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Growth Cycles, Network Effects, and Intersectoral Dependence: An Agent-Based Model and Simulation Analysis

Torsten Heinrich*

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Abstract

An agent-based model of economic growth and technological change with network effects is proposed. The dynamics generated by network externalities are self-reinforcing and may bring about rapid growth, but will also for some time prevent further innovation. This circular pattern may appear in different economic sectors (or regions), may synchronize and resonate between sectors. This gives rise to growth waves on the macro-level and may be a novel approach to explain growth cycles. The paper uses an agent-based model for the study of single sector industry dynamics. This design is extended into a multi-sector version with an intersectoral effect on the network externality terms. The model is then simulated both with interconnected (with different network structures) and - as a control treatment - with isolated sectors. The emerging wave pattern on the macro-level is analyzed using both the autocorrelation spectrum and the frequency spectrum obtained with a fast Fourier transformation (FFT) of the simulation's output data.

Keywords: Growth Cycles; Network Externalities; Technological Change; Multisector Growth Models; Agent-Based Modeling

JEL Codes: E32; E37; O33; O41

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1 Introduction

Growth cycles have fascinated economists for a long time.[1] The steady change between times of slow - even negative - and rapid output (GDP) growth serves as a reminder that the economy is indeed not in an equilibrium. Yet it remains unproven what exactly drives growth cycles. Though a number of theories have been put forward, many historical models suffer from certain shortcomings: Some did not match the empirical patterns of observed data, some did not rest on realistic theoretical foundations, some neglected crucial aspects of economic systems. Especially business cycle models based on equilibrium theories[2] were heavily criticized in the literature Lines (1990); Chen (2002). Evolutionary agent-based approaches have taken major steps toward realistic models of growth cycles. Open to computational methods (such as agent-based simulation), they are able to model economic systems in much greater detail, crucially also to include interaction between sectors Carvalho (2008); Saviotti and Pyka (2013, 2015) and dynamics of interaction networks Dosi et al (2010); Taghawi-Nejad (2010).

The present article contributes to this tradition. It presents a model of economic growth and technological change with network externalities. Network externalities denote the phenomenon that products, standards, or technologies become more valuable or efficient as the community using that technology grows. It is well-known that this leads to self-reinforcing dynamics, may impede technological progress and potentially bring about technological lock-ins Arthur et al (1987); Arthur (1988); David (1985). As a new and better technology will normally not have the advantage of a large user community, its implementation will be delayed and perhaps prevented altogether by the inertia of the system.

As a consequence, substantial efficiency gains from technological progress will be put off for significant amounts of time in systems with network externalities. If they occur, however, successful technological revolutions will bring about a period of large efficiency gains and rapid growth. This period will occur slightly after and not simultaneous with the transition to the new technology. The transition itself will always be characterized by temporary inefficiencies, loss of existing network externalities and the establishment of new ones (similar to Taghawi-Nejad's Taghawi-Nejad (2010) network restruc-

[1]For an overview, see de Groot de Groot (2006).

[2]This encompasses in particular real business cycle (RBC) models Lucas (1972, 1981) and DSGE models (e.g. Christiano and Eichenbaum (1992)), see section 2.

turation model). Efficiency gains will be realized thereafter as the user base of the new technology grows.

This brings about a pattern of irregular waves of rapid growth dominating a background regime of low growth rates. This growth pattern should be expected to emerge at a sectoral level. However, it may resonate and synchronize between technologically or economically linked sectors.

Empirically, this pattern would manifest itself in quick technological transitions that are not limited to a single sector where they originate but penetrate much of the economic system. This may most prominently include Freeman and Perez' Freeman and Perez (1988) technology paradigm changes but could also represent changes at a smaller scale. Consider two examples: the electrification of the manufacturing industry in the first decades of the 20th century on the one hand and the rise of information and communication technologies (ICT) in the most recent decades on the other. The speed and patterns of diffusion of these technologies and their impact on labor productivity has been studied extensively; Jalava and Pohjola Jalava and Pohjola (2008) give an excellent literature overview for both cases and offer a detailed analysis comparing the two technological revolutions in the context of Finland. The introduction and the rise of both technologies happened rather speedily and was associated with marked increases in labor productivity; however it did not necessarily happen at the same time in different countries. The reason for this is most likely that technology is connected to the economic structure of the regions, the investment climate, but also the local infrastructure. Especially with network externalities (and both ICT and electricity depend on networks size but also on physical networks), infrastructure is crucial to the extent that many successful technologies have achieved their success by coopting preexisting infrastructure Heinrich (2014). For instance, early computer networks employed the telephone network. Recent computer technology still relies on technological standards from the early days of the ICT. The automobile enjoyed quick success, in some countries even displacing the railroad, because it could rely on a network of streets that was already in place for use by horse carriages. Naturally, this leads to systemic problems[3] which may even act as a drag on further economic and technological development.

However, beyond the great technological revolutions, much smaller events may work in similar ways: When the ICT experienced its first phase of mag-

[3]Discussed in detail in Heinrich (2014).

nificent growth in the 1990s - fueled by electronics, widely available personal computers, and the advent of the internet - it expired dramatically in the "new economy crash" in 2001. What followed is a period of consolidation and major changes in the industry structure before the sector surprised the world again. Consider the development of high-technology exports (across all countries) as shown in figure 1. Note that high-technology manufacturing is heavily dependent on ICT. The growth of high-technology exports is interrupted twice, in 2001 by the new economy crisis and in 2007 by the global crisis[4]. After the new economy crisis in 2001, absolute growth of high-technology exports recovered relatively quickly (solid line) but the shares of high-technology in all manufacturing exports only rose after 2007 again (dashed line). After 2007, mobile devices and social networking, later also "cloud computing" led to another boom of the sector and another incident of dramatic changes in other fields of the economy. Even fields that previously were less directly connected to ICT, such as taxi services, hotels and tourism, were strongly affected. The finance sector on the other hand experienced "flash crashes", an unwanted side-effect of automatic trading. The effect that the recent emergence of "cloud computing", widely available and affordable distributed computing, will have, can barely be overestimated: "big data" has ceased to be a domain of large companies. Though this may seem to empower small and more innovative Nooteboom (1994) enterprises, it should be noted that the associated network effects themselves work in favor of large competitors, in this case those that offer "cloud computing" services.

The theoretical framework of network externalities and cycles in interconnected sectors has been laid out in earlier work by the present author Heinrich (2013). Making use of this framework, the current paper extends the analysis by simulating an economy composed of interconnected industries. It is argued that this allows macro-economic growth cycles to emerge in a model that include this mechanism. Simulations show that at the macro-level the model produces a realistic growth process including recurring waves (cycles). It should be noted that the model laid out here does not attempt to explain everything and is not calibrated to match empirical observations; it is rather designed to be as simple as possible while reproducing the wave pattern observed in economic growth as a stable and sustained process.

The paper is organized as follows: Section 2 will provide a short overview

[4]This is more clearly visible in absolute value, solid line in figure 1.

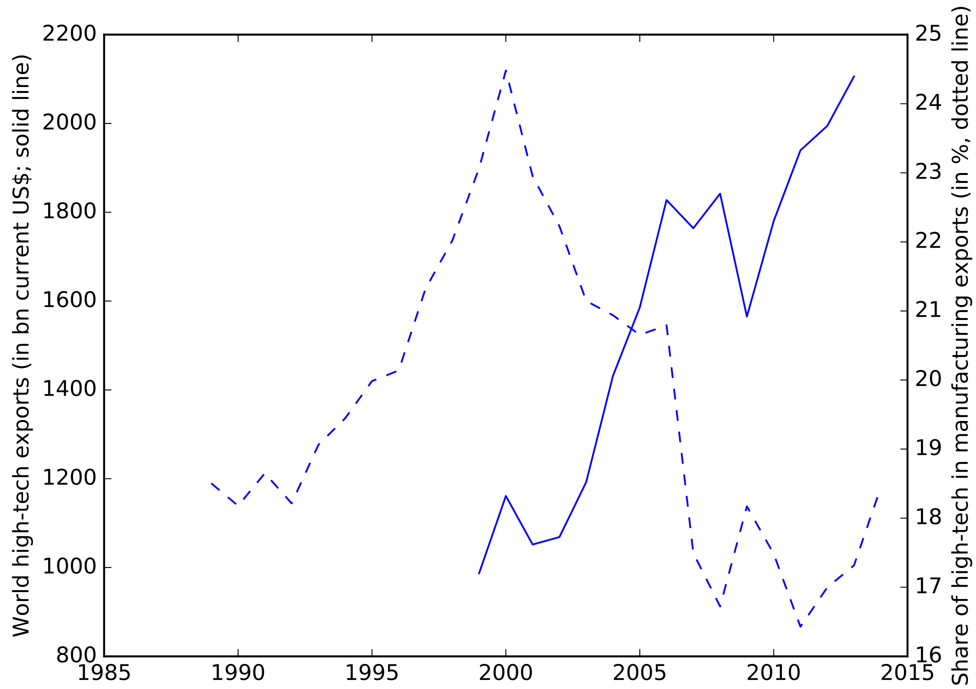

Figure 1: Development of high-tech manufacturing exports, value (solid line) and share of high-tech in total manufacturing exports (dotted line). Data from Worldbank (2016)

of existing models of growth and economic cycles. This will be followed by a discussion of a single-sector (i.e. micro-level) model which is largely equivalent to the model discussed in Heinrich Heinrich (2013) in section 3. This approach will be extended by aggregation over sectors (considering both cases of interconnected and non-interconnected sectors) to a macro-level system. Section 4 shows simulation results of both the single sector and the extended version. The last section concludes.

2 Literature Review: Modeling Growth Patterns in Economics

2.1 Patterns of Economic Growth

Traditional theories of economic growth were build around either a dynamically stable constant growth rate or an approach towards a static equilibrium. The latter is exemplified by the Solow-Swan model Solow (1956). The former, represented by AK models and endogenous growth theory Solow (1956); Uzawa (1965); Cass (1965) yields an exponential growth path.

More recent dynamic stochastic general equilibrium (DGSE) models complement endogenous growth mechanisms with additions that provide turbulence and growth cycle patterns (see, e.g. Christiano and Eichenbaum (1992)). This approach, drawing on the real business cycle (RBC) models Lucas (1972, 1981) holds that there are random shocks to which the equilibrium economy responds in a uniform way that gives rise to a cycle pattern. Typically, the exponential of an autoregressive moving average process, e.g. an AR(1) of the form

$$A_t = A_{t-1}e^{\lambda_t}$$

is used.[5] The logarithmic form of this

$$\log A_t = \log A_{t-1} + \lambda_t$$

is the standard AR(1) process and yields (by the central limit theorem) a (nearly) Gaussian distributed sum $\log A_t$. It follows that A_t is log-normally distributed and still has finite moments which leads to desirable convergent properties in the resulting model. The wave pattern over this is induced by the included moving average, which directly leads to the the Slutzky-Yule effect Slutzky (1937 [1927]) that transforms short term white noise into waves of longer period lengths. Using the log-normal instead of the normal distribution will make the spread of low and high values more prominent. The entire RBC approach, however, has been argued to rest on unrealistic assumptions Lines (1990) while other criticisms pointed out that the resulting behavior may not match the variance patterns observed in the data Chen (2002). It should also be noted that the pattern may change fundamentally

[5]Here, λ is an independently identically distributed random variable with finite mean (the drift or long term growth trend) and variance

if a more heavy tailed distribution (instead of the heavy tailed but finite variance log-normal) such as a power law is used Mandelbrot (1997).

Another endogenous growth theory that is able to take periods of rapid growth into account is the Schumpeterian endogenous growth model by Aghion and Howitt Aghion and Howitt (1992). It includes stochastic innovations which shift the growth path on another trajectory thus implying to a sudden peak in the growth rate though the model does not capture the transition process and concentrates on the properties of the new equilibrium. Some theories Samuelson (1939); Kaldor (1940); Goodwin (1967) have experimented with dynamic systems with complex eigenvalues which also generate circular motion.[6] Many such mechanisms - especially the earlier ones - behave rather clockwork-like, but other theories consider dynamic systems with stable dynamics, finding that chaotic dynamics emerge even in relatively simple systems Lorenz (1987); Keen (1995).

A major step for the explanation of cycles was taken with the emergence of evolutionary growth theory since the 1970s, notably the works of Nelson and Winter Nelson and Winter (1974, 1982): Growth can be modeled to be brought about by random scientific discoveries, their slowly following economic application, and the diffusion of the resulting technology through the economy, a process that is driven by profit opportunities for the first-comers. What results is a wave pattern in growth rates with varying lengths and sizes of the waves instead of perfectly regular cycles. Such a wave pattern would be very difficult to distinguish from stochastically disturbed regular cycles.

While for Nelson and Winter modeling growth cycles did not constitute the centrepiece of their contribution, their model is capable of doing so in a remarkable way. Nelson and Winter's seminal work proved to be the foundation of a whole new branch of economics (evolutionary agent-based modeling, ABM), and led to a number of other evolutionary growth models. Some authors kept their models close to Nelson and Winter's original model but employed Nelson-Winter-type models Freeman and Perez (1988); Conlisk (1989); Silverberg and Lehnert (1993) for the purpose of modeling economic growth with cycles. Others proposed alternative mechanisms and including, in some cases, alternative explanations for business cycles. Dosi

[6]The eigenvalues of a dynamical system's linearized Jacobian matrix capture the dynamic properties of that dynamical system. Circular motion is shown if, and only if, at least one eigenvalue is complex (has a non-zero imaginary component). For an introduction to dynamical systems in the context of economics, see e.g. Foley (1998); Elsner et al (2015).

et al. Dosi et al (2010) join Nelson and Winter's Schumpeterian approach with Keynesian modeling, that in itself can also generate cycles (cf. Minsky Minsky (1980)). Gaffeo et al. Gaffeo et al (2008) develop a model in which the business cycle - again as a wave pattern - is driven by financial fragility and the collapse of what could be called investment bubbles. Taghawi-Nejad Taghawi-Nejad (2010) considers the network-effects of technology shocks: They may induce a general restructuration process of the network among firms (i.e. firms reconsider their cooperation partners).

The different approaches are summarized in table 1.

2.2 Inter-Sectoral Effects and Standard Tying

Notwithstanding alternative models that include global effects (e.g. a financial crash with tightening investment across the economy), Nelson and Winter's mechanism should primarily operate at the level of a single sector. Why should the effect translate into the same wave pattern at the macro-level; why should the random influences not - with the law of large numbers - level out over a great number of sectors? Innovations occur in Nelson and Winter's model at random for all agents (though subject to their individual investment in R&D); a successful innovation will trigger a slow diffusion process through the sector. If random events across different sectors and in particular the technology used in different sectors were independent from one another, the law of large numbers should level out of any sectoral effects at the macro level. However, as the technology employed in sectors is not independent, an investigation of the translation of sectoral growth waves into growth waves at an aggregated level is warranted.

The current work argues that this link may be found in technological lock-ins based on network externalities in interconnected sectors. Drawing on earlier industry economic and -strategic analyses of network effects in tied sectors Choi (2004) the present author has proposed to use such a setup for modeling growth cycles Heinrich (2013) but no implementation of this has yet been published. It will be shown that it is possible to generate a wave-like pattern even with non-interconnected sectors given that radical innovations are prominent enough compared to small incremental innovations and also rare enough - so that the coincidence of two such innovations in two different sectors virtually never happens. This pattern fits the stylized facts

Model	Type	Explaining average steady growth	Explaining business cycles	Drawbacks of non-evolutionary models	Sectoral interaction
Solow-Swan model Solow (1956)	steady-state convergence			exogenous explanation of growth, cycles unexplained, neoclassical assumptions	
Marxian model Marx (1963 [1885])	investment bubble		?	no growth, pure macro-model	
AK and endogenous growth theory Solow (1956); Uzawa (1965); Cass (1965)	exponential growth	✓		neoclassical assumptions, cycles unexplained	
RBC type modelsLucas (1972, 1981); Christiano and Eichenbaum (1992)	exponential growth and AR1 disturbance	✓	✓	neoclassical assumptions, doubtful that AR1 matches cycle pattern	
Macro-dynamic models Samuelson (1939); Kaldor (1940); Goodwin (1967)	complex eigenvalues	✓	✓	pure macro-model, non-resilient	
Nelson-Winter type models Nelson and Winter (1974, 1982); Silverberg and Lehnert (1993)	evolutionary ABM, innovation-duffusion dynamic	✓	✓		
Financial fragility model Gaffeo et al (2008)	evol. ABM, financial fragility induced crises	✓	✓		
Production network model Carvalho (2008)	evol. ABM, coupled production decisions in production network	✓	✓		✓
Schumpeterian-Keynesian model Dosi et al (2010)	evol. ABM, innovation-diffusion dynamic with investment cycle	✓	✓		
Network restructuration model Taghawi-Nejad (2010)	evol. ABM, network restructuration after technology shock	✓	✓		
Industry life-cycle model Saviotti and Pyka (2013, 2015)	evol. ABM, sectoral life-cycles	(✓)	✓		✓

of innovations at least roughly.[7] However, interrelations between sectors may result in a much more pronounced and wave-pattern; this is not merely true for cross-sector spillovers, but rather and especially cross-sectoral network effects. Spillovers will not be explicitly discussed in the current investigation but work in the same direction as the effects analyzed here, they are discussed in detail in, e.g., Watanabe et al. Watanabe et al (2004).

It should be noted, that there are also alternative evolutionary economic models of business cycles that take sectors into account - however, they do not consider the aspect of network externalities and are only partly motivated by the fact that technologies are not sectorally independent. Carvalho Carvalho (2008) provides a model of a production network in which production decisions are coupled along production chains. Pyka and Saviotti studied with industry life cycles Saviotti and Pyka (2013) which in themselves also constitute a circular pattern which - potentially in conjunction with other effects - may also generate business at the aggregated level, though the authors themselves again make no claim to this.

Recently, Farmer and Lafond Farmer and Lafond (2016) and Way et al. Way et al (2017) investigated the rate of progress withing technological paradigms and their interaction with "technological lock-ins" in terms of Arthur's and David's earlier models Arthur et al (1987); Arthur (1988); David (1985) empirically. They find cumulative technological progress along exponential growth paths that are constant over the short term but different across technology types. A different approach to technological-economic systems focusses on automated model-discovery Skulimowski (2012).

The following sections will enrich the field of existing evolutionary theories of growth and business cycles by one that rests on network externalities and the tying of technologies and especially technological standards across sectors. Though only one simple model will be developed along these lines in this paper, it is likely further viable approaches exist. It will remain for later empirical research to assess which ones are indeed responsible for the growth cycles we can observe.

[7] See especially the Schumpeterian theory of technological change (most extensively in Freeman and Perez Freeman and Perez (1988)) and the discussion of stylized facts in Silverberg et al. Silverberg et al (1988). This point is taken up again in section 3.

3 Model: A Single Sector

3.1 Model Definition

Technologies, standards, and products making use of such technologies are usually subject to network externalities. That is, they grow more valuable, the larger the user base employing the same technology (or standard or product) is. This changes not only the likely corporate marketing strategies but also the dynamics of the sector in that it allows multiple equilibria; it requires either a certain number of initial users for a technology to take off or a huge technological advantage over the current incumbent technology. As a result, the network externality prevents further innovations for at least some time, an effect which has been termed a "technological lock-in" Arthur et al (1987); Arthur (1988); David (1985). The model will first be introduced as a one sector simulation model of production and technological progress with network externalities before detailing and explaining the assumptions that underlie this model. At the end of section 3 intersectoral dynamics, hence a macro-level, will be added. Simulation results of both versions will be shown in the following section. While the discussion of the model in this section highlights the aspects important from the point of view of economics, a full formal description following the ODD standard can be found in A with the algorithms of the crucial subroutines of the program shown in B.

Agents, Production Plants, Labor A number (n) of agents use their disposable capital to construct production plants. Plants are normalized for simplicity in that the construction costs and the output (and revenue) per period are identical for all plants. They do, however, require a different amount of labor (l) to produce the normalized output. This labor efficiency ($1/a(q)$) is determined by the technology (q) of the plant or, in other words, each technology results in a certain specific labor efficiency. Plants are always constructed using the best possible technology (lowest labor requirement, $a(q)$) available to the agent. Labor (L) is limited; labor is distributed to the most efficient plants first - until there is not enough labor force available to operate the next plant (see figure 2). Plants that cannot be operated do not produce revenue for their owner. All plants (i.e. capital) depreciate after a certain time (20 periods) after which they cease to exist. Note that this vintage-capital design is different from most models in evolutionary economics that work with replicator dynamic elements Nelson and Winter (1974, 1982); Silverberg et al (1988); Silverberg and Lehnert (1993); Dosi et al (2010) but follows Conlisk's - arguably more realistic - approach Conlisk (1989).

Technology, Innovations Agents have a set of technologies known to them. Every technology (q) belongs to a technology type (v); technologies of the same type are - for the network externality - considered mutually compatible. Technologies may further be improved by research which succeeds with small probabilities; if successful, the agent in question will gain a new technology q^* with a lower labor requirement (specifically the labor requirement $a(q^*)$ is multiplied by a factor $r < 1$). In line with the literature, technological change is assumed to be cumulative Silverberg et al (1988); Way et al (2017), i.e. successive improvements $r_1, r_2, ...$ available to the agent in question are combined (in this case multiplicatively $r_1 \times r_2 \times ...$) except in case they belong to different technology types - then the technologies are assumed incompatible. Roughly following Freeman and Perez' Freeman and Perez (1988) model of different types of innovations (there incremental innovations, radical innovations, technology system changes, and technology paradigm changes), innovations in the current model may take two different forms:[8]

- incremental innovations; This type of innovation is relatively likely, it succeeds with a probability of $p_{incr} = 0.05$; the actual improvement it yields in terms of labor requirement is drawn from a uniform distribution $r_{incr} = Uniform(0, 0.005)$.

- radical innovations; This type is much less likely, succeeding only with probability $p_{rad} = 0.0001$; it yields a labor requirement reduction by a factor of $r_{rad} = Uniform(0, 0.1)$.

This induces an exponential improvement in efficiency, in accordance with empirical findings of exponential cost reduction along technology lines. Farmer and Lafond (2016); Way et al (2017). Note that of the other two types discussed by Freeman and Perez, one (paradigm changes) is beyond the scale of the current model while the other (technology system change) is represented in the form of different technology types which represent different technology systems. Most of the time, one type is dominant (as the use of this type

[8]Note that this is a simple, not computation-intensive way to obtain a right-skewed distribution. It could also be accomplished with another random number generator drawing from a different probability density function.

yields benefits from network externalities as described below), but if another type was improved faster, agents will have incentives to switch to this type nevertheless, which, in turn, leads first to efficiency losses from the loss of the network effect, but then, as the new system becomes more common, large efficiency gains. This would be the present model's equivalent to Freeman and Perez' technology system change.

Finally, there are open technologies, research that is publicly available (which represents knowledge produced by universities and other public institutions). For simplicity a random 5% of new technologies are considered open and thus available to all agents.

Though this technological change mechanism is guided by the literature, it includes several components and it may seem that it would change the behavior of the entire simulation if different values were chosen. The simulation has therefore been run for different sets of parameters as well as with and without the three effects (open technologies, radical innovations, incremental innovations). As discussed at the end of section 4, this preserves the effects presented in this paper as long as the network externality mechanism (below) is large enough to unfold a cross-sectoral synchronization (which is not the case if it is small compared to the variation between technology levels between agents, between sectors, and between technology types).[9]

Network Externality All agents start with a default technology q' with $a(q') = 1.0$. Technologies (q) of the same technology type ($v(q)$) are - for the network externality - considered mutually compatible. Thus, to apply the network externality, usage shares of the technology types ($s(v)$) are used. Usage shares are computed in terms of shares in production (i.e. active plants) not in terms of shares in the number of firms, as these may have different numbers of active plants or even none at all. The network externality works to improve the labor efficiency (lower $\widetilde{a}(q)$) of commonly used technology types by a third at most (or, equivalently, as modeled here, decrease labor efficiency of uncommon ones, increasing their $\widetilde{a}(q)$ by 50% at most).[10]

[9]At least this point may, however, be considered clear for technological change: Some technologies unfold a very strong cross-sectoral impact. This includes more general technologies such as computers or alternating-current electricity, but also very specific technologies and technological standards, such as the email protocol, RJ45 ethernet cables for computer networks, 3/8-inch bolts, etc.

[10]Hence, technology types that dominate the population completely have $\widetilde{a}(q) = a(q)$ while those that are not used at all have $\widetilde{a}(q) = 1.5 \times a(q)$ (i.e. require 50% more labor to

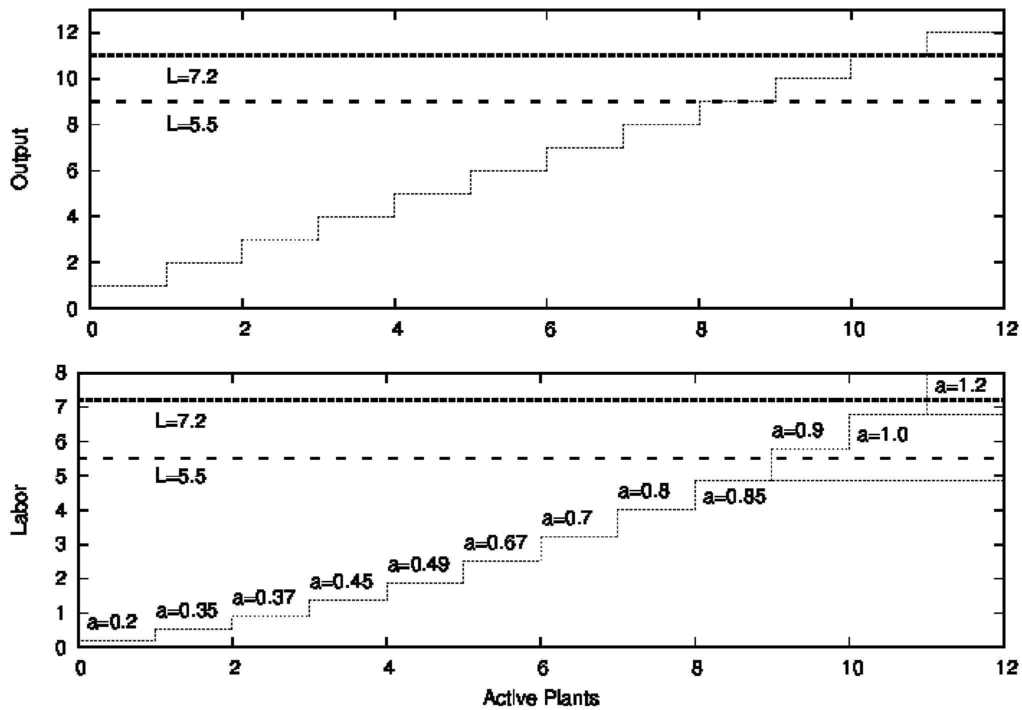

Figure 2: Labor allocation and output in the single sector model (for 2 different labor force sizes)

$$\widetilde{a}(q) = a(q)\frac{3 - s(v(q))}{2} \tag{1}$$

3.2 Assumptions and Limitations

Some assumptions are inherent in this model; they had to be made since the parameter space for a model of economic growth is potentially very large. They are designed to focus the analysis on the effect of the network externality. Most are designed to yield a simple but general case: Different effects that impact the system in the same way are reduced to a single mechanism,

generate the same output). Parameters were chosen so that the initial $\widetilde{a}(q) = 1.0$ (since the population is initially locked-in to use the default technology q' with $a(q') = 1.0$ and usage share of $s(v(q')) = 1$).

production occurs in normalized units. The following non-exhaustive list discusses the most important simplifying assumptions the relaxation of which could enrich the model by other interesting aspects and would be intriguing topics for follow-up research.

- Unlimited demand, infinite price elasticity (price does not change): For simplicity, the demand side is not included into the model. This is not intended as a statement on the relative importance of demand-pull or supply-push effects but rather as a reduction of something that does in this model not introduce substantial changes. Limited demand would add another mechanism of scarcity besides limited factor (labor) input. In fact, for the purpose of the current research (growth cycles), the model is exactly equivalent to a model that would include limited demand but unlimited labor supply, a comparison that is made simple and straightforward by the normalized size of plants: In the current model, efficiency is interpreted as labor efficiency $x(=1/a)$, hence revenue of a single plant per unit of labor input is $x(=1/a)$ (revenue is normalized to 1, labor requirement is a). In the alternative demand-side model efficiency x would be seen as the output the plant could generate with given (normalized) labor input, hence the expected revenue of a single plant per unit of labor input would be $xp_{average}(=\frac{1}{a}p_{average})$ (revenue x, labor input 1) where $p_{average}$ would be the average price of the produced commodity over the relevant time frame. Inclusion of the goods market and labor allocation thus work in the same way if only one of them is present. If both are present and none is sufficiently relaxed to be dominated by the other, they may generate interactions.

- No wage-led growth effects: Such effects would add another path-dependent aspect to the system (low wages, low growth or high wages, high growth), something that may be particularly interesting for explaining crises (as in for instance Keen (1995)) but constitute an aspect that is different from and has relatively little interaction with network effects as investigated here. As the interaction effect between the two may be complex and associated with difficulties to ascertain which part of the model (e.g. network effects or wage-led growth) would be responsible for observed effects, the choice has been made here to restrict the model to the network effect aspect and leave the investigation of the interaction for future research. As such, revenue from plants is assumed to be net revenue after wages and other expenses are deducted; the labor market is not modeled.

- Normalization of the production system to plants of equal size: Normalization of plant size allows to describe the mechanisms included in the model in a relatively straightforward way and to compare the model to other possible set-ups (see the point about unlimited demand above). Of course, in reality plants are of very different size; since, however, nothing prevents plant-owners in this model from building multiple plants, a large plant may simply be seen as represented by any multitude of small (normalized size) plants in this model. This does neglect the economies of scale resulting from building large plants on the one hand and the diversity possible when rather building many smaller plants.

- Simplified representation of production plants (and other aspects): Real production plants neither have a uniform output or uniform life span, nor are they completely characterized by their labor productivity, technology and sectoral assignment. Routines, tacit knowledge, learning curve, spillovers, geographical location and other properties are not directly represented.

- No direct economies of scale from large systems of production and no direct effects of diversity of many small plants. Neither of these two aspects is particularly close to the main mechanism under investigation in this paper, network effects, (and since both may develop complex interactions with this mechanism) they are not included in this analysis.

- Simple network of dependence between technologies (without different weights for links): Actual technologies may rely on several earlier technologies and to different degrees. They may also replace certain dependencies in its predecessors. This results in a much more complex network of dependence including different strengths of dependence. The resulting possibility space is huge and huge are the effects it may have on growth. But one thing will not change: There will still be systems of technologies that are interconnected and there would be different mutually exclusive alternatives which would imply better or poorer agreement with the technological and economic environment in the relevant sector. The current model therefore chooses to only include this one aspect (and the well-established stylized fact that technological change is cumulative Silverberg et al (1988)) and operationalize it in a very simple way, namely as (a pre-defined number of) separate co-existing technology trees.

- Stylized form (and limited extent) of network externality: The functional form in which the network externality influences the model is limited to a linear function of the usage share decreasing the labor requirements by at most 20%. Stronger functional forms (superlinear and peaking at more than 20%) yield much stronger effects. Of course, as the sector is in this case quickly monopolized, the result is less interesting and less realistic.

- Cross-financing investment into this sector from revenues from other sectors by large players or the government is excluded. Technology spillovers from research in other sectors are also excluded (though spillovers working through network effects will be included in the next section) and so are many other possible extensions of the model. Considering further mechanisms like these would open up huge possibility spaces - even huge strategy spaces for the agents - that would be difficult to study simultaneously and in detail.

3.3 Model: An Economy of Interconnected Sectors

Economic sectors do not exist isolated. This becomes obvious when considering practical examples of network externalities: For instance, an application program will have to work well with the operating system, the hardware, network protocols, file formats, other applications etc. - all with their specific technological standards. Even for more traditional sectors, say machine manufacturing, the production will have to rely on standardized parts, standardized equipment, a commonly used energy source for the machine, and will have to fit the machine with a user interface familiar to the potential operator. Industry economic and strategic consequences of this have been analyzed to some degree in the literature Shy (2001); Choi (2004); Heinrich (2013, 2014).

It is notable that this seems to follow a roughly hierarchical order (though two-way dependencies are common as well): the burden to establish compatibility rests usually on the later or more specialized technology or industry sector. This is also due to network effects since later technologies will favor compatibility to existing infrastructure and existing user groups to increase their chances of success. This is even the case if reliance on legacy infrastructure creates structural problems as discussed in Heinrich (2014).

Neglecting the two-way dependencies for simplicity, the intersectoral relationship shall be modeled as follows: 64 sectors (i.e., 2^6 sectors) are arranged one by one in a dependency tree starting with one node and then attaching the next sector as dependent on randomly one of the already integrated nodes. As we are dealing with integrated technologies, however, the sector is then also dependent on all sectors that are upstream from its immediate parent. Note that this hierarchical ordering resembles the Yule process[11] Yule (1925), and produces power law distributed sub-tree sizes.[12] Internally, each sector follows the setting explained above except that the network externality depends equally (arithmetic mean) on the shares of the technology type in the sector itself and the "parent" sector (except for the top of the hierarchy where there is no "parent" sector). Note that this assumes the same number of competing technology types for all sectors.

4 Simulation

The simulation was conducted using a Python program (both the one-sector and the aggregated runs); A describes the simulation following the ODD standard Grimm et al (2010); B lists the pseudocode of the central algorithms of the simulation.

[11]The Yule process creates a hierarchical network (tree) by starting with a single node and connecting new nodes to a randomly (with equal probabilities for all nodes) chosen node in the tree. As the probability for nodes to be added to a subtree hence depends linearly on the size of this subtree, the subtree size develops to follow the power law distribution described above.

[12]With subtree size h such that the share of the nodes (of the total number of nodes in the network) $f(h)$ with a sub-tree of size (h) is distributed according to $f(h) \sim \frac{1}{h^2+h}$ which for large h corresponds with a power law with exponent -2. While this is, of course, also a very simple model of an interdependence network between sectors, power law degree distributions bear a certain resemblance of real world interdependence networks.

4.1 Single Sector

The single sector setting is simulated with 128 agents (i.e. 2^7 agents), 21 technology types (20 and an extra technology type comprising only the initial technology q') for 300 periods. Figure 3 shows key data for a typical simulation run in panels A and C (left panels). The system starts perfectly locked-in; the lock-in is broken at some point where output growth (panel C) briefly becomes at first negative then positive, only to be followed swiftly by another lock-in dominated by another technology type.[13] This repeats for 4 times (in other simulation runs, numbers between 4 and 6 of such events in 300 iterations were common), always accompanied by a growth wave and an improved labor efficiency. Other changes between these events do occur, but are barely visible in the figure.[14]

A wave pattern is irregular but persistent; an observer could be tempted to suspect regular cycles that are merely distorted. Analyses of the autocorrelation spectrum (figure 3, panel B) and the frequency spectrum[15] (figure 3, panel D) confirm this: Frequencies of 0.02, 0.04 and 0.07-0.08 (cycle lengths of 50, 25, and 15 periods) show marked peaks; higher autocorrelations are found for 27 and 46 period time lags (15 periods is only a smaller peak). However, the pattern resulting from actually interconnected sectors as simulated in the following section (see figure 4) is much more convincing.

So far, the current model reproduces the results of a number of evolutionary economic models Nelson and Winter (1982); Conlisk (1989); Silverberg and Lehnert (1993); Heinrich (2013) using a different underlying mechanism (network externalities). As discussed above, the model can easily be used to

[13]The lock-in is also tracked in the simulation, using the normalized Herfindahl index for the technology type distribution, though this is not shown in figure 3. The Herfindahl index uses the squared Euclidean norm of the vector of usage shares s for all technology types $v = 1, ..., d$, $HI = \sum_v s(v)^2$, the normalized Herfindahl index is $HI_{norm} = \frac{HI - \frac{1}{d}}{1 - \frac{1}{d}}$ such that the HI_{norm} can actually assume all values between 0 (equal usage shares) and 1 (perfect lock-in).

[14]Note that this is because the size of the improvement from innovations is set that low. Otherwise, a slow base growth would be present, but since the intersectoral dynamic in the next section introduces further growth, this would in the intersectoral-interdependence setting lead to large growth rates, to an explosion of the number of plants and to the simulation becoming very slow.

[15]The frequency spectrum plots the intensity of signals (regular recurring cycles) of certain frequencies. A flat spectrum would mark random noise, signals of higher intensity, that stand out, indicate cyclic patterns.

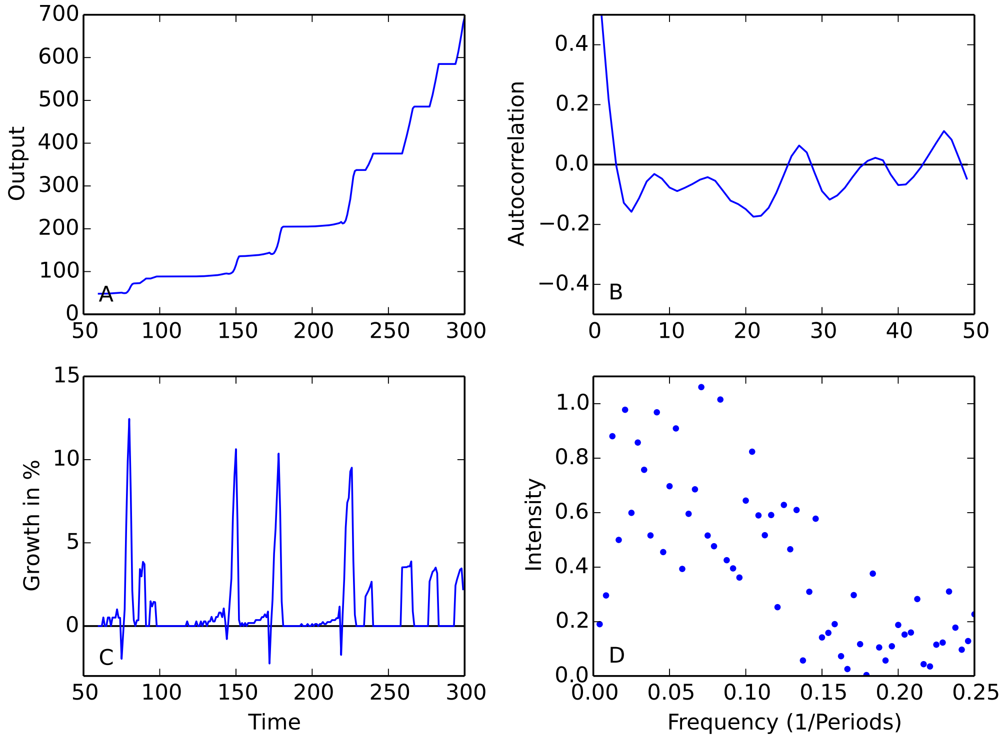

Figure 3: Development of a single fully independent sector: (A) output, (B) growth rates, (C) autocorrelation spectrum of growth rates, (D) frequency spectrum of growth rates.

investigate the aggregation from the sector-level to the macro-level.

4.2 Interconnected Sectors

Aggregated data, including the aggregated growth pattern, the number of sectors in lock-ins with the same technology type as industry leader, as well as the growth rates' autocorrelation and frequency spectrum are shown in panels C in figures 5 through 8. For comparison, models with isolated sectors (panels A in figures 5 through 8), a complete network between sectors (each sector equally dependent on each other sector, panels B in figures 5 through 8), and a 1-dimensional grid topology (sectors arranged on a ring an symmetrically dependent on their neighbors, panels D in figures 5 through

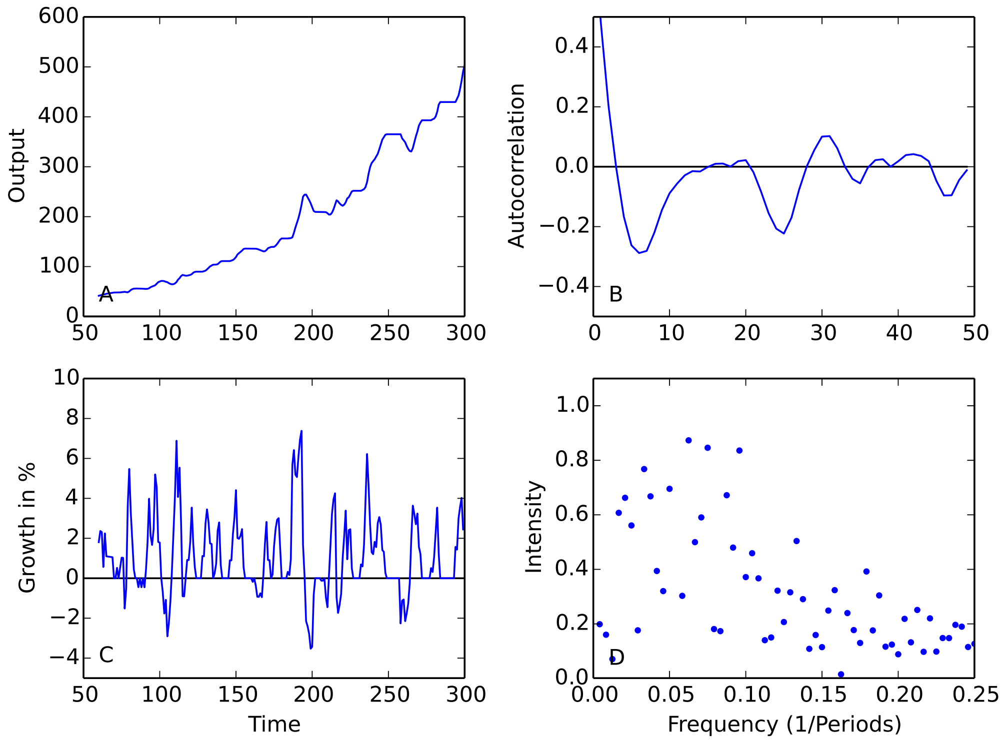

Figure 4: Development of a single sector in a multi-sector model with interconnected sectors (Yule-process generated network): (A) output, (B) growth rates, (C) autocorrelation spectrum of growth rates, (D) frequency spectrum of growth rates.

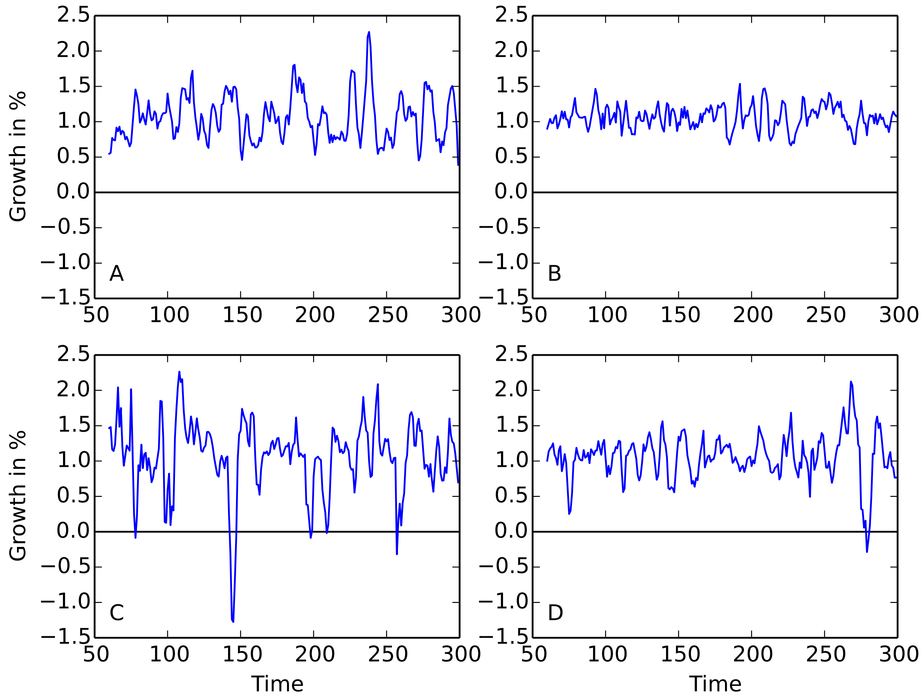

Figure 5: Growth rates at the the macro-level in the multi-sector model for different interconnectedness structures between sectors. (A) fully independent sectors, (B) complete network (i.e. all sectors have direct influence on all other sectors), (C) Yule-process generated network, (D) 1-d grid (ring) network structure.

8) are also considered. They provide interesting points of comparison but are much less realistic for most real world cases. Panels A and B show how the model behaves without actual (i.e., with empty, or complete) network structure (with and without cross-sectoral network effects in panels B and A respectively); panels D contrast the panels C's hierarchical network with a non-hierarchical but also clustered topology.

Figure 5 shows the development of growth rates resulting in the four cases (i.e., for the different topologies) while figures 7 and 8 add the autocorrelation spectrum and the frequency spectrum as measures for the cyclicity of the patterns observes in the development of growth rates. Since the growth

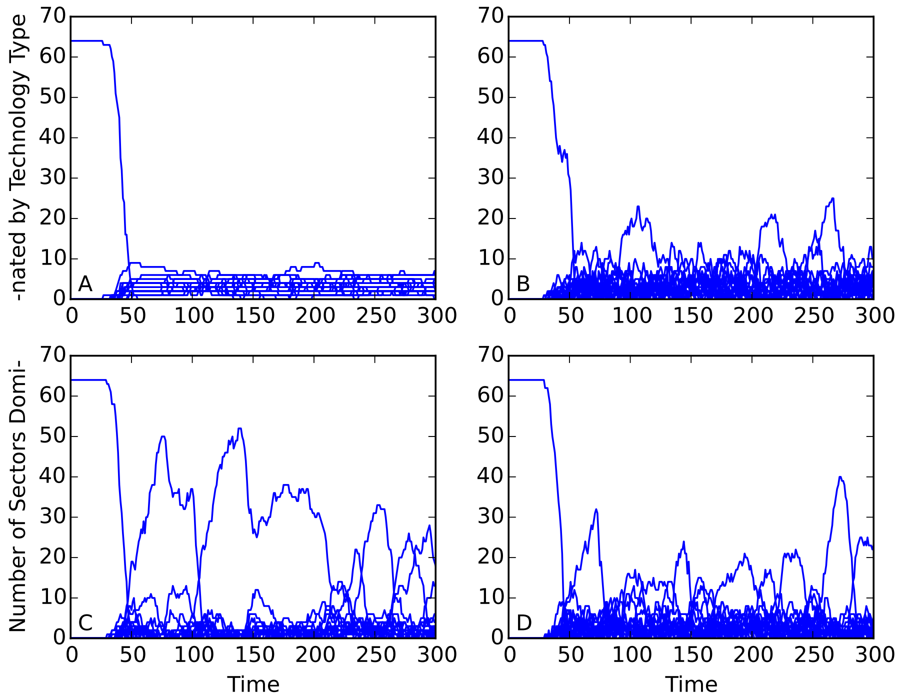

Figure 6: Number of sectors dominated by the same technology type in the multi-sector model for different interconnectedness structures between sectors. (A) fully independent sectors, (B) complete network (i.e. all sectors have direct influence on all other sectors), (C) Yule-process generated network, (D) 1-d grid (ring) network structure.

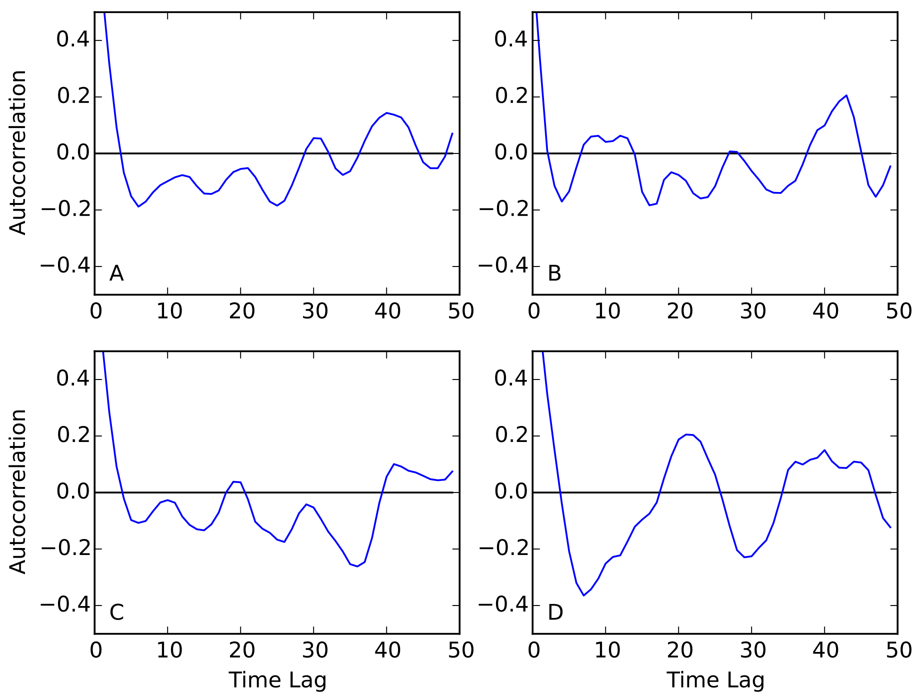

Figure 7: Autocorrelation spectrum of growth rates at the the macro-level in the multi-sector model for different interconnectedness structures between sectors. (A) fully independent sectors, (B) complete network (i.e. all sectors have direct influence on all other sectors), (C) Yule-process generated network, (D) 1-d grid (ring) network structure.

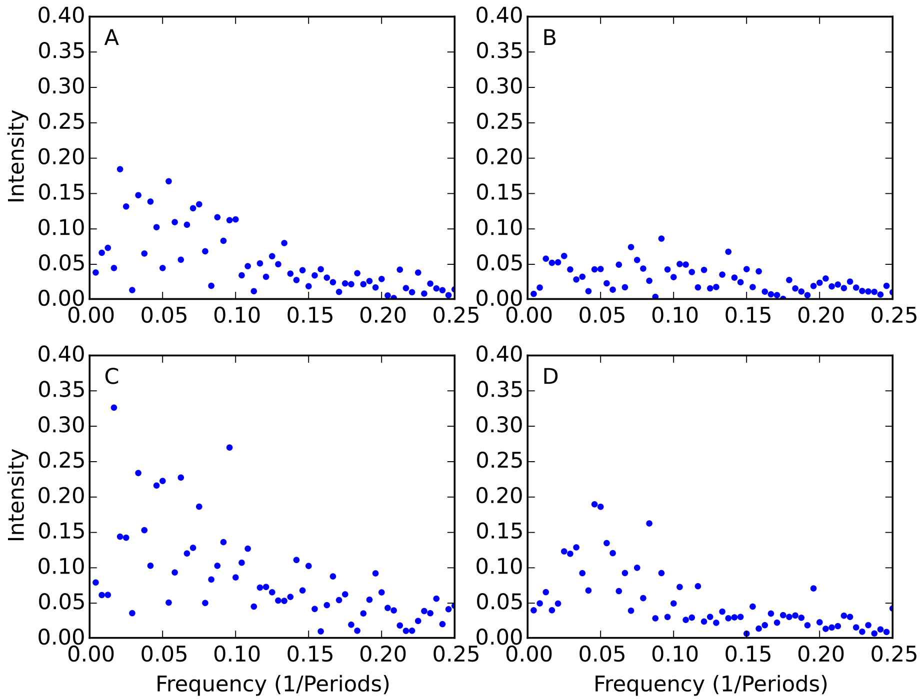

Figure 8: Frequency spectrum of growth rates at the the macro-level in the multi-sector model for different interconnectedness structures between sectors. (A) fully independent sectors, (B) complete network (i.e. all sectors have direct influence on all other sectors), (C) Yule-process generated network, (D) 1-d grid (ring) network structure.

waves at the aggregated level result from intersectoral synchronization of structural change (i.e. technology type switching), figure 6 illustrates the reason behind the weak cyclicity in the isolated and fully connected network cases (panels A and B) and the cases with much stronger cycle or wave patterns (the clustered networks shown in panels C and D): From figure 6 it is apparent that there is no or little cross-sectoral alignment of dominant technology types as a result of the network effects in the cases without non-trivial network structures (panels A and B), as would be expected. The alignment is strong in the hierarchical case (panel C), and moderate but persistent alignment in the non-hierarchical (grid) case (panel D). The role of the dominant technology type changes multiple times across the period of study of 300 iterations. This would be interpreted as technology system changes in the framework provided by Freeman and Perez Freeman and Perez (1988) as indicated above.

Since the intersectoral interaction was restricted to the network effect in the present study, few further changes from the cross sectoral effects are to be expected for cases which do not result in cross-sectoral alignment of the dominant technology types (though growth rates may change slightly) since only this enables cross-sectoral benefits from the network externality. This is exactly what is found in the figures 5, 7, and 8. The complete network case (B) averages the growth rates out while the autocorrelation spectrum remains relatively unchanged and the frequency spectrum shows that there is no indication of low frequency signals any more compared to all the other cases (including, interestingly the isolated sector case). The quasi-cycles observed in the isolated sector case stem from rare radical innovations occurring (with equal likelihood) in every one of the sectors, but with the (though unstructured and very limited) cross-sectoral effects in case B, this signal seems to be completely drowned. With the Yule-process generated network (hierarchical) and grid network cases (panels C and D) this is different: For the grid network (panel D), a very dominant 20-period cycle emerges as is apparent from the autocorrelation spectrum (figure 7) and also visible in the frequency spectrum (0.05) next to a much fainter signal of the order of 12 periods (0.08). In the - most realistic - hierarchical case (panel C), the autocorrelation spectrum does not offer strong evidence of cycles (a hint at a rather irregular pattern), but in the frequency spectrum, a number of long-term signals appear, the most prominent being of the order of 10 periods (0.1) and 50 periods (0.02) (but 15, 20, 25 periods also having strong signals).

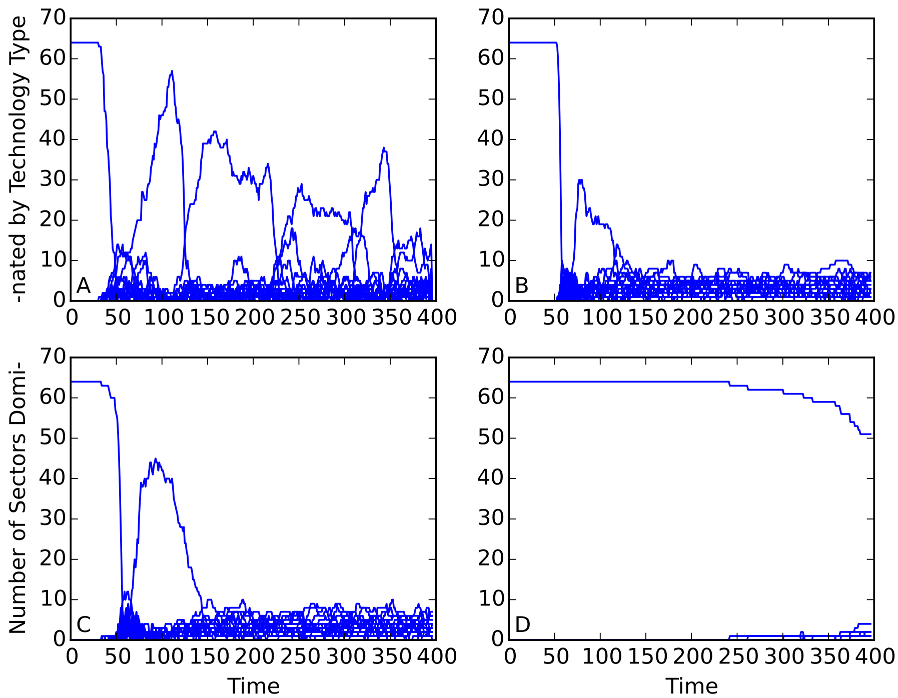

Figure 9: Number of sectors dominated by the same technology type in an interconnected multisector model (Yule-process generated network) for different research research success functions: (A) incremental innovation maximum progress factor $\alpha = 0.005$, radical innovation maximum success rate $\beta = 0.1$, public research $\gamma = 0.05$, (B) $\alpha = 0.005$, $\beta = 0.1$, $\gamma = 0$, (C) $\alpha = 0.005$, $\beta = 0$, $\gamma = 0$, (D) $\alpha = 0$, $\beta = 0.1$, $\gamma = 0$.

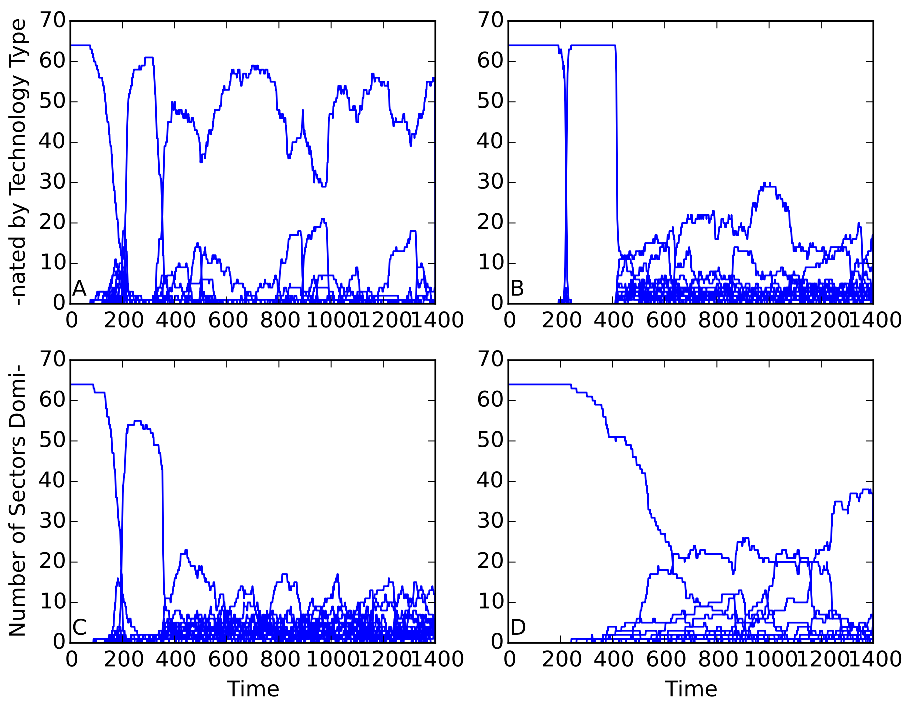

Figure 10: Number of sectors dominated by the same technology type in an interconnected multisector model (Yule-process generated network) for different research research success functions: (A) incremental innovation maximum progress factor $\alpha = 0.001$, radical innovation maximum success rate $\beta = 0.1$, public research $\gamma = 0.05$, (B) $\alpha = 0.001$, $\beta = 0.1$, $\gamma = 0$, (C) $\alpha = 0.001$, $\beta = 0$, $\gamma = 0$, (D) $\alpha = 0$, $\beta = 0.1$, $\gamma = 0$.

Brief note on incremental innovations, radical innovations, and open technologies in the model. The technology change mechanism as introduced in section 3 follows the literature and has a number of different effects. The exact values are chosen to (1) allow a prominent enough network effect, such that intersectoral alignment of the dominant technology is possible (as explained above, this is also observed in the real world and no further cross-sectoral alignment effects could realistically be expected without this) and (2) to keep the number of plants in existence from exploding beyond what the available computation capacity could manage. As is seen in figure 9, for the chosen values, the intersectoral alignment pattern breaks down if the mentioned effects (open technologies / public research, incremental innovations, radical innovation) is removed. This, however, is because sector-level incremental research then becomes the dominant force (with public research removed, progress is much slower as every agent has to rely solely on her own research even for cumulative effects); if incremental innovation is weakened, to $r_{incr} = Uniform(0, 0.001)$ (figure 10), the effect persist across all regimes (with and without open technologies, with or without radical and incremental innovations), though it is much slower now. (Note that the time scale is 1400 iterations here compared to 300 and 400 in the simulations above.)

5 Conclusion

Solow famously exclaimed in the early 1990s that computers could be seen "everywhere except in the productivity statistics" (quoted in Brynjolfsson (1993)). In 2008, empirical studies have already taken a starkly different view Jalava and Pohjola (2008) and today it becomes apparent that the entire industry structure is dependent on information and communication technologies in various ways. This dependence came in multiple ways; first electronics, then computer networks and real time control in manufacturing and trading, finally mobile devices and most recently affordable and widely available distributed computing enabling even small firms and individuals to work with "big data". The changes came in waves; they relied heavily on network externalities and lock-in effects, and they did have an impact on growth and productivity (as discussed in the introduction). It is therefore entirely opportune to take up the challenge to investigate the interrelations of network externalities and economic growth, also in the context of business cycles which may be - as it is argued in the present paper - effects of the waves of successive small technological "revolutions", technological changes that can not happen gradually as a result of network externalities and lock-ins.

Consider again the introductory examples of the electrification of the manufacturing industry[16]: they were introduced in different regions and countries at different times, but when they were, they had a pronounced impact on all aspects of the economic system. Across virtually all sectors, the system quickly became dominated by products and standards based on the new technology.

The current paper presented an alternative agent-based mechanism capable of reconstructing and explaining realistic patterns of cycles (or waves) in economic growth. Building on other models of evolutionary economics Nelson and Winter (1974, 1982); Silverberg et al (1988); Freeman and Perez (1988), the model is based on micro- (enterprise-) level processes but extends to a sectoral and an aggregated macroeconomic level. To accomplish this the central element is technological change with network externalities which are relevant for one sector but are influenced by the situation on other sectors. For interconnections between sectors, different network structures were considered.

Most importantly, micro-founded models for growth cycles have to take care that sector level cycles do not average out at the aggregated level. For the present approach using network effects it is generally plausible why this cycle pattern may by synchronized and interdependent between sectors and why therefore the growth cycle pattern may be retained on the macro level.

Strong effects were found for both Yule-process generated networks (hierarchical) and grid networks (non-hierarchical). While the non-hierarchical network amplified one circular pattern, the Yule-process generated (hierarchical) network yielded a more diverse pattern of growth waves with nevertheless strong (overlaying) signals for different period lengths.

Compared to real interdependence networks between industry standards, and thus likely also between sectors, the hierarchical network is more realistic. Base technologies such as communication systems, but also measurement standards (say, 3/8-inch screws) are widely accepted. In many other industries, firms need to comply with those systems and standards or face increased costs for in-house manufacturing and maintaining of their own incompatible systems. This descends through a highly branched system of

[16] And, slightly less pronouncedly, also the spread of ICT systems.

base technologies, say electricity and computer processor architectures, derived technologies, say personal computers, operating systems or periphery devices, but also supply sectors, raw material mining, and refinement, and specialized sub-branches, say software for specific chemical production plants, as well as meta-technologies, say social networks. Firms in all of these sectors and technologies will have to comply and will be able to benefit from network effects from compliance with the standards to some extent where the number of standards that need to be taken into account relates to the specialization. The non-hierarchical grid network would, at best, if at all, apply to relatively undifferentiated regionally organized low-technology intensive sectors.

Network externalities were not extensively studied in economic theory until recent decades, being neglected though they may constitute one of the most important and most prevalent effects in economic systems. The inclusion of this effect in the current model helps to explain growth cycles (or rather, growth waves); it may also be able to explain many more unsolved problems in contemporary economics if taken into consideration with proper models.

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References

Aghion P, Howitt P (1992) A model of growth through creative destruction. Econometrica 60(2):323–351

Arthur WB (1988) Self-reinforcing mechanisms in economics. In: Anderson KJA Philip, Pines D (eds) The Economy as an Evolving Complex System, Santa Fe Institute Studies in the Sciences of Complexity, Redwood City California, Addison Wesley, pp 9–31

Arthur WB, Ermoliev YM, Kaniovski YM (1987) Path dependent processes and the emergence of macro-structure. European Journal of Operational Research 30:294–303

Brynjolfsson E (1993) The productivity paradox of information technology. Communications of the ACM 36(12):66–77

Carvalho VM (2008) Aggregate fluctuations and the network structure of intersectoral trade. Dissertation submitted to the University of Chicago, 2008, available online: http://crei.cat/people/carvalho/carvalho_aggregate.pdf

Cass D (1965) Optimum growth in an aggregative model of capital accumulation. The Review of Economic Studies 32(3):233–240

Chen P (2002) Microfoundations of macroeconomic fluctuations and the laws of probability theory: the principle of large numbers versus rational expectations arbitrage. Journal of Economic Behavior & Organization 49(3):327 – 344, DOI 10.1016/S0167-2681(02)00003-3

Choi JP (2004) Tying and innovation: A dynamic analysis of tying arrangements. The Economic Journal 114(492):83–101

Christiano LJ, Eichenbaum M (1992) Current real-business-cycle theories and aggregate labor-market fluctuations. The American Economic Review 82(3):pp. 430–450

Conlisk J (1989) An aggregate model of technical change. The Quarterly Journal of Economics 104(4):787–821

David PA (1985) Clio and the economics of QWERTY. American Economic Review 75(2):332–337

Dosi G, Fagiolo G, Roventini A (2010) Schumpeter meeting keynes: A policy-friendly model of endogenous growth and business cycles. Journal of Economic Dynamics and Control 34(9):1748 – 1767, DOI http://dx.doi.org/10.1016/j.jedc.2010.06.018

Elsner W, , Heinrich T, Schwardt H (2015) Microeconomics of Complex Economies: Evolutionary, Institutional, Neoclassical, and Complexity Perspectives. Academic Press, Amsterdam, NL, San Diego, CA, et al.

Farmer JD, Lafond F (2016) How predictable is technological progress? Research Policy 45(3):647 – 665, DOI http://dx.doi.org/10.1016/j.respol.2015.11.001

Foley DK (1998) Introduction to 'barriers and bounds to rationality'. In: Foley DK (ed) Barriers and Bounds to Rationality: Essays on Economic Complexity and Dynamics in Interactive Systems, by Albin, P.S., with an Introduction by Foley, D.K., Princeton University Press, Princeton, N.J., pp 3–72

Freeman C, Perez C (1988) Structural crisis of adjustment, business cycles and investment behaviour. In: Dosi G, Freeman C, Nelson R, Silverberg G, Soete L (eds) Technological Change and Economic Theory, Pinter Publishers, London, N.Y., pp 38–66

Gaffeo E, Delli Gatti D, Desiderio S, Gallegati M (2008) Adaptive microfoundations for emergent macroeconomics. Eastern Economic Journal 34(4):441–463, DOI 10.1057/eej.2008.27

Goodwin RM (1967) A growth cycle. In: Feinstein C (ed) Socialism, Capitalism and Economic Growth, Cambridge University Press, Cambridge, UK, pp 54–58

Grimm V, Berger U, DeAngelis DL, Polhill JG, Giske J, Railsback SF (2010) The ODD protocol: A review and first update. Ecological Modelling 221(23):2760 – 2768

de Groot B (2006) Essays on economic cycles. PhD thesis, Published by Rotterdam School of Management (RSM) Erasmus University, Erasmus Research Institute of Management (ERIM), URL http://repub.eur.nl/res/pub/8216/

Heinrich T (2013) Technological Change and Network Effects in Growth Regimes: Exploring the Microfoundations of Economic Growth. Routledge, Oxon and New York

Heinrich T (2014) Standard wars, tied standards, and network externality induced path dependence in the ICT sector. Technological Forecasting and Social Change 81:309–320, DOI http://dx.doi.org/10.1016/j.techfore.2013.04.015

Jalava J, Pohjola M (2008) The roles of electricity and {ICT} in economic growth: Case finland. Explorations in Economic History 45(3):270 – 287, DOI http://dx.doi.org/10.1016/j.eeh.2007.11.001

Kaldor N (1940) A model of the trade cycle. The Economic Journal 50(197):78–92

Keen S (1995) Finance and economic breakdown: Modeling Minsky's "financial instability hypothesis". Journal of Post Keynesian Economics 17(4):607–635

Lines M (1990) Slutzky and lucas: Random causes of the business cycle. Structural Change and Economic Dynamics 1(2):359 – 370, DOI http://dx.doi.org/10.1016/0954-349X(90)90009-W

Lorenz HW (1987) Strange attractors in a multisector business cycle model. Journal of Economic Behavior & Organization 8(3):397 – 411, DOI 10.1016/0167-2681(87)90052-7

Lucas RE (1972) Expectations and the neutrality of money. Journal of Economic Theory 4(2):103–124

Lucas RE (1981) Studies in Business Cycle Theory. Basil Blackwell, Oxford

Mandelbrot B (1997) The variation of certain speculative prices. In: Fractals and Scaling in Finance, Springer New York, pp 371–418, DOI 10.1007/978-1-4757-2763-0_14

Marx K (1963 [1885]) Das Kapital: Kritik der politischen Ökonomie. Buch II: Der Zirkulationsprozeß des Kapitals. Dietz Verlag, Berlin, GDR, reprint in Marx-Engels Collected Works (Marx-Engels Gesamtausgabe), Volume 24

Minsky HP (1980) Capitalist financial processes and the instability of capitalism. Journal of Economic Issues 14(2):pp. 505–523, URL http://www.jstor.org/stable/4224935

Nelson RR, Winter SG (1974) Neoclassical versus evolutionary theories of economic growth: Critique and prospectus. Economic Journal 84(336):886–905

Nelson RR, Winter SG (1982) An Evolutionary Theory of Economic Change. Harvard University Press, Cambridge

Nooteboom B (1994) Innovation and diffusion in small firms: theory and evidence. Small Business Economics 6(5):327–347

Samuelson PA (1939) Interactions between the multiplier analysis and the principle of acceleration. The Review of Economics and Statistics 21(2):75–78

Saviotti PP, Pyka A (2013) From necessities to imaginary worlds: Structural change, product quality and economic development. Technological Forecasting and Social Change 80(8):1499 – 1512, DOI http://dx.doi.org/10.1016/j.techfore.2013.05.002

Saviotti PP, Pyka A (2015) Innovation, structural change and demand evolution: does demand saturate? Journal of Evolutionary Economics pp 1–22, DOI 10.1007/s00191-015-0428-2

Shy O (2001) The Economics of Network Industries. Cambridge University Press, New York, NY, USA

Silverberg G, Lehnert D (1993) Long waves and 'evolutionary chaos' in a simple Schumpeterian model of embodied technical change. Structural Change and Economic Dynamics 4(1):9 – 37, DOI DOI: 10.1016/0954-349X(93)90003-3

Silverberg G, Dosi G, Orsenigo L (1988) Innovation, diversity and diffusion: A self-organisation model. The Economic Journal 98(393):1032–1054

Skulimowski AMJ (2012) Discovering complex system dynamics with intelligent data retrieval tools. In: Zhang Y, Zhou ZH, Zhang C, Li Y (eds) Intelligent Science and Intelligent Data Engineering: Second Sino-foreign-interchange Workshop, IScIDE 2011, Xi'an, China, October 23-25, 2011, Revised Selected Papers, Springer Berlin Heidelberg, Berlin, Heidelberg, pp 614–626

Slutzky E (1937 [1927]) The summation of random causes as the source of cyclic processes. Econometrica 5(2):105–146, translated from Russian (Problems of Economic Conditions, 3:1, 1927, ed. by The Conjuncture Institute, Moscow)

Solow RM (1956) A contribution to the theory of economic growth. The Quarterly Journal of Economics 70(1):65–94

Taghawi-Nejad D (2010) Technology shocks and trade in a network. In: Li Calzi M, Milone L, Pellizzari P (eds) Progress in Artificial Economics: Computational and Agent-Based Models, Springer Berlin Heidelberg, Berlin, Heidelberg, pp 101–112, DOI 10.1007/978-3-642-13947-5_9

Uzawa H (1965) Optimum technical change in an aggregative model of economic growth. International Economic Review 6(1):18–31

Watanabe C, Matsumoto K, Hur JY (2004) Technological diversification and assimilation of spillover technology: Canon's scenario for sustainable growth. Technological Forecasting and Social Change 71(9):941 – 959, DOI http://dx.doi.org/10.1016/S0040-1625(03)00069-6

Way R, Lafond F, Farmer JD, Lillo F, Panchenko V (2017) Wright meets Markowitz: How standard portfolio theory changes when assets are technologies following experience curves. arXiv:1705.03423

Worldbank (2016) Worldbank World DataBank: http://databank.worldbank.org/data/home.aspx. Accessed 06/01/2016

Yule GU (1925) A mathematical theory of evolution, based on the conclusions of Dr. J. C. Willis, F.R.S. Philosophical Transactions of the Royal Society B 213(402-410):21–87

A Formal Description of the Simulation Model

This appendix describes the simulation model employed in this study formally; it follows the ODD standard Grimm et al (2010).

Purpose:

Investigate the interaction of (radical-incremental) innovation dynamics and network externalities as well as their effect on patterns of economic growth, especially growth cycles (growth waves).

Entities, state variables, scales:

The relevant entities in the simulation are: sectors, agents, technology categories, technologies, and production plants. The simulation (global level)

Variable Type	**Symbol**	**Unit/Scale**	**Description**	**Initial Values**
Simulation-level variables				
Parameter		Integer	Number of technology type	21
Parameter		Integer	Number of sectors	64
Parameter		Integer	Number of time steps (iterations)	300
Parameter	n	Integer	Noumber of agents per sector	128
Parameter		Share (real, ≥ 0, ≤ 1)	Share of open technologies	0.05
Parameter		No. of iterations (int.)	Plant lifetime	20
Parameter		Monetary (real)	Plant construction cost	1.6
Parameter		Monetary (real)	Plant revenue per turn	0.25
Parameter		Real	Potential labor efficiency improvement from network externality	1/3
Parameter	p_{incr}	Probability (real, ≥ 0, ≤ 1)	Probability of incremental innovation success	0.05
Parameter	p_{rad}	Probability (real, ≥ 0, ≤ 1)	Probability of radical innovation success	0.0001
Static distribution	r_{incr}	Distribution	Labor efficiency improvement of incremental innovation	$Uniform(0, 0.005)$
Static distribution	r_{rad}	Distribution	Labor efficiency improvement of radical innovation success	$Uniform(0, 0.1)$
Output var.		Monetary (real)	Cash	-
Output var.		Monetary (real)	Output	-
Sector-level variables				
Static list		List of agent objects	List of agents	(endogenous)
Parameter	L	Labor (real)	Available labor	128 (= agents per sector)
Output var.		Monetary (real)	Cash	-
Output var.		Monetary (real)	Production	-
Technology-type-level variables				
Output var.	$s(v)$	List of shares	Usage shares of technology group for each sector	all 100% for base technology type, otherwise all 0%
Variable		Boolean	Dominant technology	True for base technology type, otherwise False
Agent-level variables				
List		List of technology objects	List of technologies	only base technology q'
List		List of plant objects	List of production plants	only one plant using using base technology q'
Variable		Technology object	Most efficient technology available to agent	base technology q'
Output var.		Monetary (real)	Cash	0
Output var.		Monetary (real)	Output	-
Technology-level variables				
Static var.	v	Technology group object	Technology group	(endogenous)
Static var.	a	Labor (real)	Standalone labor requirement	1.0 for base technology (otherwise endogenous)
Variable	$\widetilde{a}$	Labor (real)	Labor requirement	-
Plant-level variables				
Static var.	q	Technology object	Technology	(endogenous)
Static var.	a	Labor (real)	Standalone labor requirement	(endogenous)
Variable	$\widetilde{a}$	Labor (real)	Labor requirement	-

Table 2: Parameter and variable table incl. variable types, scales, and initial values. Note that labor-quantity and monetary variables are real-valued; they could be interpreted as symbolizing millions of work hours and millions of (arbitrary currency) unit respectively.

has a fixed number of sectors and a fixed number of technology categories (the same across all sectors). Each sector, in turn has a fixed number of agents. The agents have a variable number of technologies and production plants. Each technology belongs to exactly one technology category and each production plant uses exactly one technology. For state variables and scales on all levels, see table 2.

Process overview and scheduling:

The sequence of events of the simulation is the following:

1. Create initial entities: sectors, agents, technology groups, base technologies
2. Time iteration (repeat fixed number of time steps)
   (a) Age production plants
   (b) Allocate labor, set production plants active or inactive (see Algorithm 1 in B)
   (c) Identify dominant technology group (the one with the most active plants, initially the base technology group)
   (d) Compute labor requirements for technologies and production plants, $\widetilde{a}$ (see Algorithm 2 in B)
   (e) Identify each agent's currently most efficient technology
   (f) Effect production for each production plant (see Algorithm 3 in B)
   (g) Reinvest revenue for each agent (see Algorithm 4 in B)
   (h) Effect research (innovations) for each agent (see Algorithm 5 in B)
3. Collect statistics about the simulation run

Design concepts:

- *Basic principles* Innovation dynamics (incremental and radical), network externalities, vintage capital production, cross-sectoral technological effects (network externalities)

- *Emergence* Emerging growth waves connected to switching of dominant technology category.
- *Adaptation* Innovation (improvement of labor efficiency); subject to labor availability only the most efficient plants are operated
- *Objectives* Maximize production by constructing production plants with most efficient available technology
- *Learning* Innovation (make better technologies available)
- *Prediction* None (Implies assumption of smooth technological progress along the lines of the currently dominant technology type.)
- *Sensing* Agents are aware of current labor allocation, and their individual-level variables (available technologies, etc.)
- *Interaction* Labor allocation and network externality are global (and thus create interaction effects)
- *Stochasticity* Innovation success, improvements from single innovations, assignment of new technologies to technology types (all Uniform)
- *Collectives* None
- *Observation* Production, dominant technology type, technology type usage shares, technology usage shares, labor usage, best available technology level (in terms of labor efficiency)

Initialization:

See table 2.

Data sources:

None

Submodels:

The algorithms defining the non-trivial subroutines of the simulation (points b, d, f, g, and h of the sequence of events above) are listed in B.

B Pseudocode of the Simulation Model

This appendix lists the pseudocode for the relevant algorithms in the simulation model used to generate the results presented in the paper. This includes algorithms for labor allocation, for the application of the network externality, for production and revenue collection, for reinvestment, and for research (listed in this order). Note that attributes A of objects B are given as $B.A$ (i.e. with connecting dot). Descriptive variable names are used for readability except for labor requirements a and $\widetilde{a}$ as well as usage shares s.

Algorithm 1 Labor allocation algorithm; run for each sector in every iteration. *FixedLabor* is set to the number of firms such that every firm can initially operate its first plant (which it is initialized with), with increasing labor productivity, more plants can be operated.

```
AvailableLabor := FixedLabor
sort plants by ã
for all plants do
    if plant.ã < AvailableLabor then
        mark plant active
        AvailableLabor := AvailableLabor − plant.ã
    else
        mark plant inactive
    end if
end for
```

Algorithm 2 Network externality application algorithm; run for each sector in every iteration. Note that $s(v)$ is computed per sector or as the arithmetic mean across different sectors depending on the setting as explained in section 3.3.

```
for all technology types v do
    for all technologies of type v do
        set potential ã to a × (3−s(v))/2
    end for
    for all plants with technology of type v do
        set plant.ã to a × (3−s(v))/2
    end for
end for
```

Algorithm 3 Production and revenue collection algorithm; run for each sector in every iteration; $FixedRevenue = 0.25$, $FixedMaximumPlantAge = 20$.

```
for all plants do
    if plant is active then
        Increase cash of plant's owner firm by FixedRevenue
    end if
    if plant.age > FixedMaximumPlantAge then
        remove plant
    end if
end for
```

Algorithm 4 Reinvestment algorithm; run for each sector in every iteration. The initial technology q', $FixedDefaultTechnology$, has an $a = 1.0$; $FixedPlantPrice = 1.6$.

```
for all firms do
    BestTechnology := FixedDefaultTechnology
    for all technologies available to firm do
        if technology.ã > BestTechnology.ã then
            BestTechnology := technology
        end if
    end for
    while firm.cash > FixedPlantPrice do
        create new plant
        set plant's technology to BestTechnology
        firm.cash := firm.cash − FixedPlantPrice
    end while
end for
```

Algorithm 5 Research algorithm; run for each sector in every iteration; randomUniform and randomUniformInteger are random number generators that are real and integer valued respectively; the number of technology types in the runs presented in the paper is 20.

---

for all $firms$ **do**
    $ResearchSuccessful := False$
    $rand := randomUniform(0, 1)$
    if $rand < p_{incr}$ **then**
        $r := randomUniform(0, 0.005)$
        $ResearchSuccessful = True$
    end if
    if $rand < p_{rad}$ **then**
        $r := randomUniform(0, 0.1)$
        $ResearchSuccessful = True$
    end if
    if $ResearchStccessful = True$ **then**
        $TechType := randomUniformInteger(0, NumberOfTechnologyTypes)$
        $Current_a := 1$
        for all $technologies$ available to $firm$ **do**
            if $technology$ is of type $TechType$ **then**
                if $technology.a < Current_a$ **then**
                    $Current_a := technology.a$
                end if
            end if
        end for
        create new technology with type $TechType$ and $a := r \times Current_a$
        $rand := randomUniform(0, 1)$
        if $rand < 0.05$ **then**
            make technology available to all firms in this sector
        end if
    end if
end for
