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# Increasing heterogeneity in the economic returns to higher education in urban China

### Anning Hu<sup>a,\*</sup>, Jacob Hibel<sup>b,1</sup>

<sup>a</sup> Department of Sociology, Fudan University, China

<sup>b</sup> Department of Sociology, University of California, Davis, USA

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#### ABSTRACT

This study investigates individual heterogeneity in the economic returns to higher education in urban China following large-scale higher education expansion. We draw on data from the urban section of two waves of the Chinese General Social Survey, analyzing a sample of 1022 individuals in total who (1) were aged between 25 and 32; (2) completed high school education; and (3) were currently employed. Individual-level estimates of the distributions of the returns to higher education are obtained using a nonparametric kernel approach. While the average rate of returns to higher education increased for the 2003–2010 period, the extent of heterogeneity in these returns increased as well. Analysis of the heterogeneous returns to higher education across the distribution of income shows that the effects of college education are greatest at the upper end of the income distribution. Moreover, effect heterogeneity across the income distribution increased from 2003 to 2010.

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#### 1. Introduction

China undertook a rapid, large-scale expansion of higher education beginning at the turn of the 21st century, nearly tripling the number of college graduates over the period between 2003 and 2010 (Ministry of Education of the PRC, 2003, 2008). In light of this increase in the number of college-educated workers, fundamental economic and sociological theories provide several reasons to expect that the economic returns to higher education in China have undergone substantial change. There has been a recent wave of empirical studies focusing on the returns to higher education in China (Chen & Hamori, 2009; Chen & Ju, 2003; Gustafsson & Li, 2000; Li, Liu, & Zhang, 2012; Wang, 2012; Wu, 2010; Zhang, Zhao, Park, & Song, 2005).

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<sup>\*</sup> Corresponding author at: 1137, Liberal Arts Building, Handan Road, 220, Shanghai 200433, China. Tel.: +86 21 65643053;

fax: +86 21 65107274.

*E-mail addresses*: huanning55@hotmail.com, huanning55@gmail.com (A. Hu), jhibel@ucdavis.edu (J. Hibel).

<sup>&</sup>lt;sup>1</sup> One Shields Avenue, Davis, CA 95616, USA. Tel.: +1 530 752 0782; fax: +1 530 752 0783.

of alleviated by education expansion (Lemieux, 2006). For these reasons, a handful of recent studies focus on returns heterogeneity in educational attainment (Brand & Xie, 2010; Heckman & Li, 2004; Tsai & Xie, 2011).

Scholars consider heterogeneous returns to education through variation in returns across a third variable's distribution. For instance, Heckman, Urzua, and Vytlacil (2006) develop a marginal treatment effects method to investigate varying returns to higher education across the spectrum of the odds of attending college. Sociologist Xie, Brand, and Jann (2012) use propensity score matching methodology to examine the same type of heterogeneity. Another common third variable approach involves modeling variation in educational returns across the income distribution. Quantile regression models are widely used in this vein. Quantile regression studies examine the independent variable's effects separately across quantiles of the dependent variable. Wang (2013) uses a related methodological approach to examine educational attainment's effect on the earnings distribution in urban China from 1995 to 2002, adjusting for endogeneity bias with an instrumental variable. Knight and Song (2003) find that returns to education are heterogeneous across earnings quantiles, with higher returns in the lower tail and lower returns in the upper tail of the earnings distribution.

Bearing this body of recent works, we take a related but distinct analytical approach and examine economic returns to college during a historically significant period of higher education expansion in China. We examine the changing degree of individual-level heterogeneity in returns to higher education in urban China by employing a nonparametric methodology that does not require analyzing heterogeneity across the distribution of a third variable. Our findings shed light on longitudinal shifts in returns to higher education dispersion following largescale higher education expansion in urban China. While our approach does not necessitate modeling the changing economic returns to education across a third variable, the nonparametric method is amenable to such analysis, as we demonstrate by presenting the heterogeneous returns to higher education across the income distribution.

Economists have used non-parametric kernel density estimation methods to study treatment heterogeneity in a variety of arenas (Henderson, Olbrecht, & Polachek, 2006; Henderson et al., 2011; Li & Racine, 2007). For example, Zhu (2011) uses a nonparametric kernel method to document a trend of rising individual-level variation in the returns to education in urban China from 1995 to 2002. Using non-parametric estimation, we investigate changing heterogeneity in the returns to college education following large-scale higher education expansion using an urban portion of the data from the Chinese General Social Survey (CGSS) 2003 and 2010.

#### 2. Methodology

#### 2.1. Generalized kernel estimation

We use generalized kernel estimation (Silverman, 1986) to estimate the conditional mean and gradient in

nonparametric regression. The nonparametric model is specified as

$$y_i = m(x_i) + \varepsilon_i \quad i = 1, 2, \dots, n \tag{1}$$

where  $y_i$  is the outcome value for individual *i*.  $m(x_i)$  is the estimated unknown smoothing function.  $x_i = [x_i^c, x_i^u]$ where  $x_i^c$  refers to the vector of continuous predictors and  $x_i^u$  is the vector of categorical predictors. The estimator of coefficients can be expressed as

$$\widehat{\delta}(x) = (X'K(x)X)^{-1}X'K(x)y$$
<sup>(2)</sup>

where X is a matrix with each row equal to  $(1, x_i^c - x^c)$ and K(x) is a matrix of kernel weighting functions for mixed continuous and categorical variables with bandwidth h (Li & Racine, 2007). Suppose there are *s* continuous predictors and *l* categorical predictors. The kernel weighting function for mixed continuous and discrete predictors is equal to

$$\prod_{q=1}^{s} \frac{1}{\hat{h}q} g\left(\frac{x_{qi} - x_{qj}}{\hat{h}q}\right) \prod_{q=1}^{l} m(y_{qi}, y_{qj}, \hat{\lambda}_q)$$
(3)

where *g* is a second-order Gaussian kernel<sup>2</sup> for continuous predictors with estimated bandwidth  $\hat{h}_q$  and *m* is a variation on Aitchison–Aitken kernel with  $m(y_{qi}, y_{qj}, \hat{\lambda}_q) = \begin{pmatrix} 1 & \text{if } y = y \end{pmatrix}$ 

 $\begin{cases} 1 & \text{if } y_{qi} = y_{qj} \\ \lambda_q & \text{otherwise} \end{cases}$  for discrete predictors (Li & Racine, 2007).

Bandwidth selection is critical to nonparametric estimation because the bandwidth length determines the bias-variance tradeoff (Wasserman, 2006). A too-large bandwidth incurs bias while a too-small bandwidth causes problematically large variance. There are two procedures to calculate the correct bandwidth, which allows robustness checks to correct bandwidth selection. We use and compare the likelihood cross-validation (LCV) procedure and the least square cross-validation procedure (LSCV) (Li & Racine, 2007). LCV determines the bandwidth *h* by maximizing the leave-one-out log likelihood function  $\sum_{i=1}^{n} \log \hat{f}_{-i}(x)$ , where  $\hat{f}_{-i}(x)$  is the leave-one-out kernel estimator of the density function. LSCV, by contrast, estimates *h* by minimizing the function CV(h, l) = $\frac{1}{n}\sum_{i=1}^{n}[y_i - \hat{m}_{-1}(x_i)]^2$ , where  $\hat{m}_{-1}$  is the leave-one-out estimator of the function *m*. According to the estimated individual-level coefficients shown in the Appendix, the bandwidth determination procedure does not alter our conclusions, indicating that our results are robust. We present the results based on the LCV procedure below.

After estimating the bandwidth, we use nonparametric regression to obtain a coefficient estimate of higher education's effect on income for each individual, which we use to examine individual-level heterogeneity in the economic returns to Chinese college education.

The Li–Racine nonparametric methodology possesses several noteworthy advantages over alternative approaches. Like other nonparametric methods, generalized kernel estimation of the returns to higher education

<sup>&</sup>lt;sup>2</sup> The Gaussian kernel is one of many commonly used weighting kernels such as the boxcar kernel, the Epannechnikov kernel, and the tricube kernel (Wasserman, 2006).

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