Effects of Higher Education on the Unconditional Distribution of Financial Literacy

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In this paper, the effect of the higher-education ratio on the distribution of financial literacy in Taiwan is investigated with the unconditional quantile estimation suggested by Firpo et al. (2009). Our empirical data are obtained from three surveys conducted in 2007, 2009, and 2011 by the Financial Supervisory Commission, R.O.C. Using the method of factor analysis suggested by van Rooij et al. (2011), the financial literacy is measured from 18 questionnaires regarding the knowledge of management of cash, savings, credit, and loans. In total, 3,155 individuals were surveyed, namely, 1,005 in 2007, 919 in 2009, and 1,231 in 2011. Our empirical results conclude that an increase in higher education not only increases the acquisition of financial literacy (which is more significant at quantiles smaller than 0.52), but also reduces the dispersion of the financial literacy distribution. This conclusion provides evidence in support of the policy of higher education expansion. Given the positive effect of financial literacy on capital income and retirement plans, the level of financial literacy will be increased and its dispersion will be decreased with the expansion of higher education, so that income inequality as a result will be...

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Introduction

In Taiwan, higher education is provided by colleges, universities, graduate schools, junior colleges and institutes of technology. In 2013, the ratio of people with higher education among Taiwanese aged above 20 was 35.74% (20.80% in 2002). Theoretically, the increment in the proportion of population with higher education should improve the productivity of Taiwanese and hence the wage level. However, the average monthly wage in 2002 was 34,746 NT$ and was 37,527 NT$ in 2013. Obviously, the growth rate of the monthly wage has been much slower than the growth in the proportion of people with higher education. This phenomenon is attributed to the over-supply of workers with higher education in Taiwan’s labor market. Is higher education over-invested in Taiwan? Is there no other benefit to the Taiwan economy as a result of the growth of higher education?

Over the last few decades, financial developments have introduced sophisticated financial instruments that require advanced skills for their proper use. Marcolin and Abraham (2006) point out that financial literacy skills have been crucial for individuals to be able to navigate the financial world. Financial literacy is defined in Noctor et al. (1992) as “the ability to make informed judgments and to take effective decisions regarding the use and management of money.” More and more studies have emphasized the effects of financial literacy on household wealth accumulation (Behrman et al. (2012)), and on retirement preparedness (Lusardi and Mitchell (2007)). van Rooij et al. (2011a) find that financial literacy is positively correlated with the access to financial markets and investment in stocks. At the macroeconomic level, Jappelli (2010) shows that the ability to reap the benefits of new investment opportunities and participate in financial markets depends crucially on economic literacy. Prete (2013) finds that income inequality grows less in countries where economic literacy is higher, and that financial development is negatively correlated with inequality growth. It is clear that both economic and
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Financial literacy has significant positive effects on financial market developments at the macro level and on wealth accumulation at the micro level. On the other hand, Carlin and Robinson (2012) emphasize the role of financial education in improving access to financial literacy. Financial education is provided mostly by the higher education system. Consequently, the acceptance of financial literacy should be positively correlated with the expansion of the higher education system at the mean level. One interesting question concerns the effect of the change in the proportion of people with higher education on the distribution of access to financial literacy.

In this paper, the impact of the proportion of people with higher education on the “unconditional” distribution of financial literacy in Taiwan is examined using the unconditional quantile estimation suggested by Firpo et al. (2009). Section 2 introduces the unconditional quantile estimations comprehensively. Using sample data collected from the surveys conducted by the Financial Supervisory Commission, R.O.C. in 2007, 2009, and 2011, Section 3 conducts an empirical study. Section 4 provides conclusions and suggestions.

2 Marginal Effects in Regressions

The measurement of the marginal effects of the explanatory variables X on the “conditional” mean of the dependent variable Y is the key issue in regression analysis. However, since the conditional distribution is difficult to explore, it is more interesting for practitioners and policy-makers to know the marginal effect of the change in the distribution of an explanatory variable on the “unconditional” distribution of Y. For example, the impact of the ratio of unionized workers on the unconditional distribution of the wage rather than on the conditional distribution is of more interest to policy-makers. In this paper, we are concerned with the impact of the ratio of people with higher education on the distribution of financial literacy in Taiwan.

In conventional regression analysis, the marginal effect measures the impact of a unit change of X on the conditional mean of Y on X. Even though the marginal effect of a political tool variable in X is confirmed, the meaning of “a unit change” is unclear. The practitioner or policy-maker still has no idea about how to make a unit
change in the political variable, even though sometimes it is relatively clear how to change a random variable slightly. For example, an increase in the proportion of people with higher education is equal to the change in the mean location measure of the dummy variable which is defined based on whether people have a higher education or not.

Put simply, suppose \(X\) and \(Y\) are random variables and that quantifying “the effect on \(Y\) of altering \(X\) a little” is the point of interest. The meaning of “altering \(X\)” is specified as moving its location. Without loss of generality, the random variable \(X\) can be decomposed in terms of its mean \(\mu_x\) as:

\[
X = \mu_x + X',
\]

with \(E(X') = 0\). We are interested in movements that arise from altering \(\mu_x\) marginally (location shifts). Consider the linear conditional mean:

\[
E(Y \mid X = x) = x' \beta = (\mu_x + x') \beta_0 = \mu_x \beta_0 + x' \beta_0.
\]

We have:

\[
\frac{\partial E(Y \mid X = x)}{\partial \mu_x} = \beta_0.
\]

Besides, according to the Law of Iterated Expectations (LIE) and given \(E(x') = 0\),

\[
E(Y) = E[E(Y \mid X = x)] = E[\mu_x \beta_0 + x' \beta_0] = \mu_x \beta_0.
\]

We also have:

\[
\frac{\partial E(Y)}{\partial \mu_x} = \beta_0.
\]

Therefore, \(\beta_0\) is playing the double roles of capturing the effect of moving \(\mu_x\) on \(E(Y)\) and \(E(Y \mid X = x)\). However, for the conditional quantile:

\[
Q_{\tau}(Y \mid X = x) = x' \beta_{\tau,0} = (\mu_x + x') \beta_{\tau,0} = \mu_x \beta_{\tau,0} + x' \beta_{\tau,0},
\]

we have:
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\[ \frac{\partial Q(Y | X = x)}{\partial \mu_x} = \beta_x. \]

However, we now face difficulty since we cannot use something like the LIE for quantiles to obtain the result regarding \( \frac{\partial Q(Y)}{\partial \mu_x} \).

Consider the regression, \( y = \alpha + \beta x + u \), that is used to study the conditional mean \( E(Y | X = x) = \alpha_x + \beta_x x \), where \( X \) is discrete with \( x = 1 \) (workers are unionized) or 0 (otherwise). It is obvious that:

\[ E(Y | X = 1) = \alpha_0 + \beta_0 \text{ and } E(Y | X = 0) = \alpha \]

and thus

\[ \beta_0 = E(Y | X = 1) - E(Y | X = 0). \]

The unconditional mean of \( Y \) is:

\[ E(Y) = E[E(Y | X)] = P(X = 1)E(Y | X = 1) + P(X = 0)E(Y | X = 0), \]

\[ = p(\alpha_0 + \beta_0) + (1-p)\alpha, \]

\[ = \alpha_0 + \beta_0 p, \]

where \( p = P(X = 1) \). Therefore, we have:

\[ \frac{dE(Y)}{dp} = \beta_0, \]

which measures the impact of the change in the distribution of \( X \) (the change in the proportion of unionized workers) on the mean of \( Y \) (wage).

However, consider a quantile regression: \( y = \alpha + \beta x + e \), to study the conditional quantile \( Q_\tau(Y | X = x) = \alpha_{\tau,\beta} + \beta_{\tau,\beta} x \). From this, we have:

\[ Q_{\tau}(Y | X = 1) = \alpha_{\tau,\beta} + \beta_{\tau,\beta} = F_{Y|X=1}^{-1}(\tau), \]

\[ Q_{\tau}(Y | X = 0) = \alpha_{\tau,\beta} = F_{Y|X=0}^{-1}(\tau), \]

and

\[ \beta_{\tau,\beta} = Q_{\tau}(Y | X = 1) - Q_{\tau}(Y | X = 0) = F_{Y|X=1}^{-1}(\tau) - F_{Y|X=0}^{-1}(\tau). \]

Since:
We have:
\[
\frac{dF_r(q_r(p))}{dp} = f_r(q_r(p)) \frac{dq_r(p)}{dp}.
\]

This indicates that the effect of increasing the proportion of unionized workers (\(X = 1\)) on the \(r\)th quantile of unconditional distribution of \(Y\) is different from \(\beta_{r,s}\). Firpo et al. (2009) provide a new approach to compute \(\frac{dq_r(p)}{dp}\) which is an interesting issue to practitioners. The logic behind the approach of Firpo et al. (2009) is that since any statistic has its own influence function and is equal to the expectation of the recentered influence function, then the law of iterative expectations is applicable. Staudte and Sheather (1990) and Essama-Nssah and Lambert (2011) provide excellent introductions to influence functions and recentered influence functions for distributional statistics. The unconditional quantile estimation of Firpo et al. (2009) is introduced briefly in the following sections.

### 3 Unconditional Quantile Estimation

Let the random variables \((Y, X)\) be defined on the sample space \(\Omega\) as:

\[
(Y, X) : \Omega \rightarrow \mathbb{R} \times \mathbb{R}^d,
\]

with the joint CDF \(F_{r,s}\). The conditional CDF of \(Y\) on \(X\) is denoted by \(F_{r|x}\), and the marginal CDFs of \(Y\) and \(X\) are \(F_r\) and \(F_x\), respectively. The problem under investigation concerns how the statistic of interest changes with the change in \(F_r\) due to alerting \(X\) a little, i.e., from \(F_x\) to \(G_x\) where \(G_x\) is close to \(F_x\). Given
the new distribution $G_x$ after the change, the unconditional distribution of $Y$ moves to $G_x = G_{yx} \cdot G_x$ where $G_{yx}$ is the conditional CDF of $Y$ on $X$. It is clear that the changes from $F_x$ to $G_x$ arise from (1) the change from $F_x$ to $G_x$ and (2) the change from $F_{yx}$ to $G_{yx}$. Put simply, Firpo et al. (2009) assumes that the conditional distribution of $Y$ on $X$ remains constant. That is, $G_{yx} = F_{yx}$ is assumed and then the counterfactual distribution $G'_x = F_{yx} \cdot G_x$ is the new distribution of $Y$ given $F_x$ changes to $G_x$ keeping $F_{yx}$ constant. Consequently, the effect of a small change in $X$ on the statistic of interest becomes

$$
\lim_{t \to 0} \frac{T(F_{x,t}) - T(F_x)}{t} = \frac{d}{dt} T(F_{x,t}) \big|_{t=0},
$$

where the mixing distribution $F_{x,t}$ is defined as:

$$
F_{x,t} = (1-t)F_x + tG_x = t(G_x - F_x) + F_x, \quad 0 \leq t \leq 1.
$$

The functional $T(\cdot)$ is Gateaux differentiable at $F_x$ if there exists a real kernel function $\phi(\cdot)$ such that:

$$
\lim_{t \to 0} \frac{T(F_{x,t}) - T(F_x)}{t} = \frac{d}{dt} T(F_{x,t}) \big|_{t=0},
\quad = \int \phi(y)d(G_x - F_x)(y) = \int \phi(y)dG_x(y) < \infty.
$$

### 3.1 Influence and Recentered Influence Functions

Let us denote $T(F_x)$ as the descriptive measure on a probability distribution function $F_x$ of a random variable $Y$. As $T$ assigns a real number to each member of a class of functions, as functions of functions, this is often referred to as a statistical function, or simply a function. Hampel’s influence function $IF(T, F_x)$ is a directional derivative of $T$ at $F_x$ and provides an approximation of the relative influence on $T$ of small departures from $F_x$. Let $G_x$ be some distribution other than $F_x$. The effect of distribution $F_x$ goes toward $G_x$ on the functional $T$ and is revealed by the directional derivative of $T$ at $F_x$ in the direction of $G_x$:

$$
\lim_{t \to 0} \frac{T(F_{x,t}) - T(F_x)}{t} = \frac{d}{dt} T(F_{x,t}) \big|_{t=0},
$$

where the mixing distribution $F_{x,t}$ is defined as:

$$
F_{x,t} = (1-t)F_x + tG_x = t(G_x - F_x) + F_x, \quad 0 \leq t \leq 1.
$$

The functional $T(\cdot)$ is Gateaux differentiable at $F_x$ if there exists a real kernel function $\phi(\cdot)$ such that:

$$
\lim_{t \to 0} \frac{T(F_{x,t}) - T(F_x)}{t} = \frac{d}{dt} T(F_{x,t}) \big|_{t=0},
\quad = \int \phi(y)d(G_x - F_x)(y) = \int \phi(y)dG_x(y) < \infty.
$$
when $F_y = G_y$, so that $F_{y,t} = F_y$ and then:

$$\int \varphi(y)dF_y(y) = E[\varphi(y)] = \lim_{t \to 0} \frac{T(F_y) - T(F_y)}{t} = 0.$$ 

Let $G_y = \Delta_y$ be a degenerate CDF with unit mass at point $y \in F_y$. That is, 

$$G_y(y') = \Delta_y(y') = \begin{cases} 0 & \text{if } y' < y \\ 1 & \text{if } y' > y \end{cases}.$$ 

The density function of $G_y = \Delta_y$ is zero everywhere except for an infinite spike at $Y = y$. In particular, we have:

$$\int_{-\infty}^{y'} \Delta_y(y)f_y(y)dy = \int_{y'}^{\infty} f_y(y)dy = F_y(y').$$

Given $G_y = \Delta_y$, the mixing distribution $F_{y\cdot\Delta_y}$ becomes:

$$F_{y\cdot\Delta_y} = (1-t)F_y + t\Delta_y.$$ 

Then, the influence function for the functional $T(\cdot)$ is defined as:

$$IF(y;T,F_y) = \lim_{t \to 0} \frac{T(F_{y\cdot\Delta_y}) - T(F_y)}{t} = \frac{d}{dt}T(F_{y\cdot\Delta_y}) \bigg|_{t=0}.$$

Therefore, $IF(y;T,F_y)$ measures the effect that a single point has on a function. Besides, the mean of the influence function is:

$$E[IF(y;T,F_y)] = \int IF(y;T,F_y)dF_y(y) = \int \varphi(y)dF_y(y) = 0.$$ 

By the von Mises linear approximation, $T(F_{y\cdot\Delta_y})$ can be represented as:

$$T(F_{y\cdot\Delta_y}) = T(F_y) + t\int IF(y;T,F_y)d(G_y - F_y)(y) + r(t,G_y;T,F_y),$$

where $r(t,G_y;T,F_y)$ is a remainder term which is $o(t)$. For $t = 1, F_{y\cdot\Delta_y} = G_y$ and it is easy to obtain:

$$T(G_y) = T(F_y) + \int IF(y;T,F_y)dG_y(y).$$
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For the case where $G_y \equiv \Delta_y$, Firpo et al. (2009) defines the Recentered Influence Function (RIF) as:

$$RIF(y; T, F_y) = T(F_y) + \int IF(y; T, F_y) d\Delta_y(y) = T(F_y) + IF(y; T, F_y).$$

It is obvious that:

$$E[RIF(y; T, F_y)] = \int RIF(y; T, F_y) dF_y(y),$$

$$= \int [T(F_y) + IF(y; T, F_y)] dF_y(y),$$

$$= T(F_y).$$

This indicates that any magnitude of interest can be seen as an expectation. Besides, based on the fact that $F_y(y) = \int F_y(x) dF_y(x)$,

$$T(F_y) = \int RIF(y; T, F_y) dF_y(y),$$

$$= \int [\int RIF(y; T, F_y) dF_y(y)] dF_y(x),$$

$$= \int E[RIF(y; T, F_y) | X = x] dF_y(x),$$

$$= E(E[RIF(y; T, F_y) | X = x]),$$

so that the random variables $X$ are introduced through the law of iterative expectations.

### 3.2 The Marginal Effects of Altering $X$

Suppose that $F_x$ changes marginally in the direction of $G_x$. Assuming that $F_{ix}$ remains constant, then:

$$\frac{\partial T(F_{x, t})}{\partial t} \bigg|_{t=0}^{*} = \int E[RIF(y; T, F_y) | X = x] d(G_x - F_x)(x),$$

where $F_{x, t} = (1-t)F_x + tG_x^t$. Note that $F_y = F_{ix} F_x$, so that $G_y = F_{ix} G_x$, where $G_x^t$ is a new CDF of $Y$ keeping $F_{ix}$ constant if we alter $F_x$ to $G_x$. The proof is as follows:
\[
\frac{\partial T(F_{\tau|X=x})}{\partial t} \bigg|_{t=0},
\]
\[
= \int \phi(y)dG'_{\tau} = \int IFdG'_{\tau} \text{ by (I)},
\]
\[
= \int IF(y; T, F_{\tau})(dG'_{\tau} - dF_{\tau}) \text{ since } \int IFdF_{\tau} = 0,
\]
\[
= \int [RIF(y; T, F_{\tau}) - T(F_{\tau})]d(G'_{\tau} - dF_{\tau}),
\]
\[
= \int RIF(y; T, F_{\tau})d(G'_{\tau} - dF_{\tau}) - \int T(F_{\tau})dG_{\tau}' + \int T(F_{\tau})dF_{\tau},
\]
\[
= \int RIF(y; T, F_{\tau})d(G'_{\tau} - dF_{\tau}) \text{ since } \int T(F_{\tau})dG_{\tau}' = \int T(F_{\tau})dF_{\tau} = T(F_{\tau}),
\]
\[
= \int \left[ \int RIF(y; T, F_{\tau})dF_{\tau|X=x} \right]dG_{\tau} - \int \left[ \int RIF(y; T, F_{\tau})dF_{\tau|X=x} \right]dF_{\tau},
\]
\[
= \int \mathbb{E}[RIF(T, F_{\tau}) \mid X = x]d(G_{\tau} - F_{\tau}).
\]

Given \( dG'_{\tau} = dF_{\tau|X=x} \) and \( dF_{\tau} = dF_{\tau|X=x}dF_{\tau} \), and where:
\[
\mathbb{E}[RIF(T, F_{\tau}) \mid X = x] = \int RIF(y; T, F_{\tau})dF_{\tau|X=x}(y).
\]

Let \( \alpha(T) \) be the vector of partial effects on \( T \) of moving each coordinate of \( X \) separately as a location shift. Then (under some regularity):
\[
\alpha(T) = \int \frac{d\mathbb{E}[RIF(T, F_{\tau}) \mid X = x]}{dx}dF_{\tau}(x).
\]

This result can be proved simply by taking the case of \( X \) as a scalar and the location shift \( G_{\tau}(x) = F_{\tau}(x - \Delta) \), where:
\[
\int \mathbb{E}[RIF(T, F_{\tau}) \mid X = x]d(G_{\tau} - F_{\tau})
\]
\[
= \int \mathbb{E}[RIF(T, F_{\tau}) \mid X = x]d(F_{\tau}(x - \Delta) - F_{\tau})
\]
and then taking the derivative.

### 3.3 RIF of Quantiles and Unconditional Partial Effect

The following discussion on the influence function of \( q_{\tau} \) is summarized from Huber and Ronchett (2009). Let \( q_{\tau} \) be the \( \tau \)th quantile of \( Y \) (unconditional). By definition,
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\[ q_t = F_{y_t}^{-1}(\tau) = \inf \{ y \mid F_y(y) \geq \tau \}, \quad 0 < \tau < 1. \]

Given \( F_{y_t} = (1-t)F_y + tG_y \), we have the identity:

\[ F_{y_t}^{-1}(F_{y_t}(\tau)) = \tau. \]

By differentiating this identity with respect to \( t \) at \( t=0 \) we then have:

\[
\begin{align*}
\frac{dF_{y_t}^{-1}(F_{y_t}(\tau))}{dt} \\ = \frac{d}{dt} \left[ (1-t)F_y(F_{y_t}^{-1}(\tau)) + tG_y(F_{y_t}^{-1}(\tau)) \right]_{t=0}, \\
= \frac{dG_y(F_{y_t}^{-1}(\tau)) - F_y(F_{y_t}^{-1}(\tau)) + dF_y^{-1}(F_{y_t}(\tau))}{dt} \left. \right|_{t=0}, \\
= \frac{dG_y(F_{y_t}(\tau)) - F_y(F_{y_t}(\tau))}{dt} + \left. \frac{dF_y^{-1}(F_{y_t}(\tau))}{dt} \right|_{t=0}, \\
= \frac{d\tau}{dt} = 0.
\end{align*}
\]

where:

\[
\hat{T}_t = \lim_{\tau \to 0} T(F_{y_t}, tG_y) - T(F_y) = \frac{dT(F_{y_t}, tG_y)}{dt} \bigg|_{t=0} = \frac{dF_{y_t}^{-1}(F_{y_t}(\tau))}{dt} \bigg|_{t=0}.
\]

Then, we have:

\[ \hat{T}_t = \frac{\tau - G_y(F_{y_t}(\tau))}{f_y(F_{y_t}(\tau))}. \]

As we know, when \( G_y = \Delta \), \( \hat{T}_t \) becomes the influence function of the \( \tau \)-quantile:

\[
IF(y; T, F_y) = \begin{cases} 
\frac{\tau - 1}{f_y(F_{y_t}(\tau))} & \text{for } x \leq F_{y_t}^{-1}(\tau) \\
\frac{\tau}{f_y(F_{y_t}(\tau))} & \text{for } x > F_{y_t}^{-1}(\tau).
\end{cases}
\]

and
\[ RIF(y; T, F_y) = T(F_y) + IF(y; T, F_y) = q_r + \frac{\tau - \mathbb{I}[y \leq q_r]}{f_y(q_r)}. \]

As \( \mathbb{I}[y \leq q_r] = 1 - \mathbb{I}[y > q_r] \),

\[ RIF(y; T, F_y) = q_r + \frac{\tau - \mathbb{I}[y \leq q_r]}{f_y(q_r)}, \]

\[ = q_r + \frac{(\tau - 1) + \mathbb{I}[y > q_r]}{f_y(q_r)}, \]

\[ = \left[ q_r + \frac{\tau - 1}{f_y(q_r)} \right] + \frac{1}{f_y(q_r)} \mathbb{I}[y > q_r], \]

\[ = c_{z_r} + c_{x_r} \mathbb{I}[y > q_r]. \]

Therefore,

\[ E(RIF(T, F_y) | X = x) = \int RIF(y; T, F_y) dF_{y|x}(y), \]

\[ = \int \left[ c_{z_r} + c_{x_r} \mathbb{I}[y > q_r] \right] dF_{y|x}(y), \]

\[ = c_{z_r} + c_{x_r} \int \mathbb{I}[y > q_r] dF_{y|x}(y), \]

\[ = c_{z_r} + c_{x_r} E[\mathbb{I}[y > q_r | X = x]], \]

\[ = c_{z_r} + c_{x_r} P[y > q_r | X = x]. \]

Thus, the unconditional partial effect is:

\[ \alpha(T) = \int \frac{dE[RIF | X = x]}{dx} dF_x(x), \]

\[ = \int \left[ d(c_{z_r} + c_{x_r} P[y > q_r | X = x]) \right] \frac{dF_x(x)}{dx}, \]

\[ = c_{x_r} \int \frac{dP[y > q_r | X = x]}{dx} dF_x(x). \]

### 3.4 Estimation: RIF-OLS

If the linear probability model (LPM) is considered as:

\[ P[y > q_r | X = x] = x'y. \]

then
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\[ \frac{d\{P(y > q_r \mid X = x)\}}{dx} = \gamma. \]

The unconditional partial effect vector is then:

\[ \alpha(\tau) = c_{x,\gamma}. \]

Given LPM:

\[ I[y > q_r] = x'\gamma + u. \]

with \( E(u \mid x) = 0, \)

\[ \text{RIF}(y; F_r) = c_{x,\gamma} + c_{x,\gamma} I[y > q_r], \]

\[ = c_{x,\gamma} + c_{x,\gamma} (x'\gamma + u), \]

\[ = c_{x,\gamma} + x (c_{x,\gamma} + c_{x,\gamma} u), \]

\[ = c_{x,\gamma} + x \gamma + u', \]

which is the RIF regression for the \( r \)th quantile. To be able to estimate the RIF regression, \( q_r \) and \( f_r(q_r) \) have to be estimated first. \( q_r \) can be estimated as the sample \( r \)th quantile, \( \hat{q}_r \), and \( f_r(q_r) \) can be estimated using the kernel density smoothing estimator at \( \hat{q}_r \), \( \hat{f}_r(\hat{q}_r) \). Then for each observation \((y_i, x_i)\), we compute:

\[ \hat{\text{RIF}}(y; F) = \hat{q}_r + \tau - \frac{I[y_i \leq \hat{q}_r]}{f_r(\hat{q}_r)} \]

and then regress \( \hat{\text{RIF}}(y; F) \) on \( x_i \) to obtain \( \hat{\gamma}' \), which equals \( \hat{\alpha}(\tau) \).

3.5 Estimation: RIF-LOGIT

By specifying a Logit model, given the estimated \( \hat{q}_r \),

\[ P(y_i > \hat{q}_r \mid X = x_i) = \frac{\exp(x_i'\gamma)}{1 + \exp(x_i'\gamma)}, \]

the marginal effect of the \( j \)th explanatory variable on \( P(y_i > \hat{q}_r \mid X = x_i) \) is:
\[
\frac{dP(y > \hat{q}_i \mid X = x_i)}{dx_i} = \gamma_i \left[ \frac{\exp(x_i \gamma)}{1 + \exp(x_i \gamma)} \right] \left[ 1 - \frac{\exp(x_i \gamma)}{1 + \exp(x_i \gamma)} \right].
\]

Denote \( \tilde{\gamma} \) as the MLE of the Logit model. Thus, the expectation

\[
\int d\{P[y > q_i \mid X = x]\}dF_x(x)
\]

could be approximated by the sample mean of the estimated marginal effects:

\[
\frac{1}{n} \sum_{i=1}^{n} \tilde{\gamma}_i \left[ \frac{\exp(x_i \tilde{\gamma})}{1 + \exp(x_i \tilde{\gamma})} \right] \left[ 1 - \frac{\exp(x_i \tilde{\gamma})}{1 + \exp(x_i \tilde{\gamma})} \right].
\]

Then, the \( j \)-th element in \( \alpha(\tau) \) can be estimated by:

\[
\tilde{\alpha}_j(\tau) = \frac{1}{\tilde{f}_j(\hat{q}_j)} \left[ \frac{1}{n} \sum_{i=1}^{n} \tilde{\gamma}_i \left[ \frac{\exp(x_i \tilde{\gamma})}{1 + \exp(x_i \tilde{\gamma})} \right] \left[ 1 - \frac{\exp(x_i \tilde{\gamma})}{1 + \exp(x_i \tilde{\gamma})} \right] \right].
\]

This method is referred to as the RIF-LOGIT estimation.

**4 Empirical Data**

Our empirical data were obtained from three surveys conducted in 2007, 2009, and 2011 by the Financial Supervisory Commission, R.O.C. In total, 6,860 individuals were surveyed, that is, 2,133 in 2007, 2,071 in 2009, and 2,656 in 2011. Using the method of factor analysis suggested by van Rooij et al. (2011), the financial literacy is measured from 18 questionnaires regarding the knowledge of management on cash, savings, credit, and loans.

The explanatory variables considered in our analysis are:

1. highedu: dummy variable, 1 for an individual having a degree from a college, university, or graduate school and 0 otherwise;
2. sex: dummy variable, 1 for male and 0 for female;
3. marriage: dummy variable, 1 for married and 0 otherwise;
4. pincome: 1 for annual personal income from NT$370,000 to NT$680,000, 2 for annual personal income from NT$680,000 to NT$1,240,000 and 3 for annual personal income above NT$1,240,000;
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5. fincome: 1 for annual family income from NT$660,000 to NT$1,230,000, 2 for annual family income from NT$1,230,000 to NT$2,150,000, and 3 for annual family income above NT$2,150,000;

6. Dfulltime: dummy variable, 1 for having a full-time job and 0 otherwise;

7. Darea: dummy variable, 1 for living in an urban area and 0 otherwise;

The summary statistics for the empirical data are shown in Table 1. As shown in Table 1, the ratio of male individuals is 0.448 and the ratio of individuals having a higher education (defined as receiving a degree from a college, university, or graduate school) is 0.461. The sample average of “pincome” is 0.686 which indicates that the average personal income is below NT$370,000. Meanwhile, the sample average of “fincome” is 0.853 which indicates that the average family income is below NT$660,000. The ratio of individuals who have full-time jobs is 0.640 and the ratio of individuals living in an urban area is 0.723.

Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>literacy</th>
<th>highedu</th>
<th>age</th>
<th>sex</th>
<th>pincome</th>
<th>fincome</th>
<th>Dfulltime</th>
<th>Darea</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min.</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Q1</td>
<td>1.957</td>
<td>0.000</td>
<td>1.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean</td>
<td>2.792</td>
<td>0.461</td>
<td>2.048</td>
<td>0.448</td>
<td>0.686</td>
<td>0.853</td>
<td>0.640</td>
<td>0.723</td>
</tr>
<tr>
<td>Median</td>
<td>2.860</td>
<td>0.000</td>
<td>2.000</td>
<td>0.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Q3</td>
<td>3.629</td>
<td>1.000</td>
<td>3.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Max.</td>
<td>4.552</td>
<td>1.000</td>
<td>4.000</td>
<td>1.000</td>
<td>3.000</td>
<td>3.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Variance</td>
<td>1.178</td>
<td>0.248</td>
<td>1.621</td>
<td>0.247</td>
<td>0.628</td>
<td>0.674</td>
<td>0.230</td>
<td>0.200</td>
</tr>
<tr>
<td>Stdev</td>
<td>1.085</td>
<td>0.498</td>
<td>1.273</td>
<td>0.497</td>
<td>0.792</td>
<td>0.821</td>
<td>0.479</td>
<td>0.447</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.335</td>
<td>0.153</td>
<td>-0.012</td>
<td>0.208</td>
<td>0.891</td>
<td>0.759</td>
<td>-0.585</td>
<td>-0.997</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>-0.624</td>
<td>-1.976</td>
<td>-1.043</td>
<td>-1.956</td>
<td>-0.025</td>
<td>0.058</td>
<td>-1.657</td>
<td>-1.005</td>
</tr>
</tbody>
</table>

4.1 Empirical UQE Estimation

The regression model considered in this paper is:

\[
\text{literacy} = \beta_0 + \beta_{\text{highedu}} + \beta_{\text{age}} + \beta_{\text{sex}} + \beta_{\text{pincome}} \\
+ \beta_{\text{fincome}} + \beta_{\text{Dfulltime}} + \beta_{\text{Darea}} + \text{error}.
\]
For purposes of comparison, the mean regression estimated using OLS, the conditional quantile regressions and unconditional quantile regressions at quantiles 0.1, 0.5, and 0.9 are considered. The results of the estimation are presented in Table 2. Robust standard errors for OLS and bootstrapped standard errors (2,000 replications) for CQR (conditional quantile), RIFOLS (RIF-OLS estimation), and RIFLOG (RIF-LOGIT estimation) are provided in parentheses. These estimations are conducted with R3.0.2. The package “ks” is used to estimate the density function and the package “boot” is used to do the bootstrapping for estimating the variance-covariance matrix of coefficients. The R codes and empirical data are available from the authors upon request.

The OLS estimated coefficient of highedu is 0.594 which indicates that the increment of the proportion of individuals with a higher education has a significant and positive impact on the conditional mean of financial literacy obtainment. At the quantiles 0.1, 0.5, and 0.9, the CQR estimated coefficients of highedu are 0.499, 0.790, and 0.394 and are all statistically significant. The impact of highedu on the conditional quantile is found to be getting large at high quantiles which demonstrates that increasing the proportion of population with a higher education increases the dispersion of the conditional distribution of obtainment of financial literacy. For the RIF-OLS (RIF-LOG), the estimated coefficients of highedu at quantiles 0.1, 0.5, and 0.9 are 0.528 (0.582), 0.840 (0.800), and 0.331 (0.355). These results indicate that the proportion of population with a higher education always has a positive effect on the quantiles of the financial literacy distribution.

The estimated marginal effects of higher education on financial literacy using CRQ, RIF-OLS, RIFLOG, and OLS for \( \tau = 0.1, 0.2, \ldots, 0.9 \) are depicted in graphical form as shown in Figure 1. From Figure 1, the estimated impacts of higher education status on financial literacy using conditional quantile regression estimations (the curve denoted as CRQ) are positive for all \( \tau \). This result indicates that higher education increases the within-group levels of financial literacy at all quantiles where the “group” consists of individuals who share the same values of the covariates \( X \) (other than higher education status). In other words, an increase in higher education will move the “conditional” distribution of financial literacy to the right. Among the quantiles from 0.3 to 0.8, the CRQ curve is almost symmetric in the middle, i.e., the 0.5 quantile. Similarly, the estimated impacts using
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unconditional quantile estimations (curves denoted as RIFOLS and RIFLOG) are also positive for all $\tau$s. This indicates that higher education also increases the between-group level of financial literacy, i.e., it also moves the unconditional distribution of financial literacy to the right. In addition, the estimated impacts using RIFOLS and RIFLOG are found to be getting larger from $\tau = 0.1$ to $\tau = 0.5$ but to be getting smaller from $\tau = 0.5$ to $\tau = 0.9$. However, the curves of RIFOLS and ROFLOG are steeper than the curve of CRQ regardless of whether the quantiles are smaller or larger than 0.5. It is worth noticing that the estimated impacts of RIFOLS and RIFLOG are always smaller than those of CRQ for all quantiles except $\tau = 0.1$ for RIFLOG and $\tau = 0.1$ and 0.5 for RIFOLS.

Table 2: Estimated Results from the OLS, CQR, and UQR Regressions

<table>
<thead>
<tr>
<th></th>
<th>$\tau = 0.1$</th>
<th>$\tau = 0.5$</th>
<th>$\tau = 0.9$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.235</td>
<td>0.686</td>
<td>0.395</td>
</tr>
<tr>
<td></td>
<td>(57.03)</td>
<td>(14.28)</td>
<td>(4.51)</td>
</tr>
<tr>
<td>highedu</td>
<td>0.594</td>
<td>0.499</td>
<td>0.528</td>
</tr>
<tr>
<td></td>
<td>(22.84)</td>
<td>(12.67)</td>
<td>(11.53)</td>
</tr>
<tr>
<td>Dage</td>
<td>0.066</td>
<td>0.083</td>
<td>0.130</td>
</tr>
<tr>
<td></td>
<td>(6.28)</td>
<td>(5.54)</td>
<td>(5.79)</td>
</tr>
<tr>
<td>sex</td>
<td>-0.139</td>
<td>-0.107</td>
<td>-0.096</td>
</tr>
<tr>
<td></td>
<td>(-5.53)</td>
<td>(-3.00)</td>
<td>(-2.01)</td>
</tr>
<tr>
<td>pincome</td>
<td>0.096</td>
<td>0.141</td>
<td>0.106</td>
</tr>
<tr>
<td></td>
<td>(4.70)</td>
<td>(4.21)</td>
<td>(2.97)</td>
</tr>
<tr>
<td>fincome</td>
<td>0.090</td>
<td>0.083</td>
<td>0.073</td>
</tr>
<tr>
<td></td>
<td>(4.98)</td>
<td>(3.08)</td>
<td>(2.24)</td>
</tr>
<tr>
<td>Dtime bombs</td>
<td>0.107</td>
<td>0.348</td>
<td>0.503</td>
</tr>
<tr>
<td></td>
<td>(3.57)</td>
<td>(7.34)</td>
<td>(8.47)</td>
</tr>
<tr>
<td>Darea</td>
<td>-0.006</td>
<td>-0.028</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(-0.24)</td>
<td>(-0.66)</td>
<td>(0.09)</td>
</tr>
</tbody>
</table>
To study the marginal effects of higher education on the unconditional distribution of financial literacy comprehensively, we estimate the sample quantiles of the financial literacy, $\hat{q}_t$, and the marginal effects using RIFLOG, $\alpha_t$, for $\tau = 0.01, 0.02, \ldots, 0.98, 0.99$. The estimated $\alpha_t$ for 99 $\tau$s (represented as the line “aftau”) and their 95% confidence intervals (represented as the lines “upper” and “lower”) are plotted in Figure 2. It is clear that all 99 $\alpha_t$s are significantly different from zero at the 5% Type I error. It is also found that the $\alpha_t$s are decreasing from $\tau = 0.01$ to 0.2 and start to increase at an increasing rate from $\tau = 0.2$ to 0.53. However, from $\tau = 0.53$ to 0.99, the $\alpha_t$s are decreasing at an increasing rate which is larger than the increasing rate from $\tau = 0.2$ to 0.53. In addition, we find that the marginal effects, $\alpha_t$, at a high $\tau$s are lower relative to the ones with a small $\tau$s.

Let us denote $\alpha_t$ (higher education) as the estimated marginal effect of higher education. Using the kernel smoothing density estimator, the density function for “before” is estimated using $\hat{q}_t$ and the one for “after” is estimated using $\hat{q}_t + \alpha_t \tau$ (higher education). The “after” density function describes the new unconditional distribution of financial literacy after a unit change in higher education. The estimated density functions are represented as shown in Figure 3.

As shown in Figure 2, the mean of the estimated “after” density function is 3.6612 which significantly larger than 2.8607, the mean of the estimated “before” density function. This indicates that an increment of higher education moves the
unconditional distribution of financial literacy to the right. In other words, an increment of higher education moves all quantiles of financial literacy to the right. However, the lower quantiles are moved to the right more than the higher quantiles are. Besides, the dispersion of the estimated “after” distribution becomes smaller than that of the “before” distribution. In addition, it is interesting to find that the “after” unconditional distribution of financial literacy becomes bimodal and the density at the right mode is much higher than the one at the left mode. This result implies that an increment of higher education not only increases the level of financial literacy but also decreases the dispersion of literacy.

![Figure 2: Marginal Effect of Higher Education on Unconditional Distribution of Financial Literacy](image)

Figure 2: Marginal Effect of Higher Education on Unconditional Distribution of Financial Literacy
To summarize, the estimated impacts of higher education on the distribution of financial literacy are concluded as follows:

1. An increment of higher education moves the unconditional distribution of financial literacy to the right which implies that higher education has a positive effect on the obtainment of financial literacy;
2. The marginal effect of higher education on financial literacy is increasing at an increasing rate when $\tau =0.2$ to $0.53$;
3. The marginal effect of higher education on financial literacy is decreasing at an increasing rate when $\tau =0.53$ to $0.99$ and the rate of increase is larger than that when $\tau =0.2$ to $0.53$;
4. An increment of higher education makes the unconditional distribution of financial literacy become bimodal and the right mode has a much higher density than the left mode.

These conclusions imply that increasing the higher education not only increases the obtainment of financial literacy (which is more significant at quantiles smaller than 0.5) but also decreases the dispersion of the financial literacy distribution.

5 Conclusions and Suggestions

This paper investigates the impact of higher education status on the conditional and
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unconditional distributions of financial literacy. Using the surveyed samples compiled by the Financial Supervisory Commission, R.O.C. in 2007, 2009, and 2011, the quantile regression of Koenker and Bassett (1978) and the unconditional quantile estimation of Firpo, Fortin, and Lemieux (2009) are used to study the conditional and unconditional distributions of financial literacy, respectively. We find that increasing the status of higher education will have positive marginal effects on the conditional and unconditional distributions of financial literacy, i.e., move the conditional and unconditional distributions to the right. However, we also find that the increase in higher education reduces the dispersion more for the unconditional distribution than for the conditional distribution. These conclusions imply that increasing the higher education not only increases the obtainment of financial literacy (which is more significant at quantiles smaller than 0.53) but also decreases the dispersion of the financial literacy distribution. Therefore, the extension of higher education in Taiwan is supported by our findings.

References


