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The Evolution of Economic Structure under Pervasive Technical Change: A Methodological and Empirical Study

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Abstract

An innovation in a general purpose technology constitutes a new technological breakthrough and has a long-term impact on the economy. It is thus distinct from other types of innovations in both its significance in the economic system and by its diffusion process over the industrial network. However, the conventional indicators for uncovering key sectors in the economy do not adequately reflect this type of technological change since they only measure the extent of vertical integration and not the structure of linkages among sectors. We thus propose a novel method for analyzing structural change based on a dynamic social network approach and in doing so derive a technical tree that represents the economic structure under the notion of pervasiveness. We apply this framework to the GPT currently at work, information and communication technologies (ICT), showing the evolution of ICT-producing sectors and their impact on the economic structure in Denmark between 1967 and 2009. Our findings reveal that the proposed framework is able to detect general purpose technologies by the locus of their production, and that ICT services, but not the ICT manufacturing sector, have become one of the core industries of the Danish economy.

Keywords: general purpose technologies, social network theory, input-output, evolutionary economics, organizational structure

1 Introduction

The economic system is an indeterminate, heterogeneous, irreversible system which is in constant disequilibrium and contains evolutionary characteristics (Janssen, 1998). This holds *a fortiori* true when a new general purpose technology (GPT) enters the system, which affects virtually all sectors due to its wide range of applicability and fosters innovative activities in the whole economy as an essential part of the adaption process. Prominent examples of the past would be the steam engine, electricity, and in the last years information and communication technologies

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(ICT). New generation technologies, and specifically nanotechnology (Youtie et al., 2008), have the high potential to become GPTs in the near future.

In the mid 90s pervasive technologies became a widely-debated issue in economics, not least because of the emergence of the new ICT whose impact became very evident in daily life and was yet not visible in the production accounts. Dynamic theories were evolving around the notion of GPTs which were introduced into the economic literature by Bresnahan and Trajtenberg (1995) , emphasizing the impact of major technological change on the economic structure and on long-term economic growth; the general content of this discussion was nevertheless not new, but can be linked to other concepts explaining long waves in economic history. Joseph Schumpeter already identified innovative activities as the heart of his theory on business cycles (Schumpeter, 1997). Since then, a variety of theories have been centered around drastic technological change (see, for example, the theory of techno-economic paradigms (Dosi, 1982; Perez, 1983), the notion of macro inventions (Mokyr, 1990), or enabling technologies (Lipsey and Bekar, 1995), spreading the seeds of evolutionary economics. As the most popular GPT models (such as Helpman and Trajtenberg 1998 and Aghion and Howitt 1998) are set out in a neoclassical framework, Verspagen (2004) calls them the American counterpart of Schumpeterian economics. Despite the similarities on the content level,[1] the concept of general purpose technologies is by no means a re-inventing of the wheel (or squaring the circle by embedding it into a dynamic equilibrium model), but has its own right to exist; not least because of its emphasis on the generality of purpose of a technological breakthrough, i.e. its inherent potential to be used throughout the economic system. All other characteristics assigned to a GPT can subsequently be derived from the notion of pervasiveness: (1) the novelty in design that ensures the technology to be demanded in all other sectors, but simultaneously prevents it from being employed upon arrival; (2) the specific life cycle of the technology in which its impact on the system unfolds itself only at a later stage, after the diffusion process has faded out; (3) the coordination problems on the meso-economic level among the GPT producing industry and its application sectors which – due to the pervasiveness of the technology – translates into cumulative effects on the macroeconomic level.

When it comes to detecting these changes in the economic structure, indicators based on direct and indirect inter-industrial linkages as reported in input-output tables have become a popular tool for identifying key sectors (see, e.g., Rasmussen 1956; Hirschman 1958; Jones 1976; Sonis et al. 1995; Lenzen 2003). An impulse given to any of those industries would not only affect sectors directly tied to them, but would eventually channel through the whole intersectoral network.

However, these conventional tools do not sufficiently explain general purpose technologies, as they do not consider the specifics of this type of technological change.[2]

[1] See Lipsey et al. (2005) for an excellent review of related concepts.

[2] Verspagen (2004), for example, undertakes a linkage analysis based on an input-output model of the U.S. economy and concludes with respect to the ICT sector and in analogy to Solow's famous statement from 1995, that 'we can see computers everywhere, except in the input-output tables'.

The methodology proposed henceforth will evolve around the notion of pervasiveness as the crucial feature that distinguishes a GPT from other radical innovations and interpretes it in the light of a general theory of economic evolution. Despite composing the heart of the theory of GPTs, the term lacks a clear-cut definition. According to Field (2011), whichever way you look at it in input-output tables – either considering only direct linkages of the GPT producting sector to other industries or also taking into account the multiplier effects – is unsatisfactory; the former would underrate the impact of a general purpose technology, the latter would subsume basically each kind of technology under the notion of a GPT.

An explanation of why 'general purpose' is a significant criterion of a technology is offered by the theory of social networks. Analogously to Bothner et al. (2010), we argue that an industry occupies a rather robust position in the economic system the more diversified the network is which it belongs to: The success and diffusion of an innovation is crucially dependent on its ability to reduce factor costs in the application sector; and then it would make a difference whether the technological breakthrough is of single or general purpose, as it leads *ad hoc* to efficiency gains in a broad range of sectors that progressively pass through to the other industries tied to them. If 'robustness' means "diversification across the diversified" (Bothner et al., 2010, p.945), GPT producing sectors form the robust base in the economy.

In support of our hypothesis, we apply the concept of organizational structure in the analysis of the inter-industrial network, in order to derive a tree data structure, called technical tree, and explore the dynamics of the evolving technical tree over time. With regard to GPTs, we hypothesize twofold: (i) Upon arrival of a new GPT, the GPT-producing industry is located somewhere at the bottom of the technical tree; (ii) Over time, advances in GPT lead to new opportunities in application, so that the GPT-producing industry evolves close to the core of the community and disposes of an increasing number of 'descendants'. The framework is subsequently applied to the Danish economy over a time span of 43 years. Annual input-output tables and investment matrices together with data on the capital consumption of 130 industries from 1967 to 2009 describe the structure of inter-industry relationships.

The paper proceeds as follows: Section 2 introduces the method, Section 3 describes the data handling, while the empirical findings are discussed in 4. Section 5 gives concluding remarks and suggests some direction for future research.

2 Methodology

A technical breakthrough leads to the (trans-)formation of a sector, but unfolds its impact on the whole economic system only via the diffusion process. The latter requires intersectoral coordination whose success/failure determines the life time of the technology and of the sector producing it, as well as the evolution of the economic system on the whole. Table 1 gives a schematic view of how intersectoral relations are depicted in an input-output table (variables in

this section will always refer to the notation displayed in this scheme): By studying the linkages

	Economic Activities				Final Demand					
	Sector 1	Sector 2	...	Sector n	Private Consumption	Public Consumption	GFCF	Changes in Stocks	Ex-ports	Gross Output
Sector 1 Sector 2 . . . Sector n	Domestic Transaction Matrix $\mathbf{Z_d} = \left\{z_{ij}\right\}_{n \times n}$				$\mathbf{y}$					x_2 x_1 x_n
Sector 1 Sector 2 . . . Sector n	Import Matrix $\mathbf{M} = \left\{m_{ij}\right\}_{n \times n}$				$\mathbf{y}_m$					
Imports nec.										
Taxes										
Gross Value Added	$\mathbf{V}$									
Gross Output	$\mathbf{x}$									

Table 1: Scheme of an IO table (industry by industry)

between the different sectors, it is possible to derive production processes on a sectoral level, which form the basis of an input-output model. As is evident by Table 1, and unlike most of the other work in the field of general purpose technologies, our analysis does not focus on the technology as such, but on the industry that provides the technology to other sectors for its potential application, which is also in line with the original work by Bresnahan and Trajtenberg (1995). We therefore follow Dopfer and Potts (2008) by putting emphasis on the meso unit as the "analytical nexus of economic evolution of structural change" (p.59).

The proposed framework draws on two distinctive approaches in the field of social network theory (Bothner et al., 2010; J.Qiu and Z.Lin, 2011) and contains three steps: (1) A modified centrality measure ranks the industries according to their importance, i.e. the degree of robustness in the network. (2) A random walk on the graph transforms the inter-industrial network into a tree data structure. (3) A tree learning algorithm allows for deriving the evolving community tree. In the following, each step will be explained separately.

2.1 Industry ranking according to robustness

Bothner et al. (2010) argue that higher concentration in social networks uncovers the fragility of some members, because their nodes in the network depend on a few others and not on a broad base. Hence, *pervasive* social relations underpin the robustness of a member's status in the network, and therefore need to be taken into account. On the methodological level, the authors combine the Hirschman-Herfindahl concentration index[3] with Bonacich's (1987) recursive method for measuring centrality in networks. As is also shown, this concept can be applied to industries as well, where the relational matrix represents the interconnectedness of sectors up and down the production process. In the context of this paper, we will use the indicator for measuring only the

[3] Hall and Trajtenberg (2004) also applied the Herfindahl Index on patent classes in order to uncover general purpose technologies in this type of data.

linkages of a sector downstream, i.e its importance as supplier of other sectors. The relational matrix based on transaction flows between industries thus transforms into:

$$\mathbf{H} = \{h_{ij}\}_{n \times n}, \tag{1}$$

$$h_{ij} = \left\{ \frac{z_{ij}}{\sum_{j}^{n-1} z_{ij}} \right\}^2 \tag{2}$$

with elements h_{ii} being zero (i.e. inner-sectoral linkages are not taken into account). z_{ij} are the deliveries of industry i to all other industries $j = 1, \ldots, n$, hence h_{ij} are the squared sectoral shares of industry i's output.

$\mathbf{H}_i$ ranges between 0 and 1. The *lower* its value, the *wider* is the range of other industries a sector is connected with. The dispersion coefficients h_{ij} are subsequently introduced into Bonacich's recursive equation to account for coupling (Bonacich, 1987, p.1173) for deriving a measure of fragility:

$$f_i(\alpha, \beta) = \sum_j (\alpha + \beta f_j) h_{ij} \tag{3}$$

or in matrix notation, given that β is less in value than the reciprocal of the largest eigenvalue λ associated with the dispersion matrix[4]:

$$f(\alpha, \beta) = (\mathbf{I} - \beta \mathbf{H})^{-1} \mathbf{He} \tag{4}$$

with $\mathbf{e}$ being a vector of ones. β represents the degree to which a member's status depends on the status of those to which she is linked to. If β is zero, the fragility measure reduces to the Herfindahl index, and thus only accounts the strength and range of direct linkages to other sectors. The higher in magnitude, the more the status of the alters is considered, and $f_i(\alpha, \beta)$ becomes a function of direct and indirect linkages in the network.

With regard to inter-industrial relations, $\mathbf{H}$ as defined above only considers the distribution of a sector's sales to the rest of the industries, and not to final demand, and neither the size of economic activity. However, it is important to take the latter into account, because the mere fact that one industry's supply to the economic network is rather diversified does not qualify it for a key sector. In order to incorporate the scale of economic activity, the fragility index of each

[4] If $\beta < \lambda^{-1}$, Eq.3, in matrix notation, becomes

$$\mathbf{f}(\alpha, \beta) = \alpha \sum_{k=0} \inf \beta^k \mathbf{H^{k+1}e} = \alpha \left(\mathbf{He} + \beta \mathbf{H^2} + \beta^2 \mathbf{H^3 e} \right),$$

which in the limit corresponds to Eq.4. $\sum_{k=1}^{\inf} \beta^{k-1} \mathbf{H}^k = \sum_{k=0}^{\inf} \beta^k \mathbf{H}^{k+1}$ is the total number of ties attached to a node in the network.

sector is weighted by its logarithmic share in output:

$$\chi_i = ln\left[\frac{x_i}{\sum_i x_i}\right](-1) \tag{5}$$

Note that all shares are below 1, thus χ turns negative by taking the log. Multiplying the logarithmic shares by (-1) results in assigning higher values to smaller shares. This is essential, since Eq.4 represents the level of fragility of an industry, and a small contribution to the annual output relative to other industries should even amplify the comparative weakness.

$$\mathbf{f}(\alpha,\beta) = diag(\chi)\left(\mathbf{I} - \beta\mathbf{H}\right)^{-1}\mathbf{He} \tag{6}$$

$diag(\chi)$ denotes a diagonal matrix whose elements represent the individual weights of the industries regarding the annual output.

Since robustness is defined as the complement to fragility, we derive the following equation for ranking industries according to their robustness:

$$\mathbf{r}(\alpha,\beta) = \mathbf{e} - \alpha\mathbf{f}(\alpha,\beta) \tag{7}$$

The last term on the right hand side represents the vector of fragility scores $\mathbf{f}$. α is a shifting parameter for normalizing $\mathbf{f}$ such that the sum of the squared lengths of the individual fragility indices equals the size of the network (see Bonacich (1987, p.1173) and Bothner et al. (2010, p.952)). A fragility index of 1 thus means that the respective industry has an average degree of fragility, irrespective of the number of members in the network. Using the unit vector $\mathbf{e}$ as the minuend, a robustness score of $r_i > 0$ indicates that industry i has a robust position in the network, while $r_i < 0$ reveals the respective industry to be rather fragile[5]. The closer r is to 1, the more robust is the industry, i.e. the more its products spread over the system. β allows determining the extent of vertical integration one wishes to analyze. Analogous to Bonacich (1987), β reflects a radius within which the robustness of a node can be measured, gradually shifting from the local structure ($\beta = 0$ and the direct network) to the global structure ($0 < \beta < \lambda^{-1}$, which considers direct and indirect linkages via coupling). The robustness score $\mathbf{r}$ will be in the following used to derive the technical tree.

2.2 Deriving the technical tree

The seminal paper of Bresnahan and Trajtenberg (1995) shows that in a decentralized economy, the generality of purposes together with increasing returns to scale in the GPT producing sector generates coordination problems among up- and downstream sectors. As a conclusion, not only the inner organization of the inventing industries must be examined more closely, but also sectoral

[5]As the industries are subsequently ranked according to their robustness score, the minuend can be chosen arbitrarily, because the ordinal structure does not change with the shifting parameter.

interrelations have to be investigated more carefully, since "the locus of technical change" matters (Bresnahan and Trajtenberg, 1995, p.85). Even though the theoretical framework is completely different, Dopfer and Potts (2008, p.50) argue in a similar way regarding the meso level, as it is primarily the carrier population – not the single carrier of a technical rule – that evolves. Questions of the industrial organization on the micro level thereby find their analogue in the problem of coordination on the macro level: While the first is triggered by inventive activities of microeconomic agents, the latter is required in consequence of a meso change. Applying a model of organizational structure on the meso level may therefore give fruitful insights into changes on the macro level.

However, so far our tool is one dimensional, as it only gives the position of each industry in a ranking, but does not reveal inter-industrial connections; we want to show the latter while preserving the original ranking. This inevitably leads to a tree structure where the most robust industries are located close to the root of the tree (see Fig.1).[6] In order to transform the sectoral network into this kind of data structure, inter-industrial relations are re-interpreted as a weighted and directed graph, where each node represents an industry which shares an edge with another node in the network if there are transaction flows between the two respective industries. The magnitude of the transaction flows gives the weight of the edge, the destination of the flows its direction (for a detailed analysis of the network topology of input-output tables, see e.g. James McNerney and Silverberg, 2013). Performing a t-step random walk on this graph would then give a measure of the volume of paths between two nodes (Szummer and Jaakkola, 2002); the higher the number, the stronger the relation between the two members. The outcome is covered by a transition probability matrix where each entry is the sum of all paths of length t between the respective pair of nodes.

In their analysis of the organizational structure of networks, J.Qiu and Z.Lin (2011) use a forward random walk on an undirected graph to derive a community tree. We follow a slightly different approach, as the graph underlying the economic structure is directed. For this sake, we revert to finite Markov processes,[7] which share the same mathematical framework with random walks on directed graphs (albeit the first was developed in probability theory, the latter in network theory). Markov processes can also be used to reflect non-stochastic relations: Kemeny and J.Snell (1976) showed that the Leontief input-output model can be interpreted as an absorbing Markov chain (AMC). In an AMC each state (as the equivalent to a node in graph theory) can reach an absorbing state that, once entered, cannot be left anymore. In the scope of an-input output model, final consumption represents the absorbing state of the system,[8] as goods that

[6] The idea of representing the economic structure as a tree was actually inspired by Bresnahan and Trajtenberg (1995, p.102) who discuss coordination problems between upstream and downstream production stages as moving down the 'technological tree'.

[7] A Markov process is a random process in which the probability distribution for the future prediction depends only on the most recent state, not on any other states in the past.

[8] A similar approach has recently been developed by Duchin and Levine (2010) who combined an input-output model with an AMC for uncovering resource-specific networks in the field of ecological economics.

end up here will not enter the production system anymore.

In the following, the technical coefficients a_{ij} of the n production processes will thus be used to derive the one-step transition probability matrix $\mathbf{Q}$ for transient states:

$$\mathbf{Q} = \{q_{ij}\}_{n \times n} \text{ where } q_{ij} = a_{ij} = \frac{z_{ij}}{x_j} \tag{8}$$

In input-output terms, a_{ij} denotes the quantity of good i *on average* necessary to produce one unit of good j. Treating the technical process as a Markov process, q_{ij} gives the probability that a process starting in state i ends in state j after one step[9]. Since any finite regular Markov process will eventually end up in an absorbing state, each ${q^n}_{ij}$ approaches zero as n tends to infinity. Therefore, the so-called fundamental matrix $\mathbf{N}$ of an AMC can be calculated as the infinite sum of the n-step transition probability matrix for transient states (see Kemeny and J.Snell (1976, p.46):

$$\mathbf{N} = (\mathbf{I} - \mathbf{Q})^{-1} = \mathbf{I} + \mathbf{Q} + \mathbf{Q}^2 + \ldots = \sum_{n=1}^{\infty} \mathbf{Q}^n \tag{9}$$

Readers familiar with input-output analysis will immediately notice the equivalence to the Leontief-Inverse $(\mathbf{I} - \mathbf{A})^{-1}$, which gives the direct and indirect inputs required for producing one unit of output x_i for final demand y_i, $i = 1, ..., n$:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1} \mathbf{y} \tag{10}$$

In terms of Markov processes, $\mathbf{N}$ denotes the mean number of times a respective process is in various transient states before reaching its absorbing state. On the basis of this matrix, we derive an algorithm which estimates for each industry its most likely parent:

Deriving the technical tree (TT):

```
TT=zeros(size(N,1))          1. Build a technical tree (TT) with all industries attached to the root
                                root nodes (TT(i)=0) for each i = 1,...n.
for i = 1:size(N)
    for j = 1:size(N)
        if i == j
            N(i,j)=0;        2. Remove inner-sectoral linkages.
        end
    end
```

[9] Absorbing Markov chains are of particular interest for studying the behavior of transient states. The ergodic set of an AMC does not change during n steps, since the probability of staying in an absorbing state is by definition 1.

```
    for k = 1:size(N)
    ind← sort N(:,k)      3. Sort supplying industries in descending order of N.
    for i = 1 : γ      4. Define the range in which the algorithm is looking for a parent node.
       if r(ind(i))≥ r(k)          5. If the robustness score of industry j is smaller than the
                                          robustness score of its most important supplier industry,
        TT(k)=ind(i);              this industry represents the parent node of sector j.
    end
    end
if TT(k)>0 break      6. As soon as a parent node is found among the top supplying industries, break
    end                        the loop.
end
```

The algorithm searches for each sector i the γ most important supplier industries (in descending order), and picks the first sector that ranks higher in robustness as parent of the industry under analysis. Note that the robustness score determines the construction of the tree; thus if the ranking position of a patential parent candidate is lower, then the corresponding industry by definition cannot act as the immediate 'leader'. In case that none of the γ most important supplier industries ranks higher than sector i, the parent node of i is the root of the tree. The resulting technical tree is derived as a column vector $\mathbf{TT}$, where element TT_i denotes the parent of industry $i, i = 1, ..., n$ (see Fig.1 for a graphical representation). Industries that are directly connected to the root node represent core industries (C) iff. they span a community, i.e. act as a parent (P) of other industries. If not, this indicates that the robustness score does 'wrong' in assigning them a high rank. This paradox happens whenever the industry to be investigated predominantly produces final consumption goods. Since the relational matrix used to derive the robustness index only takes into account the production network, an industry's contribution to final demand is ignored in the calculation. The algorithm improves the existing approach by filtering out those false core industries as leaves (denoted as L in Fig.1), i.e. nodes without descendants (D).

The core industries generate the basic grid over which the economic network is spanned. The tree data structure allows differentiating between these key industries at the root of the technical tree and other sectors that act as parent industries further down the tree. This distinction is important in so far as changes in the set of core industries trigger off processes of deep coordination on the macro level (Dopfer and Potts, 2008) and thus reveal radical structural change.

Three things need to be pointed out: First, the dependencies in the tree data structure are still not unidirectional, running from the root to the leafs; although a community depends on its parent industry, each member in the community strengthens in turn the position of its parent node, since the tree is based on the robustness score, which makes parent and child node mutually dependent. Second, parameter γ reflects the strength of the hierarchical structure; the lower γ,

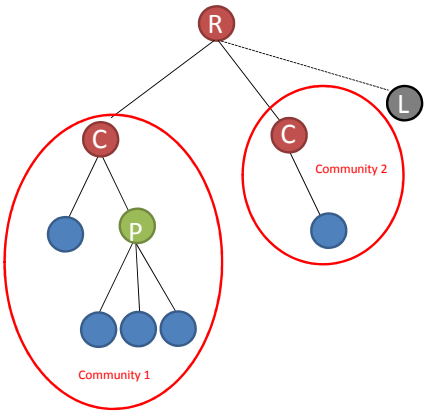

Figure 1: Example of a technical tree (R denotes the root node, C a core node, P a parent node, L a leaf).

the flatter the hierarchy, as it becomes more likely for an industry not to find a parent and remain at the root. On the other hand, if γ equals the size of the network, the whole economic system is entirely spanned up by the top ranked industry. Third, $\mathbf{N}$ represents the technical coefficients denoting the share of each intermediate good directly and indirectly used for the production of one unit of the sectoral output. This is a better indicator for inter-industrial relations than the absolute value of the direct transactions. In the following, the derived technical tree will serve as a reference tree in the process of building the evolutionary technical tree.

2.3 Deriving the evolving technical tree

The previous algorithm allows us to build a static tree, representing the economic structure at one point in time. Adding a dynamic perspective, however, would give us information on the development of the nodes respective industries. Each of these meso units act as carriers of a specific technical rule. Thus an innovation in a GPT can be seen as a new rule forming a new industry. During the phase of adoption of the new general purpose technology, the meso unit spans a growing population of industries; they in turn act as the backbone of their parent industry, empowering the latter to evolve to the core of a whole community. The investigation of the meso unit over time gives the meso trajectory, the evolution of the community structure the core trajectory. Since these 'descendants' represent meso units themselves, a community represents a cluster where members co-evolve.

If one is interested in the evolution of economic structure over a specific time span, the framework presented so far can be applied for a static comparative analysis, by investigating for

each period the corresponding technical tree. Each tree then describes the macro trajectory on a specific point in time. However, if the network size varies over time, or if the data underlying the analysis are rather volatile, a method which ensures a smoother path of the macro trajectory would be preferable.

The first argument is of less importance, since for now we deal with a fixed number of industries over time, given by the sector classification of the input-output tables. Yet the second argument is to be considered because, as will be explained subsequently, the transactions that spin the edges of the inter-industrial network vary considerably from one period to the next. This volatility would lead to a technical tree that is rather unstable over time, as industries jump from one year to the next to very different positions in the tree. For this reason, we implement a tree learning algorithm that constructs node by node hypothetical trees based on a weighted average ranking of two consecutive years. At each step of the construction process, each of these sub-trees is being compared to the static technical sub-trees of the previous and current year, respectively. The candidate that is most similar to the existing sub-trees (as measured by a tree edit distance function) is passed on to the next stage, where a new node is attached to the existing graph. In this manner, the tree evolves until all members have been considered. The algorithm follows J.Qiu and Z.Lin (2011) who used it in the context of a varying network size over time:

Deriving the evolving technical tree (ET):

In case of a varying network size (1.-3.):

$N_{ET} = N_{t-1} \cup N_t$ — 1. Get the collection of industries that belong to the economic network of the previous and current period, respectively.

for i in N_{ET}: — 2. Calculate the robustness score r_{ET} of the industries in ET as a weighted average score of the two consecutive years ($\alpha = [0, 1]$)

$r(i) = (1 - \alpha) r_{t-1}(i) + \alpha r_t(i)$

end

$N_{ET} = \{N_t - i \in N_{ET} - N_t | r(i) < \epsilon\}$ — 3. Only consider those industries whose robustness score exceeds a specific threshold parameter ϵ.

$ET = \{Root\}$ — 4. Build a technical tree which only consists of a root node.

for $i \in N_{ET}$ in descending order of r — 5. Create a collection of candidate evolving trees by putting each industry under every other industry in the tree.

$EC = \{ET|$ put i under every $k \in ET\}$

$d_n = \sqrt[2]{D(EC_n, TT_{t-1}) + D(EC_n, TT_t)}$, — 6. Calculate the distance errors between the candidate evolving tree (EC_n) and the previous (TT_{t-1}) and current technical tree (TT_t), by use of the tree edit distance algorithm $D()$.

$EC_k \leftarrow arg \underbrace{min}_{EC_n \in EC} (d)$ — 7. Choose the candidate with the minimum value in d.

if $d(EC_k) > d(ET)$ — 8. The selected tree constitutes the evolving tree for the next iteration,

$ET \leftarrow EC_k$ where a new industry will be attached as a leaf.

end

The tree edit distance $D(T_1, T_2)$ computes the minimum costs of converting tree T_1 into T_2, by deleting, inserting and relabeling nodes. As it is used only as a technical tool to add more flexibility to the model, we abstain from presenting the algorithm here and refer the interested reader to Bille (2005) for a survey on the general tree edit distance problem, and an even more avid reader to J.T.-L. Wang and D.Shasha (1994) for a rigorous discussion of the Zhang-Sasha-Algorithm on ordered trees, which was applied in this analysis.

3 Data

3.1 Denmark as a case study

The empirical analysis will focus on the evolution of the new information and communication technology (ICT) in Denmark, as the current GPT at work. Several remarks should be pointed out:

(1) Denmark has been chosen due to its position as a net-importer of ICT-products.[10] This allows us to trace the effects of ICT on the system of production without considering its impact on economic development via export activities.

(2) In national accounts, sectors are classified by the output they produce. Concerning the definition of the ICT sector, we adopt a rather broad view, including not only the manufacturing industry, but also services related to ICT. The following industrial and service classes comprise the notion of ICT in the scope of the present analysis: Manufacture of computers and communication equipment etc.; Manufacture of wires and cables; Telecommunications; Information technology service activities; Information service activities.[11] While this list certainly covers the major part of ICT producing industries, it is not exhaustive: The wholesale sector of ICT products, for example, was not included in our study, because, on the one hand, the data were only available at a fairly aggregate industry level that did not allow distinguishing different industries in the wholesale sector; and on the other hand, this sector needs to be treated carefully in input-output analysis, as the data depict the accumulated trade margins on all inputs of one sector. Wholesale therefore does not represent a producing (and consuming) industry, but a sector where commodities are 'passed through' to end up in the production process of other industries (Miller and Blair, 2009). Therefore, the wholesale sector will be excluded from the analysis.[12]

[10] The only exceptions are central processing units.

[11] This definition is widely accepted among empirical studies on ICT (see e.g. Statistics Denmark, 2001).

[12] The same case applies to the transportation sector, which reflect the transportation margins on factors of production, but to a lesser extent, since the data for this industry also record 'real' transport services for intermediate consumption.

(3) Since the paper aims at studying the impact of a general purpose technology over the whole meso-trajectory, a comprehensive investigation requires data of inter-industrial relations at a fairly detailed level and over a reasonably long time span. In this regard, Statistics Denmark also provides a very good data base that entails annual input-output tables (grouping of 127 and 69 industries, respectively, in NACE 2.1. industry classification) of domestic and import flows in basic current prices and prices of the previous year, as well as investment tables spanning from 1993 to 2007[13] and capital consumption data[14] over the whole time span.

(4) The incorporation of capital flows is essential in the analysis of technological change. In the case of ICT, most products, such as computers and office machinery, are of fixed capital type and are thus not included in the intermediate demand presented within an input-output table. In order to estimate inter-sectoral capital flows, we revert to investment tables which show the transactions from supplying sectors of fixed capital to all other industries. Since we only wanted to consider activities of reinvestment, data were smoothed across time, so that single investment peaks were eliminated. The tables were used then to derive for every industry annual coefficients which give the share of each sector in the capital formation (per fixed capital category) of the respective industry. However, these coefficients cannot be interpreted as technical coefficients any longer (Verspagen, 2004), because investments represent future consumption of fixed capital rather than current one. Therefore the coefficient matrix was subsequently multiplied by the capital consumption,[15] assuming the same time structure for capital consumption as of capital formation.[16]

(5) A time series analysis requires the unit of measurement – in our case the relative prices of the commodity produced in each industry – to be kept constant over time. Price relativities, however, do change and reflect the economic situation less and less, the further away the period under study is from the base year, i.e. the year whose prices indexes are derived from. This holds inevitably true for computers, for which relative prices have fallen considerably since the 1970s. In order to reduce this so-called substitution bias, national statistics offices have progressively started to use chained indexes in the deflation process. Deriving a chained index over a time series simply means to constantly change the base period; i.e. for each period, data are valued in current prices and prices of the previous year, which allows calculating an annual fixed weighted (usually Laspeyres or Paasche) index. Subsequently, one year is arbitrarily chosen as a reference period, and all other years are linked to that period by chaining (i.e. multiplying)

[13]For the missing years (1966-1992 and 2007-2009), we extrapolated the investment tables by calculating an average capital coefficient matrix.

[14]Capital formation and consumption data comprise the following fixed capital items: (1) buildings, (2) machinery and equipment, (3) transport, (4) structures, and (5) fixed capital n.e.c. (software, livestock, mineral exploration, and original works.)

[15]Consumption of fixed capital are based on estimates of gross capital stock from Statistics Denmark. The data are available per sector (grouping of 130 and 69 industries) vector for each category of fixed capital for the whole time period under study. The methodology for deriving these estimates can be found in Jensen (1997).

[16]This assumption can be easily modified by including time lags between capital formation and actual consumption.

the respective indices for consecutive years together (see European Communities 2001 for a detailed explanation of the methodology). Since our study is about the evolution of ICT between 1967 and 2009, we constructed a set of constant price data for all transaction flows (domestic and imported intermediate deman and capital formation, as well as final consumption, output, and value added), by calculating the Laspeyres volume index for each year of the period under investigation (43 years in total). The year 2005 was chosen as a reference period, because data on capital consumption had been compiled by Statistics Denmark in chained prices of that year. Subsequently, each time series of indices was separately re-referenced to 2005 (=100), and then weighted again with the volumes of 2005. The drawback of chained prices is the loss of additivity; this is especially the case for input-output tables which are balanced by definition. Thus, intermediate consumption and value-added do not sum up to total output anymore in years other than 2005. To overcome this issue, we follow S.Yamakaw and Peters (2011, p.307) by using the sum of chained transactions as the new output.

3.2 Organization of input-output data

In order to make a comprehensive investigation of the ICT-sector, it is necessary to cover all channels through which ICT-related products could enter the production system (presented by the transaction matrix $\mathbf{Z}$) and we therefore incorporate imports consumed domestically ($\mathbf{M}^D$) as well as domestic and imported capital flows ($\mathbf{K}$):

$$\mathbf{Z} = \mathbf{Z}^D + \mathbf{M}^D + \mathbf{Z}_K^D + \mathbf{Z}_K^M \tag{11}$$

This transaction matrix will also be used to calculate the Leontief matrix:

$$\mathbf{A}^{*D} = \frac{\mathbf{Z}}{\mathbf{x}_d} \tag{12}$$

$\mathbf{A}^{*D}$ represents the compound direct requirements matrix describing intermediate and capital demand produced domestically and imported. On the basis of these coefficients, the fundamental matrix of the AMC is determined.

The analysis was conducted on the level of 127, 69 and 36 sectors (corresponding to the standard national industry grouping). Unlike other social networks with individual entities, the treatment of industries as nodes leads *ipso facto* to different results depending on the level of aggregation (James McNerney and Silverberg, 2013). We chose to present the results of a system composed of 69 sectors, mainly for two reasons: the more detailed (127 sector-) classification may have a bigger bias due to the fact that the investment flows are recorded based on an outdated sector classification; whilst on the 69-sector level almost every industry in the new grouping corresponds to one sector in the old grouping, an analysis on the most detailed aggregation level would imply the need to break down the individual industries even further. In order to avoid

this disaggregation bias, capital flows were therefore not taken into account at that level. On the other hand, grouping the 127 industries into 36 sectors leads to large inner-sectoral transaction flows, reflecting the high aggregation level. Since the flows within a sector are not considered, a lot of information would get lost by analyzing an economic network of this size.

4 Results and Discussion

The following results were retrieved on an annual basis for a span of 43 years. MatLab was used as the main software for preparing and processing data; additionally, Python, defined by the creators as a general-purpose programming language, seemed to be a perfect fit for this study, especially concerning the tree learning algorithm. And finally, the network graphs were drawn with Cytoscape, an open-source program for network visualization.

4.1 Studying the meso trajectory: The case of ICT

Studying input-output tables over more than four decades according to a constant industry classification means that the node in the network remains the same, even though the industry assigned to it may have undergone huge organizational and technological changes. The ICT sector, for example, represents the same network member throughout the period under study, even though the industries composing this sector in 1967 have little – if anything – in common with the ICT producers of today. Thus, in the scope of input-output data, a new GPT does not form a new or further sector, but *trans*-forms an existing sector. Fig.2 shows how the population of each ICT producing sector has been evolving since the 1960s.

The share of application sectors only contains those industries that employ ICT rather extensively (as measured by an above average demand for the respective ICT commodity in the production process).[17] Back then, the ICT manufacturing sector, which produced traditional office equipment, as well as telecommunication services already formed an integral part of the economic system by being utilized in 20 and 10 percent of all sectors, respectively. While these shares did not change much between 1967 and 1980, the diffusion rate of IT services was growing rapidly from the 1970s onwards, when highly innovative companies such as Microsoft and Apple were founded, and the first microcomputers went to the market. By mid 1980s the IT service sector already exceeded the other two ICT industries and has become the most important IT sector in Denmark since then, also with regard to employment. Between 1990 and 1995, all ICT activities showed an equally significant upward trend in their adoption rate, reflecting the big advances in the development of this GPT. Comparing these figures to labor market data, the hype for the computer technology even created a bottleneck in the supply of qualified labor.

[17] Strohmaier (2013) entails a more detailed discussion of the diffusion path of the ICT sector, differentiating between intensive and extensive utilization; the first refers to the degree of utilization in each application sector, the latter to the adoption rate across sectors.

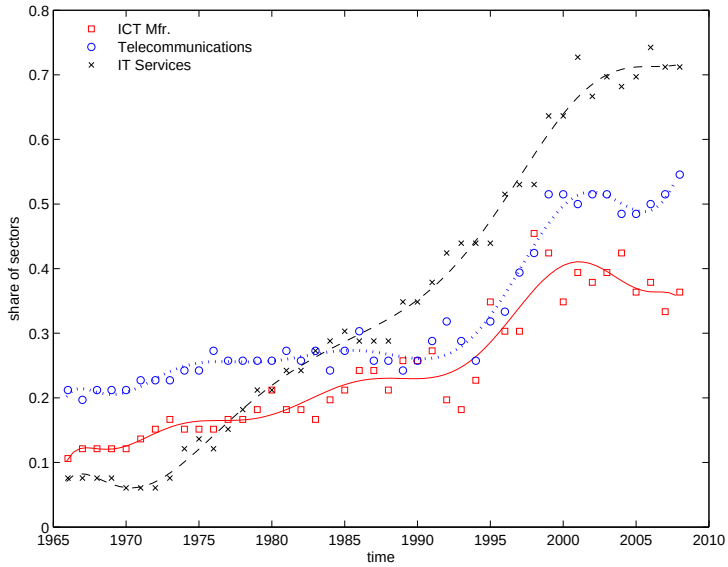

Figure 2: Share of sectors with above average demand on ICT per ICT producing sector

Danish companies saw the lack of e-skills, especially inhouse, as a main obstacle for adopting the new technology (Statistics Denmark, 2006). After the IT bubble burst in 2000, the IT manufacturing sector has shown a slight decrease, partially due to outsourcing of domestic IT activities; this has mostly affected ICT manufacturing, as the lower level of skills demanded by this sector (compared IT related services) facilitated the off-shoring of production; whereas the telecommunication sector reveals increasing shares after 2005. This sector has also become the most rapidly growing IT industry in terms of export shares of IT products, R&D investments and sectoral turnover. After 2000, the IT consultancy sector showed a relatively stable population of more than 70% of all sectors.[18]

Applying our network approach with a parameter value of 6, Table 2 shows the rank, parent node and number of descendants for each ICT industry between 1969 and 2009.

Figures 3 and 4 present the key figures graphically. The x- and y-axes denote the parent, i.e. that industry that the respective IT sector depends on upstream, as well as the number of children, i.e. the most depending industries downstream in the production process. The color of the circles indicates the ranking position with regard to the robustness score, while the radius reflects the size of the sub-tree. The development over time (depicted on the z-axis) thus shows when and to what extent ICT started to unfold their impact on the economic system, and which sector enabled this change.

[18]Note that not all IT related activities could be taken into account due to the industry classification; this especially explains the low level of adoption of ICT manufacturing products, as important sub-industries such as 'manufacture of instruments for measuring and navigation' and 'manufacture of optical instruments' could not be

Table 2: Evolution of the ICT sector 1969-2009. 'Rank' denotes the ranking position of the respective industry, numbers in 'parent node' refer to sector ID (see Table 4).

	1969	1974	1979	1984	1989	1994	1999	2004	2009
ICT manufacturing									
Rank	54	53	50	38	30	25	16	19	26
parent node	15	15	15	16	19	19	19	19	19
no. descendants	0	0	0	0	0	0	0	0	0
Telecommunication									
Rank	6	7	7	8	10	9	10	7	4
parent node	38	30	30	30	30	30	39	39	39
no. descendants	0	0	0	0	0	1	0	5	5
IT services									
Rank	28	20	11	9	11	7	3	2	3
parent node	46	45	46	46	46	46	39	39	46
no. descendants	0	0	0	1	0	1	4	12	12

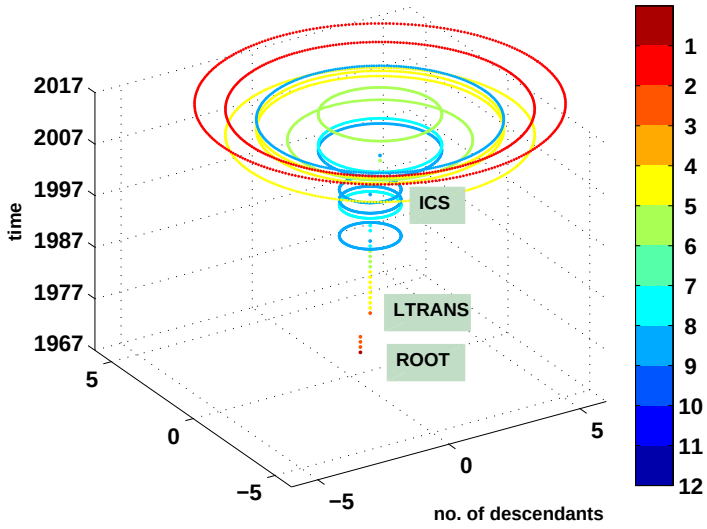

Figure 3: Evolution of Telecommunications

Fig.3 reveals that telecommunications was one of the most robust industries between 1967 and 1971 (as reflected by a rank between 1 and 3), entailing a highly diversified purchaser network. However, this sector was not able to span a community downstream, which means that it did not belong to the 6 most important suppliers for any sector in the economy. At that time, telecommunication services were also oriented towards final consumption, and to a lesser extent towards intermediate demand. From the early 1970s until 1990, the telecommunications sector was rooted in land transport, indicating that many of the services provided in this period were related to postal activities.[19] By 1987, the telecommunications sector also became an important

taken into account.

[19]In fact, the old classification based on Nace 1.1 grouped post and telecommunications together, which shows the similarity in the services provided at that time. Both activities were subsumed under transportation. With

supplier for the producer network, especially for postal activities and business services. From 1997 onwards, when the era of the internet and mobile communication began, telecommunications became member of the IT service cluster. With the change in the community, the scope of telecommunications as a supplier of intermediate products has been growing, spanning postal activities, employment activities, the private R&D sector and market research.

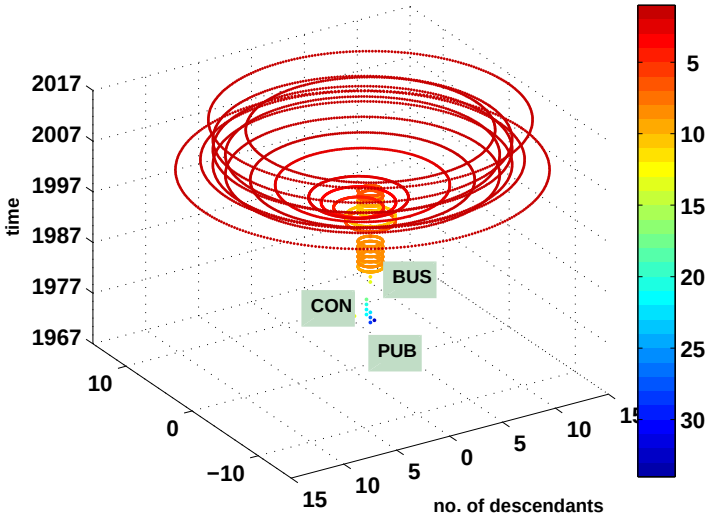

Figure 4: Evolution of IT services

In comparison to Fig.3, one can see at first glance from Fig.4 that IT services have undergone a more radical change, both in terms of their ranking position and their ability to span depending industries. Interestingly, IT services originated in the public administration sector, which supports the notion of an entrepreneurial state (Mazzucato, 2013) that takes the risk of allocating subsidies to a new technology which has the potential to become groundbreaking in the future, but bear a high level of uncertainty in the presence. In the early 1970s, the IT service sector made large investments in buildings, which made real estate the parent industry during that time. After 1977, the IT service sector joined the business services cluster and promoted the growth of this community. Eventually, in 1997, IT services became a core industry, reflecting its dominant role in the economic system. Its development since then will be discussed below, together with the other core industries in the Danish economy.

A quite different picture can be drawn from the ICT manufacturing sector. Its ranking position was almost continuously improving between 1967 and 1999 (from position 54 to 26), but it never became a parent, and much less a core industry. This may be connected to the fact that

the rise of the internet and mobile phones, NACE 2.1 gave credit to the new wireless telecommunication services and assigned them to the information and communication sector.

not all industries which manufacture ICT products could be taken into account due to the high level of aggregation in the industry classification, but also reflects the relative rise of IT services; if a company outsources activities such as software programming and data processing, the need for computer hardware inhouse decreases, which *ceteris paribus* leads to declining demand of the ICT capital on the sectoral level.

4.2 Evolution of the community structure: the core trajectory

For ease of reading, the network graphs in a time interval of 14 years between 1967 and 2009 are presented in the Appendix of this paper. Detailed data of the evolving tree for every 20 years are shown in Table 4.

Figure 5 presents the Danish economy in 1967 as a technical tree. The gray nodes directly attached to the root node display those industries that have no parent industry as immediate leader. However, not all of them are able to generate a community: as already mentioned, whenever an industry is ranked high according to the robustness criterion, but has nevertheless low significance as a supplier of immediate products to other sectors, it represents a leaf of the technical tree. That is the case, for example, in the sector 'accomodation and food service activities' (HOT), which is hanging on the root and yet does not have any industries depending on it downstream. The opposite is true for the construction sector (CON): by spawning virtually the whole economic system, it represents a core in the economic structure. The present section is devoted to the systematic analysis of these core industries and their related communities over time.

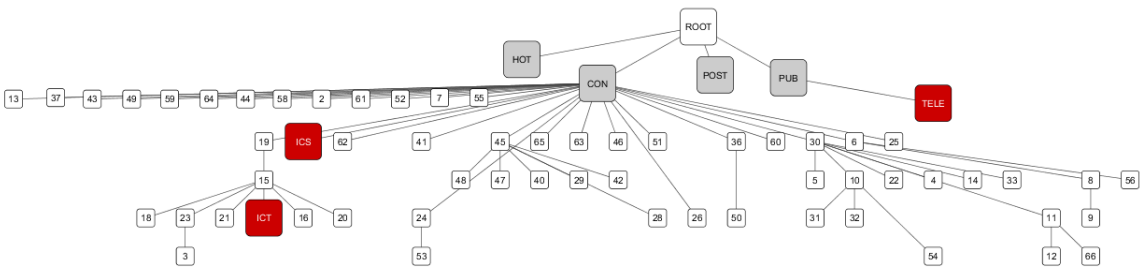

Figure 5: Technical tree in 1967. See also Fig.7 in the Appendix.

All in all, the set of core industries has been rather stable over time; From the network of 66 sectors, the algorithm picks 19 industries located at the root of the tree in at least one period of time in the course of 43 years. Out of these sectors, 10 different industries turn out to be cores in at least one industry network; the remaining sectors always act as leaves of the tree. On average, 6 sectors open up the economic system in a specific point of time. Regarding the

sector assignment, two belong to manufacturing, five to the broad class of service sectors as well as construction and transportation sector.

Taking the economic network from 1967 as a starting point, Fig.6 depicts the root path of the different industries that so far has acted as cores in a 5-year interval until 2009. The y-axis displays the parent industries, while each line denotes the path of the respective core industry. Thus, whenever a respective sector represents its own parent industry (as depicted on the y-axis), it serves as a core. Those sectors that have persistently been attached to the root (e.g. public administration) are omitted. The diagram entails 2 typical candidates for a GPT: ICT services (38,39) and electricity (24). The latter has occupied a constant position in the technical tree, except for 2002. Telecommunications (38) and IT services (39), on the other hand, have largely been part of different communities (land transport and business services). In 1997, IT services became a core industry spanning their own cluster of industries, to which the telecommunications sector has belonged to since then. Business services (46) represent the most fluctuating core industry, while construction (27) and 'mfr. of machinery' (19) show inverted development, where one acts as parent industry of the other depending on the period under study. So whenever there is a persistent switch in these core industries at the root of the tree, this signifies radical technical change on the macro level. In the case of Denmark, we could detect this kind of change in the beginning of the 1980s with regard to the construction sector which was replaced by the machinery sector, and about the same time with regard to the business sector. 10 years later, the IT core subsumed the business service sector as well as the transportation sector.

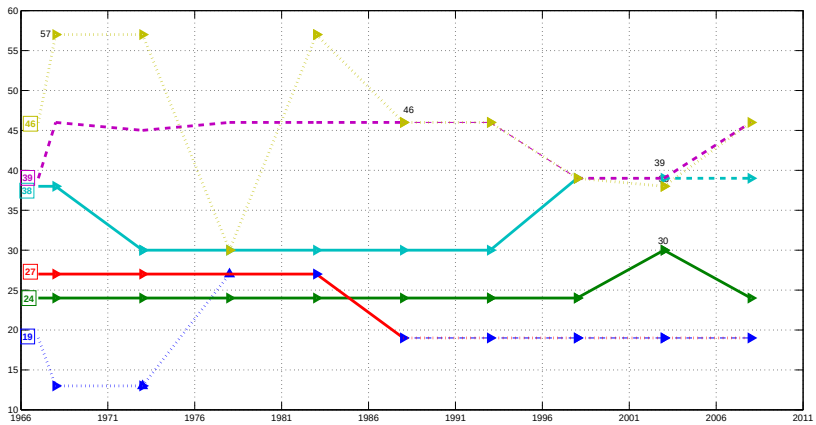

Figure 6: Path of core industries. The labels denote the following industries: (19) Mfr. of machinery and equipment; (22) Mfr. of furniture and other mfr; (24) Electricity, gas and steam; (30) Land transport; (35) Accommodation and food services; (38) Telecommunication services; (39) IT services; (57) Public Administration.

In the following, we adapt some properties of dynamic social networks from J.Qiu and Z.Lin (2011) to our purpose:(1) a community or cluster c_i within a technical tree $TT(t)$ is defined by its core industry (i.e. a specific meso unit) and the set of industries attached to it. (2) Core trajectory: while a meso trajectory depicts the origination and diffusion of a single meso unit, the core trajectory $\{C_i = c_i \in TT(1, ..., T)|\ i \text{ is the core industry}\}$ tracks the evolution of a whole industry cluster. The length of the trajectory is an indicator of the robustness of a core sector over time. (3) Promoters: Industries that are stable or recurrent members (no less than 5 times) in a community lifetime; they detect the community pattern. Additionally, we introduce (5) the range of a meso trajectory, which counts the different industries that have entered and exited the community within the period under study; dividing this metric by the number of promoters serves as a measure of 'restlessness' or volatily within the cluster. And finally, (6) stability, measured as the weighted ratio between the number of promoters and the average community size, indicates the level of institutionalization of the cluster.

Table 3: Community structure of the Danish economy 1967-2009.
The following abbreviations are used: RK (rank);t_c (length of the core trajectory), max (longest life-line))); t_p^{max} (maximum period of a promoter industry in the community c); N_p (no. of different promoters); R_c (range of distinct industries in c); N_c (average size of community); σ_c (weight: t_p^{max}/t_c); ϕ (stability).

ID	Core Activity	RK	$t_c(max)$	t_p^{max}	promoters	N_p	R_p	N_c	σ_c	ϕ
57	Public administration ect.	1	23 (9)	2	–	0	4	1.5	–	–
35	Accommodation, food service	2	12 (11)	11	39,46,55,29,45,48, 56,47	8	36	11.4	0.3	0.6
46	Business services	3	9 (4)	8	39,55,47,48,50,29, 45,52,56,34,42,38, 41,51,65	15	32	13.2	0.9	1.0
30	Land transport	4	28 (23)	15	38, 65, 59, 54	4	49	7.4	0.5	0.3
24	Electricity, gas and steam	5	27 (19)	26	53	1	7	1.4	0.8	0.5
55	Other business serv.	7	5 (3)	2	–	–	20	14.0	–	0.0
39	IT and information services	11	9 (8)	9	34,38,41,46,47,53, 56,37,42,50,51,40, 52,58,43,48,55,64, 65	19	25	17.6	1.0	1.1
19	Manufacture of machinery	19	20 (17)	20	1,3,4,5,6,7, 10,11,12,13,14,15, 16,17,18,20,21,23, 25,27,28,31,49,61, 62,63,32,44,60,8, 9,33,66,54,36	35	53	39.9	1.0	0.9
27	Construction	20	21 (21)	21	2,25,37,41,44,49, 51,60,61,62,63,3, 7,15,16,17,19,20, 21,23,58,43,1,5,12	25	58	38.2	1.0	0.7
22	Other mfr.	24	5 (3)	5	64	1	1	1.0	0.2	0.2

Applying these metrics, all core industries (in descending rank order) are listed in Table 3 which summarizes the development of the communities they generate. The two top ranked sectors, public administration and 'accomodation and food services', appear in every year between 1968 and 2009. Within these 42 years, they represent a core industry 23 and 12 times. Whereas public administration does not show any community pattern (as none of the depending industries appear more than two times in the community), the cluster generated by the accomodation and

food service sector is entirely service related (the sector IDs are given in Table 4 of the Appendix). The community itself is rather volatile, as only 8 out of 36 industries that have entered the community remain in there for more than 5 periods (while the maximum length of time of a member in the community is 11). As the average cluster consists of 11 industries, this results in a low stability index (ϕ) for the accomodation sector.

Next in the ranking is the business service sector which shows a far shorter history as a core of the network; it appeared in only 9 years, and 4 years in successive periods. Its promoters, 15 in total, all belong to the service sector. About every second industry that has ever entered the community has stayed for longer than 5 years. This, together with the average community size of 14, gives the second highest stability score. The only transportation sector represented in the core is land transport; it is located at the root of the tree in 28 periods (23 years successively). Four industries have promoted the cluster. The sector shows the highest spectrum of different industries relative to its community size, thus the community itself is less robust over time. Finally, the electricity sector, occupying the 5th rank, has one of the longest trajectories (27 times, but only 19 years in a row). As a general purpose technology, electricity was expected to span a large community; this is not at all the case, since it hardly ever belongs to the set of industries that provide one of the most important inputs to one sector. This might be due to technical change which has decreased the energy intensity in production processes. Given the high range of different industries relative to the low community size, the electricity cluster is rather unstable.

The three sectors with the lowest rank of all core industries are essentially those that span up the bulk of the industry network. As already mentioned, IT services have only recently entered the core of the economic system. More than 75% of industries entering this cluster have lasted for more than five years. Like business services, the number of recurrent sectors is even higher than the average community size of 18 industries, which makes this cluster the most stable one in the economy. The community not only comprises the bulk of financial and business sectors, but also telecommunications and the R&D sector.

Manufacturing of machinery shows similar characteristics, even though it reveals a way longer trajectory. Whereas the core service industries also generate a service oriented community, members of the machinery network are predominantly other manufacturing sectors, as well as agriculture and mining. The machinery sector essentially replaced construction which has continously acted as a core for 21 years. Almost every second industry in the community became a persistent member, as is evident by a high stability measure.

For the sake of completeness Table 3 also lists 'other business services' and 'mfr. of furniture and other manufacturing' as core industries; but they will not be discussed in detail, as they have a shorter trajectory and no commmunity pattern.

5 Conclusion

This paper has proposed a framework that uncovers changes in the economic structure under pervasive technological change. Given that one can determine the locus of production in the economy, it is possible to track a general purpose technology provided by a specific sector through space and time, by studying transaction flows between members in a dynamic industry network.

The starting point was the idea to derive an industry ranking based on industrial relations without losing the inter-sectoral information. The methodological approach was driven by recombining knowledge from different fields of research. On the one hand, the analysis of organizational structure in social groups is to some extent similar to the problem of how sectors coordinate on the meso level. On the other hand, it is also important to assess the role of an industry by the position it occupies in the network. Since pervasiveness is an essential feature of a general purpose technology, we drew on a social network approach which measures an industry by its degree of robustness. The outcome was a hierarchical structure (or technical tree), in which sectors are still mutually dependent on each other.

It is important to note that both approaches complement each other; applying the notion of robustness on industries without considering the size of economic activity nor the ability to generate communities would lead to biased results, as for example is shown in the case of the accomodation sector. By deriving the technical tree, those consumer-oriented industries are detected as leaves. On the other hand, traditional tools for studying key sectors fail to detect pervasive technologies, which led to the motivation of the paper at hand.

The application of this method to the ICT sector of the Danish economy is able to detect the current GPTs on the meso level. Moreover, it confirms the hypotheses suggested at the beginning in the case of the ICT service sector, but not for ICT manufacturing; the latter has indeed become more robust over time, but never made it to the core or created a subnetwork. In contrast, both ICT service industries have approached the root of the technical tree over time, but while IT services already act as a core industry, telecommunications do not span their own cluster, as they show a strong dependency on products from the IT service sector. However, *within* the IT community, telecommunications dispose of a growing number of adjacent industries downstream, which not only strengthens its own position in the network, but also the one of its parent industry. Moreover, these results match other figures on ICT usage which show Denmark as a highly advanced information society.

Regarding the community structure, the technical tree gives a simple representation of an otherwise complex network of transaction flows. Considering the evolution of the core industries and their related industries, the analysis demonstrated that the machinery sector replaced construction at the root, while IT services prevailed over business services. Telecommunications, on the other hand, only becomes detached from the transportation sector at a stage where ICT had already spread over the production system. Thus, our analysis of the core allows one to draw

conclusions on the ongoing structural change in the economy.

Within this framework, we have drawn analogies to the evolutionary theory of economic change. As was argued, GPTs are at odds with other technical rules in both significance and diffusion and therefore deserve special attention. Also other properties of technical rules such as their velocity or scale can be analyzed by looking at the change in the community size, and could outline a direction of future research.

For the approach to give reliable results, all channels by which a commodity can enter the production system, such as imports and capital flows, need to be taken into account. The assessment of the ICT intensity across sectors based solely on the intermediate matrix would lead to a strong underestimation of the true impact of ICT; to put simple, a USB drive would be counted whereas a laptop would not. Thus, whenever it is about technological change analyzed within an input-output framework, the incorporation of capital flows seems to be essential.

Furthermore, the focus in this study lies on the pervasive character of a GPT and not on its potential to trigger phases of high innovative activity. However, it would be easy to extend the framework to further factors of production, such as investments in R&D or the employment of heterogenous labor, by letting the algorithm search for the most innovative industries among the supplier network. This is certainly worthwhile studying, since Denmark has introduced a more pro-active IT policy to foster the domestic ICT sector. It would also draw a different picture of the electricity sector, given Denmark's position as a global leader in wind power.

A Tree dynamics

Table 4: Evolution of the technical tree. The first column gives the sector ID, the second and third column indicate the economic activity and corresponding abbreviation, respectively, the columns 4-12 record the ranking of each industry according the robustness score in descending order (pos), the parent industry (par), as well as the number of desc (desc). The value 0 in par denotes the root node, parameter α in the tree learning algorithm was set to 0.5.

			1968-69			1988-89			2008-09		
ID	Activity	Label	pos	par	desc	pos	par	desc	pos	par	desc
			1968		1969	1988		1989	2008		2009
			pos	par	desc	pos	par	desc	pos	par	desc
1	Agriculture and horticulture	AGR	63	5	0	65	5	0	65	5	0
2	Forestry	FOR	56	27	0	60	27	0	63	19	0
3	Fishing	FISH	65	19	0	66	10	0	66	19	0
4	Mining and quarrying	MIN	62	10	0	62	27	1	60	27	0
5	Manufacture of food, tobacco	MFOOD	52	30	0	50	19	2	55	19	1
6	Textiles and leather products	MTEXT	10	27	2	27	27	0	14	19	0
7	Manufacture of wood etc.	MWOOD	55	27	0	54	16	0	61	16	0
8	Manufacture of paper etc.	MPAP	24	6	1	35	27	2	41	19	1
9	Printing etc.	MPRINT	48	8	0	41	8	0	49	8	1
10	Oil refinery etc.	OIL	34	30	4	56	27	1	40	27	2
11	Manufacture of chemicals	MCHEM	36	30	2	39	19	0	27	19	1
12	Pharmaceuticals	MPHARM	64	11	0	52	11	0	53	11	0
13	Manufacture of rubber etc.	MRUB	14	27	0	21	19	1	22	19	0
14	Manuf.of glass, concrete etc.	MGLASS	61	10	0	64	4	0	64	19	0
15	Manufacture of basic metals	MBMET	39	19	6	43	19	0	48	16	0
16	Manufact. of fabricated metal	MFMET	38	19	0	32	19	1	34	19	2
17	Manufacture of ICT	ICT	54	15	0	30	19	0	26	19	0
18	Electronic/Electrical equipment	MELTR	35	19	0	24	19	0	25	19	0
19	Manufacture of machinery	MMACH	29	13	2	17	0	11	12	0	23
20	Manuf. of motor vehicles etc.	MVEH	40	15	0	48	15	0	44	19	0

Continued on next page

Table 4 – continued from previous page

			1968-69			1988-89			2008-09		
ID	Activity	Label	pos	par	sub	pos	par	sub	pos	par	sub
21	Mf. of ships, transport equip.	MTRAN	50	15	0	51	15	1	59	19	0
22	Manuf.of furniture,other manuf	MOTH	41	15	0	5	0	0	10	0	1
23	Repair, inst. of machinery etc	RMACH	53	15	0	53	15	0	54	19	0
24	Electricity, gas and steam	ELC	4	0	1	6	0	2	9	0	0
25	Water collect.purification etc	WAT	27	27	0	38	27	0	46	27	0
26	Sewerage,waste collection etc.	WASTE	9	27	0	14	46	0	17	19	0
27	Construction	CON	7	0	26	18	19	22	30	19	6
28	Sale, repair of motor vehicles	SRVEH	32	19	0	37	13	0	32	19	0
29	Retail sale	RET	23	45	0	36	45	0	24	45	0
30	Land transport, pipelines	LTRANS	11	27	7	4	0	4	13	19	0
31	Water transport	WTRANS	47	10	0	57	10	0	39	19	0
32	Air transport	ATRANS	37	10	0	49	33	0	52	19	0
33	Support activities for transp.	STRANS	43	30	0	33	30	1	35	19	0
34	Postal and courier activities	POST	3	0	0	8	46	0	11	38	0
35	Accommodation, food service	HOT	2	0	0	2	0	1	6	0	0
36	Publishing activities	PUBL	17	30	1	34	30	0	42	39	0
37	Radio,TV.Movie,video,sound pub	RADIO	30	27	0	25	39	0	37	39	0
38	Telecommunications	TELE	6	0	0	10	30	0	4	39	5
39	IT and information service	ICS	28	46	0	11	46	0	3	46	12
40	Financial service activities	FIS	26	45	0	28	27	0	23	39	2
41	Insurance and pension funding	INS	60	27	0	23	27	0	21	39	0
42	Other financial activities	OFIS	45	45	0	61	46	0	58	39	0
43	Buying, selling of real estate	REAL	59	27	0	63	27	0	56	39	0
44	Renting of resident. buildings	RENTRB	22	27	0	29	27	0	19	19	0
45	Owner-occupied dwellings	OWNB	13	27	6	19	27	2	16	19	2
46	Legal, account.,cons.activit.	BUS	5	57	0	3	0	6	2	0	1
47	Architecture and engineering	ARCH	57	45	0	58	46	0	47	39	0
48	Research and developm.(market)	RD	66	45	0	47	45	0	57	38	0
49	Research and dev. (non-market)	RD (nm)	42	27	0	46	27	0	50	45	0
50	Advertising, market research	ADV	25	36	0	16	46	0	20	38	0
51	Oth.techn.serv.,veterinary act	OTSERV	58	27	0	55	27	0	33	38	0
52	Rental and leasing activities	RLACT	33	27	0	42	46	0	18	19	0
53	Employment activities	EMPL	18	24	0	13	24	0	28	38	0
54	Travel agent activities	TRAV	15	30	0	15	0	0	29	19	0
55	Cleaning, other business serv.	OBUS	16	27	0	9	46	0	5	38	0
56	Rescue service ect. (market)	RESC	51	21	0	59	39	0	62	39	0
57	Public administration ect.	PUB	1	0	2	1	0	1	1	0	0
58	Adult-,other education(market)	OEDU	21	27	0	31	27	0	15	39	0
59	Education (non-market)	EDU	19	30	0	22	27	0	36	39	0
60	Human health activities	HEALTH	31	27	0	40	27	0	31	27	0
61	Residential care	RCARE	44	27	0	44	27	0	38	27	0
62	Arts,entertainm.,other culture	CULT	46	27	0	45	27	0	51	27	0
63	Sports, amusement, recration	RECR	20	27	0	26	27	0	45	27	0
64	Activities of membership org.	MEMB	12	27	0	7	46	0	8	39	0
65	Repair of personal goods	RPERS	8	0	0	12	0	0	7	39	0
66	Other personal services	OPSERV	49	11	0	20	27	0	43	19	0

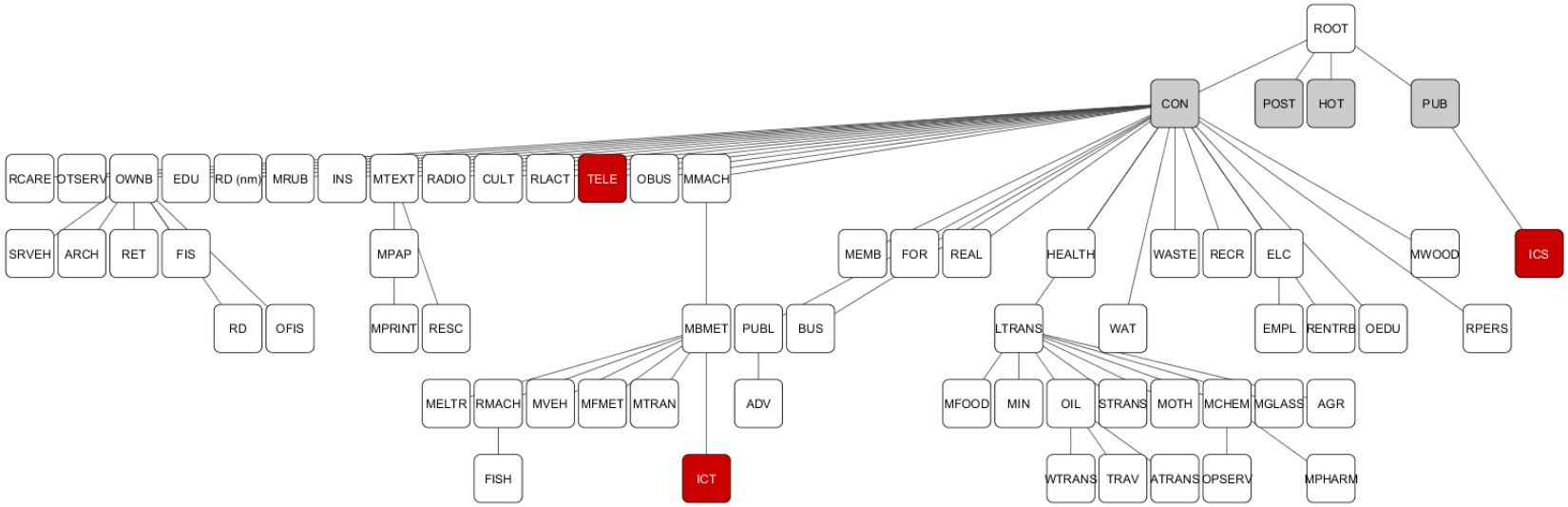

Figure 7: Industry network of Danish economy in 1967

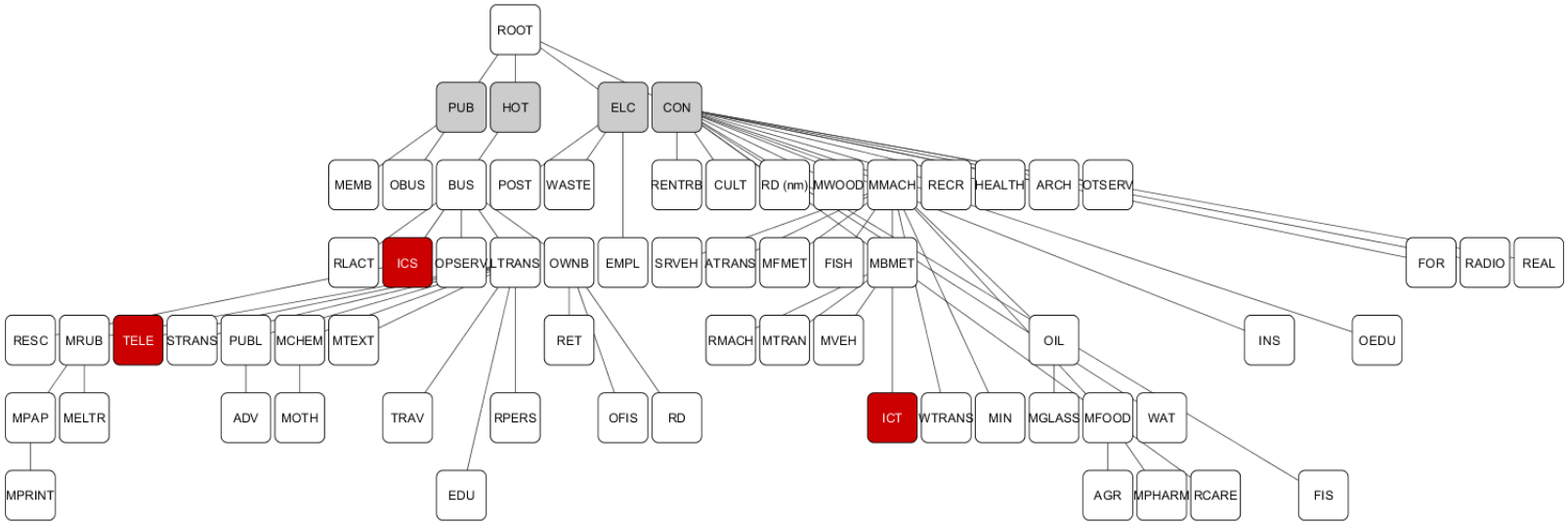

Figure 8: Industry network of Danish economy in 1981

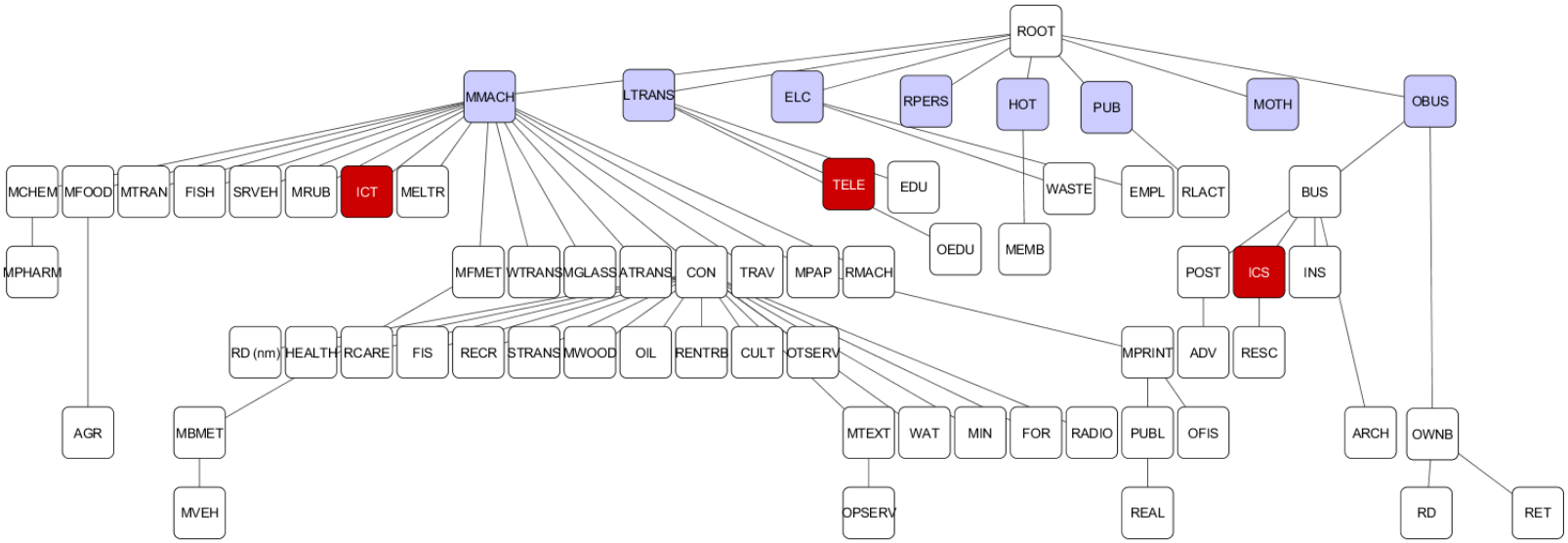

Figure 9: Industry network of Danish economy in 1995

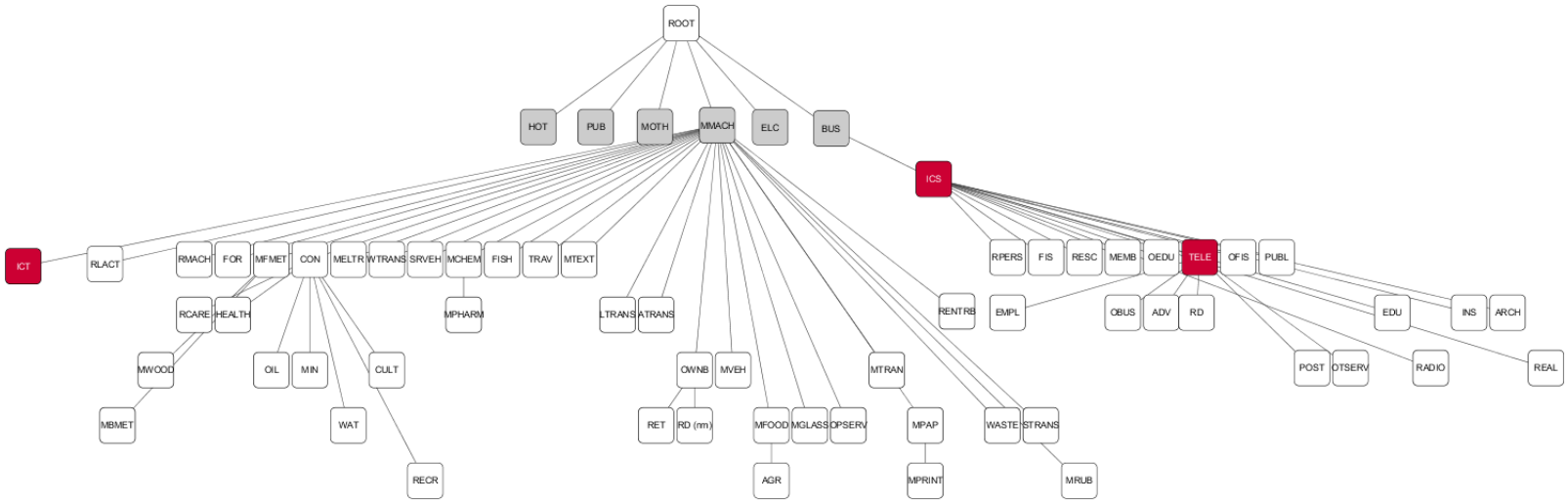

Figure 10: Industry network of Danish economy in 2009

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