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THE RELATIONSHIPS BETWEEN THE CO_2EMISSIONS AND NATIONAL INCOME UNDER QUANTILE INFERENCE

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ABSTRACT

In contrast to the conventional conditional mean approaches, this paper provides the first application of the quantile regression method, with a focus on unbalance panel data application, to re-examine the relationship between CO_2emissionsand income across different quantiles of the conditional CO_2 emissions function. The empirical findings support theinverted-U hypothesis between two variables at most conditional quantiles, and these results proverobust to different controlling variables as well as parametric model specifications. One of the main results that suggest positive income shocks have stronger impact on CO_2 emissions vary across the quantiles, indicators of environmental degradation first rise, and the fall with increasing economic development. Moreover, each quantiles in both case lead to larger marginal effects of energy use on CO_2 emissions. In line with the literature, the estimates of the energy variable are each positive, statistically significant, and large in magnitude. The findings from our more flexible approaches indicate that there are overwhelming evidences in support of the CO_2 emissions is mainly determined by energy use.

Keywords: Inverted-Ucurve, CO_2emissions, Quantile regressions, Energy

JEL classification:C14, C21; Q25, Q56

INTRODUCTION

The relationship between income and environmental pollution has motivated many theoretical works and considerable empirical studies over the last three decades. Economists frequently study the relationship between these two variables because of its importance for policy analysis. Consequently, depending on the validity of the linkage between CO_2 emissions, income and energy consumption, countries may have to prioritize policy options in the fight against global warming and climate change. Grossman and Krueger (1995) first find empirical evidence that pollution within a country first worsens and then improves as the economy develops. Many works have addressed this subject but there seems to be no consensus regarding the relationship and the direction of causality between CO_2 emissions and income in a general way.

Recently, following developments in econometric theory, environmental and energy economists have empirically examined the emissions-income nexus for different countries and time periods. The environmental Kuznetshypotheses have been illustrated to explain the direction of causality between CO_2 emissions and real gross national income. This nexus is closely related to the investigation of the validity of the inverted U-shaped curve, or the environmental Kuznets Curve

(EKC) hypothesis. However, empirical research yields conflicting conclusions about the validity of the environmental Kuznets relationship. Komen, Gerking and Folmer (1997), Schmalensee, Stoker and Judson (1998) and Soytas and Sari (2009) find no evidence to support the environment Kuznets hypothesis. Some studies, including Torras and Boyce (1998) as well asMoomawand Unruh (1997),show evidence for an N-shaped EKC. Jalil and Mahmud (2009) detect a similar quadratic inverted-U association between CO_2 emissions and income. There is early research in support of the environmental Kuznets hypothesis, including that of Kaufman et al. (1998), Chaudhuri and Pfaff (1998), Panayotou,Sachs and Peterson (1999), Bhattarai and Hammig (2001).This research illustrates that different sample countries and sample periods as well asthe use of static or dynamic model sand different estimators may lead to different estimation results.

AIM OF INVESTIGATION

Our aim is to investigate whether the inverted-U relationship is well specified for CO_2. The main energy use producing the greenhouse effect is carbon dioxide, we focus on this pollutant to investigate the existence of an inverted-U hypothesis in the 73 countries set for the period 1981-2007. We use a novel methodology, the quantile regression inference, based on Koenker (2000, 2005). The motivation to use quantile regressions to determine the relationship between CO_2 emissions and income is twofold. First, the quantile regression estimator is robust against outlying dependent variable observations. This is important because the right tail characterizes the conditional CO_2emissions distribution. Second, the quantile regression estimator potentially givesone solution to each quantile. Therefore, we may assess how policy variables affect countries according to their position with regard to the CO_2 emissions distribution. The quantile regression developed by Koenker and Bassett (1978) and popularized by Buchinsky (1998) extends the estimation of the ordinary least squares (OLS) of the conditional mean to different conditional quantile functions. Conditional quantile regressions minimize the asymmetrically weighted sum of absolute errors. Many areas of applied econometrics, such as investigations of wage structure, earning mobility, educational attainment, value at risk, option pricing, capital structure, and economic development, now employ quantile regressions for empirical work. Koenker (2000) and Koenker and Hallock (2001) provide an excellent discussion of the intuition behind quantile estimators and various empirical examples.

This paper is organized as follows. For the examination of the inverted-U hypothesis between CO_2 emissions and income, Section 2 provides a basic introduction of the conditional quantile of both parametric and semi-parametric model specifications. Section 3 describes the data sources, summarizes the empirical results, and checks the robustness of different control variables. Section 4 concludes.

Quantile regressions in CO_2 emissions and national income

To date, the most commonly used empirical model to characterize the inverted-U hypothesis is the following parametric quadratic specification:

$$CO_i = \beta_0 + \beta_1 pcgdp_i + \beta_2 pcgdp_i^2 + w_i'\gamma + \varepsilon_i , \qquad (1)$$

where 'CO' is the CO_2 emissions per capita, '$pcgdp$' denotes the per capita GDP (level of economic development) and the vector 'w' contains other determinants of emissions. If there were an inverted-U-shaped link between emissions and economic development, as conjectured by Kuznets (1955), we would expect β_1 to be significant and positive and β_2 to be significant but negative. The Ordinary Least Squares (OLS) estimation provides a convenient method of estimating such conditional mean models.

Quantile regression, developed by Koenker and Bassett (1978) and popularized by Buchinsky (1998), extends estimation of ordinary least squares (OLS) of the conditional mean to different conditional quantile functions. Conditional quantile regressions minimize an asymmetrically weighted sum of absolute errors. Quantile regression is outlined as follows:

$$y_i = x_i'\beta_\tau + u_{\tau i} \tag{2}$$

$$Quantile_\tau(y_i | x_i) = x_i'\beta_\tau \tag{3}$$

where$y_i$equals the dependent variable (i.e., CO_2 emissions), x_i' equals a vector of independent variables (i.e., $pcgdp$, $pcgdp^2$ and other control variables), $\beta_\tau$equals the vector of parameters associated with the τ^{th} percentile, and $u_{\tau i}$equals an unknown error term. Unlike ordinary least squares (OLS), the distribution of the error term $u_{\tau i}$ remains unspecified in equation (2). We only require that the conditional τ^{th} quantile of the error term equals zero, that is, $Quantile_\tau(u_{\tau i} | x_i) = 0$. $Quantile_\tau(y_i | x_i) = x_i'\beta_\tau$ equals the τ^{th} conditional quantile of y given x with $\tau \in (0,1)$. By estimating β_τ, using different values of τ, quantile regression permits different parameters across different quantiles of CO_2 emissions. In other words, repeating the estimation for different values of τ between 0 and 1, we trace the distribution of *y* conditional on *x* and generate a much more complete picture of how explanatory variables affect the dependent variable.

Furthermore, instead of minimizing the sum of squared residuals to obtain the OLS (mean) estimate of β, the τ^{th} quantile regression estimate β_τ solves the following minimization problem:

$$\min_{\beta}\left[\sum_{i\in\{i:y_i\geq x_i'\beta\}} 2\tau\left|y_i - x_i'\beta\right| + \sum_{i\in\{i:y_i< x_i'\beta\}} 2(1-\tau)\left|y_i - x_i'\beta\right|\right] \tag{4}$$

That is, the quantile approach minimizes a weighed sum of the absolute errors, where the weights depend on the quantile estimated. Thus, the estimated parameter vector remains less sensitive to outlier observation on the dependent variable than the ordinary-least-squares method. The solution involves linear programming, using a simplex-based algorithm for quantile regression estimation as in Koenker and d'Orey (1987). The median regression occurs when $\tau = 0.5$ and the coefficients of the absolute values both equal one. When $\tau = 0.75$, for example, the weight on the positive errors equals 1.5 and the weight on the negative errors equals 0.5, implying a much higher weight associates with the positive errors and leads to more negative than positive errors. In fact, the optimization leads to 75-percent (25-percent) of the errors less (greater) than zero.

Much of applied econometrics may be viewed as an elaboration of the linear regression model, illustrated in Eq. (1), and as an associated estimation method of ordinary least squares. A useful feature of the quantile regression is its distinction from the former; therefore, it does not have to represent a central tendency of a distribution. We could go further and compute several different regression curves corresponding to the various percentage points of the distributions,thus creatinga more complete picture of the set. For the entire conditional distribution, it is not satisfactory to characterize only the mean (or median) behavior. In other words, a quantile regression is robust to the presence of outliers.

DATA SOURCES AND EMPIRICAL RESULTS

Data sources

This dataset consists of a cross-section of 73 countries pooled over the 1981-2007 period andtaken from the World Development Indicators published by the World Bank. Table 1 lists the sample countries, and Table 2 provides descriptive statistics and simple correlation coefficients between the variables in the model. Allof the data are annual and in natural logarithms. The Carbon Dioxide Information Analysis Center of Oak Ridge National Laboratory and the International Energy Agency (IEA) originally provided the CO_2emissions (‘CO_2’’) and the total energy used(‘energy’). The ‘*energy*’ is in kilotons of oil; ‘CO_2’,which includes carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring, is also measured in kilotons. We proxy the level of economic development by the logarithm of per capita GDP, or *pcgdp*, which is based on purchasing power parity and spliced at 2005 as the base year.

Empirical results from the models including no conditioning variable are presented along with those including two alternative sets of conditioning variables. First, the *energy*-information set includes the energy use, in which crude oil, natural gas, and coal are important in residential and industrial energy needs, transportation, and electricity. We believe that the burning of fossil fuels is essential in every country, as it is used for the production of goods and services. The burning of fossil fuels radiates a high amount of CO_2 and pollutes our environment. Several studies have empirically and theoretically shown that an increase in energy use results in greater economic activity (see, for example, Sharma, 2011; Hooi and Smyth, 2010; Yuan, Kang, Zhao and Hu, 2008; Liu, 2005; Wolde-Rufael, 2004; Morimoto and Hope, 2004 and Stern, 2000).

Moreover, the control variables for testing the validity of the Environment Kuznets hypothesis include the total population(‘*pop*’) and the share of the industry(‘*indy*’) and service(‘*serv*’) sectors in the GDP in the model. The significant positive correlations between CO_2emissions and each of the variables considered are not unexpected because all human activities increase CO_2 emissions. These factors, in addition to per capita GDP and energy, may be important in determining a country’s level of CO_2 emissions. Indeed, two countries with similar levels of technology and endowments may have significantly different industrial structures as a result of past investment decisions. The differences in the composition of the production procedure between the industry and service sectors may lead to differences in the opportunity cost of reducing emissions. A regression of emissions to control for the difference in economics structure may improve the specification.

The main results of parametric quantile models

In Panel A of Table 3, we first summarize the results from the parametric conditional mean and quantile regressions from Eq. (2) without considering any control variables. In this simple form, the conditional mean results in column (1) show that the estimates of ‘$pcgdp$’and ‘$pcgdp^2$’ are 3.0777 and -0.1384, respectively. Bothare significant at the 1% leveland have the expected signs, thus providing preliminary support for the inverted-U hypothesis.

In contrast, five quantile estimates for the most basic specification are also obtained for τ=0.05, 0.25, 0.5, 0.75 and 0.95 and shown in columns (2) to (6). Although all coefficients have the expected signs, we find that estimate of the*pcgdp*s quared term in the 5thquantileis insignificant, which suggests that the inverted-U hypothesis is valid in the middle and upper tail distribution of CO_2 emissions but not valid in the lower quantiles. That is, the quantile approach minimizes the weighed sum of the absolute errors, where the weights depend on the quantile estimated. Therefore, the estimated parameter vector remains less sensitive to outlier observations of the dependent variable than the ordinary least squares method. The solution involves linear programming with a simple based algorithm for quantile regression estimation, similar to Koenker and d'Orey's (1987) work. These findings are suggestive of the potential information and gains associated with the estimation of the entire conditional CO_2 emissions distribution, as opposed to the estimation of the conditional mean only.

Along with output, the known energy consumption is another important determinant of CO_2 emissions. Starting with the seminal study of Kraft and Kraft (1978), a large number of studies have tested the energy consumption and economic growth nexus. Examples of this strand of research include Masih and Masih (1996), Yang (2000), Wolde-Rufael (2006), Narayan and Singh (2007), Narayan et al. (2008) andApergis and Payne (2010).Similarly, Liu (2005) determined that the inclusion of energy consumption in the regression implies that CO_2 emissions are likely to fall with income. Most of the existing literature uses the environment-growth nexus and energy-growth nexus in a single model. In Panel B of Table 3, we report the conditional mean and the conditional quantile estimates with additional explanatory factors as 'energy'. From column (1), we can see that the main finding of the conditional results does not change. This finding is a significant and positive '*pcgdp*' coefficient and a significant and negative '$pcgdp^2$' estimate. Analyzing the corresponding significance level (now both at 1%), we are inclined to conclude that the evidence of the inverted-U hypothesis is even stronger. As expected, the coefficient of energy has a positive and highly significant impact on CO_2 emissions. In other words, an increase in energy use is found increase pollution in a given countryby about 1.0557 points.

In contrast to the mean equation, the estimated regression quantiles for the conditional CO_2 emissions distribution, reported in columns (2) to (6) forτ=0.05, 0.25, 0.5, 0.75 and 0.95, shows trong evidence of an inverted-U curve for countries in all quantiles. This finding shows that energy is important in determining a country's level of CO_2 emissions. Panel A of Table 4 reports the robustness check, controlling for the additional explanatory factors such as '*pop*', '*indy*' and '*serv*' in the emissions regression model. We find that the estimates of the controlling variables are positive and statistically significant. Moreover, the results of estimated regression quantiles show similar evidence of an inverted-U curve. This finding is in sharp contrast with the results obtained when considering energy control variables. We also find that the marginal contribution of economic development on CO_2 emissions differs according to the extent of pollution levels.

In addition, the marginal effects of the control variables on the CO_2 coefficient vary significantly with the conditional emissions distribution. For example, the estimates for 'energy' are all positive and significantly different from zero across all quantiles, i.e., 'energy' is found to increase pollution in a significant way in all cases. However, the quantile process for 'energy' exhibits a nonlinear trend with a strong impact on countries in the middle quantiles of the conditional CO_2 emissions distribution. The impact of the coefficient of population, 'pop',on

CO_2 emissions is 0.3585 when using OLS estimates of the conditional mean function. The population elasticity's lowest unit reveals that there are similar results with traditional static model estimation techniques. Examples of this form of research include Dietz and Rosa (1997), Cole and Neumayer (2005) and Poumanyvong and Kaneko (2010).Despite the positive sign for the coefficients of 'pop' in all quantiles, the magnitudes are monotonically decreasing along the quantile index. In contrast to the quantile process of energy, the elasticity of the CO_2 exhibits a linear, increasing trend. There is some indication that the impact of 'energy' is larger than 'pop' for countries in the upper tail of the CO_2 emissions distribution. This result suggests that population growth will initially lead to increased pressure on natural resources because of the increasing demand for goods and services. Eventually, the population growth will expand across the landscape. With economic development, the impact of energy use has replaced population when determining CO_2 emissions. According to Sharma (2011) and Kahn and Schwartz (2008), environmental standards and regulations are often becoming a part of energy and environmental policy.

Moreover, the estimated coefficients for the two control variables for economic structure, '*indy*' and '*serv*', are related to the conditional pollution in a significantly positive way. As expected, the coefficient for the industry sector as a percentage of GDP is larger than that for the services sector as a percentage of GDP in most quantiles. Additionally, it appears that the impact of the service sector on CO_2 emissions exhibits a larger effect in the lower tails of the conditional pollution distribution. These findings are reasonable because the control variables may influence CO_2 emissions differently depending on the degree of the country's pollution.

In summation, depending on which control variables are included, we find inconsistent results regarding the validity of the inverted-U environmental Kuznets curve using a conditional mean approach. Using a quantile regression, and depending on the null or control variables and information sets that are included, we find strong evidence in support of the inverted-U environmental Kuznets curve at different quantiles of the conditional distribution of CO_2 emissions. In all cases, the middle-upper tail quantile of the pollution distribution provides strong evidence in support of the environmental Kuznets hypothesis. On the other hand, the lower tail (5^{th}) quantile of the unconditional CO_2 emissions distribution consistently suggests the opposite case, irrespective of what control variables are included. Obviously, the findings that cannot be detected by the conventional conditional mean approach encourage the use of quantile regression techniques and the estimation of the entire conditional CO_2 emissions distribution.

CONCLUDING REMARKS

This research attempted to revisit some of the issues addressed earlier in the inverted-U curve literature using the parametric quantiles models and broadly pooled data statistics. Conventionally, the inverted-U hypothesis is investigated using OLS methods to estimate the conditional mean function. In contrast, this study implements the quantile regression to re-examine the validity of the inverted-U hypothesis across different conditional quantiles ofCO_2 emissions function. We find overwhelming evidence in support of the inverted-U hypothesis atmost conditional quantiles fromthe parametric quantile model. These findings may provide some answers to the conflicting results found in the existing empirical research. In addition, we also find that the effects of other control variables on CO_2 emissions vary significantly in different quantiles.

Furthermore, energy use has a statistically significant effect on CO_2 emissions in all quantiles, and the population growth, industry and service sectors in GDP have a statistically significant and positive effect on each quantile. These findings strongly illustrate that per capita GDP is not one of the main determinants of CO_2 emissions. The main policy implications emerging from our study is as follows. First, with economic development, population growth, energy regulations and economic structures often become a part of the environmental policy based on the country's CO_2 emissions position. The second implication that is derived from our findings addresses the impact of energy consumption. We find that the energy variable has a positive and highly significant effect on all of the selective quantiles in the regression models. Therefore, regardless of a country's pollution position, as industrial outputs in countries expand, the industries will exert more pressure on the environment, leading to more emissions. Thus, we should consider stricter environmental and energy policies.

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Table 1: List of 73 countries

Country	Code	Country	Code	Country	Code
Albania	ALB	Ethiopia	ETH	Malta	MLT
Argentina	ARG	Finland	FIN	Mozambique	MOZ
Australia	AUS	France	FRA	Malaysia	MYS
Austria	AUT	Gabon	GAB	Netherlands	NLD
Belgium	BEL	United Kingdom	GBR	Norway	NOR
Bangladesh	BGD	Ghana	GHA	Nepal	NPL
Bulgaria	BGR	Greece	GRC	Pakistan	PAK
Bolivia	BOL	Guatemala	GTM	Panama	PAN
Brazil	BRA	Hong Kong, China	HKG	Philippines	PHL
Brunei Darussalam	BRN	Honduras	HND	Poland	POL
Botswana	BWA	Hungary	HUN	Portugal	PRT
Canada	CAN	Indonesia	IDN	Paraguay	PRY
Chile	CHL	India	IND	Saudi Arabia	SAU
China	CHN	Ireland	IRL	Sudan	SDN
Cote d'Ivoire	CIV	Iran, Islamic Rep.	IRN	Senegal	SEN
Cameroon	CMR	Iceland	ISL	Singapore	SGP
Congo, Dem. Rep.	COD	Italy	ITA	Sweden	SWE
Congo, Rep.	COG	Jordan	JOR	Thailand	THA
Colombia	COL	Japan	JPN	Tunisia	TUN
Cyprus	CYP	Kenya	KEN	Turkey	TUR
Denmark	DNK	Korea, Rep.	KOR	United States	USA
Dominican Republic	DOM	Sri Lanka	LKA	South Africa	ZAF
Algeria	DZA	Luxembourg	LUX	Zambia	ZMB
Egypt, Arab Rep.	EGY	Morocco	MAR		
Spain	ESP	Mexico	MEX		

Note: Sample countries are based on data available for the period 1981-2007.

Table 2: Summary statistics and correlation matrix

Panel A: Summary statistics

	CO_2	*pcgdp*	$pcgdp^2$	*energy*	*pop*	*indy*	*serv*
Mean	10.4669	8.8321	79.6095	9.8855	16.5412	3.4081	3.9619
Median	10.7348	8.9262	79.6777	9.8955	16.5881	3.4090	3.9935
Max.	15.6873	11.2175	125.8323	14.6484	20.9856	4.4049	4.5246
Min.	6.0943	5.4881	30.1196	5.7430	12.2016	1.8667	2.7662
Std.	2.0419	1.2663	21.7988	1.7346	1.6764	0.34629	0.2649
Skewness	0.1410	-0.3942	-0.1700	0.2502	-0.1782	-0.3842	-0.9315
Kurtosis	2.1983	2.2041	1.9668	2.6282	3.4648	4.0805	4.0416
Obs.	1971	1962	1962	1971	1971	1961	1961

Panel B: Sample correlation of variables

CO_2	1						
pcgdp	0.436*** (0.0000)	1					
$pcgdp^2$	0.426*** (0.0000)	0.997*** (0.0000)	1				
energy	0.938*** (0.0000)	0.243*** (0.0000)	0.248*** (0.0000)	1			
pop	0.671*** (0.0000)	-0.331*** (0.0000)	-0.334*** (0.0000)	0.804*** (0.0000)	1		
indy	0.227*** (0.0000)	0.318*** (0.0000)	0.291*** (0.0000)	0.071*** (0.0017)	-0.106*** (0.0000)	1	
serv	0.326*** (0.0000)	0.581*** (0.0000)	0.577*** (0.0000)	0.220*** (0.0000)	-0.077*** (0.0006)	-0.320*** (0.0000)	1

Note: 1. The dataset is taken from the World Development Indicator online at http://data.worldbank.org. 2. All variables are in their logarithmic form. 3.Numbers in parentheses are p-values. ***, ** and * denote significance at 1%, 5% and 10% level, respectively.

Table3: Parametric Results in Quantile regression

	OLS	0. 05th	0.25th	0.50th	0.75th	0.95th
Panel A: Simple information set						
		Quantile				
constant	-5.7073***	4.2436**	-1.1591	-13.017***	-8.4769***	-0.0881
	(1.8279)	(1.9318)	(1.5681)	(2.1707)	(1.8146)	(0.8926)
pcgdp	3.0777***	0.6026	1.6750***	4.7231***	3.8029***	2.3179***
	(0.4315)	(0.4569)	(0.3781)	(0.5126)	(0.4254)	(0.2148)
pcgdp^2	-0.1384***	-0.0259	-0.0534**	-0.2308***	-0.1678***	-0.0994***
	(0.0251)	(0.0266)	(0.0224)	(0.0298)	(0.0245)	(0.0127)
Panel B: Energy information set						
constant	-18.8921***	-23.9399***	-23.3041***	-19.2718***	-14.5180***	-7.7907***
	(0.4351)	(0.9696)	(0.3342)	(0.3298)	(0.3398)	(0.5971)
pcgdp	4.1236***	4.9677***	4.9836***	4.2639***	3.3464***	2.0094***
	(0.1015)	(0.2189)	(0.0779)	(0.0769)	(0.0794)	(0.1437)
pcgdp^2	-0.2198***	-0.2687***	-0.2658***	-0.2270***	-0.1772***	-0.1096***
	(0.0059)	(0.0128)	(0.0045)	(0.0045)	(0.0047)	(0.0086)
Energy	1.0557***	1.1310***	1.0781***	1.0276***	0.9926***	0.9928***
	(0.0058)	(0.0125)	(0.0049)	(0.0044)	(0.0053)	(0.0109)

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively. The values in parentheses are standard errors.

Table3: Robustness Check in in Quantile regression

		Quantile				
	OLS	**0. 05th**	**0.25th**	**0.50th**	**0.75th**	**0.95th**
constant	-20.2800***	-22.0326***	-23.8094***	-20.4746***	-17.6474***	-8.4729***
	(0.4296)	(0.9033)	(0.3440)	(0.2998)	(0.4033)	(0.2747)
pcgdp	2.8665***	2.6116***	3.5162***	3.2902***	2.8690***	1.2292***
	(0.1206)	(0.1616)	(0.0887)	(0.0843)	(0.1416)	(0.0676)
pcgdp^2	0.1361***	-0.1192***	-0.1687***	-0.1612***	-0.1443***	-0.0595***
	(0.0072)	(0.0089)	(0.0053)	(0.0050)	(0.0087)	(0.0042)
energy	0.7193***	0.6681***	0.6969***	0.7347***	0.8010***	0.8752***
	(0.0243)	(0.0530)	(0.0203)	(0.0170)	(0.0307)	(0.0192)
Pop	0.3585***	0.4240***	0.4144***	0.3078***	0.2158***	0.1272***
	(0.0258)	(0.0599)	(0.0229)	(0.0180)	(0.0323)	(0.0198)
Indy	0.5188***	0.4585***	0.4475***	0.4502***	0.4449***	0.4411***
	(0.0422)	(0.0866)	(0.0353)	(0.0295)	(0.0490)	(0.0355)
Serv	0.3664***	0.7672***	0.2850***	0.2072***	0.3879***	0.2847***
	(0.0607)	(0.1222)	(0.0474)	(0.0424)	(0.0771)	(0.0453)

Note: ***, ** and * denote significance at 1%, 5% and 10% level, respectively. The values in parentheses are standard errors.