Interdependencies of U.S. Manufacturing Sectoral TFP's: A Spatial VAR Approach

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Abstract

This paper examines sectoral interdependencies which is a key empirical premise to models that shun aggregate shocks as a source of business fluctuations. It investigates the joint evolution of sectoral U.S. manufacturing total factor productivity (TFP) using a semi-parametric spatial vector autoregressive framework. In this approach the interrelationship between sectors is a function on the "economic distance" between them. This distance is computed either from factor input shares or from input-output tables. It is found that sectoral TFP growth rates move independently from each other and that there is little evidence of complementarities or spillovers across sectors.

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1 Introduction

The leading theories of economic fluctuations (the RBC and New Keynesian models) invariably require large, persistent, *aggregate* shocks in order to generate realistic business cycles. Yet, research so far has produced scant evidence of the existence or empirical relevance of such shocks (see Cochrane [13] or Rotemberg and Woodford [35] for early references). A more recent variation of this critique was initiated by the work of Galí [21], and Basu, Fernald and Kimball [4] who claim that identified aggregate supply shocks do not have good business cycle properties.

The failure to identify suitable aggregate shocks has led to a renewal of interest in alternative sources of economic fluctuations. Following the suggestion of Long and Plosser [29] several researchers have investigated whether and under what conditions small idiosyncratic shocks that operate at the sectoral or firm level may not cancel out in the aggregate but build up to produce aggregate effects. Such amplification may arise from the interconnectedness of sectors. For instance, idiosyncratic shocks may exhibit a high degree of synchronization due, for example, to Marshallian externalities (Neusser [31] and Aghion and Howitt [2] and the literature cited therein) or to spillovers (see, for example, the discussion in Shea [36] and Francis [19]). Or, as Horvath [25] and [26] shows, independent sectoral shocks may induce large aggregate fluctuations when trade among sectors is characterized by a lack of substitutability in each sector's inputs. His estimates suggest that more than half of aggregate variability can be attributed to idiosyncratic shocks (see also Horvath and Verbrugge [27] and Shea [36]). A third possibility is provided by the "statistical" or "stochastic" aggregation approach. This approach relies on the insight that aggregation over independent but heterogenous AR or ARMA processes leads to an aggregate process with much higher persistence than its individual components (see Granger [22], Lewbel [28], Peseran [32], and Zaffaroni [40] among others).[1] Abadir and Talmain [1] show the viability of this approach by analyzing analytically a version of the standard monopolistically competitive RBC model.

In this paper I investigate the degree of sectoral interconnectedness in U.S. manufacturing total factor productivities (TFP). In particular, I study the joint evolution of growth rates of sectoral TFP's based on the NBER-CES Manufacturing Industry Database compiled by Bartelsman, Becker, and Gray [3]. This data provides a panel of TFP growth rates from 1958 to 1996 for the manufacturing sector, disaggregated at the four digit-level. Given the large number of sectors (458) it is not feasible to use standard econometric methods to estimate a fully interconnected model, that is, a model which allows each sector to interact with each and every other sector. It is therefore necessary to impose some structure.

One way to deal with this issue is through the use of dynamic factors models. The approach was initially proposed by Quah and Sargent [34], but has been generalized and successfully pushed forward in a series of papers by Forni and Reichlin [17] and [18], Forni, Hallin, Lippi, and Reichlin [15] and [16] (see also Peseran [33]). Although dynamic factor models are very efficient in summarizing and representing the statistical properties of the data, they are not so helpful when it comes to an economic explanation because the unobserved factors have no immediate interpretation as regards content. The paper therefore pursues an alternative route which relies on the semi-parametric spatial vector autoregressive (SVAR) model introduced

[1] Another possibility is that the distribution of idiosyncratic shocks may be fat-tailed so that their average will not disappear even for a large number of shocks (see Gabaix [20] for details).

by Chen and Conley [9]. In this model, the effect a sector has on another sector depends on the "economic distance" between them. Although there is no naturally given distance between sectors, plausible distances can be constructed from input factor shares or from input-output tables. Conley and Dupor [14] have already successfully applied this approach to U.S. productivity data using the latter.

While Conley and Dupor [14] and this paper share the same objective, they differ in several significant ways. First, I do not restrict the analysis to contemporaneous correlations, but I also allow for autocorrelation and lagged effects across sectors. This is important not only from a modelling perspective, but also because multisectoral models require some persistence in their idiosyncratic shocks to account for the observed high persistence in aggregate output. Second, I analyze TFP data at a four-digit disaggregation level instead of only a two-digit level. This increases the number of sectors from 20 to 458, making the restrictions imposed by the SVAR tighter. Third, the specifications I employ allow for the influence of some exogenous aggregate variables in order to account for cyclical variation in capacity utilization. In particular, I introduce federal defence expenditures and oil prices as additional variables. These variables are recommended by Hall [23] and [24] in a similar context and are also used as instruments by Conley and Dupor [14]. Fourth, I compute TFP's from gross output instead of value added, as suggested by Basu and Fernald [5], to mitigate mismeasurement problems. And finally, I quantify the importance of Marshallian externalities between sectors directly by estimating the coefficients of capital intensities in a spatial autoregressive regression model.[2]

[2]Neusser [31] shows how such a specification can be explicitly derived from a Long-Plosser model with Marshallian externalities.

The main finding of this paper is that sectoral TFP growth rates evolve more or less independently from each other. This result contrasts with the one reported by Conley and Dupor [14] who support the notion of sectoral complementarities. The difference can only partly be attributed to the more general specification investigated here, but seems to be an artefact of the specification of the contemporaneous spacial correlation function whose coefficients are estimated to lie on or near the boundary of the admissible parameter space.

The paper is organized as follows. Section 2 discusses two specifications and presents a brief description of the nonparametric spatial approach proposed by Chen and Conley in [9]. Section 3 treats the construction of economic distances. Section 4 presents the empirical results. Finally, section 5 concludes the paper.

2 Specification and Estimation Strategy

The paper aims at understanding the evolution of TFP growth rates in U.S. manufacturing over time and across sectors. Denote by Y_{it} the growth rate of TFP of sector i, $i = 1, \ldots, N$, in period t, $t = 1, \ldots, T$. Each sector i is associated in each period t with a location represented by a point s_{it} in the k-dimensional space $\mathbb{R}^k$. The distance between two sectors i and j in period t, denoted by $D_t(i, j)$, is then defined as the Euclidean distance between s_{it} and s_{jt}, i.e. $D_t(i, j) = \|s_{it} - s_{jt}\|$ where $\|.\|$ denotes the Euclidean distance. The distances are such that $D_t(i, j) = 0$ if and only if $i = j$. This imposes a limit on the level of disaggregation as the location s_{it} must characterize each sector in an unambiguous way. Moreover, the distances have common support $[0, d_{max}]$ with $d_{max} < \infty$. For technical reasons which will become clear in section 2.3, I restrict myself to the case $k = 3$. In this general formulation, the locations of sectors are allowed to move over time to represent structural or technological changes, their evolution is, however, assumed to be independent of the rest of the system. This rules out the possibility that the sectoral composition of the economy is itself related to technological growth.

2.1 Spatial Vector Autoregressive Model (SVARX)

I investigate two specifications. The first one is the spatial vector autoregressive model (SVARX) initially proposed by Chen and Conley [9], extended to allow for aggregate exogenous explanatory variables. This model represents the N-dimensional stationary stochastic process $\{Y_t\} = \{(Y_{1t}, \ldots, Y_{Nt})'\}$ as a first order vector autoregressive model:

$$Y_{it} = c_i + \phi_{ii} Y_{i,t-1} + \sum_{\substack{j=1 \\ j \neq i}}^{N} \phi_{ij} Y_{j,t-1} + \theta_i X_t^{(a)} + Z_{it}, \quad i = 1, \ldots, N, \tag{2.1}$$

where c_i is a sector specific constant. The idiosyncratic or sectoral shocks $\{Z_{it}\}$ are such that, for each fixed i, $Z_{it} \sim IID(0, \sigma_i^2)$ with $0 < \sigma_i^2 < \infty$ and with $\mathrm{E} Z_{it} Z_{js} = 0$ for $i \neq j$ and $t \neq s$. The only relation between the sectoral shocks is through their contemporaneous covariances $\mathrm{E} Z_{it} Z_{jt}$ whose structure is discussed in section 2.3. The specification also allows for aggregate explanatory variables $X_t^{(a)}$ which should capture aggregate demand or supply shocks (e.g. oil shocks).

As the cross section dimension N is larger than T, in my case much larger than T, there are not enough degrees of freedom to estimate the coefficients of the VAR model (2.1) freely by standard methods. Thus some a priori restrictions have to be imposed on the coefficients ϕ_{ij}. Following Chen and Conley [9], I assume that the coefficients ϕ_{ij} are a smooth function of the distance between the two sectors i and j:

$$\phi_{ij} = g\left(D_t(i,j)\right). \tag{2.2}$$

The function $g : [0, d_{max}] \rightarrow \mathbb{R}$ is assumed to be time-invariant. More importantly, the specification assumes that the function g is identical across sectors which imposes a severe symmetry restriction. Note that in the specification (2.1) the own autoregressive coefficient ϕ_{ii} is left unrestricted.

Denoting by D_t the matrix $\left(D_t(i,j)\right)_{i,j}$, the spatial vector autoregressive (SVARX) model can be written in matrix notation as follows:

$$Y_t = c + \Phi Y_{t-1} + \Theta X_t^{(a)} + Z_t \tag{2.3}$$

where $Z_t = (Z_{1t}, \ldots, Z_{Nt})'$, $c = (c_1, \ldots, c_N)'$ and $\Theta = (\theta_1, \ldots, \theta_N)'$ and where

$$\Phi = \Phi(D_t) = \begin{pmatrix} \phi_{11} & g\left(D_t(1,2)\right) & \cdots & g\left(D_t(1,N)\right) \\ g\left(D_t(2,1)\right) & \phi_{22} & \cdots & g\left(D_t(2,N)\right) \\ \vdots & \vdots & \ddots & \vdots \\ g\left(D_t(N,1)\right) & g\left(D_t(N,2)\right) & \cdots & \phi_{NN} \end{pmatrix}. \tag{2.4}$$

As the econometric theory is up to now only developed for a stationary environment, I assume that the spectral radius of $\Phi(D_t)$ is strictly smaller than one and that $\{X_t^{(a)}\}$ is a stationary process. The N-dimensional sequence of random variables $\{Z_t\}$ is supposed to be i.i.d. with mean zero and contemporaneous covariance matrix $\Sigma = \mathrm{E}\left(Z_t Z_t'\right)$.

In the course of the application additional restrictions may be imposed on $g(.)$. For example, the effect of sector j on sector i may be assumed to decrease with $D_t(i,j)$. How this can be implemented is discussed in section 2.4.

2.2 Autoregressive Spatial Regression (ARSX)

The second specification is derived from a theoretical model proposed by Neusser [31]. This model transforms the well-known multisectoral Long-

Plosser model (see Long and Plosser [29]) into an endogenous growth model by allowing for Marshallian externalities in capital accumulation across sectors. It is shown that TFPs then depend on capital intensities such that the externality of sector j on sector i is captured by the corresponding coefficient in a regression of TFP in sector i on the capital intensities of all other sectors. Other explanations for the interdependencies across sector are discussed in Shea [36].

Denoting the growth rates of capital intensities by X_{it}, I consider the specification

$$Y_{it} = c_i + \phi_{ii} Y_{i,t-1} + \sum_{j=1}^{N} \beta_{ij} X_{jt} + \theta_i X_t^{(a)} + Z_{it}. \qquad (2.5)$$

In matrix notation this model, labelled autoregressive spatial regression (ARSX), can be written as:

$$Y_t = c + \Phi Y_{t-1} + B X_t + \Theta X_t^{(a)} + Z_t \qquad (2.6)$$

where $\Phi = \mathrm{diag}(\phi_{11}, \ldots, \phi_{NN})$ and $B = (\beta_{ij})_{i,j}$. As $\{Y_t\}$ has to be stationary, it is assumed that $|\phi_{ii}| < 1$ for all i, $i = 1, \ldots, N$ and that $\{X_t^{(a)}\}$ is a stationary process. As before, the N-dimensional sequence of random variables $\{Z_t\}$ is supposed to be i.i.d. with mean zero and contemporaneous covariance matrix $\Sigma = \mathrm{E}\left(Z_t' Z_t\right)$.

For the same reason as before, an unrestricted estimation of this model is not feasible by standard methods without some a priori restriction on B. Again I pursue the strategy of modelling β_{ij} as a time-invariant function $g(.)$ of $D_t(i,j)$:

$$B = B(D_t) = \begin{pmatrix} \beta_{11} & g\left(D_t(1,2)\right) & \cdots & g\left(D_t(1,N)\right) \\ g\left(D_t(2,1)\right) & \beta_{22} & \cdots & g\left(D_t(2,N)\right) \\ \vdots & \vdots & \ddots & \vdots \\ g\left(D_t(N,1)\right) & g\left(D_t(N,2)\right) & \cdots & \beta_{NN} \end{pmatrix}. \qquad (2.7)$$

As in the previous specification, the own effect β_{ii} and the own autoregressive effect ϕ_{ii} are estimated freely.

2.3 Specification of the Error Term

In both the SVAR and the ARSX specification the error term $\{Z\}$ is assumed to be an i.i.d. mean zero stochastic process with contemporaneous covariance matrix Σ. Because sectorial TFP growth rates may affect each other also within the period which in our case is a year, it is worth to investigate the structure of the covariance matrix Σ in more detail. Conley and Dupor [14], for example, just concentrate on this aspect of interaction across sectors and do not consider interactions working through lagged TFPs or capital intensities.

In particular, I assume that the covariances between sectoral shocks also depend in a systematic way on the distances between sectors. This introduces an additional problem: one has to guarantee that the covariance matrix implied by the relation of covariances across sectors leads to a genuine covariance matrix, i.e. a matrix which is symmetric and positive definite. Such a restriction is usually hard to impose on the optimization problem underlying the estimation. I therefore followed the strategy of Chen and Conley [9].[3]

For any given $t \in \mathbb{Z}$, consider $\{Z_t(s)\}$ as a stochastic process indexed by $s \in \mathbb{R}^k$. Such a process is called a random field because the index set is multidimensional. Clearly, we have $Z_{it} = Z_t(s_{it})$. The random field is assumed to have zero mean and to be homogenous and isotropic. This means that, for any given $t \in \mathbb{Z}$, the covariance function $\gamma(s_1, s_2) = \mathrm{E}\left(Z_t(s_1)Z_t(s_2)\right)$ has the following two properties:

[3] Peseran [33] provides an interesting alternative which specifies the residuals, here the idiosyncratic shocks, to have a multifactor structure.

(i) $\gamma(s_1, s_2) = \gamma(s_2 - s_1)$ for all $s_1, s_2 \in \mathbb{R}^k$;

(ii) $\gamma(s_1, s_2) = \gamma(\tau)$ where $\tau = \|s_2 - s_1\|$ for all $s_1, s_2 \in \mathbb{R}^k$.

The first property, called homogeneity, is analogous to the definition of stationarity in the standard case of stochastic processes indexed by time. It says that the covariances between to random variables $Z_(s_1)$ and $Z_t(s_2)$ depends only on the difference between s_2 and s_1. The second property, called isotropy, is more restrictive as it states that the covariance depends only on the distance between s_2 and s_1 and not on its direction.

Yaglom [39, 348-353] shows that the covariance function $\gamma(\tau)$, $\tau = \|s_1 - s_2\|$, of homogenous and isotropic random fields on $\mathbb{R}^k$ has the representation:

$$\gamma(\tau) = 2^{(k-2)/2}\,\Gamma\left(\frac{k}{2}\right) \int_0^\infty \frac{J_{(k-2)/2}(x\tau)}{(x\tau)^{(k-2)/2}}\, d\Psi(x) \tag{2.8}$$

where $\Psi(x)$ is a bounded nondecreasing function on $[0, \infty)$ and where $J_{(k-2)/2}(x\tau)$ is a Bessel function of the first kind. The Bessel function $J_\lambda(x)$ is defined on $(0, \infty)$ for $\lambda \in \mathbb{R}$, $\lambda \neq -1, -2, \cdots$, as follows

$$J_\lambda(x) = \sum_{\nu=0}^{\infty} \frac{(-1)^\nu}{\nu!\;\Gamma(\nu + \lambda + 1)} \left(\frac{x}{2}\right)^{2\nu+\lambda}.$$

This expression greatly simplifies if $\lambda = 1/2$ or, equivalently, if $k = 3$:

$$J_{1/2}(x) = \sqrt{\frac{2}{\pi x}}\, \sin x.$$

The covariance function (2.8) then becomes:

$$\gamma(\tau) = \int_0^\infty \frac{\sin(x\tau)}{x\tau}\, d\Psi(x) \tag{2.9}$$

Because the computational burden simplifies a lot in this case, I will assume in the empirical application that $k = 3$. In the degenerate case where $\Psi(x) = x$, the covariance function becomes $\gamma(\tau) = (\pi/2)\tau^{-1}$.

Every bounded nondecreasing function $\Psi(.)$ induces through equation (2.8) a genuine covariance function of a homogenous and isotropic random field (see Yaglom [39, 353]). This implies that for every bounded nondecreasing function $\Psi(.)$

$$\Sigma = \Sigma\left(D_t\right) = \begin{pmatrix} \sigma_1^2 & \gamma\left(D_t(1,2)\right) & \dots & \gamma\left(D_t(1,N)\right) \\ \gamma\left(D_t(2,1)\right) & \sigma_2^2 & \dots & \gamma\left(D_t(2,N)\right) \\ \vdots & \vdots & \ddots & \vdots \\ \gamma\left(D_t(N,1)\right) & \gamma\left(D_t(N,2)\right) & \dots & \sigma_N^2 \end{pmatrix} \tag{2.10}$$

is a proper covariance matrix for any distance matrix D_t, i.e. $\Sigma\left(D_t\right)$ is symmetric and positive definite.

2.4 Specification of g and γ

The estimation of the unknown functions g and γ proceeds in a semiparametric way using the method of sieves (see Chen and Shen [10] for a general discussion of the method). This approach uses a sequence of a parametric family to approximate the unknown functions. Following again Chen and Conley [9], a cardinal B-spline sieve is used. The cardinal B-spline of order m, $N_m(.)$, $m = 1, 2, \dots$, is defined as

$$N_m(x) = \frac{1}{(m-1)!} \sum_{n=0}^{m} (-1)^n \binom{m}{n} \left[\max\{0, x-n\}\right]^{m-1}. \tag{2.11}$$

Thus the function $N_m(.)$ consists of piecewise polynomials of highest degree $m-1$. The pieces are tied together at the knots $\mathbb{Z}$. The resulting function N_m is thus $m-1$ times continuously differentiable in the interior of $\mathbb{R}-\mathbb{Z}$ and only $m-2$ times continuously differentiable at the knots $\mathbb{Z}$. The support of N_m is $[0, m]$ implying that $N_m \in \mathrm{L}^2(\mathbb{R})$. For $m = 1$, N_1 is just the characteristic function of $[0, 1)$. While the definition (2.11) is explicit, the cardinal B-splines can also be defined recursively using the convolution operation $*$:

$$N_m(x) = (N_{m-1} * N_1)(x) = \int_0^1 N_{m-1}(x-t)\,dt, \qquad m \geq 2.$$

From this recursion several important properties of the cardinal B-splines can be derived which make them extremely attractive analytically as well as computationally.[4] In particular, it can be shown that for any given $m \geq 2$, the two-parametric family of functions

$$\varphi_{d,n}(x) = N_m(2^d x - n), \qquad d, n \in \mathbb{Z}$$

forms a Riesz basis of square-integrable real functions $\mathrm{L}^2(\mathbb{R})$.[5] Thus the functions $g(.)$ and $\Psi(.)$ can be arbitrarily well approximated by making m and/or d sufficiently large:

$$g(x) \approx \sum_{n=-\infty}^{\infty} \alpha_n N_m(2^d x - n) \qquad (2.12)$$

$$\Psi(x) \approx \sum_{n=-\infty}^{\infty} \psi_n N_m(2^d x - n). \qquad (2.13)$$

Note, because the cardinal B-splines have compact support the infinite sums are effectively only sums over a finite number of terms. Increasing the dilation 2^d by increasing d, more terms enter the summation and the approximation improves. One advantage of using cardinal B-splines is that monotonicity requirements are easily implemented. This is important because $\Psi(.)$ must be a nondecreasing function in order for $\gamma(.)$ to be a genuine covariance function. This property can be imposed on the approximating function by constraining the coefficients to satisfy $\ldots \leq \psi_{n-1} \leq \psi_n \leq \psi_{n+1} \leq \ldots$.

[4] For a detailed treatment and their importance in wavelet analysis see, for example, Chui [12] and Strang and Nguyen [38].

[5] This means that the linear span of $\{\varphi_{d,n} : d, n \in \mathbb{Z}\}$ is dense in $\mathrm{L}^2(\mathbb{R})$ and satisfy some boundary conditions. See Chui [12] for details.

2.5 Estimation and Inference

Given a sample of size T for Y_t and X_t, $t = 1, \ldots, T$, and treating the starting value Y_0 as given, the estimation of both models proceeds in two steps. First, choose an order m_g of the polynomials and a number n_g of cardinal B-splines used in the approximation of g.[6] Next, insert the resulting approximate function (2.12) into model (2.3) or (2.6) and rearrange terms. This leads to a standard linear panel model with coefficients ϕ_{ij} replaced by $\alpha_1, \cdots, \alpha_{n_g}$. This panel model is estimated by weighted least squares such that the equation of each sector is weighted by the unconditional variance of Y_{it}.[7] In the case of the ARSX specification (2.6), the first estimation step proceeds analogously.

Using the residuals $\widehat{Z}_{it}$ from this first step and specifying the order m_Ψ and the number n_Ψ of cardinal B-splines used in the approximation of $\Psi(.)$ in (2.13), the second step minimizes the objective function:

$$\sum_{t=1}^{T} \left\{ \sum_{i}^{N} \left(\widehat{Z}_{it}^2 - \sigma_i^2 \right)^2 + \sum_{i,j,i \neq j} \left(\widehat{Z}_{it} \widehat{Z}_{jt} - \widetilde{\gamma}(D(i,j)) \right)^2 \right\} \rightarrow \min_{\substack{\sigma_i^2, i=1,\ldots,N \\ \psi_1 \leq \cdots \leq \psi_{n_\Psi}}} \tag{2.14}$$

where, using equation (2.9),

$$\widetilde{\gamma}(D(i,j)) = \sum_{n=1}^{n_\Psi} \psi_n \int_0^\infty \frac{sin(xD(i,j))}{xD(i,j)} \, dN_{m_\Psi}(2^d x - n).$$

Note that the minimization (2.14) gives the conventional estimator for σ_i^2, i.e $\widehat{\sigma}_i^2 = 1/T \sum_{t=1}^T \widehat{Z}_{it}^2$. Making the sieve finer at an appropriate rate as T goes to infinity, Chen and Conley [9] show the asymptotic normality of the estimator and derive the corresponding asymptotic covariances. As the expressions for the covariances are cumbersome and difficult to estimate, I

[6] This implicitly fixes the dilation parameter.

[7] In principle one could go one step further and do FGLS to improve efficiency. This is, however, not pursued here.

follow their suggestion and use a bootstrap procedure for inference treating the distances as fixed. The number of bootstrap replications is set to 200.

3 Data and Construction of Distances

The data come from the NBER-CES Manufacturing Industry Database compiled by Bartelsman, Becker, and Gray (See Bartelsman and Gray [3] for details). This database contains information on sales, factor inputs and their remuneration for 459 4-digit manufacturing sectors over the period 1958 through 1996.[8] In particular, it provides estimates of total factor productivity (TFP) growth for each sector based on five input factors (capital, production worker, non-production worker, non-energy material products, and energy). Thus as recommended by Basu and Fernald [5], TFP is computed using gross output rather than value added. In contrast to the analysis of Basu, Fernald and Kimball [4] my TFP measure is less sophisticated because it does not, in particular, correct for imperfect competition and variable capacity utilization. Some of these effects are, however, taken into account by allowing for aggregate regressors.

The Manufacturing Industry Database is actually also the database used by [17] and [18]. These studies rely not only on a different econometric approach but also used output growth rates, respectively labor productivity growth rates, as dependent variables instead of TFP's growth rates and covers a shorter time period.

The approach rests crucially on the specification of an appropriate distance between sectors. As there is a priori no natural candidate for such

[8] The data can be downloaded from http://www.nber.org/nberces/nbprod96.htm. I had to exclude the asbestos products industry because of the lack of data. The actual analysis thus covers only 458 sectors.

a distance, I will investigate two alternatives: a distance based on the five-factor input shares, and a distance based on the 1987 benchmark Input-Output table. These distances are denoted by D^{shares} and D^{IO}, respectively. Note that this preliminary investigation considers constant distances only and postpones time-varying distances for future research.

The first distance makes use of the input shares. As the database distinguishes between five different input factors, there corresponds to each sector i in each period t a five-dimensional location vector, s_{it}, whose elements correspond to the share of capital, non-production workers, production workers, non-energy material inputs, and energy, respectively. A boxplot of the sectoral shares averaged over time is represented in figure 1. The box and the line in the middle of the box represent the interquartile range and median of the data. This figure shows that there is quite a variation in the factor shares of the U.S. manufacturing sectors. The lower and the upper quartile of the shares of material input, for example, are around 0.4 and 0.55, respectively. The whole sample, however, covers data ranging from 0.15 up to almost 0.9. The interquartile range of the shares of attributed to capital is between 0.22 to 0.31 and corresponds therefore to the customary number of 0.3.

As explained in section 2.3, the dimension of the locations is set to three for computational reasons. The reduction from five to three dimensions is obtained by multidimensional scaling (see, for example, chapter 14 in [30]).[9] This reduction in dimension is achieved practically without loss in information: the quadratic goodness-of-fit measure is 0.999. The distance between sector i and j in period t, $D_t^{\text{shares}}(i, j)$, is then just the Euclidean distance calculated from these three dimensional vectors. As the shares can be com-

[9] It is clear that the dimension of the space of share vectors, s_{it}, is actually only four because their values add up to one.

puted for each year, we obtain a time-varying distance matrix D_t^{shares}. As I do not consider time-varying distance at this stage of the investigation, I work with the averaged factor shares to construct a time-invariant distance matrix D^{shares}. The corresponding locations in $\mathbb{R}^3$ are shown in figure 2. It shows that the locations exhibit quite a variation with very labor intensive industries like "meat packing" to rather capital intensive ones, like "toilet preparations".

The second distance matrix is obtained from the benchmark Input-Output table for the year 1987 published by the Bureau of Economic Analysis (BEA) in [7] and [8]. Here I take for each SIC industry, "the input coefficients for the commodities and for the total value added that an industry directly requires to produce a dollar of output". The commodity space is disaggregated into 521 commodities which leads to a 522-dimensional vector (including the corresponding value added as the 522-th entry) for each sector.[10] The reduction from dimension 522 to dimension three is again achieved by multidimensional scaling. This reduction is quite efficient as the quadratic goodness-of-fit measure is 0.756. Using again the Euclidian metric, the so obtained distance matrix is denoted by D^{IO}. As I just consider the 1987 Input-Output table the distance measure is without time dimension.

[10] Using the correspondence table between the IO industry classification and the SIC classification, it was , however, not possible to associate unambiguously to each manufacturing sector one such input requirement vector. Some sectors had to be aggregated which reduced the number of cross-section observations from 459 to 362.

4 Empirical Results

4.1 Results from the SVAR model

As a preliminary descriptive statistic, figure 3 plots a kernel density estimate of the first order autocorrelation coefficients of the TFP growth rates.[11] Although most the mass of the density is concentrated around zero, meaning that most of the autocorrelation coefficients are probably not significantly different from zero, an important fraction of sectors seem to show significant positive or negative serial correlation in their TFP growth rates. Indeed 35 out of 458 sectors have a first order autocorrelation coefficient larger in absolute value than twice the rule of thumb standard deviation of 0.162. Thus it is necessary to choose a specification which leaves the own coefficient of lagged TFP growth unrestricted.

In the course of the investigation it turned out that in all specifications 6 cardinal B-splines of order 4 (i.e. $n_g = 6, m_g = 4$) are sufficient to approximate the g-function accurately and that 6 cardinal B-splines of order 3 (i.e. $n_\Psi = 6, m_\Psi = 3$) are sufficient to approximate the γ-function accurately.[12] I have experimented with other specifications as well: choosing more or or less B-splines and/or choosing higher or lower orders for the B-splines. In none of these variations did the results change in a significant way. I will therefore concentrate my discussion on the results from this specification.

[11] This and all subsequent densities are estimated by an adaptive normal kernel estimator where the bandwidth is chosen according to Silverman's rule of thumb (see [37, 100–110]).

[12] The estimation uses the MATLAB code provided by Conley on the web page http://gsbwww.uchicago.edu/fac/timothy.conley/research/. Several routines have, however, been extensively revised to improve efficiency in terms of speed and accuracy and to incorporate additional features.

Consider first the results from the SVAR model where distances are computed from factor shares. The estimated coefficients are reported in column 2 of table 1. The average of the ϕ_{ii} coefficients is practically zero and therefore confirms the results from the first order autocorrelation coefficients. A plot of the kernel density in the lower left part of figure 4, however, reveals again that an important fraction of sectors have significant coefficients. The coefficients $\widehat{\alpha}_i,\ i = 1, \ldots, 6$, of the function approximating g are rather small and typically not significant. As these coefficients have no immediate economic interpretation, an examination of the implied g-function is more revealing. In this and all subsequent figures the functions are plotted for distances ranging between 0 and 0.50. This interval accounts for more than 95 percent of all distances and comprises therefore the most relevant part of the function.

As shown in upper left part of figure 4 the g-function is almost flat and practically not significantly different from the zero-function. Except for very small distances (smaller than 0.1) a small, possibly significant, positive effect can be discerned. Thus the TFP growth rate in a particular sector is influenced very little by past TFP developments in other sectors, suggesting no or very small interdependence across sectors. The bottom part of column 2 in table 1 suggests a much more pronounced positive spatial interdependence between covariances. All ψ_i coefficients are positive and highly significant. However, their values are the same up to three decimal places which suggests that in the minimization (2.14) the constraint $\psi_1 \leq \cdots \leq \psi_{n_\Psi}$ has become binding, implying $\psi_1 = \cdots = \psi_{n_\Psi}$. The spatial contemporaneous correlation between the errors terms induced by the estimated γ-function must therefore be interpreted with care. The implied shape of the γ-function as plotted in upper right part of figure 4 shows the expected pattern: the covariances of the residuals between sectors are monotonically decreasing with distance.

The function decreases from values significantly above 2 for small distances to values below 1.0 for large distances. The kernel density estimate for $\widehat{\sigma}_i^2$ plotted in the lower right part of figure 4 shows that most estimated variances lie between 0 and 60. However, the large right hand side tail indicates that there are some outlier sectors which have extremely large variances. Although based on a different data set, my results confirm by and large those from Chen and Conley (see in particular [9, 75]) and Conley and Dupor in [14]. However, I do not want to interpret this as strong evidence of complementarities across sectors given that the estimates are very close to or on the boundary of the admissible parameters space.

If distances are computed from the input-output table, the results do not change. The results are plotted in figure 5. The estimated g-function is again practically zero. Note that in this case the effect for small distances is not positive but negative. The estimated γ-function has the same shape and magnitude as before except that it looks slightly less smooth. Also the kernel density estimates of $\hat{\phi}_{ii}$ and $\hat{\sigma}_i^2$, $i = 1, \cdots, N$, are similar. Note, however, that the hump at -0.18 is more pronounced in this case and suggests that there may be actually two types of sectors.

As the evolution of TFP growth rates may depend on the overall state of the economy, I have included an aggregate variable as an additional explanatory variable to control for the possibility of common shocks. This extension seems especially warranted because the TFP growth rates were computed without taking varying capital utilization into account.[13] I have examined two such variables: the growth rate of real defense spending and the growth rate of world oil prices. Both of these variables have been suggested by

[13] The importance of including aggregate variables has been documented in this context by Francis [19].

Hall [24] because they do not respond to the state of the business cycle and can therefore be taken as exogenous. In table 1 I just report in columns 3 and 5 the results for defense expenditures, the results for oil prices are similar. Comparing these results with those obtained previously, one can see no difference. Thus the conclusions reached earlier remain.

As the US economy has undergone large structural changes during the sample period, I estimated the model for several subperiods. It turned out that the results remained robust against changes in the estimation period.

4.2 TFP growth rates and capital intensities: results from the ARSX model

This section investigates the relation between TFP growth rates and growth rates of capital intensities as represented by specification given in equation (2.6). This specification, called ARSX model, can be rationalized by a model suggested by Neusser [31]. This model extends the Long-Plosser model [29] by allowing for Marshallian externalities across sectors. According to this model, the effects of capital intensities on TFP gives the magnitude of externalities across sectors. In principle one can think that capital intensities influence TFP growth rates within the period or with a lag. I have investigated both possibilities. As the results are not sensitive with respect to this, I report in table 2 just the estimates from the specification with contemporaneous capital intensities. Like in the case of the SVAR model, the results do not depend on the order and number of the B-splines. I have therefore chosen again 6 cardinal B-splines of order 4 and 3 to approximate the g and γ function, respectively.

The results are reported in table 2. Consider first in column 2 the estimates when distances are computed from factor shares and when no aggregate variable is included. As before hardly any coefficient related to the g-function is significant. This is also true for the averaged effects of capital intensities growth rates on TFP growth rates. Interestingly, the own capital intensity has a significant negative average coefficient (see coefficient $\hat{\beta}_{ii}$ and the kernel density plot in the lower left panel of figure 6). The resulting g-function is plotted in the upper left panel of figure 6. It shows a negative and, in some regions, significant effect of capital intensities on TFP.

The coefficients related to the γ-function are as before significantly positive. They are, however, again nearly constant so that the same caveat as before applies. The γ-function is plotted in upper right panel of figure 6. This function is positive everywhere and sloping downward from 1.2 to 0.4. This suggests that the correlation of residuals is considerably lower than for the SVAR model.

Adding the growth rate of real defense spending as an aggregate regressor does not change the nature of the results. The coefficients reported in column 3 of table 2 are almost identical. Very similar conclusions are also reached when distances are computed from the input-output table rather than from factor shares as can be seen from columns 4 and 5 of table 2 and from figure 7. Finally, the results remain robust against changes in the estimation period.

4.3 Sector-Specific Results

Instead of estimating the SVAR, respectively the ARSX model for all sectors simultaneously, thereby imposing the implausible restriction that the g-function is the same for all sectors, one can estimate equation (2.1) and (2.5) on a sector-by-sector basis. The disadvantage of this strategy is that an overwhelming number of estimated g-functions is obtained which makes it often hard to discern sensible regularities. Moreover, even when using only five B-splines instead of six, the number of regressors is relatively large (e.g. seven or eight, respectively) so that the empirical results may become rather unprecise and spurious. Despite these caveats it is instructive to examine the results for a selection of sectors. In the following, I report the results for some sectors which were most influenced by other sectors.

Consider first the case of the SVAR model as given by equation (2.1). As the previous results did not depend on the inclusion of aggregate explanatory variables nor on the way in which distances are computed, I just report in figure 8 the results for the case with distances computed from factor shares and without an aggregate explanatory variable. The plot of the g-functions for four sectors ("flour and other grain mill products", "malt", "men and boy's neck wear", and "concrete block and brick") show that several shapes of g-functions can be obtained. Given the large variety of shapes, it is no surprise that the SVAR model with the g-function restricted to be the same across sector implies a rather flat and, in most instances, insignificant g-function. Another way to look at the results is to ask which are the sectors which have highest positive influence on a given sector. In the case of "flour and grain mill products" these are the sectors which are at a distance between 0.15 and 0.20 away. However, at this distance there are sectors from practically all industries so that no particular pattern emerges. Similar results are obtained also for the other three sectors. Finally, the γ-function, not displayed in figure 8, has a shape similar to those before (see in particular figure 4), although it is shifted downward due to the higher fit obtained from this much less restrictive model.

Repeating the exercise with the ARSX model given by equation (2.5), results in more intuitively plausible patterns. Figure 9 plots the estimated g-functions for some sectors with high interdependence ("industrial gases", “toilet preparations”, “semivitreous table and kitchenware”, “ammunition, except small arms”, and “computer storage devices”). TFP growth in the sector “industrial gases”, for example, is mostly influenced by the growth in capital intensities in other sectors of the chemical industry like “pharmaceutical preparations”, “toilet preparations” or “alkalies and chlorine”. These sectors are 0.108, 0.126 and 0.170 away. Even more pronounced indications of externalities can be found for the sector “computer storage devices”. The TFP development in this sector is closely related to the growth rate of capital intensities of many other sectors in the “industrial machinery and equipment” industry, and in particular in the “computer and office equipment” industry. These sectors are not only very close, but also produce large external effects as can be inferred from the corresponding g-function. The γ-function, not displayed, is again very similar in shape to the restrictive ARSX model (compare figure 7), but with smaller values due to the much less restrictive specification.

5 Conclusion

The results presented in this paper suggest that sectoral TFP growth rates evolve basically independently from each other. With the exception of some specific industries, the growth rate of TFP in a particular sector is influenced by neither lagged TFP growth rates in other sectors nor by the growth rates of capital intensities in other sectors. This finding seems to suggest the absence of sectoral complementarities or spill-overs, a mechanism that is important for non-aggregate shocks to generate business cycles. Within the spatial approach pursued in this paper, this result is robust against alternative specifications of distances between sectors, the number and order of the approximating B-spline polynomials, the inclusion of aggregate variables, and the estimation method (OLS versus WLS).

This independence result also implies that the widely documented comovements of sectoral measures of economic activity cannot be attributed to complementarities among sectoral technology shocks (see Christiano and Fitzgerals [11]). Instead must either resort to some form of aggregate shock with all the caveats alluded to in the introduction or to some internal mechanism, like the input-output structure as in Horvath [26] or costs of reallocating resources across sectors as in Boldrin, Christiano, and Fisher [6].

Of course, as every empirical study, several possible caveats remain. First and perhaps most importantly, the TFP measure used in this paper has not been cleansed from elements such as variable factor utilization, imperfect competition, or increasing returns (see Basu, Fernald, and Kimball [4]). Second, the variables may be subject to serious measurement errors. Third, the distances examined in this paper may not proxy well true technological proximity between sectors. In addition, if one acknowledges that the economy is subject to structural change, non-constant distances should be explored systematically[14]. Fourth, the symmetry restriction imposed may probably be too restrictive. Pending the investigation of these issues, one may still nonetheless conclude that models that rely on non-aggregate shocks and complementarities across sectors have yet to find supporting empirical evidence.

[14] Conley and Dupor [14] make a first attempt in this direction by interpolating consecutive input-output tables.

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Table 1: Coefficients of the SVAR model

coefficients	factor shares		input-output	
	no aggregate variable	defense expenditures	no aggregate variable	defense expenditures
average $\widehat{\phi}_{ii}$	-0.044 (0.153)	-0.057 (0.154)	-0.050 (0.151)	-0.064 (0.152)
$\widehat{\alpha}_1$	0.033 (0.024)	0.034 (0.025)	-0.025 (0.027)	-0.022 (0.028)
$\widehat{\alpha}_2$	-0.003 (0.004)	-0.003 (0.004)	0.004 (0.004)	0.004 (0.004)
$\widehat{\alpha}_3$	-0.001 (0.002)	0.001 (0.002)	-0.001 (0.003)	-0.001 (0.003)
$\widehat{\alpha}_4$	0.001 (0.004)	0.001 (0.004)	-0.004 (0.005)	-0.004 (0.004)
$\widehat{\alpha}_5$	-0.016 (0.015)	-0.015 (0.016)	0.119 (0.028)	0.118 (0.027)
$\widehat{\alpha}_6$	0.003 (0.201)	0.005 (0.220)	-0.882 (0.167)	-0.869 (0.158)
$\widehat{\psi}_2$	4.750 (0.835)	4.724 (0.924)	4.073 (0.786)	4.059 (0.902)
$\widehat{\psi}_3$	4.750 (0.824)	4.724 (0.919)	4.073 (0.719)	4.059 (0.856)
$\widehat{\psi}_4$	4.750 (0.799)	4.724 (0.900)	4.078 (0.685)	4.059 (0.834)
$\widehat{\psi}_5$	4.750 (0.799)	4.724 (0.900)	4.564 (0.732)	4.534 (0.863)
$\widehat{\psi}_6$	4.750 (0.774)	4.724 (0.850)	4.564 (0.762)	4.534 (0.893)
average $\widehat{\sigma}_i^2$	34.464 (10.826)	33.614 (10.479)	33.828 (10.634)	33.017 (10.243)

bootstrapped standard deviations in parenthesis with 200 replications

estimation by weighted least squares with six cubic, respectively quartic cardinal B-splines for g and γ

Table 2: Coefficients of the ARSX model with contemporaneous effects

coefficients	factor shares		input-output	
	no aggregate variable	defense expenditures	no aggregate variable	defense expenditures
average $\widehat{\phi}_{ii}$	-0.090 (0.140)	-0.101 (0.140)	-0.101 (0.139)	-0.112 (0.140)
average $\hat{\beta}_{ii}$	-0.193 (0.097)	-0.191 (0.098)	-0.195 (0.099)	-0.193 (0.100)
$\widehat{\alpha}_1$	-0.016 (0.011)	-0.017 (0.011)	-0.027 (0.013)	-0.030 (0.012)
$\widehat{\alpha}_2$	0.002 (0.002)	0.003 (0.002)	0.002 (0.002)	0.003 (0.002)
$\widehat{\alpha}_3$	-0.002 (0.001)	-0.002 (0.001)	-0.001 (0.001)	-0.001 (0.001)
$\widehat{\alpha}_4$	0.002 (0.002)	0.003 (0.002)	-0.000 (0.003)	-0.000 (0.003)
$\widehat{\alpha}_5$	-0.010 (0.009)	-0.015 (0.009)	0.026 (0.019)	0.026 (0.021)
$\widehat{\alpha}_6$	0.342 (0.150)	0.346 (0.152)	-0.109 (0.209)	-0.145 (0.194)
$\widehat{\psi}_2$	2.055 (0.356)	2.022 (0.068)	1.941 (0.375)	1.921 (0.060)
$\widehat{\psi}_3$	2.055 (0.349)	2.022 (0.064)	1.941 (0.361)	1.921 (0.054)
$\widehat{\psi}_4$	2.055 (0.339)	2.022 (0.064)	1.941 (0.358)	1.921 (0.055)
$\widehat{\psi}_5$	2.055 (0.339)	2.022 (0.064)	2.322 (0.335)	2.290 (0.058)
$\widehat{\psi}_6$	2.400 (0.360)	2.393 (0.064)	2.529 (0.416)	2.447 (0.069)
average $\widehat{\sigma}_i^2$	29.536 (8.851)	28.870 (1.637)	28.719 (8.527)	28.160 (1.506)

bootstrapped standard deviations in parenthesis with 200 replications

estimation by weighted least squares with six cubic, respectively quartic, cardinal B-splines for g and γ

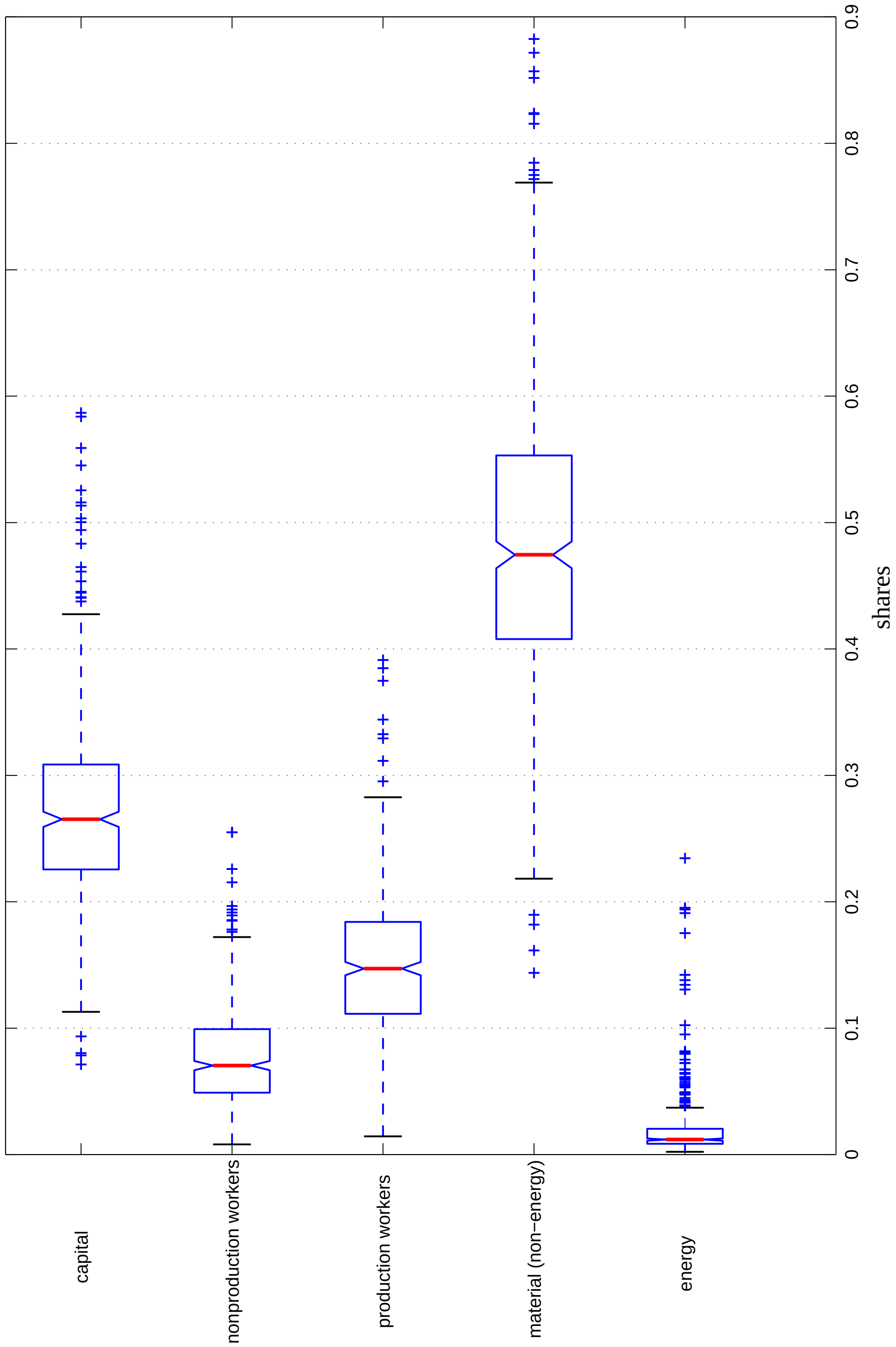

Figure 1: Boxplot of averaged shares of factor inputs

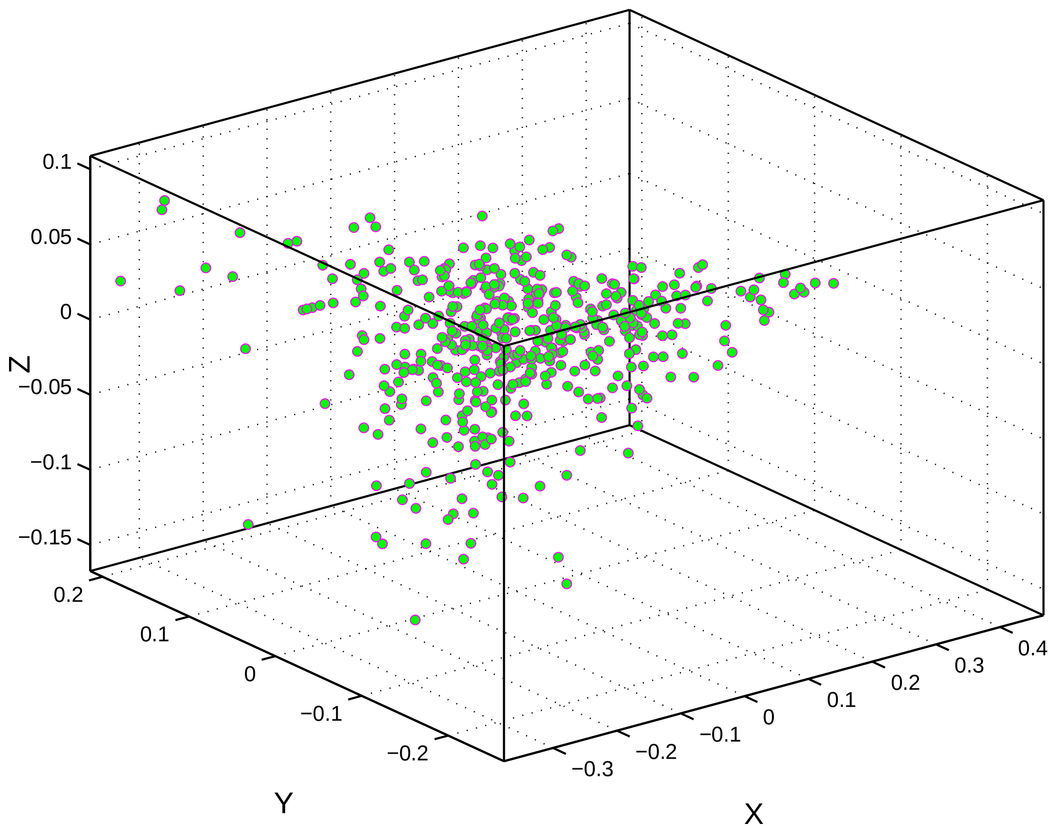

Figure 2: 3-D sector coordinates computed from average factor shares

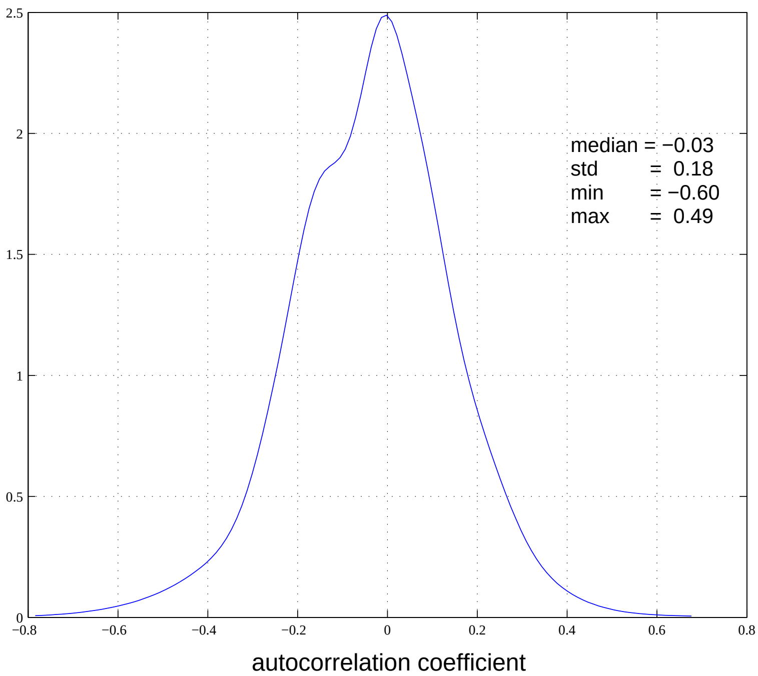

Figure 3: kernel density estimate of first order autocorrelation coefficients of TFP growth rates

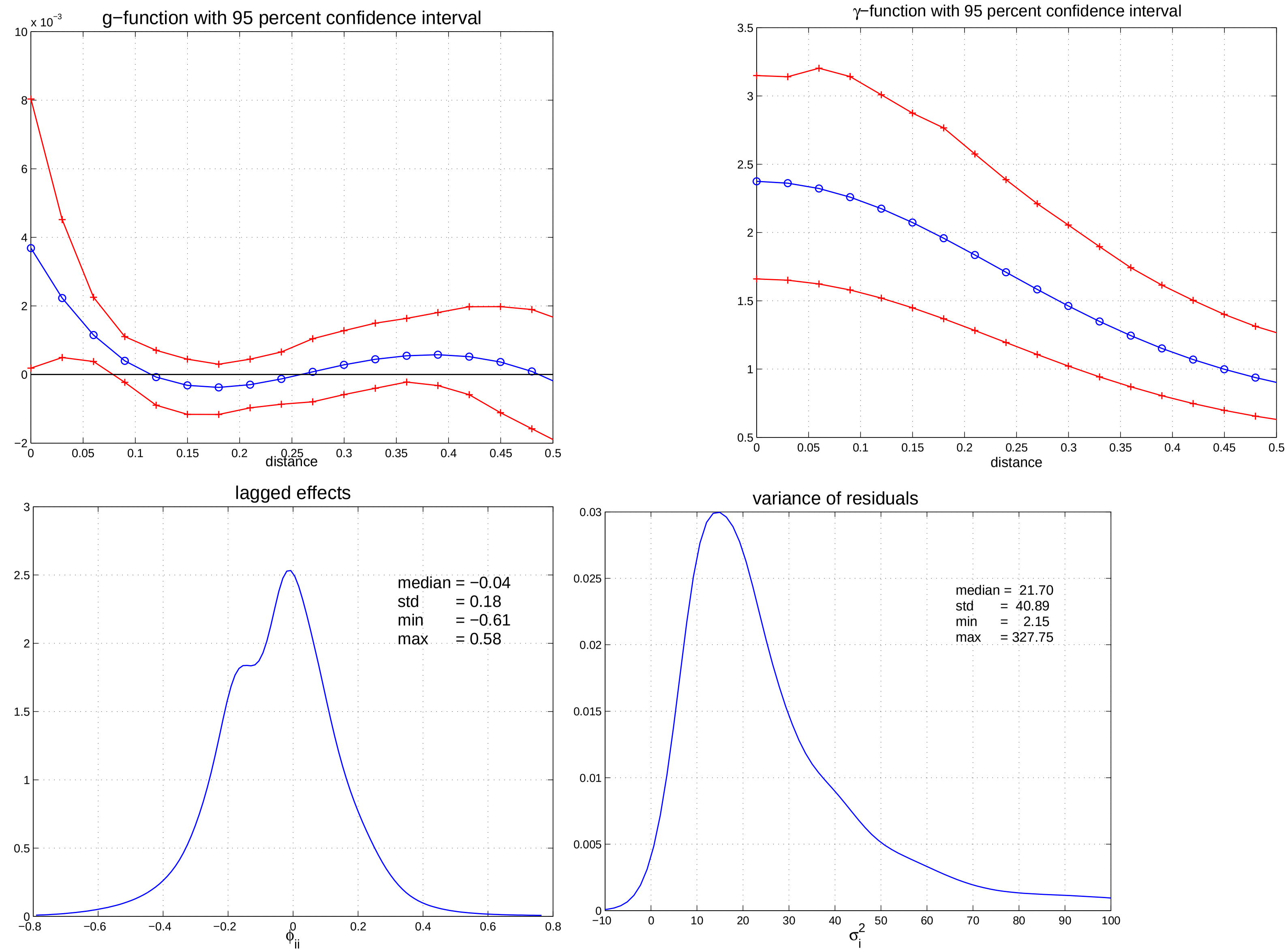

Figure 4: Results of SVAR model with distances from factor shares

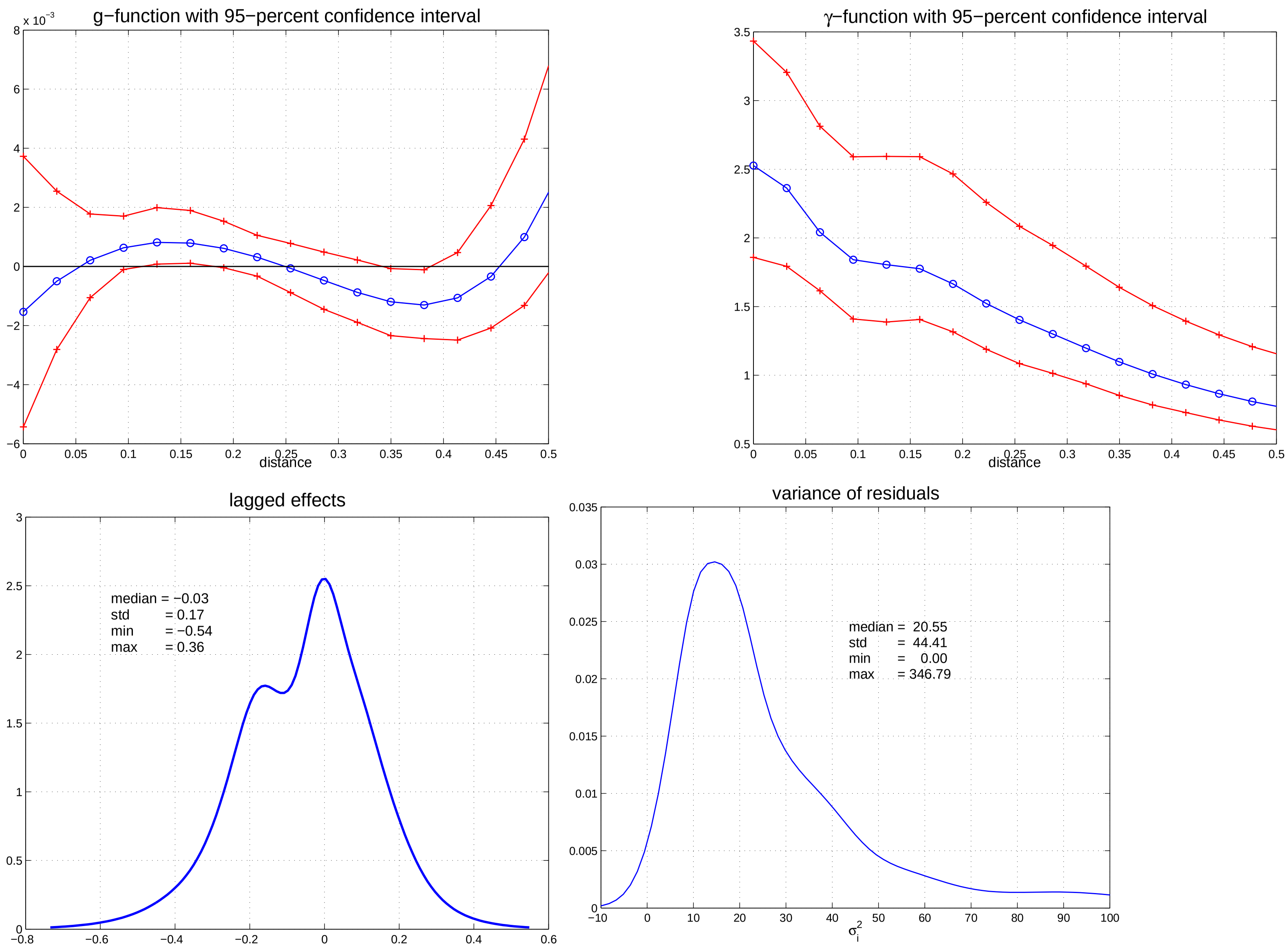

Figure 5: SVAR model with distances from IO-table

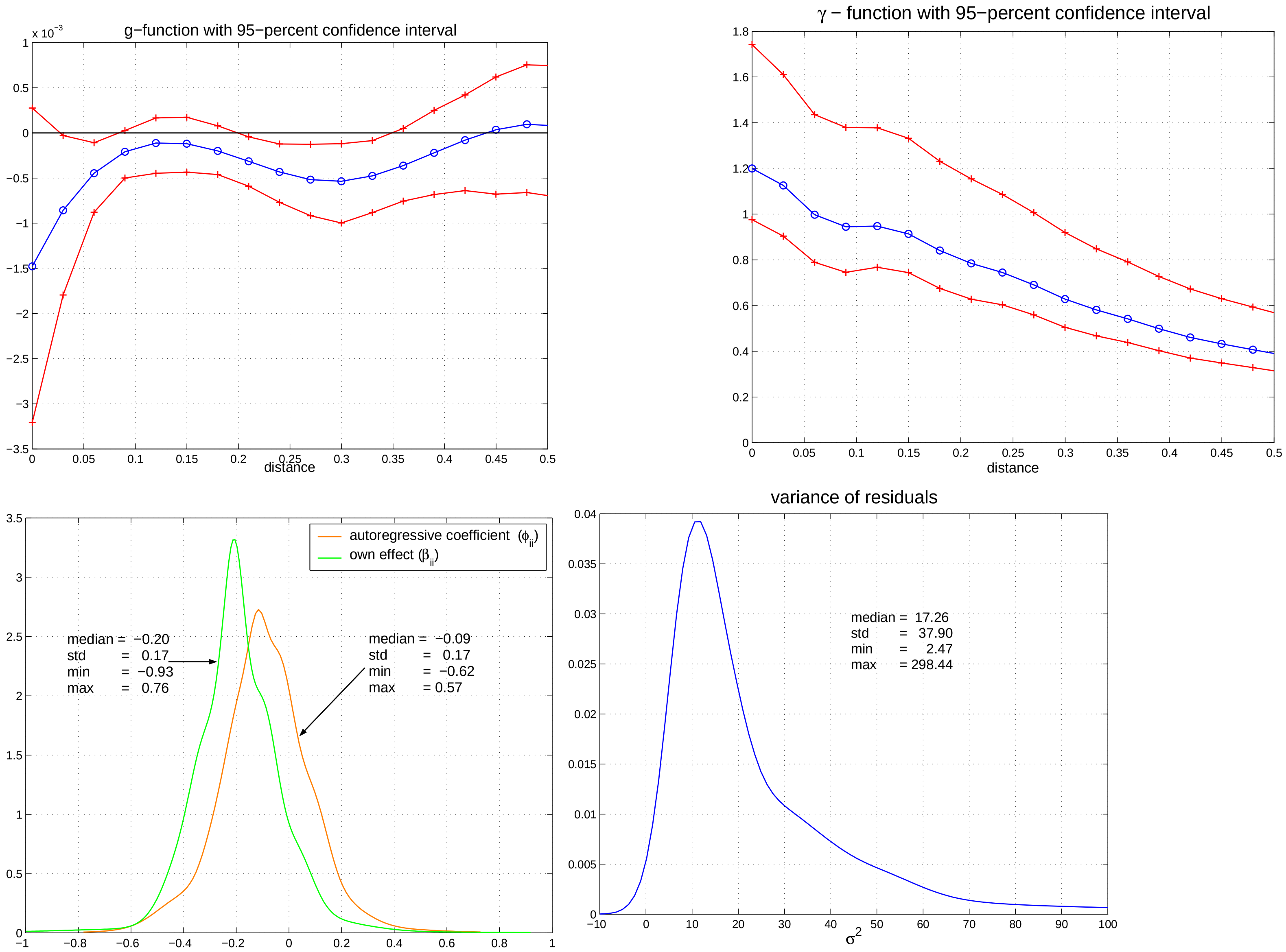

Figure 6: Influence of capital intensities: results of the ARSX model with distances from factor shares

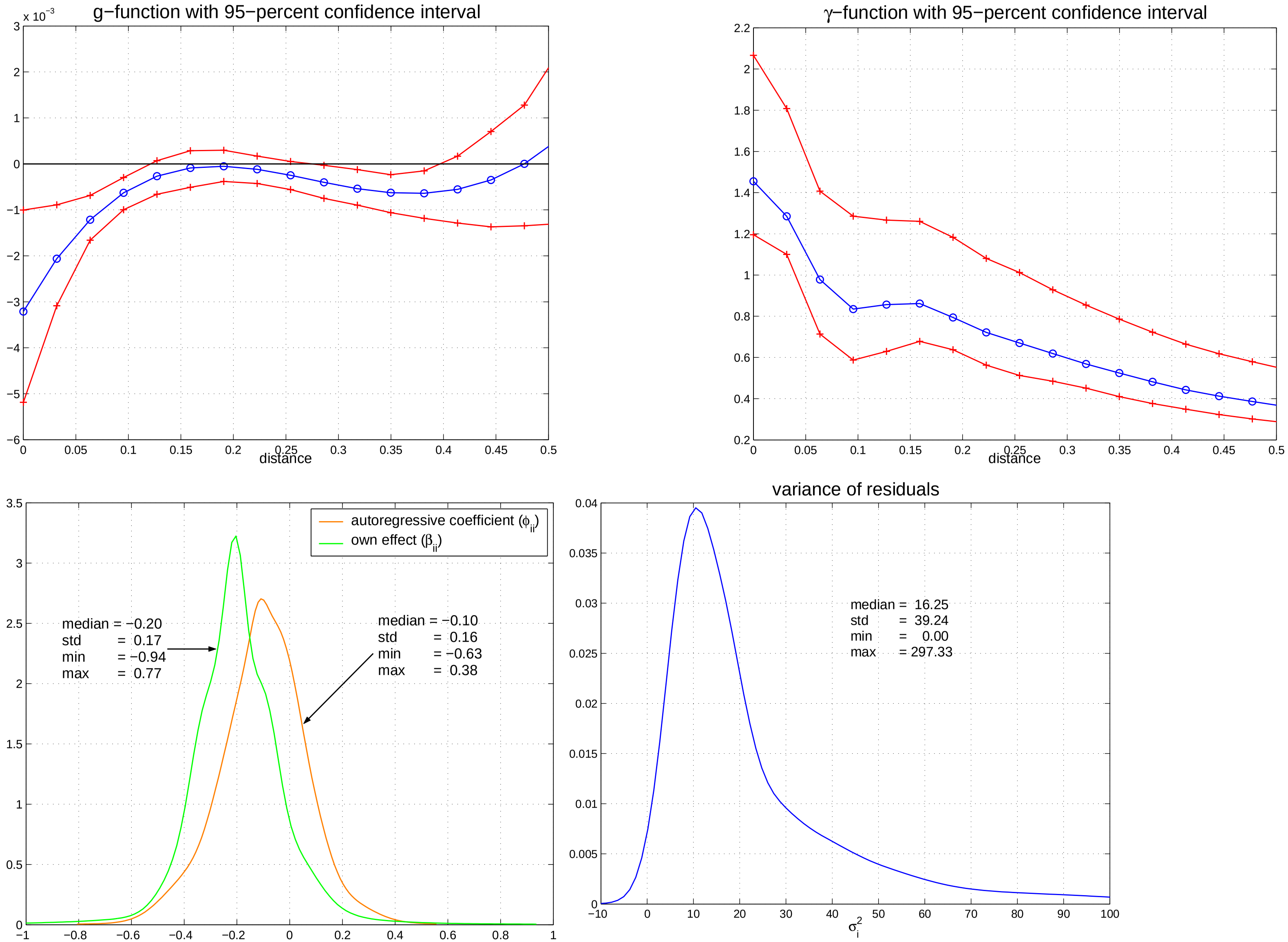

Figure 7: Influence of capital intensities: results of the ARSX model with distances from IO-table

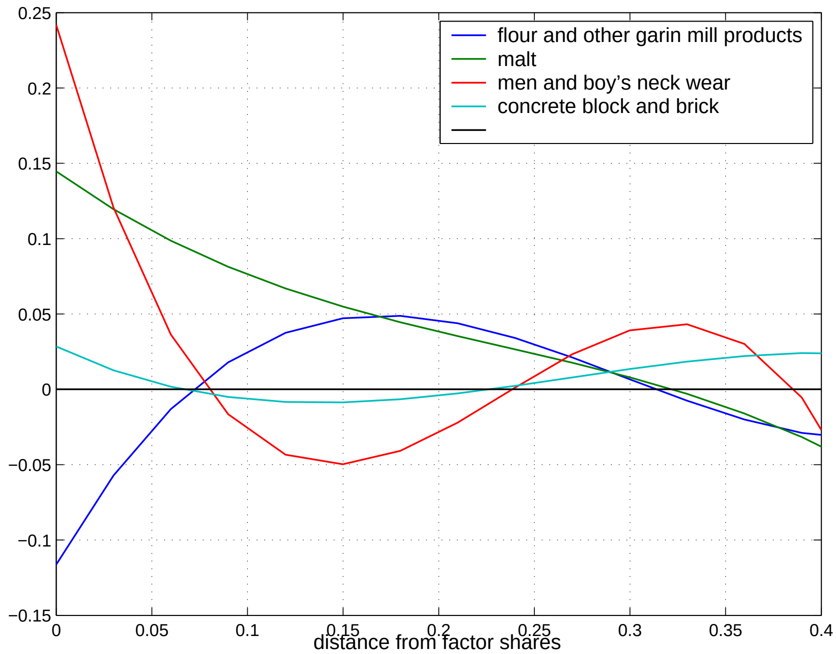

Figure 8: Some g-functions for the sector-by-sector SVAR model

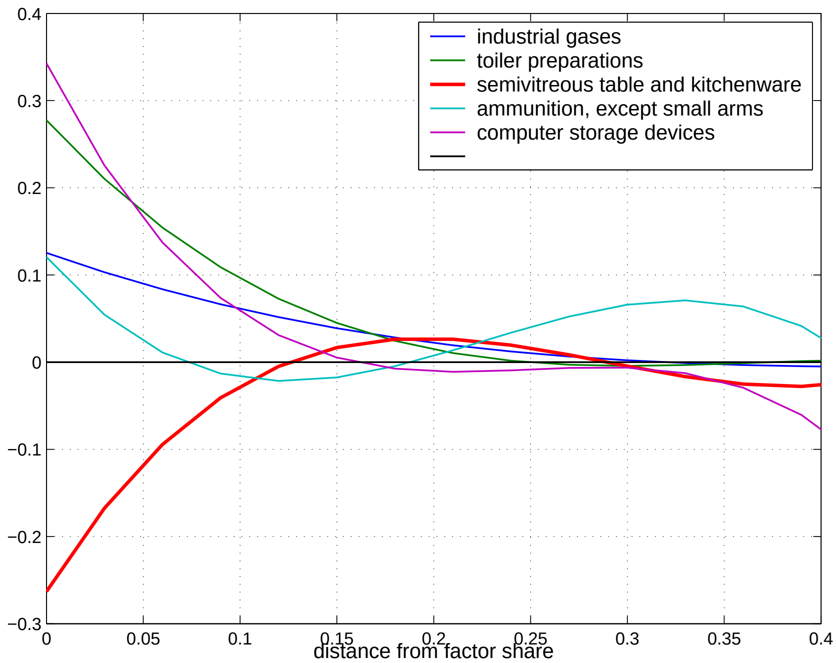

Figure 9: Some g-functions for the sector-by-sector ARSX model