ONLINE APPENDIX to the article "Causal Relations between Knowledge-Intensive Business Services and Regional Employment Growth"

## A1. Methodology details

In Equation (1) in the paper, i.e. in the structural representation of the model, all the information about past shocks is not explicitly shown, but is instead embodied in the values $y_{t-1}, y_{t-2}, \ldots, y_{t-p}$. In economic terms, that means: if the growth of KIBS and of the rest of the economy in the past are known, it is not necessary 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 only the new shocks $\epsilon_t$ need to be known. 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, 2009), the same model of Equation (1) in the paper is presented here as a moving average (WOLD, 1938):

$$y_t = \Psi_0 \epsilon_t + \Psi_1 \epsilon_{t-1} + ... + \Psi_\infty \epsilon_{t-\infty} \tag{A1}$$

where the economic situation of today is explicitly shown to depend on the whole history of exogenous shocks occurred in the past. $\Psi$ are the parameters connecting shocks and variables of interest, i.e. the 'impulse responses' to be estimated in order to assess the consequences that exogenous shocks (e.g., future policies) have over time.

The representation in Eq. (A1) is easy to obtain when knowing the 'structural' form of the model as in Eq. (1) in the paper. However, estimating the 'structural' form is not straightforward, because of the presence of contemporaneous effects as indicated by the parameter $B$ in Eq. (1) in the paper; instead, a vector autoregression in the 'reduced form'

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + u_t \tag{A2}$$

can be easily estimated (Stock and Watson, 2001). The reduced form (Eq. A2) would be structural only if there were no contemporaneous causal relations among the variables of interest, i.e. assuming that the matrix $B$ in Eq. (1) in the paper is composed only of zeroes. If this is not the case, estimating the reduced form of Eq. (A2) cannot help to define the effects of an exogenous event (Sargent, 1979; Sims, 1986).

Indeed, there are many values of the parameters of Eq. (1) in the paper that are consistent with estimates of Eq. (A2), and additional assumptions are needed to identify a preferred set of values. This 'identifiability' problem has driven the research on structural vector autoregressions over the last three decades (see Stock and Watson, 2001, for a short summary and Hashimzade and Thornton, 2013, for a detailed survey). The main strands of research have focused on searching for plausible additional assumptions drawn from economic theory. The assumptions might concern the causal ordering, that is the short-term spillovers of the shocks (in the case at hand, 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 the case at hand, 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, as argued in Section 2 of the paper, there are no clear theoretical predictions about the direction of the contemporaneous or long-term relations between the growth of KIBS and of the rest of the economy.

Recent developments in the econometric research on structural vector autoregressions, coupled with recent empirical findings about regional dynamics, allow to avoid imposing strong *a priori* causal ordering. These developments, 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 ($\epsilon_t$ in Eq. (1) in the paper entails.

Retrieving the structural form (Eq. (1) in the paper) from the estimated reduced form (Eq. (A2)) means also retrieving the current and past exogenous shocks ($\epsilon_t, \epsilon_{t-1}$ 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 the 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. 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 ($\epsilon_t, \epsilon_{t-1}$ 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 all exogenous shocks, or all shocks but one, are not only assumed to be independent but also non-Gaussian, then it is possible to retrieve them from an observable rotation of them, that is, in the case here, from the reduced-form estimation residuals (Comon, 1994; Hyvärinen and Oja, 2000).

Can it be assumed, in the context of this study, that the exogenous shocks are non-Gaussian? The data set used here is the same as the one 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; 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.

Apart from shock independence and of non-Gaussianity, the VAR-LiNGAM in Hyvärinen *et al.* (2008) and Moneta *et al.* (2013) assumes no contemporaneous feedback among the variables (the 'acyclicality' assumption). Acyclicality imposes that positive shocks on one variable immediately affect the other variable but not the other way around. The acyclicality is assumed 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. Section  of this appendix discusses the limitations brought by such assumption on this study. Further details about the VARLiNGAM estimation algorithm can be found in Hyvärinen *et al.* (2008). Pioneering applications of the model to economic fields have involved macroeconomics (Moneta *et al.*, 2013), happiness economics (Coad and Binder, 2014), energy economics (Ferkingstad *et al.*, 2011), firm dynamics (Moneta *et al.*, 2013; Coad *et al.*, 2012), and regional dynamics (Duschl and Brenner, 2013b).

## A2. Limitations of the methodological approach

Our decision of imposing contemporaneous acyclicality brings some limitations to the accuracy of the models. It implies that no short-run relationships of opposite directions can be represented. Two of the hypotheses consider short-run effects: Hypothesis **H3** points at positive impact of KIBS on other services also in the short-run, through the local multiplier effect, while hypothesis **H4** is mainly based on arguments about outsourcing which causes a negative, short-run relationship between KIBS and the rest of the economy. If the "short-run" indicated a time horizon longer than one year, then the model would be fully able to define all the causal directions, and possible feedbacks, between the variables of interest: the model would be able to disentangle all the causal relations implied by the two hypotheses. If, instead, more than one causal relation were translating into observable effects already within one year, then the model would attempt to bring all these "immediate" influences into one clear order.

While hypothesis **H3** has a clear causal direction, hypothesis **H4** contains two possible causal directions. Hence, this latter hypothesis is most difficult to reconcile with the acyclicality assumption. In this context the reader has to keep in mind that hypothesis **H4** is not based on a causal effect but on a simple relationship: Outsourcing causes a shift of employment from other parts of the economy to KIBS. This binds the growth dynamics of KIBS and other parts of the economy to each other, with the causal effect coming from the outsourcing process and implying both dynamics. With this model it is imposed that there has to be a causal relationship between the growth in KIBS employment and other employment. Hence, the results in this context should be interpreted with care.

Allowing for contemporaneous causal cycles would be a desirable feature for this model. Unfortunately, a problem of identification would arise: assuming the existence of contemporaneous cycles can expand dramatically the number of models (in the sense of combinations of causal estimates) that are consistent with the observable data. Lacerda *et al.* (2008) have suggested a new algorithm based on different assumptions, in order to restrict the number of directed causal graphs consistent with the data, while allowing for contemporaneous cycles.[1] However, the method by Lacerda *et al.* (2008) has never been applied to the SVAR framework, and a first application would require econometric reflexions far from the goals of this paper. On the other hand, employing completely different methodologies for causal modelling would entail more assumptions about the causal structure linking the observed variables, and could mislead the data-driven inspiration of this paper. For instance, using instrumental variables would imply assuming that there are exogenous variables influencing directly only some of the endogenous variables (this assumption would coexist with other, less evident, assumptions about the causal graph:

see section 25.3.3 of Shalizi, 2015). Instead, whenever possible, the assumption of any causal direction involving the two endogenous variables (the growth in KIBS and the growth in the rest of the economy) should be avoided. Given the current state of the art in statistics, the acyclicality assumption is preferred: only the prevailing causal influence at impact is modeled (the data analysis will reveal which influence is prevailing), while still allowing for all the possible causal directions after time lags. In doing so, it is possible to minimize the number of statistical assumptions based on prior economic theoretical knowledge.

## A3. Rescaling of the growth rates

To construct the six variables, the starting point is the regional employment level (denoted by $x_t$) associated to each of the variables. Then, the regional employment growth rates $g_t$ are the log-differences of employment:

$$g_t = \log(x_t) - \log(x_{t-1}) \tag{A3}$$

The growth rates $g_t$ cannot be directly fed to the 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.*, 2014). 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.

The same procedure is adopted(for details, see Duschl and Brenner, 2013a), and the rescaled growth rates, used as variables of interest in the model are obtained (i.e. as the elements of the vector denoted as $y_t$ in Eq. (1) in the paper, and Eq. A1 and A2 of this Online Appendix). For each of the six sectoral aggregations, corresponding to the six variables of interest, Table A1 below reports descriptive statistics of both the not rescaled growth rates ($g_t$) and the rescaled growth rates ($y_t$).

**Table A1: Descriptive statistics**

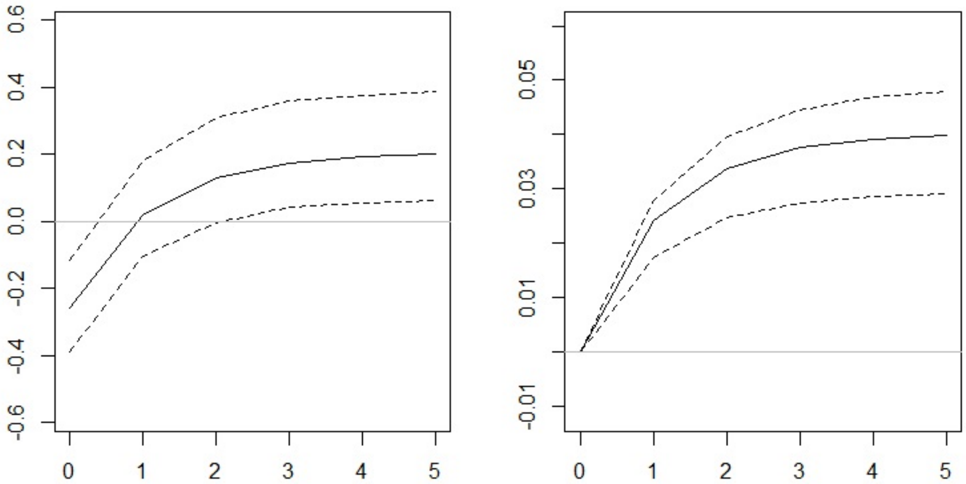
| | **Employment level** | | **Employment growth** | | | |
|---|---|---|---|---|---|---|
| | | | Not rescaled ($g_t$) | | Rescaled ($y_t$) | |
| | Mean | s.d. | Mean | s.d. | Mean | s.d. |
| **All KIBS** | 6542.8 | 16524.2 | -0.013 | 0.069 | -0.012 | 0.069 |
| Financial KIBS | 3567.2 | 7994.8 | -0.003 | 0.044 | -0.003 | 0.044 |
| Non-financial KIBS | 2975.6 | 8920.8 | 0.006 | 0.203 | 0.001 | 0.184 |
| **All other (non-KIBS) sectors** | 92259.8 | 132782.4 | -0.002 | 0.018 | -0.002 | 0.017 |
| Manufacturing | 23547.4 | 29303.8 | 0.003 | 0.034 | 0.002 | 0.033 |
| Other (non-KIBS) services | 41396.2 | 72856.0 | -0.002 | 0.030 | -0.002 | 0.028 |

# A4. Impulse Response Functions

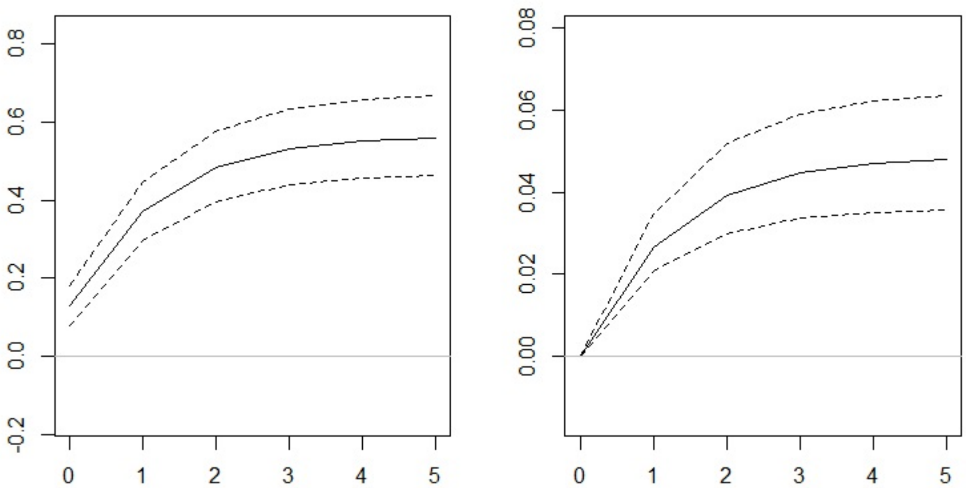
For each model, results are presented in two forms. The tables presented in the paper show the parameter estimates for the structural autoregressive form of the model, as in Eq. (1). Figures 1 to 3 in this Online Appendix illustrate the evolution of the variables of interest over time, following a shock applied to one of them.

The figures show as a solid line the accumulated response of the variable of interest to a unit shock on the growth in the other variable of interest. The dashed lines in the figures delimit a 68% confidence interval. 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.

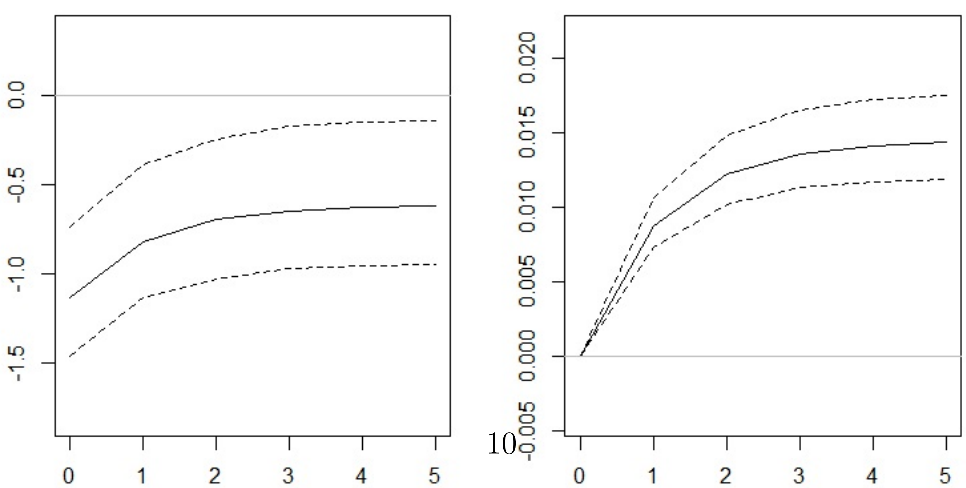
**Figure A1:** **Cumulative impulse response functions. Left: KIBS growth response to a unit shock on the growth in all the other sectors. Right: All the other sectors response to a unit shock on KIBS growth.** **The dashed lines delimit the 68% confidence intervals.**




Model 1: All KIBS vs. all other sectors.



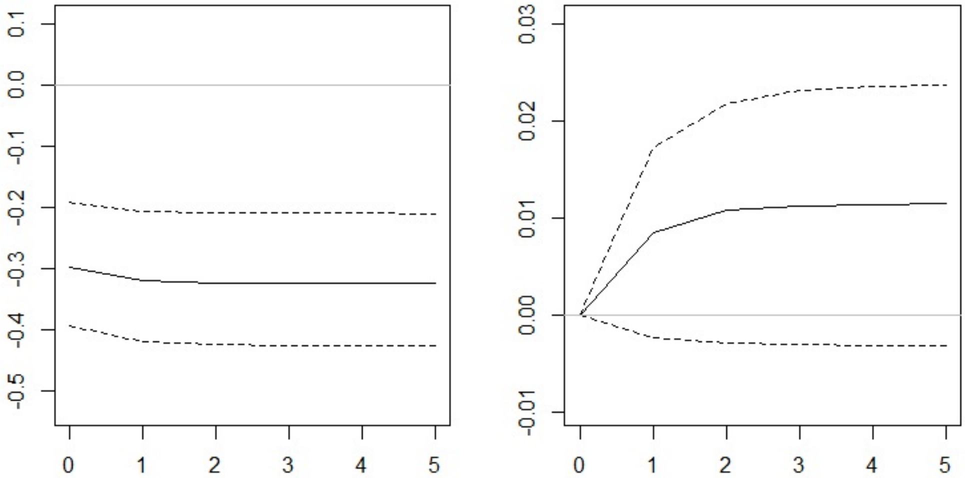

Model 2: Financial KIBS vs. all other sectors.



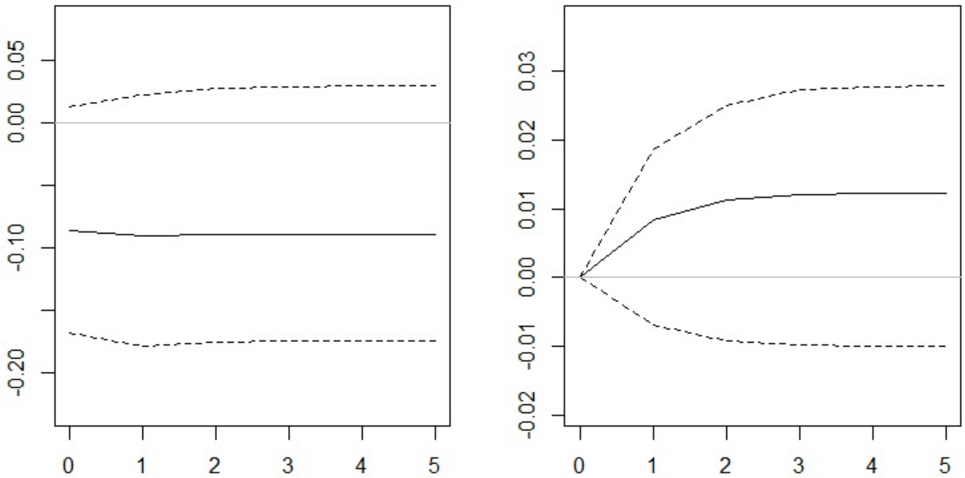



Model 3: Non-financial KIBS vs. all other sectors.

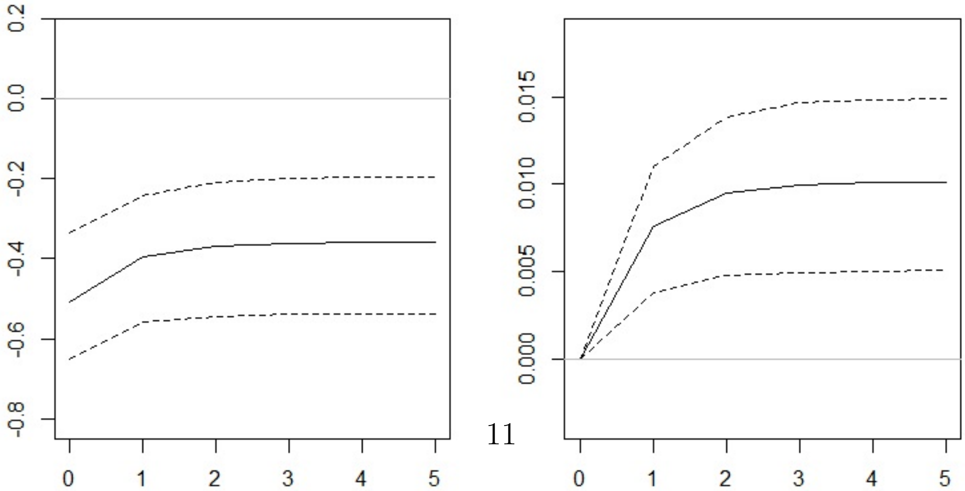
**Figure A2:** **Cumulative impulse response functions. Left: KIBS growth response to a unit shock on the growth in Manufacturing. Right: Manufacturing sectors response to a unit shock on KIBS growth.** **The dashed lines delimit the 68% confidence intervals.**




Model 4: All KIBS vs. Manufacturing.

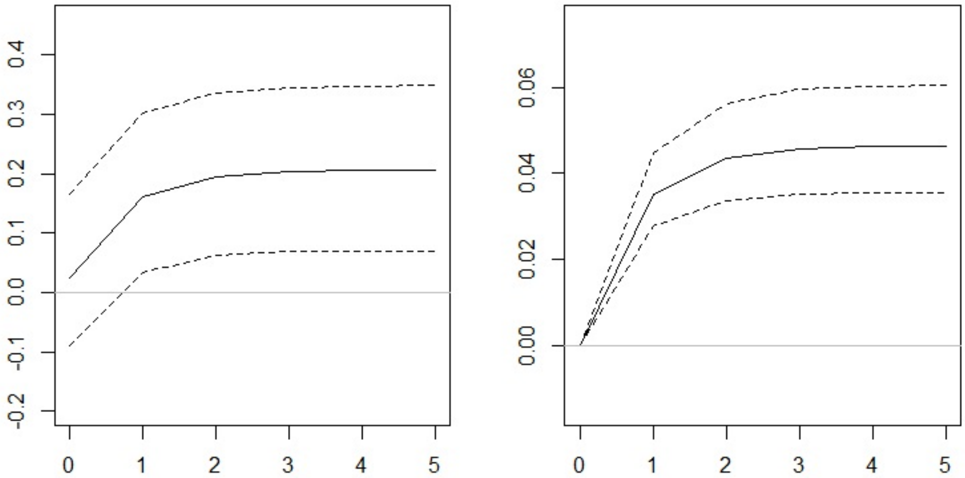



Model 5: Financial KIBS vs. Manufacturing.

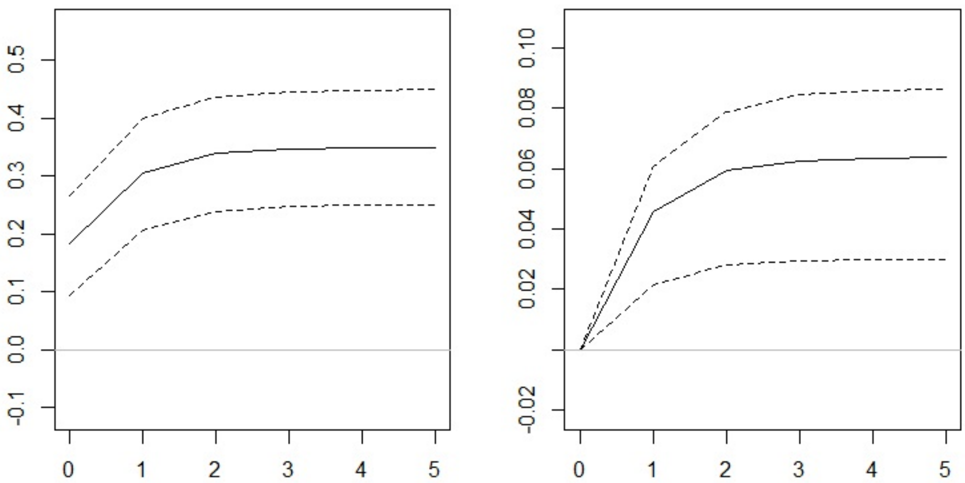



Model 6: Non-financial KIBS vs. Manufacturing.

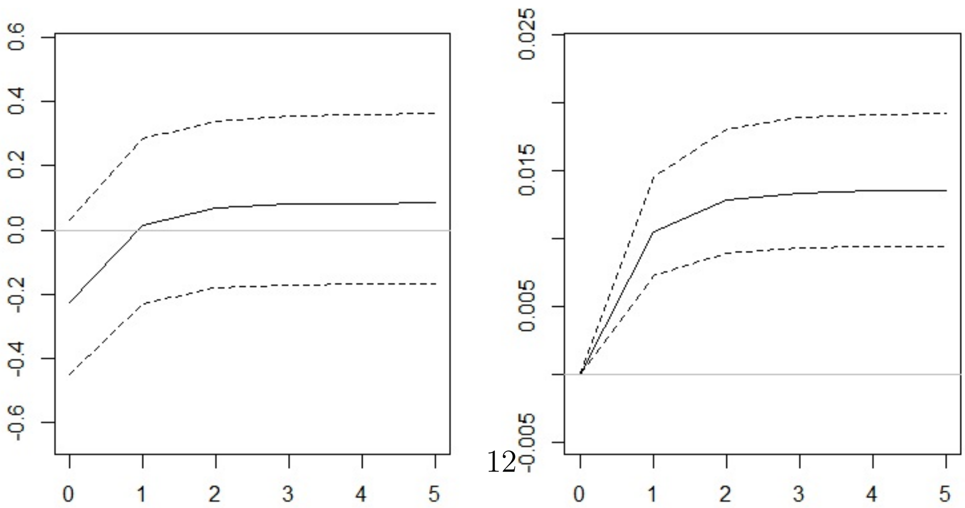
**Figure A3:** **Cumulative impulse response functions. Left: KIBS growth response to a unit shock on the growth in other service sectors. Right: Other service sectors response to a unit shock on KIBS growth.** **The dashed lines delimit the 68% confidence intervals.**




Model 7: All KIBS vs. other services.




Model 8: Financial KIBS vs. other services.




Model 9: Non-financial KIBS vs. other services.

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