [8]:

```
MacroModel.outcomes = [
                         TimeSeriesOutcome('TIME'),
                         TimeSeriesOutcome('GDP'),
                         TimeSeriesOutcome('Consumption'),
                         TimeSeriesOutcome('Investments'),
                         TimeSeriesOutcome('Government Expenditure'),

                         TimeSeriesOutcome('Growth Rate'),
                         TimeSeriesOutcome('Inflation Rate'),
                         TimeSeriesOutcome('Interest Rate'),
                         TimeSeriesOutcome('Unemployment rate'),
                         TimeSeriesOutcome('Price'),

                         TimeSeriesOutcome('Housing Price'),
                         TimeSeriesOutcome('Housing Price Delta')
                        ]
```

# Running the model

Now that we have set the constants, uncertainties, policies and outcomes of the analysis, we can finally perform the analysis. Based on the possible ranges of uncertainty (11 factors in total), we want to test each policy (read: model) 500 times. The reason for this sampling size has to do with our sampling method. In this research, we use Latin Hypercube Sampling (LHS). This sampling method is setup as a randomized experimental design based on the higher dimensional generalization of a Latin Square (Bryant & Lempert, 2010). Put simply, variables are first sampled using a even sampling method and then randomly combined sets of those variables are used for one calculation of the target function. This means that if we have a line running somewhere on the x- and y-axis and we sample 5 times, the LHS method will first cut the graph in 5 parts over the y-axis. The 5 parts are cut based on the cumulative probability (100%) divided by 5 (20%). Next, between the value of 0% and 20%, a value is chosen and used for building the sample. Next, a value between 20% and 40% of the cumulative probability (the y-axis) is chosen.

In our experiment, what sample size should we thus choose? Simple, we can base our sample size on a good representation of segments that would be divided is we apply LHS. However, how do our distributions look like? Are they linear, Poisson, geometric, Cauchy or other? In our entire experiment, we use robust distributions: all ranges are equally probable. This may not be intuitive as we can for example reason that the initial wage rate is more likely to be in the center of our estimates, and not near the outer reaches - we could thus make a normal distribution of initial wage rate that we can sample from. However, as we are interested in the possible configurations of the system, we want to sample all probabilities equally. It must be said that it is possible within the workbench to sample from distributions and it is not a technical limitation. In our thesis, we explicitly choose robust sampling.

Finally we can answer how much sampling is required to get reasonable results. Looking at our biggest numerical change, Initial Potential GDP, we see that the distance between the minimum and maximum is 30000 million. This variable is sensitive up to a point that changes of 50 million cause slightly shifting behaviour. If we thus sample 1000 times, ranges between sampling become 30 million. Also, since we sample over 4 policies, we will perform 100*4=4000 simulations. This size is more than enough to give an accurate view of the sample spaces.

In [34]:

```
nr_scenarios = 1000

#results = perform_experiments(MacroModel, nr_scenarios, policies = policies)
#save_results(results, '1000 with 4 pol')
results = load_results('1000 with 4 pol')
experiments, outcomes = results
```

```
[MainProcess/INFO] results loaded succesfully from C:\Users\niels\Dropbox\Sy
stem Dynamics - European Master\NN\EMA\1000 with 4 pol
```

# Visualisation

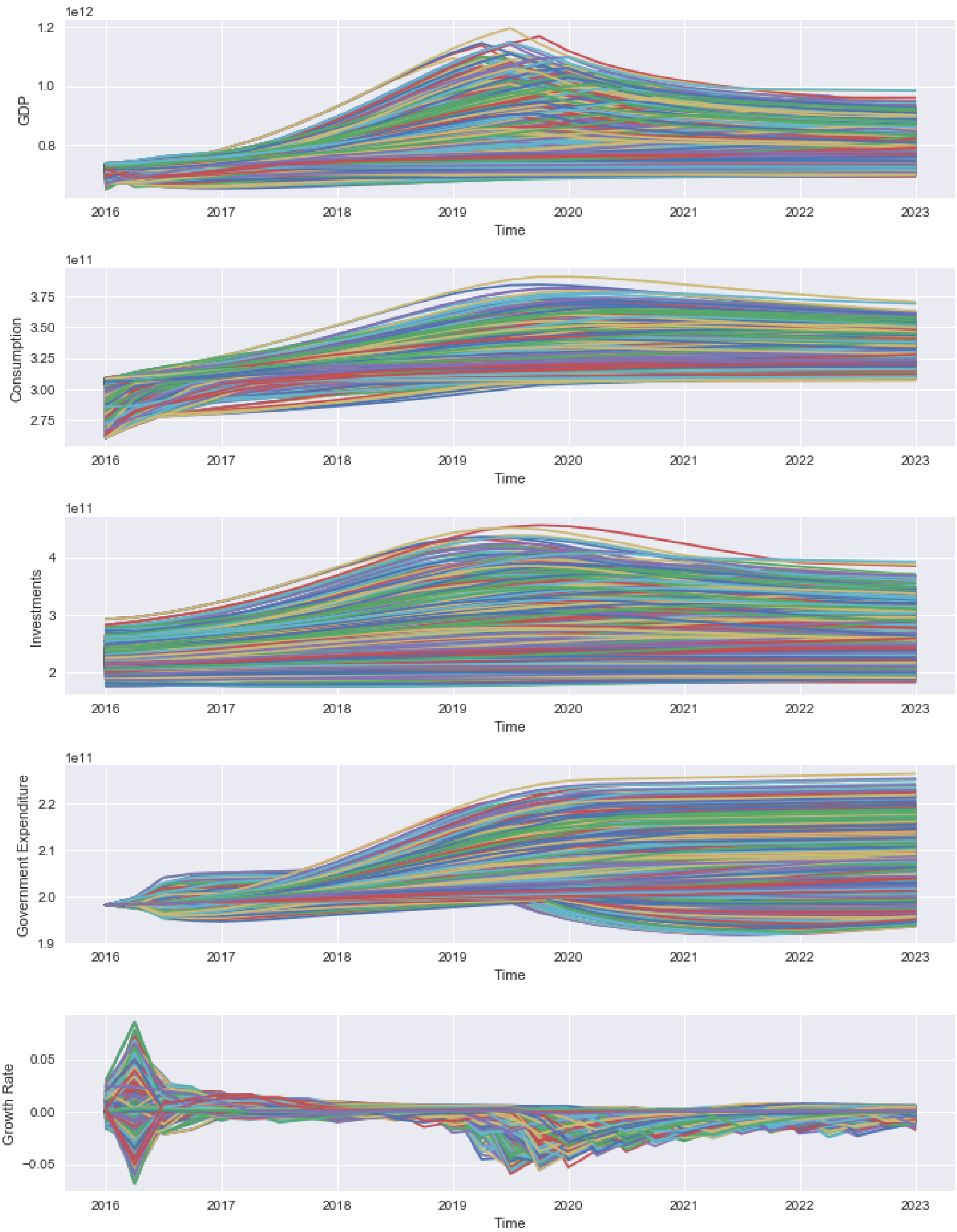
Let's take a first look at our results and see the ranges of our experiments.

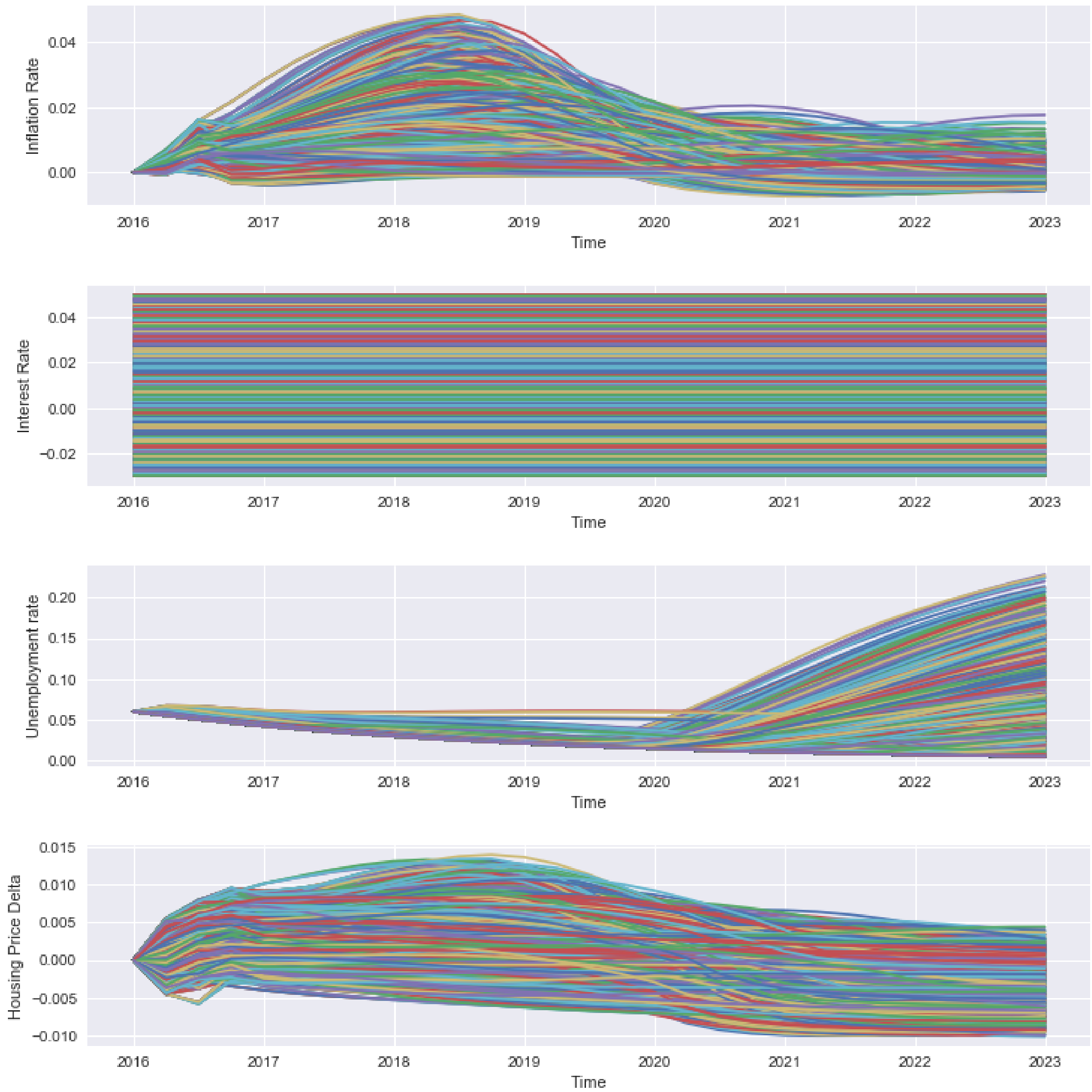
In [5]:

```
#Here, we make an ajustment to the colour of the graphs since the default
#colours are grey and do not help when presenting the data.
sns.set_style("whitegrid", {"axes.facecolor": "1"})
```

In [16]:

```
fig, axes = lines(results, titles=None, group_by=None,
                  outcomes_to_show=['GDP',
                                    'Consumption',
                                    'Investments',
                                    'Government Expenditure',
                                    'Growth Rate',
                                    'Inflation Rate',
                                    'Interest Rate',
                                    'Unemployment rate',
                                    'Housing Price Delta'])
fig.set_figheight(30)
fig.set_figwidth(12)

plt.show()
```

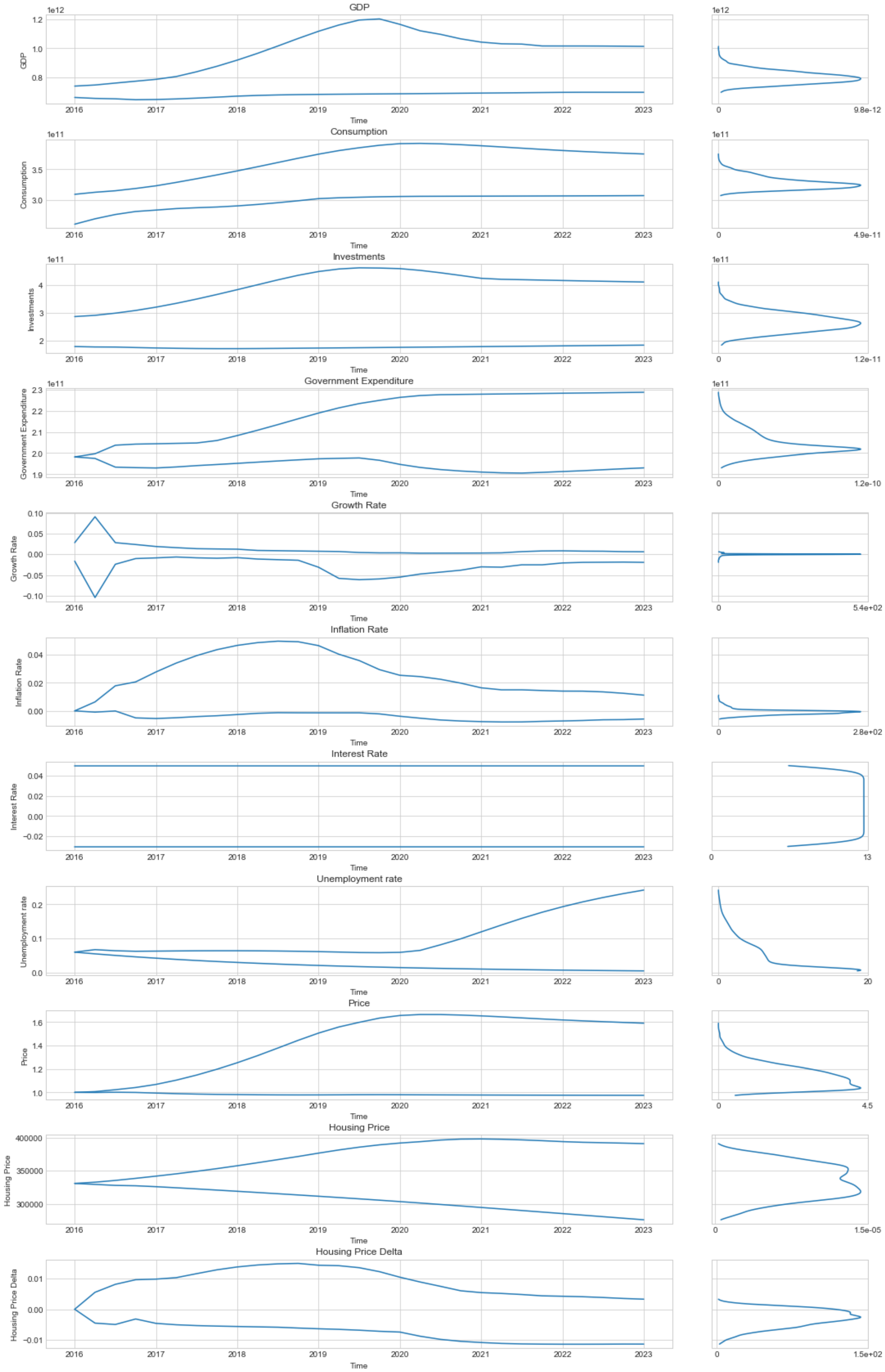





The graphs we just presented look nice, but are not very useful. There no conclusions to make based on this visual representation, except that we succeeded in producing a broad range of outcomes in most of our output. Therefore, we will organize the data such that we see the maximum development and the minimum development of each of the graphs.That way, we can visualize the uncertainty range of an outcome indicator over time between the minimum and maximum values at each time point. Next to showing upper and lower bounds, we will also add a Kernel Density Estimation (KDE) plot to the right. The KDE shows the probability distribution of density of the outcomes. It is something like a histogram, but in a smooth function. As presented here, the KDE graphs show the probable distribution over the y-axis.

In [9]:

```
fig, axes = ema_workbench.analysis.plotting.envelopes(results, group_by=None, density=KDE)
fig.set_figheight(30)
fig.set_figwidth(18)
plt.show()
```



Now, let's go one step further and organize that data such that we compare the four policies as previously defined. By organising the data this way, we can spot differences between the four decision-structures.

In [10]:

```
fig, axes = ema_workbench.analysis.plotting.envelopes(results, group_by='policy', density=K
fig.set_figheight(30)
fig.set_figwidth(18)

plt.show()
```

As we can see with our first two decision structures about governmental expenditure, we see that adjusting governmental inflation leads to a higher government spending and greatly affects the outcomes GDP, (the Red and Green line). When looking at governmental expenditure alone, we see no possible shrinkage in expenditures when also adjusting for inflation (in the Balanced Budget policy). We can also see this clearly in the distribution of the KDE plot.

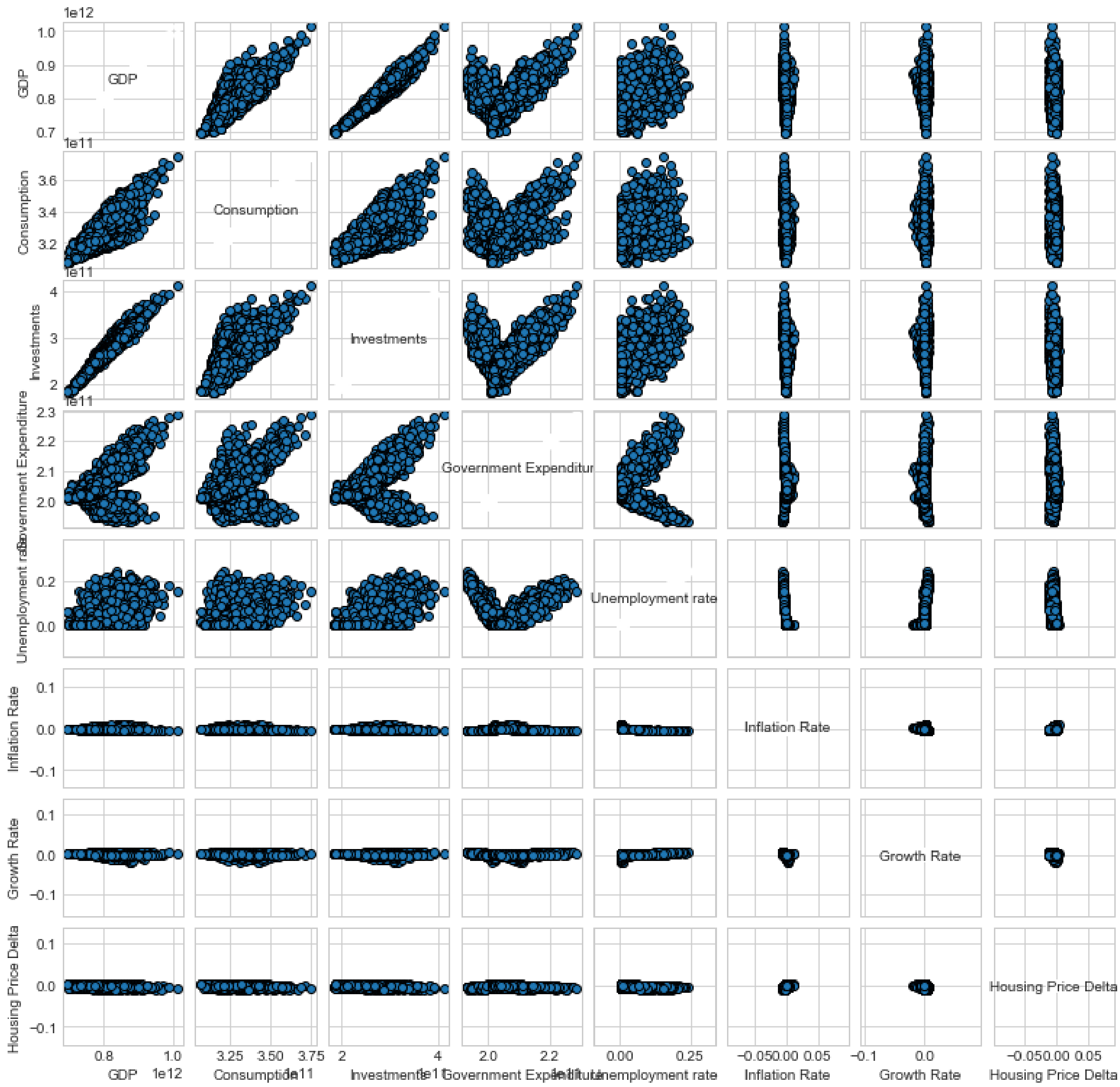
Regarding policy 3 and 4 that govern if consumers spend more according to inflation and earn more with economic growth, we also see some interesting developments (the red and blue line). As expected, consumption tends to be higher as seen in the normal and KDE graph. However, what we also notice is an effect on investments and unemployment. Also, with more consumption, there is overall a smaller tendency for unemployment. Looking at the causal structure of our model, this effect is as follows: more consumption means higher GDP, leads to more need for investment capital and labour to produce goods.

There are also effects to be noticed to the change in housing prices. Since they are rather small and the KDE densities of all four policies have an equal distribution, this difference is not worth taking into consideration.

Let's move on to our last form of visual analysis: building a scatter plot. In a scatter plot, variables are written in a diagonal line from top left to bottom right. Then each variable is plotted against each other. This means that some effects will cancel each other out while true effects will remain. Here, we have left out interest rate, since it is an exogenous input to the model. It is thus impossible for factors in the model to have an impact on the interest rate. No correlation is possible from a factor that is randomly sampled and is a constant.

In [11]:

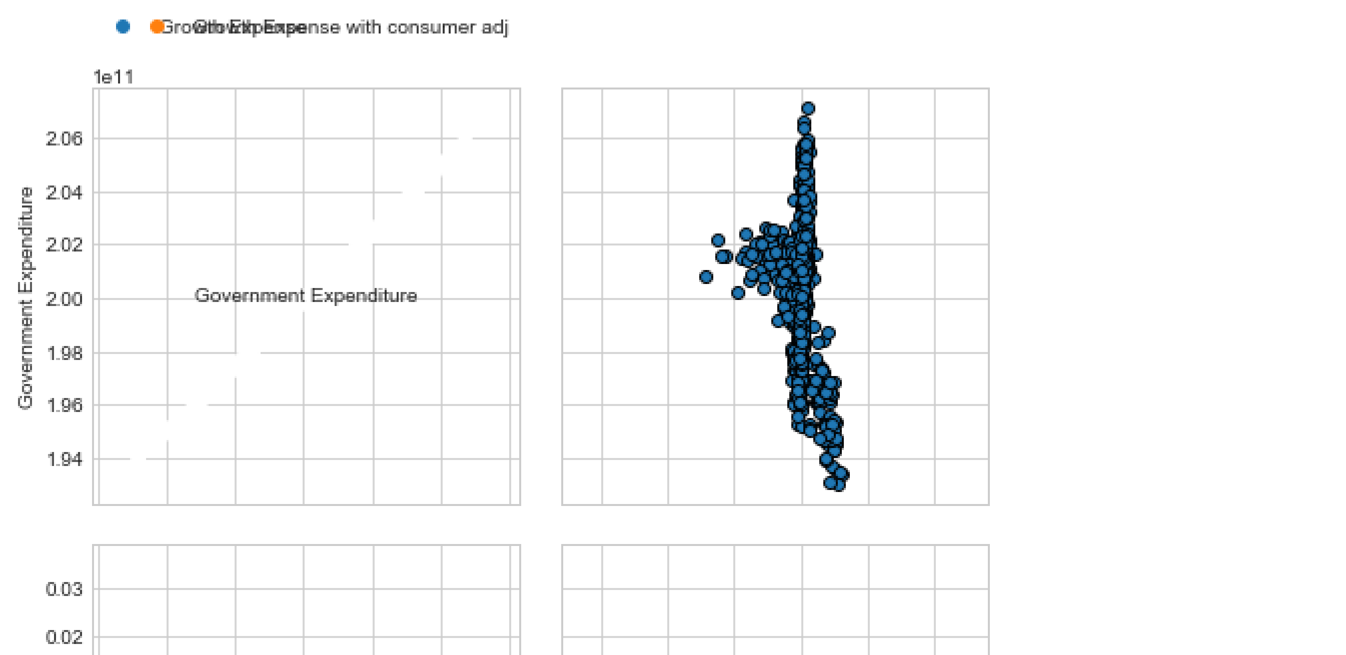
```
fig, axes = pairs_scatter(results, titles=None,
                          outcomes_to_show=['GDP',
                                            'Consumption',
                                            'Investments',
                                            'Government Expenditure',
                                            'Unemployment rate',
                                            'Inflation Rate',
                                            'Growth Rate',
                                            'Housing Price Delta'])
fig.set_figheight(13)
fig.set_figwidth(13)

plt.show()
```




Not all behaviour shown here is very clear. First off, we can see that none of our rates have a very good correlation. This is not strange as they move on very different axis. Expenditures and investments range in the billions, while rates are around the 0 and 1. As rates do influence our stocks, every rate has a tiny amount of effect. We can explain this by imagining how growth rate affects governmental expenditures. While growth rate directly influences the change in governmental expenditures during a Growth Based expenditure policy, its small dosage and other factors wash it away. We can see this when we separate the policies to only growth rate and comparing the growth rate.

In [12]:

```
fig, axes = pairs_scatter(results, titles=None, group_by='policy', grouping_specifiers=['Gr
                          outcomes_to_show=['Government Expenditure',
                                            'Growth Rate'])
fig.set_figheight(8)
fig.set_figwidth(8)

plt.show()
```

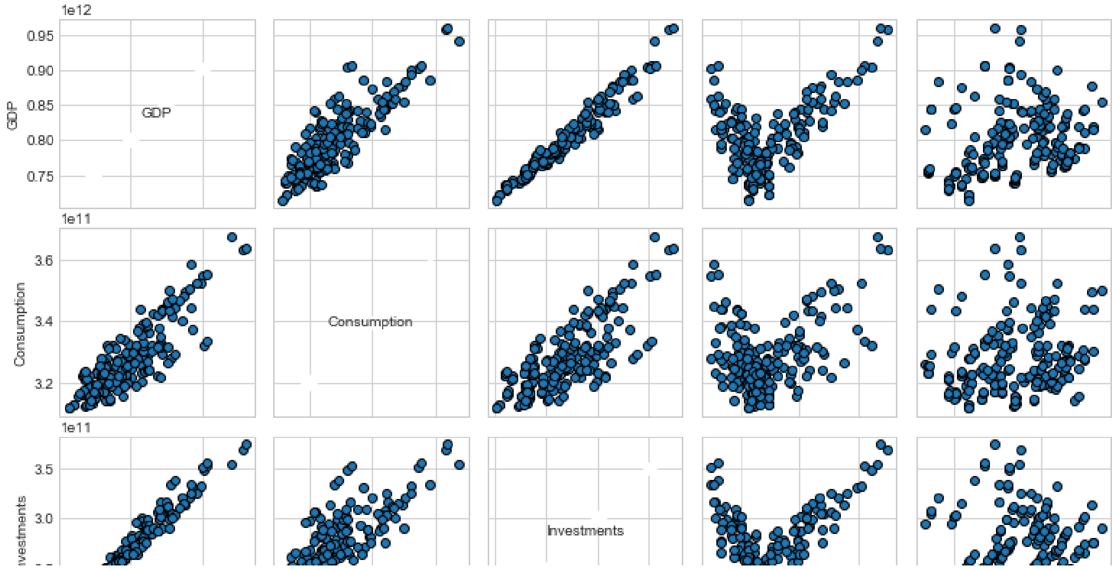



The effect of small rates is also seen with inflation rate and the housing delta. The delta seems to not be moved by anything. However, if we add the housing price to our simulation runs, we see there is more of an effect - although no correlation.

In [14]:

```
Housing_scatter = load_results(r'Runs/Housing run')
fig, axes = pairs_scatter(Housing_scatter, titles=None,
                          outcomes_to_show=['GDP',
                                            'Consumption',
                                            'Investments',
                                            'Government Expenditure',
                                            'Housing Price'])
fig.set_figheight(13)
fig.set_figwidth(13)

plt.show()
```

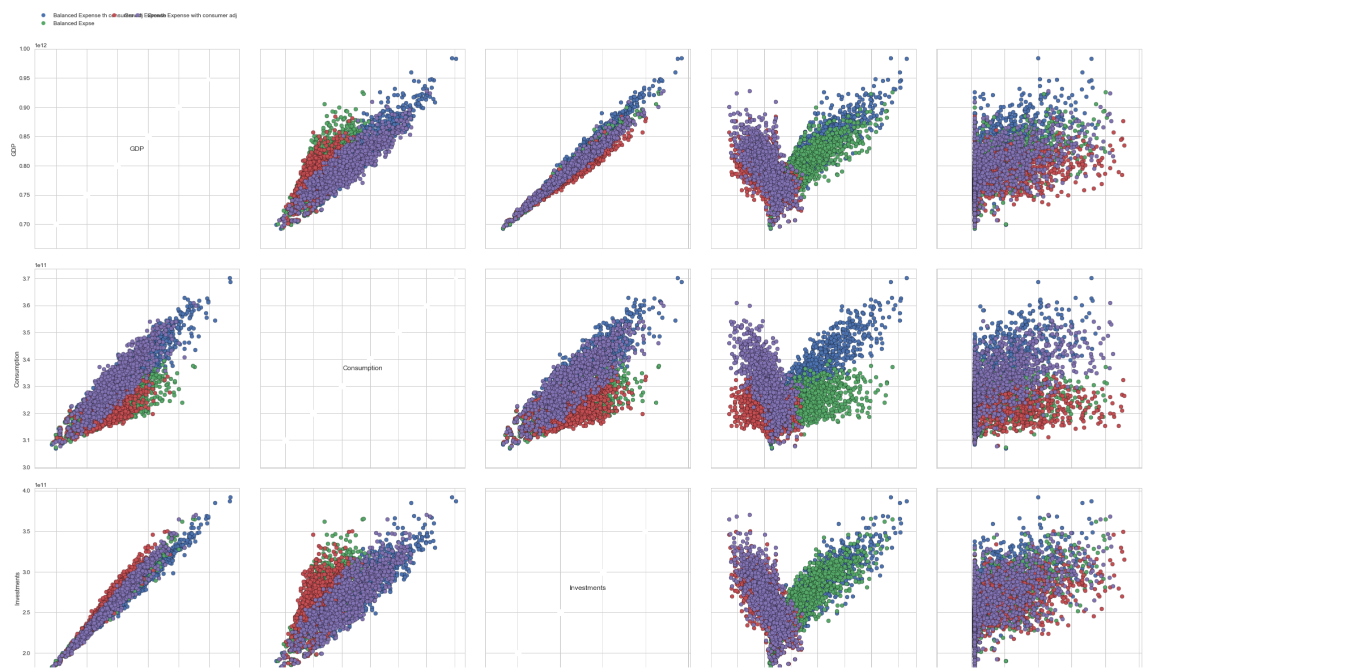
```
[MainProcess/INFO] results loaded succesfully from C:\Users\niels\Dropbox
\System Dynamics - European Master\NN\EMA\Runs\Housing run
```




Still, when analysing the data, we saw some strange behaviour in the unemployment rate correlation. It seemed to have multiple patters. Let's have another look while separating the policies and getting rid of the rates.

In [12]:

```
fig, axes = pairs_scatter(results,  group_by='policy',
                          outcomes_to_show=['GDP',
                                            'Consumption',
                                            'Investments',
                                            'Government Expenditure',
                                            'Unemployment rate'])
fig.set_figheight(35)
fig.set_figwidth(35)

plt.show()
```




To be clear, the colour coding is as follows: Green = Balance Blue = Balance & consumer adjustment Red = Growth Purple = Growth & consumer adjustment

Here, we see that switching from government spending policy can have an effect on the correlation. This is probably because when no policy is active, there is a standard growth rate in consumption behaviour and when policies are active, it can behave erratic. It is thus unwise to make too many assumptions based on this particular output.

Finally, while it is great that we can extract policies and analyse them independently, it is not important to the end conclusions of our research. Since our policies represent not actual policies, but alternative methods to model the economy, we have to analyse all simulations. Still, is good for our understanding to check the effect of the model structures and see if unexpected behaviour occurs. When for example extra consumer spending would lead to overall less consumption or a lower distribution of outcomes in the KDE graph, we would have reasons for concern. Luckily, there is no sign of such behaviour and the model behaves as expected.

# PRIM

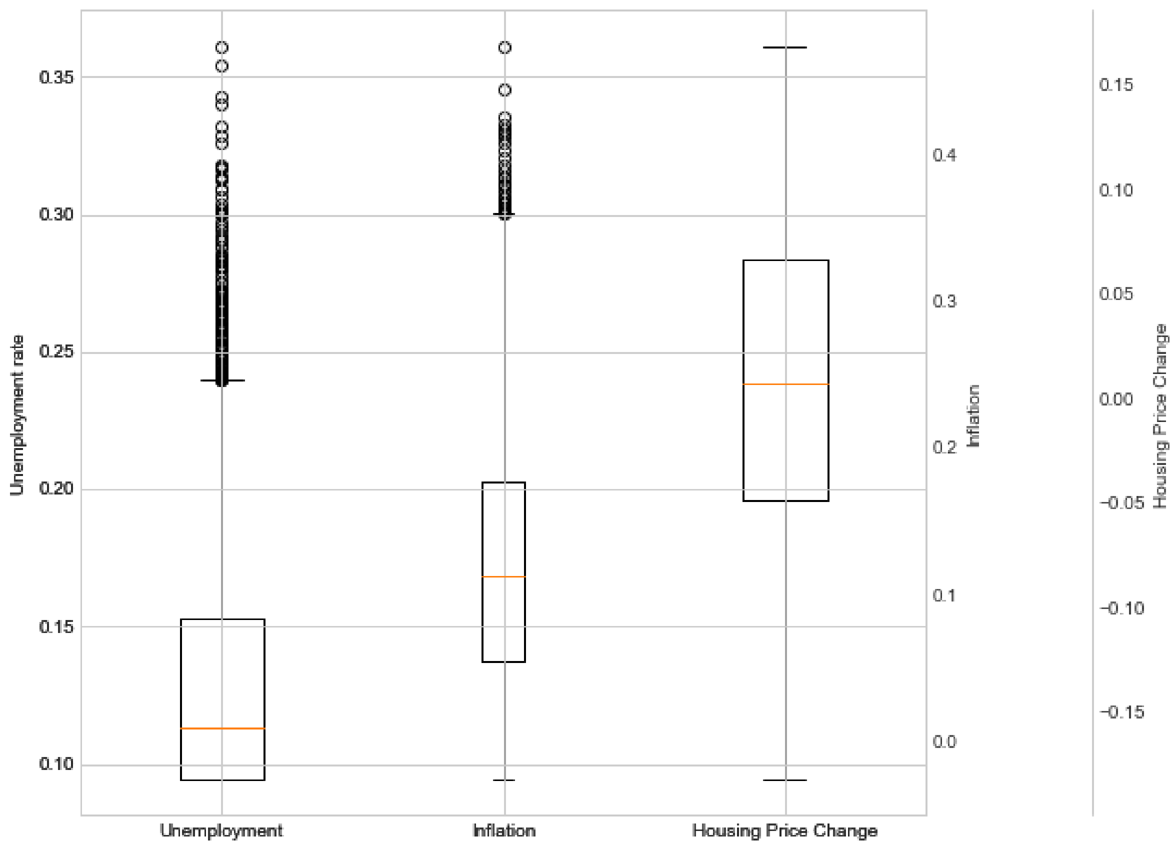
A vital part of RDM is that we can use computer algorithms to analyse big datasets. In this research, we can use the algorithm PRIM to see which factors have the most influence on our outcomes of interest. PRIM stands for Patient Rule Induction Method. This algorithm analyses the whole dataset and slices parts from that data that brings relative most improvement to the objective function, typically the mean of the data (Kwakkel & Cunningham, 2016). We can think about it visually by imagining a box of data. Each step of the algorithm, PRIM removes the upper, lover, right or left part of the data to improve the objection function. PRIM basically encloses the data in steps until an objective is met. This step-by-step procedure produces many different boxes between the starting point and the last box of data remaining. This enclosing process can be seen in a peeling trajectory - the trajectory of slices that were removed from the original data. We as analysts have to then select a box we want to explore further. Selection criteria for this are coverage, density, and interpretability (Bryant and Lempert, 2010; Kwakkel & Cunningham, 2016). Coverage is the fraction of the cases that are of interest fall within a box identified by the algorithm (Kwakkel & Cunningham, 2016). A score of 1 means that all of the cases of interest are contained in a given box. By definition, this always the first box where no data was removed. However, in such a box, the density will probably be very low. Density represents the fraction of cases of interest that are in the box, versus the cases that are not of interest, but also in the box. With a density of 1, all data-points in the box are cases of interest. The final criteria, interpretability, is not a numerical outcome but a choice of the analyst. In general, we want to have a high coverage, high density and a limited amount of dimensions (Bryant and Lempert, 2010). We now know how PRIM operates, but when does it know exactly when to stop cutting data to its bare minimum? For this, we set a threshold for PRIM when to stop. This threshold is a number between zero and one and represents the of the last box on the peeling trajectory. Sometimes, PRIM cannot fulfill its objective function if the given threshold is too high - in that case the score of desired data-points is not available in the analysis. Unfortunately, this number cannot be know in advance. Thus the threshold set in experiments is found by trial and error. With all this set, we know how to set up the experiments.

Although PRIM is a simple but effective algorithm to sort through data, there are some downsides. First, if we want to analyse multiple objectives, we have to re-do and repeat the PRIM process with new objectives. PRIM encloses an objective with a binary formulation of the objective function and so can only do one task at a time. Second, PRIM may slice off the end of a range for a parameter, which suggests that a policy may be sensitive. Its search method can also constrain useless parameters that do not predict cases of interest (Bryant and Lempert, 2010). For this purpose, Bryant and Lempert (2010) pose a quasi p-value test and resampling. The quasi p-value tests the likelihood that PRIM constrains some parameter by chance (Bryant and Lempert, 2010). With resampling, the PRIM algorithm is run different times on sub-sets of the original data. Doing this can compare the sub-sets of data and look for inconsistencies between the results to see how often the same definitions are chosen.

For our fist analysis with PRIM, we first have to give it an objective. To set this objective, let's take a look at some of the outcomes in our dataset. We will present some of the runs in a boxplot so we can inspect the boundaries of values. We will first take a look at unemployment, the change in housing price and inflation.

In [14]:

```
#We will import a matplot toolkit to customize axes for the boxplot.
import mpl_toolkits.axisartist as AA
from mpl_toolkits.axes_grid1 import host_subplot

#We now base our boxplot design on the appendix of Kwakkel & Cunningham
#(2016), but we have to make some adjustments. First we define a figure
#that is the value of cumulative outcomes divided by the amount, giving
#us the average.
oois = outcomes.keys()
data = []

for ooi in oois:
    value = outcomes[ooi]
    if len(value.shape)>1:
        value = np.sum(value, axis=1)
        value = value/np.sum(value)
        data.append(value)
fig = plt.figure()

#We take a custom boxplot that can support 3 values, but first define
#unemployment as the sum of outcomes on the first axes (that means per
#dataset, find the sumulative value and make a new array). Second, we
#divide that number by the amount of years, giving us the average rates
#per year.
Unemployment = np.sum(outcomes['Unemployment rate'],axis=1)
Unemployment = Unemployment/(2023-2016)
ax_Unemployment = host = host_subplot(122, axes_class=AA.Axes)
ax_Unemployment.boxplot([Unemployment, [], []])
ax_Unemployment.set_ylabel('Unemployment rate')

#We do the same for inflation.
Inflation = np.sum(outcomes['Inflation Rate'],axis=1)
ax_Inflation = ax_Unemployment.twinx()
ax_Inflation.boxplot([[], Inflation],[])
ax_Inflation.set_ylabel('Inflation')

#And again the same for the change in housing price, but offset the
#axis, so the numers don't intertwine.
Housing = np.sum(outcomes['Housing Price Delta'],axis=1)
ax_Housing = ax_Unemployment.twinx()
offset = 90
new_fixed_axis = ax_Housing.get_grid_helper().new_fixed_axis
ax_Housing.axis["right"] = new_fixed_axis(loc="right", axes=ax_Housing, offset=(offset, 0))
ax_Housing.axis["right"].toggle(all=True)
ax_Housing.boxplot([[], [], Housing])
ax_Housing.set_ylabel('Housing Price Change')

ax_Unemployment.set_xticklabels(['Unemployment', 'Inflation','Housing Price Change'])

fig.set_figheight(8)
fig.set_figwidth(18)
plt.show()
```




Now we know the upper and lower bounds, let's take the unemployment as an example and answer the question on what the conditions are if unemployment is in the top 25% of all possible outcomes - around 15% or higher. As we can remember from our KDE graph, high unemployment has a flat tail in the upper values, meaning the top 25% values are pretty far from each other. It would be interesting to find out what causes that behaviour.

In [16]:

```
#First, we define a new function (only for this calculation) to
#define the unemployment rate as average over time. This is the
#same calculation as we did before in the boxplot.
def classify(data):
    prim1 = 'Unemployment rate'
    outcome = np.sum(outcomes['Unemployment rate'],axis=1)
    outcome = outcome/(2023-2016)
    classes = np.zeros(outcome.shape[0])
#This is where we set our objective. We are interested in when
#the unemployment rate (the outcome) is higher then 15% (as we
#saw in the top 25% of the boxplot).
    classes[outcome>0.15] = 1
    return classes

#Now, we perform a search in the data. The threshold is set at
#.8, but really this has no objective or scientiffic standars
#it is based on.
prim_obj = prim.setup_prim(results, classify, threshold=0.75, threshold_type=1)

print("                find box:")
box_1 = prim_obj.find_box()

box_1.show_ppt()
box_1.show_tradeoff()
print("                Raw output")
box_1.write_ppt_to_stdout()
```

```
[MainProcess/INFO] 4000 points remaining, containing 1067 cases of interes
t

               find box:

[MainProcess/INFO] mean: 0.9130434782608695, mass: 0.05175, coverage: 0.17
713214620431114, density: 0.9130434782608695 restricted_dimensions: 10
```

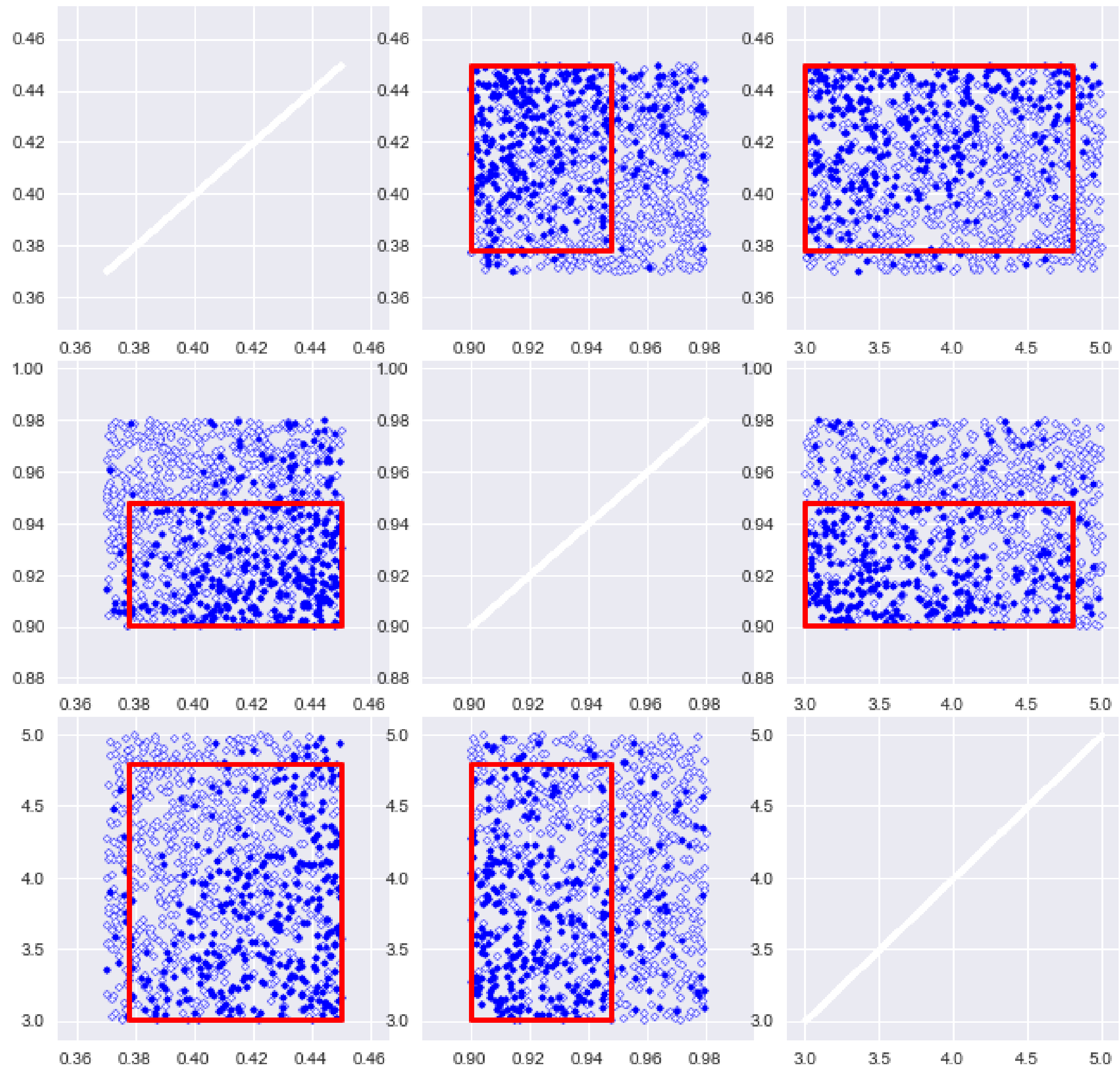
We see a pretty large list of numbers, but also see two sets of peeling trajectories. Let's first start with the output given by the logging function in our final run - the data in the red bar. Here, we see that our objective of unemployment > 15% was met in a box with a mean of .913 and a mass, coverage, density and in a domain of 10 dimensions. The mass, as displayed in the red bar and the list of raw output, is simply the number of data-points in the box, divided by the total amount of data-points (Kwakkel & Cunningham, 2016). Restricted dimensions are the amount of variables that explain a certain behaviour with a given coverage and density. For example, in box 1 (the second value of the raw output list), there is 1 restricted dimension. This means that .99 coverage and .28 density can be explained from the behaviour of one variable in the model. Although we are very satisfied with a coverage of .98, a density of .28 is rather poor: around 72% (1-.28) of the data-points in the box are not of interest. In the first figure, we see the development of the raw output as PRIM cuts data away. The last figure shows about the same, but focuses more exclusively on coverage vs. density.

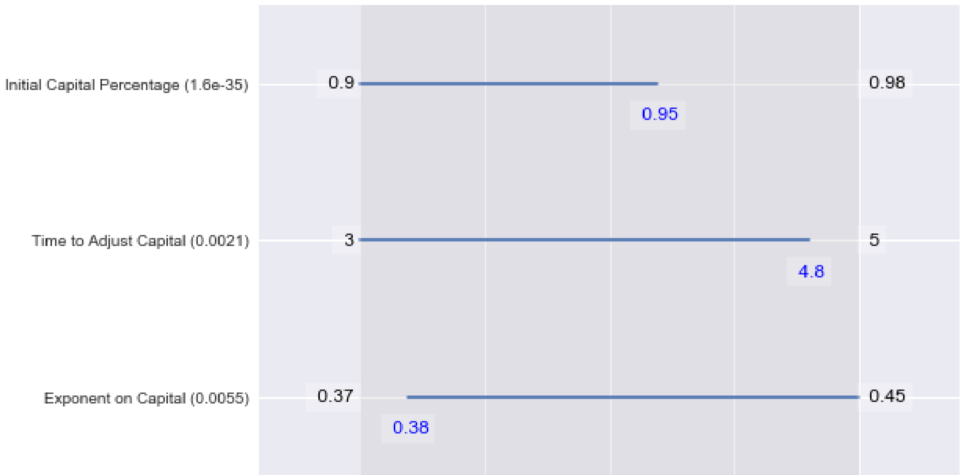
For our analysis, we have to pick a box which we want to explore. PRIM does not tell us what to explore, but we have to pick one based on the interpretability of the box. This is one of the downsides of PRIM - that there is not always an obvious answer. Unlucky for us, we also do not high scores on both density and coverage at the same time. If we look at the trade-off between density and coverage, we can take a look at box 14 with around 80% of the cases of interest, but more than half that do not meet the requirement. Let's explore further.

In [51]:

```
#We select box and display the data in a scatter plot where the
#data PRIM has selected is marked.
#Also, we add an extra line of code (the frist line) which allows us to find
#the quasi-p values of the outcomes to see the significance.
box_1.inspect(14)
box_1.select(14)
fig = box_1.show_pairs_scatter()

print('                  Box status:')
obsts = prim_obj.stats_to_dataframe()
print(obsts)
print('                                Explanation:')
objbx = prim_obj.boxes_to_dataframe()
print(objbx)

#Visualize and set figures.
print("display:")
prim_obj.display_boxes()

fig.set_figheight(11)
fig.set_figwidth(11)
plt.show()

box_1.inspect(style='graph')
plt.show()
```

```
coverage    0.797563
density     0.440476
mass           0.483
mean        0.440476
res dim            3
Name: 14, dtype: object

                              box 14
                                 min       max     qp values
Initial Capital Percentage  0.900077  0.947759  1.575348e-35
Time to Adjust Capital      3.000780  4.798202  2.062917e-03
Exponent on Capital         0.377767  0.449979  5.514886e-03

                  Box status:
       coverage   density   mass  res_dim
box 1  0.797563  0.440476  0.483        3
                                Explanation:
                               box 1
                                 min       max
Initial Capital Percentage  0.900077  0.947759
Time to Adjust Capital       3.00078    4.7982
Exponent on Capital         0.377767  0.449979
display:
```





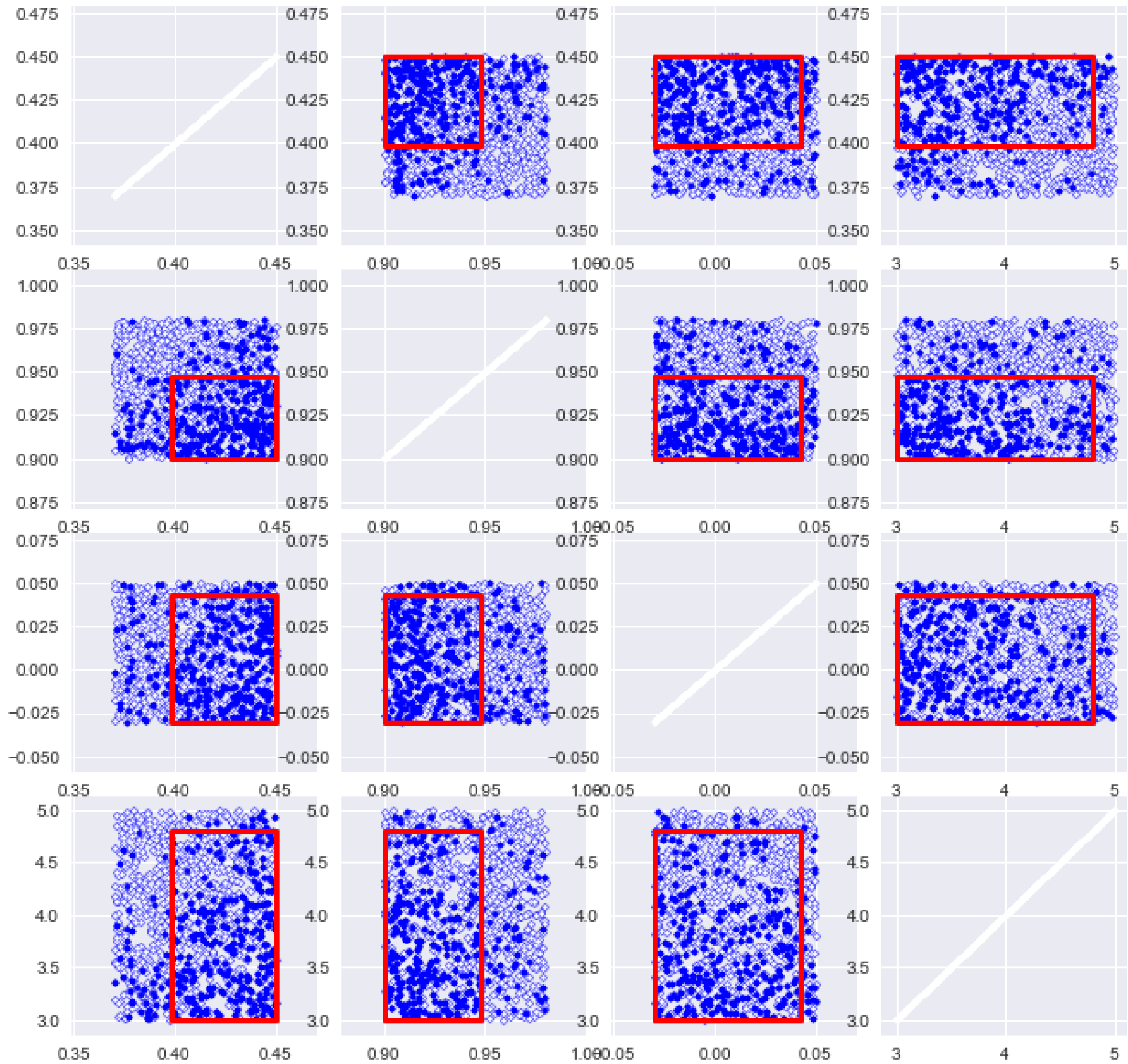

| | |
|---|---|
| coverage | 0.798 |
| density | 0.44 |

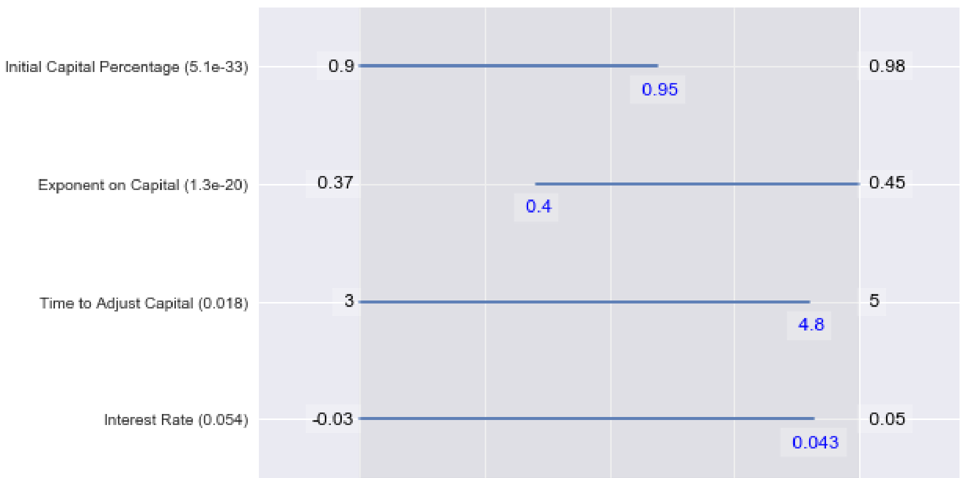
This box is not perfect, but does tell us some things. This overview tells us that this box can be explained by “Initial Capital Percentage” with a value between 0.900077 and 0.947759, “Time to Adjust Capital” with a value between 3.000780 and 4.798202, and the “Exponent on Capital” with a value between 0.377767 and 0.449979. We also have been given quasi-p values. All the quasi-p values are large and we do not reject the null hypothesis that our values are significant. However, a poor density of results inhibits us from making any conclusions. Let's pick a box that has a higher density. Box 22 might prove promising, with a mass of .318 corresponding with the box, we can try to make assumptions about 30% of the data. Finally, the box is restricted by only 4 dimensions - only one more. So let's explore box 22 further.

In [60]:

```
#We do the same as we have done before, but now for box 22.
box_1.inspect(22)
box_1.select(22)
fig = box_1.show_pairs_scatter()

print('                  Box status:')
obsts = prim_obj.stats_to_dataframe()
print(obsts)
print('                                Explanation:')
objbx = prim_obj.boxes_to_dataframe()
print(objbx)

#Visualize and set figures.
print("display:")
prim_obj.display_boxes()

fig.set_figheight(11)
fig.set_figwidth(11)
plt.show()

box_1.inspect(style='graph')
plt.show()
```

```
coverage    0.658857
density     0.552673
mass           0.318
mean        0.552673
res dim            4
Name: 22, dtype: object

                             box 22
                                min       max     qp values
Initial Capital Percentage  0.900077  0.947759  5.131815e-33
Exponent on Capital         0.398263  0.449979  1.285766e-20
Time to Adjust Capital      3.000780  4.798202  1.773885e-02
Interest Rate              -0.029991  0.042689  5.355439e-02

                  Box status:
       coverage   density   mass  res_dim
box 1  0.658857  0.552673  0.318       4
                                Explanation:
                                box 1
                                  min        max
Initial Capital Percentage   0.900077   0.947759
Exponent on Capital          0.398263   0.449979
Time to Adjust Capital        3.00078     4.7982
Interest Rate              -0.0299913  0.0426894
display:
```





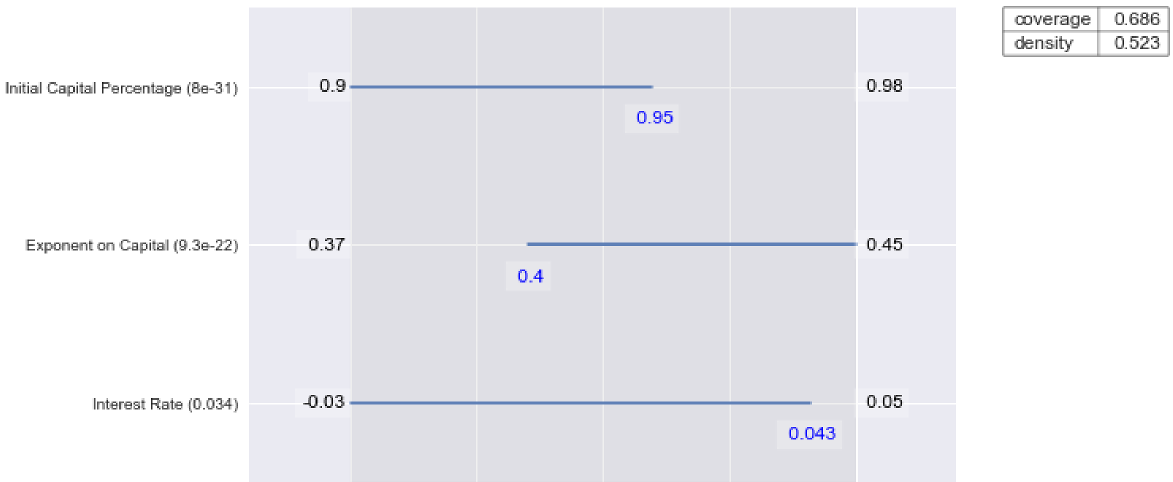

| | |
|---|---|
| coverage | 0.659 |
| density | 0.553 |

The outcomes of this analysis are still very poor. If we look at the variables, coverage and density, we are able to find a box that has 66% of the cases of interest with a density of 55%. In other words, with initial capital being between 90% and 95% of what is required in the economy, an exponent of .4 or higher and almost any time to adjust capital and interest rate, we can arrive at 66% of the cases of interest - with 45% cases that do not meet the requirement of employment averaging above 15%. With low explanatory power, we are able to give a very wide range of factors that explain this behaviour. However, instead of looking at new boxes, let's drop variables that we are not interested in. For example: it is great that the time to adjust capital can be almost anything, but this does not tell us much. What happens when we drop this variable from the analysis?

In [63]:

```
#This is where we drop the restriction for capital adjustment.
box_1.drop_restriction('Time to Adjust Capital')
box_1.inspect()
prim_obj.display_boxes()

fig.set_figheight(11)
fig.set_figwidth(11)
plt.show()

box_1.inspect(style='graph')
plt.show()
```

```
coverage    0.686036
density     0.522857
mass            0.35
mean        0.522857
res dim            3
Name: 58, dtype: object

                              box 58
                                 min       max     qp values
Initial Capital Percentage  0.900077  0.947759  7.979104e-31
Exponent on Capital         0.398263  0.449979  9.315609e-22
Interest Rate              -0.029991  0.042689  3.427577e-02
```

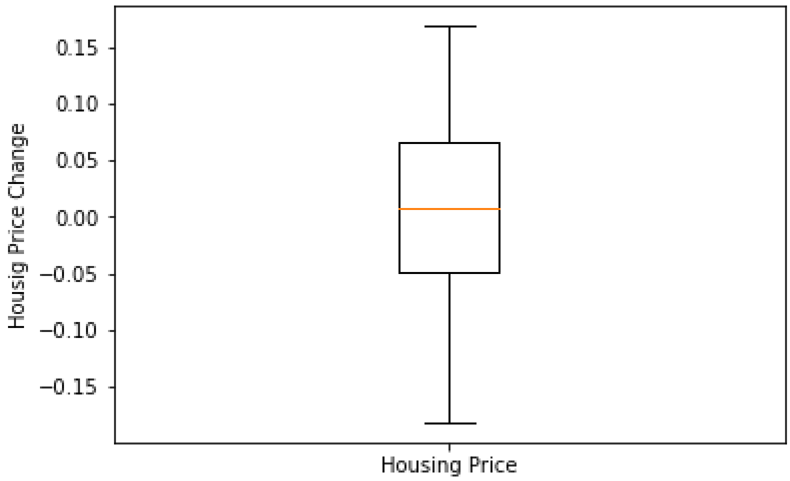



We see an increase of coverage, from 67 to 69 while keeping the same density. At the same time, we got rid of a variable that according to PRIM explained the behaviour of unemployment, but in fact was a variable used for the transition from economic theorem to System Dynamics. The box we are left with tells us that if there is an incentive to make up for capital and the payoff from capital is not too low, high unemployment is very likely. This happens under almost any circumstances of interest rates. In essence, this answer is pretty intuitive and agrees with general economic observations and theorem. Now, we are able to quantify the conditions in which such a thing is likely to happen. However, with a rather average coverage and low density this explanation is not very satisfying.

Let's analyse a new dataset to see differences that may occur when performing PRIM. This time we take the housing price change and look for drivers in its behaviour.

In [4]:

```
oois = outcomes.keys()
data = []

for ooi in oois:
    value = outcomes[ooi]
    if len(value.shape)>1:
        value = np.sum(value, axis=1)
        value = value/np.max(value)
        data.append(value)
fig = plt.figure()

House = np.sum(outcomes['Housing Price Delta'],axis=1)
ax_House = fig.add_subplot(111)
ax_House.boxplot([House])
ax_House.set_ylabel('Housig Price Change')

ax_House.set_xticklabels(['Housing Price'])

plt.show()
```




As we can see in the boxplot, it is about as likely that prices will drop as they will rise. Let's try to find out in what conditions the price of houses may rise. Thus we set our objective to outcomes that larger than zero.

In [5]:

```
def classify(data):
    prim1 = 'Housing Price Delta'
    outcome = np.sum(outcomes[prim1], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0] = 1
    return classes

#perform prim on modified results
prim_obj = prim.setup_prim(results, classify, threshold=0.6, threshold_type=1)

print("                find box:")
box_1 = prim_obj.find_box()
print("                raw output:")
box_1.show_ppt()
box_1.show_tradeoff()
box_1.write_ppt_to_stdout()
```

```
[MainProcess/INFO] 4000 points remaining, containing 2130 cases of interes
t

                find box:

[MainProcess/INFO] mean: 1.0, mass: 0.257, coverage: 0.48262910798122066,
 density: 1.0 restricted_dimensions: 3

                raw output:
    coverage   density   mass      mean res dim
0   1.000000  0.532500  1.000  0.532500       0
1   1.000000  0.560526  0.950  0.560526       1
2   1.000000  0.590355  0.902  0.590355       1
3   1.000000  0.622079  0.856  0.622079       1
4   1.000000  0.654982  0.813  0.654982       1
5   0.999061  0.689119  0.772  0.689119       1
6   0.995305  0.723056  0.733  0.723056       1
7   0.991080  0.758261  0.696  0.758261       1
8   0.984977  0.793495  0.661  0.793495       1
9   0.968545  0.822568  0.627  0.822568       1
```

The housing price is not affected by many dimensions. If we think back to our model, this is true. Also, since we gave a static number to interest change, this variable has no effect at this moment. This only leaves the market sentiment, housing pressure and inflation. Going back to the raw output from PRIM, box 11 has a good coverage and density, 91% and 86% respectively. Let's see what the drivers are in this set.

In [6]:

```
box_1.inspect(11)
box_1.select(11)


print('                  Box status:')
obsts = prim_obj.stats_to_dataframe()
print(obsts)
print('                                Explanation:')
objbx = prim_obj.boxes_to_dataframe()
print(objbx)


box_1.inspect(style='graph')
plt.show()
```

```
coverage    0.913146
density     0.860619
mass           0.565
mean        0.860619
res dim            1
Name: 11, dtype: object

                            box 11
                               min       max      qp values
Initial Housing Shortage  0.900083  1.012976  3.266854e-242

                  Box status:
       coverage   density   mass  res_dim
box 1  0.913146  0.860619  0.565        1
                               Explanation:
                             box 1
                               min      max
Initial Housing Shortage  0.900083  1.01298
```

From the remaining variables that can affect housing price, the housing pressure effect is strongest. This effect is shown in whenether there are enough houses for the demand, or not. Here, we see a rise in housing prices is imminent when the current state of the market is that there are not enough houses. Thus, without taking into account the effect of interest rate, a rise in housing price is likely when current conditions state a housing shortage. With a coverage of 95% of the cases and a very high density, we can be pretty sure of this event happening (if we assume the model is correct).

Unfortunately, this is all we can so with the workbench as of now. With these results, we can assess the likelihood of scenarios with certain parameters, but we cannot assess the effect of interventions. A financial institution would thus be able to assess likelihood of scenarios and have key indicators to track in the economy. If in the future we would be able to also build in interventions and choices for the institution, we can optimize policy decisions.

Because it is unfortunate to end on the note that now we should wait for a financial institution to reassess scenarios based this information or wait for a new model that contains decisions, we are going to set up a small experiment ourselves. This would serve as a proof of concept to financial institutions as well as a general example of Exploratory Modelling & Analysis. In our example, we are going to answer what the government can best do if they want to stimulate investments.