Comparison of Approaches to Measuring the Causes of Income Inequality

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1. Introduction

This paper proposes a comparison of both parametric and semiparametric estimation of causes of income equality. In the United States of America, income inequality had followed the Kuznets' hypothesis of an inverse-U shape along the developmental process since the Great depression until the early 1950s. That is, the inequality rising with industrialization and then declining, as more and more workers join the high-productivity sectors of the economy (Kuznets 1955). There was a remarkable decrease in relative gap between high-income Americans and low-income American. From about 1950 until the early 1970s, this narrowing gap stayed constant (Ballard and Menchik 2010). However, since the late 1970s, the income distribution has followed a U-shaped pattern. Piketty and Saez (2003) argued that it is just a remake of the previous inveres-U curve. A new industrial revolution or wave of development had taken place in services industries, thereby leading to increasing inequality. Inequality will decline again at some point in time as more and more workers benefit from innovations and market mechanism in which it will shift the worker from industrial sector to service sector. That is, income can be more equalized when labor can leap the benefit from new technology and innovation. However, since the early 1980s, there is no sign of reducing inequality. In United States, the share of top 10 percentile income bracket rises from 32.87 percent in 1980 to 45.60 percent in 2008 (Saez 2008).

Despite abundant literature on the income distribution at the national and international level, there has been relatively little attention to the causes of income inequality in the regional as well as state level. Also, most of the inequality literature in the United States and developing countries has focused on average treatment effect of education and fringe benefit provided by government as determinants of income inequality. However, most of the analysis of the causes of income inequality has employed the conditional mean estimation in either cross-section or panel data setup that ignores the possibility of various effects of education or government policies on income distribution. It has been well recognized that the resulting estimates of effects of education on the conditional mean of income are not necessary indicative of size and nature of the return to education on the upper and lower tail of income distribution (Abadie et.al 2002). Also, the partial effects of government policies such as Medicaid, Medicare, and food stamp on income fall under the same context. Quantile regression offers a complementary mode of analysis and gives a more complete picture of covariate effects by estimating the conditional quantile functions.

Furthermore, in the recent development literature, it has been pointed out that there exists the endogeneity issue regarding the causality of income and education attainment. Hence, the estimating results of treatment effect might be inconsistent. Taking advantages of the newly developed quantile regression with control function, this study compares the result from conventional quantile regression to the results of this new estimation method. Our findings reveal a way to improve the robustness of estimation results and provide a case study for more complete picture of the covariate effects.

Semiparametric methods have been used in estimation of quantile regression for quite some time, as summarized in Koenker (2005). In most theoretical studies, the semiparametric models have been compared with parametric quantile regression model by simulation. Koenker (2005) point out that semiparametric model will be more robust when the parametric specifications fail and data analysis must require flexible weight function. Frolich and Melly (2008) had categorized the estimation of quantile treatment effect into four different cases. There are conditional and unconditional treatment effects and whether the selection is “on observables” or “on unobservables”. Selection on observables is referred to the case of exogenous treatment choice and selection on unobservable is referred to the case of endogenous treatment choice.

In empirical application, if the model of interest are conditional quantile treatment effects with exogenous regressor, the parametric method as in Koenker(2005)(K) can be used. However, if the conditional treatment is endogenous, the method suggested by Abadie, Angrist and Imbens(2002) (AAI) might be used. This method contains the semiparametric element in the estimation of instrumental variables in reduced form equation. They found out that the semipametric results are robust and can be used as a complementary procedure along with the parametric estimation. Firpo(2007) (F) developed semiparametric estimation for the quantile treatment effect that is unconditional. This method consists of two steps estimation that consists of nonparametric estimation of the propensity score and computation of the difference between the solutions of two separate minimization problems. Frolich and Melly(2008) (FM) developed the instrumental variable method for unconditional quantile treatment effects that reaches semiparametric efficiency lower bound. Lee(2007) considers conditional endogenous treatment effects with the use of control function rather than IV estimation. This method is easier to compute than the IV method and can be extend to cover more flexible estimation since it is a special case of sieve estimation. These semiparametic methods can be used to check whether the parametric model encounters any inconsistency problems because of endogeneity and unobserved heterogeneity.

The methods that will in this paper to compare estimation in the quantile regression are Koenker (K), Abadie, Angrist and Imbens (AAI), Firpo (F), Frolich and Melly(FM) and sieve semiparametric estimator (S). The comparison includes the estimated treatment effects as well as the estimated standard errors.

In section two, I provide the background of Great Lakes state regarding income distribution within the Great Lake Region and USA from 2000-2009 given that there are two recessions within this period of time span: Dot com meltdown of 2001 and financial crisis of 2008. This can help in choosing the independent variables to use in comparison of both parametric and semiparametric models. In section three, I present detail of each methodology. While section four presents data empirical results and section five provides concluding remarks. With the new estimation methods, the results show that the choice of model can influence the results.

2. Great Lake and USA income distribution

The Great Lake states comprises of Michigan, Illinois, Indiana, Ohio and Wisconsin that is based on Bureau of Economic Analysis(BEA) regions in 2009. These states share certain economic characteristics as well as have been most severely hit by current financial crisis. In 2009, real gross domestic product of the whole region fall by 3.4 percent. At the bottom of the region is Michigan with 5.2 percent reduction followed by 3.6 percent in Indiana, 3.4 percent in Illinois, 2.7 percent in Ohio and 2.1 percent in Wisconsin. Moreover, the real per capita GDP of the Great Lakes are the second lowest in the country at the value of 38,856 dollars. Among these states, Michigan has the lowest real per capita GDP of 34,157 dollars BEA (2009).

Despite the facts that financial meltdown and housing price bubble lead to the national wide reduction in real GDP in 2009. Great Lakes states have been hardly hit by the decline of manufacturing goods sector since 2005. On average, this industry has been accounted for about 20 percent of this regional GDP. In 2009, the durable-goods manufacturing (i.e. automobile), contributed to more than 2 percentage points to the decline in real GDP in Michigan and Indiana, and more than 1 percentage point in Ohio and Wisconsin. That is, these states are facing contraction of their main industry.

On the income distribution side, by using the Current Population Survey data (CPS), this region share similar story particularly regarding the change in income of the top 10 percentile and 50 percentile(median). In Michigan, for the household at 50 percentile, real income grew by only 3.4 percent over the period of 1976-2006. While the top 10 per centile real income grew by 31.6 percent over the same time. In Ohio, the situation is quite similar; the top 10 percentile income grew by 37.2 percent while the median group income grew by 18.3 percent. In Illinois, the top 10 percentile income grew by 36.5 percent and the median income grew only 10.1 percent. Certainly the worsening income distribution across the region makes leaping the benefit of innovation to become more crucial if they want to reduce such inequality.

In summary, over the past 30 years, the income growth rates of these states have been lower than the national average as well as exhibit the pattern of income distribution that is worse than the national level. Given that and combined with population of these five states that is approximately 50 million, the causes of inequality in this region is well worth studied since there are numerous literature that points out to the adverse effects income inequality.

Conventionally, the main explanation for household income inequality has been driven by an increase in gap of *labor-market earnings or wage*. The neoclassical explanation is that there has been a sharp increase in the demand for highly skilled labor due to globalization, innovation, and changing in demand based on Engle curve. Following agricultural product and food, the income elasticities of demand for manufacturing product, both durable and non-durable, have been declined. These led to changes in corporate-governance procedures. The wage gaps between those with more education and those with less education and experience have increased greatly given the shift in consumer demand and need to minimize the cost of operation.

Other explanations include the decline in the relative strength of labor unions either in public and private setup, the decrease in the real value of the minimum wage, and the increase in immigration of low-skilled workers. These explanations are well understood and certainly affect people more at the bottom of income distribution. For discussion of these trends, see Levy and Murnane (1992), Bound and Johnson (1992), Saez and Piketty (2003), Autor, Katz, and Kearney (2008), and Bakija and Heim (2009). Also, empirical results of these studies come from finding the average relationship between indexes of income inequality to the interested regressors.

However, that staggering fact is that in 2007 the incomes share of the richest first percentile reached a staggering 18.3%. The last time America was such an unequal place was in 1929, when the equivalent figure was 18.4% (Economist 2011). Also, the income (excluding capital gains) of the richest one percentile is approximately 3 times of the richest 10 percent while including the capital gain the results is 5 times (Saez 2008). Applying the neoclassical growth theory that the main hypotheses for the different in income will tell a story that the group of top 1 percent is three times more skilled, educated, and productive than the top 10 percent might seems questionable.

One way to explain this phenomenon might be looking at the Endogenous Growth Theory (Acemoglu 2008). In the age of innovation where growth have been highly associated with investment in human capital and endogenous creation of new products and technology, the real returns to labor with lower skilled than the frontier will be reduced. While only labor at the highest possible frontier or with diversified skill and capital holders will leap more benefit out of the growth. In order to capture the causes of income equality this study need to employ the method of quantile regression.

Why should we worry about income inequality? There are two economic schools of thought opting from the possibility of social fairness and conflicts. There are the effects of income inequality on the mortality in US. The papers by Kaplan et.al (1996) and Kawachi et.al.(1997) found the positive correlation between income inequality and mortality. Moreover, there are several studies pointed out that region with high income inequality are more prone to natural disaster than the other. Kahn(2005) found that area with higher income inequality measured by Gini coefficient suffer more deaths and damage in the wake of natural disasters. Anbarci et.al.(2005) discussed how the number of fatalities from earthquake positively response to income inequality. Shaughnessy et.al.(2010) provided the evidences of effects of Hurricane Katrina on income inequality.

In the neoclassical economic idea, the quote of “That (inequality) it is not a big concern if the rich are getting richer so long as the poor are doing well too.”(Economist 2011) is still relevant. However, in recent, the incorporation of political economy and endogenous growth model, Acemoglu(2008), Rajan(2010), and Ritchie(2010) pointed out the adverse effect of income inequality on the prospect of economic growth via political policy and innovation process of the economy.

Rajan(2010) reckoned that technological progress increased the relative demand for skilled workers. This led to a widening gap in wages between them and the lower-skilled workforce. He argued that this growing gap lays the ground for the housing credit boom that precipitated the financial crisis. The US government put on the two state enterprises, Fannie Mae and Freddie Mac, to lend more to poorer people as instruments of public policy. Subprime mortgages rose from less than 4% in 2000 to a peak of around 15% in 2008. This credit boom led to an enormous housing bubble and the worst financial crisis since great depression. According to this, he argued that well-intentioned political responses to the rise in inequality might lead to devastating side effects.

On the innovation and technological development part, Ritchie(2010) argues that country with high level of natural resources, distributional alliances of political party and ruling elites, education systems that has political priorities rather than economic and technology priorities, and high income inequality will lead to low levels of technical intellectual capital. That is, it might be suitable to explain lower level of higher education attainment by in the U.S. For example, percentage of bachelor's degrees awarded in mathematics and science of USA in 2006 is lowest among the OECD average, even lower than Mexico (http://nces.ed.gov). Also, if we look at the U.S. Census Bureau of last year out of 226,793 observations of people with the age over 18, only 17.7 percent got there bachelor degree, and only 9.3 percent attained the degree higher than bachelor. Following the argument in Acemoglu(2008) and Murray(2008), when income is not normally distributed and more skewed to the right (evidence of high income inequality), it is harder for household with average income to attain college not even to mention higher education. Also, if the students inherited skill is normally distributed, given such income structure and cost and benefit of college and higher degree, the rate of attainment for higher education will also be lowered. In turn, this will lead to lower prospect of growth since innovation and technological adoption relies heavily on human capital.

3. Estimation Methods

The estimated model in this study is specified as system of equations as followed:

$$y_i = Q(D_i, x_i, u_i) \tag{1}$$

$$D_i = G(z_{i,} x_i, v_i) \tag{2}$$

where $Q(.)$ is quantile function; y_i is continuous outcome; D_i is binary treatment variable; x_i are exogenous covariates; z_i are excluded instrumental variables; u_i and v_i are possibly related unobservable; and, $G(.)$ is unknown function. If treatment is exogenous and conditional upon given covariates, then the use of standard quantile regression will be used. That is, equation (2) will not be estimated. For comparison of this study, method suggested in Koenker(2005) will be used.

3.1 Quantile Regression

Koenker's Quantile regression (K) exhibits a more complete picture of relationship between y and x at the different points in the conditional distribution of y. The qth quartile estimator of $\hat{\beta}_q$ and $\hat{\alpha}_q$minimizes over β_q and α_q on the objective function

$$(\hat{\beta}_q, \hat{\alpha}_q) = \text{argmin}_{\beta,\alpha} \sum \rho_q(\, y_i - D_i\alpha_q - x_i{}'\beta q) \qquad (3)$$

where q lies between 0 and 1 and $\rho_q = u * \{q - 1(u < 0)$ as in Koenker(2005). Then, $\hat{\alpha}_q, \hat{\beta} q$ represent the choices of quantile that will estimate for the different value of α, β. For example, if $q = 0.9$, much more weight will be put at the income at 90 percentile and when $q = 0.5$, the estimated result is the same as least absolute deviation estimators. Let $X = (D_i, x_i')$ and $\gamma_q = \left(\alpha_q, \beta q'\right)'$, the asymptotic distribution of estimator defined in (3) is given by

$$\sqrt{n}(\hat{\gamma}_q - \gamma_q) \to N(0, J_q^{-1}\Sigma_q J_q^{-1}) \qquad (4)$$

where $J_q = E[f_{y|X}(X'^{\gamma_q}) * XX']$ and $\Sigma_q = q(1-q)E[XX']$. The term Σ_q is estimated by $q(1-q)n^{-1}\sum[XX']$. J_q has been estimated by kernel method

$$\widehat{J_T} = \frac{1}{nh_n}\sum k(\frac{Y_i - X'\hat{\gamma}_q}{h_n})\, XX' \qquad (5)$$

Koenker(2005) point out the advantages of QR as followed. First, it is not sensitive to outlier and will be more efficient when the dependent variables are not normally distributed. That is, in the case of studying income distribution which is not normally distributed, it is certainly better than ordinary least squares(OLS). Secondly and most important for our study, QR study the impact of covariate on the full distribution of income at any particular percentile of distribution, not just the conditional mean. Finally, it is consistent without requirement of conditional mean and the monotone function can pass through and transform the conditional quantile.

3.2 Abadie, Angrist and Imbens(2002) (AAI)

If the treatment is endogenous or self-selected as in case of education attainment, the traditional quantile regression will be biased and the use of instrumental variable (IV) might be used as suggested by AAI with the following assumptions. For almost all values of X:

(i) Independence: (y_i, D_i) is jointly independent of z_i given x_i.

(ii) Nontrivial assignment: $P(z_i = 1|x_i) \in (0,1)$.

(iii) First-stage: $E[D_1|x_i] \neq E[D_0|x_i]$.

(iv) Monotonicity: $P[D_1 \geq D_0|x_i] = 1$.

(v) Linear model for potential outcomes

$$y_i = x_i'\beta_q + D_i^{\prime\alpha_q} + \varepsilon_i \text{ and } Q_{\varepsilon_i}^q = 0, \quad (6)$$

where $Q_{\varepsilon_i}^q$ refers to the q-th quantile of the random variable ε. Given assumptions (i)-(v), AAI show that the conditional quantile treatment effect for the compilers (i.e. observations with $D_1 \geq D_0$) can be estimated by weighted quantile regression:

$$(\hat{\beta}_q^{IV}, \hat{\alpha}_q^{IV}) = \text{argmin}_{\beta,\alpha} \sum W_i^{AAI} * \rho_q(\, y_i - D_i{}'\alpha_q - x_i'\beta q) \quad (7)$$

$$W_i^{AAI} = 1 - \frac{D_i(1-z_i)}{1-P(z_i=1|x_i)} - \frac{(1-D_i)z_i}{P(z_i=1|x_i)}$$

This is a two-step estimator in which the $P(z_i = 1|x_i)$ is need to be estimated first, in this paper the local logit estimator has been used as in Frolic and Melly(2007). Moreover, in order to avoid the problem of non-convex optimization problem, AAI suggest the use of positive weights

$$W_i^{AAI+} = E[W^{AAI}|y_{i,}D_i, x_i] \qquad (8)$$

Equation(8) will be estimated by linear regression and if some of these estimated weights are negative in the finite samples, they will be set to zero.

Then, the asymptotic distribution of the AAI estimator is given by

$$\sqrt{n}(\hat{\alpha}_q^{IV} - \alpha_q) \rightarrow N(0, I_q^{-1}\Omega_q I_q^{-1}), \qquad (9)$$

Where $I_q = E\left[f_{y|X,D_1>D_0}\left(X\alpha_q\right) * X'X\middle|D_1 > D_0\right] * P(D_1 > D_0)$ and $\Omega_q = E(\psi\psi')$ with $\psi = W_i^{AAI} m_q(X, y_i) + H(X)(Z - P(Z = 1|X))$ and $m_q(X, y_i) = \left(q - 1(Y - X'^{\gamma_q} < 0)\right)X$ and $H(X) = E[m_q(X, y_i)\left(-\frac{D_i(1-z_i)}{\left(1-P(z_i=1|x_i)\right)^2} + \frac{(1-D_i)z_i}{P(z_i=1|x_i)^2}\right)|X]$.

I_q will be estimated by kernel estimation that uses Epanechnikov kernel as suggested by Abadie et.al.(2002)

$$\hat{I}_q = \frac{1}{nh_n}\sum \widehat{W}_i^{AAI+} * k\left(\frac{y_i - X'\hat{\gamma}_q^{IV}}{h_n}\right)XX' \qquad (10)$$

where $\widehat{W}_i^{AAI+}$ are estimates of the projected weights. $\widehat{H(X)}$ is estimated by regression of

$\left(q-1\left(y_i-X'\hat{\gamma}_q^{IV}<0\right)\right)X\left(-\frac{D_i(1-z_i)}{\left(1-\hat{P}(z_i=1|x_i)\right)^2}+\frac{(1-D_i)z_i}{\hat{P}(z_i=1|x_i)^2}\right)$ on X. Lastly,

$$\hat{\psi}=W_i^{AAI}\left(q-1\left(y_i-X'\hat{\gamma}_q^{IV}<0\right)\right)X+\widehat{H(X)}(Z-\hat{P}(Z=1|X)) \quad (11)$$

$$\hat{\Omega}_q=E(\hat{\psi}\hat{\psi}') \quad (12)$$

3.3 Unconditional quantile treatment effect Firpo(2007) and Frolich and Melly(2008)

The unconditional treatment effect for quantile q can be defined as

$$\Delta_q = Q_q^{Y1}-Q_q^{Y0} \quad (13)$$

The distinct feature between the conditional and unconditional treatment effects is that the unconditional effect, by definition, will not change with respect to the different set of covariates X. This might be an advantage over the conditional treatment effect since there is no need to assume conditional independence of Y_i on D_i given X. Also, unconditional effects can be estimated consistently at the $\sqrt{n}$ rate without any parametric restrictions. That is, these estimators will be entirely nonparametric, and the assumption (i) will not be needed. Also, in estimating this nonparametric model, it is needed to assume that the support of the covariates X. is the same independently of the treatment. For almost all values of X,

$$0<P(D_i=1|X)<1 \quad (14)$$

However, the unconditional method still needs the inclusion of covariates X for various reasons. First, X are needed to make the identification plausible. Secondly, including X

will improve efficiency. Following Frolich and Melly(2007), it is better to explain the endogenous treatment with a binary instrumental variable z_i first. Given assumption(iv), the estimator for Δ_q is as followed:

$$\left(\hat{\alpha}^{IV}, \hat{\Delta}_q^{IV}\right) = arg\ \min_{\alpha,\Delta} \sum W_i^{FM} * \rho_q(y_i - \alpha - D_i\Delta) \tag{15}$$

$$W_i^{FM} = \frac{z_i - P(z_i = 1|X)}{P(z_i = 1|X)(1 - P(z_i = 1|X))} * (2D_i - 1). \tag{16}$$

W_i^{FM} need to be estimated first as same as in the case of W_i^{AAI}. Also, the optimization in (15) will face the same non-convex problem as in equation (7). Therefore, the alternative weight has to be used. That is,

$$W_i^{FM+} = E[W^{FM}|y_{i,}D_i, x_i] \tag{17}$$

Firpo(2007) and Frolich and Melly(2007) use assumption (ii) and (14) together to identify unconditional treatment effect. The estimator of Firpo(2007) is a special case of (15), when the instrument variable D_i is used to be its own instrument or $D_i = z_i$. The weighting estimator and weight for the estimate of Δ_q are as followed:

$$\left(\hat{\alpha}, \hat{\Delta}_q\right) = arg\ \min_{\alpha,\Delta} \sum W_i^F * \rho_q(y_i - \alpha - D_i\Delta) \tag{18}$$

$$W_i^F = \frac{D_i}{P(D_i = 1|x_i)} + \frac{(1 - D_i)}{1 - P(D_i = 1|x_i)}. \tag{19}$$

Then, the process to estimate the weight function will be employed as same as in the case of W_i^{FM+} and W_i^{AAI+}.

Firpo (2007) and Frolich and Melly(2008) provides the asymptotic distribution of the estimated treatment effects as followed. From equation (18), Firpo(2007) states that $\hat{\Delta}_q$ distributes as

$$\sqrt{n}(\hat{\Delta}_q - \Delta_q) \rightarrow N(0, \nu) \qquad (20)$$

with

$$\nu = \frac{1}{f_{y1}^2\left(Q_q^{y1}\right)} E\left[\frac{F_{Y|Di=1,X}\left(Q_q^{y1}\right)\left(1 - F_{Y|Di=1,X}\left(Q_q^{y1}\right)\right)}{P(D_i = 1|X)}\right]$$
$$+ \frac{1}{f_{y0}^2\left(Q_q^{y0}\right)} E\left[\frac{F_{Y|Di=0,X}\left(Q_q^{y0}\right)\left(1 - F_{Y|Di=1,X}\left(Q_q^{y0}\right)\right)}{1 - P(D_i = 1|X)}\right]$$
$$+ E[\{\vartheta_1(X) - \vartheta_0(X)\}^2],$$

where $\vartheta_d(X) = \frac{q - F_{Y|D=d,X}(Q_q^{Yd})}{f_{Yd}(Q_q^{Yd})}$. Q_q^{Y1} and Q_q^{Y0} have been estimated by $\hat{\alpha} + \hat{\Delta}_q$ and $\hat{\alpha}$. The densities $f_{Yd}(Q_q^{Yd})$ are estimated by kernel estimators with Epanecnikov kernel function and Silverman bandwith choice.

$$\hat{f}_{Yd}\left(\hat{Q}_q^{Yd}\right) = \frac{1}{nh_n} \sum_{D_i=d} \widehat{W}_i^F \cdot k\left(\frac{y_i - Q_q^{Yd}}{h_n}\right) \qquad (21)$$

$F_{Y|Di=d,X}\left(Q_q^{yd}\right)$ is estimated by local logit estimator. For the case of endogenous treatment, the detailed formula is in Appendix(7.1). Also, the density will be estimated by kernel regression as in the case of the exogenous treatment.

3.4 Sieve estimator

Sieve estimation refers to one class of semiparametric estimation that solves the problem of infinite dimensional parameter. The sieve method employs the optimization routine that tries to optimize the criterion function over finite approximated parameter spaces (sieves). The sieve method, in the simplest form, might be similar to how we choose the bandwidth and numbers in plotting the histogram. As pointed out by Chen (2007), the method of sieves is very flexible in estimating complicated semiparametric models with (or without) endogeneity and latent heterogeneity. It can easily incorporate prior information and constraints, and it can simultaneously estimate the parametric and nonparametric parts, typically with optimal convergence rates for both parts.

The main reason that this paper employs the sieve estimator is that it can simplify semiparametric inference for the treatment effects. So far, the four methods of estimation employs at least certain degree of semiparametric estimation for their respective variances with relatively complicated formulation and computationally intensive. Following the results in Ackerberg(2009), it has established the numerical equivalence between two estimators of asymptotic variance for two-step semiparametric estimators when the first-step nonparametric estimation is implemented. That is, in the first stage, the sieve estimator (Sieve maximum likelihood, Sieve minimum distance, series estimator) will be applied to the model of interest, and then in the second stage, estimation can be set up as if the problem is completely parametric for the purpose of inference on treatment effects.

In this method, the endogeneity will be treated as linear triangular simultaneous equations model of equation (1) and (2). The paper corrects for endogeneity by adopting the control function approach as in case of Lee(2007) but there is a different in first stage and second stage estimation. The first step is to construction of estimated residuals $\hat{v}_i = D_i - X\hat{\delta}(i = 1, \dots, n)$ by a sieve-M estimator of D_i on $(1, X)$. Given the discrete nature of D_i, Khan(2005) proposed a estimation method that is a further expansion of Horowitz(1992) method. The important assumption is the conditional median restriction to ensure the identification of estimated parameters $\hat{\delta}$.

$$med(v_i|X) = 0 \tag{22}$$

and symmetric distribution of the error terms the local nonlinear least squares estimator for

$$\hat{\delta} = arg\min_{\delta} \sum_{i=1}^{n} \left[D_i - G\left(\frac{X\delta}{h_n}\right)\right]^2 \tag{23}$$

where h_n is a sequence of positive numbers such that $h_n \to 0$ as $n \to \infty$. This estimator will yield the estimated $\hat{\delta}$ with one of the estimated element to be normalized to 1 as usual for semiparametric estimation. Blevins and Khan(2009) provides the procedure to estimation equation(13), they suggested the use of probit criterion function for the sieve nonlinear least squares. The criterion function is

$$\mathrm{B}(\delta, \mathrm{l}) = -\frac{1}{n}\sum_{i=1}^{n} \left[D_i - \Phi\left(\frac{X\delta}{\exp(l(X))}\right)\right]^2 \tag{24}$$

where $l(X)$ is finite dimensional scaling parameter. Then, they introduce a finite-dimensional approximation of $l(X)$ using a linear-in-parameters sieve estimator as in Chen(2007). The choice of criterion function is arbitrary and can be any possible series such as power and polynomial series, spline, or logistic. In this study, the logit and probit criterion function that contains the power series of (X) will be used as a domain.

After getting the estimated $\hat{v}_i$ from equation (24), it will be plug in to the (3) as an additional independent variables. Then, the variance of the treatment effect can be estimated either by bootstrap or as in equation (4). The reason that we proceed in two step estimation is that we can apply the results from Ackerberg et.al.(2009) in order to estimate the asymptotic variance by using parametric approximation since it requires less restrict assumptions in order to get establish consistency and asymptotic normality as in the case of Lee(2007). That is, Lee(2007) required the data $\{(Y_i, X_i, Z_i): i = 1, \ldots n,\}$ are i.i.d. in assumption (3.1). To conclude this section, there are certain insights that might be gained from comparing these five methods of estimation. The conditional treatment effect models are computationally simple and should be unbiased if there is no underlying endogeneity. On the other hands, the four semiparametric models in this paper have each own advantages and heuristic comparison can be made to see different in treatment effects across income distribution. Also, results from unconditional treatment effects, it might be helpful for policy makers and applied economists since they capture the effects in the entire population rather than a large number of effects for different covariate conbinations.

4. Data and Estimating Results

In this paper, I apply the methods described above to estimating the causes of income inequality in USA and Great Lake States. The data come Currently Population Survey (CPS) from the period of 2001 to 2009. During this period there were two shocks that potentially effect household income in the top quantile. They are the dot-com crisis of the 2001 and the Financial Crisis of 2008. The measurement of household income will be used as dependent variable while household characteristics, education, union coverage, and housing type are used as dependent variables in finding quantile treatment effect.

Table1

Percentiles, cut-off level of nominal household income ($)

	10th	25th	50th	75th	90th
2000	10344	20720	40551	70646	108487
2001	10572	21521	42024	73000	112040
2002	10632	21500	42125	74900	114504
2003	10580	21384	42381	75000	114626
2004	10500	21620	43160	76803	118662
2005	10890	22108	44097	78000	121012
2006	11250	23010	46001	81000	126838
2007	12000	24600	48020	85028	133726
2008	12143	25000	50000	88294	136435
2009	12157	25000	50000	89133	138774

As shown in Table 1, the income different between the top 10 percent and the bottom 10 percent is approximately 10 times. This trend has persisted over the past 10 years. Only in 2001 and 2008, is the period where the income of the top 10 percent stagnated since the recession. On the other hands, for the household at the median of income distribution, the difference is about four times compared to the bottom 10 percent. Without considering the people at the top 1 percent as in Saez(2008), there is a certain evidence of income inequality.

Table 2

Summary statistics for the year 200-2009

	2001	2005	2009
Average Household income	55482	60432	68409
Percentage of Household with high school	0.201	0.192	0.192
Percentage of Household with College	0.296	0.321	0.332
Percentage of Household with higher than college	0.116	0.132	0.149
Percentage of Household with house ownership	0.675	0.700	0.681
Percentage of Household in Manufacturing Sector	0.015	0.014	0.013
Percentage of Household in Management and Financial Sector	0.115	0.079	0.083
Number of observations (Household)	49633	76447	76185

Table 2 contains statistics of some key variables that will be used in estimation. The average income shows a steady growth despite two recessions during the period of sample. On the education attainment, household with the high school education refers to the case where the most educated person in the household achieve high school degree where the household with college refers to most educated person in the household holds bachelor degree. It is clear that for the past ten years, the household with highschool degree from the survey stays at about 20 percent. There is a growth of household with college degree from 29 percent to 33 percent and household with higher than college degree from 11 to 14 percent. For the home ownership, the percentage of household with their own house remains constant at about 68 percent despite the housing price bubble.
From, the sample, only about 1.3 percent of the household member with highest education attainment works in manufacturing sector while there is about 8 percent working in the management and financial sector.

The linear quantile effects model of income determination with the interested explanatory as discussed in section 2 will be as follows:

$$hhinc = \beta_0 + \beta_1 highschool + \beta_2 college + \beta_3 Mcollege + \beta_4 tenure + \beta_5 uncov + \beta_6 white + \beta_7 Manu + \beta_8 MaFi + \beta_9 Greatlake + u_i \qquad (25)$$

where hhinc is household income,

highschool = 1 if household member of highest education got high school degree = 0 otherwise.

college = 1 if household member of highest education got bachelor degree = 0 otherwise

Mcollge = 1 household member of highest education got high degree than bachelor = 0 otherwise

Tenure = 1 if household own their own house = 0 otherwise

uncov = 1 if household member of highest education is under union coverage = 0 otherwise

White = 1 if household member of highest education is white = 0 otherwise

Manu = 1 if household member of highest education worked in Manufacturing sector last year = 0 otherwise

MaFi = 1 if household member of highest education woked in Management and Financial sector last year = 0 other wise.

Greatlake = 1 if the household lives in the Great Lake States

The dummy of level of most educated household member will be used to represent education attainment. The model will be estimated assuming that education attainment is exogenous at first in order to provide a quick picture of how factors that determine income change overtime. The linear model will be estimated by qreg command in stata with the weight equals to household weight from CPS. The results are in Table 3, 4 and 5.

Table 3

Estimate result assuming education attainment is conditionally exogenous, 2001

Estimation	OLS	QR_10	QR_50	QR_90	QR_99
highschool	12830.9	4372.5	12228	53367.9	38373
	(526.275)	(308.342)	(445.017)	(2024.190)	(7682.690)
college	31199.1	9980	26267	88458.9	174913
	(632.417)	(282.183)	(403.283)	(1863.66)	(7368.63)
Mcollege	65365.1	19519.5	52127.5	158299	260764
	(1297.65)	(383.807)	(542.002)	(2078.59)	(9577.29)
Tenure	20457.8	5800	15949.5	36542	67355
	(490.793)	(250.982)	(354.28)	(1801.32)	(5837.01)
uncov	3009.63	2803.75	3574.5	1976	-1423.5
	(420.225)	(168.739)	(250.127)	(1150.35)	(4362.12)
white	5491.14	2392.5	3800.5	7260	22520
	(624.265)	(306.625)	(454.956)	(2318.67)	(7454.76)
Manu	-2705.6	-392.5	515	42608.9	-4202
	(1513.45)	(904.452)	(1362.57)	(3476.99)	(22319.4)
MaFi	27144.6	14472.5	21143.5	44650	109899
	(1211.23)	(356.079)	(512.758)	(1689.13)	(10460.8)
Greatlake	-1111.5	825	971.5	-4632	-19705
	(651.304)	(307.155)	(439.381)	(2067.14)	(7438.42)

Notes: (i) The standard errors for the coefficients are in parenthesis

Table 4

Estimate result assuming education attainment is conditionally exogenous, 2005

Variable	OLS	QR_10	QR_50	QR_90	QR_99
highschool	13968.1	4403	145996	22124	30943
	(490.49)	(302.182)	(898.301)	(1907.51)	(8108.351)
college	32605.9	10317	104470	114398	123925
	(530.291)	(274.156)	(792.906)	(1393.25)	(6658.796)
Mcollege	69411.3	19579	90843.9	120800	358154
	(1201.91)	(365.875)	(1045.81)	(1906.18)	(9146.273)
Tenure	22603.1	7162	37034.9	-28598	59548
	(452.797)	(247.175)	(718.328)	(1122.59)	(6117.291)
Uncov	2526.35	3488	-6820.5	1827.5	5234.5
	(428.368)	(189.194)	(560.259)	(994.548)	(4725.112)
white	4914.84	2479	80166.8	8300	13674
	(551.272)	(263.742)	(799.388)	(1439.8)	(6925.783)
Manu	5444.49	3098	-32676	15460	31042
	(2092.4)	(970.645)	(2750.01)	(3715.21)	(21227.38)
MaFi	34779.7	15098	-12323	48008	217824
	(1412.58)	(417.191)	(1195.58)	(1832.16)	(11104.3)
Greatlake	-2904.7	1215	55828.8	55637.4	-25494
	(572.773)	(296.82)	(869.507)	(1022.15)	(7492.125)

Notes: (i) The standard errors for the coefficients are in parenthesis

From all table 3, 4, and 5, the effects of education attainment on the household income are significant across all the years. Moreover, not only the effects are significant at the average, but also partial effects are significant through income distribution. Since 2001, there is clear sign that getting college degree lead to higher household income than the high school degree as projected by conventional economic theory. However, not until 2009, that there is a growing gap between the return to higher education that is beyond college level graduate. From table 4, the differences are minimal even at the 90^{th} quantile.

One can argue that there is no need return to graduate education compared to undergrad degree. However, this figure might be true only when the US economy is on the growth path. From table 5, after the financial crisis, it has become clear that partial effect of college education has dropped back to the similar level as in 2001 both at the average and median level. Although, there is no big increase of partial effect of graduate education attainment from 2005 to 2009, at least there is no steep decline as in the college partial effects.

As pointed out in Neoclassical Growth theory, the reduction in demand for the college graduate might be related to skill-set demanded in the current world economy. Globalization makes outsourcing of the college skill-set possible. That is, not only the US corporation can conduct foreign direct investment abroad to lower the cost of low-skill labor(high school) but also firm can lower the cost of high-skill labor(college), too. Wan(2008) pointed out that the cost of hiring US engineer to design computer chip is approximately three times higher than hiring Chinese engineer and two times higher than hiring Korean engineer of the same caliber. Also, in Endogenous Growth theory, this might be the indicator of the economy where only people at the highest end of human capital spectrum will leap more benefit from economy. On the other hands, it might be possible to look through one of the most popular graduate level program, Master in Business Administration (MBA). According to http://www.businessweek.com/interactive_reports/roi_rankings.html, the average salary of the newly graduate top 20 business school is about 100,000 dollars for the graduate of 2008 class. To conclude, these phenomena might be able to explain why the partial effects of the higher education are still flat over the past 10 years while the partial effects of college education have plummeted.

Table 5

Estimated result assuming education attainment is conditionally exogenous, 2009

Variable	OLS	QR_10	QR_50	QR_90	QR_99
highschool	13863.5	4416	12997	57770.4	1023856
	(521.388)	(338.854)	(475.504)	(14163.4)	(254164.1)
college	36937.2	10671	32211	59096	635534.3
	(559.534)	(303.605)	(417.052)	(14932.2)	(291541)
Mcollege	77288.4	21619	62247	146238	-190612
	(1162.3)	(390.77)	(532.547)	(17094.9)	(771626.2)
tenure	24471.2	7691	19230	32846.3	-453119
	(487.277)	(265.214)	(368.156)	(12116.3)	(215898.4)
uncov	3638.22	3867	4021	8837.86	-261738
	(470.987)	(208.29)	(300.149)	(8835.18)	(353823.4)
white	6158	3019	4788	37198.4	-1524445
	(574.573)	(279.438)	(404.871)	(17945.2)	(139213)
Manu	11483.3	6217	7311	34039	134252
	(2802.12)	(1019.8)	(1480.09)	(42877.2)	(779044.9)
MaFi	39443.5	19310	30575	17809.6	-827470
	(1459.95)	(445.091)	(614.111)	(23840.9)	(979243.4)
Greatlake	-3356.2	753	-788	-10154	-544042
	(686.42)	(334.828)	(474.791)	(16385.7)	(555746.3)

Notes: (i) The standard errors for the coefficients are in parenthesis

The effects of owing the house on income are positively and significant. Nevertheless, they becomes insignificant at the lower part of income distribution. For the union coverage, it is positively and significantly; however, at the partial effects of union coverage is minimal as same as race variable; that is, being white leads to higher income.

As discussed in previous section 2, the decline of manufacturing industry in Great Lake State and USA is quite significant. The household members who work in such industry face a significant lower income distribution. On the other hands, when consider household member working in the management and finance sector, there is positive and significant effect to income relative to other occupation.

Table 3, 4, and 5 provides the overview of partial effects of interested exogenous variables on the household income; however, the estimates are not robust to heteroskedasticity as pointed out by Cameron and Trivedi(2010), and Frolich and Melly(2010). For example, if the errors term can be written as increasing function of exogenous variable(x_i), the partial effect of such variable will increase as quantile increase. Therefore the estimation method K and F proposed in section will be used. However, for the method F to be working properly, the education attainment will be redefined as CM. It is equal to 1 if household member of highest education got degree higher than or equal to college, and 0 otherwise. Also, the other reason for aggregating these two groups is to examine how this group of highly educated household member had been adversely affected by recession.

The results reported in Table 6 shows that the estimated effects of education attainment are positive and significant throughout income distribution, especially in the year 2001 and 2005. The results are quite similar to table 3 and 4. As suspected, at the higher income quantile, there are higher returns to education. However, there are odd results in the year 2009. For some quantile, the estimated partial effects show no monotonically increasing pattern as in the year 2001 and 2005. 2009 is the special year where the effects of financial crisis and countrywide recession have been realized by American household. This idiosyncratic shock might make the seemingly positive partial effects of education to be negative and significant for certain income quantile. The negative unconditional partial effects of the 50th and 60th quantile might be the indication of how the recession hit the household at the median income with college education.

Table 6

Estimate results from F and K methods

	2001		2005		2009	
	Education Attainment is exogenous					
quantile	F	K	F	K	F	K
10th	9985	10174	10816	11854.3	-125500	13257
	(316.367)	(289.913)	(284.225)	(256.747)	(7310.838)	(279.791)
20th	15675	15412	17047	18235	-108492	20010
	(342.628)	(307.55)	(298.9917)	(264.83)	(6499.141)	(299.606)
30th	19928	19803	22200	22921	112728.6	25757.5
	(386.066)	(332.886)	(329.9552)	(288.513)	(1889.06)	(325.297)
40th	23986	23526.5	26750	26848	59856	30828.5
	(416.304)	(363.55)	(365.791)	(317.615)	(668.7604)	(353.167)
50th	27627	27128	30978	30162	-84881	1913
	(458.571)	(414.421)	(401.109)	(348.319)	(7087.151)	(556.811)
60th	31063	30748	35014	33489	-73758	22508
	(529.422)	(469.29)	(445.935)	(396.559)	(6251.693)	(436.31)
70th	35500	34710	39357	38533	46710	72292
	(621.571)	(544.954)	(524.048	470.8)	(570.963)	(1837.05)
80th	42360	41030	46588	45042	55435	28932.8
	(734.809)	(694.42)	(660.002)	(627.96)	(770.193)	(1599.21)
90th	57247	56006	62993	60908	72857	189563
	(1302.073)	(1242.25)	(991.698)	(980.421)	(1149.897)	(17618.8)

Notes: (i) The standard errors for the coefficients are in parenthesis

As well as in the conditional partial effect at 50^{th} in 2009, the effect of having high education is barely minimal compared to the other years. One possible explanation is that these group of household member faced more adverse effects from recession, ranging from lay-offs, decline of house value, and loss in securities market than the other household member from the other top quantile. At the top 10^{th} quantile, the partial effects of the high education in 2009 turns out to be higher than previous years.

It might be of concerns that having college degree or higher might be endogenous. The instrumental variable that will be used for the education attainment will be the variable names “samelevel”. It is the dummy variable telling whether the two most educated household member sharing the same level of education attainment or not. The main reason for choosing this instrument is that there is an hypothesis telling that income inequality in the modern day comes as a result of people of the same economic background, education caliber, and social status tends to marry each other’s or living together. Wald test has been used in the reduced-form equation estimation by Probit and Logit with robust standard errors. The education attainment: CM, college, Mcollege, exhibit a strong correlation with the instruments “samelevel”. The test that all coefficients are the same also rejects with 95 percent confidence. Hence, the test indicates that “samelevel” can be used as a good instrument to control for endogeneity as in AAI and FM method. Also, it is possible to use “samelevel” in conducting the control function approach for the sieve method. Then, the AAI, FM, and S methods will be used to estimate the quantile treatment effects when education attainment is endogenous.

Table 7

Estimates allowing education attainment to be endogenous

	2001	2005	2009
	Education Attainment is endogenous		
quantile	S	S	S
10th	10619.6	10767.66	11998
	(222.929)	(204.802)	(966.589)
20th	16027	17525.02	19424.96
	(272.687)	(271.288)	(260.034)
30th	20505	22477	25181.63
	(281.201)	(257.153)	(273.442)
40th	24265.73	26719	30533
	(320.530)	(281.335)	(381.722)
50th	28398.22	30176.51	35587
	(390.513)	(285.315)	(348.237)
60th	31812.13	34346.51	40775
	(474.979)	(427.926)	(460.790)
70th	36231	39391.29	46546
	(478.043)	(482.712)	(478.518)
80th	42196	46443.06	90858.38
	(671.698)	640.0952	(7356.322)
90th	58590.4	63494.41	73420
	(1096.209)	(891.448)	(905.288)

Notes: (i) The standard errors for the coefficients are in parenthesis

The estimated coefficients of the inserted error terms are significant, indicating that the graduation attainment might not be conditionally exogenous. At first, these results are similar to the case where education attainment is assumed to be exogenous for the year 2001 and 2005. Nevertheless, the S method gives more monotonic results for the estimated partial effects in 2009. It might be the indicator that the recession affect the entire household income generated from every working member. Comparing the estimated partial effects from AAI, FM, and S are quite similar; hence, it is uncertain to say which methods are more appropriate to use. However, for the S method, it is more flexible in term of calculating the standard errors since they rely heavily on the nonparametric kernel estimation. Moreover, in choosing between the control function and instrumental variables, the latter are more sensitive to the choices of variable whether they are strong or weak. In some cases of simulations and empirical applications, the AAI and FM methods yield completely different result than the S, F, and K methods. It implies that these methods are more complement to each other in order to compute treatment effects.

4. Concluding Remarks and Further Study

Unlike previous studies on income distribution, this empirical study examines the relationship between determinants of income throughout entire distribution by using quantile regression. Also, various methods of quantile treatment effects that are robust to heteroskedasticity and endogeneity have been employed. The quantile regression reveals interesting results, the return of higher education have been significantly increasing over the past ten years. And at the high income spectrum, it proves out that bachelor degree is not enough for the current state of the economy. Moreover, focusing the regional economy only on the manufacturing sector will not be enough for ensuring income prosperity.

Regarding policy implications, on the surface, it might be suitable to say that government should promote higher education attainment; however, there are more concerned issues. At first, higher education is not cheap and given the current state of income inequality and economy, only the people at the higher end of the spectrum will be able to leap the benefit. Also, some might argue the definition of education whether the university should provide knowledge that can be practically used and related to the economy or being holistic. Also, there is a differences opinion regarding the education system, in the East Asian countries, it is a beliefs that judgementalism and incentive system are an important elements in leading the student to study science and technology as well as pursuing higher education than bachelor degree Wan(2008). Future research into this issue might consider the Monte Carlo and empirical study of endogenous effect of income inequality on education not only in the cross sectional context but also panel data. Also, the choices of control function, sieve estimator, as well as instrumental variable do really affect the estimated results. Further sensitivity analysis should be conducted to sure that the estimates are robust. The study should provide a clearer picture that in country with high income inequality might has lower human capital and in turn lower productivity and competitiveness overtime.

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