

# **Changing Dynamics of Foreign Direct Investment in China's Automotive Industry**

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#### Abstract

China's automotive industry has developed dramatically in recent years as more and more major multinational corporations (MNCs) in this industry began to invest in China. Most of these investments have developed in the form of joint-ventures with Chinese state owned enterprises (SOEs). This paper contributes to the current literature by studying the effect of foreign direct investment (FDI) on the productivity of the automotive industry in China using panel data during the 1999 –2008 period. Channels through which FDI may directly and indirectly affect the productivity are investigated using pooled ordinary least squares model (POLS) and fixed effects model (FES) to estimate the influence of FDI on productivity in the automotive industry. The results suggest that FDI plays a negative role in this industry and suggests that there is a need for Chinese government to modify its policies and practices in order to improve the productivity of such a key industry in the Chinese economy.

Keywords: FDI, Automotive Industry, Productivity Spillovers, China, Emerging Markets

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# I. Introduction

Automobile industry has been the main driver of the intensification of technological changes in the 19<sup>th</sup> century (Womack, Jones, and Roos, 1990). More importantly, however, in recent years, automobile industry has been one of the most important heritors of Foreign Direct Investment (FDI), especially in emerging markets. The importance of automotive industry is very well accepted in the field of international

business as it contributes to the economic development of any region where it is established. This is mostly due the fact that when established it creates millions of direct and indirect manufacturing employment, and hence generates growth of related upstream and downstream industries. In the United States, for example, the automotive industry and its related industries comprise 10 % of the GDP (Maxton and Wormald, 2004). In the developing countries, a burgeoning domestic auto industry is a key contributing factor of the industrialization process. This is especially true in the case of China.

However, industrial development is not a new phenomenon in China. The Chinese auto industry developed rapidly after economic reform and a policy of openness to business were implemented with the open door policy since 1978.

Yet, despite the economic reforms and increased openness, a large quantity of automobiles was still imported to satisfy the domestic market demand. In the beginning, FDI entered into China through joint ventures and the first joint venture in China's automotive industry was established between the Shanghai Auto Factory and the German Volkswagen in 1985. Since then, several multinational corporations (MNCs) have invested in the Chinese automotive industry. Joint venture operations continued in the 1990s and major automotive industry MNCs cooperated with their Chinese partners to establish joint-ventures. After China's admittance into the World Trade Organization (WTO) in December 2001, the domestic auto production increased dramatically. In 2009, China produced more than 13 million vehicles, which was equivalent to 18 % of the total world production, and thus became the largest automotive producer surpassing the US and Japan (Chang, 2010).

According to previous literature, FDI plays an important role in the development of China's automotive industry. In theory, FDI promotes the host country's industrial productivity through following: the 1) the development of new products and processes; 2) the demonstrationimitation effect; and 3) the linkages effect and the worker training effect (Romer, 1990; Grossman and Helpman, 1991; Markusen and Venables, 1999).

However, previous literature have also suggested that at times the industrial productivity in a host country may not benefit from FDI because of technology diffusion restrictions imposed by MNCs, particularly those with affiliations in the host countries that decrease the linkage effects or keep the skills and the know-how secret (Teece, 1977; Das, 1987; Caves, 1996). To better understand the contradictory results that previous literature offers and the relationship between FDI and II. productivity of the Chinese automotive industry, empirical analysis is required.

Hence, the purpose of our empirical investigation is to estimate the effects of FDI on the productivity of the Chinese automotive industry during the period of 1999-2008. Specifically, we examine the channels through which FDI may affect the productivity of the auto industry and whether the interaction between FDI and human capital can influence the FDI–productivity link. The paper is organized as follows: in Section II, a literature review is presented. In Section III, the model, data and methodology are described. In Section IV, the results are discussed and in Section V, the conclusion, the limitations of the present research as well as recommendations for further research are presented.

### **II.** Literature Review

According to surveyed the literature of theories on the FDIproductivity links, five there are interrelated modes through which FDI may impact a host country's productivity directly and indirectly (Caves, 1996; Markusen and Venables, 1999). The direct effect of FDI is defined as the impact on the productivity of firms that receiving FDI. results from The introduction of capital, new products, ideas and practices, new management skills lead to direct transfers of technology. The establishment of R&D centers is also considered a direct effect of FDI.

The indirect effect of FDI. however, is the influence that a MNC's presence has on the productivity of local firms in the form of spillovers from foreign firms to local ones. In other words, what MNCs attempt to keep as proprietary knowledge and technology, will eventually result in indirect transfers of technology (Blomström and Persson, 1994). For example, backward and forward linkages, training effects. demonstration-imitation effects and competition effects are observed in those spillovers.

### **Direct Effects of FDI**

New ideas, products and procedures: Here, new technologies can be introduced with the presence of FDI in the form of new ideas, products and procedures. New skills to operate the technologies are introduced and developed by FDI (Das, 1987; Grossman and Helpman, 1991). Furthermore, a host country's stock of ideas can be augmented by those new ideas brought by MNCs, thus innovation is stimulated.

**R&D Centers**: Although most of the R&D centers are located in the MNCs' headquarters avoid to technology diffusion and keep their competitive advantage, **MNCs** are expenditures increasing their R&D overseas and establishing R&D centers in host countries (Braconier, Ekholm and Midelfart-Knarvik, 2001;UNCTAD, 2005). The capacity of generating knowledge in the host country is improved by participating in the R&D activities of MNCs.

# **Indirect Effects of FDI**

**Backward and Forward Linkages:** A Backward linkage is the linkage between MNCs and suppliers, while a forward linkage occurs between the MNCs and their customers and the companies that buy their products (Rodriguez-Clare, 1996). Backward linkages may help local suppliers promote their productivity by providing technical and information assistance (Belderbos, Capannelli and Fukao, 2001; Javorcik, 2004). In forward linkages local distributors and downstream firms can benefit from the MNC's knowledge to access higher-quality and/or lowerpriced products.

## **Demonstration-imitation**

effect: Due to technological differences between foreign and local firms, advanced technologies are introduced by foreign companies to the local industry. Local companies improve their productivity by watching and imitating the way foreign companies operate. Through learning by watching, local firms who are competitors of MNCs improve their production processes through the disclosure of foreign advanced technology (Blomström, Kokko and Zejan, 1994).

**Training effect:** MNCs train their foreign partners, foreign buyers or suppliers, and local companies to maintain their competitiveness. Employees who are employed by foreign companies may diffuse knowledge, skills, and management practices learned to local companies through labor turnover or if they run their own businesses (Fosfuri and Saggi, 2002).

**Competition effect:** Because of the increased competition in the domestic market with the presence of MNCs, local firms are obligated to operate competently to avoid losing their market position (Bertschek 1995). Generally, this kind of spillover takes place at the intra-industry level. In other

words, companies in the same industry can be affected by competition imposed by MNCs with advanced technology.

Although FDI has the potential to improve productivity in the host country, the benefits are not guaranteed and are not independent of the conditions of each host country. The particular characteristics of the host country will determine the extent of those benefits. Specifically, an absorptive capability is with required to cope the new technology (Girma, 2003; Crespo and Fontoura. 2007). Sometimes. technologies MNCs bring to a host country are inappropriate for local companies and industries. Therefore, local companies are not able to improve their market position. In order to benefit from technology transfer, domestic firms and industries need to make certain investments. Spillover mainly depends on the absorptive capability of local

firms to become equal to the more developed foreign firms (Teece, 1977). When the technological gap between MNCs and local companies is significant, spillovers may not occur constructively.

At times, inward FDI can even worsen the host country's productivity. The technology transferred from the MNCs may have little influence on the country's technological host development and may even slow down the local productivity by restraining the local entrepreneurship since MNCs tend to dominate the local markets. There is also the possibility that the competition effect may have a negative impact on the local economy when local companies are not efficient enough to compete with foreign ones. Furthermore, local companies may become even less competitive and are eventually pushed of business by foreign ones out

(Cantwell 1995). Likewise, with FDI presence, the local productivity can decrease as the goal of those MNCs is to gain local market-share, by attracting demand from local competitors, which eventually decreases local the productivity (Aitken and Harrison, 1999). In addition, MNCs may tend to keep advanced technology and not transfer it to the host country in order to hold their monopoly status in technology (Ram and Zhang, 2002). Finally, foreign companies may draw the best workers from the local labor pool, leaving local companies with workers that are less skilled and less productive.

# III. Model, Data and Methodology

We employ the widely adopted Cobb-Douglas production function model to test the relationship and the link between productivity and FDI.

Since changes in technology add value (Romer, 1990; Grossman and Helpman, 1991; Barro and Sala-i-Martin, 1995) to production, by incorporating technical factors associated with FDI and domestic factors into the original Cobbproduction function, Douglas we incorporate the following form of the equation:

$$Y = f(L, K, H, R, F, S, G, E)$$
  
(1)

Where: Y (productivity) is taken as the current value-added in each subsectors of China's automotive industry.

L (input of labor) is measured by the total number of employees in each sub-sector.

K (Domestic capital stock) is defined by the current value of total domestic capital formation in each subsector. This suggested definition is in line with previous research, which

assumes that FDI leads to increases on the domestic stock of capital and production capacity (According to Egger and Pfaffermayr, 2001).

H (Human capital) is measured by the ratio of the number of technical staff to the annual average number of employees in each industry sub-sector. Human capital demonstrates the level of skill or education of employees.

R (Domestic technological efforts) is taken as the ratio of R&D expenditure by the total output in each sub-sector. Innovation stands for new ideas, methods and products that are introduced into production process or into the market, representing the technological capability of domestic economy.

F (Direct effects from FDI) is measured by the current value of FDI stock in each sub-sector. Since FDI transfers capital, technology and management skills to their affiliates in host country, the greater value the foreign investment inflows will lead to the higher productivity.

S (Spillovers of FDI) is proxied by the ratio of output by foreign-invested enterprises in the sub-sectors of China's automotive industry to each sub-sector's total output.

G (Absorptive Capacity) is measured by the product of each subsector's human capital and FDI stock (H \* F), which shows the ability of domestic firms to catch up with the technical knowledge of foreign firms and complementarities between domestic technological capacity and FDI.

E (Firm Size) is measured by the ratio of the total value of industrial output in each sub-sector to the number of firms in each sub-sector. Firm size stands for the economies of scale since it is an important factor that affects the productivity in the automotive industry.

Based on the adopted production function, the following hypotheses are postulated:

H<sub>1</sub>: The number of employees (L) has a positive impact on each subsector's productivity in China's automotive industry.

H<sub>2</sub>: value of domestic capital (K) has a positive impact on each subsector's productivity in China's automotive industry.

H<sub>3</sub>: the ratio of the number of technical staff to the annual average number of employees (H) has a positive impact on each sub-sector's productivity in China's automotive industry.

H<sub>4</sub>: the ratio of R&D expenditure to total output (R) has a positive impact on each sub-sector's productivity in China's automotive industry.  $H_5$ : the value of FDI stock (F) has a positive impact on each subsector's productivity in China's automotive industry.

 $H_6$ : the ratio of output by foreign-invested enterprises to total output (S) has a positive impact on each sub-sector's productivity in China's automotive industry.

H<sub>7</sub>: the product of human capital and FDI (G) has a positive impact on each sub-sector's productivity in China's automotive industry.

 $H_8$ : the ratio of the value of industrial output to the number of firms (E) has a positive impact on each subsector's productivity in China's automotive industry.

It is expected that all of the individual independent variables has a positive impact on the productivity of the Chinese automotive industry. Hence,

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a panel data set of each sub-sector in the industry is employed to test the model. The time period studied captures the period from 1999 to 2008. All the data the obtained from were Chinese Automotive Industry Yearbook 2000-2009, in which the industry is divided into five sub-sectors: automanufacturing, auto-assembling, motormanufacturing, vehicle-engines, and vehicle-parts.

Consequently, a logarithmic model is employed to measure the elasticity of the impact of the independent variables on the dependent variable as described by the equation below:

 $Ln(Y_{it}) = \alpha_i + \beta_1 Ln(L_{it}) + \beta_2 Ln(K_{it}) + \beta_3 Ln(H_{it}) + \beta_4 Ln(R_{it}) + \beta_5$  $Ln(F_{it}) + \beta_6 Ln(S_{it}) + \beta_7 Ln(G_{it}) + \beta_8 Ln(E_{it}) + \epsilon_{it} (2)$ 

Where *i* and *t* denote the subsectors of the industry and time, respectively;  $\alpha$  is the intercept and  $\epsilon$  is the stochastic error term. The coefficients  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ ,  $\beta_4$ ,  $\beta_5$ ,  $\beta_6$ ,  $\beta_7$  and  $\beta_8$ show the percent change in Ln(Y) related with percent change in variables L, K, H, R, F, S, G and E respectively.

Three statistical models are usually applied to estimate panel data sets: a pooled ordinary least squares model (POLS), a fixed effects model (FES), and a random effects model (RES). The main differences among these models are the assumptions, which are related to the intercepts and the error terms. Both the POLS model and the FES model are used to estimate equation (2). The RES model cannot be used in this research because the number of independent variables is larger than the number of cross-sections. Hence, the

Likelihood ratio (LR) test is used to determine which model is better (POLS or FES). We favor the FES estimation since the value of LR is significantly different from zero.

# **IV.** Empirical Results

The empirical results from the POLS and FES model are summarized in the following (in Table 1??) table. As the table indicates, the FES model is preferred to the POLS model because of its large and significant LR-value. Therefore, the discussion is based only on the estimates of the FES model.

Results of Panel Data Estimations, 1999-2008 are as follows:

Variable	POLS	FES
Ln(L)	-0.7574(0.2250)	0.0820(0.1976)
Ln(K)	4.9277(0.2621) ***	-0.2162(0.2156)
Ln(H)	-1.1838(1.7500)	-2.0470(0.9068)**
Ln(R)	-3.7140(0.1249) ***	0.2683(0.0820)***
Ln(F)	-1.1926(1.7488)	-1.9853(0.8983)**

Ln(S)	-0.3735(0.0681)	0.0226(0.0691)
Ln(G)	1.1930(1.7580)	2.0187(0.9038)**
Ln(E)	-0.0844(0.0818)	1.1076(0.1201)***
Adjusted		
R-squared	l 0.9340	0.9813
F-Statistic	80.2458	214.9333
Sample		
Size (N)	50	50
Ln		
likelihood	-8.874	27.2686

Notes: (1) Standard errors are in parentheses.

(2) \*\*\* significant at 1%,\*\* significant at 5%, \* significant at 10%.

The results from the FES model display that domestic technological efforts Ln(R), absorptive capacity Ln (G) and firm size Ln(E) are positive as expected. Ln(R)and Ln(E)are statistically significant at a 1 % level and Ln(G) is statistically significant at a 5 % level. The coefficient for Ln(R) is positive and statistically significant at the 1 % level, indicating that R&D positively affects the productivity in China's automotive The industry.

magnitude of Ln(R) may mean that when other variables are kept constant, a 1% increase in R&D increases productivity by 0.268 %.

The coefficient for Ln (G) is positive and statistically significant at the 5 % level, showing that the absorptive capability positively affects productivity in China's automotive industry and that domestic human capital plays a role in capturing the benefits from FDI. In addition, The magnitude of Ln(G) indicates that when other variables are kept constant, a 1% increase in absorptive capability will raise productivity by 2.018744 percent.

The magnitude of the coefficient Ln (E) indicates that when other variables are kept constant, a 1% increase economy of scale will raise productivity by 1.108 %. The coefficient for Ln (E) is positive and statistically significant at the 1 % level, demonstrating that economy of scale positively affects productivity in China's automotive industry. This is an important finding and contribution to the emerging markets literature.

On the other hand and surprisingly, foreign direct investment Ln (F) and human capital Ln (H) are negative and statistically significant. Input of labor Ln (L) and spillover in FDI Ln(S) are positive as expected; however, statistically they are insignificant at different levels. Similarly, domestic capital stock Ln (K) is negative but statistically insignificant at various levels as well.

Furthermore, the coefficient for Ln (F) is negative and statistically significant at the 5 % level, demonstrating that direct FDI effects negatively affect productivity in China's

automotive industry. The magnitude of coefficient Ln (F) displays that when other variables are kept constant, a 1% increase in the direct FDI effect causes a decrease in productivity by 1.985 %. Hence, the result suggests that MNCs may not tend to transfer technology to host countries since they prefer to keep their monopoly status in technology (Ram and Zhang, 2002). This seems be the case in China, since the Chinese government only allows FDI in the form of Joint-Ventures in the automotive industry. thus **MNCs** may be discouraged to transfer their core technological capabilities.

The coefficient for Ln (H) is negative and statistically significant at the 5 % level, showing that human capital negatively affects productivity in China's automotive industry. The magnitude of Ln (H) shows that when other variables are kept constant, 1% increase in human capital will decrease productivity by 2.047 percent. The result reflects the fact that compared to the total number of employees, the number of technically skilled employees is needed more in this industry since imported production lines are highly automated and only trained workers can operate them efficiently.

Although Ln (L), Ln (S) and Ln (K) are not significant at all levels, the coefficients of Ln (L) and Ln (S) are as expected indicating that these two factors contribute to productivity. However the coefficient of Ln (K) is negative, suggesting that the domestic capital negatively affects productivity in China's automotive industry. This result proposes that there may be capital market imperfection in this industry. This proposition may further be

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supported by the status quo that SOEs have privileges to access capital and may be able to obtain subsidies from the government; thus compared to small and medium size enterprises (SMEs), they may lack the incentive to use capital efficiently.

Interestingly, our results contradict the FDI theories that suggest FDI has a positive impact on the host country's industrial productivity through both direct and indirect effects. This may be related to the competition effect and the unwillingness of core technology transfer. Based on the results, we can suggest that the Chinese government should not continue to place an ownership limit on FDI in the Chinese automotive industry.

Our results also indicate that the most influential factors to increase the productivity in the automotive industry are the domestic technology effort, the domestic absorptive capability and the economy of scale. Hence the results suggest that it crucial for the Chinese government to continue to encourage R&D and consolidation to improve productivity level in the industry within the current development period. Furthermore, the results suggest that the domestic capital has a negative impact on the productivity in the industry indicating the existence of capital imperfection in the industry and suggesting that the government should treat SOEs and SMEs indifferently to improve their comparative advantages in order to compete not only in the domestic market. also but in international markets.

# V. Conclusion

This paper focuses on the effects of FDI on the productivity of the Chinese automotive industry by using a panel data set consisting of five subsectors over a period of ten years - from 1999 to 2008. Thus, the paper contributes to the empirical evidence concerning the FDI-productivity linkages in the economies of developing countries through a unique approach that emphasizes on a particular sector. In this paper, we model two channels, namely, the direct effects and spillovers through which FDI may affect local industries. We also test how human capital in the host country may behave together with FDI in influencing industrial productivity.

The results indicate an important finding and suggest that inward FDI plays a negative role in raising productivity in the automotive industry, which is one of the most crucial key sectors in Chinese economy. Yet, productivity-augmenting effects from FDI on Chinese automotive industry do transpire neither through direct methods nor through spillovers. Hence, the results contradict the theory of FDI that MNCs play an important role to improve the host country's economy through introducing and transferring capital, advanced technologies and managerial skills. The results may also denote that governmental policies introduced to attract FDI are not effective enough to promote productivity.

Consequently, based on the results it is crucial to suggest that it may not sensible for the Chinese government to keep imposing ownership limits on the inflow of FDI in the automotive industry as this practice decreases the productivity and does not allow the industry to benefit from direct effects of FDI. It is also recommended that the

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Chinese government should treat SOEs and SMEs equally, stop giving privileges to SOEs, and encourage them to compete with the rest of the industry by incorporating efficiency and competency.

In conclusion, it is important to point out that due to data limitations, the time period studies in this paper is only10 years. If the time span is extended to include the preceding years of 1990s and 1980s, the result would undoubtedly be very different. This is mostly attributable to the fact that the development of the Chinese automotive industry could have not been achieved without the participation of MNCs, especially in the early stages.

Finally, although in this study, it is shown that FDI has a negative impact on the productivity of the automotive industry, as a whole, it is likely that some sub-sectors benefit from FDI and others do not. In order to clarify the benefits of FDI, and the ones that benefit from FDI, as well as to further understand the cause and effect relations in China, further study is required. It is, however, certain that the implications of our empirical results are valuable to government decision makers and jointventure managers to promote their productivity and eventually enable them to compete globally.

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# Appendix

**Regression Output** 

# Conduct, Interpret and Test the Regression

# Estimation Command:

	Dependent	Variable: Ll	N(?Y)		EST(F,B,M=500,C=0.000
	Method: Poo	oled Least S	quares		LN(?L) LN(?K) LN(?H) L
	Date: 03/19	/11 Time:	21:49		LN(?S) LN(?G) LN(?E)
	Sample	e: 1999 200	8		
	Included of	bservations	: 10		Estimation Equations:
1	Number of cro	oss-sections	used: 5		
Tota	al panel (bala	nced) obser	vations: 50		LN(_AUTOMY) =
Variable	Coefficient	Std. Error	t-Statistic	Prob.	C(1)*LN(_AUTOML)
LN(?L)	0.081986	0.197583	0.414946	0.6806	C(2)*LN(_AUTOMK)
LN(?K)	-0.216175	0.215563	-1.002841	0.3225	C(3)*LN(_AUTOMH)
LN(?H)	-2.047024	0.906785	-2.257452	0.0300	C(4)*LN(_AUTOMR)
LN(?R)	0.268329	0.082033	3.270992	0.0023	C(5)*LN(_AUTOMF)
LN(?F)	-1.985265	0.898289	-2.210052	0.0334	C(6)*LN(_AUTOMS)
LN(?S)	0.022643	0.069100	0.327679	0.7450	C(7)*LN(_AUTOMG)
LN(?G)	2.018744	0.903825	2.233555	0.0316	C(8)*LN(_AUTOME)
LN(?E)	1.107633	0.120074	9.224608	0.0000	
ixed Effects					LN(_AUTOAY) =
AUTOMC	5.326694				$C(1)*LN(\_AUTOAL)$
AUTOAC	6.834744				$C(2)*LN(\_AUTOAK)$
IOTORM					C(3)*LN(_AUTOAH)
С	5.455930				C(4)*LN(_AUTOAR)
_VEC	4.534370				C(5)*LN(_AUTOAF)
_VPC	8.484960				$C(6)*LN(\_AUTOAS)$
R-squared	0.985857	Mean dep	endent var	5.424238	$C(7)$ *LN(_AUTOAG)
Adjusted R-	0.001051		1.	1 101222	C(8)*LN(_AUTOAE)
squared	0.981271	S.D. depe	endent var	1.191332	LN( MOTORMY) =
S.E. of	0.1620.40	G	1 . 1	0.0025.41	$LN(\_MOTORMY) = C(1)*LN(\_MOTORML)$
regression	0.163040	Sum squa	ared resid	0.983541	$C(1)^*LN(\_MOTORML)$ $C(2)*LN(\_MOTORMK)$
n likelihood	27.26855	F-sta	tistic	214.9333	$C(2)^*LN(\_MOTORMIK)$ $C(3)*LN(\_MOTORMH)$
Durbin-	0 1 6 9 4 5 1	Duch (E		0.000000	$C(4)*LN(\_MOTORMR)$
Watson stat	2.168451	Prod(F-	statistic)	0.000000	$C(4)$ $EN(_MOTORMIC)$ $C(5)*LN(_MOTORMF)$
					$C(6)*LN(\_MOTORMS)$
					C(7)*LN(MOTORMG)
					$\mathcal{L}$

 $LN(\_VEY) = C(12) + C(1)*LN(\_VEL) + C(2)*LN(\_VEK) + C(3)*LN(\_VEH) + C(4)*LN(\_VER) + C(5)*LN(\_VEF) + C(6)*LN(\_VES) + C(7)*LN(\_VEG) + C(8)*LN(\_VEE)$ 

$LN(\_VPY) = C(13) + C(1)*LN(\_VPL) +$	
C(2)*LN(_VPK) + C(3)*LN(_VPH) +	
C(4)*LN(_VPR) + C(5)*LN(_VPF) +	
C(6)*LN(_VPS) + C(7)*LN(_VPG) +	
C(8)*LN(_VPE)	

Substituted Coefficients:

LN(AUTOMY) = 5.326693765	+
0.08198634807*LN(_AUTOML)	-
0.216175275*LN(_AUTOMK)	-
2.047023508*LN(_AUTOMH)	+
0.268329243*LN(_AUTOMR)	-
1.985264718*LN(_AUTOMF)	+
0.02264279557*LN(_AUTOMS)	+
2.018744196*LN(_AUTOMG)	+
1.107632601*LN(_AUTOME)	
LN(AUTOAY) = 6.834743645	+
0.08198634807*LN(_AUTOAL)	-
0.216175275*LN(_AUTOAK)	-
2.047023508*LN(_AUTOAH)	+
0.268329243*LN(_AUTOAR)	-
1.985264718*LN(_AUTOAF)	+
0.02264279557*LN(_AUTOAS)	+
2.018744196*LN(_AUTOAG)	+
1.107632601*LN(_AUTOAE)	
LN(MOTORMY) = 5.455930021	+
0.08198634807*LN(_MOTORML)	-
0.216175275*LN(_MOTORMK)	-
2.047023508*LN(_MOTORMH)	+
0.268329243*LN(_MOTORMR)	-
1.985264718*LN(_MOTORMF)	+
0.02264279557*LN(_MOTORMS)	+
2.018744196*LN(_MOTORMG)	+
1.107632601*LN(_MOTORME)	

LN(VEY) =	4.534369629 +	
0.08198634807*LN(_	_VEL) -	
0.216175275*LN(_V	EK) -	
2.047023508*LN(_V	EH) +	
0.268329243*LN(_V	ER) -	
1.985264718*LN(_V	EF) +	
0.02264279557*LN(_	_VES) +	
2.018744196*LN(_V	EG) +	
1.107632601*LN(_V	EE)	

LN(_VPY)	=	8.484959842	+
0.0819863480	07*LN(	(_VPL)	-
0.216175275	*LN(_\	/PK)	-
2.047023508	*LN(_\	/PH)	+
0.268329243	*LN(_\	/PR)	-
1.985264718 <sup>3</sup>	*LN(_\	/PF)	+
0.022642795	57*LN(	(_VPS)	+
2.018744196	*LN(_\	/PG)	+
1.107632601*	*LN(_\	/PE)	

$$\begin{split} \widehat{\text{Ln}(Y_{it})} = & \alpha_i + 0.082 \text{*Ln}(L_{it}) - 0.2162 \text{*Ln}(K_{it}) - 2.047 \text{*Ln}(H_{it}) + 0.2683 \text{*Ln}(R_{it}) - 1.9853 \text{*Ln}(F_{it}) + 0.0264 \text{*Ln}(S_{it}) + 2.0187 \text{*Ln}(G_{it}) + 1.1076 \text{*Ln}(E_{it}) \end{split}$$

	(0.1976)	(0.2156)	(0.9068)	(0.082)	(0.8983)	(0.0691)	(0.9038)	(0.1201)
Т	0.415	-1.0028	-2.2575	3.271	-2.2101	0.3277	2.2336	9.2246

Fixed Effects	$\alpha_i$
_AUTOMC	5.326694
_AUTOAC	6.834744
_MOTORMC	5.455930
_VEC	4.534370
_VPC	8.484960

# N=50 *R*<sup>2</sup>=0.9813 DW=2.1685

#### **Descriptive Statistics**

	?Y	?L	?K	?H	?R	?F	?S	?G	?E
Maaa	446.9	35.2	1767.	0.12	0.01	28.7	0.23	3.03	11.4
Mean	340	4000	664	0606	8306	6000	7105	5949	4342
C	2234	1762	8838	6.03	0.91	1438	11.8	151.	572.
Sum	6.70	.000	3.20	0287	5314	.000	5526	7974	1709
Median	196.2	20.6	702.1	0.11	0.01	8.20	0.24	0.76	3.64
Weulall	000	5000	000	1492	5852	0000	8120	1331	0682
Maxim	2135.	101.	7549.	0.47	0.06	167.	0.48	20.3	88.6
um	300	9000	000	4970	8710	8000	4372	8165	7830
Minim	19.80	5.00	224.8	0.00	0.00	0.10	0.00	0.01	0.39
um	000	0000	000	8881	4190	0000	3071	8220	5206
Sum	1497	3975	1.62	0.18	0.00	7866	1.06	925.	1747
Sq.	1427	4.08	E+08	1494	4428	6.42	1033	2253	3.68
Dev.	1427	4.00	LIUU	1474	4420	0.42	1055	2255	5.00
Std.	552.7	28.4	1819.	0.06	0.00	40.0	0.14	4.34	18.8
Dev.	561	8346	152	0860	9506	6791	7152	5359	8401
Skewne	1.656	0.73	1.371	4.24	3.19	1.66	0.04	1.95	2.37
SS	683	9366	115	4056	5501	4027	0006	2353	7623
Kurtosi	4.715	2.32	3.891	24.9	17.0	5.14	1.67	6.92	8.26
S	386	9692	937	9973	6770	5007	5742	1447	2093
Jarque-	29.00	5.49	17.32	1158	497.	32.6	3.66	63.8	104.
Bera	197	1579	369	.409	3856	6043	6792	0100	7958
Probabi	0.000	0.06	0.000	0.00	0.00	0.00	0.15	0.00	0.00
lity	001	4198	173	0000	0000	0000	9870	0000	0000
Observ	50	50	50	50	50	50	50	50	50
ations									
Cross									
section	5	5	5	5	5	5	5	5	5
S									
<b>F-Tes</b>	sting								

## **F**-Testing

Hypothesis:  $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = 0$ 

$$H_a$$
: at least one  $\beta_{t} \neq 0$ 

In the regression output, the probability of F-statistic=0, so we can reject  $H_0$  at 1% level. Therefore, the overall fit of the equation is statistically significant at 1% level.

#### **Hypothesis Testing**

 Test the sign and significance of Ln(L) at the 1%, 5% and 10% level.

Hypothesis:  $H_0: \beta_{I.n(I.)} \leq 0, \quad H_a: \beta_{Ln(L)} > 0$ 

The slop coefficient of Ln(L) is positive as we expected. The P-value is 0.3403 for one tail, which is insignificant at 1%, 5% and 10% level. Therefore, we cannot reject H<sub>0</sub> at all levels.

 Test the sign and significance of Ln(K) at the 1%, 5% and 10% level.

 $\begin{array}{ccc} & & Hypothesis: \ H_{0} \colon & \beta_{I.n \ (K)} \leq 0, & H_{a} \colon \\ & & \beta_{Ln \ (K)} > 0 \end{array}$ 

The slope coefficient of Ln(K) is negative as we unexpected. The P-value is 0.1613 for one tail, which is insignificant at 1%, 5% and 10% level. Thus, we cannot reject H<sub>0</sub> at all levels.

 Test the sign and significance of Ln(H) at the 1%, 5% and 10% level.

The slope coefficient of Ln(H) is negative as we unexpected. The P-value is 0.015 for one tail, which is insignificant at 1% level of confidence, however is significant at 5% and 10% level of confidence. Therefore, we cannot reject  $H_0$  at all levels.

 Test the sign and significance of Ln(R) at the 1%, 5% and 10% level.

The slope coefficient of Ln(R) is positive as we expected. The P-value is 0.00125 for one tail, which is significant at 1%, 5% and 10% level. As a result, we can reject H<sub>0</sub> at all levels.

5. Test the sign and significance of

Ln(F) at the 1%, 5% and 10% level.

Hypothesis:  $H_0: \beta_{I,n(R)} \leq 0, \quad H_a: \beta_{Ln(F)} > 0$ 

The slope coefficient of Ln(F) is negative as we unexpected. The P-value is 0.0167 for one tail, which is insignificant at 1% confident level but 5% and 10% level. Therefore, we cannot reject H<sub>0</sub> at all levels.

6. Test the sign and significance of Ln(S) at the 1%, 5% and 10% level.

Hypothesis:  $H_0: \beta_{I,n}(s) \leq 0, \quad H_a: \beta_{Ln}(s) > 0$ 

The slope coefficient of Ln(S) is positive as we expected. The P-value is 0.3725 for one tail, which is insignificant at 1%, 5% and 10% level. As a result, we cannot reject  $H_0$  at all levels.

 Test the sign and significance of Ln(G) at the 1%, 5% and 10% level.

The slope coefficient of Ln(G) is positive we expected. The P- value is 0.0158 for one tail, which is insignificant at 1% level but significant at 5% and 10% level. Therefore, we cannot reject H<sub>0</sub> at 1% level but we can reject H<sub>0</sub> at 5% and 10% level.

 Test the sign and significance of Ln(E) at the 1%, 5% and 10% level.

Hypothesis:  $H_0: \beta_{I,n(F)} \leq 0, \quad H_a: \beta_{Ln(E)} > 0$ 

The slope coefficient of Ln(E) is positive as we expected. The P-value is 0 for one tail, which is significant at 1%, 5% and 10% level. Thus, we can reject  $H_0$  at all levels.

# Irrelevant Variables and Omitted Variables Testing Ln(L)

Dependent Variable: LN(?Y) Method: Pooled Least Squares

Date: 03/20/11 Time: 00:00

Sample: 1999 2008

Included observations: 10

Number of cross-sections used: 5

Total panel (balanced) observations: 50

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN(?K)	-0.171756	0.185055	- 0.928135	0.3592
LN(?H)	-2.077665	0.893875	- 2.324336	0.0256
LN(?R)	0.273355	0.080245	3.406479	0.0016
LN(?F)	-1.996759	0.888028	- 2.248531	0.0304
LN(?S)	0.029097	0.066589	0.436968	0.6646
LN(?G)	2.028649	0.893615	2.270161	0.0290
LN(?E)	1.089716	0.110815	9.833683	0.0000
Fixed Effects				
_AUTOMC	5.337568			
_AUTOAC	6.795396			

_MOTORM C	5.406406		
_VEC	4.440478		
_VPC	8.481541		
R-squared	0.985792	Mean dependent var	5.424238
Adjusted R- squared	0.981679	S.D. dependent var	1.191332
S.E. of regression	0.161255	Sum squared resid	0.988118
Ln likelihood	27.15249	F-statistic	239.6784
Durbin- Watson stat	2.208052	Prob(F-statistic)	0.000000

- 1. Theory: as hypothesis 1 mentioned, this variable is sound theoretically.
- 2. T-test: The P-value of Ln(L) for one tail is 0.3403, which is insignificant at all levels. Thus, it should be an irrelevant variable.
- $\overline{R}^{2}$ 3. Adjusted R-squared: the increased slightly from 0.9813 to 0.9817. It indicates that Ln(L) should not belong to this equation.
- 4. Bias: with Ln(L) removed, all coefficients changed slightly. Therefore, it should be an irrelevant variable.

To sum up, the variable Ln(L) should belong to this equation.

# **Testing Ln(K)**

Dependent Variable: LN(?Y) Method: Pooled Least Squares Date: 03/20/11 Time: 00:06 Sample: 1999 2008 Included observations: 10

Total panel (balanced) observations: 50					
Variable	Coefficient	Std. Error	t-Statistic	Prob.	
LN(?L)	-0.016412	0.171511	- 0.095691	0.9243	
LN(?H)	-2.141613	0.901934	- 2.374468	0.0227	
LN(?R)	0.275813	0.081699	3.375962	0.0017	
LN(?F)	-2.031471	0.897173	- 2.264301	0.0293	
LN(?S)	0.049296	0.063789	0.772801	0.4444	
LN(?G)	2.055809	0.903137	2.276298	0.0285	
LN(?E)	0.999257	0.052339	19.09212	0.0000	
Fixed Effects					
_AUTOMC	4.274776				
_AUTOAC	5.751558				
_MOTORM C	4.446693				
_VEC	3.567653				
_VPC	7.204965				
R-squared	0.985473	Mean dep	endent var	5.424238	
Adjusted R- squared	0.981268	S.D. depe	endent var	1.191332	
S.E. of regression	0.163053	Sum squa	ared resid	1.010274	
Ln likelihood	26.59810	F-sta	tistic	234.3462	
Durbin- Watson stat	2.222591	Prob(F-	statistic)	0.000000	

Number of cross-sections used: 5

- 1. Theory: as hypothesis 2 mentioned, this variable is sound theoretically.
- 2. T-test: The P-value of Ln(K) for one tail is 0.1613, which is significant at 5% and 10% level. Thus, it should belong to the equation.
- $\overline{R}^{2}$ 3. Adjusted R-squared: the decreased slightly from 0.9813 to 0.9812. It indicates that Ln(K)should be a relevant variable.

 Bias: with Ln(K) removed, some coefficients changed significantly. Therefore, it should belong to the equation.

To sum up, the variable Ln(K) should belong to this equation.

# Testing Ln(H)

Dependent Variable: LN(?Y) Method: Pooled Least Squares Date: 03/20/11 Time: 00:07 Sample: 1999 2008 Included observations: 10 Number of cross-sections used: 5 Total panel (balanced) observations: 50

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN(?L)	0.118310	0.207269	0.570803	0.5715
LN(?K)	-0.266792	0.225653	-1.182314	0.2444
LN(?R)	0.262277	0.086295	3.039304	0.0043
LN(?F)	0.022470	0.132820	0.169173	0.8666
LN(?S)	0.005416	0.072285	0.074930	0.9407
LN(?G)	0.001194	0.141792	0.008418	0.9933
LN(?E)	1.132610	0.125842	9.000260	0.0000
Fixed Effects				
_AUTOM C	5.577782			
_AUTOAC	7.053500			
_MOTORM- -C	5.671369			
_VEC	4.766150			
_VPC	8.775257			
R-squared	0.983909	Mean dep	endent var	5.424238
Adjusted R- squared	0.979252	S.D. depe	endent var	1.191332
S.E. of regression	0.171603	Sum squared resid		1.119006
Ln likelihood	24.04263	F-sta	tistic	211.2395
Durbin- Watson stat	2.113126	Prob(F-	statistic)	0.000000

- 1. Theory: as hypothesis 3 mentioned, this variable is sound theoretically.
- T-test: The P-value of Ln(H) for one tail is 0.015, which is significant at 5% level. Thus, it should belong to the equation.
- 3. Adjusted R-squared: the  $\overline{R}^2$  decreased slightly from 0.9813 to 0.9792. It indicates that Ln(H) should be a relevant variable.
- Bias: with Ln(H) removed, most of the coefficients changed significantly. Therefore, it should belong to the equation.

To sum up, the variable Ln(H) should belong to this equation.

# Testing Ln(R)

Dependent Variable: LN(?Y) Method: Pooled Least Squares Date: 03/20/11 Time: 00:08 Sample: 1999 2008 Included observations: 10 Number of cross-sections used: 5 Total panel (balanced) observations: 50

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN(?L)	0.177401	0.218942	0.810263	0.4228
LN(?K)	-0.280316	0.240510	-1.165505	0.2511
LN(?H)	-1.950082	1.015399	-1.920507	0.0623
LN(?F)	-1.673329	1.000736	-1.672099	0.1027
LN(?S)	0.138016	0.066573	2.073150	0.0450
LN(?G)	1.694066	1.006501	1.683124	0.1006
LN(?E)	1.176640	0.132435	8.884653	0.0000
Fixed Effects				
_AUTOM	2.014600			
С	3.814688			
_AUTOAC	5.765333			
_MOTORM-	4.095647			

-C			
_VEC	3.213681		
_VPC	7.147873		
R-squared	0.981768	Mean dependent var	5.424238
Adjusted R- squared	0.976490	S.D. dependent var	1.191332
S.E. of regression	0.182667	Sum squared resid	1.267954
Ln likelihood	20.91854	F-statistic	186.0192
Durbin- Watson stat	2.080478	Prob(F-statistic)	0.000000

- 1. Theory: as hypothesis 4 mentioned, this variable is sound theoretically.
- T-test: The P-value of Ln(R) for one tail is 0.00125, which is significant at 1% level. Thus, it should belong to the equation.
- 3. Adjusted R-squared: the  $\overline{R}^2$  decreased slightly from 0.9813 to 0.9765. It indicates that Ln(R) should be a relevant variable.
- Bias: with Ln(R) removed, some coefficients changed significantly. Therefore, it should belong to the equation.

To sum up, the variable Ln(R) should belong to this equation.

# Testing Ln(F)

Dependent Variable: LN(?Y) Method: Pooled Least Squares Date: 03/20/11 Time: 00:09 Sample: 1999 2008 Included observations: 10 Number of cross-sections used: 5

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN(?L)	0.095451	0.207337	0.460368	0.6479
LN(?K)	-0.240611	0.226014	- 1.064585	0.2938
LN(?H)	-0.062855	0.133738	- 0.469985	0.6411
LN(?R)	0.249082	0.085637	2.908584	0.0060
LN(?S)	0.024155	0.072543	0.332982	0.7410
LN(?G)	0.022112	0.027982	0.790205	0.4343
LN(?E)	1.123657	0.125831	8.929871	0.0000
Fixed Effects				
_AUTOMC	5.363287			
_AUTOAC	6.871578			
_MOTORMC	5.468140			
_VEC	4.552025			
_VPC	8.549084			
R-squared	0.983990		ependent ar	5.424238
Adjusted R- squared	0.979356	S.D. depe	endent var	1.191332
S.E. of regression	0.171171	Sum squa	ared resid	1.113377
Ln likelihood	24.16871	F-sta	tistic	212.3250
Durbin-Watson stat	2.106214	Prob(F-	statistic)	0.000000

Total panel (balanced) observations: 50

- 1. Theory: as hypothesis 5 mentioned, this variable is sound theoretically.
- T-test: The P-value of Ln(F) for one tail is 0.0167, which is significant at 5% level. Thus, it should belong to the equation.
- 3. Adjusted R-squared: the  $\overline{R}^2$  decreased slightly from 0.9813 to 0.9794. It indicates that Ln(F) should be a relevant variable.
- 4. Bias: with Ln(F) removed, some coefficients changed significantly.

Therefore, it should belong to the equation.

To sum up, the variable Ln(F) should belong to this equation.

# Testing Ln(S)

Dependent Variable: LN(?Y) Method: Pooled Least Squares Date: 03/20/11 Time: 00:10 Sample: 1999 2008 Included observations: 10 Number of cross-sections used: 5 Total panel (balanced) observations: 50

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN(?L)	0.096561	0.190237	0.507583	0.6147
LN(?K)	-0.243344	0.196629	-1.237580	0.2235
LN(?H)	-2.014210	0.890591	-2.261656	0.0295
LN(?R)	0.282050	0.069708	4.046180	0.0002
LN(?F)	-1.988180	0.887632	-2.239870	0.0310
LN(?G)	2.025247	0.892932	2.268088	0.0291
LN(?E)	1.115672	0.116151	9.605330	0.0000
Fixed Effects				
_AUTOM C	5.568539			
_AUTOAC	7.031517			
_MOTORM- -C	5.678094			
_VEC	4.760362			
_VPC	8.737241			
R-squared	0.985816	Mean dep	endent var	5.424238
Adjusted R- squared	0.981711	S.D. depe	endent var	1.191332
S.E. of regression	0.161114	Sum squa	ared resid	0.986395
Ln likelihood	27.19611	F-sta	tistic	240.1030
Durbin- Watson stat	2.178565	Prob(F-	statistic)	0.000000

- 1. Theory: as hypothesis 6 mentioned, this variable is sound theoretically.
- T-test: The P-value of Ln(S) for one tail is 0.3725, which is significant at 5% and 10% level. Thus, it should belong to the equation.
- 3. Adjusted R-squared: the  $\overline{R}^2$  increased slightly from 0.9813 to 0.9817. It indicates that Ln(S) should be an irrelevant variable.
- Bias: with Ln(S) removed, some of the coefficients changed significantly. Therefore, it should belong to the equation.

To sum up, the variable Ln(S) should belong to this equation.

# Testing Ln(G)

Dependent Variable: LN(?Y) Method: Pooled Least Squares Date: 03/20/11 Time: 00:10 Sample: 1999 2008 Included observations: 10 Number of cross-sections used: 5

Total panel (balanced) observations: 50

Variable	Coefficien t	Std. Error	t-Statistic	Prob.
LN(?L)	0.093641	0.20762	0.45101	0.6545
		2	8	
LN(?K)	-0.235864	0.22640	-	0.3041
		5	1.04178	
			2	
LN(?H)	-0.044293	0.14207	-	0.7569
		5	0.31176	
			2	
LN(?R)	0.248207	0.08570	2.89591	0.0062
		9	5	

LN(?F)	0.020240	0.02784 6	0.72687 8	0.4718
LN(?S)	0.026032	0.07261 9	0.35846 8	0.7220
LN(?E)	1.123061	0.12600 9	8.91251 7	0.0000
Fixed				
Effects				
_AUTOM	5.331692			
С				
_AUTOAC	6.842342			
_MOTORM-	5.436364			
-C				
_VEC	4.522267			
_	4.522267 8.517270			
_	8.517270	Mean de	pendent	5.42423
VPC	8.517270	Mean de	•	5.42423 8
VPC	8.517270 0.983950	Vá	ar	8
VPC R-squared	8.517270 0.983950	Vá	ar	8
_VPC R-squared Adjusted R-	8.517270 0.983950	va S.D. depe	ar endent var	8 1.19133 2
_VPC R-squared Adjusted R- squared	8.517270 0.983950 0.979305	va S.D. depe	ar endent var	8 1.19133 2
_VPC R-squared Adjusted R- squared S.E. of	8.517270 0.983950 0.979305	va S.D. depe Sum squa	ar endent var	8 1.19133 2 1.11615
_VPC R-squared Adjusted R- squared S.E. of regression	8.517270 0.983950 0.979305 0.171384	va S.D. depe Sum squa	ar endent var ared resid	8 1.19133 2 1.11615 3
_VPC R-squared Adjusted R- squared S.E. of regression Ln	8.517270 0.983950 0.979305 0.171384	va S.D. depe Sum squa F-sta	ar endent var ared resid	8 1.19133 2 1.11615 3 211.788
VPC R-squared Adjusted R- squared S.E. of regression Ln likelihood	8.517270 0.983950 0.979305 0.171384 24.10645	va S.D. depe Sum squa F-sta	ar andent var ared resid tistic	8 1.19133 2 1.11615 3 211.788 3

- 1. Theory: as hypothesis 7 mentioned, this variable is sound theoretically.
- 2. T-test: The P-value of Ln(G) for one tail is 0.0158, which is significant at 5% level. Thus, it should belong to the equation.
- $\overline{R}^{2}$ R-squared: the 3. Adjusted decreased slightly from 0.9813 to 0.9793. It indicates that Ln(G)should be a relevant variable.
- 4. Bias: with Ln(G) removed, some coefficients changed significantly. Therefore, it should belong to the equation.

To sum up, the variable Ln(G)should belong to this equation.

# **Testing Ln(E)**

Dependent Variable: LN(?Y) Method: Pooled Least Squares Date: 03/20/11 Time: 00:11 Sample: 1999 2008 Included observations: 10 Number of cross-sections used: 5 Total panel (balanced) observations: 50

Variable	Coefficient	Std. Error	t- Statistic	Prob.
LN(?L)	-0.573421	0.330473	- 1.735151	0.0908
LN(?K)	1.573491	0.168411	9.343153	0.0000
LN(?H)	-2.817801	1.618479	- 1.741018	0.0898
LN(?R)	0.401285	0.144755	2.772167	0.0086
LN(?F)	-2.485638	1.607226	- 1.546539	0.1303
LN(?S)	0.152894	0.121248	1.261006	0.2150
LN(?G)	2.498364	1.617406	1.544673	0.1307
Fixed Effects				
_AUTOMC	-2.902205			
_AUTOAC	-2.212636			
_MOTORMC	-2.497163			
_VEC	-2.935549			
_VPC	-2.378402			
R-squared	0.953332	Mean de va	-	5.424238
Adjusted R- squared	0.939823	S.D. depe	ndent var	1.191332
S.E. of regression	0.292247	Sum squa	ared resid	3.245509
Ln likelihood	-2.578155	F-sta	tistic	70.56896
Durbin-Watson stat	1.441169	Prob(F-s	statistic)	0.000000

- 1. Theory: as hypothesis 8 mentioned, this variable is sound theoretically.
- T-test: The P-value of Ln(E) for one tail is 0, which is significant at all levels. Thus, it should belong to this equation.
- 3. Adjusted R-squared: the  $\overline{R}^2$  decreased slightly from 0.9813 to 0.9398. It indicates that Ln(E) should be relevant variable.
- Bias: with Ln(E) removed, all coefficients changed significantly. Thus, it should belong to the equation.

To sum up, the variable Ln(E) should belong to this equation.

# **Serial correlation**

# **Durbin-Watson testing**

The D-value from the regression output is 2.1685, N=50, and K=8.

There is potential of serialcorrelation, since the data set contains time-series data.

 $H_0$ : ρ=0 (no serial correlation),  $H_a$ : ρ ≠ 0 (serial correlation)

$$d_{L} = 1.2$$
,  $d_{U} = 1.93$ 

Since  $4 - d_L = 2.8 > D$ -value=2.1685 >  $4 - d_U = 2.07$ , the result is inconclusive, we cannot be sure if there exists serial-correlation in the equation at 5% level. Thus, General Least Square model is not required.