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Abstract: Households' or individuals' decision regarding charitable giving may differ by type of recipient of the gift. In light of the relative paucity of empirical research on the impact of tax incentives on charitable giving outside Western countries, empirical research on this topic in South Korea is valuable in order to compare effects across difference tax regimes and in different institutional environments. We use the Korean Labor and Income Panel Study (KLIPS), whose panel structure helps alleviate the omitted variable bias that has often appeared in previous literature using cross-sectional data. This study aims to perform a robust estimation of tax price and income elasticities for charitable contributions in South Korea. First, we use exogenous changes in tax rates resulting from Korean Tax Reform to construct instrumental variables (IVs) for the change in the price of giving. Two tests are undertaken to determine whether the IVs are weak or not: a size-corrected test of a weak IV robust inference for the linear instrumental variable model with autocorrelation and heteroscedasticity recently devised by Finlay and Magnusson; and the LIML CUE-GMM estimation. We find that our instruments are not weak. Following Smith and Blundell, and Rivers and Vuong , we then estimate the random effect (RE) Tobit Model using a control function based on the IVs. Using the procedure developed by Mundlak, we estimated a fixed effect model from the RE Tobit model. The tax price and income elasticities from the pseudo-fixed effect Tobit model are found to be significant and the magnitudes are similar to those from the GMM fixed effect and CUE-GMM models. To investigate additional features of the conditional distribution of charitable giving in South Korea, we use the Censored Quantile regression with instrumental variables (CQIV) recently proposed by Chernozhukov, Fernandex-Val, and Kowalski. These estimates indicate that the price elasticity of charitable giving is very heterogenous among donors, while income has a quite uniform and positive effect over the whole range of the giving distribution significantly.

JEL Classifications: H2, H4

Key Words: Tax Reform, South Korea, Korean Labor and Income Panel Study, Charitable Giving, Pseudo-fixed effect Tobit, Censored Quantile Regression with IVs, Weak Instruments

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1 Introduction and Overview of Models and Findings

The main purpose of this study is to estimate the price and income elasticity of charitable giving by households. Estimating the price elasticity of giving is of policy significance. As Andreoni (2006) has noted, when the provision of public goods privately by charities is a substitute for government provision of such goods, an absolute price elasticity of giving is a type of "gold standard." At one extreme, if the price elasticity of giving is zero, allowing tax deductions for charitable giving has no effect on the amount of giving to charities. In this case, if the purpose of the tax deduction is to increase the supply of public good(s), the deduction fails to achieve this objective, and direct government spending is more efficient means of providing the public goods. As the price elasticity of giving increases in absolute value, however, more of the foregone tax revenue actually goes to charities in the form of greater giving.[1] A price elasticity of zero implies that the incentive does not have any effect on giving. A larger absolute elasticity implies that more of the transfer is actually going to charities. Hence, the estimation of the elasticities has been an important task in policy evaluation.

Although there is an extensive literature on taxes and charitable giving in western countries, most notably the United States, relatively little related work exists outside of western countries. Given that country-specific heterogeneity, resulting from difference in social norms or institutions, influences the charitable giving decision, empirical research on the determinants of giving in non-western countries is useful addition to our understanding of the role of economic incentives in motivating charitable giving.[2] (For example, Peloza and Steel (2005) who include several studies of giving in emerging economies such as Russia and Singapore in their survey. Note that "the few estimates that are available from these emerging cultures show significantly higher elasticity than those found in other western cultures." A reasonable question is whether these higher elasticities are due to differences in empirical methods, or perhaps reflect differences in giving behavior.)

Since the 1998 economic crisis in South Korea, charitable contributions have risen in potential importance as institutions for improving the welfare of society. Simultaneously many nonprofit organizations (NPOs) have also been founded to complement government failures and market failures. Most NPOs in South Korea, in fact, have suffered from financial difficulties due to shortage of voluntary donation. As Table 1 shows, the ratio of individual charitable giving to GDP in Korea was below 0.5% in 2005 even though it has increased over time.[3] The ratio of charitable giving to the total annual after-tax income has remained low over time as Table 2 shows. The "culture of giving" in Korea has not yet matured mainly due to the late

Table 1: Yearly Individual Charitable Giving in South Korea

		1999	2000	2001	2003	2005
Total Charitable Giving		2.9	4.45	4.67	5.9	7.13
Individual	Wage and Salary Worker	0.8	2	2.7	3.2	3.6
	Global Income Tax Filer	0.05	0.23	0.28	0.54	0.74
	Subtotal	0.85	2.23	2.98	3.74	4.34
	Ratio (%)	29.3	50.1	63.8	63.4	60.9
Ratio of Charitable Giving to GDP(%)		0.16	0.37	0.46	0.49	0.50

Source: Ministry of Strategy and Finance, Korea.

[a] All are measured in 100 billion Won and percent (%).

[b] Ratio means Subtotal Giving divided by Total Giving.

advent of civil society relative to the West economies and societies. Moreover, 80% of individual donations target religious organizations, according to the Ministry of Strategy and Finance, Korea.[4]

Table 2: Ratio of Charitable Giving to Household Income in Korea

Year	2003	2004	2005	2006
$\frac{\texttt{Total charitable giving}}{\texttt{Total household income}}$	1.02%	0.93%	0.89%	0.97%

Source: The Korean Labor and Income Panel Study, Korea

Therefore, we first examine indirectly whether a trade-off exists between government subsidy and charitable giving, and then explore which factors influence household's contribution and how much of an effect these factors have on giving based on estimates from various econometric models. Following Andreoni (1990, 2006), if the tax price of giving negative and significant (large in absolute value) in South Korea, the revenue foregone from allowing tax deductions for charitable contributions increases giving, and hence the financial resources of Korean nonprofits.

The data that is used for the empirical analysis is from the Korean Labor and Income Panel Study (KLIPS), which has information on individuals and households, including the amount of charitable giving during the year prior to the survey. In addition, the panel structure of the data helps alleviate the omitted variable bias that often arises in previous literature using cross-sectional data.

The basic empirical strategy is to use techniques that result in robust estimation of tax price and income elasticities for charitable contribution in South Korea. Most previous studies use the "first-dollar after-tax price of giving" as an exclusion restriction to address the endogeneity problem. Using the "first-dollar after-tax price of giving" is used as an exclusion restriction in the fixed effect estimation, however, raises potential problems of multicollinearity.

As an alternative, this study uses information from the Korean Tax Reform to construct instrumental variables (IVs). It is, however, the case that point estimates from empirical specifications with weak instruments are biased, and the Wald test can be unreliable (Angrist and Pischke, 2009). Stock, Wright, and Yogo (2002) suggest a rule of thumb test of weak identification using F-statistics on exclusion restrictions. However, it is only a rough tool. To account for any concerns about weak instruments, we make use of additional estimation approaches take after estimating the basic models: (1) the two stage Least Square (2SLS), Generalized Method of Moment (GMM), and (2) Limited Information Maximum Likelihood (LIML) Continuously Updated Estimation (CUE) of GMM-fixed effect models.[5] We use the Finlay and Magnusson's (2009) size-correct test of weak IV robust inference for the linear instrumental variable model with autocorrelation and heteroscedasticity. Then, we use CUE-GMM to estimate the linear IV model and compare the results from these alternative estimators with other linear fixed effect models, since LIML CUE-GMM estimators are more robust than other IV estimators when IVs are weak, as noted by Hahn, Hausman, and Kuersteiner (2004). Both procedures indicate that our instruments are not weak, which increases the confidence that the estimates do not suffer from a finite-sample bias from weak instruments.

After confirming that our instruments are not weak, we use the instruments to estimate a random-effect Tobit Model to address the endogeneity problem. However, we cannot simply substitute fitted values from first stage regression into the model since substituting fitted values for an endogenous variable is appropriate only in the case of linear models. Instead, we use a control function following Smith and Blundell (1986) and Rivers and Vuong (1988).

2SLS and GMM do not require distributional assumptions, while the Tobit model does. If the distributional assumptions are satisfied, the Tobit model with a control function may provide more efficient estimates than those from the 2SLS and GMM. However, the Tobit model does not allow one to transform the data to estimate a fixed effect model. By adding group mean values of time-varying variables into the estimation equation, following Mundlak (1978), we construct a pseudo-fixed effect Tobit model. Doing so is a means of removing household unobservable heterogeneity by estimating the random effect model. The tax price elasticity of giving is significant, and the magnitude is around -0.83, which is similar to those from the GMM fixed effect and the CUE-GMM models, respectively -0.94 and -0.899. Income elasticities are also significant in all models, but the sizes of them are very small, around 0.1. (See Table 5 and Table 6 for the estimates.)

To investigate additional features of the conditional distribution of charitable giving in South Korea, we also estimate a Censored Quantile regression with instrumental variables (CQIV) proposed by Chernozhukov et al. (2009). This method adapts control function to address the endogeneity problem. These results imply that the price elasticity of charitable giving is very heterogeneous along donors' giving distribution, while income has a significantly uniform and positive effect over the whole range of the giving distribution.

This study consists of 5 sections. The next section 2 and section 3 cover the brief literature reviews and data respectively. Estimation methods and estimation results are presented in section 4. In the final section 5, conclusion and policy implications are expressed.

2 Literature Review

In a world in which there are no tax deductions for charitable contributions, the out-of-pocket cost of giving \$1 to charity is \$1. If, however, individuals are allowed to take an income tax deduction for charitable contributions the out-of-pocket cost of giving falls from \$1 to $\$(1-t)$ where t is the individual's marginal tax rate. Many researchers have estimated the relationship between the after-tax cost of giving, $\$(1-t)$ and the amount of giving in order to assess whether allowing tax deductions on charity is an efficient way of subsidizing the private provision of public goods by charities. In Korea, there are few studies to date on how the deduction affects charitable contribution, in contrast to the United States, where there is an extensive empirical literature on this topic. Studies using U.S. cross-section data have consistently found relatively large price elasticity and small income elasticity.[6] According to Clotfelter (1985), the estimated price elasticities of charitable giving vary from -0.04 to -2.5 based on variables, data sets, and specifications. A consensus was that tax incentives had a strong positive effect on charitable giving. However, Steinberg (1990) updating this survey of empirical findings presents the possibility that price elasticity could be less than unity in absolute value when panel data sets are used. In fact, more recent studies using panel data report significantly lower price elasticities than those using cross-sectional data.

In order to overcome the drawbacks of cross-sectional data,[7] Randolph (1995) uses panel data to separate the effects on giving of permanent changes in the giver's after-tax price from transitory effects. He finds that permanent income effects are much stronger than the transitory changes, and the temporary price elasticities are much stronger than the permanent price elasticities. His results imply that individuals will respond more strongly to transitory changes in price. In contrast, Auten, Sieg, and Clotfelter (2002) reach the opposite conclusion that charitable contributions are more sensitive to the changes in the both permanent price and income, while they use the expanded version of Randolph's (1995) data.[8] This difference is caused by the adaptation of a different econometric approach. In any case, it is obvious that changes in tax policies that change the marginal tax rates of givers can either increase or decrease the amount of giving, even though magnitude of such changes estimated by Randolph (1995) and Auten et al. (2002) are different.[9] In any case, it is obvious that the tax policies help either increase or decrease the amount of giving, even though the conclusions given by Randolph (1995) and Auten et al. (2002) are different.[10]

Barrett et al. (1997) use the following specification that allows for an estimation of the effects of habits by including lagged giving as an explanatory variable, time shifting, and consumption smoothing on the time path of adjustment and estimate the permanent and temporary effects of tax policy on charitable giving.

$$\begin{aligned} \ln g_{it} = \alpha_0 + \beta_1 \ln g_{it-1} + \beta_2 \ln I_{it-1} + \beta_3 \ln P_{it-1} + \beta_4 \ln I_{it} + \beta_5 \ln P_{it} + \beta_6 \ln P_{it+1} \\ + \beta_7 \ln I_{it+1} + X\delta + \epsilon_{it}, \end{aligned} \tag{1}$$

where g_{it} represents contribution of individual i at time t, P represents the price of contribution, I represents income, and X represents other explanatory variables. The model in equation (1) is estimated with a panel of 1,382 individual taxpayers filing itemized returns in the years of 1979-86 from the Statistics of Income (SOI) panel of returns from the Ernst and Young Tax Research Database. Barrett et al. (1997) find that the long-run price elasticity is -0.47, and the transitory price elasticity is -1.40. The effects of habits in giving are small.

A consensus about the effect of tax incentives on charitable giving has not been established yet in the United States. In addition, a smaller number of studies explore the phenomenon in countries other than the United States, including Canada, the United Kingdom, Russia, and Singapore (Peloza and Steel, 2005).

Brooks (2002) examines Russian charitable giving using the World Bank's Household Expenditure and Income Data for Transitional Economies (HEIDE). He finds that Russian households donate an average of 0.6% of their annual after-tax income to charity in 1993. His Full Information Maximum Likelihood (FIML) Tobit model finds that income and price elasticity are respectively 2.78 and -6.68, which are considerably higher than estimates of these parameters from studies using data from the United States.[11]

Chua and Wong (1999) investigate the relationship between charitable giving and tax incentive in Singapore, using 1989 tax files obtained from the Inland Revenue Authority of Singapore. They estimate income and price elasticities for givers with differing education levels. This study finds that the income elasticities are positive, but below unity. The price elasticities are in the range of -3 to -6, which indicates a very strong response of charitable contributions to the tax price of giving in Singapore.

Wu, Huang, and Kao (2004) use the Survey on Family Income and Expenditure on Taiwan to estimate peer effects on charitable giving, and income and price elasticities of giving. From the Tobit model, they find that for metropolitan area the price elasticity of household level charitable contributions is around -3.3, and for non-metropolitan area it is around -2.2. These estimates are greater than those of the United States in absolute value.

Research on charitable giving in Korea is limited. After the 1998 economic crisis in South Korea, encouraging charitable contributions emerged as an issue in improving the welfare of society due to the deepened economic polarization in Korea; i.e., the rich are getting richer, while the poor are getting poorer. However, studies on this subject are still at an early stage because of the scarcity of the data. Park and Park (2004) use the survey of household giving from July 3 until July 17 of 2002, which was conducted by Volunteer 21, a non-government organization in Korea. They found that both income and giving price are not significant in explaining charitable giving behavior, using the Tobit model and the Heckman's two-step estimation.

In addition, Bradley, Holden, and McLelland (2005) raised concerns about the assumptions of parametric estimation on which much of the emprical literature on charitable giving – in the U.S. and elsewhere – is based. They find that the maximum likelihood estimation including the Tobit model produces much higher price elasticities than those from semi-parametric methods. Their results suggest that the parametric assumptions, especially normality assumption, may not hold.

In the above-cited studies on giving in emerging economies, researchers estimate price elasticity from cross-sectional or pooled models under the parametric distribution assumptions. The results from studies using data from the United States suggest that estimates of the price elasticity are greater when estimated with cross-sections than with panel data. Moreover, the findings from Bradley et al. (2005) suggest that charitable price elasticity estimated with a Tobit model is significantly larger than that estimated with semi-parametric models. It is somewhat of a puzzle that research with Korean data fails to find any significant estimates of income and price elasticities at any conventional level.[12] We use new panel data to estimate the price and income elasticity with parametric methods. Furthermore, a semi-parametric method (i.e., censored quantile regression), is adapted to compensate for some drawbacks of the parametric methods.

3 Data: Korean Labor and Income Panel Study

Research on charitable giving in Korea as relied on two sources of data: survey data and tax-filer data. In Korea, the National Tax Service (the Korean IRS) does not yet provide public-data on tax filers.[13] Here, we use the Korean Labor and Income Panel Study (KLIPS) from 2004 to 2007. Only during these periods is the information available on household total charitable donation.[14] The KLIPS sample is an equal probability sample of households from the seven metropolitan cities and urban areas in eight provinces (excluding Cheju Ireland), and is designed to yield 5000 households and their members (aged 15 and over) interviewed. There are largely two types of KLIPS data sets: the household data set derived from the Household Questionnaire and the individual data set compiled from the Individual Questionnaire administered on the household members aged over 15. The household data set includes demographics, changes in household members, family relations, and financial resource exchange between generations, type of accommodation, children's education and child care; household income and consumption including charity, assets, and debts; financial status; and consumption requirements that put pressure on household finance. The individual data set includes a wide array of categories such as the person's state of economic activity; income-earning activities and consumption; education and vocational training; employment characteristics, work hours, job-seeking activities; professional and life satisfaction; and labor market mobility. In addition, both after- and before-tax wages and salaries of the husband and wife are reported by the respondents. We only use the households that have information on before-tax information.[15]

The KLIPS includes a specific question on the amount of charitable giving. Only 24% of total households record positive pure charitable giving. In the estimation, to avoid the problem creating by having a logarithm of zero, we take a logarithm of the reported amount of giving plus 1.[16]

Tax price of giving indicates indirectly how much the donor bears the cost of monetary giving. Peloza and Steel (2005) shows how previous studies treat this variable as one of the most important determinants affecting charitable giving. Given the tax deduction, the tax-price of giving is computed by "1-the marginal tax rate" conventionally.

In addition, the marginal tax rates are computed by the information on before-tax wage and salary, after-tax wage and salary, number of kids, and tax schedules for the relevant year to compute.[17] In the case that both the husband and wife receive wage or salary income, we use the primary earner's tax price of giving as the tax price of giving for the household.[18]

The survey that we use does not include the information on individuals' itemizing status.[19] Moreover, Table 3 shows that a high proportion of non-tax payers exists in the earned income tax. About 45% of employees do not pay any income tax. In our data, about 40% of households do not pay any income tax.[20] Considering the tax credit given to low-income groups, we note that about 69% of the households including the non-tax payers are located below the marginal tax rate of 0.06. (See Appendix Table A-14 for details.)

Table 3: Proportion of Taxpayers in Korea

Year (in thousand persons)	2003	2005	2007
Number of employee taxpayers[1]	11,547	11,903	13,376
Non-taxpayers under tax threshold[2]	5,457	5,796	5,631
Taxpayers[1]	6,090	6,107	7,745
Ratio of taxpayer	52.7%	51.3%	57.9%

Source: Statistical Yearbook of National Tax, National Tax Service, Korea

[a]Units are 1,000 persons.

[b]For example, the tax threshold is 15.8 million Won for the household with 4 members including 2 kids under 20 years old in 2006.

The estimations were based on household panel data from surveys conducted over the period of 2004-2007. All money values were adjusted with the base year 2005, using the consumption price index. All descriptive statistics are Table A-1 in the Appendix. In the fixed effect model, we use 13,613 observations since we remove the households that only appear for a single year.[21]

Andreoni and Vesterlund (2001) find that women are more generous than men in cases in which it is relatively expensive to give. Given that female-headed households are more likely to have less income than their counterparts in South Korea, it is natural that contributions from a female-headed household is less than those from a male-headed household in terms of the absolute amount. If female-headed households demonstrate the characteristics of male-headed households, the prediction may be changed. These results may imply which gender is more generous on average. From the prediction of regression, we find that female-headed households are more generous on average. The detailed discussion can be found in section 4.2.1.

Table 4: Giving by Gender

	Average of Real Giving per year		
Gender of Head	Full sample	Sub-sample (charity>0)	Household Income
Female Headed	20.19	89.70	2619.57
Male Headed	36.73	150.54	4591.58
Total	34.61	143.28	4356.38

Source: KLIPS 2004-2007

[a]Units are 10 thousand Won.(1,000 won $\simeq$ \$1)

Table A-2, A-3, and A-4 in the Appendix show the transition matrix of changes in contributors' giving behavior between two time periods. According to each table, non-donors during the current year are more likely to act as non-donors during the following year; i.e., about 88% of non-donors do not give any contribution during the next period. However, if donors ever experience giving, they tend to contribute the next time as well. Moreover, the proportions increase over time: 58% (2003 to 2004), 66% (2004 to 2005), and 69% (2005 to 2006). The main reason for the increment is the decrease in the proportion of ever-donors to non-donors during the next period: 41.7% (2003 to 2004), 34% (2004 to 2005), and 30% (2005 to 2006). Non-donors have a strong tendency to remain in the status of non-donors. It seems to be important that policymakers note this point and provide more incentives for non-donors to venture out of it. The high proportion of non-donors can be interpreted as an immature culture of donation. However, this high proportion of non-donors may rather present an opportunity for NPOs in South Korea, because the financial health of the NPOs would be strengthened if non-donors participated in giving.

The average contribution dropped a bit in 2004 in full sample of Table A-1. This reduction may be due to the economic recession in 2003 in South Korea.[22] However, the amount of charitable giving has kept increasing in the sub-sample of Table A-1. This phenomenon may imply that the polarization of charitable giving appears in Korea.

4 Estimation Models and Results

4.1 Identification Strategy

An issue that any empirical study of charitable giving needs to address is that of potential reciprocal causation between the marginal tax rate at which charitable deductions are taken and the amount of charitable deductions. For taxpayers itemizing their deductions, their taxable income decreases simultaneously as their charitable giving increases, and their corresponding marginal tax rate can change if they fall into lower tax brackets. Therefore, the marginal tax rate could be a function of charitable giving, and thus the least square (LS) estimates of the tax effects on charitable giving may be biased. In fact, there is not much difference between the last-dollar and the first-dollar price of giving in Korea due to the small amount of charitable giving per household and a large tax bracket.[23] Accordingly, deductible charitable giving may not change households' marginal tax rate. That is, deductible charitable giving probably will not reduce the tax base enough to make the applicable marginal tax rate drop to a lower rate. If there is no endogeneity problem, the estimation is much simpler. Hence, we test whether the endogeneity problem exists with various methods.[24] We detect the existence of edogeneity problem.

Past and future prices of giving can be good candidates of instrumental variables in order to identify tax effect. However, considering that current giving may be related to past and future tax prices of giving as well as that charitable giving may be serially correlated across time, past and future tax prices of giving are not appropriate. Hence, the most common procedure used in this context was to use "first-dollar giving price" as the instrumental variable. Since the "first-dollar tax rate" was the tax price on the first dollar of charitable giving, the "first-dollar" tax rate was uncorrelated with charitable giving. The first dollar tax price of giving is a good instrument in identifying the price elasticity, but it often causes collinearity problem in fixed effect estimation.[25]

Following Bakija (2000), we use the tax reform information in Korea to generate exclusion restrictions, since the tax reform is an exogenous shock that generate the changes in tax price of giving. We first construct an excluded variable which is strongly correlated with the mixture of transitory and permanent tax prices, $\ln P_t(\overline{M}_{it})$, and then we construct another instrumental variable that is correlated with permanent variation in tax price, $\ln P_s(\overline{M}_{is})$. We use the difference between them as an instrument variable for the transitory tax prices to identify the elasticity of charitable giving. In the estimation, excluded variables include all interaction terms with explanatory variables.[26] These variables are actually based on the first dollar price of giving so that they don't violate the exclusion restriction. Hansen's J statistic is used to test the exogeneity of the instruments. In addition, we test whether the exclusion restriction is weakly correlated with the endogenous variable in the linear fixed effect model setting. The conditional likelihood test (CLR), proposed by Moreira (2003), can be applied only under i.i.d. assumption. Recently Finlay and Magnusson (2009) propose tests for weak-instrument robust inference for a general class of instrumental variables models. The results are reported in Table A-15 in the Appendix. The instruments pass all the tests. The detailed explanation is covered within section 4.2.1.

4.2 Parametric Estimation

4.2.1 Linear Fixed Effect Models with IVs

Since many taxpayers have no charitable deductions, many studies of charitable giving have used the Tobit model to estimate the effect of tax incentive on charity.[27] We estimate the linear random and fixed effect model using instrumental variables with full samples in order to compare their estimates to the correspondence of pseudo-fixed effect Tobit model. All specifications have the time dummies. The time dummies remove the time series variation in the average of tax rates across the full sample from the identifying variation.

In the random effect model, the household-specific effects remove differences in tax rates across households that are constant across time from the identifying variation. The first column in Table 5 represents the results relying on a two-stage least-squares random-effects estimator under the assumption of $Cov(X_{it},\ u_i) = 0$. We treat the u_i as random variables that are independent and identically distributed (i.i.d.) over the panels. Standard errors are computed by the panel bootstrap with 200 replications. In section 3, we assert that giving behaviors of male- and female-headed households may differ on average. To test this assertion, adjusted predictions of giving by gender is computed from the specification (1) and (2). Here we only report the results from (1): 1.491, which would be the expected value of ln charitable giving if everyone in the data were treated as if they were female. 0.975 would be the expected value of ln charitable giving if everyone were treated as if they were male. The female-headed households seem to make more charitable donations than the counterparts. Decomposition of the each of those numbers allows us to test whether female-headed households donate more than the male-headed.[28] We have four cases: 1a. the logarithm of average charitable giving from treating females as females is 0.912; 1b. treating males as females 1.573; 2a. the expected value of ln charitable giving from treating females as males is 0.396; and 2b. treating males as males 1.057. It would be interesting to test the equality of 2b and 1b, to determine whether the expected value of ln charitable giving for males treated as males is equal to that for males treated as females. The test performed on the model would be a test of whether the charitable giving differs between male-headed households and female headed, when they have the same attributes. The hypothesis that two numbers of logarithm of average charitable giving are equal is rejected at any conventional level ($\chi_1^2 = 49.10$, p-value$= 0.000$). Hence, female-headed households significantly donate more than male headed if the female-headed households have the same values of attributes that the male-headed households have.[29]

Column (2) in Table 5 shows the two stage least square fixed effect estimates under the independently identically distributed error assumption. Column (3) and (4) in Table 5 represent the estimates from GMM estimation of the fixed-effect model with heteroscedasticity and autocorrelation robust variance covariance matrix. Column (5) in Table 5 reports limited information maximum likelihood (LIML) continuously updated GMM estimates proposed by Hansen, Heaton, and Yaron (1996). Hahn et al. (2004) point out that LIML estimators are more robust than other IV estimators when the instruments are weak.

Instrumental variable methods rely on two assumptions: the excluded instruments are distributed independently of the error process, and they are sufficiently correlated with the included endogenous regressors. From all the fixed effect models in Table 5, the Sargan-Hansen test (a test of overidentifying restrictions) is performed. The joint null hypothesis is that the instruments are uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. The second specification of column (2) in Table 5 under i.i.d. rejects the null hypothesis at the 10% level. The Sargan test statistic, however, is only valid under i.i.d. assumption. Since we detect the heteroscedasticity in this specification, it is not reliable.[30] Instead, we use Hansen's J-statistic, which is known as robust against heteroscedasticity. We fail to reject the null hypothesis even at the 20% level in all other fixed-effect models except the second model having heteroscedasticity. (p-values of Hansen's J statistic are 0.28, 0.23, and 0.24 respectively for columns (3), (4), and (5).) In addition, we test the null hypothesis that the reduced form coefficients are underidentified by Wald version of Kleibergen and Paap (2006) rank statistic.[31] The underidentification test determines whether the excluded instruments are correlated with the endogenous regressors. From the fixed-effect model (3), (4), and (5) in Table 5, the null hypothesis is rejected at any conventional level.

Estimates from instrumental variable models will not be reliable when excluded instruments are only weakly correlated with the endogenous regressors.[32] According to Stock et al. (2002), the rule of thumb test for weak identification is to see if F-statistic on the excluded instruments of the first stage regression is greater than 10 when one endogenous variable exists. Although

Table 5: Omniscient Estimation with IVs: 2SLS, GMM, CUE-GMM

Dependent Variable ln Giving	(1) RE G2SLS w/Boot error	(2) FE w/IID 2SLS	(3) GMM	(4) Preferred GMM	(5) CUE GMM
ln Giving price	-1.112***	-1.171***	-0.919***	-0.940**	-0.899**
	(0.409)	(0.283)	(0.319)	(0.367)	(0.366)
ln Income	0.146***	0.111***	0.111***	0.109***	0.109***
	(0.0285)	(0.0246)	(0.0258)	(0.0301)	(0.0301)
Schooling Year	0.0887***	0.0425	0.0437	0.0411	0.0415
	(0.00931)	(0.0386)	(0.0439)	(0.0523)	(0.0522)
Head Age	0.0453***	0.0184	0.0179	0.0190	0.0192
	(0.0153)	(0.0379)	(0.0348)	(0.0422)	(0.0420)
Age squared	-0.000186	-0.000274	-0.000258	-0.000267	-0.000268
	(0.000154)	(0.000378)	(0.000356)	(0.000436)	(0.000435)
Gender of Head	-0.516***	-0.541**	-0.505***	-0.489**	-0.487**
(male=1)	(0.0737)	(0.216)	(0.177)	(0.207)	(0.207)
Marital status	0.291***	0.181*	0.193**	0.195*	0.197*
(married=1)	(0.0674)	(0.104)	(0.0950)	(0.116)	(0.115)
Family Size	0.0408	0.0271	0.0300	0.0283	0.0283
	(0.0254)	(0.0319)	(0.0315)	(0.0386)	(0.0385)
ln Financial Asset	0.0173***	0.0174***	0.0181***	0.0178***	0.0178***
	(0.00501)	(0.00417)	(0.00442)	(0.00522)	(0.00522)
House owned (=1)	0.0212	0.107**	0.103**	0.106*	0.105*
	(0.0414)	(0.0455)	(0.0474)	(0.0575)	(0.0575)
2004	-0.127***	-0.0874***	-0.0904***	-0.0910***	-0.0907***
	(0.0313)	(0.0316)	(0.0309)	(0.0352)	(0.0350)
2005	-0.113***	-0.0361	-0.0376	-0.0381	-0.0384
	(0.0321)	(0.0433)	(0.0398)	(0.0449)	(0.0444)
2006	-0.0842**	0.0244	0.0208	0.0223	0.0218
	(0.0363)	(0.0580)	(0.0516)	(0.0568)	(0.0560)
Constant	-2.872***	-2.55e-10	-0.00168	-5.35e-11	-4.13e-11
	(0.423)	(0.00899)	(0.00897)	(1.07e-09)	(1.06e-09)
σ_u	1.383				
σ_e	1.242				
N	13613	13613	13613	13613	13613
log likelihood		-19961.4	-19953.0	-19953.7	-19952.5

[a]Standard errors in parentheses

[b]* p<.10, ** p<.05, *** p<.01

[c]Column (1) uses random effect panel model with generalized 2SLS. Standard errors are computed by 200 replications of bootstrap.

[d]Column (2) uses fixed effect panel model with 2SLS under i.i.d. assumption.

[e]Column (3), (4), and (5) uses GMM fixed effect panel model.

[f]Column (3) and (4) uses robust and clustering variance-covariance matrix.

[g]Column (5) uses GMM CUE fixed effect panel model with HAC robust covariance matrix.

[h]The Two Stage Least Square (2SLS) estimation and Generalized Method of Moment (GMM) are reviewed in the Appendix B.1.

F-statistics are greater than 10 from all specifications, this high F value does not always imply that the instrument is not weakly correlated. The rule of thumb is, however, only a rough tool to determine whether the instruments are weak.

To account for any concerns about weak instruments, we take the following steps after estimating various models.[33] (i.e., the 2SLS, GMM, and CUE-GMM fixed-effect models) First, we use Finlay and Magnusson's (2009) size-correct test of weak IV robust inference for the linear instrumental variable model with autocorrelation and heteroscedasticity. The test results are shown in Table A-15 in the Appendix. In order to implement this, we re-estimate the column (2) specification in Table 5 by 2 Stage Least Square (2SLS) with the cluster-robust standard error, because heteroscedasticity was detected previously.[34] Table A-15 reports Moreira's (2002) conditional likelihood ratio (CLR) test statistic, the Anderson and Rubin (1949) test, the J statistic,[35] and the Lagrange Multiplier (LM) test.[36] The Anderson and Rubin (1949) test and the CLR test determine the significance of the null hypothesis that the coefficients of the endogenous regressors in the structural equation are jointly equal to zero and whether the overidentifying restrictions are also valid, which is robust to weak instruments simultaneously. The Wald test is not robust against weak instruments. The confidence set from the Wald test is a little bigger, and is in fact almost similar to those from other robust statistics, which indicates that our instrumental variables are not weak.[37] Hence, the coefficient of endogenous variable, the price elasticity of giving, is significant. Second, we use Limited Information Maximum Likelihood (LIML) CUE-GMM to estimate the linear IV model and compare the estimates with those from other linear fixed effect models, since LIML CUE-GMM estimators are more robust than other IV estimators when IVs are weak, as Hahn et al. (2004) point out. The LIML CUE-GMM standard error of the endogenous variable is almost similar to that of other models. Hence both results suggest that our instrumental variables are not weak and that finite sample bias arising from weak instruments is unlikely to be a problem.

Finally, we test the endogeneity of the endogenous regressor (i.e., giving price) by the Wu-Hausman F-test version of the endogeneity test. The test rejects the null hypothesis that the endogenous variable can be treated as exogenous at 1% level. The estimated equation, hence, has an endogeneity problem, while the exclusion restrictions resolve the problem.

From the various specifications, we prefer the fixed-effect GMM model with heteroscedasticity and autocorrelation robust variance-covariance matrix in the fourth column of Table 5. Most coefficients in the random effect model in the first column of Table 5 are statistically significant. Unobserved heterogeneity (i.e. generosity or dignity), however, may be correlated with household heads' education level, age, and house ownership. If the correlations exist, the random effect model is not consistent while the fixed effect model is consistent.[38] The second specification (2) in Table 5 is estimated by the fixed effect model under i.i.d. assumption. We test the null hypothesis that the disturbance is homoscedastic by the Pagan and Hall (1983) heteroscedasticity test after the fixed-effect IV estimation.[39] We reject the null hypothesis of the homoscedasticity in 1% significance level. The fifth column of Table 5 reports the limited information maximum likelihood (LIML) continuously updated GMM estimates proposed by Hansen et al. (1996). Hahn et al. (2004) point outs that LIML estimators are more robust than other IV estimators when the instruments are weak.[40] Given that the instrumental variables pass the weak instrument robust test as well as that giving behaviors in the current year are correlated with those in the last year, we prefer the specification (4) in Table 5.

Based on specification (4), price and income elasticities are statistically significant at the 5% level, while all the specifications report that price elasticities of giving are statistically significant at that level. Since we fail to reject the null hypothesis that price elasticity of giving is equal to -1 at any conventional level, we can conclude that allowing charitable donations to be deducted provides some incentive to increase charitable giving in South Korea. The income elasticity of giving is significant, but its magnitude is reported around 0.11. The magnitude of income elasticity is somewhat smaller than those of the previous studies such as Brooks (2002) and Chang (2005). This may be good news for NPOs in South Korea, since it would imply that the severe income recession may not does not badly adversely affect the finances of NPOs. This is consistent to the descriptive statistics in Table A-1: for the sub-sample of the households that giving is greater than zero, the mean value of amount of donation keeps increasing through the 2004 recession over all data periods, while the average amount of donation for all sample decreased during the 2004 recession. In other words, income growth may not generate a large impact on the donation to NPOs.

Interestingly, age and education are not significant in the preferred fixed-effect model (4) in Table 5 as well as all other fixed-effect models. If the effect of age and education can be taken as proxies for the effect of permanent income, we may say that charitable contribution in South Korea does not depend on permanent income. Other factors held constant, the change in gender of household head, (i.e., from female-headed to male-headed households), decreases contribution by about 40%, which is statistically significant at the 5% level.[41] If a single household head gets married, with other conditions unchanged, the contribution increases by about 20.8%, which is marginally significant. A 10% increase in financial assets significantly increases about 0.2% in contributions at any conventional level. The amount of financial assets significantly affects the decision of participation, but it is unlikely to affect severely the decision regarding the amount of giving. The status of house ownership is marginally significant when a household decides to participate in giving. When a household owns its house, the contribution goes up by about 11%. Comparing the specifications (3) and (5) with (4) in Table 5 as a robustness check method, the sizes of price and income elasticities are almost similar. In addition, there is no loss of significance for all the explanatory variables across all the specifications.

4.2.2 Pseudo-Fixed Effect Tobit Model with Control Function

Since the amount of charitable giving is continuous over strictly positive values but it takes on zero with positive probability, using a linear model for the charitable giving does not necessarily pose problems. However, negative fitted values could be obtained and then it leads to negative prediction for the charitable giving. In addition, the assumption that an explanatory variable appearing in level form has a constant partial effect on conditional expectation of giving is not consistent with such data. To obtain more plausible partial effects we therefore estimate the pseudo-fixed effect Tobit model using Rabe-Hesketh, Skrondal, and Pickles (2005) GLLAMM.[42] The pseudo-fixed effect model includes group mean values of time varying explanatory variables (Mundlak, 1978).[43] By doing so, we can remove unobservable heterogeneity within the random effect estimation.

Let us compose $X_{it} = (x_{it1}, z_{it})$, where z_{it} can be an exclusion restriction of the price, $\ln p_{it}$. The linear reduced form for the price of charitable giving, $\ln p_{it}$, is represented by the following:

$$\ln p_{it} = \psi + X_{it}\delta_2 + \bar{X}_i\alpha_2 + v_{it2}, \quad t = 1, .., T \tag{2}$$

Since the price p_{it} is a continuous endogenous explanatory variable, the above equation can be estimated by regressing p_{it} on the time dummies, all exogenous variables, and group means to get the residuals, $\hat{v}_{it2}$. These residuals are included in the pseudo-fixed effect Tobit model along with time dummies, $\ln p_{it}$, x_{it}, and $\bar{X}_i$.

$$\ln g^*_{it} = \alpha_1 \ln p_{it} + x'_{it1}\beta + \bar{X}'_{it1}\xi_1 + \rho\hat{v}_{it2} + \varepsilon_{it} \tag{3}$$

$$\ln g_{it} = \max(0, \ln g^*_{it}) \tag{4}$$

$$\varepsilon_i|(X_i, v_{it2}) \sim_{iid} N[0, \sigma^2_\varepsilon] \tag{5}$$

This control function approach is adapted following Smith and Blundell (1986) and Rivers and Vuong (1988) under the assumption that the endogenous variable, the price of charity, has a linear reduced form with additive normal error independent of the exogenous variables.[44] The general idea of the control function approach is to model endogeneity as an omitted variable. Since the last dollar price of giving is a continuous endogenous explanatory variable, we can combine the pseudo-fixed effect Tobit model with the control function approach. Since we use the two-step procedure, the standard errors in the second stage should be adjusted for the first stage estimation.[45]

The Tobit model relies on normality and homoscedasticity in the underlying latent variable model. If normality assumptions in equation (5) fail, the estimates may not be consistent. One informal way to evaluate whether the Tobit model is appropriate is to compare the estimates from the Tobit with estimates from a probit model.[46] We fail to find certain problematic signs comparing both the estimates of Table A-17 and Table A-18.[47] Hence, we estimate the pseudo-fixed effect Tobit model under the assumption that individual specific effect and idiosyncratic error are independently identically normally distributed.

Table 6 shows the estimated results. The unconditional marginal effects from the pseudo-fixed effect Tobit specification are similar to coefficients estimated in the fixed effect model produces. We detect endogeneity problem, since the coefficient of the control function is significant at any conventional level.[48] The estimation results go with those in linear panel models in Table 5. Roughly comparing Table 6 with the Table 5, all coefficients in Table 6 have the same sign as the corresponding estimates in Table 5, and the statistical significance of the estimates

Table 6: Pseudo-Fixed Effect Tobit Model

Dependent Variable ln Total Giving	Coefficient	S.E.	Unconditional Marginal Effect	S.E.	Conditional Marginal Effect	S.E.
ln Giving Price	-3.350***	(1.284)	-0.830***	(0.319)	-0.806***	(0.309)
ln Income	0.512***	(0.126)	0.127***	(0.031)	0.123***	(0.030)
Schooling year	0.180	(0.178)	0.045	(0.044)	0.043	(0.043)
Head Age	0.154	(0.185)	0.038	(0.046)	0.037	(0.044)
Age squared	-0.002	(0.002)	0-.00045	(0.0005)	-.00044	(0.0004)
Gender of Head (male=1)	-2.830**	(1.120)	-0.884**	(0.427)	-0.765**	(0.339)
Marital status (married=1)	1.200**	(0.582)	0.275**	(0.123)	0.278**	(0.130)
Family Size	0.119	(0.150)	0.029	(0.037)	0.029	(0.036)
ln Financial Asset	0.068***	(0.020)	0.017***	(0.005)	0.016***	(0.005)
House owned (=1)	0.354*	(0.213)	0.087*	(0.052)	0.085*	(0.051)
2004	-0.461***	(0.148)	-0.111***	(0.035)	-0.11***	(0.035)
2005	-0.330*	(0.200)	-0.080*	(0.048)	-0.079*	(0.047)
2006	-0.048	(0.268)	-0.012	(0.066)	-0.012	(0.064)
Control function	5.347***	(1.633)	1.325***	(0.406)	1.287***	(0.393)
Constant	-20.818***	(2.027)				
Group Means						
Mean price	-3.428	(2.985)	-0.850	(0.739)	-0.825	(0.718)
Mean income	0.291	(0.237)	0.072	(0.059)	0.070	(0.057)
Mean schooling year	0.107	(0.181)	0.027	(0.045)	0.026	(0.043)
Mean Age	0.047	(0.197)	0.012	(0.049)	0.011	(0.047)
Mean Age squared	0.001	(0.002)	0.00024	(0.0005)	0.00023	(0.0005)
Mean Gender	0.196	(1.188)	0.048	(0.294)	0.047	(0.286)
Mean Marital status	0.850	(0.702)	0.211	(0.174)	0.205	(0.169)
Mean family size	-0.006	(0.187)	-0.001	(0.046)	-0.001	(0.045)
Mean financial Asset	-0.018	(0.046)	-0.005	(0.011)	-0.004	(0.011)
Mean house owned	-0.619*	(0.325)	-0.153*	(0.081)	-0.149*	(0.078)
σ_u	4.711***	(0.113)				
σ_e	3.210***	(0.052)				
N	13613					
log likelihood	-13288.068					

[a]Robust standard errors in parentheses

[b]* p<.10, ** p<.05, *** p<.01

[c]Standard errors of partial effects are computed by Delta-method.

is similar.

The GMM fixed effect model (4) in Table 5 and pseudo-fixed effect model with the Mundlak (1978) approach in Table 6 agree with each other. The schooling years of household head and the age of head are not significant at any conventional level. In addition, the magnitudes of unconditional marginal effects are very similar to each other.[49] We find that we have endogeneity problem, since the coefficient of control function is significant at any conventional level. Price and income elasticities in Table 5 and Table 6 are significant, and the sizes are similar. Here, we also fail to reject the null hypothesis that the price elasticity is equal to -1 at any conventional level. Therefore, we cannot conclude that the tax incentives are not effective in raising the amount of donations made to NPOs in South Korea.[50]

4.3 Censored Quantile Regression with IVs

Since the estimation of the effect of tax incentive on charitable giving focuses on the various effects on the conditional mean of charitable giving, the size and nature of these effects were not represented on the lower tail of the charitable giving distribution.[51] Applying censored quantile regression to the corner solution case allows one to account for more features of the conditional distribution of charitable giving in the estimation.[52]

Literature on the quantile regression models using panel dataset has been small but growing (Abrevaya and Dahl, 2008; Canay, 2008; Honore, 1992; Koenker, 2004; Rosen, 2009)). The difference between an equation (10) and a panel quantile model is the existence of the unobserved c_i. If c_i were observable and the parameter of interest is $\beta(\tau)$,

$$Y_{it} = X_{it}'\beta(U_{it}) + c_i, \quad P(Y_{it} \leq X_{it}'\beta(\tau) + c_i | X_i, c_i) = \tau, \tag{6}$$

where t=1,...,T, and i=1,...,n under the assumption that $U_{it} \sim U[0,1]|X_i$, c_i and the function $\tau \to X'\beta(\tau)$ is assumed to be strictly increasing in $\tau \in (0,1)$. However, the random variable c_i is not observable and could be correlated with other random variables, which hinders consistent estimation of the model.[53] The literature on the mixture of censored panel data and quantile regression is much rarer.[54] Hence, we don't use the quantile fixed effect model. Instead, we use censored quantile regression with instrumental variables (CQIV) for cross-sectional data, since quantile regression itself can account for the unobserved heterogeneity and heterogeneous effect in a cross-sectional setting.

Chernozhukov, Fernandex-Val, and Kowalski (2009) demonstrate a simple way of estimating censored quantile regression with instrumental variables (CQIV) for cross-sectional data. They adapt the Iterative Linear Programming Algorithm (ILPA) proposed by Chernozhukov and Hong (2002) and the control function approach to handle endogeneity. However, Fitzenberger (1997) points out that ILPA is not guaranteed to converge and convergence does not even guarantee a local minimum of the CQR problem. Here, we adapt the resampling strategy introduced by Bilias et al. (2000) for censored quantile regression and the control function approach under the mean independence assumption between the tax price variable and the new error term having the control function.[55]

The censored quantile instrumental variable model is formalized as

$$\ln g = \max(\ln g^*, 0) = T((\ln g_i)^*) \tag{7}$$

$$(\ln g)^* = Q_{(\ln g)^*}(U|P, X, V) \tag{8}$$

$$P = \phi(V, X, Z), \tag{9}$$

where $\ln g$ is the logarithm of observed year-end charitable giving, and $T(x) \equiv \max(x, 0)$ is the transformation function that censors the unobserved uncensored value of $(\ln g_i)^*$ at 0, where 0 is lower limit for censoring following Chernozhukov et al. (2009). P is the last dollar marginal tax price of giving, and X are covariates described in the previous section except education level of household head,[56] Z is the instrumental variables, V is a latent unobserved regressor working as control functions, and U satisfies the assumption that $U \sim U(0,1)|P, X, 0, V$. The functional form allows for random coefficients that vary with the percentiles of the charitable giving distribution:

$$(\ln g)^* = \alpha(\tau) + X'\beta(\tau) + \gamma(\tau)V$$

The control term, $\hat{V}$ is estimated by predicting the OLS residuals from the first stage equation. The 90% confidence intervals on the coefficients are obtained by bootstrapping with 500 replications.

The estimates are only from the 2004 cross-sectional data. We choose 2004 data because we believe that the variation of charitable giving during this year is larger than in other years, since household income decreased due to the 2004 recession and giving price from the 2005 tax reform expected an increase.[57] Roughly 23% of the households give charitable contributions greater than zero. Many unobserved charitable giving and little price variation hinders obtaining precise estimates below the 0.77 quantile of the charitable giving distribution. Although estimates can be obtained below the 0.77 quantile, the values are not reliable. Hence, we only report the 0.77 quantile and above.

In the cross-sectional model, we use the first dollar price of giving as an instrument variable following the tradition of this research area because the tax reform information cannot be applied to the cross-sectional data. Figure A-3 in the Appendix A.6 presents a summary of censored quantile regression results. The solid line with dots represents the point estimates $\hat{\beta}_j(\tau) : j = 1, ..., 14$ with the dotted lines depicting a 90% pointwise confidence band. The significance of the variables is similar to that of the random effect model.

In the first panel of the figure A-3 in the Appendix A.6, the intercept of the model may be interpreted as the estimated conditional quantile function of the charitable giving distribution of female-headed with no-house ownership having a head with less than a high school education. The price elasticity is significant at the lower and middle tail, but it is insignificant at the higher tail. At the lower tail, the donors are very sensitive to the price changes. Given income and other variables, the households with a high level of giving at the right tail are insensitive to price. Low tax awareness makes the estimated tax price elasticities insignificant or small in absolute value. Schokkaert (2006) points out that the differences in tax awareness are related to underlying motivations of giving.[58] If crowding-out occurs in the large donors' side, they may be dutiful altruists. For example, religious giving represents about 80% of total giving in South Korea, according to the Korean government. In that case, tax price of giving may not be significant.[59]

Income has a significantly uniform and positive effect over the whole range of the distribution, and the magnitude is small. A large increase in income may not cause a large increase in contributions across all distribution of giving. The effect of university education differs across the conditional distribution. As household heads' education increases, the percentage increase in charitable giving increases over the whole range of the conditional distribution. Except in the household with a very high level of charitable giving, female-headed households give less charitable contributions than male-headed. Households with very high contributions are not sensitive to the change in the gender of household head. Households with very high contributions do not respond to the age of household head, but across other conditional distribution, an increase in the age of household head significantly increases charitable giving. Households with a moderate level of contribution increase giving, with a decreasing rate with an increase in age. Married status among heads significantly positively affects the percentage of change in charitable giving across all ranges of the distribution except the right tail. Generally speaking, we find that households' charitable giving decisions are affected by the different factors across the distribution of charitable giving. Households with large amount of giving are not affected by price, head sex, head age, and marital status in South Korea. When policymakers set up policies about tax and charitable giving, they should note that the behaviors of big-contributors are different from those of small-donors.

5 Conclusion and Policy Implications

This study analyzes the household's determinants of charitable giving and effect of tax incentive on charitable giving in South Korea. We find that the charitable giving in South Korea is determined by household income, tax price of giving, gender of household head, marital status of head, amount of financial asset, and house ownership from the pseudo-fixed effect estimation. Household heads' education and age do not affect whether the households choose to donate.

All specifications report that the price elasticity of giving is significant, although its estimated size is not 1 in absolute value. The estimated price elasticities are similar or somewhat smaller than those based on the data from the United States or other Western countries. The income effect on giving is also significant, but the magnitude is very small. Although per capita GDP increases over time, the ratio of giving to GDP in Korea may not be expected to increase. Hence, tax incentive is a more important tool to boost up the charitable contribution in South Korea.

The maturity of civil society can be measured by how well nonprofit sectors complement the functions that are the primary responsibility of the government.[60] Since the late 1990s, many NPOs, including public-serving nonprofit and voluntary and grassroots associations, have been founded in South Korea, but they have suffered from financial difficulties. To alleviate their financial difficulties, Korean government implemented an Act for Nonprofit Organization Aid in 2000, through which the government directly provides financial support to NPOs. The government's direct financial support requires responsibility; for example, obeying the management standard and procedure imposed by the government. Hence, the direct financial support may affect organizational autonomy, financial autonomy, and program autonomy. In addition, the government can only choose and support the NPOs that are favored by the government.[61] Therefore, the best way to support NPOs is to increase voluntary donation.

Given the low participation rate of charitable giving in South Korea, the increase of the ratio is required. From all the various specifications in this study, the tax price of giving is a significant determinant when households decide whether to take part in donation or not. Considering that ever-donors, in addition, are likely to take part in giving repeatedly in the future[62] (See Appendix A.2 Transition matrix), the expansion of tax deductibility has the potential to increase the participation rate. Naturally, a culture of giving will be also fostered. Therefore, the expansion of tax deductibility or tax credit is an effective method to support NPOs without hurting the NPOs' autonomy as well as to foster the culture of donation.[63] The tax deduction helps provide the financial resources that NPOs need to provide collective public goods. Furthermore, it can help facilitate the creation of new NPOs' particularly in the early stage of a civil society like South Korea.[64]

Notes

[1]According to Vesterlund (2006, p.581), "necessary for a unit elastic demand to be the threshold for efficiency is also that individuals truly make the contributions they report on the tax form, and that the government is able to make a direct transfer without adversely affecting the contributions by others." Therefore, considering that religious organizations do not receive government expenditures as a substitute for private contribution, the concepts of "treasury efficient" or "golden rule" may not be rigorously applicable to analysis of our data because our data does not allow classification of the aim of charitable giving.

[2]Cordes (2001) points out that the uncertainties about the price sensitivity of giving will disappear as data improve. But he argues that consideration of charitable giving will require more than estimates of price elasticity. List (2007) also points out that institutions are important in the decision of charitable giving.

[3]According to Giving USA 2008, the ratio of individuals' charitable giving to GDP was about 1.7% in the 2000s' in the United States.

[4]The Korean Labor and Income Panel Study (KLIPS) does not have information about the aims of donation.

[5]These models can work as a good reference for the Tobit model as if a linear probability model is a good reference for a probit model.

[6]A cross-sectional data set only allows us to examine the relationship between current price and income and current charitable giving. Using the cross-sectional data, the omitted variable bias appears, for example, the expected future price of giving. Bakija (2000) points out that, if the current price is different from the expected future price, and if people are willing to respond by changing the timing of their giving, then estimates that involve only the current price would be biased to estimate the permanent price elasticity.

[7]Barrett, Mcguirk, and Steinberg (1997) summarize the advantages of using panel data set in this topic: First, sufficient information of panel data set allows us to control for a variety of unobserved but confounding influences. Second, panel data set that spans statutory tax changes helps us account for the independent effect of price and income on giving. Third, timing and other dynamic effects can be estimated within panel setting.

[8]The permanent price elasticity exceeds the absolute value of 1.

[9]Auten et al. (2002) directly estimated the variance and covariance matrix of income and prices by explicitly modeling the dynamic process determining prices and incomes.

[10]It is due to the statistical assumptions to identify the permanent response from the transitory response in the data.

[11]He argues that high price elasticity may be due to the measurement error on deductible contribution or income. He also maintains that certain parts of the population are more likely to file tax returns than others.

[12]Park and Park (2004) mentioned Park, Park, and Jeong (2002), one of their previous studies on the same topic. Park et al. (2002) also fail to find significant estimates of income and price elasticities in Korea.

[13]Tax-filer data might be more accurate than survey data because variables, such as income, age, donation, itemizing status, and so on, are taken from income tax returns.

[14]Peloza and Steel (2005) take Clotfelter's (1985) argument about speculation of using survey data; elasticities derived from survey data may be artificially high.

[15]The limitation of our data is that all workers are treated as wage and salary workers. Hence, the profit of self-employed workers or business owners is not included in this study, since large measurement error can occur through the inclusion of the profit or loss.

[16]As a robustness check, we estimate censored quantile regression models censored at contribution of 5 again. We fail to find any loss of significance.

[17]While NBER's TAXSIM can be used for research on the United States, it cannot be used for Korean data. Moreover, there is no standardized version of any computing programs for marginal tax rates of South Korea. Therefore, marginal tax rates for each year are computed by the author using the given information. Appendix A.4 presents how to compute the marginal tax rates.

[18]The tax report is based on the individual unit. Hence, the joint report does not necessarily give benefit to filers in South Korea. In the case that a household has many dependents, it is more beneficial to report separately; for example, the household head gets deduction from the number of dependents and the wife also gets a deduction using the other dependents that are not included in the household head's tax report.

[19]Korean tax system does not classify the itemizers.

[20]The difference in the numbers is due to KLIPS only including information from urban areas. For the most part, income in urban areas is greater than that of rural areas.

[21]Cook's distance, standardized residuals, studentized residuals, and DFBETA are used to detect bad influential observations. The detected observations are removed, leaving us with 14,266 observations.

[22]Real GDP growth rate in Korea decreased from 7.2% in 2002 to 2.8% in 2003. The number of donors also decreased from 900 in 2003 to 790 in 2004.

[23]The last dollar-price of giving is defined as "1-the marginal tax rate after all deductions," while the first dollar price of giving is defined as "1-the marginal tax rate evaluated at zero dollars giving"

[24]We test whether the endogeneity problem exists by the control function approach in both the pseudo-fixed effect Tobit and censored quantile model with IV as well as by Wu-Hausman F-test in all fixed effect models.

[25]We also have the same problem in the fixed effect estimation. The collinearity arises from the property of the marginal tax rate: marginal tax rate is a non-linear function of income, and the function is largely the same for everyone during a given year. In addition, the first dollar price may itself be correlated with the unobserved determinants of contributions if the unobserved determinants of giving (for example, generosity or dignity) are correlated with other deductions or income sources.

[26]Methods to construct these variables are given in Bakija (2000, pp. 17-20). He constructs $\ln P_s(\overline{M}_{is})$, the log price function based on the known year s tax schedules, evaluated at an "averaged" measure of taxable income $\overline{M}_{is}$. $\overline{M}_{is}$ is based on four-year individual averages of before-tax income and deductions other than charity, adjusted for known features of the year s definition of taxable income. The instrument constructed for transitory variation in price is $\ln P_t(\overline{M}_{it}) - \ln P_s(\overline{M}_{is})$, the difference between year t and year s marginal tax rates due

entirely to legislated changes in the tax schedules. Here t represents current year and s represents next year when currently enacted tax law is fully phased-in.

[27]We treat charitable giving as a consumption good following the same track of the previous empirical research. Andreoni (1990) and Andreoni (2006) propose "warm-glow" theory, in which individuals get some utility from consuming charitable contributions. Following the tradition, the demand for charitable giving by donors can be explained by utility maximization. The optimal amount of giving can be determined within the utility maximization. In addition, the effect of income tax on giving can be analyzed within this framework, and the optimal consumption level of charity is determined subject to tax-price of giving and total income. A utility maximization problem for charitable giving may be represented by $U_i(x, g) = x + a_i \ln(1 + g)$, where x is annual consumption and g is annual charitable giving. The variable a_i determines the marginal utility of giving for household i.

$$\begin{aligned} \max \quad & U_i(x, g) = x + a_i \ln(1 + g) \\ s.t. \quad & I_i = x_i + p_i g_i \\ & x \geq 0, \quad g \geq 0, \end{aligned}$$

where I_i is household income and p_i is the tax price of charitable giving. Hence, a corner solution, $g_i = 0$ exists if $a_i \leq p_i$ by the Kuhn-Tucker conditions.

[28]The following test is different from the overall significant test of head-gender variable.

[29]However, we cannot conclude that female-headed households are more generous than male headed over the whole range of a contribution distribution since the test performed above is only evaluated at the conditional mean. The detailed study is for another project.

[30]Pagan and Hall (1983) heteroscedasticity test is performed after the fixed-effect IV estimation. We reject the null hypothesis of the homoscedasticity in 1% level.

[31]The traditional test of the rank of a matrix for the standard (stationary) case is the Anderson canonical correlations test (Anderson, 1951). But this version of the test is not robust to heteroscedasticity.

[32]As Angrist and Pischke (2009, chap.4) summarize, point estimates with weak instruments are biased, and naturally Wald test is unreliable.

[33]These models can work as a good reference for the Tobit model as if a linear probability model is a good reference for the probit model.

[34] Moreira (2002) discusses alternative test statistics that are also robust for weak instruments. After "within-transformation" of data, we use the Stata command "condivreg" to estimate coverage-corrected confidence sets and p-values for the null hypothesis that the coefficient of endogenous variable is not significant under i.i.d. Both the conditional likelihood ratio test and the Lagrange Multiplier test reject the null hypothesis at any conventional level. 95% confidence sets are reported as $[-1.717302, -.6335934]$ and $[-1.717556, -.6333413]$, respectively, and both sets do not include 0. This test does not support robust standard error.

[35]It tests only the overidentification restrictions evaluated at the null hypothesis. It differs from Hansen's J statistic.

[36]It only tests whether the structural parameters are significant.

[37]In case of weak instruments with intracluster-dependent errors, the confidence set from the Wald test is far greater than those from other robust statistics. In the Table A-15 in the Appendix, we also find that our exclusion restrictions are not weak.

[38]The Hausman test can determine the existence of the correlation. The null hypothesis is marginally rejected that the estimates from the random effect model are consistent. ($\chi^2_{(12)}$=19.20 and p-value=0.083)

[39]The fixed IV estimation procedure is as follows: the "within transformation" is first applied to the data, (i.e., all variables have group means subtracted), and then an IV estimation is performed on the demeaned data.

[40]LIML is less precise than 2SLS but also less biased.

[41]Following Halvorsen and Palmquist (1980), the interpretation of the coefficients of dummy variables when the dependent variable is log-transformed is given in: $100(\exp(b - V(b)/2) - 1)$, where b is a coefficient and $V(b)$ is a variance of b.

[42]Rabe-Hesketh, Skrondal, and Pickles' (2005) GLLAMM allows us to use adaptive quadrature method, while Stata's command "xttobit" only has the fixed quadrature method. If the percent contribution to the total variance of the panel-level variance component is large, the fixed quadrature approximation can become less accurate.

[43]Estimating the fixed effect model for the censored panel data is practically and theoretically difficult in the Tobit model setting. Since g_{it} in (4) is observed only after transformations, difference-estimation and within-estimation are impossible. Large N and fixed T require many dummy variables d_i so that it is practically impossible to estimate the fixed effect model. Moreover, theoretically, the incidental parameter problem can appear as the number of parameter increases with N and fixed T.

[44]This method, (i.e., the control function approach) has a few advantages against plugging the fitted values. The addition of predicted residuals of the reduced form into the random effect model can solve the endogenous problem regardless of how the endogenous variable appears. Plugging fitted values for the endogenous variable only works in the case in which the model is linear in the endogenous variables. In addition, the control function approach makes it much easier to test the null hypothesis of endogeneity of the variable as well as compute average partial effects.

[45]Alternatively, the panel bootstrap can be used to compute standard errors, even though it consumes too much computing time.

[46]Table A-18 in the Appendix shows the estimates of the random effect probit and the pseudo-fixed effect probit models. The standard errors are computed by the panel bootstrap with 200 replications.

[47]Both Tables have the standard errors from 200 replications of bootstrap.

[48]Robust standard errors of coefficients are included. All standard errors are adjusted for the first stage regression.

[49]Unconditional marginal effect can be compared to the coefficients in Table 5. The unconditional marginal effects in Table 6 are computed by multiplying the adjustment factor with the Tobit estimates: $\frac{\partial E(g|x)}{\partial x_j} = \beta_j \Phi(x\beta/\sigma)$. Evaluated at the sample mean values of the explanatory variables, the factor $\Phi(\bar{x}\hat{\beta}/\hat{\sigma})$ is about 0.248, which is a consistent estimate of probability of giving > 0 conditional on the explanatory variables $Pr(g > 0|x)$. In addition, the conditional partial effects for the sub-sample of households with charity>0 can be computed by the factor, 0.2407.

[50]As a robustness check, we estimate the same specification using Stata's command "xttobit" with 200 replications of bootstrap to compute standard errors. Bootstrap standard errors are known as robust against heteroskedasticity. We draw pairwise plots of the standardized residuals and each regressor. The control function and the standardized residual plot show that the control function may be a candidate causing heteroscedasticity. Also, estimates of censored quantile regression imply that the control function may cause heteroscedasticity. In addition, we detect the existence of heteroscedasticity in the fixed effect model (2) of Table 5.

[51]We have estimated models with a corner solution, because charitable contribution has a mass point at zero. The Tobit model generates a few features of conditional distribution of charitable contribution given the explanatory variables, such as $Pr(g|g > 0, X)$, $E(g|g > 0, X)$, and $E(g|X)$.

[52]Since Powell (1986) introduced censored quantile regressions (CQRs), one can estimate quantiles of the conditional distribution.

$$\min_{\hat{\beta}(\tau)} \sum_{i=1}^{n} \rho_\tau(\ln g_i - T(X_i^{'}\beta(\tau))), \tag{10}$$

where $\rho_\tau(u) = \{(1-\tau)I(u < 0) + \tau I(u > 0)\}|u|$. It allows $\sqrt{n}$-consistent estimates of β without assuming a particular distribution for the error term and without even assuming that the error and covariates are independent.

[53] Rosen (2009) shows that a conditional quantile restriction alone does not identify $\beta(\tau)$. If the equation (6) is represented as

$$Y_{it} = X_{it}'\beta(\tau) + c_i + e_{it}, \quad P(e_{it}(\tau) \leq 0|X_i) = \tau, \tag{11}$$

where $e_{it} \equiv X_{it}'[\beta(U_{it}) - \beta(\tau)]$, the conditional quantile restriction $Q_{e_{it}}(\tau|X_i) = 0$ does not have enough identification power since e_{it} is not identical across t. Canay (2008) argues that Abrevaya and Dahl's (2008) method of obtaining an estimator of $\beta(\tau)$ could be problematic based on Rosen's (2009) proof. Abrevaya and Dahl (2008) use the correlated random-effect model with the Chamberlain (1982) approach, which views the unobservable individual heterogeneity as a linear projection onto the observables plus a disturbance.

[54]Honore (1992) uses an assumption that errors are conditionally independent and identically distributed. Showing that assumption implies symmetry of the distribution of observed outcomes, he consistently estimates the parameters of the censored model. However, this is not applicable in the heavily censored case, because Honore's (1992) estimation is a version of censored least absolute deviation (CLAD); i.e., median regression. Due to the fact that our data is heavy censored, we use cross-sectional model instead of Honore (1992).

[55]The advantages of CQIV are summarized by Kowalski (2009): first, the CQIV allows the coefficients to vary with the quantile of interest; second, CQIV allows for endogeneity and handles censoring nonparametrically. One of disadvantages of quantile regression is attenuation bias caused by censoring, which also occurs in the parametric mean regression.

[56]Household head's education year dummies are generated into four categories: university graduates, some college education, high school, and under high school

[57]Time adjustment effect for donors may be expected, i.e., people can donate more to avoid a future high price of giving after tax reform. To confirm that our estimates are not affected by the time adjustment effect, we estimate the marginal distribution functions of contribution during 2003 and 2004, controlling for the relevant explanatory variables following Machado and Mata (2005). The difference between them is not significant over

the whole range of giving distribution. The 95% confidence bands for the differences are computed by 1000 replications of bootstrap. Hence, there is no evidence of time adjustment effect in South Korea from 2003 to 2004. (See Appendix Figure A-1.)

[58]Schokkaert (2006) summarizes the motivations of giving: material self-interest, social prestige, reciprocity, dutiful altruism, social pressure, pure altruism, and empathy.

[59]Eckel and Grossman (2004, p.273) argue that the extremely religious households could not respond to price change, while income elasticity could be equal to 1 in the extreme case.

[60]A role of the nonprofit sector is to complement the market failure and government failure. Brinkerhoff, Smith, and Teegen (2007) summarize the complementary roles of the third sector: providing services; advocating policy process; demanding an appropriate mix of public goods from governments and donors; intermediating among local communities, other civil society actors, governments, donors, and private sectors; and building the capacity of community groups to interface with government and private sector actors.

[61]The conflict between the government and NPOs makes social benefits smaller than they might be under more cooperative arrangements (Brinkerhoff et al., 2007, chap. 3). On the other hand, the government's direct support may be beneficial to NPOs; it may establish credibility of NPOs by recognition. The credibility acquired by the government's support helps NPOs to garner more donations.

[62]Sociological work suggests the existence of "the memory" effect, such as learning by doing or developing a role identity (Piliavin and Charng, 1990).

[63]France allows tax credit for charitable giving instead of tax deductibility.

[64]Fortunately, the Korean government plans to extend the tax deductibility of giving in the 2010 Tax Reform. This reform increases the tax deductible cap up to 20% of the taxable income from the current 10%.

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Appendix A

A.1 Descriptive Statistics

Table A-1: Descriptive Statistics

	Full Sample		Sub Sample: Charity>0	
	Mean	SD	Mean	SD
Charitable Giving	35.05	131.2	144.41	234.82
2003	33.46 (N=3,201)	114.87	129.03 (N=830)	196.43
2004	31.77 (N=3,412)	103.76	139.31 (N=778)	179.62
2005	34.16 (N=3,612)	122.06	147.22 (N=838)	218.21
2006	40.82 (N=3,388)	173.02	161.16 (N=858)	314.48
Last-dollar price	0.93	0.09	144.41	0.09
Total Household income	3624.6	3485.22	0.91	3732.31
Head education year	12	3.7	4358.18	3.78
Head Age	46.23	11.57	12.66	11.05
Head Sex(Male=1)	0.88	0.33	47.83	0.32
Marital Status(marry=1)	0.8	0.4	0.89	0.34
Number of Family Member	3.32	1.24	0.87	1.16
Financial asset(log)	4.58	3.47	3.51	3.43
House owned(=1)	0.59	0.49	5.07	0.48
N	13,613		3,304	

Source: The Korean Labor and Income Panel Study, Korea.

[a]All values are adjusted to 2005 values using Korean Consumer Price Index.

[b]SD stands for standard deviation.

A.2 Transition Matrix of Giving Behaviors

Table A-2: Transition of Giving Behaviors 2003 to 2004

	Giving 2004		
Giving 2003	0	1	Total
0	1,957	261	2,218
	(88.23)	(11.77)	(100.00)
1	322	451	773
	(41.66)	(58.34)	(100.00)
Total	2,279	712	2,991
	(76.20)	(23.80)	(100.00)

Source: KLIPS 2004-2007

[a]The ratio (%) in parentheses from year to year.

[b]1 represents that households contribute. Otherwise, 0.

Table A-3: Transition of Giving Behaviors 2004 to 2005

	Giving 2005		
Giving 2004	0	1	Total
0	2,169	274	2,443
	(88.78)	(11.22)	(100.00)
1	244	474	718
	(33.98)	(66.02)	(100.00)
Total	2,413	748	3,161
	(76.34)	(23.66)	(100.00)

Source: KLIPS 2004-2007

[a]The ratio (%) in parentheses from year to year.

[b]1 represents that households contribute. Otherwise, 0.

Table A-4: Transition of Giving Behaviors 2005 to 2006

	Giving 2006		
Giving 2005	0	1	Total
0	2,200	297	2,497
	(88.11)	(11.89)	(100.00)
1	237	528	765
	(30.98)	(69.02)	(100.00)
Total	2,437	825	3,262
	(74.71)	(25.29)	(100.00)

Source: KLIPS 2004-2007

[a]The ratio (%) in parentheses from year to year.

[b]1 represents that households contribute. Otherwise, 0.

A.3 Tax Schedule Change

Recently Korean government has decreased the income tax rate by 1% over gross income hierarchies since January 1, 2005. Based on the tax schedule, the tax-price of giving can be computed. In addition, the ceiling for the earned income tax credits is raised to 55% of assessed tax liabilities from the previous 45% in 2004–but 50 % was applied only in 2003. Due to the wage and salary income tax credit, the marginal tax rate of low income earners is reduced. We include tax credit computing the marginal tax rates.

Table A-6 represents the amount of charitable Giving in Korea over income distribution. As income increases, the amount of charitable giving increases over all years. In 2004, there was a recession in Korea. That recession may affect households located within the lowest income quantile, considering participants only between 2003 and 2004. From the full sample, we find the reduction of charitable giving in other income quantiles. This suggests that a recession could hinder households from participating in charitable giving.

Tax rate change generates tax price of giving since tax price of giving is defined as "1-marginal tax rate" in this paper. We expect that decreases in the income tax rate by 1% over all yhr gross income hierarchies increase tax price of giving over all income hierarchies; 1.087%, 1.205%, 1.351%, and 1.538% for each income hierarchy, respectively. Table A-7 provides change of charitable giving just before and after policy change. Price changes, based on tax reform, could affect the amount of charitable giving decision in Korea heterogeneously depending on which income quantiles households are located in: Households within the lowest income group reduce charitable giving by about 10%, while households with high income (4th and 5th quantiles) slightly reduce or increase the charitable giving. (Due to the small number of participants, the t-test fails to reject the null hypothesis that the amount of charitable giving before and after policy change is the same.)

Table A-5: Income Tax Schedule in Korea

Taxable annual income (in won)	Taxable annual income (in dollar)	Tax Rate (2002-2004)	Tax Rate (2005-2007)
less than 10m	less than $9,891	9 %	8 %
10m-40m	$9,891-$39,565	18 %	17 %
40m-80m	$39,565-$79130	27 %	26 %
more than 80m	more than $79,130	36 %	35 %

[a]The dollar figures are computed by the 2005 exchange rate of $1=1011 won.

Table A-6: Charitable Giving in Korea over Income Distribution

Year	Quantile 1 [1020.68]	Quantile 2 [2087.09]	Quantile 3 [2948.48]	Quantile 4 [4119.14]	Quantile 5 [7948.25]
Full Sample					
2003	12.810	15.741	28.184	44.437	72.880
2004	10.580	19.583	23.207	43.748	67.856
2005	9.1725	18.109	24.184	35.848	80.517
2006	10.516	14.743	25.366	45.925	93.507
Total	10.755	17.124	25.251	42.425	79.698
Sub Sample: Giving>0					
2003	68.057	74.274	107.531	146.858	209.716
2004	63.822	109.240	117.793	152.764	204.875
2005	57.876	103.838	112.285	151.668	219.539
2006	61.080	82.589	110.500	168.316	247.218
Total	62.959	92.339	111.622	155.274	222.729

Source: The Korean Labor and Income Panel Study, Korea.

[a]All values are adjusted to 2005 values using Korean Consumer Price Index.

[b]Average income of each quantile is in square brackets.

Table A-7: Change of Giving Before and After Policy Change (Giving>0)

Income Quantile	(1) Pre-Policy Change 2004	(2) Post-Policy Change 2005	(3) Percentage Change	(4) t-statistics H_0:(1)=(2)
1	63.822	57.876	-10.274(%)	0.6155
2	109.24	103.838	-5.202(%)	0.3476
3	117.793	112.285	-4.905(%)	0.4005
4	152.764	151.668	-0.723(%)	0.0596
5	204.875	219.539	6.679(%)	-0.5504
Population	139.312	147.222	5.373(%)	-0.7922
N	778	838		

Source: The Korean Labor and Income Panel Study, Korea.

[a]All values are adjusted to 2005 values using Korean Consumer Price Index.

A.4 Marginal Tax Rate

Table A-8: Wage and Salary Tax Credit 2003

tax amount	2003	tax base
tax$\leq$ 500,000	tax $\times$ 0.5	5,555,600
500,000<tax$\leq$1,166,666	250,000+(tax-500,000) $\times$ 0.3	11,481,478

Table A-9: Wage and Salary Tax Credit 2004

tax amount	2004	tax base
tax$\leq$500,000	tax$\times$0.55	5,555,600
500,000<tax$\leq$ 1,250,000	275,000+(tax-500,000)$\times$0.3	11,944,444

Table A-10: Wage and Salary Tax Credit 2005-2008

tax amount	2005-2008	tax base
tax$\leq$500,000	tax$\times$0.55	6,250,000
500,000<tax$\leq$1,250,000	275,000+(tax-500,000)$\times$0.3	12,647,059

Table A-11: Marginal Tax Rate and Giving Price 2003

2003 tax base (G)	marginal tax rate	Giving Price
G$\leq$10 million	$.09\times .50 = .045$	1-$(.09\times.5) = .955$
10 million<G$\leq$11.481 million	$.18\times0.30 = 0.054$	1-$(.18\times.3) = .946$
11.481 million<G$\leq$40 million	.18	1-.18 =.82
40 million <G$\leq$80 million	.27	1-.27 = .73
80 million<G	.36	1-.36 = .64

Table A-12: Marginal Tax Rate and Giving Price 2004

2004 tax base (G)	marginal tax rate	Giving Price
G$\leq$10 million	$.09\times 0.55 = 0.0495$	1-$(.09\times .55) = .951$
10 million < G$\leq$11.944 million	$.18\times0.3 = 0.054$	1-$(.18 \times.30) = .946$
11.944 million< G $\leq$ 40 million	.18	1-.18 =.82
40 million<G$\leq$80 million	.27	1-.27 = .73
80 million<G	.36	1-.36 = .64

Table A-13: Marginal Tax Rate and Giving Price 2005-2008

2005-2008 Tax Base (G)	Marginal Tax Rate	Giving Price
G$\leq$10 million	$.08\times0.5= 0.04$	1-$(.08\times0.55) = 0.956$
10 million<G$\leq$12.647 million	$.17\times0.3 = 0.051$	1-$(.17\times0.3) = 0.949$
12.647 million<G$\leq$40 million	.17	1-.17 = .83
40 million<G$\leq$80 million	.26	1-.26 = .74
80 million<G	.35	1-.35 = .65

Table A-14: Marginal Tax Rate in Korea

	Year				
Marginal Tax Rate	Round 7	Round 8	Round 9	Round 10	Total
0	1,358	1,284	1,368	1,213	5,223
.044	0	0	883	792	1,675
.045	773	0	0	0	773
.0495	0	892	0	0	892
.051	0	0	242	205	447
.054	120	185	0	0	305
.17	0	0	930	938	1,868
.18	825	906	0	0	1,731
.26	0	0	156	196	352
.27	104	122	0	0	226
.35	0	0	33	44	77
.36	21	23	0	0	44
Total	3,201	3,412	3,612	3,388	13,613

Sources: KLIPS each year and Income Tax Schedule in Korea

A.5 Regression Results Tables

Table A-15: Weak Instrument Robust Tests and Confidence Sets for Linear IV with Cluster VCE

H_0: β[ln tax price]= 0.

Test Statistic	Value	P-value	95 % Confidence Set
CLR	stat(.)= 9.14	0.0025	[-1.70192, -.28692]
AR	$\chi^2_{(12)} = 23.09$	0.0270	[-1.84192, -.14692]
LM	$\chi^2_{(1)} = 7.55$	0.0060	[-1.70192, -.28692]
J	$\chi^2_{(11)} = 15.54$	0.1590	
LM-J	H_0 rejected at 5 % level		[-1.73692, -.25192]
Wald	$\chi^2_{(1)} = 6.58$	0.0103	[-1.65877,-.221803]

[a]Wald test is not robust to weak instruments. The confidence set from Wald test with weak instrument is likely to be much larger than that from other robust statistics in the linear IV model with intracluster-dependent errors based on Monte Carlo simulation by Finlay and Magnusson (2009).

Table A-16: Estimation with IVs using Sub-sample (Charity > 0)

Dependent Variable ln Giving	(1) RE G2SLS	(2) FE w/IID 2SLS	(3) FE w/H GMM	(4) FE w/HAC GMM	(5) FE w/weak IV CUE
ln Giving Price	-0.862**	-1.252***	-1.139**	-1.161**	-1.183**
	(0.436)	(0.439)	(0.481)	(0.469)	(0.469)
ln Income	0.224***	0.167***	0.173***	0.170***	0.168***
	(0.0393)	(0.0437)	(0.0514)	(0.0514)	(0.0513)
Schooling Year	0.0621***	-0.0266	-0.0228	-0.0218	-0.0206
	(0.00847)	(0.0579)	(0.0609)	(0.0526)	(0.0532)
Head Age	0.0197	0.0567	0.0519	0.0469	0.0470
	(0.0174)	(0.0632)	(0.0548)	(0.0583)	(0.0582)
Age squared	-0.000108	-0.000240	-0.000183	-0.000134	-0.000133
	(0.000176)	(0.000609)	(0.000601)	(0.000641)	(0.000639)
Gender of Head	-0.255**	0.00922	-0.0340	-0.0438	-0.0542
(male=1)	(0.107)	(0.432)	(0.336)	(0.337)	(0.340)
Marital Status	0.171*	-0.0593	-0.0834	-0.0870	-0.0773
(Married=1)	(0.104)	(0.279)	(0.185)	(0.202)	(0.203)
Family Size	0.0426*	0.0169	0.0190	0.0249	0.0240
	(0.0234)	(0.0451)	(0.0490)	(0.0548)	(0.0546)
ln Financial Asset	0.00575	0.0116*	0.0122*	0.0126*	0.0127*
	(0.00515)	(0.00632)	(0.00679)	(0.00705)	(0.00706)
House owned (=1)	0.0205	0.162**	0.150**	0.141**	0.137**
	(0.0441)	(0.0651)	(0.0677)	(0.0692)	(0.0689)
2004	0.0519	0.0190	0.0233	0.0276	0.0267
	(0.0353)	(0.0487)	(0.0391)	(0.0386)	(0.0384)
2005	0.0905**	0.0381	0.0298	0.0268	0.0255
	(0.0353)	(0.0722)	(0.0420)	(0.0426)	(0.0421)
2006	0.0646*	0.00203	-0.00192	-0.00110	-0.00167
	(0.0360)	(0.0995)	(0.0471)	(0.0480)	(0.0471)
constant	0.590				
	(0.507)				
N	3304	2618	2618	2618	2618
log likelihood		-1948.0	-1945.5	-1946.2	-1946.8

[a]Standard errors in parentheses
[b]* p <.10, ** p<.05, *** p<.01

Table A-17: Robustness Check: Pseudo-Fixed Effect Tobit Model with Bootstrap

Dependent Variable ln Giving	Coefficient	S.E.	Unconditional Marginal Effect	S.E.	Conditional Marginal Effect	S.E.
ln Giving Price	-3.349**	(1.411)	-0.832	(0.319)	-0.807	(0.338)
ln Income	0.512***	(0.130)	0.127	(0.031)	0.123	(0.031)
Schooling year	0.180	(0.198)	0.045	(0.044)	0.043	(0.048)
Head Age	0.154	(0.205)	0.038	(0.046)	0.037	(0.049)
Age squared	-0.002	(0.002)	-0.0005	(0.0005)	-0.0004	(0.0005)
Gender of Head (male=1)	-2.829**	(1.132)	-0.884	(0.427)	-0.765	(0.344)
Marital status (married=1)	1.200*	(0.714)	0.275	(0.123)	0.278	(0.160)
Family Size	0.119	(0.157)	0.029	(0.037)	0.029	(0.038)
ln Financial Asset	0.068***	(0.022)	0.017	(0.005)	0.016	(0.005)
House owned (=1)	0.354	(0.234)	0.087	(0.052)	0.085	(0.056)
2004	-0.460***	(0.157)	-0.111	(0.035)	-0.110	(0.037)
2005	-0.329	(0.228)	-0.08	(0.048)	-0.079	(0.054)
2006	-0.048	(0.311)	-0.012	(0.066)	-0.012	(0.075)
Control function	5.365***	(1.763)	1.332	(0.406)	1.292	(0.423)
Constant	-20.755***	(2.156)				
Group Means						
Mean price	-3.389	(3.078)	-0.842	(0.739)	-0.816	(0.741)
Mean income	0.290	(0.244)	0.072	(0.059)	0.070	(0.059)
Mean Schooling year	0.106	(0.200)	0.026	(0.045)	0.026	(0.048)
Mean Age	0.045	(0.213)	0.011	(0.049)	0.011	(0.051)
Mean Age squared	0.001	(0.002)	0.0002	(0.0005)	0.0002	(0.0005)
Mean Gender	0.213	(1.179)	0.053	(0.294)	0.051	(0.284)
Mean Marital status	0.832	(0.783)	0.207	(0.174)	0.200	(0.188)
Mean family size	-0.006	(0.182)	-0.001	(0.046)	-0.001	(0.044)
Mean financial Asset	-0.018	(0.044)	-0.005	(0.011)	-0.004	(0.010)
Mean house owned	-0.618*	(0.356)	-0.154	(0.081)	-0.149	(0.086)
σ_u	4.738***	(0.061)				
σ_e	3.203***	(0.013)				
N	13613					
log likelihood	-13286.614					

[a]Bootstrap standard errors are in parentheses

[b]* p<.10, ** p<.05, *** p<.01

[c]Standard errors of partial effects are computed by Delta-method.

[d]Stata command "xttobit" is used. Table 6 is estimated by GLLAMM.

Table A-18: Random Effect and Pseudo-Fixed Effect Probit

Dependent Variable ln Giving	(1) Random Effect Probit		(2) Pseudo-Fixed Effect Probit	
ln Giving Price	-1.099**	(0.447)	-0.955**	(0.487)
ln Income	0.176***	(0.0452)	0.160***	(0.0493)
Head Education	0.0915***	(0.0114)	0.0687	(0.0711)
Head Age	0.0651***	(0.0207)	0.0653	(0.0818)
Age squared	-0.000311	(0.000208)	-0.000774	(0.000756)
Gender of Head	-0.821***	(0.109)	-0.960**	(0.436)
Marital Status	0.557***	(0.107)	0.358	(0.227)
Family Size	0.0424	(0.0287)	0.0508	(0.0613)
ln Financial Asset	0.0227***	(0.00643)	0.0234***	(0.00724)
House owned (=1)	0.0224	(0.0576)	0.112	(0.0820)
2004	-0.228***	(0.0483)	-0.185***	(0.0526)
2005	-0.225***	(0.0495)	-0.141	(0.0831)
2006	-0.164***	(0.0493)	-0.0367	(0.112)
Control term	1.617***	(0.580)	1.490**	(0.604)
Group Means				
Mean price			-1.189	(1.017)
Mean income			0.0687	(0.0843)
Mean Schooling year			0.0211	(0.0714)
Mean Age			0.000209	(0.0851)
Mean Age squared			0.000484	(0.000770)
Mean Gender			0.120	(0.452)
Mean Marital status			0.299	(0.260)
Mean family size			-0.0202	(0.0722)
Mean financial Asset			-0.00329	(0.0162)
Mean house owned			-0.189	(0.121)
Constant	-6.045***	(0.559)	-6.517***	(0.710)
$\ln \sigma_u^2$	0.837	0.064	0.839	(0.058)
N	13613		13613	
log likelihood	-5989.8739		-5984.3207	

[a]Standard errors in parentheses are computed by bootstrap with 200 replications.

[b]* p<.10, ** p<.05, *** p<.01

A.6 Figures

Figure A-1: Difference of Marginal Distribution: 2003 and 2004 (Giving>0)

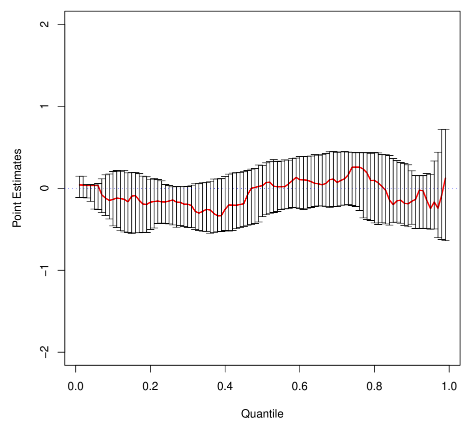


Figure A-2: Cumulative Distribution of Giving: 2003 and 2004

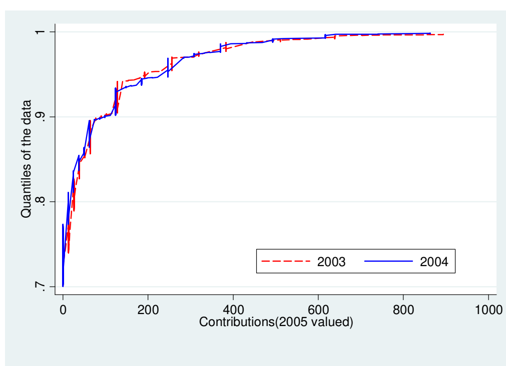
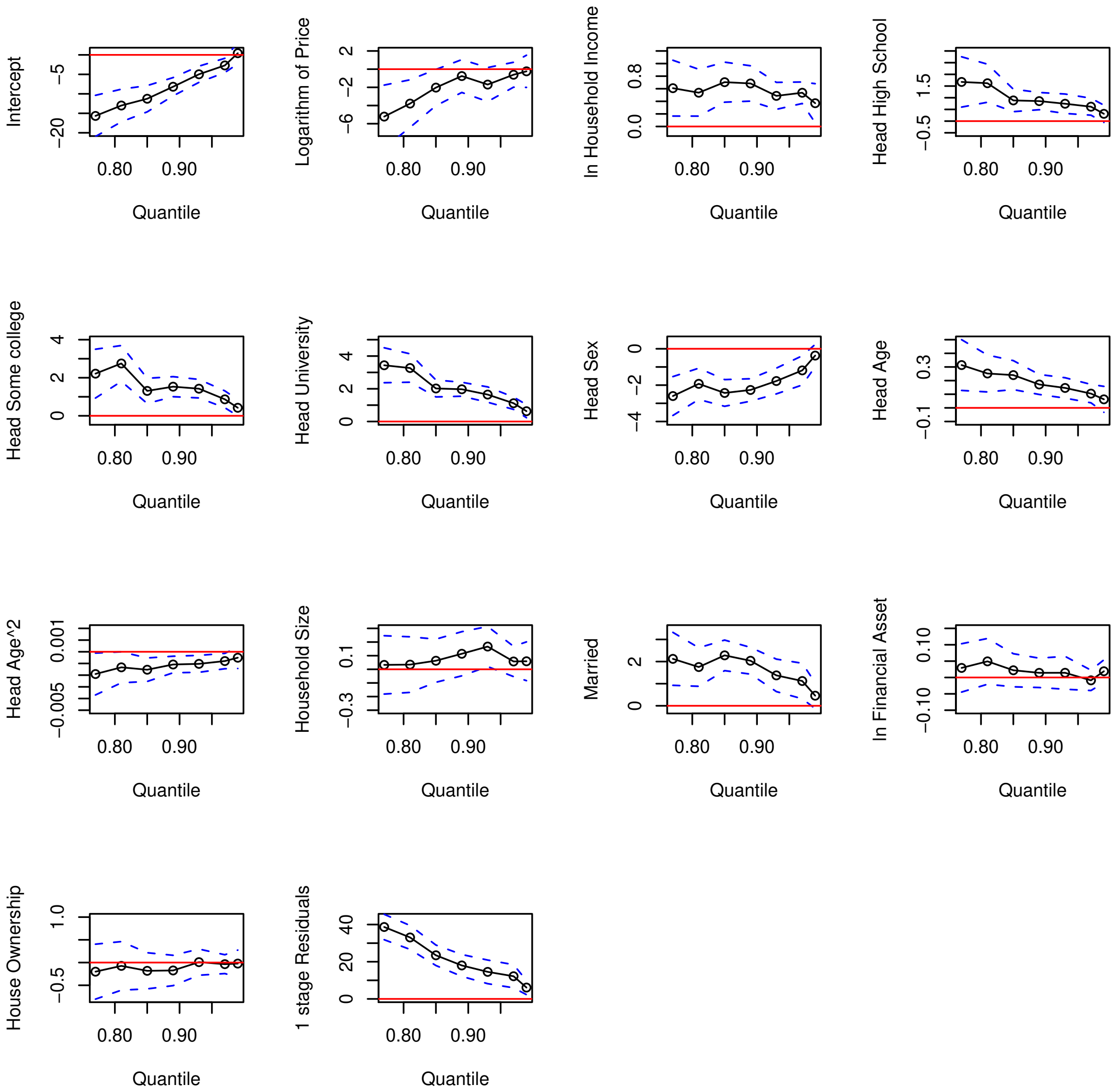


Figure A-3: Censored Quantile Regression for Giving



Appendix B

B.1 Review of 2SLS and GMM Estimation Methods for Panel Data

We can define various GMM estimators depending on how to define the weighting matrix. For detailed explanation and references see Hayashi (2000) and Wooldridge (2002).

B.1.1 Fixed Effect IV Estimation

Suppose that the following equation is estimated.

$$y_{it} = x_{it}'\beta + e_{it}, \tag{12}$$

where $e_{it} = c_i + v_{it}$, $i = 1, 2, ..., n$, and $t = 1, 2, ..., T$. c_i represents individual specific unobservable effects, v_{it} is idiosyncratic errors, following $IID(0, \sigma_v^2)$. If $E(x_{it}c_i) \neq 0$, and then we have to adapt the fixed effect estimation method such as difference, demeaning, or dummies, since Least Square (LS) method including the random effect estimation is inconsistent. But if $E(x_{it}v_{it}) \neq 0$, $t = 1, 2, ..., T$ is a potential problem, we have to consider another estimation method.

Assume that we find an instrument z_{it} that satisfies the contemporaneous exogeneity assumption, $E(z_{it}v_{it}) = 0$, $t = 1, 2, ..., T$. A stronger assumption is that weak exogeneity, $E(z_{it}v_{it}) = 0$, $s \leq t$, $t = 1, ..., T$.[1]

In our estimation setting, we find that the random effect estimates may not be consistent. Hence, we adapt the differenced estimation method as a fixed effect estimation method, which remove the c_i's, in order to get consistent estimates.

$$\tilde{y}_{it} = \tilde{x}_{it}'\beta + \tilde{v}_{it}, \tag{13}$$

where $\tilde{y}_{it} = y_{it} - y_{it-1}$, $\tilde{x}_{it} = x_{1it} - x_{1it-1}$, and $\tilde{v}_{it} = e_{it} - e_{it-1}$.

A consistent estimates is yielded under the condition $E(z_{is}\tilde{v}_{it}) = 0$ with $s \leq (t-1)$, that is, we can use z_{it-1}, z_{it-2}, ... as instruments. Suppose we have a matrix of instruments, Z_i, satisfying the condition $E(z_{is}\tilde{v}_{it}) = 0$ with $s \leq (t-1)$, with $Z_i = [z_{i1}' \cdots z_{iT-1}']$; $\tilde{v}_i = [\tilde{v}_{i2} \cdots \tilde{v}_{iT}]'$.

$$\tilde{\beta}_{2SLS} = \arg\min[\sum_{i=1}^{n} Z_i'\tilde{v}_i]'(Z'Z)^{-1}[\sum_{i=1}^{n} Z_i'\tilde{v}_i] = \arg\min \tilde{v}_i'Z(Z'Z)^{-1}Z'\tilde{v}_i \tag{14}$$

We have

$$\tilde{\beta}_{2SLS} = (\tilde{X}'Z(Z'Z)^{-1}Z'\tilde{X})^{-1}\tilde{X}'Z(Z'Z)^{-1}Z'\tilde{y} = (\tilde{X}'P_z\tilde{X})^{-1}\tilde{X}'P_z\tilde{y}, \tag{15}$$

where $Z = [Z_1 Z_2 ... Z_N]'$, $\tilde{X} = [\tilde{X}_1\tilde{X}_2...\tilde{X}_N]'$, and $\tilde{X}_i = [\tilde{x}_{i2}\tilde{x}_{i3}...\tilde{x}_{iT}]'$. In fact, $\tilde{\beta}_{2SLS}$ is inefficient GMM estimator.

B.1.2 GMM Estimation

We know that the instrumental variables Z are exogeneous and $E(Z_i\tilde{v}_i) = 0$. Hence, the L instruments generate a set of L moments.

$$m_i(\beta) = Z_i'\tilde{v}_i = Z_i'(\tilde{y}_i - \tilde{X}_i\beta), \tag{16}$$

where m_i is $L\times 1$. This L moment conditions will be satisfied at the true value of β: $E(m_i(\beta)) = 0$. Given that we have N observations and $T-1$ equations with cross equation restrictions, i.e., the same β, each of L moment equations corresponds to a sample moment. For some give estimator $\hat{\beta}$, we can write these L sample moments as

$$\bar{m}_N(\hat{\beta}) = \frac{1}{N}\sum_{i=1}^{N} Z_i'(\tilde{y}_i - \tilde{X}_i\hat{\beta}) = \frac{1}{N}Z'\tilde{v}. \tag{17}$$

The moment restrictions upon which we use a difference GMM estimation are $E(Z_i'\tilde{v}_i) = \mathbf{0}$, $i = 1, 2, ..., N$. The GMM estimators for β based on $E(Z_i'\tilde{v}_i) = \mathbf{0}$ is

$$\tilde{\beta} = \arg\min_{\tilde{\beta}} \bar{m}_N(\tilde{\beta})'W\bar{m}_N(\tilde{\beta}). \tag{18}$$

Hence, we have arbitrary GMM estimator,

$$\tilde{\beta} = (\tilde{X}'ZWZ'\tilde{X})^{-1}\tilde{X}'ZWZ'\tilde{y}. \tag{19}$$

This GMM estimator is consistent for any symmetric positive definite weighting matrix W. If $W = (Z'Z)^{-1}$, then $\tilde{\beta}$ is the 2SLS estimates, but it may not be efficient.

In order to get the efficient GMM estimator, we need minimum asymptotic variance. We know that we have the following $T-1$ equations.

$$\tilde{y}_{i2} = \tilde{x}'_{i2}\beta + \tilde{v}_{i2} \tag{20}$$

$$\tilde{y}_{i3} = \tilde{x}'_{i3}\beta + \tilde{v}_{i3} \tag{21}$$

$$\vdots \tag{22}$$

$$\tilde{y}_{iT} = \tilde{x}'_{iT}\beta + \tilde{v}_{iT} \tag{23}$$

Thus, given $\tilde{v}_i = [\tilde{v}_{i2}, ...\tilde{v}_{iT}]'$, the instrument matrix is the following.

$$Z_i = \begin{bmatrix} Z'_{i1} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & Z'_{i2} & & \vdots \\ \vdots & & \ddots & \mathbf{0} \\ \mathbf{0} & \cdots & \mathbf{0} & Z'_{iT-1} \end{bmatrix} \tag{24}$$

The minimization problem is that

$$\hat{\beta}_{2SGMM} = \arg\min_{\hat{\beta}} \bar{m}_N(\hat{\beta})'\hat{V}^{-1}\bar{m}_N(\hat{\beta}). \tag{25}$$

Solving this problem gives

$$\hat{\beta}_{GMM} = (\tilde{X}'Z\hat{V}^{-1}Z'\tilde{X})^{-1}\tilde{X}'Z\hat{V}^{-1}Z'\tilde{y}, \tag{26}$$

where $Z = [Z_1 Z_2 ... Z_N]'$, and $\tilde{X} = [\tilde{X}_1\tilde{X}_2...\tilde{X}_N]'$. The asymptotic covariance matrix of the moment condition $\hat{V}$ is estimated by the following.

$$\hat{V} = \frac{1}{N}\sum_{i=1}^{N} Z'_i\tilde{\tilde{v}}_i\tilde{\tilde{v}}'_i Z_i, \tag{27}$$

where $\tilde{\tilde{v}}_i = \tilde{y}_i - \tilde{X}_i\tilde{\beta} \xrightarrow{p} \tilde{y}_i - \tilde{X}_i\beta = \tilde{v}_i$, where $\tilde{\beta} = (\tilde{X}'Z(Z'Z)^{-1}Z'\tilde{X})^{-1}\tilde{X}'Z(Z'Z)^{-1}Z'\tilde{y}$, which is estimated by the panel data 2SLS estimation.

B.2 CUE GMM Estimation

Hansen (1996) devised the GMM continuously updated estimator (CUE). The minimization problem is that

$$\hat{\beta}_{CUE} = \arg\min_{\hat{\beta}} \bar{m}_N(\hat{\beta})'\hat{V}(\hat{\beta})^{-1}\bar{m}_N(\hat{\beta}), \tag{28}$$

where the weighting matrix is a function of the β being estimated. That is, the estimation of V is done simultaneously with the estimation of β and the minimization problem is solved by numerical methods.

Notes

[1]For a static model, we can impose the strong exogeneity assumption, $E(z_{is}v_{it} = 0)$, $s, t = 1, 2, ..., T$, that is to say, past, present, and future values of the instrumental variables should be mean independent of v.