Development Economics and Public Policy

WORKING PAPER SERIES

Paper No. 15

DO TECHNOLOGY SHOCKS SHIFT OUTPUT? AN EMPIRICAL ANALYSIS OF A TWO FACTOR MODEL

Hulya Ulku
University of Manchester

May 2005

ISBN: 1 904143 72 5

Further details: Institute for Development Policy and Management
Published by: University of Manchester,
Harold Hankins Building, Precinct Centre,
Oxford Road, Manchester M13 9QH, UK
Tel: +44-161 275 2798 Fax: +44-161 275 0808
Email: idpm@man.ac.uk Web: http://idpm.man.ac.uk

Do Technology Shocks Shift Output?
An Empirical Analysis of a Two Factor Model

Hulya Ulku[1]

Abstract

This study identifies the effect of technology shocks on aggregate output using confirmatory factor analysis employed by Griliches, Hall and Pakes (1991). The analysis is based on the assumptions that there are two distinct shocks in an economy, demand and technology shocks, and that the patent data contain additional information on technology shocks. The findings show that, while the patent and R&D data do not contain significant information on technology shocks in the full sample of OECD countries, they do have significant information on these shocks in the G13 countries. The results suggest that, in the G13 countries technology shocks can explain almost all of the unexpected changes in patent stock, half of those in R&D stock and a quarter of the unexpected changes in GDP.

Keywords: technology shocks, innovation; R&D; patents; output.

INTRODUCTION

This study aims to identify the effect of technology shocks on aggregate output using confirmatory factor analysis employed by Griliches, Hall and Pakes (1991), GHP hereinafter. Following GHP[2], it is assumed here that the shifts in aggregate output can be explained by two distinct shocks in an economy, namely demand and technology, and that patent data provide additional information on technology shifts to that already available in R&D data. Demand shocks are driven by macroeconomic shifts in aggregate demand, population, exchange rate, and relative factor prices. Thus they shift all the variables of the production function, namely employment, capital stock, R&D, patents and GDP. Technology shocks originate from technological and scientific breakthroughs, thus in the short term they only affect R&D, patents and GDP, but not capital stock and employment.[3] Based on these assumptions, we construct a two-factor model of innovations[4] in employment, capital, R&D, and patent stock, and GDP to identify the effects of technology shocks on aggregate output. The empirical analysis covers 22 OECD countries and the G13 group for the period 1982-1997.

The results of the two-factor confirmatory factor analysis (CFA) suggest that, except for the patent stock, demand shocks have significant affect on the variables of the production function, in both the full OECD sample and G13 group. However, the effect of technology shocks on R&D and patent stock, and GDP are significant only in the G13 countries that have higher levels of R&D and patents than other OECD countries. According to the results of two-factor model in G13 group, technology shocks can explain almost all the unexpected changes in patent stock, half of those in R&D stock and a quarter of the unexpected changes in GDP. In addition, demand shocks appear to explain half of the total unexpected changes in GDP, employment and capital stock and around a quarter of those in R&D stock. These results support the presumption that patent data contain additional information on technology shocks, and technology shocks shift aggregate output.

The following section presents the model used in this study, and section three describes the data and methodology. Section four, documents the empirical analysis and section five concludes the paper.

THE MODEL

The model is based on the following assumptions: (1) there are two distinct shocks in an economy, namely technology and demand shocks; (2) while demand shocks affect all the variables of the production function, technology shocks affect only R&D, patent and GDP; (3) innovations (stochastic changes) in the patent data contain additional information on technology shocks. The innovations in each variable are computed by estimating the production function in R&D based growth models with seemingly unrelated regression (SUR) analysis. Each regression equation in the analysis is assumed to take the following form:

$$
\begin{aligned}
&Emp = \alpha_0 + \alpha_1 L(Emp) + \alpha_2 (GDP) + \alpha_3 (Cap\ stock) + \alpha_4 (Pop) + \alpha_5 \mu_t + \varepsilon_1 \\
&Cap\,stock = \sigma_0 + \sigma_1 L(Cap\,stock) + \sigma_2 (GDP) + \sigma_3 (Emp) + \sigma_4 (Pop) + \sigma_5 \mu_t + \varepsilon_2 \\
&R\,\&\,D\,stock = \delta_0 + \delta_1 L(R\,\&\,D\,stock) + \delta_2 (GDP) + \delta_3 (Pop) + \delta_4 (Pat\,stock) + \delta_5 (Sec) + \delta_6 \mu_t + \varepsilon_3 \\
&Pat\,stock = \lambda_0 + \lambda_1 L(Pat\,stock) + \lambda_2 (GDP) + \lambda_3 (Pop) + \lambda_4 (R\,\&\,D\,stock) + \lambda_5 (Sec) + \lambda_6 \mu_t + \varepsilon_4 \\
&GDP = \rho_0 + \rho_1 L(GDP) + \rho_2 (Pop) + \rho_3 (Pat\,stock) + \rho_4 (Sec) + \rho_5 (Emp) + \rho_6 (Cap\,Stock) + \rho_6 \mu_t + \varepsilon_5
\end{aligned}
\tag{1}
$$

where emp, cap, pop, pat, sec and $\varepsilon's$ represent employment, capital stock, population, patent stock, secondary school enrolment and innovations in the dependent variables, respectively. All variables are in natural logs and all regressions include year dummies, μ_t. In addition to the main explanatory variables in each equation, we also include the lagged dependent variables, population and GDP to control for endogeneity and the size of the economy. Based on the assumptions mentioned above, the innovations in the variables of the model are assumed to comprise the following structure,

$$
\begin{aligned}
&\varepsilon_1 = e^* = \beta_0 d + e_1 \\
&\varepsilon_2 = c^* = \beta_1 d + e_2 \\
&\varepsilon_3 = r^* = \beta_2 d + \eta_1 t + e_3 \\
&\varepsilon_4 = p^* = \gamma r^* + \eta_2 t + e_4 = \gamma\beta_2 d + (\gamma\eta_1 + \eta_2) t + \gamma\varepsilon_3 + e_4 \\
&\varepsilon_5 = g^* = \eta_3 t + \beta_3 d + e_5
\end{aligned}
\tag{2}
$$

where *e*, c*, r*, p** and g* represent innovations in employment, capital stock, R&D stock, patent stock and GDP respectively, and *d* refers to the demand shocks that affect employment, capital, R&D and patent stock, and GDP, while *t* refers to the technology shocks that affect R&D stock, patent stock and GDP. The e's are specific error terms and are assumed to be uncorrelated with each other, *t* and *d*. Since in the focus here is on the effect of a unit shock in technology and demand on the variables of the model, the variance of technology and demand shocks are normalized to one. The resulting variance-covariance matrix is,

$$\begin{array}{lllll}
\beta_0^2 d^2 \sigma_1^2 & \beta_0\beta_1 d^2 & \beta_0^2 \gamma d^2 & \beta_0\gamma\beta_2 d^2 & \beta_0\eta_4 d^2 \\
 & \beta_1^2 d^2 + \sigma_2^2 & \beta_1\beta_2 d^2 & \gamma\beta_1\beta_2 d^2 & \beta_1\beta_3 d^2 \\
 & & \beta_2^2 d^2 + \eta_1^2 t^2 + \sigma_3^2 & \beta_2^2\gamma d^2 + (\gamma\eta_1^2 + \eta_2)t^2 + \gamma\sigma_{23}^2 & \gamma\beta_2\beta_3 d^2 + \eta_3(\gamma\eta_1 + \eta_2)t^2 \\
 & & & \gamma^2\beta_2^2 d^2 + (\gamma\eta_1\eta_2)^2 t^2 + \gamma\sigma_3^2 + \sigma_4^2 & \gamma\beta_2\beta_3 d^2 + (\gamma\eta_1 + \eta_2 + \eta_3)t^2 \\
 & & & & \eta_3^2 t^2 + \beta_3^2 d^2 + \sigma_5^2
\end{array} \quad (3)$$

where d^2 is the variance of *d* and t^2 is the variance of *t*. In the model there are 13 parameters to be estimated and 15 variances and covariances of the residuals. Therefore, the model is over identified. The variances and covariances are fit to model using generalized least square (GLS) estimation method in LISREL software. The section below documents the data and methodology and the results are presented in section 4.

DATA AND METHODOLOGY

The data used in this paper are patent applications, gross expenditure on R&D (GERD) and data on other macroeconomic variables for 22 OECD countries.[5] Patent applications are obtained from the NBER Patent Citation Database, which include the patent applications of inventors of different countries made to U.S. Patent Office for the period of 1983-1997. These applications consist of utility patents in the manufacturing sector and are classified in five main categories: chemical, computers and communication, drugs and medical, electrical and electronic and others. The 'others' category includes agriculture-husbandry-food, amusement devices, apparel and textile, earth working and wells, furniture house fixtures, heating, pipes and joints, receptacles.

Gross expenditure on R&D (GERD) is obtained from the OECD Main Statistics and Technology Indicators database. GERD is defined as the total intramural expenditure on R&D in the national territory during a given period. It includes R&D performed within a country and funded from abroad, but excludes payments made abroad for R&D, and covers R&D expenditures made in business enterprises, government sector, higher education and non-profit firms.

GDP and gross fixed investment are obtained from the World Development Indicators (WDI) and employment data is derived from the OECD database. All GERD, GDP and gross fixed investment are in 1995 \$U.S. Patent and R&D stocks are computed using a depreciation rate of 0.20, and capital stock is computed using 0.10 depreciation rate. The initial stock values of the variables are calculated using the formula $V_{S\ t-1} = V_t /(r+\delta)$, where $V_{S\ t-1}$ is the stock value of the variable at year t-1, V_t is the value of the variable at year t, r is the average growth rate of the variable, and δ is the depreciation rate. Once the initial stock value of the variable is computed, the stock values of the variable for subsequent years is calculated using the perpetual inventory method, $V_{S\ t} = Vt+(1- \delta)\ V_{t-1}$.

EMPIRICAL ANALYSIS

The empirical analysis is carried out in three stages. First, the innovations in the variables are obtained by estimating the model in equation (1) in section 2 using the SUR technique.[6] Second, pairwise correlation matrix of the innovations are computed. Finally, the variance-covariance matrix presented in equation (3) in section 2 is fitted into the estimated correlation matrix of the innovations by generalized least square (GLS) estimation.[7] In addition to the two-factor model, we also estimated a one-factor model to check the robustness of our presumption that there are two distinct shocks in an economy. To identify whether the results differ between the full sample and the technologically more advanced OECD countries, the analysis is carried out for the full OECD sample of 22 countries and the G13 group.

The results for the full OECD sample are documented in Tables 1 and 2. Table 1 presents the correlation matrix of the innovations. As expected, the innovations in the R&D and patent stock are positively correlated with each other and the innovations in GDP. However, the magnitude of the correlation between the innovations in GDP and patent stock is only 0.07, implying that the link between aggregate output and technology shocks that work through patents is not strong. The results of the confirmatory factor analysis are reported in Table 2. The first column documents the results of the one factor analysis, which assumes that there is

Table 1. Correlation Coefficients of the Innovations, Full Sample, 1982-1997*

	e*	c*	r*	p*	g*
e*	1.00	0.26	0.06	0.06	0.20
c*		1.00	0.18	0.07	0.36
r*			1.00	0.14	0.30
p*				1.00	0.07
g*					1.00

*See appendix 1 Table A1.2 for the covariance matrix of the innovations

Table 2. Confirmatory Factor Model, Full Sample, 1982-1997

	One Factor Model	Two Factor Model
Loadings on Factor 1	Demand Shocks	Demand Shocks
e*	0.33 (4.76)	0.36 (4.97)
c*	0.57 (7.54)	0.70 (6.44)
r*	0.40 (5.78)	0.23 (2.98)
p*	0.14 (2.16)	0.10 (1.35)
g*	0.67 (8.40)	0.51 (5.81)
Loadings on Factor 2		Technology Shocks
e*	--	-
c*	--	-
r*	--	1.01 (0.81)
p*	--	0.11 (0.73)
g*	--	0.17 (0.77)
Idiosyncratic Variances		
e*	0.86 (11.6)	0.86 (11.2)
c*	0.67 (8.41)	0.51 (3.54)
r*	0.80 (10.7)	-0.09 (0.03)
p*	0.95 (12.6)	0.97 (11.9)
g*	0.54 (5.71)	0.69 (6.39)

X^2	10.62 (p = 0.059)	0.87 (p=0.65)
Model AIC	32.47	26.89
DF	5	2
Number of observations	334	334
Number of countries	22	22

Figures in the parentheses are t statistics.

only one type shock in an economy that affects all the variables of the production function. Although the effect of this one type shock on the variables of the model is positive and significant, the model is rejected as indicated by the low p value of the chi square test.[8]

The second column of Table 2 documents the results of the two-factor model, which assumes that there are two distinct shocks in an economy: demand and technology shocks. Demand shocks are assumed to affect all the variables of the model, while technology shocks affect only R&D and patent stock and GDP. As the table shows, the effect of demand shocks on all the innovations in the variables of the model is positive and significant, suggesting that demand shocks explain a significant fraction of the unpredicted changes in the variables of production function. However, the loadings on technology shocks are not significant, which implies that R&D and patent data do not provide sufficient information on technology shocks in the full OECD sample. Yet, these results could be caused by the fact that the countries in the sample differ substantially in terms of the levels of R&D and patent stocks. To see if the results improve when we include only the countries with similar R&D and patent stock we also estimated the model for the G13 countries.

The correlation and the variance-covariance matrices for the G13 countries are reported in Tables 3 and 4.[9] As seen from Table 3, the correlations between the innovations in GDP, R&D and patent stock are higher than those in the full sample. This implies that there is more scope to identify the effect of technology shocks on GDP. Table 4 reports the results of one and two-factor models. As evident from the first column, the assumption that there is only one type shock that is driven by changes in demand conditions is not rejected.[10] According to the results, these demand shocks explain a significant portion of the unexpected variations in all the variables of the production function, except for the patent stock. However, the fact that this one type shock does not explain the total unexpected variations in the variables suggests that there might be other shocks in the economy, supporting our presumption that there are, at least, two shocks in an economy.

The results of the two-factor model, which incorporates technology as well as demand shocks, are reported in the second column of Table 4. Inclusion of the technology shocks into the model substantially improves the fit of the model as indicated by a significant drop in the value of chi square test from 6.09 to 0.73 and an increase in its p value. In addition, loadings on both demand and technology shocks are positive and significant, as postulated by the model presented in equation (2) in section 2. Specifically, demand shocks are able to explain 56% of the unexpected variation in GDP.

Table 3: Correlation Coefficients of the Innovations, G13 Countries, 1982-1997

	e*	c*	r*	p*	g*
e*	1.00	0.28	0.14	-0.07	0.25
c*		1.00	0.98	-0.07	0.30
r*			1.00	0.48	0.27
p*				1.00	0.19
g*					1.00

*See appendix 1 Table A1.3 for the covariance matrix of the innovations

Table 4: Confirmatory Factor Analysis, G13 Countries, 1982-1997

	One Factor Model	Two Factor Model
Loadings on Factor 1	Demand Shocks	Demand Shocks
e*	0.32 (3.60)	0.52 (5.25)
c*	0.56 (5.71)	0.55 (5.41)
r*	0.40 (4.37)	0.22 (2.04)
p*	0.15 (1.63)	-0.13 (1.22)
g*	0.67 (6.36)	0.57 (4.81)
Loadings on Factor 2		Technology Shocks
e*	-	-
c*	-	-
r*	-	0.55 (4.00)
p*	-	0.93 (4.19)
g*	-	0.28 (3.00)

Idiosyncratic Variances		
e*	0.86 (8.82)	0.73 (6.85)
c*	0.67 (6.36)	0.69 (6.27)
r*	0.80 (8.15)	0.65 (4.82)
p*	0.96 (9.52)	0.12 (0.29)
g*	0.55 (4.32)	0.65 (6.16)
X^2	6.09 (p = 0.30)	0.73 (p = 0.69)
Model AIC	27.15	26.74
DF	5	2
Number of observations	192	192
Number of countries	12	12

Figures in the parentheses are t statistics.

Similarly, they explain 55%, 52% and 22% of the total unexpected variations in capital stock, employment and R&D stock respectively. Technology shocks, on the other hand, explain 93%, 55% and 28% of the total unexpected variations in patent stock, R&D stock and GDP respectively. According to these results, technology shocks can explain almost all the unexpected variations in the patent stock, confirming our assumption that patent data contain additional information on technology shocks. However, the total effect of technology shocks on the innovations in the patent stock includes both direct and indirect effect of technology shocks. The direct effect is computed as 130% with a t value of 3.94, while the indirect effect through R&D stock is computed as –33% with a t value of 4.78.[11] This means that the direct effect of technology shocks on patent stock is more than twice as much as their effect on R&D stock. This information combined with the finding that demand shocks do not have any significant effect on patent stock provides strong evidence for the argument that technology shocks can be identified using patent data. Furthermore, as seen from the second column of Table 4, demand and technology shocks can explain 57% and 28% of the total unexpected variation in GDP, respectively. Together they can explain 85% of the unexpected variation in GDP.

In short, the results of the confirmatory factor analyses reveal that patent and R&D data do not provide significant information on technology shocks in the full sample of OECD countries. However, once the analysis is restricted to the G13 countries, which are technologically more advanced and more homogenous in their levels of R&D and patent stocks, the results provide strong evidence that technology shocks shift output. In particular, in the G13 group technology socks account for almost all of the unexpected changes in patent stock, half of those in R&D stock, and a quarter of the unexpected changes in GDP. Furthermore, demand shocks have an important effect on employment, investment and R&D stock but do not have any significant effect on patent stock in both the full OECD sample and the G13 countries.

CONCLUSION

The objective of this study was to apply the two-factor model developed by Griliches, Hall and Pakes (1991) to aggregate production function to identify the effect of technology shocks on aggregate output. The findings of the two-factor confirmatory factor analysis suggest that patent data contain additional information on technology shocks only in the G13 countries, which have higher levels of R&D and patent stock than the rest of the OECD countries in the sample. In the G13 countries, technology shocks can to explain a quarter, while demand shocks can explain half of the unexpected changes in GDP. These results are in line with the postulation of Griliches, Hall and Pakes (1991) that patent data have additional information on technology shocks and technology shocks shift output.

References

Griliches, Z., B.H. Hall and A. Pakes (1991) 'R&D, Patents, and Market Value Revisited: Is There a Technological Opportunity Factor?' *Journal of Economics of Innovation and New Technology*, 1, pp.183-201.

Joreskog, K.G. and D. Sorbom (1996) Lisrel 8: User's Reference Guide, Scientific Software International.

Appendix 1: List of Countries and Covariance Matrices of the Innovations

Table A1.1-List of the Countries and Number of Observations

G13 group*	Number of observations per country	**Other OECD** countries in the sample	Number of observations per country
Australia	15	Austria	16
Canada	16	Belgium	16
Denmark	16	Finland	16
France	16	Greece	16
Germany	16	Iceland	16
Italy	16	Ireland	16
Japan	16	New Zealand	16
Netherlands	16	Portugal	15
Norway	16	Spain	16
Sweden	16	Switzerland	16
United Kingdom	16		

*United States is not included in the analysis as the patent data are obtained from the U.S. Patent Office.

Table A1.2. Covariance Matrix of the Innovations, Full Sample, 1982-1997

	e*	c*	r*	p*	g*
e*	0.000475	0.000068	0.000023	0.000067	0.000077
c*		0.000147	0.000042	0.000041	0.000081
r*			0.000392	0.000147	0.000110
p*				0.002749	0.000071
g*					0.000337

Table A1.3. Covariance Matrix of the Innovations, G13 Group, 1982-1997

	e*	c*	r*	p*	g*
e*	0.000523	0.000063	0.000042	0.000043	-0.000088
c*		0.000093	0.000012	0.000018	0.000044
r*			0.00017	0.000166	0.000053
p*				0.000703	0.000078
g*					0.000232

Appendix 2. Derivation of the Variances and t Statistics of γ and η_2

The coefficients γ and η_2 indicate the direct effect of demand and technology shocks on patent stocks, respectively. Since the values of these parameters are not directly observable from the regression output, we need to calculate them and their t statistics, using the information in the model presented in equation (1) in section 2,

$$\begin{aligned}
\varepsilon_1 &= e^* = \beta_0 d + e_1 \\
\varepsilon_2 &= c^* = \beta_1 d + e_2 \\
\varepsilon_3 &= r^* = \beta_2 d + \eta_1 t + e_3 \\
\varepsilon_4 &= p^* = \gamma r^* + \eta_2 t + e_4 = \gamma\beta_2 d + (\gamma\eta_1 + \eta_2)t + \gamma\varepsilon_3 + e_4 \\
\varepsilon_5 &= g^* = \eta_3 t + \beta_3 d + e_5
\end{aligned} \qquad (1)'$$

The coefficients $\gamma\beta_2$ and $(\gamma\eta_1 + \eta_2)$ show the total effect of demand and technology shocks on patent stocks, respectively. For notational convenience we can denote $\gamma\beta_2$ as δ and $(\gamma\eta_1 + \eta_2)$ as ϕ. Since we know the values of δ, ϕ and β_2 the values of γ and η_2 can be calculated using the relationship shown above: $\gamma = \delta / \beta_2$, and $\eta_2 = \phi - \gamma\eta_1$. The variance of γ and η_2 are then calculated using the generic following formula

$$Var(\gamma) = \nabla f(\mathrm{B})' \, Var(B) \nabla f(\mathrm{B}) \qquad (4)$$

where $\nabla f(\mathrm{B})$ refers to the gradient vector of a non-linear function with respect to its parameters. This formula allows us to compute the variance of a parameter, which is a non-linear function of the parameters, whose variance and covariance matrices are known.

Using the information shown above, the value of γ is calculated as –0.5999 ($\gamma = \delta / \beta_2 = -0.13/0.22$).

The first order partial derivative of γ with respect to δ and β_2 is documented below:

$$\partial\gamma / \partial\delta = 1/\beta_2 = 1/0.22 = 4.514$$
$$\partial\gamma / \partial\beta_2 = -\delta / \beta^2{}_2 = -(-0.13/0.22^2) = 2.70$$

The variances and covariances of δ and β_2 :

Var(δ) = 0.012, Var (β_2) = 0.012 and the Cov(δ , β_2) = 0.006

Substituting the values of partial derivatives and the variances and covariances of these parameters in the formula above the variance, standard deviation and t value of γ is calculated as follows:

$$Var(\gamma) = \begin{bmatrix} 4.514 & 2.70 \end{bmatrix} \begin{bmatrix} 0.012 & 0.006 \\ 0.006 & 0.012 \end{bmatrix} \begin{bmatrix} 4.514 \\ 2.70 \end{bmatrix}$$

Var (γ)=0.2556

Std dev (γ) = $\sigma_\gamma = 0.50562$

$$t_\gamma = \gamma / \sigma_\gamma = -0.5999 / 0.50562 = -1.1864$$

The value of η_2, the direct effect of technology shocks on patent stock, is calculated as 1.25 [$\eta_2 = \phi - \gamma\eta_1$ = 0.93-(-0.5999*0.55)]. The variance of η_2 is computed using equation (4) shown above. The first order partial derivative of η_2 with respect to ϕ, γ and η_1 is:

$\partial\eta_2 / \partial\phi = 1$

$\partial\eta_2 / \partial\gamma = -\eta_1 = -0.55$

$\partial\eta_2 / \partial\eta_1 = -\gamma = -0.5999$

Variances and covariances of the parameters: Var(ϕ) = 0.0492, Var(γ) = 0.50562, Var(η_1) = 0.019, Cov (ϕ, η_1) = -0.024. Cov (γ, η_1) and Cov(ϕ, γ) are assumed to be zero, i.e. the demand and technology shocks are independent.

The variance, standard deviation and t value of η_2 are calculated as follows:

$$\text{Var}(\eta_2) = \begin{bmatrix} 1 & -0.5478 & -0.5999 \end{bmatrix} \begin{bmatrix} 0.0492 & 0 & -0.024 \\ 0 & 0.0153 & 0 \\ -0.024 & 0 & 0.019 \end{bmatrix} \begin{bmatrix} 1 \\ -0.5478 \\ -0.5999 \end{bmatrix}$$

Var(η_2) = 0.104

Std dev (η_2)= $\sigma_{\eta_2} = 0.322$

$t_{\eta_2} = \eta_2 / \sigma_{\eta_2} = 1.26 / 0.0.322 = 3.937$

Indirect effect of technology shocks on patent stock through R&D stock is equal to –0.33% to ($\gamma\eta_1$), and its t statistics is equal to 4.78 ($\gamma\eta_1$/($sd_\lambda * sd_\eta$), where $\gamma\eta_1$ is the indirect effect of technology shocks on patent stock, sd_γ (0.50562) and $sd_{\eta 1}$ (0.13672) are the standard deviation of γ and η_1 respectively).

Appendix 3. Results of Seemingly Unrelated Regression (SUR) Analysis

Table A3.1. Seemingly Unrelated Regression Analysis, Full OECD Sample, 1982-1997

Equation	Obs	"R-sq"	chi2	P
GDP	334	0.9998	6.95e+08	0.0000
Patent Stock	334	0.9994	603466.6	0.0000
R&D stock	334	0.9999	7.96e+07	0.0000
Capital Stock	334	0.9999	1.65e+09	0.0000
Labour	334	0.9997	1.30e+06	0.0000

Equations	Coefficient	Std. Err.	z	P>|z|
Dependent Variable: GDP				
L1. GDP	.9777944	.0106113	92.15	0.000
Patent Stock	.0041821	.0014614	2.86	0.004
Capital Stock	.0045742	.0070739	0.65	0.518
Labour	-.014873	.010224	-1.45	0.146
Secondary School Enr.	.0109146	.0085581	1.28	0.202
Population	.0270557	.0091748	2.95	0.003
Dependent Variable: Patent Stock				
L1. Patent Stock	.9998678	.0075231	132.91	0.000
R&D Stock	-.0123868	.0153251	-0.81	0.419
Secondary School Enr.	.0497693	.024031	2.07	0.038
Population	.007761	.0122386	0.63	0.526
GDP	.0031124	.0168475	0.18	0.853
Dependent Variable: R&D Stock				
L1. R&D stock	.9648067	.0053114	181.65	0.000
Patent Stock	.0020598	.0027323	0.75	0.451
Secondary School Enr.	.0204007	.0090045	2.27	0.023
GDP	.0286204	.0062232	4.60	0.000
Population	.0016937	.0045593	0.37	0.710
Dependent Variable: Capital Stock				
L1.Capital Stock	.9878589	.0044176	223.62	0.000
Labour	.0103446	.0064788	1.60	0.110
GDP	.0114353	.0051191	2.23	0.025
Population	-.0068656	.0055201	-1.24	0.214
Dependent Variable: Labour				
L1. Labour	.9706869	.0116792	83.11	0.000
Capital Stock	-.0016074	.0081299	-0.20	0.843
GDP	.0084214	.0093647	0.90	0.369
Population	.0223853	.0099741	2.24	0.025

Note: All variables are in natural logs, and all regressions include year dummies and a constant. L1. stands for the first lag of the variable.

Table A3.2. Seemingly Unrelated Regression Analysis, G13 Group, 1982-1997.

Equations	Obs	"R-sq"	chi2	P
GDP	191	0.9998	6.16e+08	0.0000
Patent Stock	191	0.9997	563416.00	0.0000
R&D stock	191	0.9999	1.85e+06	0.0000
Capital Stock	191	0.9999	2.70e+06	0.0000
Labour	191	0.9996	445118.04	0.0000

Equations	Coefficient	Std. Err.	z	P>|z|
DV: GDP				
L1. GDP	.9924291	.0107477	92.34	0.000
Patent Stock	-.0020349	.0026223	-0.78	0.438
Capital Stock	.0064738	.0065826	0.98	0.325
Labour	.0018687	.0117645	0.16	0.874
Secondary School Enr.	.0111273	.0109935	1.01	0.311
Population	.00228	.0106509	0.21	0.830
DV: Patent Stock				
L1. Patent Stock	1.030067	.0075694	136.08	0.000
R&D Stock	-.093543	.0140531	-6.66	0.000
Secondary School Enr.	.0432197	.0194355	2.22	0.026
Population	.0136785	.0103419	1.32	0.186
GDP	.0523784	.0102738	5.10	0.
DV: R&D Stock				
L1. R&D stock	.9399331	.0061985	151.64	0.000
Patent Stock	.023312	.0034653	6.73	0.000
Secondary School Enr.	.0045361	.0095045	0.48	0.633
GDP	.0266011	.0050212	5.30	0.000
Population	.0037484	.0050463	0.74	0.458
DV: Capital Stock				
L1.Capital Stock	.9945955	.0041789	238.01	0.000
Labour	.0291495	.0072945	4.00	0.000
GDP	.0136515	.0061414	2.22	0.026
Population	-.0303021	.0067515	-4.49	0.000
DV: Labour				
L1. Labour	.9575628	.0168749	56.74	0.000
Capital Stock	.0021142	.0098822	0.21	0.831
GDP	.0061722	.0145697	0.42	0.672
Population	.0348177	.0157815	2.21	0.027

Note: All variables are in natural logs, and all regressions include year dummies and a constant.
L1. stands for the first lag of the variable.

Appendix 4: Covariance Matrix of the Parameters

A4.1. Covariance Matrix of Parameter Estimates, Full Sample

	η3	β3	*Φ*	δ	η1	β2	β1	β0
η3	0.05421							
β3	-0.00450	0.00791						
Φ	0.03434	-0.00177	0.02573					
δ	-0.00604	0.00083	-0.00433	0.00574				
η1	-0.28055	0.01220	-0.18867	0.03145	1.56053			
β2	-0.00287	0.00279	-0.00092	0.00100	0.00396	0.00618		
β1	0.00539	-0.00508	0.00220	-0.00098	-0.01480	-0.00234	0.01189	
β0	-0.00096	0.00136	-0.00036	0.00035	0.00234	0.00047	-0.00210	0.00543

A4.2. Covariance Matrix of Parameter Estimates, G13 Group

	η3	β3	*Φ*	δ	η1	β2	β1	β0
η3	0.00878							
β3	-0.00213	0.01155						
Φ	-0.01075	0.00825	0.04921					
δ	-0.00314	0.00234	-0.00113	0.01177				
η1	0.00716	-0.00486	-0.02395	-0.00045	0.01869			
β2	0.00427	0.00936	-0.00303	0.00568	-0.00531	0.01173		
β1	0.00065	-0.00177	-0.00461	0.00048	0.00244	-0.00090	0.01033	
β0	0.00066	-0.00133	-0.00399	0.00030	0.00208	-0.00037	-0.00013	0.00977

Notes

[1] I am grateful to Adam Jaffe for his invaluable comments and suggestions.

[2] Based on the assumption that patent data contain additional information on technology shocks, Griliches, Hall and Pakes (1991) employ a two-factor model to separate the effect of technology shocks from demand shocks on the market value of the manufacturing firms in the U.S. However, except for the pharmaceutical sector, they fail to identify additional information on technological shocks in patent data. Our study essentially applies the two-factor model employed in GHP on aggregate production function, with the expectation that macro level patent data might contain more information on technology shocks than the sector level patent data.

[3] The assumption that technology shocks affect only R&D, patents and GDP in the short term is appropriate as it takes time for firms to adjust their investment and employment to new developments in technology. On the other hand, the immediate outcome of scientific and technological breakthroughs should be an increase in R&D investment and patent applications as they become more profitable (or less costly) for given demand conditions.

[4] The term "innovation" is used to refer to the stochastic or unexpected changes in the variables, as in the GHP.

[5] All OECD countries that have data for more than ten consecutive years are included in the analysis. See appendix 1, Table A1.1 for the list of the OECD countries included in the analysis, and the availability of data for each country.

[6] The results of SUR analysis are documented in appendix 3.

[7] GLS estimates are obtained by means of iterative procedure that minimizes a particular fit function by successively improving the parameter estimates. Specifically, the model is fitted by minimizing a fit function $F[S, \Sigma(\theta)]$ of S (sample covariance matrix) and $\Sigma(\theta)$ (covariance structure for the observable random variables) which is non-negative and zero when there is a perfect fit in which case $S=\Sigma(\theta)$.

[8] The null hypothesis for the chi square test is that the model adequately accounts for the data, while the alternative is that there is a significant amount of discrepancy. In our analysis, the null hypothesis for the chi square test is that the variance covariance matrix we derived in equation (3) in section 2 fits well to the estimated correlation matrix.

[9] G13 countries include Australia, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Sweden, and United Kingdom. United States is not included as the patent data are obtained from the U.S.

[10] The computed chi square test is 6.09, which is smaller than the critical value of the chi square test at five degrees of freedom, 11.09, thus the model is not rejected.

[11] See appendix 2 for the calculations of the direct and indirect effect of technology shocks on patent stock and their t values.