ESTIMATING CES AND CET PARAMETERS FOR VIETNAM ECONOMY USING MAXIMUM ENTROPY APPROACH

ỨNG DỤNG PHƯƠNG PHÁP MAXIMUM ENTROPY TRONG ƯỚC LƯỢNG| CÁC THAM SỐ CES VÀ CET CHO NỀN KINH TẾ VIỆT NAM

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Abstract - Faced with this limited information, in order to give the "best" conclusions based on the data at hand and without assumptions about something we do notknow, Jaynes (1957) proposed making use of the entropy concept. This paper presents the theoretical concept used to estimate the Constant Elasticity of Substitution (CES) and Constant Elasticity of Transformation (CET) parameters. Applying the maximum entropy method, the study tries to estimate trade parameters, i.e. CES and CET, the value of which are just assumed in many CGE models. We use the static CGE model to find Cross Entropy estimates of parameters. It is the first time that these parameters are estimated for Vietnam based on the Vietnamese SAM 2007. Because CGE results are sensitive to the value of CES and CETparameters, it is believed that when they are used for simulating in the CGE model, the results will reflect the Vietnamese actual situation more precisely.

Key words - CES; CET; CGE model; maximim entrophy; cross entropy.

Tóm tắt - Trong điều kiện không có đầy đủ thông tin phục vụ việc phân tích, để đưa ra kết luận "tốt nhất" mà không cần bổ sung thêm các giả định, Jaynes (1957) đã đề xuất vận dụng khái niệm Entropy để xử lý. Bài báo trình bày cơ sở lý thuyết dùng để ước lượng các hệ số co giãn thay thế (CES) và hệ số co giãn chuyển đổi (CET) trong các ngành kinh tế.Ứng dụng phương pháp Maximum Entropy, nghiên cứu này tiến hành ước lượng các tham số CES và CET cho nền kinh tế Việt Nam.Thông thường, các tham số CES và CET được giả định có sẵn hoặc sử dụng các tham số của các nước. Đây là lần đầu tiên các tham số CES và CET được ước lượng riêng cho nền kinh tế Việt Nam dựa trên bảng Ma trận hạch toán xã hội năm 2007. Độ chính xác của mô hình CGE phụ thuộc vào giá trị của các tham số CES và CET, do đó các kết quả ước lượng sẽ giúp tăng tính chính xác khi mô phỏng nền kinh tế theo mô hình CGE.

Từ khóa - CES; CET; mô hình cân bằng tổng thể; maximim entrophy; cross entropy.

1. Introduction

One of the most debated issues in the CGE literature concerns the validity of the key behavioral parameters used in the calibration process. In fact, CGE modelers seldom estimate these parameters empirically, preferring to borrow from the handful of estimates available in the literature. However, these estimates usually are of countries other than the one the CGE model is trying to represent. Estimating key parameters is very crucial since CGE results are sensitive to the value of parameters (Nganou, 2004).

Following Arndt Robinson and Tarp (2002) and Nganou (2004), this study uses a robust econometric technique - the Generalized Maximum Entropy (GME) - to estimate CES and CET parameters of Vietnam economy.

2. Brief Theoretical Background

2.1. Maximum entropy

As discussed in Golan, Judge, and Miller (1996), the traditional maximum entropy (ME) is based on the entropy-information measure of Shannon (1948), which allows one to use available data, taking into account all relevant constraints and prior information about parameter values, to recover unknown parameters. Available information does not need to be complete or even internally consistent. The ME estimator may be used in several circumstances such as the case when the sample is small, when there are many covariates, or when the covariates are highly correlated. Moreover, the ME method is very flexible since it can allow the user to easily impose nonlinear and inequality constraints.

The concept of Maximum Entropy can be briefly clarified as follows. We observe the outcome of an economic variable y. However, our interest focuses on the unknown and unobservable frequencies $p = (p_1, p_2, ..., p_k)'$ that represent the data generating process. Since we can not measure p directly, in order to recover it we must use indirect measurements on the observables. In this context, for recovering the unknown parameters, we are faced with an inverse problem that can be formalized in the following way:

$$y = X_p \tag{1}$$

where $y = (y_1, y_2, ..., y_N)'$ is a N-dimensional vector of observations, p is an unobservable K dimensional vector of unknowns and X is a known (N x K) linear operator. Thus, we know X and observe y, and wish to determine the unknown and unobservable parameter vector p, where $\sum_{k=1}^{K} p_k = 1$ and $p_k \geq 0$.

Faced with this limited information, in order to give the "best" conclusions based on the data at hand and without assumptions about something we do not know, Jaynes (1957) proposed making use of the entropy concept, which has a rich history dating back to the works of Shannon (1948), in determining the unknown distribution of probability in Equation (1).

To explain the philosophy of this approach, Golan et al. (1996) started from the concept of combinatorics, or counting the number of possible outcomes. Let suppose that nature or society is carrying out N trials (repetitions) of an experiment that has K possible outcomes. Since there are N trials and each trial has K possible outcome, there are K^N possible outcomes in the sequence of N trials.

Let $N_1, N_2, ..., N_k$ be the number of times that each outcome occurs in the experiment of length N, where

$\sum_k N_k = N$, $N_k \geq 0$ and $k = 1,2,...,k$. (2)

The number of ways of a particular set of N_k is:

$$W = \frac{N!}{\prod_k N_k!} \tag{3}$$

The probability that the outcome of the experiment occurs in such a way is thus

$$P(W) = W / K^N = \frac{N!}{\prod_k N_k!} * \frac{1}{K^N} \tag{4}$$

or

$$P(W) = \exp\left[\ln N! - \sum_k \ln N_k! - N \ln K\right]. \tag{5}$$

Using the Stirling's approximation:

$\ln x! \approx x \ln x - x$, as $o < x \to \infty$

We obtain

$$P(W) \approx \exp\left[N \ln N - N - \sum_k N_k \ln N_k + \sum_k N_k - N \ln K\right] \tag{6}$$

Since $\sum_k N_k = N$, we have

$$P(W) \approx \exp\left[N \ln N - \sum_k N_k \ln N_k - N \ln K\right] \tag{7}$$

The ratio N_k/N represents the frequency of the occurrence of the K-th outcome in a sequence of N

and $\frac{N_k}{N} = p_k$ as $N \to \infty$ (8)

We thus have

$$\begin{aligned} P(W) &\approx \exp\left[N \ln N - \sum_k Np_k \ln Np_k - N \ln K\right] \\ &= \exp\left[N \ln N - \sum_k Np_k \ln N - \sum_k Np_k \ln p_k - N \ln K\right] \\ &= \exp\left[N \ln N - \sum_k N_k \ln N - N\sum_k p_k \ln p_k - N \ln K\right] \\ &= \exp\left[- N\sum_k p_k \ln p_k - N \ln K\right] \\ &= \exp\left\{N\left[- \sum_k p_k \ln p_k - \ln K\right]\right\} \\ &= \exp\left\{N\left[H(p) - \ln K\right]\right\} \end{aligned} \tag{9}$$

Where $H(p)$ is the Shannon measure:

$$H(p) = -\sum_k p_k \ln p_k \tag{10}$$

The philosophy of the maximum likelihood approach addresses that the reason why we observe a set of outcomes is because its probability is the greatest in nature. Equation (9) implies that the maximum value of $P(W)$ is obtained when $H(p)$ is maximized. We can thus choose the set of p_k that maximizes

$$H(p) = -\sum_k p_k \ln p_k \tag{11}$$

subject to data consistency and normalization-additivity requirements

$$y = Xp \tag{12}$$

and

$$\sum_k p_k = 1 \tag{13}$$

2.2. Cross Entropy

In many situations normally found in practice we have some information about the unknown $p = (p_1, p_2,..., p_K)'$ in the form of a prior distribution of probabilities $q = (q_1, q_2,..., q_K)'$. When such prior knowledge exists, we wish to incorporate it in the ME estimation. As stated by Kullback (1959) and Good (1963), we can then use the principle of minimum cross-entropy (CE) and choose, given the constraints (12) and (13), the estimate of p that minimize the cross-entropy between p and q

$$I(p,q) = \sum_k p_k \ln\left(p_k / q_k\right) = \sum_k p_k \ln p_k - \sum_k p_k \ln q_k \tag{14}$$

If the prior information q is consistent with the data, then $\tilde{p} = q$ and (14) is zero. This means that the data in (12) has no additional information to the prior. If q is a uniform distribution, $q_k = 1/K$ for all K, then the results of CE and ME are the same.

2.3. Generalized maximum entropy (GME) and Cross Entropy (GCE)

The ME and CE formulation presented in the previous sections seek point estimates of the unknown probabilities p_k given the available data, adding-up constraints and possibly a discrete prior q_k. In this section, the ME and CE formulations will be generalized to recover unknowns that do not have the properties of probabilities and the observations include noises. The general linear inverse problem with noise can be written as

$$y = X\beta + e \tag{15}$$

Where y is N-vector of noisy observations, X a (N x K) design matrix composed of explanatory variables and β a K-vector of unknown parameters. The unobservable disturbance vector, e, represents one or more sources of noise in the observed system.

Because the elements of the unknown vector β are no longer enough to retain the properties of probability, we use a procedure, referred as reparameterization, in which for each β_k we assume there exists a parameter space $z_k = [z_1, z_2,...,z_M]'$ with corresponding probabilities $p_k = [p_{k1}, p_{k2},...,p_{kM}]'$ such that

$$\beta_k = \sum_m z_{km} p_{km} \tag{16}$$

For $k=1,2,...,K$; $m=1,2,..,M$ and $M \geq 2$.

Similarly, the vector of disturbances, e, is assumed to be

$$e_n = \sum_j v_{nj} w_{nj} \tag{17}$$

For $n = 1, 2,..., N; j = 1, 2,..., J,$ and $2 \leq J < \infty$

Where $v_n = [v_{n1}, v_{n2},...,v_{nJ}]'$ is support space for errors and $w_n = [w_{n1}, w_{n2},...,w_{nJ}]'$ is the corresponding probabilities.

The generalized maximum entropy problem is to select $p,w \geq 0$ that

$$\text{Max } H(p,w) = -\sum_k \sum_m p_{km} \ln p_{km} - \sum_n \sum_j w_{nj} \ln w_{nj} \tag{18}$$

s.t. to Equations (15), (16), (17) and additivity constraint sets

$$\sum_m p_{km} = 1 \tag{19}$$

$$\sum_j e_{nj} = 1 \tag{20}$$

If the prior distributions are non-uniform and given informative prior distributions on z_k and v_n (i.e. $p_k = [q_{k1}, q_{k2}, ..., q_{Kn}]'$ and $u_n = u[u_{n1}, u_{n2}, ..., u_{nJ}]'$), the problem can be restated in terms of generalized cross entropy criterion:

Min

$$I(p,q,w,u) = \sum_k \sum_m p_{km} \ln\left(\frac{p_{km}}{q_{km}}\right) + \sum_n \sum_j w_{nj} \ln\left(\frac{w_{nj}}{u_{nj}}\right) \quad (21)$$

s.t. equations (15), (16), (17), (19), and (20).

The entropy objective (21) is used to find the set of "posterior" distributions on the supports that satisfy the observations and are "closest" to the prior distribution.

2.4. The discrete-time, linear inverse system

In this section, we focus on linear dynamic systems that are used to recover the parameters of a discrete-time linear stochastic relation when facing noisy economic data. The theoretical concept presented here is used to estimate the CES and CET parameters.

Consider the following non-stationary statistical model in the form of discrete-time linear observation equation:

$$y_t = X_t \beta_t + e_t \quad (22)$$

and the process or state (system) equation:

$$\beta_t = f_t(\beta_{t-1}) + \varepsilon_t, \quad (23)$$

Where y_1, y_2,..., y_T is a sequence of noisy (N x 1) observation vectors, X_t is a known (N x K) measurement-design matrix, e_t is a (N x 1) vector of observation errors, β_t is a (K x 1) state vector and ε_t is a (K x 1) vector of state or system errors. Typically it is assumed that the random vectors $e_t \sim N_P(0, \Sigma_t)$ and $\varepsilon_t \sim N_K(0, \Psi_t)$, that Σ_t and ψ_t are known and that e_t and ε_t are mutually independent. Further, prior information on the initial condition β_0 may exist. Given the above specification, the objective is to find estimates of unknown and unobservable K-dimensional state vector β_t, and the noise component e_t and ε_{tk}.

We can reparameterize unknown parameters as follows:

$$\sum_m z_{tkm} p_{tkm} = \beta_{tk}, \text{ for } k = 1,2,..., K; \ t = 1,2,..., T, \quad (24)$$

$$\sum_j v^e_{tnj} w^e_{tnj} = e_{tn}, \text{ for } t = 1,2,..., T; \ n = 1,2,..., N, \quad (25)$$

$$\sum_i v^\varepsilon_{tki} w^\varepsilon_{tki} = \varepsilon_{tk}, \text{ for } k = 1,2,..., K; \ t = 1,2,..., T, \quad (26)$$

where z, v^e and v^ε are the support spaces with $M \geq 2, J \geq 2, I \geq 2$ and for β_t, e_t and ε_t respectively.

Under this reparameterization, the non-stationary GCE problem is stated as:

Min $I(p, w^e, w^\varepsilon)$

$$= \sum_t \sum_k \sum_m \mathrm{p_{tkm}} \ln(\mathrm{p_{tkm}} / \mathrm{q_{tkm}}) + \sum_t \sum_n \sum_j \mathrm{w^e_{tnj}} \ln(\mathrm{w^e_{tnj}} / \mathrm{u^e_{tnj}}) + \sum_t \sum_k \sum_i \mathrm{w^\varepsilon_{tki}} \ln(\mathrm{w^\varepsilon_{tki}} / \mathrm{u^\varepsilon_{tki}}) \quad (27)$$

s.t.the data

$$\sum_k \sum_m z_{tkm} p_{tkm} x_{kt} + \sum_j v^e_{tnj} w^e_{tnj} = y_{tn} \quad (28)$$

for $t = 1,2,..., T; \ n = 1,2,..., N$

$$\beta_{tk} = f_{tk}\left(\sum_m z_{t-1,km} p_{t-1,km}\right) + \sum_i v^\varepsilon_{tki} w^\varepsilon_{tki} \quad (29)$$

for $t = 1,2,\ldots, T; \quad k = 1,2,...,K$

and the normalization-adding-up constraint

$$\sum_m p_{tkm} = 1 \text{ for } t = 1,2,..., T; \ k = 1,2,...,K \quad (30)$$

$$\sum_j w^e_{tnj} = 1 \text{ for } t = 1,2,\ldots, T; \ n = 1,2,.., N \quad (31)$$

$$\sum_i w^\varepsilon_{tki} = 1 \text{ for } t = 1,2,\ldots, T; \ k = 1,2,..., K \quad (32)$$

The prior information on the errors is, in the absence of other information, specified as, $u^e_{tnj} = 1/J$ for all j, n, t, and $u^\varepsilon_{tki} = 1/I$ for all i, t and k. The parameter spaces v^e_{tnj} and v^ε_{tki} are specified to be uniform and symmetric around zero. The prior information on the β_{tk} is specified as q_{tkm}. If no prior information exists, we specify $q_{tkm} = 1/M$ for all t, k and m, where z_{tkm} is chosen such that it spans a sensible parameter state-space for each β_{tk}. If initial information such as non-negativity, non-positivity or an upper or lower bound exists for β_{tk}, it is included when we specify z_{tkm}.

Solving the above specified optimization problem yields the solutions $\tilde{p}_{tkm}$, $\tilde{w}^e_{tnj}$ and $\tilde{w}^\varepsilon_{tki}$, and then:

$$\tilde{\beta}_{tk} = \sum_m z_{tkm} \tilde{p}_{tkm}, \quad (33)$$

$$\tilde{e}_{tn} = \sum_j v^e_{tnj} \tilde{w}^e_{tnj}, \quad (34)$$

$$\tilde{\varepsilon}_{tk} = \sum_i v^\varepsilon_{tki} \tilde{w}^\varepsilon_{tki}. \quad (35)$$

If no prior information exists, the above problem is reduced to the GME formulation

Max $H(p, w^e, w^\varepsilon)$

$$= -\sum_t \sum_k \sum_m \mathrm{p_{tkm}} \ln(\mathrm{p_{tkm}}) - \sum_t \sum_n \sum_j \mathrm{w^e_{tnj}} \ln(\mathrm{w^e_{tnj}}) - \sum_t \sum_k \sum_i \mathrm{w^\varepsilon_{tki}} \ln(\mathrm{w^\varepsilon_{tki}}) \quad (36)$$

s.t. Equations (28) to (32).

This is a special case of GCE problem where all the prior weights q_{tkm}, u^e_{tnj} and u^ε_{tki} are uniform.

2.5 Special case of the discrete-time, linear inverse system

In the case that the unknown vector β_{tk} does not change overtime, i.e.:

$$\beta_{1k} = \beta_{2k} = ... = \beta_{Tk} = \beta_k \quad \text{for } k = 1,2,\ldots,K$$

Equations (22) and (23) become:

$$y_t = X_t \beta + e_t \quad (37)$$

Where $\beta_1, \beta_2, ..., \beta_K$ is a (K x 1) state vector. The reparameterization of β_k becomes:

$$\sum_m z_{km} p_{km} = \beta_k \tag{38}$$

The GCE problem becomes:

$$\text{Min } I(p, w^e) = \sum_k \sum_m p_{tkm} \ln(p_{tkm} / q_{tkm}) + \sum_t \sum_n \sum_j w^e_{tnj} \ln(w^e_{tnj} / u^e_{tnj}) \tag{39}$$

subject to the data

$$\sum_k \sum_m z_{km} p_{km} x_{kt} + \sum_j v^e_{tnj} w^e_{tnj} = y_{tn} \tag{40}$$

for $t = 1,2,\ldots, T$; $n = 1,2,\ldots, N$

and the normalization-adding-up constraints

$$\sum_m p_{km} = 1 \text{ for } t = 1,2,\ldots, T;\ k = 1,2,\ldots, K \tag{41}$$

$$\sum_j w^e_{tnj} = 1 \text{ for } t = 1,2,\ldots, T;\ n = 1,2\ldots,N \tag{42}$$

Using the above theoretical background, the following section presents the method to find behavioral parameters, specifically CES and CET parameters, of a CGE model.

3. Estimation Method

In this section, we describe the estimation method developed by Arndt el al. (2002). View a classic static CGE model in the following form:

$$F(X, Z, B, \delta) = 0, \tag{43}$$

where F is an I-dimensional vector valued function, X is an I-dimensional vector of endogenous variables, Z is a vector of exogenous variables, B is a K-dimensional vector of behavioral parameters such as CES and CET parameters to be estimated, and δ is a second vector of behavioral parameters whose values are uniquely implied by choice of B, and data for the base year. Static CGE analysis proceeds by changing the vector of exogenous variables, Z, and examining the resulting vector of endogenous variables, X, which satisfies Equation (43).

To estimate B, we need the historical record on X_t and Z_t over T time periods ($t=1,2,\ldots,T$). However, in practice we may not observe all elements of Z_t vector. Therefore, the Z_t vector is partitioned into exogenous variables observable from historical data, Z_t^0, and those not observable from historical data , Z_t^u.

When the model is calibrated for the base year, which is labeled year t', a unique relationship between δ and B comes out. We can have

$$\delta = \Phi(Z_{t'}, B_0) \tag{44}$$

We can hence have

$$F(X_t, Z_t^0, Z_t^u, B, \delta) = 0, \quad \forall t \in T \tag{45}$$

And use this to estimate values B and Z_t^u, imposed values Z_t^0, and calibrated values δ . The solution (45) is predicted historical time paths for endogenous variables. We can compare these with actual historic time paths for key variables in the following manner:

$$Y_t = G(X_t, Z_t^0, Z_t^u, B, \delta) + e_t, \tag{46}$$

Where Y_t is an N-dimensional vector of historical targets, G is a function producing the vector of model predicted values for the targets, and e is an N-dimensional vector representing the discrepancy between historical targets and predicted values. Calibration to the base year implies that $e_{t'} = 0$.

The estimation problem is set up using the dynamic cross entropy concept. We treat each B_k ($k=1, \ldots, K$) as a discrete random variable with compact support and $2 \le M < \infty$ possible outcomes. So, we can have

$$B_k = \sum_{m=1}^{M} z_{km} p_{km} \tag{47}$$

Where p_{km} is the probability of outcome z_{km} and the probabilities must be non-negative and sum to one.

Similarly, treat each element ofe_t, i.e.e_{tn}, as a finite and discrete random variable with compact support and $2 \le J < \infty$possible outcomes. We have

$$e_{tn} = \sum_{j=1}^{J} v_{tnj} w_{tnj}, \tag{48}$$

Where w_{tnj} is the probability of outcomev_{tnj}. In actual applications, support sets are typically specified with three or more points.

Elements of Z_t^u may be similarly reparameterized, but following Arndt et al. (2002), we forgo this step for simplicity. This is equivalent to assume that all elements of Z_t are known.

The CE formulation can be written as follows:

Min

$$\sum_{k=1}^{K} \sum_{m=1}^{M} p_{km} Log\left(\frac{p_{km}}{q_{km}}\right) + \sum_{t=1}^{T} \sum_{n=1}^{N} \sum_{j=1}^{J} w_{tnj} Log\left(\frac{w_{tnj}}{u_{tnj}}\right) \tag{49}$$

$$\text{s.t } F(X_t, Z_t^0, Z_t^u, B, \delta) = 0 \ \forall t \in T \tag{50}$$

$$Y_t = G(X_t, Z_t^0, Z_t^u, B, \delta) + e_t \ \forall t \in T \tag{51}$$

$$\delta = P(Z_{t'}, B_0) \tag{52}$$

$$B_k = \sum_{m=1}^{M} z_{km} p_{km} \quad \forall k \in K \tag{53}$$

$$e_{tn} = \sum_{j=1}^{J} v_{tnj} w_{tnj} \quad \forall t \in T,\ \forall n \in N \tag{54}$$

$$\sum_{m=1}^{M} p_{km} = 1 \quad \forall k \in K \tag{55}$$

$$\sum_{j=1}^{J} w_{tnj} = 1 \quad \forall t \in T,\ \forall n \in N \tag{56}$$

If the priors are chosen to be uniform, we can use the maximum entropy formulation.

4. Estimating trade elasticity parameters for Vietnam economy

We use the static CGE model to find Cross Entropy estimates of parameters. The base year is 2007, the most recent year a detailed social accounting matrix is available. The data set comprises of 6 years (2007-2012). The GDP deflator is used to convert all data to real 2007 values.

The following exogenous historical data series are imposed upon the model: (1) Tariff rates by commodity, (2) Capital stock by sectors, (3) Total labor supply by categories, and (4) Foreign transfer to household. The other exogenous parameters, derived from the 2007 social accounting matrix, are kept constant throughout the estimation period. These include: Input - output coefficients, value added coefficients, indirect tax rates, household and government savings rates, direct tax rates on labor and capital, shares of investment expenditure, shares of government consumption expenditure, government transfer rates to household, distribution rates of labor income, distribution rates of capital income, and distribution rates of government transfer.

Eight sets of variables are targeted, including: (a) Gross domestic product, (b) Total sales by activity, (c) Value of imports by commodity, (d) Value of exports by commodity, (e) Total government revenue, (f) Value of capital formation by commodity, (g) Value of household consumption by commodity, and (h) Value of government consumption by commodity.

Three point prior distributions were set on CES and CET parameters, with the lower point at 0.1, the central point at 2.0, and the upper point at 12.0. The central point was given a weight of 0.5. Weights on the upper and lower points were set such that the expected value of the prior distribution become 2.0.

This distribution reflects our expectation of Armington elasticity values. The estimates cannot be less than 0.1 or more than 12.0. We expect estimated elasticities to be approximately 2.0 for each commodity, which is why the central point receives a relatively heavy weight of 0.5. We applied the same prior distribution for each commodity.

Table 1: *Support Spaces and Prior Distribution of Parameters*

	Low	Central	High
Support space of CES and CET parameters	0.100	2.000	12.000
Prior distribution	0.421	0.500	0.079

As for the support space on the error term, we used the three-sigma rule around zero, as is recommended in Golan et al. (1996) for each equation. The dimension of the support space on the disturbance terms is 3 (i.e., 3 elements). The support space for the errors is therefore: [-3.*stdev;* 0*;* 3.*stdev*], where *stdev* is the empirical (data) standard deviation of the dependent variable. The estimates are shown in Table 2.

Table 2. *Trade Parameter Estimates*

No	Sector	Import Elasticity				Export Elasticity			
		Estimate	Low (0.1)	Center (0.2)	High (12.0)	Estimate	Low (0.1)	Center (0.2)	High (12.0)
1	Crops cultivation	**1.584**	0.468	0.479	0.041	**2.231**	0.421	0.472	0.094
2	Livestock and poultry	**2.064**	0.457	0.514	0.085	**1.945**	0.429	0.509	0.076
3	Forestry	**2.618**	0.385	0.487	0.128	**2.467**	0.413	0.499	0.094
4	Fishery	**1.884**	0.436	0.507	0.082	**2.148**	0.417	0.501	0.079
5	Mining and quarrying	**2.324**	0.364	0.476	0.122	**1.523**	0.489	0.484	0.029
6	Processed seafood and by products	**2.066**	0.418	0.503	0.078	**1.672**	0.461	0.474	0.041
7	Alcohol, beer, water and soft drinks	**1.842**	0.421	0.518	0.094	**2.104**	0.423	0.507	0.074
8	Cigarettes and tobacco products	**2.103**	0.386	0.463	0.114	**2.215**	0.421	0.493	0.092
9	Other food manufactures	**2.571**	0.429	0.504	0.085	**2.016**	0.424	0.500	0.075
10	Chemical manufacturing	**2.428**	0.445	0.501	0.077	**1.451**	0.476	0.482	0.031
11	Non-metallic mineral, ferrous metals	**1.842**	0.461	0.500	0.098	**2.086**	0.424	0.508	0.086
12	Machinery and equipment	**3.007**	0.352	0.469	0.173	**1.541**	0.461	0.496	0.033
13	Rubber and plastic products	**1.864**	0.467	0.498	0.069	**1.877**	0.408	0.500	0.076
14	Vehicles	**2.148**	0.431	0.500	0.074	**2.305**	0.369	0.487	0.104
15	Textile, garment	**1.349**	0.518	0.462	0.023	**1.732**	0.423	0.498	0.058
16	Leather	**1.147**	0.572	0.437	0.006	**0.496**	0.756	0.243	0.001
17	Wood and wood products	**2.321**	0.411	0.499	0.094	**1.887**	0.425	0.500	0.078
18	Other manufacturing products	**2.814**	0.392	0.496	0.118	**2.421**	0.387	0.499	0.108
19	Electricity , gas and water supply	**2.672**	0.359	0.494	0.125	**1.753**	0.442	0.496	0.052
20	Trade	**1.315**	0.517	0.458	0.014	**3.110**	0.347	0.472	0.174
21	Hotels, restaurants and tourism	**2.224**	0.422	0.502	0.087	**1.709**	0.438	0.495	0.041

22	Transport services	**2.346**	0.405	0.500	0.099	**2.018**	0.433	0.500	0.081
23	Communication services	**2.104**	0.436	0.500	0.085	**1.842**	0.451	0.488	0.056
24	Financial services	**2.140**	0.428	0.514	0.080	**1.812**	0.427	0.500	0.085
25	Public services and other services	**2.512**	0.394	0.496	0.124	**1.831**	0.426	0.500	0.084

Source: *Author's calculations.*

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