Two modes of scheduling in a simple economic agent-based model

Sarah Wolf, Steffen Fürst, Wiebke Lass, Daniel Lincke, Antoine Mandel, Carlo C. Jaeger

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Abstract

Agent-based models (ABMs) are used in economics in order to represent the economy as a complex system in which macro-features emerge from the interaction of many heterogeneous agents. In economic systems in the real world, many actions and interactions by various agents take place in parallel. Representing this on a computer where steps are carried out sequentially raises timing issues. While for independent actions the order in which agents act is irrelevant, interaction that involves the state of more than one agent can introduce a bias. This paper presents work in progress, using a simplified economic ABM of firms that trade and produce goods in order to explore and discuss two alternative modes of scheduling: the timetable model, where all agents complete one step after the other, and the heliotropic model, where one agent after the other completes steps. We find that the timetable model is better suited for working with data from national statistics, while the heliotropic model dispenses with random shuffling that is often introduced to avoid a bias between agents which arises from sequential computations. The latter can be used in completely deterministic fashion, providing a baseline case for studying the system’s dynamics.
1 Introduction

Agent-based models (ABMs) are used in economics to represent the economy as a complex system in which macro-features emerge from the interaction of many heterogeneous agents. Implementing a system of agents on a computer and observing simulation runs to study the system’s behaviour poses the question whether some of the observations owe to computational features of the implementation rather than being characteristic of the system under study. For example, in real-world economic systems, many actions and interactions take place in parallel. On the computer, parallel actions are usually represented by sequential steps, and some observations might occur due to sequential computation.

This paper presents work in progress, using a simplistic economic ABM of firms that trade and produce goods in order to explore and discuss two alternative modes of scheduling: the **timetable model**, where all agents complete one step after the other, and the **heliotropic model**, where one agent after the other completes steps. Before turning to the model in Section 2 and discussing implications of scheduling (Sections 3 and 4), this introduction sketches the motivation for the work (Section 1.1) and sets the context of agent-based models (Section 1.2) and scheduling issues (Section 1.3).

1.1 Motivation

The motivation for our work with ABMs stems from the climate change context. Climate policy analysis and recommendations are generally based on economic modelling that compares a business as usual (BAU) growth path with a situation where measures for the mitigation of greenhouse gas emissions are taken. The most frequently used models are optimal growth models (e.g. Nordhaus, 1977; Stern, 2007) and CGE models (e.g. Capros et al., 1999).

Both modelling approaches are rooted in the neoclassical paradigm. An underlying idea is that scarce resources have to be allocated to people with insatiable desires. Rational agents optimize utilities or profits, and equilibrium is obtained when all markets clear, i.e. supply balances demand. These ideas are formalized in the mathematical theory of general equilibrium as developed by Arrow and Debreu in the 1950ies. The theory shows that economic equilibria need not be unique or stable. For the models, however, assumptions are made to guarantee a unique and stable equilibrium, including that of a single representative agent, discussed for example by Kirman (1992).

Climate policy measures are introduced as a deviation from the BAU growth path that is considered optimal in the short run. Greenhouse gas emissions are an external effect of the present upon future generations: the current generation uses the atmosphere (as also a few previous generations did) as a “waste dump” for greenhouse gas emissions without taking into account the effect this will have on future generations. Future climate change, resulting from present emissions due to the time lag in the reaction of the climate system, is a negative effect on future generations, so that for these the BAU path is not optimal. Introducing
a price on emissions, this externality can be internalized, that is, eliminated. However, on the BAU growth path this implies costs in the short run, often expressed in terms of a reduction in GDP, because the current generation will have to pay for using the atmosphere, that before it simply used “for free”. This argument frames mitigation as a welfare trade-off between present and future generations.

The widely accepted welfare trade-off argument has coined a narrative on climate change in which mitigation is defined a problem of burden sharing. While the mitigation costs are legitimated by the benefits of avoided climate change and impacts, these benefits lie in a rather distant future, so that on shorter planning horizons, such as the election periods of politicians, the costs seem much more relevant. In this setting, international negotiations have made little progress towards significant world-wide reductions of emissions.

There is, however, in this argument a fundamental assumption that is problematic: the existence of a unique stable equilibrium growth path is warranted neither by economic theory nor, much more importantly, by real-world observations as summarized in empirical data.

For example, Ormerod et al. (2009) find that the US, the UK, and the German economic system from time to time switch from a steady to a weak pattern. Also, the comparison of countries that at a certain point in time were in similar situations but now differ in economic growth, such as Poland and Hungary at the moment, deserves the consideration of different growth paths.

Dispensing with the assumption of a unique stable equilibrium growth path, the narrative of climate change mitigation as a burden is not the only story to be told. Win-win opportunities arise from shifting to a new equilibrium growth path that is in some sense “better” than the current one, for example in terms of employment. Climate policy can trigger this shift. The study “A New Growth Path for Europe” (Jaeger et al., 2010), which analyses effects of moving the EU emission reduction target by 2020 from 20% to 30% as compared to 1990 levels, finds that a virtuous cycle of feedback effects between investment into green technology, learning-by-doing and the expectations of investors can steer the European economy onto a new growth path with lower emissions but higher employment and growth. The micro-costs for mitigation measures, such as increased energy prices due to emission trading, can be more than compensated by the macro-benefits of this path. A few other studies identify similar win-win strategies for climate policy for China (Shi and Zhang, 2011) and the US (Acemoglu et al., 2012).

Jaeger et al. (2012) suggest to “reframe the problem of climate change, from zero-sum game to win-win solutions”, that is, mitigation measures which are beneficial for the economy. When one considers several equilibria possible, the mitigation question transforms from a problem of scarcity to a coordination problem (Jaeger, 2012). As for the case of conventions (such as driving on the left or driving on the right) there are several viable alternatives – which one is in place depends on people’s interaction in a repeated coordination game and on institutions evolving within the socio-ecological system under consideration. In order to change a convention, agents need to re-coordinate to another alter-
native. Here, economic ABMs come into play: Including interactions between many agents, they allow to consider coordination problems in a dynamic setting.

1.2 Agent-based models

Agent-based models present a relatively new approach to studying the macro-level behaviour of economic systems as arising from action and interaction of agents at the micro-level. This is done by computer simulations. An agent-based model (ABM) implements agents at the micro-level on the computer, equipping them with rules for (inter)action. Simulation runs are then used to study the evolution of the system at the macro-level (e.g. Epstein and Axtell, 1996; Galegatti and Richiardi, 2009; Tesfatsion and Judd, 2006).¹

The literature on economic ABMs is growing quickly, ranging from rather conceptual works (e.g. Tesfatsion and Judd, 2006), to a variety of ABMs concerned with certain aspects of the economy, such as leverage effects in financial markets (Farmer and Foley, 2009). Macro-economic ABMs are developed and applied both for policy analysis (e.g. Dawid et al., 2011) or to study theoretical questions. For example, Gintis (2006, 2007) investigates price dynamics in an exchange economy, that Mandel et al. (2009) extend to the case where capital is accumulated; Dosi et al. (2008) study innovation. In particular since the recent financial crisis, a need for agent-based modelling in economics has been stated (e.g. Farmer and Foley, 2009; Boero and Terna, 2011). Similarly, in the climate change context, ABMs have been discussed as an appropriate methodology (Balbi and Giupponi, 2009).

ABMs have a dynamic perspective, that is found wanting in standard economic models. In a simulation, iterations compute one new state after the other from a given initial state of all agents and their environment. Hence, an ABM could be described as a dynamical system given by a state space together with a transition function. Explicitly writing these down is, however, deemed impossible and sometimes unnecessary (Fontana, 2005; Page, 2008). While an ABMs simulations allow to observe the system’s dynamics, this does not necessarily mean that one can also understand these dynamics. Mathematical descriptions that would facilitate the further study of properties of the system, are rare (see, however, Izquierdo et al., 2009; Edwards et al., 2003; Guilmi et al., 2012).

ABMs are variously considered deterministic systems (e.g. Epstein, 2006) or Markov processes, that is, probabilistic systems (Tesfatsion, 2006; Gintis, 2007). In the model’s implementation, randomness can be discussed away with the argument that the computer generates pseudo random numbers, however, this point of view may not be very helpful for understanding the dynamics of the system. Randomness may be introduced in ABMs for various reasons. For example, mutations, that is, changes occurring with small probability, are often used to represent innovation. In other cases, randomness may be necessary to avoid a bias between agents, as discussed below (Section 3).

¹See also Leigh Tesfatsion’s website on agent-based computational economics: http://www2.econ.iastate.edu/tesfatsi/ace.htm
ABMs provide the modeller with great freedom of representing agents’ behaviour. Bounded rationality, imperfect knowledge, heuristics as decision rules and other features can be included without compromising the solvability of a closed form model, simply because there is none. This facilitates the inclusion of insights from behavioural economics or psychology. However, this freedom also comes with a downside: many similar and yet differing ABMs are being built in an ad hoc mode. Despite some works that promote good practice for developing and describing ABMs (e.g. Macal and North, 2011; Grimm et al., 2006, 2010), there is no commonly accepted theoretical basis that economic ABMs build on and no common language to describe, let alone analyse and compare them. As a second track besides complex economic ABMs, strongly simplified economic ABMs can be useful in order to study their properties as dynamical systems.

1.3 Scheduling

Various platforms for agent-based modelling (such as Swarm, Repast, MASON, Netlogo, etc.) provide tools for representing time and scheduling actions. ABMs may implement a simple sequence of agents all conducting the same action one after the other, or complex message passing systems between agents that trigger actions in event-driven simulation. Parallel computation makes truly parallel operations on the computer possible, but one may not have the powerful computational infrastructure and the knowledge of the techniques needed to parallelize an ABM at hand. Also, it may not always be desirable to use parallel computation because trajectories from one model run are generally not reproducible in another run: the order in which tasks are completed depends on the order in which processors accept these tasks, which differs from one simulation run to another.

Most works related to ABMs provide little detail on how simulations are executed and rather focus on describing agents and their environment, as stated by Mathieu and Secq (2012), who discuss updating of the environment and agent scheduling policies at a conceptual level. They find that the representation of notions such as time and scheduling in the simulator used, as well as sequential or parallel execution of actions can have crucial impacts on simulation results.

Another exception from the rule is given by Axtell (2000) who studies “Effects of Interaction Topology and Activation Regime in Several Multi-Agent Systems”. This work compares in particular an activation mode where all agents are active exactly once in each period with one where the number of activations of each agent is random (with a mean of 1).

The present paper focuses on the case of sequential computations with a fixed schedule\(^2\) and uses a concrete example ABM to investigate two types of scheduling and their consequences. Here, we are particularly interested in whether randomness is necessary, whether and how the model behaviour becomes mathematically tractable, and in relating model input and output to

\(^2\)Here fixed is meant as in opposition to event-driven. The schedule may still involve randomness in the order in which agents act.
economic data from national statistics. While such work is further away from real-world applications such as climate policy analysis, it aims at small improvements of our understanding of economic ABMs – which in turn may be very helpful in that context.

2 The simple ABM – Lagom2basic

The model used here is based on the Lagom model family of economic ABMs (e.g. Mandel et al., 2009; Wolf et al., 2012). These represent economic systems via the interactions between firms, households, a government, and a financial system. Agents have limited or local information and use rules of thumb for their decision making. Firms are grouped into sectors and produce the good of their sector. Production requires intermediary inputs, where the production structure is based on an input output table, and produces emissions. Households work for firms, may own shares of firms, and gain utility from consumption. Agents may imitate other agents who are doing well (e.g. in terms of profit or of utility) and mutation of agents’ characteristics can introduce innovation.

Lagom2basic, as used here, is in a sense a “too basic” model, reducing the economic system represented to a set of firms, that “trade” and produce goods.

The only economic input data considered to initialise parameters and state variables are the total production per sector, an input-output table for intermediary inputs, and the inventory depreciation rate. The model shall be used in order to add complexity in a step-by-step procedure, but already at this stage, scheduling issues can be studied.

Like other Lagom models, the model used here is implemented in Scala (see Odersky and al., 2004) – an object-oriented, functional, statically typed programming language. Scala provides features such as type inference, implicits and high-order methods, allowing to write code that is more concise and expressive than its Java equivalent.4 We use an extended version of MASON (see Luke et al., 2005), a discrete-event multi-agent simulation library in Java, with which Scala interoperates. Lagom models are endowed with a graphical user interface for setting the initial state in a simulation run and for observing model output. In particular, state variables of single agents, as well as some aggregates can be dynamically represented at runtime in a set of line charts, bar diagrams, etc, or written into files for further processing and analysis. Lagom models can be used in connection with SimEnv, a multi-run simulation environment (see Flechsig et al., 2010) that enables experiments with large numbers of runs.

The model uses a caricature of trade, without any payments being made. Rather than of “buying goods”, one might speak of “obtaining presents”. With this simplification, prices are irrelevant in this model version.

See, for example, the blog entry “No, seriously, why Scala?” by David R. MacIver http://www.drmaciver.com/2007/12/no-seriously-why-scala/
2.1 Parameters and state variables

Sectors are denoted \( s \in S \), with \( S \) the number of sectors. When needed, \( i \) is used as an index for firms. Firms’ parameters\(^5\) are a desired production \( d \in \mathbb{R}_{\geq 0} \), input coefficients for circulating capital \( \gamma \in [0, 1] \), and an inventory depreciation rate \( r \in [0, 1] \). An underlying idea in Lagom models is that agents are myopic, here that means that firms generally only see a few firms from each sector. However, the number of firms observed is an input parameter, meaning that the model user can experiment with this myopia, and in particular, complete information can be represented by setting the parameter to the number of firms there are in the sector. The set of firms that a firm observes from sector \( s \) is denoted \( O_s \). Another input parameter determines how this set is chosen: if the model user chooses fixed suppliers, a firm “sees” the firms listed just before itself in the model’s firm list.\(^6\) Else, the set of observed firms is determined randomly each time the firm looks for suppliers of the input goods.

In the simplistic model version used here, it suffices to consider the inventory \( I \in \mathbb{R}_{\geq 0} \) as the firms’ state variable. Further variables introduced below are auxiliary, used for notational convenience.

2.2 Activities: trade and production

For each sector \( s \in S \), firms try to “buy” the goods they need to produce their desired production \( d \). To this end, they first find out the available supply of inputs among the firms they observe for each sector. This is \( a_s = \sum_{i \in O_s} I_i \) for sector \( s \). The quantity to be produced is determined as \( q = \min \left( d, \min_{s \in S} \frac{a_s}{\gamma_s} \right) \) and the required amounts of inputs are then given by \( q \cdot \gamma_s \). The firm then buys \( q \cdot \gamma_s \) for each sector \( s \), and the sellers subtract the respective amounts the firm has bought from their inventories.\(^7\)

The production activity corresponds to a simple change of state variables for a firm: the produced quantity \( q \) is added to the inventory. In particular, production changes state variables for the active firm only, while trade makes changes to the state variables of other firms as well.

\(^5\)Some of the parameters are variable in more sophisticated Lagom models. The desired production is a state variable in other models, updated using rules of thumb, while the coefficients can change due to imitation and mutation.

\(^6\)More complex and evolving networks of visibility are planned to be considered in further versions of the model.

\(^7\)This is a typical case of interaction in an economic ABM that is easy to describe in words and rather easy to implement, but not so easy to describe mathematically in terms of a dynamical system. The activity of a firm changes the state variables of other firms as well, and the amount \( q \) that is bought may depend on the inventory of some firm in \( O_s \) that again may depend on how much other firms have previously bought from this firm in the same time step of the model. See also Section 4.2.
2.3 Time and two modes of scheduling

Time is modeled discretely; the temporal resolution of the model is given by a period, where in each period each agent carries out each activity once. Activities are triggered by the “central clock” provided by the counting of periods, however, within periods, we consider two modes of scheduling.

In the timetable model, a period consists of two steps. In the trade step, each firm trades, that is, buys goods. In the production step, each firm produces. Here, the real time interpretation of a period in the model is the unit of time taken for the computation of flows used as data (e.g., production). In particular, if a period is chosen to represent a year, data from national statistics can be immediately used for production and the input-output table. As firms produce “independently” from each other, the production step corresponds to actually simultaneous actions. The trade step, however, has a “first come first serve”-element, therefore, the order in which firms trade is important. The first firms that trade find most other firms with full inventories, while firms that trade later may have difficulties to buy all the supply they need for the next production step.

In the heliotropic model, firms enter activity phases one after the other. Within an activity phase, a firm first trades and then produces. This means that production is not modeled as simultaneous, with the consequence that the interpretation of aggregate production is more difficult here. A period cannot easily be mapped to a time interval in the real world because the production from one period is not clearly separated from that of another one: firms can use goods that others have already produced in the same period as inputs for production. This complicates the link with national statistics data. However, in the trade step, all agents are “in the same situation”: when a firm trades, it will find some other firms that have just produced goods with a full inventory, while others may have sold most of their inventory since they last produced. That is, in this model no bias arises from the order in which agents trade.

2.4 Simulations

We consider an economic system in which the production inputs are scarce so that effects of trading first or last in the timetable model can be seen. Input parameters have been calibrated so as to identify a range of parameter values where the model is susceptible to changes in scheduling. The inputs used are toy data, for example, all entries in the input-output table are equal to 1 for simplicity. With a production value of 5.1 for all sectors, we use initial economic data that produce input coefficients which are high compared with the desired production and inventories that firms start out with. Also, for the simulations with the timetable model, the inventory depreciation rate is set rather high (to 0.7), so that inventories stay low compared to the demand of production inputs in later periods. This rate can be seen as a work-around for the missing consumption in the simplistic model: inventory is decreased, which it would

8Otherwise the data has to be scaled to match the length of time represented by a period.
also be if the good was sold to consumers. As money does not play a role here, this approximation is good enough for our purposes. For the heliotropic model, this rate is later varied as described below. The number of observed firms for buying goods is set to 5, that is a quarter of the available firms in each sector, and observed firms are drawn randomly.

3 The importance of shuffling in the timetable model

As in the simple model version used here the desired production is fixed and equal for all firms, the produced quantity $q$ of firms is expected to be the same when inputs for production are available. Only a firm that does not manage to buy enough input goods, will have a reduced production. Figure 1 shows that shuffling of firms at the beginning of the trade step is indeed necessary to avoid a bias that favours firms who trade first: reduced productions occur only for the last firms in the list when no shuffling takes place, while, when firms are shuffled at the beginning of each trade step, the reduced production amounts are scattered over all firms.

The fact that shuffling results necessary in the timetable model is here related to the input data used: without scarcity effects, the order in which firms trade would not have mattered. However, it might not always be as obvious that shuffling is required to provide symmetric expectations for agents. In more complex models, there are many more possibilities of how the order in which agents act can affect their performance: when suppliers offer goods at different prices, the firms trading last might have to buy more expensive supplies; in a representation of the labor market, firms looking for workers last might not find the workers with the desired skills, or might have to offer higher wages etc. There may be many other situations which make shuffling essential so as to avoid a bias between agents that would be artificially introduced by the sequential operations on the computer that represent parallel actions in the real world.

However, this shuffling introduces randomness that is not actually essential to the modelled system, but required to guarantee symmetric expectations for agents. This means that randomness is introduced for computational reasons. It is therefore worth asking the question whether this randomness should be represented in a mathematical description of the model. If the setup in terms of periods and steps is maintained in such a description, it seems there is no way of eliminating this randomness because the bias would then similarly occur in a dynamical system that represents the ABM.

Randomness in ABMs implies that the interpretation of model output becomes more involved. One should consider many model runs and statistical evaluations of these to learn about the distributions of states. Looking at sin-

\footnote{Other sources of randomness, such as random mutations to represent innovation, may be essential to the model, but are not of interest here.}
Figure 1: Timetable model with (above) and without (below) shuffling before trade. Columns represent sectors, each cell shows one firm, displaying its produced quantity. The desired production lies at the upper border of the cell, and a smaller production than the desired one is seen in the model output as a downward spike. All parameters (including random seed) are the same in the two example runs.

gle trajectories one might see some effects of improbable events having taken place in just this run. While in ergodic systems the probability distributions over states converge regardless of the initial state chosen, one does not necessarily know when the system arrives “close enough” to the limit and while distributions converge, this does not mean one only sees “average” trajectories.
4 The heliotropic model

This model provides a means to do without shuffling of firms. The randomness that owes to the implementation of the timetable model can be eliminated here, allowing for a simpler starting point for analysing the ABM. In the efforts that are being made to create economic ABMs which are mathematically tractable, this is a step forward.

4.1 Scarcity in the heliotropic model

In fact, the heliotropic model, run with almost the same input data as used above for the timetable model, can – without a need to shuffle firms – indeed produce output that resembles the one seen in Fig. 1 with shuffling.

![Figure 2: Heliotropic model without shuffling. The parameters are the same as above for the timetable model, only the inventory depreciation rate was raised.](image)

However, in this model one sees less scarcity effects. In fact, to produce a similar picture, the inventory depreciation rate was raised (from 0.7 to 0.82). This was to be expected as firms trading late in a period may buy goods from firms that have already produced in that period. This underlines the difficulty of mapping output to national statistics data. Produced goods may enter back into the production scheme in the same period when they were produced, meaning the separation between production inputs and produced goods is lost.

In this model, randomness can be completely eliminated by choosing “fixed suppliers”. Then, each firm buys from the firms that have produced last, right before itself in the firm list. Keeping all other parameters the same, however, we observe no lower productions than the desired ones. This means that fixed suppliers increase stability in the model: in fact, each firm, observing the last 5 firms that have produced in each sector, finds enough production inputs for its
desired production. Tackling this “problem” by providing a more sophisticated initialisation of firms’ inventories, is one of the planned next steps.

4.2 Deterministic baseline case

With fixed suppliers, the heliotropic model can be used to construct a completely deterministic baseline case for then adding randomness in a step-by-step fashion and investigating its effects. At this point, the following is work in progress. A thorough analysis of this kind is planned for the near future.

Depending on the choice of data for the initialisation one can create an economy in equilibrium, where stocks remain the same or grow, or an economy in decline that will in the end have to crash.\textsuperscript{10} For the following toy experiments, the inventory depreciation rate has been “switched off”, that is, set to 0, for simplicity. With the input-output table stating that a firm needs 1 unit from each sector to produce its good, the economy stagnates when the production is set to 5. This has been confirmed by looking at firms’ produced quantities and inventories: everything stays constant in this case.\textsuperscript{11} For production values below this, the economy declines, and production goes down to 0 (except for round-off errors), and this the more quickly, the lower the initial production value is set, of course. With an initial production value greater than 5, firms always succeed in producing their desired production, and inventories simply increase.

Using different initial production values for the different sectors, the economy takes some time to adjust to its equilibrium. This is again a production of approximately 0 in all sectors as soon as one initial production value is below 5, since it suffices to have one sector with a production that is not sustainable to create an economy that is not sustainable. Figure 3 shows that the inventories in the sector with an unsustainable initial production value decline, and when these are empty, produced quantities in all sectors go down. Inventories in the other sectors then simply stagnate.

Considering this model as a dynamical system, this is a truly deterministic system. Writing down state space and transition function is still a lengthy undertaking, and therefore not done in this paper, but it becomes clearer how the system functions. It can thus be a starting point for adding bits and pieces of complexity and observing, and hopefully for understanding, its effects.

5 Conclusions and outlook

This paper presented work in progress on the comparison of two scheduling modes for a simple economic ABM. We find that the different schedules can produce similar model output. However, the timetable model, where all firms

\textsuperscript{10}This can also be interpreted as an equilibrium, however, with produced quantities equal to 0.

\textsuperscript{11}The corresponding image of model output is not interesting enough to deserve being printed here.
complete one step after the other, is closer to data from national statistics, facilitating their use as input and the interpretation of aggregates in the model output. The heliotropic model, where one firm after the other completes all steps, can do without shuffling that in the other model is necessary to avoid favouring agents who act first. This means that the heliotropic model eliminates randomness – that was artificial, because required due to sequential computations.

For the task of helping to generate theoretical insights, it can be helpful to start from simple economic ABMs and add complexity in a step-by-step manner. In fact, this is the aim of the models used here: too simple to study real-world economic systems, they may allow a better understanding of issues that can be studied already at this simple stage. Indirectly, a better understanding of economic ABMs as dynamical systems then may contribute to policy analysis of real-world problems – as for example the questions of multiple equilibria and win-win strategies for climate policy sketched above.

At the same time, efforts are being made to create economic ABMs which are empirically satisfactory (Fagiolo et al., 2006; Boero and Squazzoni, 2005, for example). Here, the timetable model shows an advantage. The “closed form” of periods, meaning that all goods produced in a given period can be used as production inputs at the earliest in the next period, allows to consider the aggregate production of all firms in a period as corresponding to the real-world production of the time span that this period represents. Greater ease of mapping data from national statistics to input data, and vice versa mapping model output to data from national statistics, facilitates the empirical validation
of the model. As national statistics data are in a format fit for standard modeling approaches, ABMs that can be fed and validated with these data formats are at an advantage for data availability. Requirements for and availability of other data formats are a topic for further research relating to economic ABMs.

The difficulty of mapping a period’s production to the production represented in national statistics data, observed for the heliotropic model, can recur similarly for models using parallel computation. It is much less clear what is considered an input and what is considered an output good for a certain time span when these are not separated in the model’s representation of this time span.

Further work on simple economic ABMs, in particular on the completely deterministic version of the heliotropic model as a benchmark and on these models as dynamical systems in the mathematical sense, seems worthwhile. It is certainly aspired at by the authors of this preliminary paper in order to present a more complete account of scheduling issues in this setting.

References


