

Causal relations between knowledge intensive business services and regional employment growth

THOMAS BRENNER^a, MARCO CAPASSO^b, MATTHIAS DUSCHL^a,
KOEN FRENKEN^c AND TANIA TREIBICH^{b,d}

^a Department of Geography, Philipps University Marburg

^b School of Business and Economics, Maastricht University

^c Copernicus Institute, Utrecht University

^d GREDEG-CNRS, University of Nice-Sophia Antipolis and LEM, Scuola Superiore Sant'Anna, Pisa

This draft: October 2014

Preliminary draft, please do not quote.

Abstract

This paper studies the causal relations between growth in Knowledge Intensive Business Services (KIBS) and overall regional growth. Using regional employment data from 270 labour-market regions in Germany between 1999 and 2012, we compute one-year growth rates of employment in the KIBS sector and in the rest of the regional economy. Adopting a recently developed technique, we are able to estimate a structural vector autoregressive model in which the causal directions between KIBS and other sectors are examined including various time lags. We find evidence of negative short-term effects of regional growth on nonfinancial KIBS, of a procyclical behaviour of financial KIBS, of a marked influence of financial KIBS on other services, and in general of a long-term positive effect of KIBS development on the whole regional economy.

JEL codes: C53, O33, R10

Keywords: Employment growth; growth spillovers; KIBS, industrial dynamics.

1. INTRODUCTION

New global challenges call for more efficient research and innovation policies, relevant to all the sectors of the economy (Potočnik, 2009). A more efficient policy would aim at fostering an entrepreneurial process of discovery: entrepreneurs should be enabled to discover the research and innovation domains in which a region can hope to excel, by gathering localized information about the region's skills, materials, environmental conditions, and market access conditions (Foray et al., 2009). Service innovation (coming from either services or manufacturing sectors) can boost entrepreneurial dynamism, by closing the gap between scientific innovation and market requirements, and facilitating a cross-sectoral fertilization which ultimately contributes to growth and jobs (European Commission, 2012). Inherent difficulties in supporting novelty creation in the form of services rather than goods (Rubalcaba et al., 2012, and Janssen, 2014) may explain why in the European Union only a few countries have implemented policies explicitly focused on the services sectors (European Commission, 2009).

Nonetheless, services sectors may occupy key positions in the network of inter-sectoral knowledge flows. In particular, knowledge-intensive business services (henceforth: KIBS) are able to provide advanced technological knowledge directly to other industrial sectors, and indirectly to the whole economy (Castellacci, 2008). Business service industries can be defined as KIBS if they are private organisations that rely heavily on professional knowledge, and supply intermediate products and services that are knowledge-based (Miles et al., 1995; Den Hertog, 2000). The knowledge generated by the KIBS stems from interactive learning with a diverse set of economic actors, and the same actors can benefit collectively of such knowledge even in the absence of bilateral connections among them: local knowledge is diffused throughout the economy (Leiponen, 2001; Jensen et al., 2007). The contribution of KIBS to the productivity of the other industrial sectors may well exceed the productivity gains as measured within the KIBS sector itself (Castaldi, 2009). Indeed, the process of "knowledge re-engineering" operated by the KIBS when interacting with other enterprises, and in particular with small and medium ones, causes KIBS to be a "relevant object" for both innovation and regional policies (Muller and Zenker, 2001). The peculiarity of such process of knowledge creation has often prevented researchers from obtaining a precise evaluation of the innovative contribution of KIBS (Muller and Doloreux, 2009).

Also for what concerns the impact of KIBS on growth (either at regional or at national level), there is no conclusive evidence in the literature (Kox and Rubalcaba, 2007). Still, it is often conjectured that future urban employment will be increasingly dependent on KIBS (Wood, 2006). The geographic distribution of KIBS is not generally more concentrated than other economic branches (Merino and Rubalcaba, 2013) but, at the same time, shows abnormally high values in some cities (Bryson et al., 2004). This could be explained by the tendency of KIBS to co-locate with multinational enterprises (Jacobs et al., 2014) and, in general, to rely on resources available externally (Herstad and Ebersberger, 2014). Especially in the early stages after foundation, KIBS benefit from their proximity to suppliers and clients (Koch and Stahlecker, 2006), and, in general, both demand-side influences and localized "collective

learning" processes seem to determine the clustering of KIBS firms (Keeble and Nachum, 2002). As a consequence, some authors argue that public policy should not be aimed directly at KIBS growth, but rather at fostering regional diversification and technological upgrading which in turn would drive KIBS growth through a demand-pull process (Wernerheim and Sharpe, 2003; Meliciani and Savona, *forthcoming*). Research is needed to further investigate the system-wide interactions of KIBS, and to assess how different typologies of KIBS and manufacturing segments interact (Corrocher and Cusmano, 2014).

This study investigates the causal relations between regional employment growth in the KIBS sector and regional employment growth in the rest of the economy. By means of a recent development of the VAR approach, we are able to investigate empirically the effects of changes of the KIBS and the rest of the economy on each other and the respective time frame of these effects. The analysis is conducted over 270 labour market regions in Germany, observed between years 1999 and 2012.

Section 2 explains the methodology used, and the reasons for adopting it. Section 3 describes the data. Section 4 shows the results. Section 5 concludes.

2. METHODOLOGY

There are two variables of interest in our benchmark model, before proceeding to further disaggregation: regional employment growth in KIBS, and regional employment growth in the rest of the economy (i.e. in all the other industrial sectors, considered altogether). The two variables of interest are endogenous: they influence each other, although we do not know to what extent nor over which time frame. We denote by y_t the vector containing the two variables of interest, as observed in year t .

The goal of this study is determining how changes in one variable of interest, like a policy action which suddenly changes the employment growth in KIBS or in the rest of the economy, influence the evolution over time of both variables. We assume that the whole regional economic system evolves in reaction to some exogenous events. These events are assumed to be drawn from a zero-mean probability distribution, and they are temporally uncorrelated; contemporaneous events are independent. In the literature on the VAR method these effects are called shocks and we use this language in the methodological part, calling changes that are triggered from exogenous events shocks. We denote by ε_t the vector of shocks impacting the variables of interest in year t .

We assume that the development of the regional economic system, independently of the sign and size of the shocks, can be described by the following Vector AutoRegression (VAR):

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

where the number of lags p will be selected according to several information criteria, as explained in the next section. Equation (1) shows the dynamics of the regional economic system that we assume "structural" with respect to interventions on the shocks, and thus allows to predict the behavior of the variables of interest following the exogenous events (Hurwicz, 1962). The economic system evolves according to a law connecting the current growth of KIBS and of the rest of the economy (the vector y_t on the left side of the equation) to its past values (the vectors $y_{t-1}, y_{t-2}, \dots, y_{t-p}$) through the parameters Γ . Current growth of KIBS and of the rest of the economy is also connected to the current exogenous shocks ε_t , and to itself through the matrix parameter B . Indeed, there are contemporaneous relations among the variables of interest, by which a shock to one variable may affect another variable "instantaneously" (within one time unit, i.e. within one year).¹

Notice that, in Equation (1), all the information about past shocks is not explicitly shown, but is instead embodied in the values $y_{t-1}, y_{t-2}, \dots, y_{t-p}$. In economic terms, that means: if we know the growth of KIBS and of the rest of the economy in the past, we do not need to reconstruct the whole history of previous exogenous shocks (i.e. why in the past the system evolved in that way) in order to understand what will happen to the economy this year, but we only need to know the new shocks ε_t .

Of course, the economic situation of one year ago or two years ago resulted in turn from other previous exogenous shocks. Under a stability condition (see Luetkepohl, 2006), we can easily represent the same model of Equation (1) as a moving average (Wold, 1954):

$$y_t = \Psi_0 \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \dots + \Psi_\infty \varepsilon_{t-\infty} \quad (2)$$

where the economic situation of today is explicitly shown to depend on the whole history of exogenous shocks occurred in the past. Ψ are the parameters connecting shocks and variables of interest, i.e. the "impulse responses" we want to estimate in order to assess the consequences that exogenous shocks have over time. The information about the past shocks $\varepsilon_1, \varepsilon_2, \dots, \varepsilon_t$, that was shown in equation (1), as embodied in the past values of y , is now explicitly expressed in terms of all previous exogenous shocks that in the past have hit the variables of interest, i.e. all shocks (including policy actions) that have shaped the evolution of the KIBS sector and of the rest of the economy. In order to assess the possible outcome of, e.g., future policies, we want to know the impulse responses Ψ , as in Equation (2).

The representation in Equation (2) is easy to obtain when knowing the "structural" form of the model as in Equation (1). However, estimating the "structural" form is not straightforward, because of the presence of contemporaneous effects as indicated by the parameter B in Equation (1); instead, a vector autoregression in the "reduced form"

¹ In the final part of this section, we will explain why the existence of (almost) instantaneous relations among the variables of interest (in our case: of fast spillovers from KIBS growth to the other industries' growth, or vice versa) is an important issue that often prevents from a proper estimation of the structural form of the model.

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + u_t \quad (3)$$

can be easily estimated (Stock and Watson, 2001). The reduced form (3) would be structural only if there were no contemporaneous causal relations among the variables of interest, i.e. assuming that the matrix B in Equation (1) is composed only of zeroes. If this is not the case, estimating the reduced form of Equation (3) cannot help to define the effects of an exogenous event (Sargent, 1979; Sims, 1986).

Indeed, there are many values of the parameters of Equation (1) that are consistent with estimates of Equation (3), and additional assumptions are needed to identify a preferred set of values. This “identifiability” problem, as it is called by econometrics scholars, has driven the research on structural vector autoregressions over the last three decades (see Stock and Watson, 2001, for a short summary, and Kilian, 2012, for a detailed survey). The main strands of research have focused on searching plausible additional assumptions drawn from economic theory. The assumptions might concern the short-term spillovers of the shocks (in our case, for instance, deciding *a priori* that KIBS affects the rest of the economy within one year, but not vice versa) or the long-term effects of the shocks (in our case, for instance, deciding *a priori* that a shock to KIBS does not influence regional growth in the long run, while a shock to the rest of the economy does).

However, recent developments in the econometric research on structural vector autoregressions, coupled with recent empirical findings about regional dynamics, enable us to avoid imposing strong economic assumptions on our model: no causal ordering will be assumed for the variables, nor long-run differences in their behavior, nor signs of conditional correlations. The developments to which we refer, brought to the attention of the economic research community by Moneta et al. (2013), are based upon a deeper investigation of what the assumption of independence of the exogenous shocks (ε_t in Equation 1) entails.

Retrieving the structural form (1) from the estimated reduced form (3) means also retrieving the current and past exogenous shocks ($\varepsilon_t, \varepsilon_{t-1}$ etc.) from the current and past residuals of the reduced-form estimation residuals (u_t, u_{t-1} etc.). In algebraic terms, this is equivalent to finding a rotation of the residual matrix which can be a possible structural shock matrix, i.e. a rotation of the residual matrix that is consistent with the assumptions about structural shocks. Traditionally, a way to consider a rotation of the residuals as a candidate for being the matrix of structural shocks is checking the correlation of its elements. However, the independence assumed for our model’s shocks is a more restrictive concept than uncorrelatedness (lack of correlation is a necessary but not sufficient condition for independence). Therefore, the number of rotations, of the reduced-form residuals, which are characterized by independence is lower than the number of rotations which are characterized by uncorrelatedness. Roughly speaking, a deeper investigation of the independence property of the shocks allows to decrease the number of matrices that are potential candidates for representing the structural shocks ($\varepsilon_t, \varepsilon_{t-1}$ etc.), and thus to decrease the number of additional assumptions needed to

choose among those candidates. Finding the rotations that have the independence property is known, in the signal processing literature, as “independent component analysis”: if we assume that all exogenous shocks, or all shocks but one, are not only independent but also non-Gaussian, then it is possible to retrieve them from an observable rotation of them, that is, in our case, from the reduced-form estimation residuals (Comon, 1994; Hyvärinen and Oja, 2000).

Can we assume, in our context, that the exogenous shocks are non-Gaussian? We employ the same data set for which Duschl and Brenner (2013a) have observed a non-Gaussian (almost Laplacian) distribution of regional industry-specific employment growth rates (the data will be described in the next section). This finding can be connected to previous studies which found heavier-than-Gaussian tails in the empirical distributions of firm (sales and employment) growth rates (Stanley et al., 1996; Bottazzi et al., 2011), of industry (value added) growth rates (Castaldi and Sapio, 2008) and of country (aggregate output) growth rates (Fagiolo et al., 2008). Non-Gaussian distributions might in principle result from a stochastic process governed by Gaussian shocks (Brock, 1999). However, when the dependent variable of a linear model is characterized by a fat-tailed distribution (resembling a Laplace, or Exponential Power distribution), it is common practice to assume that the shocks are drawn from a similar distribution, and consequently to estimate the model by Least Absolute Deviation (LAD) regressions rather than by ordinary least squares (see e.g. Coad, 2010, and Coad and Broekel, 2012). Non-Gaussianity of errors can thus be considered a reasonable assumption also for a model explaining industry growth rates at regional level.

The assumptions of independence and of non-Gaussianity of the shocks are not sufficient to identify the structural form (1); we need the third assumption that there is no contemporaneous feedback among the variables, an assumption which Moneta et al. (2013) refer to as the “acyclicity” assumption. It must be interpreted as follows: if, in our model, an exogenous shock to one variable is immediately able (within one time-unit, that is within one year in our context) to affect a second variable, then it is not possible that an exogenous shock to the second variable is immediately able to affect the first variable. Notice that there is no need to define *a priori* the ordering of the variables in the described causal structure. The Vector Auto-Regression Linear Non-Gaussian Acyclic Model (VAR-LiNGAM) algorithm (Shimizu et al., 2006; Hyvärinen et al., 2008), which we employ in this research, will define through a data-driven procedure whether a shock to KIBS is able to immediately affect the rest of the economy, or the other way around. The acyclicity is imposed only for the same time period in which the shock hits the economy, and the acyclic ordering is supposed to be constant over time: the immediate inter-sectoral propagation of the shock always goes in the same direction. However, the non-immediate propagation, that is the inter-sectoral spillover happening with a time lag equal or higher than one, is not restricted: the effect of any shock occurred in a given year (no matter whether the shock originated in the

KIBS sectors or in other industries) can in principle propagate over the whole economy during the following years, and possibly generates cycles of growth across different sectors.²

3. DATA AND VARIABLES

Our data cover 270 labour market regions observed in Germany between years 1999 and 2012. The labour market regions result from aggregating the 413 German NUTS3 districts, and have been defined according to commuting flows (Binder and Schwengler, 2006). They have been shown to capture well the regional dimension of innovation processes (Broekel and Binder, 2007), and have already been used as geographical units for the estimation of a vector autoregression having regional employment growth as a variable of interest (Buerger et al., 2012).

We adopt the empirical classification in Jacobs et al. (2014), in turn based on the theoretical considerations by Strambach (2008), to define the KIBS sectors according to their NACE (Rev. 2) industry code (see Table 1). According to this classification, the financial organizations are considered as KIBS. Part of the literature shares the same view (e.g., Wood, 2006), while other studies prefer to adopt a more restrictive definition of KIBS (e.g., Koch and Stahlecker, 2006). To account for potential differences in their interaction with the regional economy, we also consider financial KIBS and nonfinancial KIBS separately (see Table 1). Unfortunately, given the amount of data available, the model estimation is not possible when the variables of interest are more than two. Therefore, we will estimate separate models in which, in turn, the “KIBS” variable of interest refers to all the KIBS, or only to the financial KIBS, or only to the nonfinancial KIBS.

Table 1: Definition of KIBS in terms of NACE industry classification

KIBS category	NACE	Description
Financial KIBS	64.1	Monetary intermediation
	64.2	Activities of holding companies
	64.3	Trusts, funds and similar financial entities
	64.9	Other financial service activities, except insurance and pension funding
	66.1.1	Administration of financial markets
	69.2	Accounting, bookkeeping and auditing activities; tax consultancy
Nonfinancial KIBS	62.0.1	Computer programming activities
	62.0.2	Computer consultancy activities
	70.1	Activities of head offices
	70.2	Management consultancy activities
	73.1	Advertising
	73.2	Market research and public opinion polling
	72.1	Research and experimental development on natural sciences and engineering
	72.2	Research and experimental development on social sciences and humanities

² Details about the VARLiNGAM estimation algorithm can be found in Hyvärinen et al. (2008). Pioneering applications of the algorithm to economic fields have involved macroeconomics (Moneta et al., 2013), happiness economics (Coad and Binder, 2014), energy economics (Feringstad et al. 2011), firm dynamics (Moneta et al., 2013; Coad et al., 2012), and regional dynamics (Duschl and Brenner, 2013b).

Analogously, the peculiar relations observed between KIBS and manufacturing sectors (e.g., Corrocher and Cusmano, 2014) bring us to not limit our estimations to a model having KIBS and rest of the economy as the two variables of interest. Instead, we also estimate two models having, as a second variable of interest opposed to KIBS, respectively manufacturing and services sectors. We consider as services the sectors having 2-digit NACE code: 33; 45 to 82 included; 90 to 96 included (for our analysis, we exclude from this list the sectors that we consider as KIBS, to avoid double counting).³

Summing up, we have six variables divided into: a set of three variables associated to KIBS (one of them representing all KIBS), and a set of three variables associated to the rest of the economy (one of them including all the non-KIBS sectors). We will estimate nine models, each one considering, as variables of interest, only one variable from the first (KIBS) set, and only one variable from the second (rest of the economy) set. In other words, the variables of interests of each model are always two: one “KIBS” variable and one “nonKIBS” (or “rest of the economy”) variable. Said in terms of the Equation (1) notation, there are always only two elements constituting the vector y_t . See Table 2 for a summary of each model in terms of its variables of interest.

Table 2: Summary of the nine models

(column labels indicate the first variable of interest, i.e. the first element of y_t in Equation 1;

row labels indicate the second variable of interest, i.e. the second element of y_t in Equation 1)

	First variable of interest:		
	all KIBS	financial KIBS	nonfinancial KIBS
Second variable of interest:			
All the other (nonKIBS) sectors	Model 1	Model 2	Model 3
Manufacturing sectors	Model 4	Model 5	Model 6
Other (nonKIBS) service sectors	Model 7	Model 8	Model 9

To construct the six variables, our starting point is the regional employment level (which we denote by x_t) associated to each of the variable. The second column of Table 3 show the mean and standard deviations, computed across regions and across years, of the employment

³ The rationale behind our NACE code list is the following. The OECD (the official OECD website: <http://stats.oecd.org/glossary/detail.asp?ID=2435>) does not consider construction, nor energy, nor public administration sectors as part of the services sector. Castaldi (2009) excludes, from her analysis of intersectoral linkages, also education, health and social work "because, by responding only partially to market forces, they follow different patterns of competition and growth". Because of similar reasons (building of waste disposal plants, which can involve mainly construction and manufacturing processes; partial dependence on state control) we also exclude the sectors related to water supply, sewages and waste management from our services NACE list.

level respectively for the six variables. Then, we compute the regional employment growth rates g_t as log-differences of employment:

$$g_t = \log(x_t) - \log(x_{t-1}) \quad (4)$$

We cannot directly feed the growth rates g_t to our estimation algorithm, because of a negative relation between the levels of the region-industry employment, and the variance of their growth rates (Duschl and Brenner, 2013a). Such “variance scaling” relation is well-known in industrial dynamics: the lower is the firm size, the higher is the variance of its growth rate (Stanley et al., 1996). This empirical law seems to hold also for regional dynamics, and cannot be ignored when modeling growth rates, because the heteroscedasticity generated by the law can bias the estimation (Bottazzi et al., 2010). Duschl and Brenner (2013a) show that the problem can be circumvented by an appropriate rescaling of the growth rates, based on the estimation of the variance scaling parameters. We adopt the same procedure (for details, see Duschl and Brenner, 2013a), and we obtain the rescaled growth rates which we will use as variables of interest in our model (i.e. as the elements of the vector denoted as y_t in Equations 1, 2 and 3). For each of the six sectoral aggregations, corresponding to the six variables of interest, Table 3 reports descriptive statistics of both the not rescaled growth rates (g_t) and the rescaled growth rates (y_t). Henceforth, when referring simply to “growth”, we will mean “rescaled growth”.

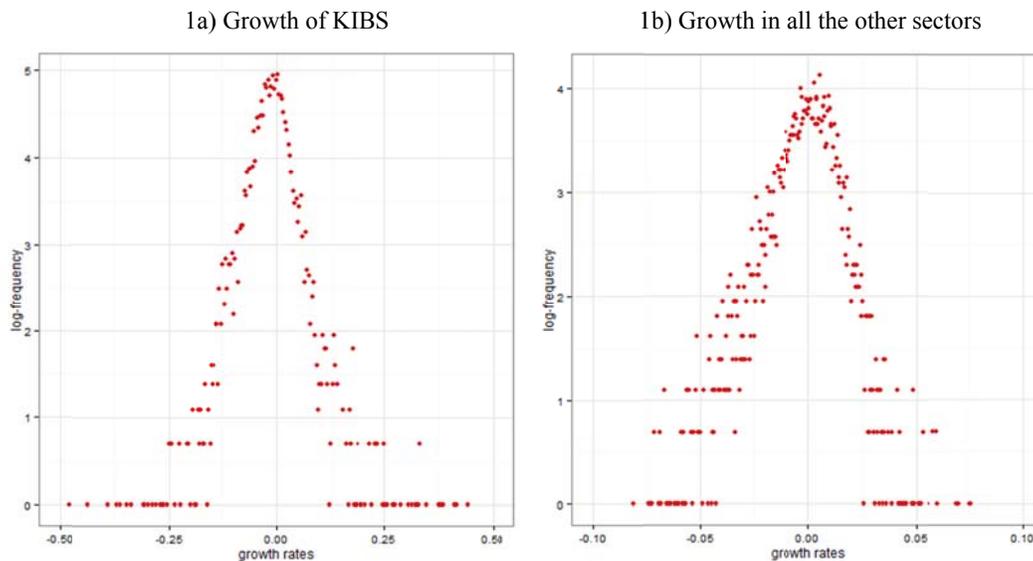
Table 3: Descriptive statistics

	Employment level		Not rescaled growth		Rescaled growth	
	Mean	s.d.	Mean	s.d.	Mean	s.d.
all KIBS	6542.8	16524.2	-0.0134	0.0692	-0.0122	0.0688
financial KIBS	3567.2	7994.8	-0.0033	0.0443	-0.0030	0.0439
nonfinancial KIBS	2975.6	8920.8	0.0062	0.2032	0.0011	0.1842
all other (nonKIBS) sectors	92259.8	132782.4	-0.0021	0.0179	-0.0018	0.0173
manufacturing	23547.4	29303.8	0.0029	0.0340	0.0023	0.0330
other (nonKIBS) services	41396.2	72856.0	-0.0023	0.0295	-0.0020	0.0281

In Figures 1a and 1b, we show the empirical distribution of regional growth rates for, respectively, KIBS and all the other sectors (pooling together the regional growth rates of all the yearly cross-sectional waves). With log frequency on the vertical axis, the distributions look clearly tent-shaped, thus confirming the finding by Duschl and Brenner (2013a) that the

Laplace-like features of growth rate distributions can be retrieved also at regional level.⁴ As previously explained, this finding hints that non-Gaussian shocks are driving the dynamics of our data, an important prerequisite for the estimation of the structural form of the models.

Figure 1: Growth rate distributions



There are other variables that influence the variables of interest, and are not influenced by them: they are assumed to be exogenous to our model, and we control for them. Such control variables are measured only at the initial time of our dataset (later observation might invalidate the exogeneity assumption) and are: population density, share of KIBS employment over total employment, and a dummy variable equal to 1 if the region belongs to the former East Germany (and zero otherwise). Although we do not report the statistics and estimations relative to them, the control variables are always included in our models.

The selection of the number of lags p in the vector autoregression 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, which is driven by the disproportionate loss of information that is not counterbalanced by additional explanatory power from the inclusion of further lags. 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.

⁴ For all the other variables we consider, the empirical growth distributions (not shown here) display similar features.

4. RESULTS

For each model, we present our results in two forms. Tables 4 to 6 will show the parameter estimates for the structural autoregressive form of the model, as in Equation (1). Figures 2 to 4 will illustrate the evolution of the variables of interest over time, following a shock applied to one of them. We can trace the evolution by, first, moving from the autoregressive representation (1) to the moving average representation (2) (i.e. from the autoregression parameters B and Γ to the impulse responses Ψ), and then by computing the cumulative sum of the impulse response function as:

$$\Psi_l^a = \sum_{j=0}^l \Psi_j \quad (5)$$

where l indicates the number of time units (lags) after the shock impact. The “accumulated” impulse response function Ψ_l^a in Equation (5) is instrumental to answer our research question because of the complicated time structure of impulse responses in Equation 2. To explain why this is the case, we need to reflect, in economic terms, on the model representations in Equations (1) and (2). Having only one lag in the autoregressive representation (1) means that the level, this year, of a variable of interest, say of employment growth in KIBS, has an influence on next year’s level of the other variable of interest, say of growth in the rest of the economy. But the growth of the rest of the economy next year will influence the growth of KIBS, and of the rest of the economy, the following year (i.e. in two years from now): an exogenous shock applied today to any variable can change the whole evolution of all the variables throughout all the following years. That is why, in the moving average representation of Equation (2), we see that the current growth rate of a variable depends on the exogenous shocks that occurred in the system in all the previous years. In order to understand the overall effect on the rest of the economy, after five years, of a shock to KIBS that occurred today, we need to sum all the effects that today’s shock will have year after year: we need the accumulated impulse response function of Equation (4).⁵

In the tables, each estimated coefficient must be interpreted as measuring the effect of the row variable on the column variable. The estimates of the instantaneous spillovers (the spillovers occurring within one year, that is the elements of the matrix parameter B of Equation 1) are, then, in the rows having, as label on the left column, the variables with the “(t)” suffix; while the estimates of the spillovers occurring at lag 1 (i.e. the spillovers Γ_1 occurring after one year) are in the rows having, as label on the left column, the variables with the “(t-1)” suffix.

Table 4 shows the estimates of the parameters of the structural autoregression (1) when modelling KIBS growth versus growth in all the other sectors (i.e. versus rescaled growth of total regional employment minus KIBS employment). In particular, the top panel of Table 4

⁵ We do not show any graphs of the accumulated response of a variable to a shock on the same variable, since the focus of our study is on growth spillovers across different industries.

shows the estimates for Model 1, when not distinguishing between financial and nonfinancial KIBS. Because of the “acyclicality” assumption we impose, the VARLiNGAM algorithm has to choose the prevailing causality direction for instantaneous inter-sectoral diffusion, and the algorithm chose the causality direction going from the rest of the economy to KIBS (estimation value: -0.258). Notably, the parameter estimation is negative: an increase in employment in the regional economy brings immediately a decrease in the employment in KIBS. This could be due to a labour-supply effect by which, in the very short term, employees move from KIBS firms to the rest of the economy. Another, more likely, explanation can be found in the outsourcing of service activities, which is a strong recent trend. Manufacturing firms have outsourced many service activities, such as cleaning and building management but also research, computer-related and marketing activities, leading to decreases in their employment. As a consequence, the respective service firms increases in number and employment. After one year, however, the picture is completely different: the growth in the rest of the economy calls for a higher demand of business services, which in turn translates into KIBS growth (parameter estimate: +0.381).

To understand which effect prevails in the long run, we need to inspect the left panel of Figure 2a, showing the accumulated response of KIBS growth (as a solid line) to a unit shock on the growth in the rest of the economy. The dashed lines in the figure delimit a 68% confidence interval.⁶ It appears that, after one year, KIBS are likely to recover from the initial negative impact, and after three years the cumulated effect becomes significantly positive. Taking into account that part of the changes in employment are the effects of economic activities moving from non-KIBS to KIBS due to outsourcing, our analysis clearly underestimates the real effects. On the one hand, a large part of the immediate effects can be explained by this shift. Eliminating this part would cause the lines in Figure 2a to start from much higher values. On the other hand, if it would be possible to eliminate all changes that are caused by outsourcing (which is not really an exogenous event), the exogenous shocks would be smaller and the parameter estimates could be expected to be higher. This would further add to the positive cumulated effects.

The central and lower panel of Table 4 (where, respectively, only financial and only nonfinancial KIBS have been considered) show that the nonfinancial KIBS are the only ones experiencing the instantaneous negative repercussion (parameter estimate: -1.133). According to our explanation above, this means that outsourcing mainly concerns nonfinancial service activities. Financial KIBS, instead, experience a positive effect already during the first year of general growth in the region (parameter estimate: +0.130), although we are not able to discern whether the negative repercussion does not exist at all, or is simply overcompensated by a very fast increase in demand for financial expertise from the rest of the economy. The left panel of Figure 2b puts in evidence how nonfinancial KIBS may never fully recover from the negative impact. However, again the negative impact is much overestimated due to outsourcing. The development of nonfinancial and financial KIBS in the following years as a response to an exogenously caused change in the rest of the economy are quite similar.

⁶ The 68% confidence interval is often used because of its comparability with the Gaussian case. When the distribution of the estimation errors is Gaussian, by adding (subtracting) exactly one standard deviation to (from) the mean estimation, the upper (lower) bound of the 68% confidence interval is obtained.

At this point, we need to remind the reader that the relations of our system, as modeled in Equation 1 and 2, are linear, and thus symmetric: a positive effect of a positive shock corresponds to a negative effect of a negative shock. In our tables, a positive estimated coefficient indicates a positive causal relation between variables, and also as a potential source of contagion to other industries of a crisis originated in one sector. In this sense, the fact that our results point toward a procyclical behavior of financial KIBS, i.e. the fact that financial KIBS seem to prosper during the good times of the economy, must be taken into account also when evaluating the potential impact of a crisis in the rest of the economy: financial KIBS are going to suffer already in the immediate aftermath of a bad event affecting the region. Contributing to the “cycle” of growth connecting financial KIBS to the rest of the economy, there is the high positive estimate (+0.027, third column of the central panel of Table 4) of the parameter linking growth in the rest of the economy to the previous year’s growth of financial KIBS.

The rest of the economy profits also from growth in nonfinancial KIBS (+0.009, lower panel of Table 4), so, in general, we can say that a positive exogenous shock on KIBS, although with some lag, creates employment growth in the rest of the economy. We can now investigate whether the positive shock of KIBS spills over the whole economy indistinctly, or instead employment is created only in some industries.

The right columns of Table 5 show that the manufacturing sector seems to profit with a time lag of one year from growth in nonfinancial KIBS (+0.008, significant) but not from growth in financial KIBS (+0.008, not significant). When considering KIBS as a whole (top panel of Table 5), the manufacturing sector appears not to be significantly affected by growth in KIBS, while KIBS seem to be affected by positive manufacturing growth only negatively. Indeed, the contemporaneous negative influence of manufacturing growth on KIBS is high (parameter estimate: -0.298), as a result of the strong negative effect on nonfinancial KIBS (-0.508, in the bottom panel of Table 5) not compensated by any influence on financial KIBS (-0.086, not significant). However, this is again in line with our above argument on outsourcing and might be completely the result of the related transfer of economic activity from the manufacturing sector to the nonfinancial KIBS industries. Therefore, the fall of KIBS, following a positive shock to manufacturing growth (left panels of Figures 3a) should not be overinterpreted. In figure 3b the separation between the financial KIBS and the manufacturing sector is evident: none of the two variables experiences an appreciable effect of a shock to the other variable. The right panel of Figure 3c, instead, shows that the manufacturing sector employment grows after a positive shock to nonfinancial KIBS.

Similarly, the rest of the service sector follows, with some lag, the growth in nonfinancial KIBS (+0.011, bottom panel of Table 6), and, contrary to the manufacturing case, it is less likely to “steal” employees from nonfinancial KIBS or the other way round (-0.224, not significant); so, over time, its growth can reach higher levels (Figure 4c, right panel). The interaction between financial KIBS and other service industries is strong (high and significant

estimates in the central panel of Table 6), with financial KIBS experiencing an immediate growth spurt following a positive change in other services (Figure 4b).

5. CONCLUSIONS

Our findings can be summarized in four messages.

First, there are clear connections between KIBS and the rest of the economy, at regional level and in terms of employment growth. Growth in other industries can influence the expansion of KIBS and leads the feedback to the regional economy. Hence, regions might experience a positive feedback loop for some years if either KIBS activities or activities in the rest of the economy are triggered by exogenous events, such as policy measures. This offers interesting policy options for fostering the regional economy. A more detailed analysis of good starting points for such a positive feedback cycle is an interesting topic for future research.

Second, part of such a more detailed study is done here. We find little evidence for a positive feedback cycle between the manufacturing sector and the KIBS industries. The manufacturing sector reacts to some extent to changes in nonfinancial KIBS (the reaction being in the same direction of the shock), but they seem to experience no appreciable consequences after changes in financial KIBS. In general, financial KIBS seem to have connections only with the services industries, and their interactions with the overall regional growth seem to occur uniquely through their effect on, and influences from, the growth in other services.

Third, while KIBS growth can result from growth in the rest of the economy, especially in other service industries, we find a negative relationship between growth in the rest of the economy and in KIBS. However, we argued that this results reflects an impact of the recent trend of outsourcing, mainly effecting the relationship between the manufacturing sector and the nonfinancial KIBS.

Fourth, the effects of growth in the rest of the economy, especially the other service industries on financial KIBS seems to be strongest. Financial KIBS do not suffer from the mentioned short-term negative interactions with the rest of the economy, and seem instead to feed back on the rest of the economy in the short and in the long term, and at higher magnitude levels than the other KIBS. In bad times, such procyclical behaviour could backfire: in case of a negative shock to the economy, no matter whether the original shock hits the financial KIBS or some other industries, the crisis can enter a vicious depressing circle. Thus, financial KIBS can be seen as accelerators in the regional economy as well in positive developments as in negative developments.

Table 4: Estimates of the parameters of the structural autoregression (1) when modelling KIBS growth versus growth in all the other sectors.

* 10% significance; ** 5% significance; *** 1% significance; bootstrapped standard errors in brackets.

Model 1: all KIBS vs all other sectors

	all KIBS (t)		all other sectors (t)	
all KIBS (t)	-	-	-	-
all other sectors (t)	-0.258*	(0.1392)	-	-
all KIBS (t-1)	0.015	(0.0145)	0.024***	(0.0051)
all other sectors (t-1)	0.381***	(0.0793)	0.391***	(0.0270)

Model 2: financial KIBS vs all other sectors

	fin. KIBS (t)		all other sectors (t)	
fin. KIBS (t)	-	-	-	-
all other sectors (t)	0.130***	(0.0498)	-	-
fin. KIBS (t-1)	0.078***	(0.0206)	0.027***	(0.0071)
all other sectors (t-1)	0.181***	(0.0460)	0.395***	(0.0278)

Model 3: non-financial KIBS vs all other sectors

	nonfin. KIBS (t)		all other sectors (t)	
nonfin. KIBS (t)	-	-	-	-
all other sectors (t)	-1.133***	(0.3498)	-	-
nonfin. KIBS (t-1)	0.014	(0.0117)	0.009***	(0.0016)
all other sectors (t-1)	0.763***	(0.1886)	0.391***	(0.0278)

Table 5: Estimates of the parameters of the structural autoregression (1) when modelling KIBS growth versus growth in the manufacturing sectors.

* 10% significance; ** 5% significance; *** 1% significance; bootstrapped standard errors in brackets.

Model 4: all KIBS vs Manufacturing

	all KIBS (t)		Manufacturing (t)	
all KIBS (t)	-	-	-	-
Manufacturing (t)	-0.298***	(0.0938)	-	-
all KIBS (t-1)	0.011	(0.0208)	0.009	(0.0107)
Manufacturing (t-1)	0.056	(0.0416)	0.247***	(0.0269)

Model 5: financial KIBS vs Manufacturing

	fin. KIBS (t)		Manufacturing (t)	
fin. KIBS (t)	-	-	-	-
Manufacturing (t)	-0.086	(0.0835)	-	-
fin. KIBS (t-1)	0.099***	(0.0219)	0.008	(0.0158)
Manufacturing (t-1)	0.026	(0.0281)	0.249***	(0.0272)

Model 6: non-financial KIBS vs Manufacturing

	nonfin. KIBS (t)		Manufacturing (t)	
nonfin. KIBS (t)	-	-	-	-
Manufacturing (t)	-0.508***	(0.1604)	-	-
nonfin. KIBS (t-1)	0.005	(0.0114)	0.008**	(0.0036)
Manufacturing (t-1)	0.239***	(0.0733)	0.249***	(0.0262)

Table 6: Estimates of the parameters of the structural autoregression (1) when modelling KIBS growth versus growth in all the other services sectors.

* 10% significance; ** 5% significance; *** 1% significance; bootstrapped standard errors in brackets.

Model 7: all KIBS vs other Services

	all KIBS (t)		other Services (t)	
all KIBS (t)	-	-	-	-
other Services (t)	0.025	(0.1321)	-	-
all KIBS (t-1)	0.019	(0.0161)	0.035***	(0.0086)
other Services (t-1)	0.132***	(0.0483)	0.222***	(0.0272)

Model 8: financial KIBS vs other Services

	fin. KIBS (t)		other Services (t)	
fin. KIBS (t)	-	-	-	-
other Services (t)	0.184**	(0.0796)	-	-
fin. KIBS (t-1)	0.075***	(0.0211)	0.046**	(0.0187)
other Services (t-1)	0.067**	(0.0298)	0.212***	(0.0291)

Model 9: non-financial KIBS vs other Services

	nonfin. KIBS (t)		other Services (t)	
nonfin. KIBS (t)	-	-	-	-
other Services (t)	-0.224	(0.2414)	-	-
nonfin. KIBS (t-1)	0.006	(0.0123)	0.011***	(0.0034)
other Services (t-1)	0.290***	(0.1029)	0.216***	(0.0269)

Figure 2: Cumulative impulse response functions when modelling KIBS growth versus growth in all the other sectors.
 The dashed lines delimit the 68% confidence intervals.

Figure 2a: Model 1 (all KIBS vs. all other sectors)

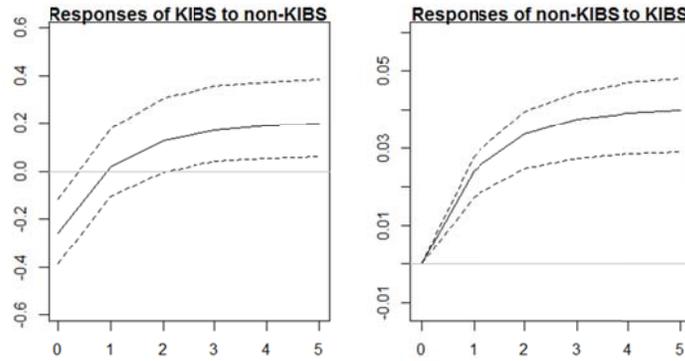


Figure 2b: Model 2 (financial KIBS vs. all other sectors)

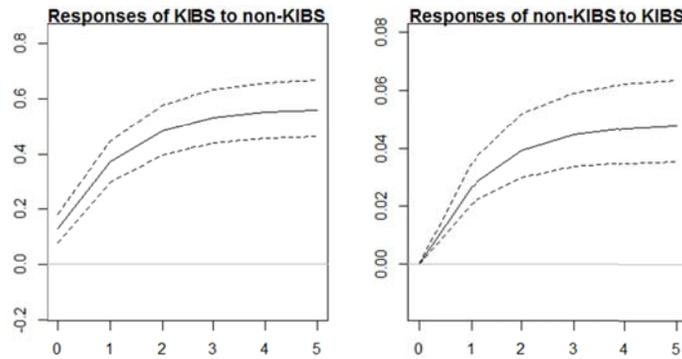


Figure 2c: Model 3 (nonfinancial KIBS vs. all other sectors)

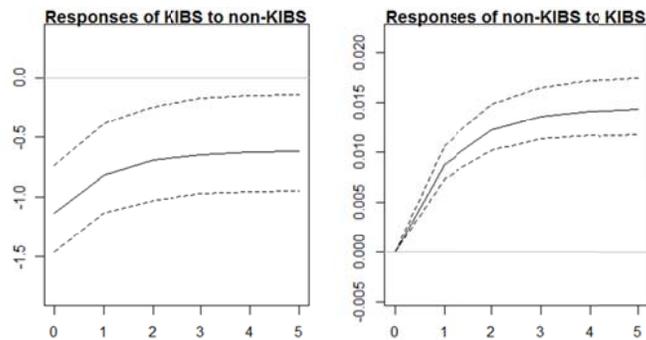


Figure 3: Cumulative impulse response functions when modelling KIBS growth versus growth in the manufacturing sectors.

The dashed lines delimit the 68% confidence intervals.

Figure 3a: Model 4 (all KIBS vs. Manufacturing)

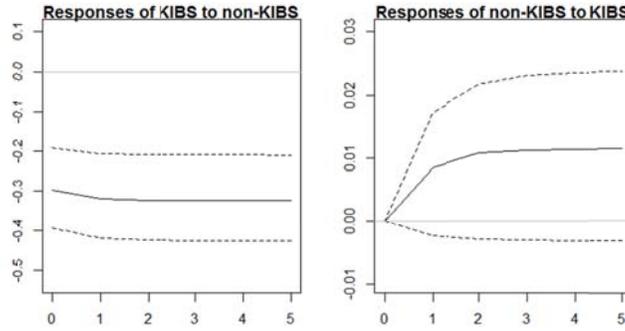


Figure 3b: Model 5 (financial KIBS vs. Manufacturing)

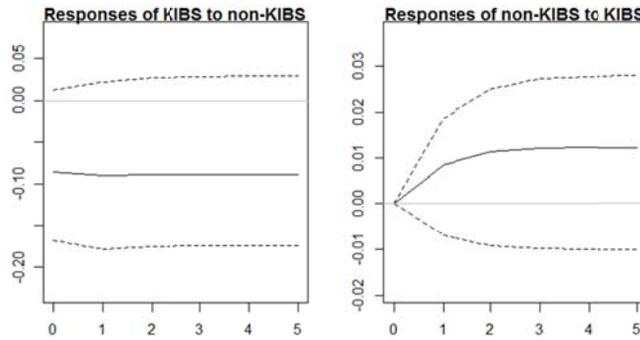


Figure 3c: Model 6 (nonfinancial KIBS vs. Manufacturing)

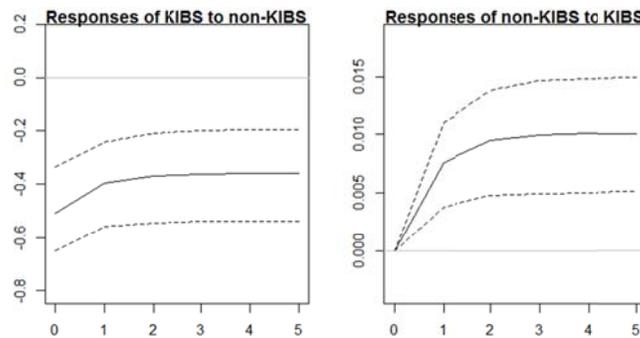


Figure 4: Cumulative impulse response functions when modelling KIBS growth versus growth in all the other services sectors.

The dashed lines delimit the 68% confidence intervals.

Figure 4a: Model 7 (all KIBS vs. Services)

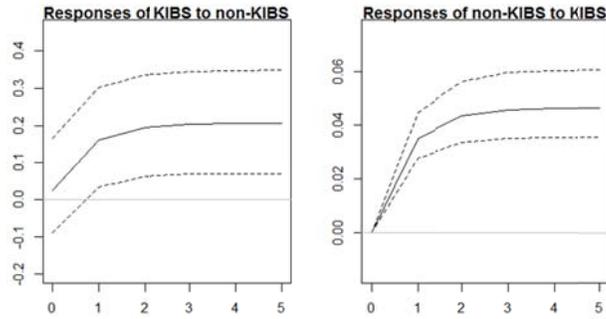


Figure 4b: Model 8 (financial KIBS vs. Services)

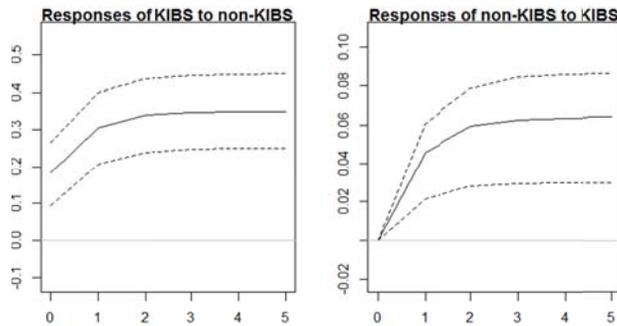
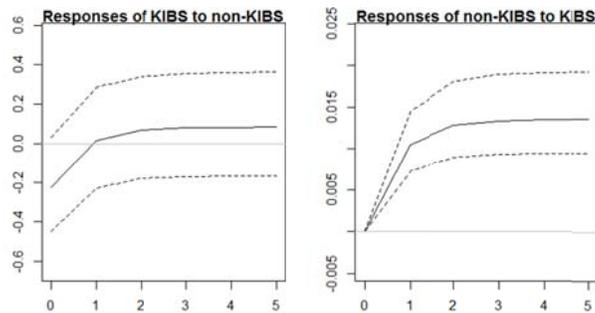


Figure 4c: Model 9 (nonfinancial KIBS vs. Services)



References

- Axtell, R. L. (2001), 'Zipf Distribution of U.S. Firm Sizes', *Science* **293**(5536), 1818-1820.
- 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.', Technical report, IAB Forschungsbericht 4/2006.
- Bottazzi, G.; Secchi, A. & Tamagni, F. (2010), 'Financial constraints and firm dynamics', Technical report, Discussion Paper 99/2010, DSE-University of Pisa.
- Bottazzi, G., Coad, A., Jacoby, N., & Secchi, A. (2011). Corporate growth and industrial dynamics: Evidence from French manufacturing. *Applied Economics* **43**(1), 103-116.
- Brock, W. (1999), 'Scaling in economics: a reader's guide', *Industrial and Corporate Change* **8**, 409-446.
- Broekel, T. & Binder, M. (2007), 'The regional dimension of knowledge transfers – a behavioral approach', *Industry and Innovation* **14**, 151-175.
- Bryson, J.; Daniels, P. & Warf, W. (2004), *Service Worlds*, Routledge, London.
- Buerger, M.; Broekel, T. & Coad, A. (2012), 'Regional dynamics of innovation: Investigating the co-evolution of patents, research and development (R&D), and employment', *Regional Studies* **46**(5), 565-582.
- Castaldi (2009), 'The relative weight of manufacturing and services in Europe: An innovation perspective', *Technological Forecasting & Social Change* **76**, 709-722.
- Castaldi, C. & Sapio, S. (2008), 'Growing like mushrooms? Sectoral evidence from four large European economies', *Journal of Evolutionary Economics* **18**(3), 509-527.
- Castellacci, F. (2008), 'Technological paradigms, regimes and trajectories: Manufacturing and service industries in a new taxonomy of sectoral patterns of innovation', *Research Policy* **37**, 978-994.
- Coad, A. (2010), 'Exploring the processes of firm growth: evidence from a vector auto-regression', *Industrial and Corporate Change* **19**(6), 1677-1703.
- Coad, A. & Binder, M. (2014), 'Causal linkages between work and life satisfaction and their determinants in a structural VAR approach', *Economics Letters* **124**, 263-268.
- Coad, A. & Broekel, T. (2012), 'Firm growth and productivity growth: evidence from a panel VAR', *Applied Economics* **44**(10), 1251-1269.
- Coad, A.; Cowling, M. & Siepel, J. (2012), 'Growth processes of high-Growth firms in the UK', *Nesta Working Paper No. 12/10*, Technical report, Nesta Working Paper 12/10.
- Comon, P. (1994), 'Independent component analysis a new concept?', *Signal Processing* **36**,

287-314.

Corrocher, N. & Cusmano, L. (2014), 'The 'KIBS engine' of regional innovation systems: Empirical evidence from European regions', *Regional Studies* **48**(7), 1212-1226.

Hertog, P. D. (2000), 'Knowledge-intensive business services as co-producers of innovation', *International Journal of Innovation Management* **4**(4), 491-528.

Duschl, M. & Brenner, T. (2013a), 'Characteristics of regional industry-specific employment growth rates' distributions', *Papers in Regional Science* **92**(2), 249-271.

Duschl, M. & Brenner, T. (2013b), 'Growth dynamics in regional systems of technological activities - A SVAR approach', Technical report, Philipps-Universität Marburg Working Papers on Innovation and Space 12.13.

Commission, E. (2012), 'The smart guide to service innovation', Technical report, European Commission's Enterprise and Industry Directorate-General, http://ec.europa.eu/enterprise/policies/sme/regional-sme-policies/documents/no.4_service_innovation_en.pdf.

Commission, E. (2009), 'Challenges for EU support to innovation in services', Technical report, Innovation policy initiative PRO INNO Europe - Commission Staff Working Document 1195, http://ec.europa.eu/enterprise/policies/innovation/files/swd_services_en.pdf.

Demiralp, S. & Hoover, K. (2003), 'Searching for the Causal Structure of a Vector Autoregression', *Oxford Bulletin of Economics and Statistics* **65**, 745-767.

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.

Ferkingsta ; E., Lølanda, A. & Wilhelmsen, M. (2011). 'Causal modeling and inference for electricity markets'. *Energy Economics* **33**(3), 404-412.

Foray, D.; David, P. & Hall, B. (2009), 'Smart specialisation - the concept', Technical report, Knowledge Economists Policy Brief no. 9, June 2009, http://ec.europa.eu/invest-in-research/pdf/download_en/kfg_policy_brief_no9.pdf?11111.

Herstad, S. J. & Ebersberger, B. (2014), 'Urban agglomerations, knowledge-intensive services and innovation: establishing the core connections', *Entrepreneurship & Regional Development* **26**(3-4), 211-233.

Hurwicz, L. ; Nagel, E.; Suppes, P. & Tarski, A., ed., (1962), *Logic, Methodology and Philosophy of Science*, Stanford University Press, chapter On the structural form of interdependent systems, pp. 232-239.

Hyvarinen, A. & Oja, E. (2000), 'Independent component analysis: algorithms and applications', *Neural Networks* **13**, 411-430.

Hyvarinen, A.; Shimizu, S. & Hoyer, P. O. (2008), Causal modelling combining

instantaneous and lagged effects: an identifiable model based on non-Gaussianity, in 'Proceedings of the 25th International Conference on Machine Learning', pp. 424-431.

Jacobs, W.; Koster, H. R. A. & van Oort, F. (2014), 'Co-agglomeration of knowledge-intensive business services and multinational enterprises', *Journal of Economic Geography* **14**, 443-475.

Janssen, M. (2014), 'A holistic view on service innovation: Four approaches for developing systemic policy mixes', Technical report, Paper presented at the DRUID Society Conference 2014, CBS, Copenhagen, June 16-18, druid8.sit.aau.dk/druid/acc_papers/l4evl68pmr75xgkkfshoa8d6ujp4.pdf.

Jensen, M. B.; Johnson, B.; Lorenz, E. & Lundvall, B. A. (2007), 'Forms of knowledge and modes of innovation', *Research Policy* **36**, 680-693.

Keeble, D. & Nachum, L. (2002), 'Why do business service firms cluster? Small consultancies, clustering and decentralization in London and Southern England', *Transactions of the Institute of British Geographers* **27**, 67-90.

Kilian, L. Hashimzade, N. & Thornton, M. A., ed., (2012), *Handbook of Research Methods and Applications in Empirical Macroeconomics*, Elgar, chapter Structural vector autoregressions, pp. 515-554.

Koch, A. & Stahlecker, T. (2006), 'Regional innovation systems and the foundation of knowledge intensive business services. A comparative study in Bremen, Munich, and Stuttgart, Germany', *European Planning Studies* **14**(2), 123-146.

Kox, H. L. & Rubalcaba, L. Rubalcaba, L. & Kox, H. L., ed., (2007), *Business Services in European Economic Growth*, Palgrave Macmillan, chapter Analysing the Contribution of Business Services to European Economic Growth.

Leiponen, A. (2001), 'Knowledge services in the innovation system', Technical report, Research Institute of the Finnish Economy - ETLA report 185.

Luetkepohl, H.T. (2003), 'Vector Autoregression', in: Baltagi, B. (Eds.) *A companion to theoretical econometrics*. Blackwell Publishing: Malden, MA, 678-699.

Luetkepohl, H.T., M. & K., P., ed., (2006), *Palgrave Handbook of Econometrics, Volume 1: Econometric Theory*, Palgrave Macmillan, chapter Vector autoregressive models, pp. 477-510.

Meliciani, V. & Savona, M. (forthcoming), 'The determinants of regional specialisation in business services: agglomeration economies, vertical linkages and innovation', *Journal of Economic Geography*.

Merino, F. & Rubalcaba, L. (2013), 'Are knowledge-intensive services highly concentrated? Evidence from European regions', *Tijdschrift voor Economische en Sociale Geografie* **104**(2), 215-232.

Miles, I.; Kastrinos, N.; Bilderbeek, R.; den Hertog, P.; Flanagan, K.; Huntink, W. &

Bouman, M. (1995), *Knowledge-intensive business services. Users, carriers and sources of information.*, European Commission, Brussels.

Moneta, A.; Entner, D.; Hoyer, P. O. & Coad, A. (2013), 'Causal inference by independent component analysis: theory and applications', *Oxford Bulletin of Economics and Statistics* **75**(5), 705-730.

Muller, E. & Doloreux, D. (2009), 'What we should know about knowledge-intensive business services', *Technology in Society* **31**, 64-72.

Muller, E. & Zenker, A. (2001), 'Business services as actors of knowledge transformation: the role of KIBS in regional and national innovation systems', *Research Policy* **30**, 1501-1516.

Potočník, J. (2009), 'Foreword', Technical report, Knowledge Economists Policy Brief no. 9, June 2009, http://ec.europa.eu/invest-in-research/pdf/download_en/kfg_policy_brief_no9.pdf?11111..

Rubalcaba, L.; Michel, S.; Sundbo, J.; Brown, S. W. & Reynoso, J. (2012), 'Shaping, organizing, and rethinking service innovation: a multidimensional framework', *Journal of Service Management* **23**(5), 696-715.

Sargent, T. J. (1979), 'Estimating vector autoregressions using methods not based on explicit economic theories', *Federal Reserve Bank of Minneapolis Quarterly Review* **3**(3), 8-15.

Shimizu, S.; Hoyer, P. O.; A., H. & Kerminen, A. (2006), 'A linear non-Gaussian acyclic model for causal discovery', *Journal of Machine Learning Research* **7**, 2003-2030.

Sims, C. A. (1986), 'Are forecasting models usable for policy analysis?', *Federal Reserve Bank of Minneapolis Quarterly Review* **10**(1), 2-16.

Stanley, M. H. R.; Amaral, L. A. N.; Buldyrev, S. V.; Havlin, S.; Leschhorn, H.; Maass, P.; Salinger, M. A. & Stanley, H. E. (1996), 'Scaling behaviour in the growth of companies', *Nature* **379**(6568), 804-806.

Stock, J. H. & Watson, M. W. (2001), 'Vector autoregressions', *Journal of Economic Perspectives* **15**, 101-115.

Strambach, S. (2008), 'Knowledge-Intensive Business Services (KIBS) as drivers of multilevel knowledge dynamics', *International Journal of Services Technology and Management* **10**, 152-174.

Wernerheim, M. C. & Sharpe, C. (2003), 'High order producer services in metropolitan Canada: how footloose are they?', *Regional Studies* **37**, 469-490..

Wold, H. (1954), *A Study in the Analysis of Stationary Time Series*, Almqvist & Wiksell, Uppsala.

Wood, P. (2006), 'Urban development and knowledge-intensive business services: too many unanswered questions?', *Growth and Change* **37**(3), 335-361.