Working Title:

An agent-based approach to modelling the cost of sea-level-rise associated with climate change

*Motivation*

This project has been motivated by a desire to explore the power of agent-based modelling in the consideration of various questions pertaining to climate change. As a preliminary effort we consider the cost of action, or inaction, as sea levels rise and coastal areas are flooded. Our inspiration for this question is doctoral dissertation work by Delavane Diaz who utilised a dynamic programming approach to determine a least-cost strategy to deal with global sea level rise in terms of whether or not a region should adapt to the rise, for example by building a sea wall, or optimally retreat. To complement Diaz’s analysis we approach the question of the costs of sea-level rise by constructing an agent-based model. This choice is for four main reasons. First, agent-based modelling is extremely flexible in the sense that it requires very little exogenous structure on the environment in which agents interact. Second, agent-based models are very amenable to considerations of, often extreme, heterogeneity. Third, the explicit allowance of emergent behaviour by agent-based models is a characteristic that, we think, is fertile ground for novel analyses of climate policy. Finally, the algorithmic approach taken in agent-based modelling allows us to relax the traditional economic assumptions of rational optimising agents and instead consider behaviours that are closer to observed human behaviour. While the possibilities of questions to ask are seemingly endless, our project starts with a simple focus: whether or not to act or do nothing in response to potential, or realised, sea-level-rise and surge events. Our agents are coastal regions and our focus is on their choice of action over a defined time period given their beliefs of their probability of flooding as well as consideration of what is happening to neighbouring regions. Our hope is that our model is a step towards harnessing the power and flexibility of agent-based modelling to obtain insight into questions of climate policy.

Before directly considering the question of action, or inaction, in the face of climate change induced sea level rise, we first make our argument for why an agent-based modelling approach is appropriate for the task at hand. This is followed by a more detailed description of our model and how it complements the Diaz analysis.

*Background*

We often ask economic questions using terminology such as ‘efficient’, ‘cost-effective’ or ‘welfare-maximising’. Much of climate policy analysis is at least tangentially, if not directly, related to considerations of the optimisation that are inherent in considerations of equilibrium. Such an approach has its merits. It is useful to understand what the optimal is/would be in order to have a benchmark against which to measure where we stand today. However, the core assumption that economic actors behave ‘as if’ they were optimising agents (therefore allowing us to utilise optimisation in determining outcomes), is one that should be questioned more strongly. Much of economic thought throughout history has considered the mechanisms of the ever-dynamic economic system. It has only been in the past century or so that the application of optimisation theory to economics has become mainstream. In this way economics was able to take on a much more quantitative theoretical flavour. While there has been much insight brought from this approach, we have lost some of the ‘human’ side of economics in favour of what Richard Thaler refers to as the ‘Econ’. In recent decades a new field of economics, behavioural economics, has developed and worked towards better understanding and incorporating humans back into economic theory.

Brian Arthur has championed what he refers to as ‘complexity economics’: the study of an economy that is constantly growing, moving and evolving. Essentially, an ever-developing pattern that agents are continuously both making and reacting to. Just as optimisation arose as a quantitative tool for one class of economic questions, agent based modelling (ABM) has arisen as a quantitative tool useful in answering some of the questions posed by complexity economics. Rai and Henry highlight several characteristics of ABM that make it attractive for this purpose: it allows for deep endogeneity, the ability to have more realistic settings for choices to be made within, the allowance for the emergence of consumer systems and the allowance for behaviour that departs from the traditional rational actor model. By treating individuals as algorithmic beings, rather than optimising agents, we allow agents within the model to react to an ever-changing decision environment. ABM is therefore a method for simulation that allows much greater behavioural flexibility that could prove to be valuable in obtaining greater insights into complex systems.

The economics of climate change is inherently complex and uncertain. At an extremely basic level the field attempts to evaluate the economic impact of a changing climate. To do this many things have to be considered: what the drivers of climate change are, how human economic activity contributes to such drivers, what the global climate system’s reaction to said drivers will be, how such a reaction will impact the global economy and what should be done in light of these feedbacks, to name a few. Some analyses consider one aspect of the climate change issue and others, such as integrated assessment models, attempt to tackle multiple facets of the problem at once. Many methods have been utilised to answer such questions including, but certainly not limited to, dynamic programming, optimisation, econometric analysis, and analytical economic models. Due to the inherently complex nature of the climate change question, we believe that agent-based modelling is an additional method for insight into many of the questions we are asking. Additionally, at the core of the climate change issue is human behaviour; we are interested in how our actions affect the climate, how those effects subsequently affect us and finally, how we respond. Carbon dioxide, and other greenhouse gasses, are released into the atmosphere due to actions taken by agents. Agents then feel the consequences of these actions and then take experience into account in some manner to make subsequent decisions which will again create consequences that they will have to, again, react to. ABM has many characteristics that make it well-suited for analysing such a system.

Overall, many analyses to date have been very interested in the ‘what *should* be’ of climate policy questions. There has been great emphasis on our ability to identify the optimal path and/or outcome. ABM allows us to approach the question from yet another angle. We aim to utilise this tool to investigate ‘what *could* be’ based on what we know about human behaviour and the global economic and climate systems.

*Adapt, Retreat or Do Nothing?*

The current project takes an ABM approach to the question of whether or not regions should act in the face of climate change induced sea level rise. Our reasons for why an ABM approach is appropriate for this question are three fold: first, it is a question where there is a clear decision that agents can make: to act or not. The strategy set for agents is therefore simple. Second, it is a decision that, in real life, is very likely not to be made purely on optimising or cost-minimising grounds, especially if there is the possibility of extreme events and there are elements not only of uncertainty, but also of irrational risk aversion or fear, for example. Third, the question of adaptation or retreat is not a new one; there have been other studies that have investigated it using more traditional methods. One such study is the referenced dissertation work by Diaz who takes a dynamic programming approach to finding the optimal (i.e. cost-minimising) strategy for each of a number of coastal regions. We have deliberately calibrated our approach to be as directly comparable to hers as possible. In this way our analysis will be able to quantify the costs of various types of sub-optimal behaviour.

Our model considers the same 12,148 coastal regions as Diaz’s analysis. However, unlike in Diaz’s model, where each ‘segment’ optimises independently, irrespective of its neighbours, our regions take each other’s actions, or inaction, into account when making their own decisions. Sea-level-rise is represented by a flooding of a given coastal region. In this way we differ from the Diaz analysis because her model considered a continuous distribution of sea-level-rise and severity of flooding events. We initialise our model with a probability that a given region is flooded, . In the simplest case, the probability of flooding is the same for all regions. That is, the following holds where R represents the full set of coastal regions:

Each region is then initialised with a probability of action, . It is assumed that given enough time, each region would act with a probability of 1. This complements Diaz’s analysis where at the end of the considered time period every region has either adapted or retreated (the two actions available). However, in our analysis we are considering a finite time period within which it is not guaranteed that every region will take action. In this way we reflect the inertia that many regions feel in reality when it comes to implementing action plans (a very simple motivating example is the region who continuously puts off action because they keep carrying out feasibility studies). Because this probability of action parameter is a construct of our model and there is no good data as to suggest what it might be, we have chosen to give it a lower bound of 0.15 and an upper bound of 0.4. This reflects our belief that regions are more likely to experience inertia than not when it comes to taking action against sea-level-rise flood events. Sensitivity analysis on this parameter will consider scenarios where the probability of action for regions is much higher, up to 0.9. We emphasise that in all cases this parameter reflects a given scenario rather than an observed reality.

In addition to assigning each region an initial probability of action, we also allow this probability to update itself after each iteration. The mechanism that dictates how this parameter updates is as follows: first, we define an ‘alpha probability’ for each region, , which is a weighted average of the impacts of previous flooding on a given region and all other regions. In the equation, the parameter alpha represents the weight you put on the impacts to your region as opposed to all others.

We then take this alpha probability and use it to determine a region’s probability of action for the subsequent iteration. We define the updated probability of action as the maximum of its initial probability of action and the initial probability of action multiplied by the ratio of the last period’s alpha probability to the actual probability of a flood. We note that if a region perfectly perceived the probability of flood then the probability of action would never update from the initial condition. For iteration i, the probability of action for a given region, r, is therefore as follows:

In each iteration each region chooses to act, or not, and then is, or is not, flooded according to the aforementioned probabilities. The iteration between regions updating their probabilities of action, choosing whether or not to act and then being flooded, or not, then continues for a pre-determined number of time steps.

Figure 1 is from Diaz’s dissertation and represents the costs associated with sea-level-rise in scenarios with and without opportunities for action (i.e. adaptation or planned retreat). Our analysis is complementary to this figure in the following ways: first, we also consider the costs in a world where no action is possible. To do this we run our simulation (xx) times and report the cost distribution. This allows us to understand how closely our analysis tracks Diaz’s given that there is not a one-to-one translation between the approaches. We then take the optimal action for each region from Diaz’s analysis and utilise that as a benchmark in the context of our model as to what the most efficient course of action would be. Finally, we run our simulation (xx) more times, this time allowing regions to take action, and report the distribution of costs associated with these actions. It is the comparison of these results to the costs given optimal action that allows us to quantify the costs of inertia reflected in a region’s probability of action being distinctly less than 1.

[FIGURE 1]