Key activities under joint Input-Output, Econometric and DEA approaches: the case of Turkey.

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Abstract

Recent contributions in input-output analysis (ten Raa and Rueda-Cantuche, 2007) show that input-output multipliers can alternatively be computed by using firms' supply and use micro data with econometric techniques, thus keeping main statistical properties of consistency and unbiasedness. In particular, the analysis has been carried out only for backward multipliers but can be easily extended to forward multipliers and with supply and use tables instead of micro data. Standard input-output analysis generally takes the Leontief and the Ghosh inverses to provides these two impact measures as starting points to identify key sectors by means of several indicators, for which there is no general agreement on the most appropriate. In order to circumvent this controversial issue, this paper contributes to the literature by adding a DEA approach to the extended econometric input-output framework with the aim of identifying key activities (and key sectors) in terms of backward and forward potential increase of outputs and employment. Hence, our approach is independent of the quite often criticized methods for identifying key sectors while it fulfills several desirable statistical properties. The empirical work is carried out for the Turkish economy.

Keywords: Stochastic input-output analysis, input-output multipliers, key sectors, DEA, input-output linkages, supply and use tables, composite indicators.

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1. Introduction

Interindustrial linkage analysis, which is used to examine interdependence in production structures, has a long history in the field of input-output analysis by examining the interdependence in production structures. One of the main uses of input and output accounts is the estimation of multiplier effects, such as the employment and output effects of one-unit increases in alternative final demand components. These two impact measures are used as starting points to identify key sectors by means of several indicators, for which there is no general agreement on the most appropriate.

The multipliers are given by the Leontief or the Ghosh inverses of the input–output coefficients matrix. The practice of interrelating accounts and input–output multipliers can be decomposed into three stages. Firstly, the System of National Accounts – SNA (UN, 1993) provides guidelines to construct the so-called use and make tables, *U* and *V*, which display, respectively, inputs and outputs of industries in terms of commodities. The off-diagonal elements of the make table depicts secondary outputs. Secondly, the SNA reviews several technology assumptions in order to obtain an input–output coefficients matrix, A. And thirdly, the calculation of the Leontief inversion as $(I - A)^{-1}$ would be the last stage.

The theory of input–output coefficients addresses different models for the construction of input-output coefficients matrices. However, results are partial and problems such as negatives would remain. Basically, input–output coefficients measure the amount of inputs requirements needed per unit of output, thus bringing about a nonlinear operation involving the inverse of the make table.

The stochastic input–output literature focuses on the analysis of transmission of errors under the Leontief inverse. Here the problem is also nonlinearity, but not this time related to the presence of secondary products. The Young's theorem yields that the expectation of the Leontief inverse exceeds the Leontief inverse of expected input–output coefficients, which follows that, assuming unbiasedness of input-output coefficients, the standard Leontief inverse would underestimate its true value. Simonovits (1975) and Kop Jansen (1994) extended this result, albeit under rather restrictive assumptions such as independency of technical coefficients. Dietzenbacher (1995) and Roland-Holst (1989) found more overestimation than underestimation. Ten

Raa and Rueda-Cantuche (2007) econometrically estimated unbiased and consistent backward multipliers on the basis of micro data and overcoming problems associated to the construction of technical coefficients matrix A and to the transmission of errors in the Leontief inverse. Moreover, they confirmed Dietzenbacher (1995) and Roland-Holst (1989) findings about overestimated multipliers.

However, on the one hand the availability of data at the level of establishments is usually restricted and needs at least financing. Besides, this information needs to be carefully used in terms of filling data gaps, imputing values to non-observed establishments, and having domestic values and transactions at basic prices (once deducting net commodity taxes, non-deductible value added tax (VAT) and distribution margins). But on the other hand, there is an increasing availability of U and V matrices over the Internet for free and ready-to-be-used. Following the approach initiated by ten Raa and Rueda-Cantuche (2007), this paper makes three interrelated contributions to the literature. Firstly, the accuracy of multipliers is neither measured from stochastic assumptions on the input–output coefficients nor from the variability of the underlying input and output statistics across establishments. Instead, we use aggregated products and industries data (given by official use and make tables). Secondly, we extend the calculation of input-output impact effects to forward multipliers by means of linear econometrics (as in ten Raa and Rueda-Cantuche, 2007). The derived results will be tested against those computed traditionally from U and V matrices published by Turkstat, under the commodity technology assumption (actually recommended by UN, 1993). And thirdly, we introduce data envelopment analysis (DEA) in order to detect key-activities and thus overcome all controversial issues regarding composite indicators.

The paper is structured as follows: the next section explains in detail the econometrics behind the estimation of unbiased and consistent linkages and presents the empirical results for the Turkish economy. The third section discusses several problems of traditional linkages analysis and provides a new approach on the basis of DEA to identify key activities using the results obtained in the previous section. Finally, the last section concludes with a summary of the most prominent findings.

2. Review of approaches to calculate input-output linkages

2.1. Traditional Approach

Sectoral linkages are essential to understand the structure of an economy, which is in turn important to formulate policy actions. Linkage indexes are often constructed and used as criteria for the identification of 'key' sectors. In the literature, backward and forward linkages (BL and FL, respectively) are widely accepted concepts for describing inter-sectoral relationships; yet, how to measure them is still controversial. In hope of discerning the differences among major linkage measures in the literature and understanding their controversies, we assess them from different perspectives.

2.1.1. Backward linkages (BL):

In general, direct purchases and sales coefficients are the basis for, respectively, BL and FL measures (Chenery & Watanabe, 1958). However, they only capture direct effects (DBL and DFL, respectively) thus leaving indirect impacts out of the scheme. A number of linkage measures are suggested to capture both direct and indirect linkages but a consensus is yet to be reached (Jones, 1976; Hewings, 1982; Cella, 1984; Sonis *et al.*, 1995; and Miller & Lahr, 2001; and Sánchez-Chóliz & Duarte, 2003, for an attempt to provide generalized linkage indicators).

For simplicity, we chose the Rasmussen's 'power of dispersion' (Rasmussen, 1956) as the standard BL measure to capture both direct and indirect linkages. In sum, they represent the column sums of the Leontief inverse. Although it is not free of controversy, it is perhaps the least controversial linkage measure since their results are quite similar to those provided by more sophisticated approaches (Iráizoz, 2006) such as with hypothetical extraction methods (HEM) or with the Cai & Leung's approach (Cai & Leung, 2004). Hence,

$$BL_{\bullet j} = \sum_i \alpha_{ij} \qquad RBL_{\bullet j} = \frac{\sum_i \alpha_{ij}}{\frac{1}{n}\sum_{ij} \alpha_{ij}} = \frac{BL_{\bullet j}}{\frac{1}{n}\sum_j BL_{\bullet j}} \tag{1}$$

where $BL_{.j}$ is the backward linkage of sector j (the sum of the elements of the j-th column of the Leontief inverse); α_{ij} are the elements of the Leontief inverse; and $RBL_{.j}$ the normalized backward multiplier of the *j-th* sector, expressed in relative terms to its average.

2.1.2. Forward linkages (FL):

The row sums of the Leontief inverse are a traditional but somewhat controversial FL measure. They are interpreted as the impact on sector *i*'s output of simultaneous unit changes in each and every sector's final demands. This is objected by Jones (1976) for the unrealistic 'simultaneous unit changes' assumption and by Beyers (1976, p. 231) for having 'calculated forward linkages on the basis of the strength of backward linkages'. Despite the controversies, this FL measure is widely supported by many authors (Alauddin, 1986; Haji, 1987; Hewings *et al.* 1989; Sonis *et al.* 2000, …). On the contrary, the row sums of the Ghosh inverse (Ghosh, 1958) are suggested to replace the Leontief's approach in estimating FL (Augustinovics, 1970; Beyers, 1976; and Jones, 1976). Despite being endorsed by many authors either conceptually or empirically (Bulmer-Thomas, 1982; Dhawan & Saxena, 1992; Dietzenbacher, 2002; Miller & Blair, 1985; Oosterhaven, 1988; Poot, 1991; among others), the Ghosh inverse row sums (as a FL measure) are criticized by a few hard to neglect authors (e.g. Cella, 1984), who are mainly concerned about the 'implausibility' of the Ghosh model (Oosterhaven, 1988, 1989).

Nevertheless, the row sums of the Ghosh inverse are widely used as a standard FL measure to capture both direct and indirect linkages. Although it is not free of controversy, it is perhaps the least controversial forward linkage measure. On experimental work (Iráizoz, 2006) Ghoshian measures present again similar results to those provided by HEM or Cai & Leung (2004). Then, we will use the Rasmussen's coefficients under the Ghoshian transformation:

$$FL_{i\bullet} = \sum_j \beta_{ij} \qquad RFL_{i\bullet} = \frac{\sum_j \beta_{ij}}{\frac{1}{n}\sum_{ij} \beta_{ij}} = \frac{FL_{i\bullet}}{\frac{1}{n}\sum_i FL_{i\bullet}} \tag{2}$$

where $FL_{i\cdot}$ stands for the forward linkage of sector *i*, this is the sum of the elements of the row *i* of the Ghosh Inverse; β_{ij} are the elements of the Ghosh Inverse and $RFL_{i.}$ the normalized forward multiplier of sector *i* expressed in terms of its average.

2.2. Econometric Approach

2.2.1. Backward linkages (BL):

Ten Raa and Rueda-Cantuche (2007) obtained linear, unbiased and consistent estimates of output and employment BLs (in the line of Rasmussen linkages) for the Andalusian economy using inputs and outputs data at the level of establishments (micro-data). It is as follows:

Output backward Linkages (BLP):

Let μ be a column vector of BLPs given by the column totals of the Leontief inverse:

$$\mu = e(I - A)^{-1} \tag{3}$$

where $e = (1,\ldots,1)$ is a unit row vector. If the commodity technology model is assumed to construct the technical coefficients, $A = UV^{-T}$, then equation (3) would yield:

$$\mu = e\left[I - UV^{-T}\right]^{-1} = eV^{T}V^{-T}\left[I - UV^{-T}\right]^{-1} = eV^{T}\left[\left(I - UV^{-T}\right)V^{T}\right]^{-1} = eV^{T}\left(V^{T} - U\right)^{-1} \tag{4}$$

and

$$eV^{T} = \mu\left(V^{T} - U\right) \tag{5}$$

where eV^T is a row vector of total outputs of *m* establishments (of order *m*) and μ, a row vector of output multipliers (of order *n*), *V* is a make matrix of order *m x n*, and *U* is a use matrix of order *n x m*.

If there are more industries (or number of establishments) than commodities (*m*>*n*), then the equations system (5) is overdetermined and an error term ε (row vector of *m* independent and normally random disturbance errors with zero mean and constant variance,) must be attached. Finally, the BLPs become into a regression coefficients vector, μ:

$$eV^{T} = \mu\left(V^{T} - U\right) + \varepsilon \tag{6}$$

Since our approach uses published supply and use tables *m x n* instead of micro data (ten Raa and Rueda Cantuche, 2007), we had to aggregate commodities in order to get enough degrees of freedom in the regression. Hence, we used the simplified CPA classification for 60 products (m products).Notice that observations in the regression are now sectoral data rather than establishments inputs and outputs.

Backward linkages of employment (BLE):

Analogously, the same authors estimated BLEs. By assuming the commodity technology model, labour coefficients are determined by the following expression:

$$L = lV^T \tag{7}$$

where L represents a row vector of labour employment (of order m), l is a row vector of labour coefficients and V^T the transposed make matrix. Inflation by the Leontief inverse yields the BLEs (vector λ):

$$\lambda = l(I - A)^{-1} \tag{8}$$

The only difference with equation (3) is the replacement of the unit vector e by the row vector of labour coefficients l. BLEs (8) measure the employment generated by a one monetary unit increase in the final demand of a certain commodity. It is no workers per worker figure, but a kind of return-on-investment measure.

In traditional input–output analysis all matrices are square (m=n) and equation (8) implies the well-known commodity technology coefficients $A = U\left(V^T\right)^{-1}$ and $l = L\left(V^T\right)^{-1}$ (Kop Jansen and ten Raa, 1990). In this case, the BLEs (8) reduce to:

$$\lambda = L\left(V^T\right)^{-1}\left[I - U\left(V^T\right)^{-1}\right]^{-1} = L\left\{\left[I - U\left(V^T\right)^{-1}\right]V^T\right\}^{-1} = L\left(V^T - U\right)^{-1} \tag{9}$$

or

$$L = \lambda\left(V^T - U\right) \tag{10}$$

Analogously to the system of equations (10), if there are more industries than commodities $(m > n)$, then an error term must be added, ε, and BLEs become a vector of regression coefficients λ:

$$L = \lambda\left(V^T - U\right) + \varepsilon \tag{11}$$

In (11), L is a row vector of order m with labour, λ is a row vector of order n with employment multipliers, having V, U and ε, the same meanings as for BLPs.

It must be noted that m is the number of establishments or observations and that net outputs by commodities would therefore constitute the independent variables of the resulting model. Note that observations are sectoral official data instead of establishments data (as in ten Raa and Rueda-Cantuche, 2007).

2.2.2. Forward Linkages (FL):

The already presented approach for BL can be easily extended to the calculation of FLs, as it is shown below.

Forward Linkages of Production (FLP):

A vector of FLPs, η, is given by the row totals of the Ghosh inverse (B)

$$\eta^T = \left(I - B\right)^{-1} e^T \tag{12}$$

By assuming the commodity technology model, where $B = V^{-T}U$ the FLPs (12) are represented by:

$$\eta^T = \left[I - V^{-T}U\right]^{-1} e^T = \left[I - V^{-T}U\right]^{-1} V^{-T}V^T e^T = \left[V^T\left(I - V^{-T}U\right)\right]^{-1} V^T e^T = \left(V^T - U\right)V^T e^T \tag{13}$$

and

$$V^T e^T = \left(V^T - U\right)\eta^T \tag{14}$$

Analogously to the system of equations (5) but transposing the whole, it yields:

$$eV = \eta\left(V^T - U\right)^T \tag{15}$$

When there are fewer sectors than commodities $(m < n)$, this is, fewer independent variables (and consequently regression coefficients) than observations, these FLPs become regression coefficients. Then, the system of equations (15) is overdetermined and an error term ε must be attached. Net outputs would be considered again as exogenous variables.

$$eV = \eta\left(V^T - U\right)^T + \varepsilon \tag{16}$$

where eV is a row vector of total outputs of products (of order n) and η, a row vector of FLPs (of order m), having V, U and e the same meaning as for backward multipliers formulae. Next, we aggregate this time sectors to get simplified NACE Rev.1.1 classification A60 (60 sectors) and thus providing the regression with enough degrees of freedom. Note that, in FLs calculation, observations are now data on products data instead of data on sectors, which were used for BLs calculations.

Forward Linkages of Employment (FLE):

Under the commodity technology assumption, labour coefficients are determined by the following expression:

$$L = lV^T \quad L^T = V^T l^T \tag{17}$$

where L^T represents a column vector of employment (of order n), l^T is the column vector of labour coefficients and V^T the transposed make matrix. Inflation by the Ghosh inverse, $(I - B)^{-1}$, yields the FLEs vector (γ):

$$\gamma^T = (I - B)^{-1} l^T \tag{18}$$

FLEs (18) measure the employment generated by a monetary one-unit increase of the value added of a certain industry. In this case, the FLEs (18) reduce to:

$$\gamma^T = \left(I - \left(V^T\right)^{-1} U\right)^{-1} \left(V^T\right)^{-1} L^T = \left[V^T \left(I - \left(V^T\right)^{-1} U\right)\right]^{-1} L^T = \left(V^T - U\right)^{-1} L^T \tag{19}$$

or

$$L^T = \left(V^T - U\right)\gamma^T \tag{20}$$

Analogously to system of equations (14), but transposing the whole, the FLEs become a vector of regression coefficients, γ:

$$L = \gamma\left(V^T - U\right)^T \tag{21}$$

If there are more commodities than sectors $(m < n)$, the system of equations (21) is overdetermined and an error term (row vector of independent normally random disturbance errors with zero mean and constant variance, with order n) must be attached.

$$L = \gamma \left(V^T - U\right)^T + \varepsilon \tag{22}$$

where L is a row vector of order n (primary commodities produced by sectors) with labour employment and γ is a row vector of order m (sectors) with FLEs. So, the estimation of FLE becomes a matter of multiple linear regression analysis, with linear, unbiased and consistent estimations, as proposed by ten Raa and Rueda-Cantuche (2007) for BLs. Note that, again, observations are now product data instead of sectoral data, being used for BLs calculations.

3. Data for the empirical work

Ten Raa and Rueda-Cantuche, 2007 used firms' supply and use micro data with econometric techniques. The problem arises when micro-data (data at establishments' level) is not available easily or even inaccurate. Firstly, most of the times gathering a reliable database needs financing since it is not publicly available information. Secondly, this sort of information is previous to the filling of data gaps, the extrapolation of imputed values to non-observed establishments and the balancing procedures prior to the construction of supply and use matrices. Therefore, if data are not carefully prepared, multiple problems may arise. To circumvent these problems we use supply and use tables instead of micro data. Rectangular or square matrices fit in our approach since it starts with a previous aggregation process (either of products in the case of BLs or industries in the case of FLs) to get rectangular tables and thus enough degrees of freedom.

The empirical work is carried out for the Turkish economy, with supply and use tables for 1998 (97 industries/commodities) at basic prices expressed in millions of current Turkish Lire.

We have made estimations of linkages according to the A60 CPA (EC, 2002). However, the Turkish economy does not have some of the activities included in the A60 CPA (activities nº 12, 37, 99). On the other hand activities 67 and 90 had to be aggregated with activities 65 and 85, respectively. This ends with an analysis that has been performed for 55 activities, which gives the model 39 degrees of freedom to let stochastics work in order to get multipliers as regression coefficients.

Nevertheless, for comparison purposes, the linkages based on input–output traditional matrix manipulation (Table 2) were not constructed on the basis of the official A_{97x97} matrix published by TURKSTAT, but on a pure commodity technology basis for our aggregation to 55 sector/product, A_{55x55} (Table 1). This means that equations (3) and (7) were computed using published use and make tables and $A = UV^{-T}$. The same applies to FL respect to B matrix, computed as $B = V^{-T}U$.

Unfortunately, TURKSTAT has total annual full-time equivalent employment data, but without a sufficient breakdown by industries, especially A60. They started to ask enterprises 'paid hours worked' after 2002, but it has been not disseminated yet. For that reason, we finally had to skip the calculations of employment multipliers with the proposed methodology.

4. Unbiased and consistent Input-Output Linkages

4.1. Output backward linkages (BLP):

The BLP estimates are presented in Table 2. In comparison, the second column displays the multipliers based on the traditional approach under the commodity technology assumption. The model has been estimated for 55 commodities by means of ordinary least squares. The resulting R-squared is 0.9961, which is quite satisfactory. Due to the presence of certain forms of unknown heteroskedasticity, the White estimate (White, 1980) of the covariance matrix of estimated coefficients was used to provide consistent and robust standard errors. We do not find problems of autocorrelation (as expected in cross-sectional data) and multicollinearity do not plague our analysis. Only 7 out of the 1,485 (0.471380%) possible off-diagonal elements of the correlations matrix with 55 different explanatory variables were significant at a significance level of 5% being only two higher than 0.75. Eventually, 51 estimated BLPs are significant at the 95% confidence level. All remaining estimators are assumed to be zero (no impact) since the null hypothesis is accepted in each one of these cases. Negative values of multipliers are not significant either.

Three major contributions are provided by the results presented in Table 2:

a) As in ten Raa and Rueda-Cantuche (2007), in most cases, the Leontief inverse based multipliers overestimate the true values. Indeed, 48 out of 55 (87.27%) commodities have lower estimated BLPs than those calculated with the traditional approach, while only 6 (10.91%) have higher values. Moreover, the estimated average bias is higher for overestimated (5.16%) than for underestimated coefficients (0.12%). Our findings may contradict Simonovits' (1975) underestimation conclusions about the Leontief inverse, or rather better said, his restrictive assumptions, such as e.g. technical coefficients independency. Finally, our results firm up the conclusions of Dietzenbacher (1995), Roland-Holst (1989) and ten Raa and Rueda-Cantuche (2007).

b) Input–output estimates are unbiased and consistent, providing confidence intervals for BLPs. These intervals might be seen as a measure of the true estimates of multipliers accuracy. Notice that all multipliers derived from the traditional approach fell within the confidence intervals.

c) The estimated bias of BLPs is generally positively related with secondary production (Pearson correlation coefficient = 0.7). Commodities of which a large share is produced as secondary output have BLPs with larger estimated bias, as it was also found in ten Raa and Rueda-Cantuche (2007).

The Pearson and Spearman correlation coefficients between econometric and traditionally estimated multipliers are 0.782 and 0.935, respectively (both significant at a confidence level of 99%), which means that econometrical procedures arrive at coherent results when comparing with the traditional approach. Additionally, the top five positions in the ranking do not change, i.e. basic metals, Leather and leather products, electrical machinery and other apparatuses rubber and plastic products, and fabricated metal products, except machinery and equipment. Some macro checks have been carried out to test the robustness and coherence of the results by using equations (5) and (10) with our estimated input–output multipliers and the published net outputs matrix. Consequently, the estimated total output, which yields 90,883 thousand billions of Turkish Lires, is just 0.04% lower than published total productions (90,923 thousand billions).

4.1.2. Output forward linkages (FLP):

With the same number of observations as in the last section, the FLPs are presented in Table 2. The proposed model has been estimated for 55 industries by means of ordinary least squares and, with quite satisfactory goodness of fit, too (R-squared equals 0.968).

The White (1980) estimated covariance matrix of estimated regression coefficients was used to obtain consistent standard errors. The model is again free from serial correlation and multicollinearity issues. None of the 1,485 possible correlations was neither significant nor higher than 0.5 (in absolute value).This time, 51 estimated multipliers are significant at a 5% significance level (which does not mean that they were exactly the same industries as in BLP). There are not negative values.

FLPs provide similar results as BLPs:

a) Mostly, traditionally computed output multipliers overestimate rather than underestimate the true values of input-output multipliers. It is remarkable that 52 out of 55 (94.55%) FLP estimated multipliers are lower than those computed under the traditional approach, whilst only 2 (3.64%) commodities present higher FLP values. Again the estimated average bias is greater for overestimated coefficients (7.63%) than for underestimated figures (0.01%). Most of the traditional FLPs are overestimated and not underestimated, confirming the works of Dietzenbacher (1995), Roland-Holst (1989) and ten Raa and Rueda-Cantuche (2007).

b) FLPs are unbiased and consistent, having confidence intervals where 76.36% of the traditional estimated multipliers are within.

The Pearson and Spearman correlation coefficients between estimated and traditionally computed multipliers are 0.991 and 0.919, respectively, (both significant at a confidence level of 99%), which means that econometrical procedures arrives at coherent results when comparing with traditional procedures. Additionally, the top four positions in the ranking do not change (Crude petroleum and natural gas; services incidental to oil and gas extraction excluding surveying, Office machinery and computers, Research and development services and Metal ores).

Macro checks have been performed to contrast the robustness and coherence of the results by using equations (5) and (10) with our estimated input–output multipliers and the published production data. Consequently, the estimated total output, which yield 83,884 thousand billions of Turkish Lires, is 7.74% lower than published total productions (90,923 thousand billions).

Generally, the FLPs are more accurate than the BLPs. 61.82% of the p-values for FLPs in Table 2 are smaller than the corresponding BLPs.

However, the dispersion on FLPs is greater than in BLPs (Pearson coefficients of variation equal 0.376 and 1.384, respectively). Moreover, the econometrically computed multipliers have a slightly higher dispersion than those traditionally computed (with coefficients of variation 0.2333 and 1.2749, respectively). This is mainly because non significant multipliers are assumed to be zero in the econometric approach, which may increase observed dispersions.

In addition, the Pearson and Spearman correlation coefficients between BLPs and FLPs (both estimated through the econometrical approach) yield -0.576 and -0.361, respectively (both significant at a 99% confidence level), which means that the dispersion power and absorption capacity are slightly related.

5. DEA for valuating key-activities

5.1. Traditional key sector analysis

The traditional key sector analysis focuses on linkages compared with their average (see equations 1 and 2). The main advantage derives from their easy comparison with the unit, where sectors are classified depending whether they have higher or lower than one RBL and RFL linkage values. In this sense, Table 3 shows the results obtained under both econometrical and traditional approaches and Figure 1 depicts them graphically. On the whole, there are 6 activities where both approaches differ in classification (other mining and quarrying products, coke, refined petroleum products and nuclear fuels, chemicals, chemical products and man-made fibres, office machinery and computers, medical, precision and optical instruments, watches and clocks and electrical energy, gas, steam and hot water). As expected, since the econometric approach corrects the potential overestimation of linkages, it tends to identify less number of key sectors (RBL>1 & RFL>1) than the traditional approach. Not surprisingly, it also identifies less number of weakly linkaged sectors (RBL<1 & RFL<1).

One of the main difficulties in traditional key sector analysis is its average dependence to classify sectors, which is due to the fact that most activities are concentrated around the average of linkages, which are highly affected by outliers. Then, we will focus our attention on several alternatives to average comparisons. In this sense, we propose comparisons with: (a) averages; (b) averages (but excluding outliers)[2] ; and (c) the median, a rather simple descriptive statistic which is not affected by outliers Table 3 shows the different classifications reported by each proposal. Results under the (b) and (c) options are quite similar because outlier's effects have been neutralized. But however, one way or another, this way of identifying key sectors relies on "drawing a line" (e.g. average, median, etc.), which might not be quite satisfactory in terms of providing a comprehensive measure of linkages 'distance to the line'. In this sense, we have assumed equally weighted criteria (for BLP and FLP), which might be the easiest weighing scheme, but not necessarily the best/fairest one. In other words, BLP and FLP are considered of the same importance. As stated by Cherchye *et al.* (2006), by keeping a weighing system fixed, eventual rankings still may depend on the particular (and so-called 'preliminary') normalization option. Despite their common use, looking at single indicators separately is controversial. Why should we consider that both BL and FL are equally important? For instance, why – the manufacture of pulp, paper and paper products should be better (as a key sector) –than the manufacture of crude petroleum and natural gas; services incidental to oil and gas extraction excluding surveying (an only FL oriented activity) just because only the former has both BL and FL (2.0564 and 3.4840) greater that their respective averages (1.6473 and 2.4903). Keeping in mind how sensible an average is to outliers, is the average so informative? If FL_{11} (24.8003) is seven times greater than FL_{21}, then is still activity 21 - Pulp, paper and paper products -, anyway, a 'key' sector? Why don't we give the 'benefit of the doubt' to the indicators (RBL and RFL)? Cherchye *et al.* (2006) present well documented further discussion about the problems in the construction of composite indicators in relation to: units of measurement, normalization processes and arguable fixed weighing schemes.

Moreover, the problem becomes more important if we consider not only output linkages (OL) but employment multipliers (EL). How are we going to interpret a sector which is a key sector in terms of outputs but only backward oriented in terms of employment? Again, why should we consider them (OL and EL) equally important? Why don't we give the 'benefit of the doubt' to the indicators? In key sector analysis, these are questions that need to be addressed.

[2] Consider an outlier to be a value outside one and a half times the interquartile range.

5.2. Key activities by means of DEA

DEA may offer a solution for the structural linkage assessment issue by means of calculating 'key-values' (DEA VRS-O Score) instead of dealing with somewhat strict classifications affected by problems such as meaningful bounders and equality of weights in indicators. In this sense, Data Envelopment Analysis (DEA) may be instrumental in overcoming these limitations. It fills the informational gap in the 'right' set of weights by generating flexible 'benefit of the doubt'-weights for each evaluated activity. The dependence of the specific weighing scheme used to aggregate sub-indicators and the consequent disagreement among experts cannot be thus invoked to undermine the credibility of the resulting composite indicators (Cherchye *et al.*, 2006). In addition, DEA can deal with variables measured in different units (e.g. in monetary terms – outputs – and physical terms – employees). Finally, DEA outcomes are rather easy to interpret. They may help to make a single ranking of sectors having a relative measure of their 'key-value' (in the range 0-1 or 0-100, easily understood as percentage).

Next paragraphs describe briefly DEA and the related 'Benefit of the Doubt' method (see Cherchye *et al.* (2006) for a detailed explanation). We will focus our attention on fundamental intuitions rather than on technical and computational aspects of DEA, which can be found in detail in specific textbooks (Charnes *et al.*, 1995 or Cooper *et al.*, 2000).

Following Farrell (1957), Data Envelopment Analysis (DEA) is a non-parametric linear-programming-based technique developed by Charnes *et al.* (1978) and further extended by Banker *et al.* (1984). DEA generalizes the basic concept of efficiency, understood as productivity (ratio of outputs over inputs) and converts multiple input and output measures for a set of Decision-Making Units (DMU) into a single comprehensive measure of efficiency. DEA models identify a frontier of 'best-in-class' units that are used to measure the relative efficiency of remaining units in terms of their distance to the frontier. To our purpose, we will relate 'key-values' of activities to their efficiency in DEA terms.

The DEA linear program estimates fully feasible weights of inputs and outputs for each DMU, thereby obtaining the maximum value of the efficiency index for each firm.

Thus, the resulting efficiency indexes are real maximum-efficiency upper limits (equal to or less than one for input-oriented models and equal to or greater than one for output-oriented models[3]). Then, DEA offers a solution for the choice of weights. The DEA weights assignation system do not damage any particular activity since the most profitable one shall always be selected, among other DEA feasible options. The underlying system awards activities with a good performance (in terms of potential increase of output or employment) instead of punishing them due to a potential failure in the attainment of a certain variable. DEA calculates the production frontier by non-parametric procedures with a flexible weighing scheme, overcoming the difficulties of the previous approaches with a fixed and arguable weighing scheme. On an efficiency calculation process, DEA let the introduction of inputs and outputs without market, and then without price, like in output and employment linkages. Besides, the capacity of DEA to manage variables of different natures is very useful when dealing with a combination of a set of variables (i.e. output and employment linkages).

The variables to be considered in our empirical work will consist of four kinds of outputs (forward and backward linkages of employment and production) and a dummy input (there will be no real inputs since outputs are ratios). For the Turkish case, calculations carried out has been made only taking into account output multipliers since employment multipliers could not be computed because lack of data (please, look at section 3). Then, our single input will be a fictitious variable with the same value for all activities (i.e.: 1), since all output variables are measures of impacts *per* unit.

Note that, strictly speaking, the concept of efficiency is not necessarily the same as the degree of intersectoral linkage ('key-value'). In fact, they can develop in opposite ways (Karigiannis and Tzouvelekas, 2003), i.e. efficiency is related to low consumption of inputs whereas strong backward linkages are related to a great consumption of inputs. Our approach of 'key-value' as DEA Score is built on the variables selection (IO linkages). In this sense, the 'key-value' might be seen as a measure of the social efficiency for the economic development of an economy (i.e. how efficient an activity is in terms of its potential impacts over the rest of the economy).

[3] In order to make an easier comprehension of 'key-value', DEA VRS-O Scores, $\theta^* \in [1, \infty)$, results of 'key-value' are presented as $100/\theta^* \in [0,100]$.

For our application, we propose using the Variables Returns to Scale (VRS) model (Banker *et al.*, 1984) with Output orientation (VRS-O). Since we will analyze all economic activities, it is not consistent to assume constant returns to scale. Output orientation becomes fully justified since our model has no inputs. With regards to the analysis of IO multipliers, we will consider expanding outputs (that is what multipliers shows, the potential output/employment increase), rather than reducing inputs.

5.3. Data

Since DEA compares data with leaders in class (*maxima*), it is also affected by outliers. In order to avoid such problems, values that have prominent impact over the calculated efficiency of the rest of activities are dropped of the comparative set.

Note that they are not necessarily the classical descriptive concept of outliers (outside three times the interquartile range). To that purpose, the iterative procedure developed by Thanassoulis (1999) was performed. Basically, it progressively eliminates DMUs whose attainment is not to be used as benchmark for other activities because of their exceptionality. Exceptional DMUs to be dropped are identified by making use of the concept of super-efficiency, firstly introduced by Andersen and Petersen (1993). Hence, basic metals had to be dropped since its absence produces a significant change over the measured efficiency (+9.98% with econometrical dataset and +3.58% with the dataset of traditionally computed linkages). In order to evaluate basic metals, there are two common approaches: (a) to rescale down BL and FL data to make its efficiency score 100%, or (b) to take into account its super-efficiency score just to make a difference with respect to other activities with 100% key-value.

5.4. Results of key-value:

The last column of Table 3 shows the ‘key-values’ of each activity and Table 4 presents some descriptive statistics regarding comparative analysis between the two different traditional and econometric based classification approaches (a-c).

Traditionally based key values are generally lower than econometrically based estimates. It is not really surprising although the former provides overestimated linkages. Indeed, they are compared with respect to the most efficient linkage and thus, comparisons between key values obtained by means of different approaches (i.e. traditional and econometric) are nonsense.

Some further considerations are as follows:

a) On average, key values of key sectors are higher than those single oriented (either forward or backward). Moreover, the key values of backward oriented sectors are generally greater than those sectors with (only) relevant forward impacts. And lastly, the weakly linkaged sectors show the lowest key values.

b) The assumption of zero impact where linkages are not statistically significant involves that minimum key values of weakly linkaged sectors might be greater than those of forward oriented sectors.

c) The maximum key value (100) might appear in non key sectors. Linkages with highest values should be valued as 100 just to compare with other linkages. We found 13 backward oriented sectors and one single forward oriented sector for which their key value is 100.

d) There are several sectors (e.g. medical, precision and optical instruments, watches and clocks; and real estate services) that are located (see Figure 1) pretty close to the border line where they would become key sectors. This does not mean that they must have similar key values.

e) The weighing system gives extremely high importance to those linkages that better perform. On the contrary, they give relatively low importance to those with inefficient performance. This would explain why the key value for other transport equipments (backward oriented) is greater than that of the computer and related services (weakly linkaged), albeit the former presents a zero impact linkage. Some limits to the weighing scheme should therefore be advisable.

Finally, the top 25 activities with highest key values (see Table 3) are mainly related with manufacturing industries (leather and leather products, basic metals, fabricated metal products, electrical machinery and other apparatuses, etc), some energy sectors (e.g. crude petroleum) and several services such as supporting and auxiliary transport services including travel agency services, recreational, cultural and sporting services, real estate services and construction.

6. Conclusions

Technical coefficients are the subject of two disjoint bodies of literature: the construction of technical coefficients is linked to flow data (use and make matrices), but stochastics are imposed on the coefficients. Due to the nonlinearity of the Leontief inverse, the multiplier estimates are biased. Ten Raa and Rueda-Cantuche (2007) overcame this issue by the econometric estimation of multipliers with establishment data. Collecting and manipulating this data is expensive and rather difficult to manage. By contrast, use and make matrices are usually for free on the Internet.

In this paper, we use *supply* and *use* matrices to circumvent the problems of collecting and manipulating micro data. This paper shows, however, that an integrated analysis, from the use and make data directly to the multipliers, provides simple, unbiased and consistent estimates.

Our Backward and Forward multipliers are normally distributed and do not suffer from over or underestimation. Our results for the Turkish economy indicate that the Leontief and Ghosh inverses are not underestimated but overestimated in most cases.

We have shown that no matter what kind of correction has been made to either the traditionally or econometrically based linkages (in relative terms with respect to the average, average without outliers or median), the problems of average dependency and multi-indicator composites (BLP; FLP; BLE; FLE) remain. To solve this issue, a new approach for the identification of key activities is presented by using the so-called 'key-value' concept under a DEA approach.

Empirical results show that traditionally based key activities have the highest key-values on average, which is not surprising. However, our new proposal provides additional information whenever backward and forward linkages have opposite outcomes. The so-called key value would represent therefore the potential impacts of an activity over the rest of the economy in terms of efficiency, and no matter how close are their backward and forward linkages to become a key sector.

Finally, it is shown that DEA procedures need careful specifications in order to avoid activities with null linkages but obtaining good scores.

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Table 1: Products Classification

A60 Code	CPA Description*
01	Products of agriculture, hunting and related services
02	Products of forestry, logging and related services
05	Fish and other fishing products; services incidental of fishing
10	Coal and lignite; peat
11	Crude petroleum and natural gas; serv. incidental to oil & gas extraction excluding surveying
13	Metal ores
14	Other mining and quarrying products
15	Food products and beverages
16	Tobacco products
17	Textiles
18	Wearing apparel; furs
19	Leather and leather products
20	Wood & products of wood & cork (except furniture); articles of straw & plaiting materials
21	Pulp, paper and paper products
22	Printed matter and recorded media
23	Coke, refined petroleum products and nuclear fuels
24	Chemicals, chemical products and man-made fibres
25	Rubber and plastic products
26	Other non-metallic mineral products
27	Basic metals
28	Fabricated metal products, except machinery and equipment
29	Machinery and equipment n.e.c.
30	Office machinery and computers
31	Electrical machinery and apparatus n.e.c.
32	Radio, television and communication equipment and apparatus
33	Medical, precision and optical instruments, watches and clocks
34	Motor vehicles, trailers and semi-trailers
35	Other transport equipment
36	Furniture; other manufactured goods n.e.c.
40	Electrical energy, gas, steam and hot water
41	Collected and purified water, distribution services of water
45	Construction work
50	Trade, maintenance & repair serv.motor vehicles & motorcycles; retail sale of automotive fuel
51	Wholesale trade and commission trade services, except of motor vehicles and motorcycles
52	Retail trade serv.except motor vehicles & motorcycles; repair serv.personal & household goods
55	Hotel and restaurant services
60	Land transport; transport via pipeline services
61	Water transport services
62	Air transport services
63	Supporting and auxiliary transport services; travel agency services
64	Post and telecommunication services
65+67	Financial intermed.serv.except insurance & pension funding serv.+Serv.aux.financial intermed.
66	Insurance and pension funding services, except compulsory social security services
70	Real estate services
71	Renting services of machinery & equipment without operator & of personal & household goods
72	Computer and related services
73	Research and development services
74	Other business services
75	Public administration and defence services; compulsory social security services
80	Education services
85+90	Health & social work serv. + Sewage & refuse disposal serv. sanitation & similar serv.
91	Membership organisation services n.e.c.
92	Recreational, cultural and sporting services
93	Other services
95	Private households with employed persons

Note: * This classification is equivalent to A60 NACE Rev 1.1 (EC, 2001).
We refer to sectors or commodities without distinction.

Table 2: Backward and Forward Linkages of Output

A 60			BLP Bounds				Ranking				FLP Bounds				Ranking	
Code	BLP T	BLP E	Lower	Upper	p_value	Bias	BLP T	BLP E	FLP T	FLP E	Lower	Upper	p_value	Bias	FLP T	FLP E
01	1.52	1.51 **	1.25	1.76	0.00	0.01	27	27	1.63	1.49 **	0.95	2.02	0.00	-0.14	11	11
02	1.19	1.15 **	1.02	1.29	0.00	0.04	19	19	2.46	2.17 **	1.73	2.62	0.00	-0.29	30	30
05	1.31	1.30 **	1.23	1.36	0.00	0.01	31	31	1.30	1.24 **	1.04	1.43	0.00	-0.06	73	73
10	1.54	1.50 **	1.31	1.69	0.00	0.04	25	25	4.33	4.00 **	3.77	4.23	0.00	-0.33	13	13
11	1.25	0.20	-3.18	3.18	0.90	1.04	28	28	26.23	24.80 **	23.77	25.83	0.00	-1.43	71	70
13	1.58	1.54 **	1.18	1.90	0.00	0.04	18	36	5.68	4.95 **	4.45	5.45	0.00	-0.73	70	71
14	1.35	1.30 **	1.13	1.48	0.00	0.05	36	18	2.75	2.54 **	2.28	2.81	0.00	-0.21	27	10
15	2.18	2.23 **	1.91	2.55	0.00	-0.05	34	34	1.42	0.91 *	0.24	1.59	0.01	-0.51	10	27
16	2.10	2.09 **	1.96	2.22	0.00	0.02	24	29	1.09	0.07	-3.29	3.29	0.97	-1.02	21	21
17	2.16	2.09 **	1.97	2.22	0.00	0.07	20	15	1.99	2.01 **	1.05	2.98	0.00	0.02	24	40
18	2.36	2.32 **	2.24	2.40	0.00	0.04	29	33	1.23	1.12 **	0.84	1.40	0.00	-0.11	33	14
19	2.54	2.52 **	2.38	2.67	0.00	0.02	33	32	1.66	0.78	-2.09	2.09	0.47	-0.88	14	23
20	2.28	2.16 **	1.92	2.41	0.00	0.12	15	20	2.42	1.94 **	1.00	2.88	0.00	-0.49	40	33
21	2.09	2.06 **	1.91	2.20	0.00	0.04	17	24	3.93	3.48 **	2.84	4.13	0.00	-0.44	23	61
22	1.96	1.94 **	1.64	2.25	0.00	0.01	32	17	2.00	1.74 *	0.25	3.23	0.03	-0.26	61	24
23	1.42	1.14 *	0.30	1.98	0.01	0.28	16	63	2.62	2.51 **	2.42	2.59	0.00	-0.12	2	92
24	2.29	2.15 **	1.65	2.66	0.00	0.13	63	16	3.45	2.31 **	1.25	3.38	0.00	-1.14	20	2
25	2.39	2.37 **	2.04	2.70	0.00	0.03	21	21	1.90	1.13	-1.91	1.91	0.25	-0.77	92	64
26	1.83	1.76 **	1.61	1.91	0.00	0.07	45	45	2.06	2.06 **	1.69	2.43	0.00	-0.01	41	66
27	2.71	2.74 **	2.62	2.87	0.00	-0.04	22	22	4.40	3.79 **	3.39	4.19	0.00	-0.62	64	41
28	2.37	2.35 **	2.15	2.56	0.00	0.02	92	92	2.21	2.04 **	1.79	2.29	0.00	-0.17	66	74
29	2.25	2.31 **	2.18	2.43	0.00	-0.06	30	55	1.56	1.49 **	0.75	2.24	0.00	-0.07	28	26
30	1.91	-0.87	-3.25	3.25	0.60	2.77	35	61	9.41	9.25 **	7.99	10.52	0.00	-0.16	74	28
31	2.42	2.42 **	2.34	2.50	0.00	0.01	55	62	1.53	1.37 **	0.85	1.89	0.00	-0.17	26	17
32	2.13	2.17 **	2.04	2.30	0.00	-0.04	61	35	1.76	1.73 **	1.55	1.90	0.00	-0.04	65	65
33	2.21	2.18 **	2.01	2.36	0.00	0.03	26	26	2.85	2.43 *	0.63	4.22	0.01	-0.42	22	20
34	2.33	2.31 **	2.23	2.39	0.00	0.02	62	70	1.48	1.45 **	1.37	1.54	0.00	-0.03	17	72
35	1.87	1.77 **	1.25	2.30	0.00	0.09	72	91	1.92	1.35	-1.62	1.62	0.10	-0.57	72	50
36	2.36	2.33 **	2.18	2.48	0.00	0.02	80	80	1.08	0.89 **	0.37	1.41	0.00	-0.19	35	22
40	1.59	1.44 **	1.03	1.85	0.00	0.15	91	72	2.69	2.55 **	2.40	2.69	0.00	-0.14	25	32
41	1.22	1.23 **	1.09	1.36	0.00	-0.01	40	74	2.24	2.10 **	1.95	2.25	0.00	-0.14	50	62
45	2.00	1.98 **	1.92	2.04	0.00	0.02	70	93	1.03	1.02 **	1.02	1.03	0.00	0.00	32	29
50	1.35	1.34 **	1.29	1.38	0.00	0.01	93	13	1.89	1.82 **	1.78	1.87	0.00	-0.06	19	1
51	1.30	1.29 **	1.27	1.31	0.00	0.01	13	1	1.48	1.42 **	1.37	1.46	0.00	-0.06	1	60
52	1.30	1.28 **	1.26	1.31	0.00	0.01	74	66	1.40	1.34 **	1.29	1.39	0.00	-0.06	29	34
55	1.86	1.86 **	1.77	1.95	0.00	0.01	71	65	1.28	1.28 **	1.10	1.46	0.00	0.00	31	51
60	1.50	1.44 **	1.29	1.60	0.00	0.06	65	10	1.53	1.47 **	1.43	1.52	0.00	-0.06	60	31
61	1.86	1.81 **	1.67	1.95	0.00	0.05	66	60	2.56	2.37 **	2.23	2.51	0.00	-0.19	62	52
62	1.82	1.79 **	1.66	1.93	0.00	0.03	10	40	1.52	1.51 **	1.41	1.60	0.00	-0.01	34	55
63	2.10	2.09 **	2.02	2.16	0.00	0.02	1	85	0.95	0.90 **	0.72	1.09	0.00	-0.05	51	5
64	1.19	1.19 **	1.16	1.21	0.00	0.01	60	50	2.23	2.17 **	2.12	2.22	0.00	-0.06	15	80
65+67	1.55	1.51 **	1.45	1.56	0.00	0.04	85	95	2.03	1.96 **	1.88	2.04	0.00	-0.07	52	18
66	1.54	1.51 **	1.43	1.59	0.00	0.04	23	14	2.21	2.12 **	2.03	2.21	0.00	-0.09	5	93
70	1.59	1.64 **	1.09	2.18	0.00	-0.05	14	5	4.91	4.61 **	4.01	5.20	0.00	-0.31	55	91
71	1.55	1.82	-2.47	2.47	0.15	-0.27	50	51	5.63	4.57 **	2.00	7.15	0.00	-1.06	18	85
72	1.74	1.59 **	1.37	1.81	0.00	0.15	95	52	1.93	1.83 **	1.62	2.04	0.00	-0.10	80	45
73	1.30	2.26	-6.03	6.03	0.46	-0.95	5	41	7.55	7.52 **	6.50	8.54	0.00	-0.03	93	75
74	1.58	1.56 **	1.51	1.61	0.00	0.02	73	64	2.13	2.07 **	1.90	2.23	0.00	-0.07	16	95
75	1.00	1.00	1.00	1.00	-	0.00	51	2	1.00	1.00	1.00	1.00	-	0.00	91	15
80	1.64	1.60 **	1.53	1.67	0.00	0.04	52	23	1.19	1.14 **	0.99	1.28	0.00	-0.05	36	63
85+90	1.43	1.41 **	1.33	1.48	0.00	0.02	11	75	1.04	1.04 **	1.03	1.05	0.00	0.00	85	36
91	1.62	1.60 **	1.56	1.64	0.00	0.02	41	11	1.09	1.08 **	1.05	1.11	0.00	-0.01	45	16
92	1.91	1.89 **	1.81	1.98	0.00	0.02	2	30	2.42	2.28 **	2.10	2.47	0.00	-0.14	75	19
93	1.58	1.55 **	1.46	1.65	0.00	0.03	64	71	1.17	1.10 **	0.86	1.34	0.00	-0.07	95	25
95	1.31	1.30 **	1.29	1.32	0.00	0.01	75	73	1.00	1.00 **	0.99	1.00	0.00	0.00	63	35

Notes: P-values = 0.00: P-values lower than 10^{-3} that are been rounded, but different from null.
BLP T: Backward Linkage of Production Traditionally computed with equation (1)
BLP E: Backward Linkage of Production Econometrically computed with equation (6)
FLP T: Forward Linkage of Production Traditionally computed with equation (2)
FLP E: Forward Linkage of Production Econometrically computed with equation (16)
**: Significant at a significance level of 1%
*: Significant at a significance level of 5%

Table 3: Secondary productions & Classification of Activities

A 60 Code	% Secondary production per Sector	% Secondary production per Product	Type of Activity: Traditional Approach	Econometrical Approach a)	Econometrical Approach b)	Econometrical Approach c)	Key value Approach
01	9.76%	0.01%	W	W	W	W	64.84
02	0.00%	0.02%	W	W	F	F	53.76
05	1.39%	0.00%	W	W	W	W	55.57
10	4.81%	0.00%	F	F	F	F	74.64
11	3.63%	5.92%	F	F	F	F	100.00
13	2.13%	0.00%	F	F	F	F	80.01
14	1.22%	0.06%	W	F	F	F	61.01
15	1.74%	15.25%	B	B	B	B	91.23
16	1.61%	0.00%	B	B	B	B	82.76
17	5.34%	2.42%	B	B	K	K	89.73
18	4.46%	4.83%	B	B	B	B	95.38
19	3.24%	1.92%	B	B	B	B	100.00
20	2.55%	0.68%	B	B	K	K	92.22
21	6.52%	3.65%	K	K	K	K	94.28
22	22.40%	1.19%	B	B	K	B	82.86
23	0.74%	2.14%	W	F	F	F	54.58
24	3.11%	3.18%	K	B	K	K	93.33
25	2.22%	2.98%	B	B	B	B	93.88
26	1.87%	0.37%	B	B	F	K	76.88
27	5.47%	1.19%	K	K	K	K	100.00
28	6.73%	9.72%	B	B	K	K	100.00
29	9.04%	9.08%	B	B	B	B	96.14
30	28.86%	56.36%	K	F	F	F	37.31
31	10.01%	2.80%	B	B	B	B	100.00
32	7.25%	9.60%	B	B	K	B	91.72
33	6.61%	10.36%	K	B	K	K	94.90
34	8.63%	1.51%	B	B	B	B	96.12
35	4.80%	1.13%	B	B	W	B	70.36
36	1.99%	1.28%	B	B	B	B	95.17
40	0.95%	0.39%	W	F	F	F	66.34
41	3.91%	3.74%	W	W	F	F	56.32
45	1.40%	0.06%	B	B	B	B	81.67
50	3.20%	0.93%	W	W	F	W	59.47
51	3.92%	5.80%	W	W	W	W	56.13
52	3.68%	1.96%	W	W	W	W	55.45
55	0.79%	0.62%	B	B	B	B	77.68
60	1.02%	3.37%	W	W	W	W	62.21
61	0.02%	4.04%	B	B	K	K	80.00
62	15.79%	0.00%	B	B	B	B	75.95
63	14.09%	15.58%	B	B	B	B	85.56
64	0.20%	0.00%	W	W	F	F	55.02
65+67	0.00%	0.00%	W	W	F	F	66.66
66	0.00%	0.97%	W	W	F	F	67.34
70	0.02%	71.09%	F	F	F	K	82.43
71	0.12%	85.20%	F	F	F	F	18.44
72	0.00%	2.64%	W	W	F	F	69.38
73	0.00%	83.72%	F	F	F	F	30.31
74	0.83%	12.15%	W	W	F	F	69.14
75	0.00%	0.00%	W	W	W	W	43.05
80	1.04%	0.37%	W	W	W	W	67.09
85+90	0.35%	0.08%	W	W	W	W	59.11
91	0.00%	0.00%	W	W	W	W	66.91
92	0.40%	1.01%	B	B	K	K	83.08
93	0.11%	0.00%	W	W	W	W	65.08
95	0.00%	0.00%	W	W	W	W	54.97

Notes: Type of Activity:
- K: Key Activity (RBL>1, RFL>1)
- B: Backward Oriented Activity (RBL>1, RFL<1)
- F: Forward Oriented Activity (RBL<1, RFL>1)
- W: Weakly Linkaged Activity (RBL<1, RFL<1)

Linkages compared with
- a) Average
- b) Average without outliers
- c) Median

Table 4: Industrial Analysis

Traditionally Computed Linkages

Type of Sector	Num. of Activities	Key Value		
		Average	Max	Min
K	5	92.42	100	87.38
B	22	84.90	100	72.25
F	6	73.99	100	64.69
W	22	57.54	69.94	40.00

Notes: Type of Activity:
K: Key Activity (RBL>1, RFL>1)
B: Backward Oriented (RBL>1, RFL<1)
F: Forward Oriented (RBL<1, RFL>1)
W: Weakly Linkaged (RBL<1, RFL<1)
Comparison Approach:
a) Average
b) Cor. Average
c) Median

Econometrically Computed Linkages

a)

Type of Sector	Num. of Activities	Key Value		
		Average	Max	Min
K	2	97.14	100	94.28
B	24	88.61	100	70.36
F	10	60.51	100	18.44
W	19	60.39	69.38	43.05

a)

Type of Sector	Key Value					
	[0, 45]	(45, 60]	(60, 75]	(75, 90]	(90, 100]	Total
K	0	0	0	0	2	2
B	0	0	1	10	13	24
F	3	1	3	2	1	10
W	1	9	9	0	0	19
	4	10	13	12	16	55

b)

Type of Sector	Num. of Activities	Key Value		
		Average	Max	Min
K	11	91.10	100	80.00
B	13	90.12	100	75.95
F	19	62.05	100	18.44
W	12	60.06	70.36	43.05

c)

Type of Sector	Num. of Activities	Key Value		
		Average	Max	Min
K	11	89.71	100	76.88
B	16	88.53	100	70.36
F	16	60.02	100	18.44
W	12	59.16	67.09	43.05

Figure 1: Sectoral Analysis