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Growth dynamics in regional systems of technological activities – A SVAR approach

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Abstract:

This paper analyses the causal relationships in regional technological systems within a structural vector autoregression (SVAR) framework. Applying a data-driven identification strategy based on Independent Component Analysis, it shows how the regional growth dynamics of economic, research, innovation and educational activities affect each other instantaneously and over time in five different industries. Referring to the type of industry and its knowledge base, expectations are derived on how industry-specific growth processes unfold. Knowledge on the causal relations among the various activities in such regional technological systems is of utmost relevance to the design and implementation of efficient policy instruments.

Keywords: regional growth, SVAR, non-normality, innovations, universities, R&D, regional technological systems.

JEL Classifications: C33, O30, R11

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1 Introduction

The development of regional economies is closely related to the various technological activities taking place, such as economic, research, innovation, or educational activities. These activities, which compose a regional technological system, evolve and unfold in an endogenous and interdependent way. The interrelated dynamics are of utmost interest for regional scientists and policy makers who aim to foster regional development and to spur economic growth. Since policy instruments are usually tailored to specifically support one of the above activities, knowledge about the causal structure of the dynamic interdependencies in regional technological systems is essential to efficiently design, focus and implement policies. Does an increase in research automatically lead to more innovations and economic growth, as the traditional linear thinking would suggest, or do successful innovations generate economic opportunities and set incentives to perform further research? Are educational and innovation activities direct generators of economic growth? Are there industries in which economic growth (for instance, due to the expansion into export markets) lead to further innovation and workforce skilling? By ignoring questions like these policies often fail to reach their goal of contributing to regional development.

In the literature, the relationships between the activities are mostly studied in isolation. For instance, a huge bulk of literature exists that investigates the link between regional innovation and economic growth (e.g., RODRÍGUEZ-POSE and CRESCENZI, 2008). However, the simultaneous and endogenous development with other interdependent activities, such as research efforts or university education, tends to remain unaddressed. They cannot be neglected if the causal structure in the growth dynamics of regional economies as coherent, multi-dimensional systems should be uncovered. Besides, only few studies exist which take an explicit industry-specific perspective (e.g., BUERGER et al., 2012). Therefore, the study at hand uses a structural vector autoregressive (SVAR) framework to address the issue of causality in systems of endogenous and interdependent variables. The models, which are estimated separately for five industries, go beyond simple temporal associations by recovering the instantaneous causal effects, which would be missed if only the lagged effects are considered (COAD et al., 2012).

For identifying SVAR models, the literature usually refers to theory to derive the necessary identification restrictions. Because theory is not always unambiguous and assumptions like market clearance or perfect factor mobility are rather controversial, the insights from the results are often put into question. Only recently, data-driven identification techniques, which do not rely on any *a priori* theoretical assumptions, have been developed in the machine-learning community (HYVÄRINEN et al., 2010). This paper uses a strategy based on Independent Component Analysis (ICA), as introduced by MONETA et al. (2012) into the economic literature. By exploiting the non-normality of residuals' distributions to establish causal relationships, this strategy is particularly suited for the analysis of systems governed by economic shocks – the existence of fat tails in economic growth rate distributions has emerged as a stylized fact from a huge body of literature (see COAD, 2013 for an overview).

The paper is structured as follows. The first part of Section 2 describes the vector autoregression methodology and discusses identification issues of the structural version. Furthermore, related empirical applications in the literature are summarized. The second part of Section 2 sketches a conceptual model of regional systems of technological activities and derives hypothesis on the industry-specific causal linkages among these activities. Section 3 presents the identification algorithm based on ICA in detail and discusses further empirical aspects concerning the estimation. Having provided an overview on the data in Section 4, in the subsequent Section 5 the results on the causal relationships are presented and discussed. Section 6 concludes by drawing policy recommendations.

2 Literature

2.1 Vector autoregression and related empirical applications

A brief introduction into vector autoregression

Vector autoregression (VAR) was advocated by Nobel-laureate Christopher SIMS (1990) to analyse fluctuations of interrelated variables in macroeconomic systems. Meanwhile, this multiple equation approach is widely used in empirical economics to investigate co-evolutionary dynamics of systems of variables (MONETA et al., 2012; BUERGER et al., 2012). By treating all variables as endogenous (LÜTKEPOHL, 2003), it is especially suited to analyse how (regional) economic systems adjust to exogenous shocks (ALECKE et al., 2010; PATRIDGE and RICKMAN, 2003).

In the basic model, a system of K variables $y_1, \dots, y_K$ is driven by a linear combination of the contemporaneous values of the other variables at time *t*, the past values (up to lag *p*) of all variables, and a vector of random disturbances:

$$y_t = By_t + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{p-1} + \varepsilon_t \qquad (1)$$

with B and Γ_j $(j = 1, \dots, p)$ being K*K coefficient matrices and ε_t a K*1 vector representing a zero-mean white noise error process (MONETA et al., 2012). By definition, the diagonal of B is set to zero. In the structural setup, Γ_j contain the autoregressive effects, while B contains the contemporaneous effects which occur within one time period *t*. Equation 1 is often transformed, by denoting $\Gamma_0 = I - B$, into the standard SVAR form:

$$\Gamma_0 y_t = \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{p-1} + \varepsilon_t \tag{2}$$

Because equation 1 and 2 are endogenous, and hence, the direct estimation of the model biased, a reduced-form VAR model is often derived (MONETA et al., 2012):

$$\begin{aligned} y_t &= \Gamma_0^{-1}\Gamma_1 y_{t-1} + \cdots + \Gamma_0^{-1}\Gamma_p y_{p-1} + \Gamma_0^{-1}\varepsilon_t \\ &= \mathrm{A}_1 y_{t-1} + \cdots + \mathrm{A}_p y_{p-1} + u_t \end{aligned} \tag{3}$$

Equation 3 corresponds to K individual regressions of the variables y_t on the past values of their own and the other variables (STOCK and WATSON, 2001; GOTTSCHALK, 2001). $u_t = \Gamma_0^{-1}\varepsilon_t$ denotes a vector of random disturbances. In contrast to the structural version, this system of equations, which simply describes inter-temporal relations, can be directly estimated. Hereby, usually a constant term or further control variables are included. However, the reduced-from does not provide any information on the instantaneous effects. Rather, A_p mixes up B with the lagged effects Γ_p. This implies that only the temporal co-evolution of a system can be observed (i.e. correlation), but not which variable directly drives the others within-the-period (i.e. causality) (COAD et al., 2012).

Therefore, the reduced-form is an explorative tool, which is useful for time-series forecasting but not for policy analysis (PARTRIDGE and RICKMAN, 2003). Knowledge on the causal relationships is required to assess the expected effects of an exogenous policy stimulus to one variable on the other variables (MONETA et al., 2012; BUERGER et al., 2012). Compared to the reduced-form VAR model, the structural equivalent allows to observe how random shocks unfold and propagate throughout the system (GOTTSCHALK, 2001; MONETA et al., 2012). This is achieved by disentangling the contemporaneous effects, which occur when measurements have a lower time resolution than the causal mechanisms, from the lagged effects, which occur when the time resolution is higher (HYVÄRINEN et al., 2010). Reversed causality, which often is prevalent in dynamic and endogenous systems, is not an issue, "because by tracing out the dynamics of the system to an unexpected shock the causality is pinned down and runs unambiguously from the shock to the other variables in the model" (GOTTSCHALK, 2001, 27). Thus, GOTTSCHALK (2001) and KUERSTEINER (2008) conclude that the shock analysis of the SVAR is the best alternative for situations where the variables are endogenously determined and where controlled experiments are not feasible.

The main challenge lies in the identification of the SVAR model. The VAR parameters, which are directly estimable, are not sufficient to recover the parameters in B and Γ_p, which are much more in numbers (MONETA et al., 2012). Without any further assumptions, the same reduced-form model could support infinitely different SVAR models (GOTTSCHALK, 2001). In the literature, two general approaches exist to identify the structural information. On the one hand, economic theory provides non-sample information that can be used as external identifying restrictions (STOCK and WATSON, 2001; LÜTKEPOHL, 2003). However, this approach faces several problems. Already SIMS (1980) noted that only few powerful *a priori* restrictions can be derived from theory. Often, competing theories exist, or one theory even allows alternative causal orderings of the variables (DEMIRALP and HOOVER, 2003; MONETA et al., 2012). This problem becomes aggravated in larger systems of variables, as the number of necessary restrictions grows exponentially with K. On the other hand, data-driven approaches try to overcome the difficult search for credible restrictions by letting data speak (DEMIRALP and HOOVER, 2003). The approach used here is based on a Linear Non-Gaussian Acyclic Model (LiNGAM), which was introduced in the machine-learning community by SHIMIZU et al. (2006) and extended by HYVÄRINEN et al. (2010) to the SVAR framework. The identification becomes possible by making three basic assumptions (MONETA et al., 2012). First, the model is acyclical, i.e. there are no cycles or feedback loops in the causal relations within one time period. Second, the SVAR errors ε_t are independent. Finally, ε_t are not normally distributed. Taken together, the three assumptions suffice to fully recover the contemporaneous causal relations by using Independent Component Analysis. More precisely, the information of non-normality helps to identify a set of independent latent shocks. Subsequently, the estimates of B and Γ_0 are recovered by searching for an acyclical causal ordering of the variables (MONETA et al., 2012). The exploitation of the information on the distributional characteristics of the error terms makes this approach particularly attractive for the analysis of economic systems. From a huge body of literature it has emerged as a stylized fact that their growth dynamics, independent of the level of aggregation, are not normally distributed but can be characterized by fat tails (see, for example, BOTTAZZI et al., 2011 for firms; DUSCHL and BRENNER, 2013 for regions; or FAGIOLO et al., 2008 for countries).

Empirical applications of VAR/SVAR methodology in related fields

The reduced-form VAR methodology has been introduced in regional science by BLANCHARD and KATZ (1992), who analyse the effects of demand shocks on employment, unemployment and wages. With ALECKE et al. (2010) and VEGA and ELHORST (2013) we highlight two recent studies which were inspired by this seminal contribution. Whereas the former investigates the linkages between regional labour market variables and internal migration flows among German states within a panel VAR setup, the latter extends the BLANCHARD and KATZ model using a dynamic spatial panel data approach to assess both the temporal and spatial propagation of labour demand shocks. Focusing more on the innovation aspects of regional development, BUERGER et al. (2012) analyse the co-evolution of patents, R&D and employment of German labour market regions separately for different industries.

To fully grasp the causal relations among the variables, soon the structural version has become popular. For example, FRITSCHE and LOGEAY (2002) study unemployment dynamics of the German national economy, while PATRIDGE and RICKMAN (2003) tackle the famous question in urban economics whether people follow jobs or jobs follow people. Both studies are based on simple labour-market models to deduce identification restrictions. The latter, for instance, assumes the equality of labour-demand supply, constant returns to scale, perfect labour and capital mobility in the long run.

To provide an alternative to the theory-guided view, MONETA et al. (2012) has recently introduced a data-driven identification strategy, named VAR-LiNGAM, into the empirical economic literature. In two cases studies, the authors apply this methodology to understand the dynamics and causal relationships of different aspects of firm growth and the impacts of changes in monetary policy on macroeconomic variables. COAD et al. (2012) confirm the usefulness of this approach in a more comprehensive empirical contribution which seeks to understand how growth processes of high growth firms unfold.

However, a data-driven identification strategy, which does not rely on often untenable theoretical assumptions, has not yet been applied at the level of regional economies. Hence, we position the present study within the existing body of literature as an advancement of BUERGER et al. (2012) by introducing the VAR-LiNGAM identification strategy of a structural VAR model into the literature of regional science and economic geography.

2.2 Causal relations in the dynamics of regional systems of technological activities

The framework of regional system of technological activities

We conceptualize a regional technological system as consisting of four activity categories: economic, research, innovation and educational activities. The dynamics in economic activities are generated by the growth, exit or entry of firms. Research is measured by R&D conducted in firms, which expand or reduce their engagement in (private) research activities. Furthermore, a regional economy is often assessed by its innovative capacity or the innovation activities taking place in firms or the public research institutes. Finally, education assumes a key role in the modern knowledge-based economy.

These activities are strongly interrelated and their dynamics evolve highly endogenously. The growth of one activity impacts on the growth of the others, which in turn propagates further throughout the system.[1] Therefore, this section aims to derive hypotheses on the expected causal linkages among the four interdependent activities of a regional technological system by elucidating the underlying mechanisms. Besides, these linkages

[1] Because of this endogeneity, STORPER and SCOTT (2009, 157) note that the cross-section regression analysis of regional growth is problematic: "causalities are in practice both multidirectional and diachronic". For a more extensive discussion on the use of structural models in the light of endogeneity to analyze regional growth, see BREINLICH et al. (2013).

depend on the industries under consideration. Already PAVITT (1984) observed that industries differ in their innovation patterns. Likewise, the literature on technological regimes (WINTER, 1984) and subsequent work on sectoral innovation systems (BRESCHI et al., 2000; MALERBA, 2002) have highlighted several dimensions along which industries systematically differ. More recently, the literature stresses industry-specific knowledge bases, which impact on innovation and learning processes. Here, ASHEIM and co-authors (e.g., ASHEIM and GERTLER, 2005) mainly distinguish between the analytical and synthetic knowledge base. Industries, in which the analytical knowledge base predominates, tend to rely more on scientific knowledge generated both internally and externally. Compared hereto, industries that are characterized by a synthetic knowledge base generate innovation through application and novel combinations of existing knowledge in the context of daily problem-solving situations (ASHEIM, 2007).

This paper analyses and compares five industries. First, the chemical industry (CHEM) is a typical representative of science-based manufacturing. Mainly based on analytical knowledge, it strongly relies on systematic R&D for generating innovations (ASHEIM, 2007). Additionally, patents play an important role to appropriate returns from innovations (BRESCHI et al., 2000). Secondly, the machine tool industry (MACH) can be classified as specialised supplier manufacturing (see PAVITT, 1984, or revised taxonomies such as BOGLIACINO and PIANTA, 2010). Foremost in Germany this industry consists of rather small and relatively specialized firms, which tend to rely on a synthetic knowledge base. Here, other appropriation methods than patents play a more important role. The electronics industry (ELEC) can be regarded as an industry that shares both the properties of science-based and specialised supplier manufacturing and that combines elements from a synthetic and analytic knowledge base. In contrast hereto, scale-intensive manufacturing, like in the metal (META) or transportation (TRAN) industry, is characterized by a high concentration of rather large firms (BOGLIACINO and PIANTA, 2010). Yet the two mentioned industries differ in their knowledge base. Whereas synthetic knowledge prevails in TRAN (ASHEIM, 2007), META is considered to share many characteristics of the analytical knowledge base of CHEM.

Implications of the industries' properties are considered in the subsequent discussion of the expected causal linkages among the different activities in regional technological systems.

Expectations on the causal relations in the dynamics of the activities

From the literature, expectations on bivariate causal linkages among the four different activities can be derived. Figure 1 summarizes the causal relations that below are discussed in detail.

Affected variables	Causing variables: Economic	Research	Innovation	Educational
Economic			+ / -	+ (MACH)
Research	+		+ (MACH, TRAN)	
Innovation		+ (CHEM, META)		+ (CHEM, ELEC)
Educational				

Figure 1 Expected causal relations in the dynamics of the activities of regional technological systems (if the causal relations are expected especially in some industries, these industries are given in brackets)

The link between research and innovation activities seems to be clear at a first glance. Private R&D is usually regarded as an important innovation generator both at the organisational and regional level (Brenner and Brökel, 2011; or Cooke et al., 1997 in the context of innovation systems). Hence, we expect that an increase in research activities leads to more innovations, especially so in science-based industries. However, the linear thinking has recently been challenged. Instead, a success-breeds-success phenomenon often is observed empirically (Buerger et al., 2012). We argue that this is mainly an "engineering phenomenon" and can be observed in industries based on synthetic knowledge, such as MACH and TRAN. Here, innovations are often generated through learning-by-doing and interactively with suppliers or customers. Once innovations promise economic success, investments in systematic R&D are intensified. In short, a positive causal effect can be inferred from theory into both directions, probably depending on the industry.

The link between innovation and economic activities is less unambiguous. Extending the linear model, innovations which result from research are often seen as an important driver of economic growth. Focusing on the effects of employment, which is the preferred indicator of economic activities in this paper, an additional distinction between product and process innovation becomes necessary. Whereas positive employment effects are expected due to growth opportunities as a result of new products, negative effects may arise from rationalisation measures as a result of process innovations (see Buerger et al., 2012 for a literature overview). Hence, the net effect remains an empirical question.

A direct link is also expected for research and economic activities. In the empirical literature on firm growth strong evidence exists that growth in employment is associated with subsequent growth in R&D (Coad and Rao, 2010). As firms expand, they also tend to reinforce investments in R&D. We argue that the same rationale holds at the aggregate level of regions. This stands in contrast to the main idea of endogenous growth theories which assume that economic growth is driven by accumulation of new knowledge through intentional R&D (e.g., ROMER, 1990). This link rather works indirectly (via innovations) and with some time lag.

Considering educational activities, a clear relationship seems to exist with innovation activities. “Man- (or, better, brain-) power […] are needed for creating innovations” (BRENNER and BROEKEL, 2011, 12). For instance, graduates from higher educational institutes bring up-to-date knowledge into firms to enable innovation processes (BRENNER and SCHLUMP, 2013). Although being the most mobile group in society, a large fraction of graduates stay in their region of education after graduation (MOHR, 2002). We expect that the impact of higher education on innovations is strongest in industries which rely on new scientific knowledge, such as CHEM and ELEC.

Furthermore, educational activities can be assumed to directly impact economic activities. The role of human capital as a main driver of economic growth (LUCAS, 1998) is widely acknowledged at the regional level (e.g., CRESCENZI, 2005). In this context it has been shown empirically that especially strongly expanding firms rely on the local presence of qualified graduates (DUSCHL et al., 2012). Brenner and SCHLUMP (2013) argue that regional growth is fostered by universities only if regional labour markets offer job opportunities. Otherwise, graduates tend to leave their region of education. Hence, we expect that the impact of educational activities on economic activities is strongest in industries where the supply of qualified labour is relatively scarce, which foremost should be the case in MACH.

No direct link in either ways is expected to be found between educational activities and research activities.

3 Empirical method

This section introduces the VAR-LiNGAM identification algorithm using ICA. Both the ICA and the underlying assumptions for identification are described in more details. Finally, further aspects concerning the empirical implementation are discussed.

The VAR-LiNGAM identification algorithm using ICA

Once having estimated the reduced-form VAR regressions of equation 3, the goal is to recover Γ_0 and thus B, which contains the contemporaneous causal relations. The strategy chosen here is to relate the VAR errors to the SVAR shocks by the expression $u_t = \Gamma_0^{-1}\varepsilon_t$ (MONETA et al., 2012). Γ_0 can be uniquely identified using ICA given three general assumptions: the shocks ε_t are independent and not normally distributed and the contemporaneous causal structure among y_t is acyclic. With the help of ICA, latent components, which are not directly observable, can be recovered from the observed random variables, provided that these components are statistically independent and not normally distributed (HYVÄRINEN and OJA, 2000). In other terms, the original independent components, representing economic shocks, are recovered by exploiting the information of non-normality in the error terms. However, the components are only found up to permutation, sign and scaling, meaning that they still allow various specifications of Γ_0 (MONETA et al., 2012). To finally establish a unique correspondence between the identified components and the variables, an acyclical causal structure is assumed. This implies that $B = I - \Gamma_0$ should be lower triangular if the variables are ordered accordingly, i.e. the entries above the diagonal become zero (HYVÄRINEN et al., 2010). Hence, by arranging the variables and by finding a permutation of B for which the elements in the upper triangle are as close to zero as possible, the unique contemporaneous causal structure is identified. In the following section, we want to provide the intuition behind ICA and to discuss the three assumptions underlying the identification strategy.

Independent Component Analysis

ICA represents the basic building block of the SVAR identification strategy. As a probabilistic method it seeks to recover the original signals or processes, which cannot be directly observed, from measured signal mixtures. Because the latent, unobservable signals, also called independent components, usually contain important information, this method has become popular in various fields like digital image processing, biomedical signal processing, telecommunication, neurology, or finance (HYVÄRINEN and OJA, 2000; HYVÄRINEN, 2013). The most prominent example is the cocktail-party problem, which assumes two simultaneously speaking individuals and two microphones. The microphones can only record mixtures (the observed random variables) of both voices (the independent components). Because the microphones are located in different parts of the room, the voices are present with different weights in the recorded signal mixtures. By linearly transforming the random variables, ICA aims to find those components that are as statistically independent as possible. The central limit theorem implies that the sum of independent random variables moves closer to normality than any of its original variables (HYVÄRINEN and OJA, 2000). In other words, the additive mixture distribution is closer to normality than any of its independent components, which, consequently, can be found by maximizing some measure of non-normality. Various measures like kurtosis or negentropy exist which can handle both leptokurtic and platykurtic distributions, that means distributions with tails fatter or thinner than the normal one. Negentropy is more robust than kurtosis-based measures and from statistical theory the optimal estimator for non-normality, however it is difficult to compute as the densities of the independent components must be known

(HYVÄRINEN and OJA, 2000). With FastICA, a fixed point, semi-parametric ICA algorithm, the negentropy can be efficiently approximated (HYVÄRINEN, 1999).

The three assumptions for full identification

As mentioned above, the SVAR model can be uniquely identified given three general assumptions: the shocks ε_t are independent and not normally distributed and the contemporaneous causal structure among y_t is acyclical.

Statistical independence means that information of a value of one variable does not give any information on the value of the other variable.[2] In economic terms, ε_t are regarded as structural innovations or "primitive" exogenous forces, which affect the system at each time period and cause its dynamics and oscillations, but do not depend on the shocks before (GOTTSCHALK, 2001; MONETA et al., 2012). However, only mixtures of the structural economic shocks are observed. Therefore, testing for statistical independence only provides information on the independence structure of the decomposed components by ICA. Whether or not the true economic shocks are independent ultimately has to be judged on background knowledge on economic processes (MONETA et al., 2012). Thus, it is not clear whether this assumption is satisfied and we will empirically check it below.

The independent components are recovered by maximizing their non-normality. However, this does not work if the components, here the economic shocks ε_t, are normally distributed. In that case, their joint density would be completely symmetric, thus providing insufficient information for the decomposition of the observed signal mixtures (HYVÄRINEN and OJA, 2000). This assumption, fundamentally empirical in nature (HYVÄRINEN et al. 2010), is supported by a huge body of literature which argues that economic shocks tend to deviate from normality (e.g., MCKELVEY and ANDRIANI, 2005). Non-normality usually remains even after controlling for other variables (MAASOUMI et al., 2007) or the lag structure (BOTTAZZI et al., 2012). Nevertheless, it is suggested to test for non-normality. Any form of non-normality is allowed (MONETA et al., 2012) and if only one independent component is normally distributed, ICA still is possible (HYVÄRINEN and OJA, 2000). To sum up, if the independent components deviate from normality, the information on their distribution can be exploited to identify the SVAR model using ICA (MONETA et al., 2012). The assumption of non-normality of economic shocks is supported by and will be additionally tested for our case.

The full identification in form of a unique contemporaneous causal ordering of the variables in y_t, however, becomes only possible if acyclicity is assumed. The implied recursive structure restricts two variables from being their mutual cause in one time period, giving rise

[2] In case of non-normal distributed random variables, this requirement is stronger than linear uncorrelatedness (MONETA et al., 2012).

to self-reinforcing feedback loops (COAD et al., 2012; MONETA et al., 2012): if a causes b, then b cannot cause a (HYVÄRINEN, 2013). With this additional assumption the permutation, sign and scaling indeterminacies of ICA can be fixed and the SVAR shocks ε_t uniquely connected to the components of u_t in a one-to-one relationship. Therefore, B is arranged and permuted in such a way that the major causal directions receive more weight, whereas the relatively minor causal directions are minimized towards zero (MONETA et al., 2012; COAD et al., 2012). This leads to a causal ordering of the variables so that the shock to y_1 feeds into $y_2, \ldots, y_K$ within the same time period, the shock to y_2 into $y_3, \ldots, y_K$, and so forth (DEMIRALP and HOOVER, 2003). Even though acyclicity is a common assumption in the literature (MONETA et al., 2012), a cyclical alternative was proposed by LACERDA et al. (2008), which might be of interest in future research. Our theoretical discussion above has shown that only in the case of one pair of variables (research and innovation) we have theoretical arguments that lead us to expect a mutual causal relationship. Hence, this assumption seems to be not far from reality.

Summary of the algorithm

Before we highlight further aspects concerning its empirical implementation in the context of regional economic growth, Figure 2 summarizes the algorithm for identifying a structural VAR model. For a detailed mathematical description we refer to MONETA et al. (2012), SHIMIZU et al. (2006) or HYVÄRINEN et al. (2010).[3]

[3] The named authors also provide an implementation of the algorithm for R, which was adapted for the use in this paper (http://www.cs.helsinki.fi/u/entner/VARLiNGAM).

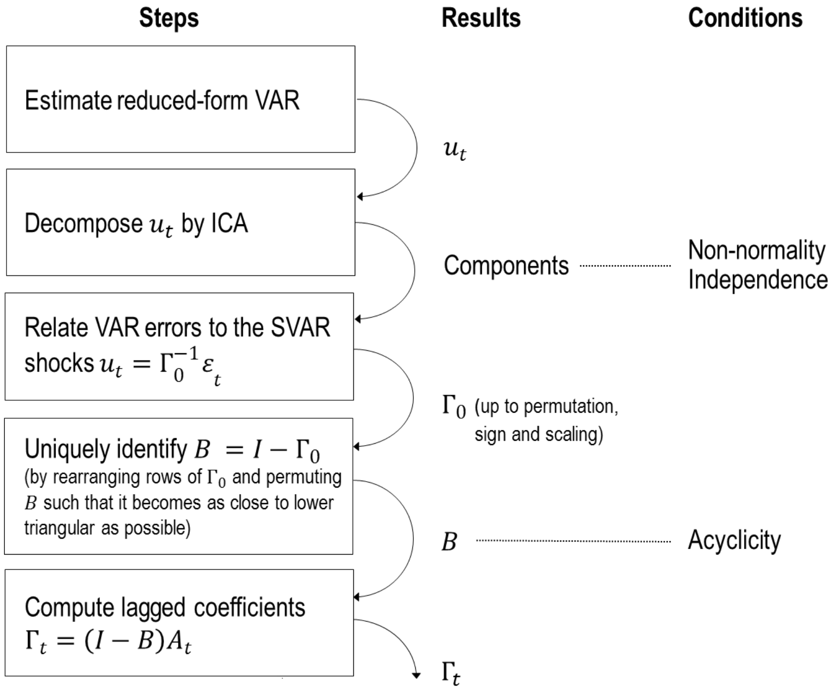

Figure 2 Summary of the identification algorithm

Further empirical aspects concerning the implementation

To remove the time-invariant region-specific effects (MONETA et al., 2012), growth rates $g_{i,t}$ instead of levels $S_{i,t}$ are used for the variables $y_{i,t}$:

$$g_{r,i,t} = \log(S_{r,i,t+1}) - \log(S_{r,i,t}) \tag{4}$$

with r denoting the region. Next, the growth rates are rescaled to control for the inverse relationship between their size and variance, a universal feature in the growth of complex economic organisations (AMARAL et al., 2001). BOTTAZZI et al. (2012) model the scaling relationship directly by introducing a heteroskedasticity term into the stochastic growth process:

$$g_{r,i,t} = \alpha_i + v_{r,i,t} \tag{5}$$

where α_i is a constant term that converges to the average growth rate. The error term can be written as $v_{r,i,t} = \exp(\beta_i(s_{r,i,t} - \bar{s}_i))\, e_{r,i,t}$, with $s_{r,i,t} = \log(S_{r,i,t})$ and $\bar{s}_i$ is the corresponding industry-specific arithmetic mean over regions and time. This expression takes into account that the functional form of heteroskedasticity might be non-linear, as recently observed in the firm growth literature (e.g., BOTTAZZI et al., 2011). Replacing the heteroskedastic error term and solving for $e_{r,i,t}$, we get:

$$e_{r,i,t} = \frac{g_{r,i,t} - \alpha_i}{\exp(\beta_i(s_{r,i,t} - \bar{s}_i))} \quad (6)$$

The last equation yields the rescaled and normalized growth rates $\tilde{g}_{r,i,t} := e_{r,i,t}$. Rescaling cleans the data from heteroskedasticity and normalization from the average growth trend. The latter controls for common macroeconomic shocks and cyclical effects (PARTRIDGE and RICKMAN 2003) and shifts the focus on the stochastic part, which usually contains the "behavioural relations" (LÜTKEPOHL, 2003). Anticipating non-normality, equation 7 with two unknown parameters is estimated by minimizing the absolute deviations (LAD):

$$\{\beta_{i,t}; \alpha_{i,t}\} = \operatorname{argmin}_{\beta,\alpha} \sum_r \left| \frac{g_{r,i,t} - \alpha_i}{\exp(\beta_i(s_{r,i,t} - \bar{s}_i))} \right| \quad (7)$$

The rescaling step is performed for each industry, year and variable separately to account for possible differences in the variance-size relationship.

Being more than a pre-requisite for the VAR-LiNGAM identification strategy, non-normality also concerns the estimation of the single VAR equations. In this case, OLS may provide unreliable results. When errors follow a double exponential distribution, minimizing the absolute deviations is equivalent to the log-likelihood function. In all other cases, tail events affect less the estimators compared to OLS, in which the residuals are squared. Hence, LAD provides more reliable results than OLS in particular for fat-tailed error distributions (DASGUPTA and MISHRA, 2004; MAASOUMI et al., 2007).

The selection of the number of lags *p* is based on various statistics, like the Akaike Information, the Hannan-Quinn or the Schwarz Criterion (LÜTKEPOHL, 2003). Here, all criteria advocate a 1-lag model. Because the selection of lag lengths might statistically collide with the determination of the causal ordering (DEMIRALP and HOOVER, 2003), we checked whether the latter stays robust when increasing the number of lags. No changes in the causal ordering are observed and the estimates remain very similar in a 2-lag model.

Finally, p-values are estimated by bootstrapping with 500 replications. The bootstrap analysis is also used to assess the stability of the causal ordering of the variables. This is important because the effects of a shock might depend on the way the variables are arranged (LÜTKEPOHL, 2003).

4 Data

To measure the co-evolving activities of a regional technological system, namely economic, research, innovation, and educational activities, the following variables are constructed.

Regional economic activities can be measured by the number of employees (*Empl*). The German Institute for Employment Research (IAB) provides industry-specific employment data. Private research activities are approximated by R&D employees (BRENNER and BRÖKEL, 2011). These are defined as the occupational groups of engineers, chemists and natural scientists (BADE, 1987) and retrieved from the same database as *Empl*.[4] Education activities can be measured by the number of graduates from higher educational institutes (*Grad*). Data on graduates stems from the German Federal Statistical Office (destatis) and encompasses universities in a narrower sense as well as universities of applied science, that is, all graduates with a technical, diploma, bachelor and master degree. Innovation activities are reflected by patents (*Pat*). Although this indicator is not without problems, it is the most widely used in the literature (see SMITH, 2005 for an extensive discussion). All patents with at least one inventor address in Germany are taken from the European Patent Organization's (EPO) Worldwide Statistical Patent Database, the so-called PATSTAT database. To assign the patents to the regions, the inventor's addresses are used as they most closely represent the places where the innovations took place (BRENNER and SCHLUMP, 2013).

Further control variables can be included into the reduced-form VAR model (equation 3). Here, two variables are chosen that account for the general regional socio-economic environment. First, the population density (*Pop*) represents a catch-up variable of several unobserved region-specific factors (FRITSCH and SLAVTCHEV, 2011). For instance, it measures urbanization economies, which are rather independent from the surrounding industrial structure (BUERGER et al., 2012). Second, the unemployment rate (*UR*) reflects the vitality of the regions' socio-economic conditions. In the special case of Germany it also accounts for structural differences along the east-west and north-south divide. Data on both variables is obtained from destatis. Because of their asymmetry, they were first normalized by division through the mean value and then made symmetric by the transformation $\tilde{x} = (x-1)/(x+1)$.

The spatial unit of analysis are 270 labour market regions as defined by the IAB (BINDER and SCHWENGLER, 2006), which have been also used in the related study of BUERGER et al. (2012).[5] All variables span the years 1999 to 2008. Furthermore, the four main variables are measured separately for various industries. The industries are represented by five broad groups, which result from aggregating up 19 distinct technological fields (BROEKEL 2007). The technological fields are used as an intermediary to match both data based on the International Patent Classification (IPC), like *Pat*, and data based on the standard industry classification (NACE Rev. 1.1), like *Empl* and *RD*, according to a current version of the concordance developed by SCHMOCH et al. (2003).[6] *Grad*, distinguishable by their field of study, is assigned to IPC based on a professor-patent matching. Therefore, all German

[4] For statistical reasons, the number of R&D employees is subtracted from *Empl*, because they build their own variable (*RD*).

[5] Using Moran's I test statistics, spatial autocorrelation in the growth rates variables were not found to be present.

[6] The current version is an update of the concordance originally published by SCHMOCH et al. (2003) and was obtained directly from the author. For a full list see BRENNER and SCHLUMP (2013).

patent applicants with a professor title are identified and, if possible, affiliated to a university faculty. From this, the graduates can be assigned to the technologies according to the resulting contribution shares for each study field to the patents classes (BRENNER and SCHLUMP 2013). Figure 3 summarizes the matching and aggregation procedure of differently classified data, resulting in a unique database, which embraces multi-dimensional aspects for five clearly separated industries.[7]

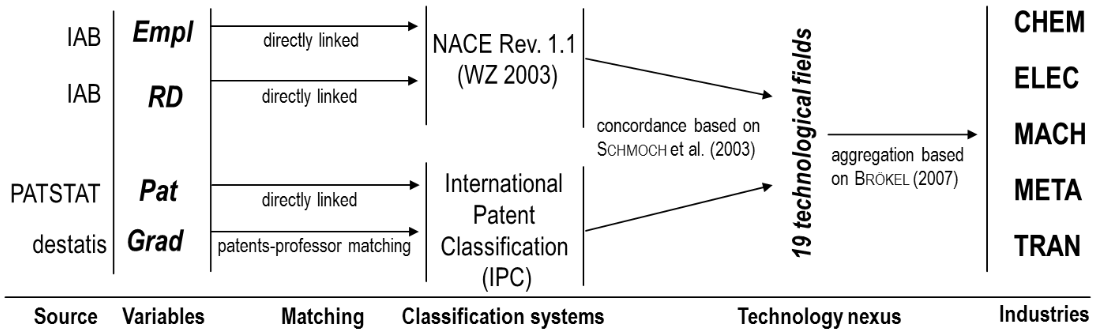

Figure 3 Data matching and aggregation

Hence, industry-specific growth rates are constructed for all activity variables.[8] In the previous section it is argued that the growth rates should be corrected for the general growth trend and heteroskedasticity. Optimizing equation 7 yields an industry- and year-specific normalization $\alpha_{i,t}$ and rescaling $\beta_{i,t}$ parameter. Whereas the general growth trend varies for the variables and years, the rescaling parameter mostly ranges between the values of -0.2 and -0.3, which confirms the literature (AMARAL et al., 2001; DUSCHL and BRENNER, 2013).

5 Results

Testing the three identifying assumptions

The non-normality assumption of ε_t is assessed by three test statistics: the Shapiro-Wilk (SW) normality test, which is generally known to have a high test power; the Kolmogorov-Smirnov (KS) test against normality, which is more robust against outliers; and the Jarque-

[7] The bivariate correlation coefficients between the growth variables $\tilde{g}_{r,i,t}$ are all below the threshold of 0.70 and, except for the pair *Empl* and *RD*, tend to be rather small. Hence, multicollinearity is not an issue and the variables seem to reflect different facets of regional economic development.

[8] To ensure statistical reliability, growth events which are based on less than five units of their corresponding level variable are excluded from the analysis. An unbalanced panel is possible, unless in one single region-year the values for all variables are available (COAD et al., 2012).

Bera (JB) test, which focuses on the skewness and kurtosis. Finally, the flexible 5-parameter Asymmetric Exponential Power (AEP) distribution (BOTTAZZI and SECCHI, 2011), often used in the literature to describe fat-tailed economic growth processes, is fitted to the four recovered components. Because the normal distribution is a special case of the AEP-density family, the likelihood-ratio (LR) test can be used to assess whether the normal distribution is significantly outperformed in terms of asymmetry and/or tail behaviour. Table 1 shows the number of components for which the normality tests do not reject the null hypothesis. Above it is noted that ICA is still possible if only one independent component is normally distributed (HYVÄRINEN and OJA, 2000). This condition holds consistently for each industry except for META if the KS-test is used. Hence, our theoretical expectation that non-normality is prevalent in most cases is confirmed empirically.

Table 1 Validity of the three identifying conditions

Condition	***Non-Normality***				***Independence***	***Acyclicity***
Test	*SW-test*	*KS-test*	*JB-test*	*LR-test*	*GG-test*	*Bootstrapping*
n	*4*	*4*	*4*	*4*	*6*	*500*
CHEM	1 (25%)	1 (25%)	1 (25%)	1 (25%)	1 (17%)	194 (39%)
ELEC	0 (0%)	1 (25%)	0 (0%)	0 (0%)	1 (17%)	232 (47%)
MACH	1 (25%)	1 (25%)	0 (0%)	1(25%)	1 (17%)	218 (44%)
META	0 (0%)	2 (50%)	0 (0%)	1 (25%)	0 (0%)	253 (51%)
TRAN	0 (0%)	1 (25%)	1 (25%)	0 (0%)	0 (0%)	264 (53%)

The independence assumption is assessed by a test statistic, as recently developed by GRETTON and GYÖRFI (2010), which is based on kernel estimates of the distance between the joint densities and the product of the marginal densities. Here, each of the six possible pairings of the recovered components is tested. In none of the industries more than one pair of components is identified to be statistically dependent at a 5%-significance level (see Table 1). Because ICA has proven to be robust against some degree of dependence (HYVÄRINEN, 2013), this condition can be said to hold.

The acyclicity assumption cannot be tested directly. Therefore, its validity is assessed by bootstrapping in order to see whether the causal ordering of the variables remain robust. The analysis reveals that in around half of the 500 replications the same causal ordering of the variables results. Considering that the probability that one specific ordering occurs by chance is $1/4! = 1/24 = 0.042\%$, the results provide some evidence against randomness in the ordering.[9] The frequency distribution of all causal orderings (see Fig. X1 in the appendix), resulting from the bootstrapping analysis, shows that there exist at maximum one

[9] We thank Alex Coad for pointing this out.

or two alternative orderings. Hence, as expected, cyclicity plays a minor role but cannot be excluded completely.

Results

All assumed conditions being validated, the SVAR model can be recovered from the reduced-form VAR model. The estimated coefficients for the five industries are depicted in Table 2, while the contemporaneous and lagged effects among the variables are visualised in Figure 4. Significant relationships at the 5%-level are connected by an arrow indicating the causal direction of the impact.

Table 2 Estimation results from SVAR model

		B				$\mathbf{\Gamma_1}$				
		Empl	*RD*	*Pat*	*Grad*	*Empl*	*RD*	*Pat*	*Grad*	*N*
CHEM	*Empl*	-				.080	-.054	.015	-.015	511
	RD	.695*	-		-.065	-.054	.083	.004	.024	
	Pat	-.049	.114*	-	.172*	-.016	-.022	-.308*	.413*	
	Grad	.021			-	-.012	.032	.003	-.230*	
ELEC	*Empl*	-			.021	.016	.040*	.003	-.008	1352
	RD	.989*	-		-.018	.042	.059*	.012	.023	
	Pat	.109	.024	-	.117*	-.060	.038	-.212*	.117	
	Grad				-	.017	-.025	-.009	-.134*	
MACH	*Empl*	-				.075*	-.003	.018*	.019	913
	RD	1.128*	-		.001	.016	-.006	-.007	-.014	
	Pat	.091	-.039	-	.016	.032	-.042	-.251*	-.080	
	Grad	.093*			-	.015	-.015	.015	-.186*	
META	*Empl*	-				.048	.019	-.011	-.027	266
	RD	.939*	-		.009	.131	.003	.029	.025	
	Pat	-.418	.197*	-	.187	-.157	-.011	-.238*	-.095	
	Grad	.015			-	.108	-.029	.029	-.268*	
TRAN	*Empl*	-	.460*		.060	.014	.019	-.001	-.019	425
	RD		-		-.089	-.052	.069	.052*	-.008	
	Pat	.050	-.043	-	.127	.338*	-.146	-.168*	.143	
	Grad				-	.020	-.018	-.005	-.249*	

*p-values: * < 0.05*

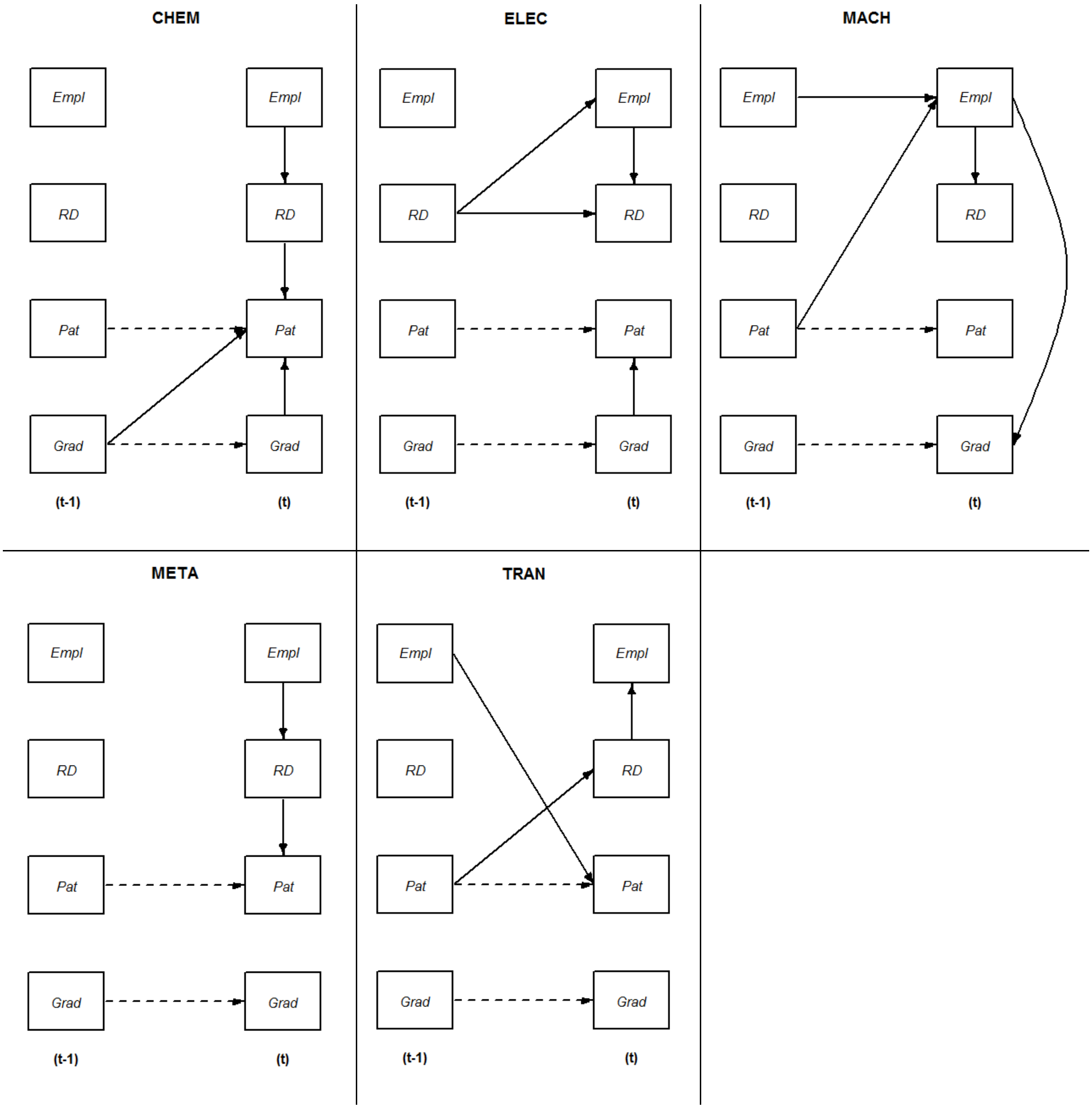

Figure 4 The contemporaneous causal and the lagged effects. Positive relationships are indicated by a solid line, negative ones by a dashed line.

The purely horizontal connections from *t-1* to *t* (or the diagonal entries for Γ_1 in Table 2) represent the temporal autocorrelations of the variables. Whilst *Grad* and *Pat* show a negative autocorrelation, *Empl* and *RD* tend to show a positive, however, less often significant autocorrelation. This reflects the different nature of the variables. Growth of the latter means changes in the regular and research-related stock of employees. The positive autocorrelations indicate the existence of some sort of self-reinforcing mechanisms. In contrast hereto, growth in patents and graduates stems from differences in the yearly realizations of stochastic outcome variables. The negative autocorrelations indicate the existence of year-to-year fluctuations that are much larger than the year-to-year changes due to the overall development. Although the temporal autocorrelation patterns provide interesting insights, the focus of this research is on the causal relationships in the dynamics among the variables. Here, differences between the industries immediately become evident.

Increasing *RD* leads to more *Pat* in CHEM and META. For both industries, a traditional linear thinking seems to apply, which argues that systematic research leads to innovations. For ELEC, the link is still positive, yet insignificant. In contrast hereto, no positive contribution of *RD* on *Pat* is found within-the-period for MACH and TRAN. Rather, more *Pat* leads to more *RD* in the next period for TRAN, and indirectly via *Empl* for MACH. Hence, the more engineering-oriented industries seem to be driven by success: innovations, not necessarily resulting from systematic R&D, provide incentives to increase subsequent research efforts.

In MACH, innovations are also found to be an important driver of economic growth. *Pat* translates into more *Empl* in the subsequent time period. Here, the positive effects of new growth opportunities due to product innovations clearly surpass the negative ones of rationalization endeavours as a result of process innovations. An indirect contribution of *Pat* to *Empl* is observed in TRAN via *RD*. The negative forces tend to prevail in META, however, not significantly. In the remaining industries, the two opposite forces seem to be neutralized.

The growth of research and economic activities goes strongly hand in hand. In most industries, first the stock of regular employees grows (*Empl*), followed by a change into the same direction of research-related employees (*RD*). This result reproduces findings from the empirical literature on firm growth. Only for TRAN, a reversed relationship is observed, resembling the traditional assumption from the endogenous growth theories that economic growth is driven by accumulating new knowledge through intentional research activities.

The instantaneous causal effect of *Grad* on *Pat* is positive for all industries, however significantly only for CHEM and ELEC. This confirms our expectations that educational activities are an important factor for innovation activities, especially so in industries which rely on new scientific knowledge. In CHEM, the link even remains significant over time. We have to highlight in this context that *Grad* is our only variable that is connected to university activities. Hence, we cannot be sure whether this variable works (only) as a direct operationalization of university education or (also) as an indirect operationalization of university research (which is highly correlated with university education in space). The strong link to the patent activity suggests that university research is the more important part in our analysis.

This is further supported by the fact that *Grad* is found to influence neither *Empl* nor *RD*. Whilst the lack of a significant relationship with *RD* is not surprising, the lack of a significant relationship with *Empl* is unable to support our expectation that expanding firms rely on the local presence of qualified graduates. Hence, firms either source their highly-qualified employees supra-regionally, or employment growth generally depend less on university graduates (see, for example, DUTZ et al. (2011), who find that even innovation-driven employment growth mainly depends on the unskilled workforce). For MACH, even a reversed causal link is observed. Here, fluctuations in economic activities and demand in labour might send signals both to students for timing their graduation and to universities for aligning their study and course program.

To summarize, the following general model of how regional technological systems develop can be sketched for CHEM and META: increasing economic activities (*Empl*) imply expanding research activities (*RD*), which then translate into more innovations (*Pat*). For the science-based industry CHEM, educational activities (*Grad*) become an additional factor regarding innovations. A different, rather success-driven pattern is observed for MACH and TRAN: past innovations generate opportunities to expand economic activities, which also facilitate the widening of research activities (MACH), or they set incentives to perform further research, which also demands hiring more regular employees (TRAN). The new employees, in turn, increase research activities in the following time period. ELEC, finally, stands in-between. On the one hand, the expansion of innovation activities relies on educational activities. On the other hand, more research activities in the past increase both research and economic activities in the present. Because economic activities also increase research activities within-the-period, a highly dynamic process, similar to the notion of circular and cumulative causation (MYRDAL, 1959), might unfold in this industry.

6 Conclusions

This paper applies a new identification strategy for SVAR models to the analysis of regional systems of technological activities. In contrast to the approaches used so far, which often make untenable prior theoretical assumptions on the existence of causal effects, the identification of causal relationships is achieved empirically by exploiting the information of non-normality (HYVÄRINEN et al., 2010). This data-driven approach is particularly useful for analysing dynamics in systems like regional economies, which are well-known to show fat-tailed growth rate distributions. More precisely, non-normality enables the recovering of the independent components by ICA from the errors of a reduced-form VAR model. Assuming acyclicity in the contemporaneous effects, a causal ordering of the variables is possible. Finally, the lagged effects are corrected by taking into account the contemporaneous effects (HYVÄRINEN et al., 2010; MONETA et al., 2012).

The literature agrees upon the usefulness of SVAR models as a tool for policy analysis in situations where controlled experiments are not feasible (GOTTSCHALK, 2001; PARTRIDGE and RICKMAN, 2003; MONETA et al., 2012). COAD et al. (2012) suggest that policy interventions to be efficient need to focus on the causal mechanisms: “a well-placed intervention will target one particular variable to have predictable effects on other variables as the shock propagates throughout the system. Without knowledge on causal relations, a misplaced intervention might have no effect (or even perverse effects) if the variable targeted has no causal effect or unexpected effects) on the other variables". Curing the symptoms does not necessarily cure the diseases (PEARL, 2009). Analysing the dynamics in a regional system of technological activities, this papers draws the following policy conclusions.

Our variable *Grad* is found to foster patenting especially in science-based industries, like CHEM or ELEC. Hence, in these industries policy makers that seek to increase innovation activities should stimulate higher university activities. It can be assumed that fitting research activities at universities are especially relevant. If innovation, and ultimately structural change (e.g., DOSI, 1988), is the aim, one should facilitate economic and research activities. This, however, is only true in industries which follow a linear model, like META or CHEM. In the rather engineering-oriented and success-driven industries like TRAN or MACH, policy makers are advised to directly stimulate innovation activities and the transfer of innovations, which then would lead to economic growth. Finally, by stimulating research activities in ELEC, a highly dynamic economic growth process is expected to unfold. Briefly stated, this paper suggests that sound policies should be based on the industry-specific causal relationships among the regional technological activities.

Besides helping to specify industry-specific policy instruments, the results might also have implications for national industrial policies. Which industries are most suitable to pick to become large export-oriented national champions? This strongly depends on how much a policy stimulus, which propagates throughout the whole system of technological activities, translates into longer-term success. For ELEC, the highly dynamic feedback loop between research and economic activities was already highlighted. But also MACH and TRAN seem to be promising candidates. In MACH, innovations lead to subsequent economic growth, which in turn instantaneously contributes to the skilling of the workforce and to increase research activities, while economic growth by itself shows a self-reinforcing dynamic. In TRAN, innovations set incentives to further research, instantaneously translating into economic growth, which in the next period feeds back to more innovations. Policy stimuli for innovations might contribute that these industries to become large export-oriented national champions.

To yield the desired outcomes, (regional) policies need to be designed and implemented on basis of a profound understanding of the underlying mechanisms. This paper might guide further research in uncovering the mechanisms that led to the observed causal effects.

Literature

ALECKE, B., MITZE, T., UNTIEDT, G. (2010) Internal migration, regional labour market dynamics and implications for German East-West disparities: results from a Panel VAR. *Jahrbuch für Regionalwissenschaften*, 30: 159-189.

AMARAL, L., GOPIKRISHNAN, P., PLEROU, V., STANLEY, E. (2001) A model for the growth dynamics of economic organizations. *Physica A*, 299: 127-136.

ASHEIM, B., GERTLER, M. (2005) The geography of innovation – regional innovation systems. In: FAGERBERG, J., MOWERY, D., NELSON, R. (Eds) *The Oxford Handbook of Innovation*. Oxford University Press, p. 291-317.

ASHEIM, B. (2007) Differentiated knowledge bases and varieties of regional innovation systems. *Innovation: The European Journal of Social Science Research*, 20: 223-241.

BADE, F. (1987) Regionale Beschäftigungsentwicklung und produktionsorientierte Dienstleistungen. Sonderheft 143. Deutsches Institut für Wirtschaftsforschung, Berlin.

BINDER, J., SCHWENGLER, B. (2006) Neuer Gebietszuschnitt der Arbeitsmarktregionen im Raum Berlin und Brandenburg: Kritische Überprüfung der bisher gültigen Arbeitsmarktregionen und Vorschläge für einen Neuzuschnitt. Forschungsbericht 4/2006, IAB.

BOGLIACINO, F., Pianta, M. (2010) Innovation and Employment: a Reinvestigation using Revised Pavitt classes. *Research Policy*, 39: 799-809.

BOTTAZZI, G., SECCHI, A. (2011) A new class of asymmetric exponential power densities with application to economics and finance. *Industrial and Corporate Change*, 20: 991-1030.

BOTTAZZI, G., COAD, A., JACOBY, N., SECCHI, A. (2011) Corporate growth and industrial dynamics: evidence from French manufacturing. *Applied Economics*, 43: 103-116.

BOTTAZZI, G., SECCHI, A., TAMAGNI, F. (2012) Financial constraints and firm dynamics. *Small Business Economics*, DOI 10.1007/s11187-012-9465-5.

BREINLICH, H., OTTAVIANO, G., TEMPLE, J. (2013) Regional growth and regional decline. In: AGHION, P., DURLAUF, S. (Eds) *Handbook of Economic Growth*, Vol. 2, The Netherlands: North-Holland, forthcoming December 2013.

BRENNER, T., BRÖKEL, T. (2011) Methodological issues in measuring innovation performance of spatial units. *Industry and Innovation*, 18: 7-37.

BRENNER, T., SCHLUMP, C. (2013) Universities, Public Research and Regional Innovation Output: An Empirical Study of 19 Technologies in Germany. Marburg Working Paper on Innovation and Space 03.13.

BRESCHI, S., MALERBA, F., ORSENIGA, L. (2000) Technological regimes and Schumpeterian patterns of innovation. *The Economic Journal*, 110: 388-410.

BROEKEL, T. (2007) A Concordance between Industries and Technologies: Matching the technological fields of the Patentatlas to the German Industry Classification. *Jena Economic Research Papers* 2007-041.

BUERGER, M., BROEKEL, T., COAD, A. (2012) Regional Dynamics of Innovation – Investigating the Co-Evolution of Patents, R&D, and Employment. *Regional Studies*, 46: 565-582.

COAD, A. (2013) The meso-level: structural-persistency. In: CANTNER, U., GUERZONI, M. (Eds) *Handbook on industrial dynamics and evolutionary economics*. forthcoming

COAD, A., RAO, R. (2010) Firm growth and R&D expenditure. *Economics of Innovation and New Technology*, 19: 127–145.

COAD, A., COWLING, M., SIEPEL, J. (2012) Growth Processes of High-Growth Firms in the UK. Nesta Working Paper No. 12/10.

COOKE, P., URANGA, M., ETXEBARRIA, G. (1997) Regional innovation systems: Institutional and organisational dimensions. *Research Policy*, 26: 475-491.

CRESCENZI, R. (2005) Innovation and regional growth in the enlarged Europe: the role of local innovative capabilities, peripherality, and education. *Growth and Change*, 36: 471-507.

DASGUPTA, M., MISHRA, S. (2004) Least Absolute Deviation Estimation of Linear Econometric Models: A Literature Review. MPRA Paper No. 1781.

DEMIRALP, S., HOOVER, K. (2003) Searching for the Causal Structure of a Vector Autoregression. *Oxford Bulletin of Economics and Statistics*, 65: 745-767.

DOSI, G. (1988) Sources, Procedures, and Microeconomic Effects of Innovation. *Journal of Economic Literature*, 26: 1120-1171.

DUSCHL, M., BRENNER T. (2013) Characteristics of regional industry-specific employment growth rates' distributions. *Papers in Regional Science,* 92: 249-270.

DUSCHL, M., SCHOLL, T., BRENNER, T., LUXEN, D., RASCHKE, F. (2012) Industry-specific firm growth and agglomeration. Working Papers on Innovation and Space 06-12.

DUTZ, M., KESSIDES, I., O'CONNELL, S., WILLIG, R. (2011) Competition and Innovation-Driven Inclusive Growth. The World Bank: Policy Research Working Paper No. 5852.

FAGIOLO, G., NAPOLETANO, M., ROVENTINI, A. (2008) Are output growth-rate distributions fat-tailed? Some evidence from OECD countries. *Journal of Applied Econometrics*, 23: 639-669.

FRITSCH, M., SLAVTCHEV, V. (2007) Universities and Innovation in Space. *Industry and Innovation*, 14: 201-218.

FRITSCHE, U., LOGEAY, C. (2002) Structural Unemployment and the Output Gap in Germany: Evidence from a SVAR Analysis within a Hysteresis Framework. DIW-Diskussionspapiere 312.

GOTTSCHALK, J. (2001) An Introduction into the SVAR Methodology: Identification, Interpretation and Limitations of SVAR models. Kiel Working Paper No. 1072.

GRETTON, A., GYÖRFI, L. (2010) Consistent Nonparametric Tests of Independence. *Journal of Machine Learning Research*, 11: 1391-1423.

HYVÄRINEN, A. (1999) Fast and robust fixed-point algorithms for independent component analysis. *IEEE Transactions on Neural networks*, 10: 626-634.

HYVÄRINEN, A. (2013) Independent component analysis: recent advances. *Philosophical Transactions of the Royal Society* A, 371: 1-19.

HYVÄRINEN, A., Oja, E. (2000) Independent Component Analysis: Algorithms and Applications. *Neural Networks*, 13: 411-430.

HYVÄRINEN, A., ZHANG, K., SHIMIZU, S., HOYER, P. (2010) Estimation of a Structural Vector Autoregression Model Using Non-Gaussianity. *Journal of Machine Learning Research*, 11: 1709-1731.

KUERSTEINER, G. (2008) Granger-Sims causality. In: DURLAUF S, BLUME, L. (Eds) *The New Palgrave Dictionary of Economics*, 2nd Edition, Palgrave Macmillan. Doi:10.1057/9780230226203.0665.

LACERDA, G., SPIRTES, P., RAMSEY, J., HOYER, P. (2008) Discovering cyclic causal models by independent components analysis. *Proceedings of the 24th Conference on Uncertainty in Artificial Intelligence*.

LUCAS, R. (1988) On the mechanics of economic development. *Journal of Monetary Economics*, 1: 3-42.

LÜTKEPOHL, H. (2003) Vector Autoregression. In: BALTAGI, B. (Eds.) *A companion to theoretical econometrics*. Blackwell Publishing: Malden, MA, p. 678-699.

MAASOUMI, E., RACINE, J., STENGOS, T. (2007) Growth and convergence: A profile of distribution dynamics and mobility. *Journal of Econometrics*, 136: 483-508.

MCKELVEY, B., ANDRIANI, P. (2005) Why Gaussian statistics are mostly wrong for strategic organization. *Strategic Organization*, 3: 219-228.

MALERBA, F. (2002) Sectoral systems of innovation and production. *Research Policy*, 31: 247-264.

MOHR, H. (2002) Räumliche Mobilität von Hochschulabsolventen. S. 249-281 in: BELLMANN, L., VELLING, J. (Eds) Arbeitsmärkte für Hochqualifizierte. Nürnberg.

MONETA, A., ENTNER, D., HOYER P., COAD, A. (2012) Causal Inference by Independent Component Analysis: Theory and Application. *Oxford Bulletin of Economics and Statistics*: 75: 705-730.

MYRDAL, G. (1959) *Economic Theory and Under-developed Regions*. Gerald Duckworth & Co, London.

PARTRIDGE, M., RICKMAN, D. (2003) The waxing and waning of regional economies: the chicken-egg question of jobs versus people. *Journal of Urban Economics*, 53: 76-97.

PAVITT, K. (1984) Sectoral patterns of technical change: towards a taxonomy and a theory. *Research Policy*, 13: 343-373.

PEARL, J. (2009) Causal inference in statistics: An overview. *Statistical Surveys*, 3: 96-146.

RODRÍGUEZ-POSE, A., CRESCENZI, R. (2008) Research and Development, Spillovers, Innovation Systems, and the Genesis of Regional Growth in Europe. *Regional Studies*, 42: 51-67.

ROMER, P. (1990) Endogenous Technological Change. *Journal of Political Economy*, 98: 71-102.

SIMS, C. (1980): Macroeconomics and reality. *Econometrica*, 48: 1-48.

SHIMIZU, S., HOYER, P., HYVÄRINEN, A., KERMINEN, A. (2006) A Linear Non-Gaussian Acyclic Model for Causal Discovery. *Journal of Machine Learning Research*, 7: 2003-2030.

SMITH, K. (2005) Measuring Innovation. In: FAGERBERG, J., MOWERY, D., NELSON, R. (Eds) *The Oxford Handbook of Innovation*. Oxford University Press, p. 148-177.

STORPER, M., SCOTT, A. (2009) Rethinking human capital, creativity and urban growth. *Journal of Economic Geography*, 9: 147-167.

STOCK, J., WATSON, M. (2001) Vector autoregressions. *Journal of Economic Perspectives*, 15: 101-115.

VEGA, S., ELHORST, J. (2013) Modelling regional labour market dynamics in space and time. *Papers in Regional Science*, DOI: 10.1111/pirs.12018.

WINTER, S. (1984) Schumpeterian competition in alternative technological regimes. *Journal of Economic Behavior & Organization*, 5: 287-320.

Appendix

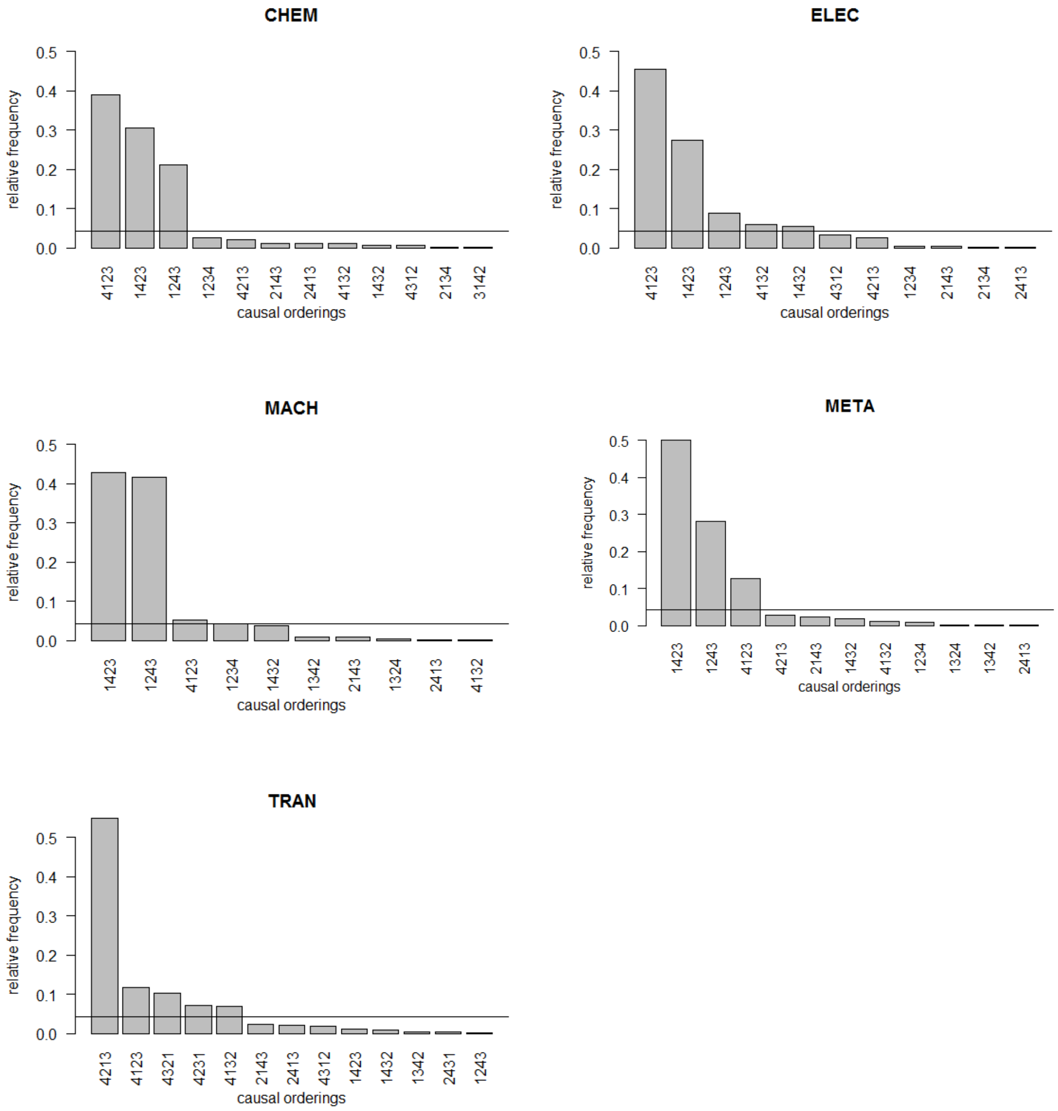

Figure X1 Frequency distribution of alternative causal orderings resulting from the bootstrapping analysis (n=500). The number indicate the ordering of the variables, with 1=*Empl*, 2=*RD*, 3=*Pat* and 4=*Grad*.