Zagreb International Review of Economics & Business, Vol. 26, No. 1, pp. 77-96 2023

Faculty of Economics and Business, University of Zagreb and Sciendo. Printed in Croatia.
ISSN 1331-5609; UDC: 33+65
DOI: 10.2478/zireb-2023-0004

A Spillover Effect of Human Capital on Gross Capital Formation: A Quantile Regression Approach

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Abstract: *The major aim of this paper is to examine the extent to which human capital spillover effects are responsive to different quantiles of gross capital formation across selected 19 OECD countries for the period 1980-2017. We develop an endogenous model for estimating the spillover effects on investment regarding the bargaining power of workers. In this sense, different quantile regression models are applied to analyze this miscellaneous linkage and to correct possible diagnostic problems stemming from the endogenous regressors. The empirical results suggest that there are statistically significant spillover effects of human capital on investment level due to a change in the degree of threat option of capital and thereby a decrease in bargaining power of labor. Moreover, the findings reveal the fact that there is significant heterogeneity of human capital spillovers across different quantiles, which means that lowest quartile of investment activities are confronted with higher value of spillovers.*

***Keywords*:** Human Capital; Gross Capital Formation; Investment; Spillover Effect; Quantile Regression

***JEL Classification*:** F21, J24, J52

Introduction

One of the recent interests in the literature is based on the investigation of the spillover effect of several indicators on investment and thereby economic growth. In other words, the relevant literature is widely recognized that spillovers play a crucial role in the behavior of the firms in terms of their competitiveness and cost-efficiency. For instance, a bulk of studies concentrates on the topic which relates to the average effect of knowledge spillovers on innovation or productivity growth (Jaffe, 1986;

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Griliches, 1992; Verspagen, 1997; Serrano and Cabrer, 2004; Damijan et al., 2006; Bar and Leiponen, 2012; Aghion and Jaravel, 2015; Aldieri and Vinci, 2017; Audretsch and Belitski, 2020). However, the direct impact of human capital spillovers has been substantially excluded from the research in the sense of its linkage with educational returns and the degree of investment. A glance at the previous studies can provide some prime outcomes where the knowledge exchange among workers is considered as the engine of economic growth (Romer, 1986; Lucas, 1988; Jovanovic and Rob, 1989). Workers may not be fully compensated for their contributions to economic output, as this type of knowledge exchange does not be obtained by them due to its feature that the production process only reflects their direct input (O'Mahony and Riley, 2012). A growing number of studies is proven that the increasing degree of workers' capacity and capability throughout a very recent period has led to the occurrence of such that externalities at different levels of indicators: (i) the geographical level (Moretti, 2004; Rosental and Strange, 2008; Ramos et al., 2010; Park, 2012; Abbott and Gallipoli, 2017), (ii) industrial level (Moretti, 2002; Apergis et al., 2009; Hamid and Pichler, 2009; Diwakar and Sorek, 2017; Badinger et al., 2019), and (iii) workplace level (Sloane et al., 2003; Belfield et al., 2004; Metcalfe and Sloane, 2007; Benos and Karagiannis, 2016). In consideration of the above classification, the literature shows that there are positive externalities in human capital that are statistically significant for aggregate economic activities. For example, Cabrales (2011) provides evidence of that positive implication which leads us to help in the examination of development variances across different countries and regions. Also, Ciccone and Peri (2006) identify the aggregate human capital externalities by suggesting that the strength of those externalities equalizes with the effect of human capital on the average wages when conditions are suitable for holding the labor force skill composition constant. Besides, Thönnessen and Gundlach (2013) provide strong cross-country evidence of the size of a substantial human capital externality, implying that human capital accumulation should be at the core of a theory that stimulates to analyze the mutual linkage between the persistency of long-run income growth and the transitional movements of static traditional society to a modern dynamic state, which also eventuates with systematic shifts in many economic, political, and cultural indicators. Meanwhile, Malley and Woitek (2019) estimate the quantitative implications of human capital externalities in a two-sector endogenous growth framework with knowledge spillovers and find that there are positive externalities to aggregate human capital, showing that the elimination of the sources of market failure concludes with sizeable increases in education time, endogenous growth, and total welfare.

Even though the present empirical literature draws conclusions on the evidence of positive externalities in human capital by using different estimation procedures such as Mincerian or life-cycle approaches, there are also others which of them adopt an identification approach (Rauch, 1993) to estimate the education returns simultaneously through multi-level analysis. In this paper, we use different quantile regression methods for panel data to estimate the parameters at different points on the investment level. In other words, we could assume that slope parameters may change at different quantiles of the conditional distribution due to heterogeneity of firms' investment. Besides, the use of those methods depends on the reason that it may provide some advantages for having robust estimates of coefficients since it can mitigate the problem of bias resulting from the outliers. Meanwhile, in contrast to the Ordinary Least Squares (OLS) estimators, the quantile regression approach can obtain more efficient and statistically significant estimators when the disturbance term is not simply white noise. In particular, quantile regression techniques are available for discerning the relationship between predictor variables and the conditional distribution of the response variable. Therefore, these methods are used to estimate conditional quantile treatment effects. In that vein, quantile regression is considered as the extension of linear regression since the conditions of linear regression may not meet.

The spillover effects from education to workers can be affected by the changes in the labor market conditions. In that sense, the level of employability, which implies the life-long, continuous cycle of acquiring experience, new knowledge, and skills, become one of the core factors for expanding their opportunities in employment and for increasing the level of earnings through various shifts in the labor market. Therefore, a higher level of employability is explicitly reckoned as a sign of improving labor market performance and conditions. Since the role of education can be reflected with the spillover effects, it may directly lead to the occurrence of heterogeneous outcomes in production structures of various sectors and implement changes to the organizational structure along with an increasing degree of competitive pressure in labor markets. Meanwhile, this spillover effect of education to workers may result in a change in the rules of competition, which tends to exacerbate both intra- and inter-class conflict in the production. Along with these potential factors, it seems natural to find out the reasons why and how the spillover effects of human capital affect the level of investment through the consideration of a change in the fallback option of workers. To best of our knowledge, this question has not been answered yet in the light of current literature. To further enhance the empirical findings which have been provided crucial determinants so far, this study considers whether a higher degree of human capital may contribute to an increase in the level of aggregate investment within a country, in control of bargaining power of workers irrespective of their skills, experience or knowledge.

The *a priori* structure of reasons are indeed several but some of them can be listed as follows: First, a change in fallback options of workers may indirectly affect the spillover effects of human capital on investment. This occurs due to the transfers of income to employers from the workers for those who may have a chance to design the use some part of their income to develop new skills on the job. However, an increase in the degree of threat option of capital may mitigate the positive externalities of human capital on the level of investment due to widening income disparity through the redistribution of income in favor of the capital. Second, the employers may opt to outsource part or all of their activities to oversees if the fallback option of capital is limited, implying that the spillover effects of human capital on investment will be negative due to lowering employment opportunities and having a decrease in wages along with an excess supply of labor over the demand. Third, the spillover effects of human capital on investment may be mitigated since the external factors may push the economy towards capital-augmenting technical change. Consequently, depending on the elasticity of substation for each input, further economic development may increase the share of capital by pushing a great number of individuals towards out of educational attainment.

To examine the relationship between investment and spillovers from human capital towards the changes in intermediate channel such that the bargaining power of workers, we measure the degree of human capital by considering both returns to education and the rate of schooling at an aggregate level. All in all, the paper is structured as follows. The next section presents the details about the theoretical model to investigate the above-mentioned relationship. Section 3 describes the empirical methodology and the data. Section 4 summarizes the empirical findings. Finally, section 5 concludes.

Theoretical Underpinnings

This section identifies the theoretical underpinnings to understand the spillover effects of progress in human capital on the level of investment, suggesting that there might be produced some negative externalities in terms of workers' time, effort, and skills due to a change in a fallback option of capital in the production process. This analytical background of that theoretical context is obtained from the work of Aldieri and Vinci (2017: 107-108) and readopted to the case of spillover effects of human capital in the presence of given presumptions. Alternatively saying, this section is devoted to the investigation of the transmission of investment in human capital obtained during educational attainment. First and foremost, we adopt a simple non-overlapping generation model towards Acemoglu (1996) where each generation of two typologies of workers, living for two periods, is assumed to consist of a continuum of people having with equality of opportunity in education normalized to unity and with a zero intertemporal preference rate. People who largely invest in human capital, are defined as skilled workers, while those who select not to spend time for educational attainment and self-development are regarded as unskilled workers; all of them are assumed to be productive at different scales.

On the one hand, at time $t=0$ people are assumed as identical in terms of their skills, experience, and knowledge (i.e., having no education). On the other hand, at time $t=1$ accumulation of knowledge and capability takes place in the form of a partnership of skilled and unskilled workers, the productive skills are increased through the continuity of schooling. In that vein, workers will be classified as skilled and unskilled upon their attempt to enhance the level of education over time. The accumulation of skills and knowledge function, in line with Romer (1994), takes the functional form as represented in Eq. (1):

$$\dot{h} = \mu e^{\psi u} A^{\eta} h^{1-\eta} \tag{1}$$

where u denotes the amount of time an individual spends accumulating skill instead of working, and ψ is the constant parameter, A is the world technology frontier (i.e., the index representing the most advanced capital good invented to date), and h is the individuals' skill level. Also, we assume $\mu>0$ and $0<\eta\leq 1$. More formally, u can be considered as years of schooling. In that sense, Eq. (1) explicitly implies that the level of skills in production will be proportionally increased with additional time spend on accumulating skills. We also assume that the change in skills is a weighted average of the frontier level, A, and the individuals' skill level, h (Jones and Vollrath, 2013: 142). So that, the skill accumulation can be obtained by dividing both sides by h in Eq. (1):

$$\frac{\dot{h}}{h} = \mu e^{\psi u} \left(\frac{A}{h} \right)^{\eta} \tag{2}$$

Meanwhile, the investment decisions of the firms depend on two strategies: (i) how much labor and how much of each capital good to use for producing output and (ii) what are the most efficient ways to provide cost-minimization. Eq. (3) is represented for achieving to the solution of profit-maximization/cost-minimization problem in the presence of these two strategies which must be done for providing efficiency in investment along with having positive externalities of human capital spillover:

$$\max_{L,x_j} L^{1-\alpha} \int_0^A x_j^{\alpha} dj - wL - \int_0^A p_j x_j dj \quad \text{with: } 0<\alpha<1 \tag{3}$$

where x_j is the capital good j, p_j denotes the rental price for capital good j and w is the wage share accrued to workers. Next, we need to elaborate on the ways of labor allocation in an aggregate economy. This case leads us to decide how much labor works to produce output (L_Y) and how much devotes to produce new ideas (L_A), assuming that these two activities represent the total supply of labor in the economy:

$$L_A + L_Y = L \tag{4}$$

where $L_R / L = s_R$ and $L_Y / L = s_Y$ (i.e., $s_Y = 1 - s_R$). While s_R produces new ideas in the R&D sector, the remaining fraction, s_Y, produces output in the final-goods sector. Alternatively saying, s_R illustrates the mental labor and s_Y defines the manual labor.

In consideration of this division, the earning functions for mental and manual labor can be given by Eqs. (5) and (6), respectively:

$$w_{i,t}^{R} = \frac{\lambda_i \left(1 + l_{i,t}\right)^{(1+\gamma)}}{(1+\gamma)} W_{i,t}^{0} - C_{i,t} \tag{5}$$

$$w_{j,t}^{Y} = \frac{\theta_j \left(1 + e_{j,t}\right)^{(1+\gamma)}}{(1+\gamma)} W_{j,t}^{0} - C_{j,t} \tag{6}$$

where λ_i and θ_j measure the wage loss from the bargaining power of capital, $C_{i,t}$ and $C_{j,t}$ denote the level of consumption, $l_{i,t}$ and $e_{j,t}$ are the degree of human capital for L_R and L_Y, respectively. Finally, the parameter γ shows the other variables that may negatively affect the wage level and $W_{i,t}^{0}$ and $W_{j,t}^{0}$ are the expected wages of mental and manual labor, respectively.

First, Eqs. (5) and (6) imply that the fallback option of capital may vary in the R&D sector and final-goods sector, which means that the skill levels of workers have the power to affect the behavior of the firms in terms of their negative sanctions in income allocation. Second, the level of wages will be varied based on the degree of human capital, the bargaining power of capital, and the expenditures on consumption. Finally, the sum of $w_{i,t}^{R}$ and $w_{j,t}^{Y}$ will implicitly yield the total amount of wages acquired to a given amount of labor supply in the economy. In consideration of these outcomes, the expected wages can be also defined as follows:

$$W_{i(j)}^{0} = \left(\int_{0}^{1} h_{i(j),t} - \int_{0}^{1} X_{i(j),t} \right) di\,(dj) \tag{7}$$

where h is the individuals' skill level for i^{th} person employing in R&D sector and for j^{th} person employing in the final-goods sector. X denotes the other factors which of those are negatively affected the level of expected wages in those two sectors. Moreover, $h_{i,t}$ and $h_{j,t}$ for i^{th} and j^{th} individuals employing in the R&D sector and final-goods sector, respectively, can be given as follows:

$$h_{i,t} = \left(1 + u_{i,t}\right)\left(1 - \beta\right) n \tag{8}$$

$$h_{j,t} = \left(1 + u_{j,t}\right)\left(1 - \beta\right) n \tag{9}$$

where u is the years of schooling, β is the number of obstacles to education, and n is the population growth. The total incomes, in which we produce in Eqs. (5) and (6), can be derived from a bargaining process implementing to an allocational framework according to given propositions as $\delta = w_{i,t}^{R}$ and $1 - \delta = w_{i,t}^{Y}$. From the first-order conditions of the maximization process, we may easily derive the following Eqs. (10) and (11):

$$h_{i,t} = \left\{ \frac{\delta\left(1+u_{i,t}\right)^{\gamma+1}\left(1-\beta\right)^{\gamma} nA^{\eta} X_{i,t}^{(1-\gamma)}}{\lambda_i} \right\}^{\frac{1}{\gamma+1-\eta}} \tag{10}$$

$$h_{j,t} = \left\{ \frac{\left(1-\delta\right)\left(1+u_{j,t}\right)^{\gamma+1}\left(1-\beta\right)^{\gamma} nA^{\eta} X_{j,t}^{(1-\gamma)}}{\theta_j} \right\}^{\frac{1}{\gamma+1-\eta}} \tag{11}$$

Assuming $\lambda_i = \lambda$ and $\theta_j = \theta$, there exist positive externalities between human capital and investment. When a group of firms increases investment in high-tech physical capital, other firms, due to competitive pressure, will positively respond, and the equilibrium rate of return for skilled labor will increase. In other words, the redistribution of income within the labor market will be towards the skilled workers and thus it leads to an excess supply of unskilled workers, implying that the level of wages for those workers will be lower compared to skilled workers. However, this case may not hold since the other factors can be operated along the way that the fallback option of capital will not be stable in the presence of profit-maximization/cost-minimization target. Meanwhile, the positive externalities will be higher for lower levels of high-tech physical capital.

The above assumptions consider that the expected positive externalities will have different magnitudes depending on the expected rate of return and the initial level of high-tech physical capital for different groups of firms. In order to estimate that given assumption, we introduce different quantile regression approaches, whose estimates are summarized in the section of empirical findings. The next section discusses the theoretical basis of this approach along with the selection of research data.

Data and Empirical Approach

Data

The paper tests a balanced panel set (i.e., yearly data from 1980 to 2017) for selected 19 OECD countries. The gross capital formation from the World Bank, World Development Indicators (WDI) database is used to depict the level of investment. The major aim for obtaining this variable from the WDI database is caused by the fact that balanced panel data can be acquired for those selected countries and thus it directly leads to get reliable estimation results.

The human capital index is measured as a weighted average of two core indicators, i.e., the returns to education and the years of schooling, which is obtained from the Penn World Table (PWT) version 9.1 database (Feenstra et al., 2015). The bargaining power indicators for the workers are proxied by the unemployment rate (% of total population) and the trade union density (%) in the WDI database and OECD statistics, respectively.

Finally, the consumption share as a part of Gross Domestic Product (GDP) is obtained from the PWT version 9.1 database. All variables are calculated in their natural logarithms. As Gelman and Hill (2007) state that the major reason to prefer natural logs is to directly interpret the coefficients on the natural-log scale as a way to approximate proportional differences.

The *lnGFC*, *lnHC*, *lnCS*, *lnUNEMP*, and *lnUNION* represents those above variables in abbreviations for gross capital formation, human capital index, consumption share, unemployment rate, and trade union density, respectively. All in all, Table 1 summarizes the sources of data and its measurement method.

Table 1: Data Sources and Measurement

Variable	**Abbreviation**	**Measurement**	**Source**	**Number of Observations**
Gross Capital Formation	lnGFC	Current US$ (in natural logarithm)	World Bank, World Development Indicators	722
Human Capital	lnHC	Index (in natural logarithm)	Penn World Tables version 9.1	722
Consumption Share	lnCS	% of GDP (in natural logarithm)	Penn World Tables version 9.1	722
Unemployment Rate	lnUNEMP	% of total labor participation (in natural logarithm)	World Bank, World Development Indicators	722
Trade Union Density	lnUNION	% (in natural logarithm)	OECD Statistics	722

Empirical Approach

Conventional regression analysis such as the least-squares method is widely dealt with the conditional mean of a dependent variable given explanatory variables. Also, it bears on the discussion of the conditional distribution. If there is a concern about the tails of the conditional distribution, one can be focused on different procedures such that the quantile regression (Koenker and Bassett, 1978), expectile regression (Newey and Powell, 1987), and M-quantiles (Breckling and Chambers, 1988). All these tools for analyzing the regression based on the selected variables can be referred to as generalized quantile regressions for those which are widely used in different disciplines. This procedure is also useful to estimate the parameters at different points of the spillover effects of human capital on investment through minimizing the biases resulting from the current outliers.

In contrast to the estimators obtained by the implementation of the standard least-squares method, the estimators of quantile regression can be assumed as more efficient if the error terms are not white noise. Meanwhile, the estimates, in case of using conventional regression analysis, produce the average effect of the explanatory variables on the dependent variable, which may lead to unbiased results. In that vein, this study considers the quantile regression to estimate the linear models, which provides two advantages. First, the quantile findings are supposed to be robust to outliers (Buchinsky, 1994). Second, the quantile regression consists of the entire conditional distribution of the response variable (Coad and Rao, 2011). In addition to the above advantages, we also consider two assumptions. The first one is related to the error terms which are defined as not being identically distributed for the entire conditional distribution. On the other hand, the slope parameters are not constant for different quantiles of the conditional distribution. In that vein, the quantile regression is represented as follows (Koenker and Bassett, 1978):

$$y_{it} = x_{it}\beta_{\theta} + u_{\theta it} \tag{12}$$

and

$$Quant_{\tau}\left(y_{it} / x_{it}\right) = x_{it}\beta_{\tau} \tag{13}$$

where y is the response variable, x is a vector of regressors, β is the vector of estimated parameters, and u is a vector of residuals. $Quant_{\tau}\left(y_{it} / x_{it}\right)$ denotes the τ^{th} conditional quantile of y given x. Based on this method, the empirical specification applies the generalized quantile regression approach initiated by Powell (2017), which introduces the additional covariates for measuring the changes in the estimated coefficient on the treatment variable to assess whether it is considered valid. The conditional distribution for the natural logarithmic form of the dependent variable can be specified for τ^{th} quantile ($0 < \tau < 1$) of a given set of explanatory variables X_{it} as follows:

$$Q_{\tau}\left\{\frac{lnHC_{it}}{X_{it}}\right\} = \alpha_{\tau} + \beta_{\tau}X_{it} + \alpha_{\tau}\left(1 + v_{it}\right) \tag{14}$$

where $lnHC_{it}$ identifies the natural logarithmic form of a human capital index of country i for time t and X_{it} is the vector of explanatory variables. v_{it} represents the unobserved factors. The parameters are also obtained by the minimization of the absolute value of the residuals. Eq. (15) shows the objective function:

$$Q_{\tau}\left(\beta_{\tau}\right) = \min_{\beta}\sum_{i=1}^{n}\left[\left|lnHC_{it} - \beta_{\tau}X_{it}\right|\right] \tag{15}$$

In consideration of the minimization process for an absolute value of the residuals, the following methodologies can be produced in the empirical framework for quantile regression. First, Koenker (2004) utilizes the shrinkage method to estimate the vector of fixed effects. Second, Canay (2011) produces a new method in the presence of using two-step process to estimate panel quantile regression models with fixed effects. Third, Powell (2016) yields alternative fixed effects quantile estimators through the inclusion of individual fixed effects, which change the context of the estimated coefficient on the treatment variable.

In this study, the quantile regression model for panel data is estimated with nonadditive fixed effects which further obtains nonseparable disturbance term commonly related to quantile estimation (Baker et al., 2016). By using the dataset, which is provided in the previous section 3.1, we estimate the panel quantile regression model by the following accumulation of skills and knowledge function in Eq. (16):

$$lnGFC_{it} = \beta_0 + \beta_1 lnHC_{it} + \beta_2 lnCS_{it} + \beta_3 lnUNEMP_{it} + \beta_4 lnUNION_{it} + u_{it} \quad (16)$$

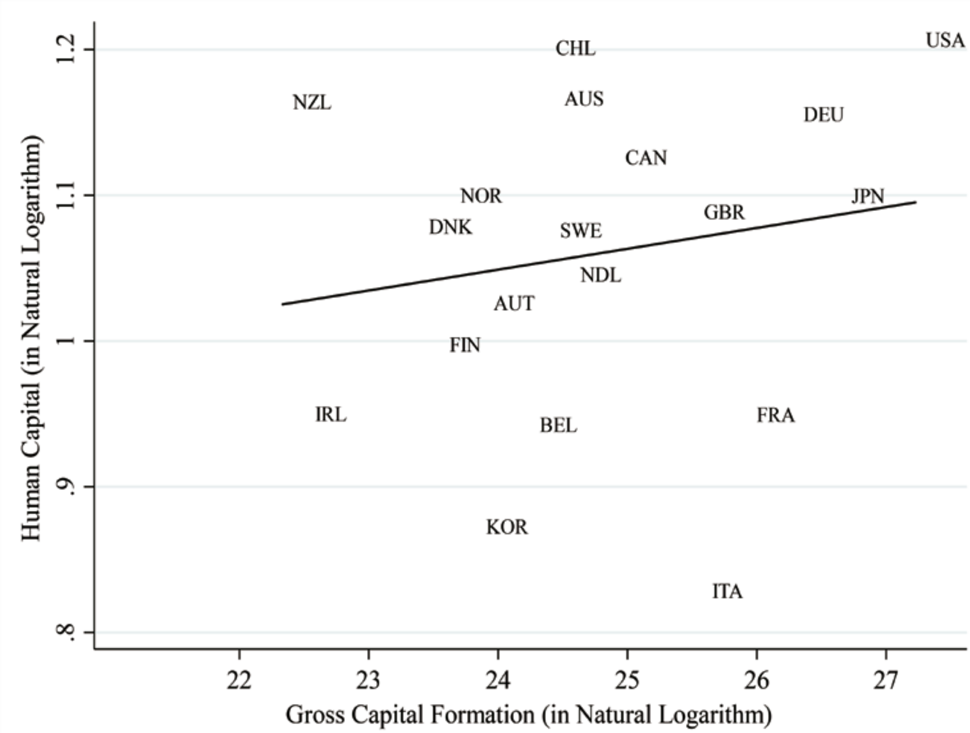
where $lnHC_{it}$ is the degree of human capital index, $lnGFC_{it}$ is the gross capital formation (% of GDP), $lnCS_{it}$ is the share of consumption expenditure (% of GDP), $lnUNEMP_{it}$ is the unemployment rate (% of total labor), and $lnUNION_{it}$ is the trade union density (%). All variables are measured in natural logarithmic form.

Table 2 represents the descriptive statistics of the variables which of those are employed in the empirical estimation. Moreover, Figure 1 presents the human capital-gross capital formation nexus for the period 1980-2017. In the next section, we summarize the empirical findings on the basis of several quantile regression approach.

Table 2: Descriptive Statistics

	Min.	**Max.**	**Mean**	**Median**	**Variance**	**Skewness**	**Kurtosis**
lnGFC	22.15	29.02	25.47	25.36	1.951	0.191	2.657
lnHC	0.829	1.324	1.162	1.177	0.009	-0.663	3.089
lnCS	3.313	4.273	3.992	4.030	0.023	-1.233	5.584
lnUNEMP	-1.609	2.894	1.778	0.555	0.309	-1.319	7.737
lnUNION	2.140	4.577	3.449	3.477	0.378	-0.224	2.163

Figure 1: Human Capital-Gross Capital Formation Nexus, 1980-2017



Note: The country abbreviations are as follows: AUS: Australia, AUT: Austria, BEL: Belgium, CAN: Canada, DNK: Denmark, FIN: Finland, FRA: France, DEU: Germany, IRL: Ireland, ITA: Italy, JPN: Japan, KOR: Republic of Korea, NDL: Netherlands, NZL: New Zealand, NOR: Norway, SWE: Sweden, CHL: Switzerland, GBR: United Kingdom, USA: United States of America. These countries also depict the selected sample of 19 OECD countries that we use in the empirical analysis.

Empirical Findings

Our purpose is to estimate Eq. (16) using the quantile regression approach. In that sense, for comparison purposes, we first report two different nonparametric regression models, including simultaneous quantile regression (SQREG) and bootstrapped quantile regression (BSQREG). While SQREG produces the same coefficients as standard quantile regression for each quantile by obtaining an estimate of standard errors via bootstrapping in case of between-quantile blocks, BSQREG is equivalent to SQREG with one quantile by considering that the data are conditionally heteroskedastic. However, each of these two methods provides a bootstrapped estimate of the entire variance-covariance matrix of the estimators. Also, they obtain standard errors by randomly resampling the data. In Table 3, we show the results for simultaneous quantile regression with bootstrapped standard errors (Koenker, 2005). As expected, human capital spillovers affect positively the gross capital formation of industrial economies at all quantiles of the conditional distribution.

Meanwhile, the estimation results show that the other variables (i.e., consumption share, unemployment rate, and trade union density) are statistically significant at almost all quantiles and cohere with the hypothesized propositions. For example, the positive sign coefficient of the unemployment rate implies that a higher rate of that indicator strengthens the bargaining power of capital by way of having more power on the threat of lowering the wages.

Also, in parallel to this result, the negative sign coefficient of trade union density indicates to the case that a higher rate of unionization empowers the workers' conditions along with a considerable degree of right to impact the production structure. Besides, an increase in the share of consumption promotes a higher level of investment. All in all, the empirical outputs identify a significant heterogeneity of human capital spillovers across quantiles: the highest value of spillovers is mostly captured at quartiles between the 10th and 40th.

Table 3: Simultaneous Quantile Regression with Bootstrapped Standard Errors: SQREG Results

	Dependent variable: lnGFC								
	τ=10th	τ=20th	τ=30th	τ=40th	τ=50th	τ=60th	τ=70th	τ=80th	τ=90th
lnHC	5.38*** (0.78)	5.98*** (0.63)	6.34*** (0.65)	5.82*** (0.59)	5.84*** (0.50)	5.56*** (0.41)	5.80*** (0.55)	2.55* (1.47)	1.39*** (0.45)
lnCS	-1.28*** (0.31)	0.04 (0.32)	0.58** (0.26)	1.22*** (0.36)	1.68*** (0.36)	1.80*** (0.43)	2.44*** (0.54)	1.84*** (0.47)	1.42*** (0.37)
lnUNEMP	0.17** (0.08)	0.30*** (0.06)	0.33*** (0.07)	0.34*** (0.07)	0.29*** (0.11)	0.18 (0.17)	-0.15 (0.19)	-0.17 (0.13)	-0.31* (0.17)
lnUNION	-1.12*** (0.14)	-1.03*** (0.12)	-1.09*** (0.05)	-1.15*** (0.06)	-1.17*** (0.06)	-1.15*** (0.05)	-1.13*** (0.06)	-1.41*** (0.16)	-1.49*** (0.11)
Constant	26.66*** (2.15)	20.68*** (1.36)	18.51*** (1.37)	17.03*** (1.75)	15.52*** (1.36)	15.69*** (1.47)	13.65*** (1.81)	21.29*** (3.55)	25.15*** (1.80)
Pseudo-R^2	0.2539	0.2756	0.3110	0.3292	0.3428	0.3576	0.3636	0.3638	0.4199
No. of obs.	722	722	722	722	722	722	722	722	722

Note: Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10. The bootstrap replications are selected as 100.

Table 4 also shows the bootstrapped quantile regression results in which the coefficients are the same, but the standard errors are changed in all estimations. As the empirical findings indicate that our hypotheses are still validated by using the BSQREG method.

In order to admit statistical variation of coefficients in consideration of the conditional distribution of *lnGFC*, we also draw the quantile regression coefficients and confidence intervals for each regressor and the constant term in Figure 2. The horizontal lines describe the OLS point estimates and confidence interval, respectively. The second plot depicts the human capital spillovers in which the estimated coefficient is positive, indicating that lower quantiles have much higher effects on the level of investment. Also, Figure 3 shows the hanging rootogram to compare an empirical distribution to a theoretical distribution (Tukey, 1965, 1972; Wainer, 1974; Friendly, 2000).

Table 4: Bootstrapped Quantile Regression: BSQREG Results

	Dependent variable: lnGFC								
	τ=10th	τ=20th	τ=30th	τ=40th	τ=50th	τ=60th	τ=70th	τ=80th	τ=90th
lnHC	5.38*** (0.82)	5.98*** (0.60)	6.34*** (0.70)	5.82*** (0.54)	5.84*** (0.52)	5.56*** (0.39)	5.80*** (0.49)	2.55* (1.41)	1.39*** (0.40)
lnCS	-1.29*** (0.32)	0.04 (0.31)	0.58*** (0.22)	1.22*** (0.31)	1.68*** (0.34)	1.80*** (0.35)	2.44*** (0.53)	1.84*** (0.39)	1.42*** (0.40)
lnUNEMP	0.17** (0.08)	0.30*** (0.07)	0.33*** (0.07)	0.34*** (0.08)	0.29*** (0.11)	0.18 (0.17)	-0.15 (0.19)	-0.17 (0.12)	-0.31* (0.16)
lnUNION	-1.12*** (0.17)	-1.03*** (0.10)	-1.09*** (0.05)	-1.15*** (0.06)	-1.17*** (0.07)	-1.15*** (0.05)	-1.13*** (0.07)	-1.41*** (0.16)	-1.49*** (0.11)
Constant	26.66*** (2.43)	20.68*** (1.48)	18.51*** (1.36)	17.03*** (1.43)	15.52*** (1.20)	15.69*** (1.16)	13.65*** (1.96)	21.29*** (3.28)	25.15*** (1.80)
Pseudo-R^2	0.2539	0.2756	0.3110	0.3292	0.3428	0.3576	0.3636	0.3638	0.4199
No. of obs.	722	722	722	722	722	722	722	722	722
Raw sum. dev.	168.1	270.3	340.4	385.1	404.9	402.4	367.4	293.3	184.9

Note: Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10. The bootstrap replications are selected as 100.

Figure 2: Quantile Regression Coefficients and Confidence Intervals

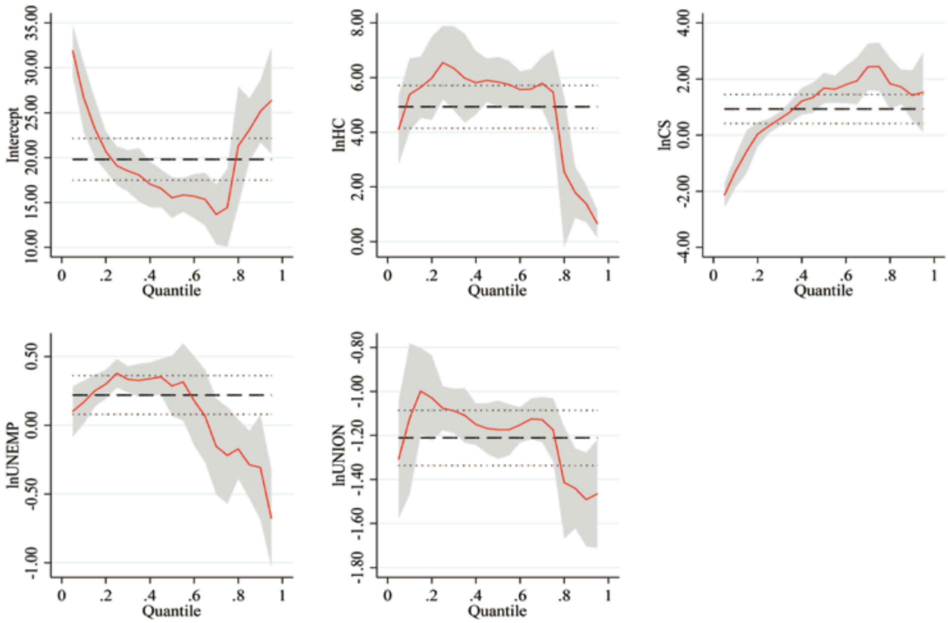
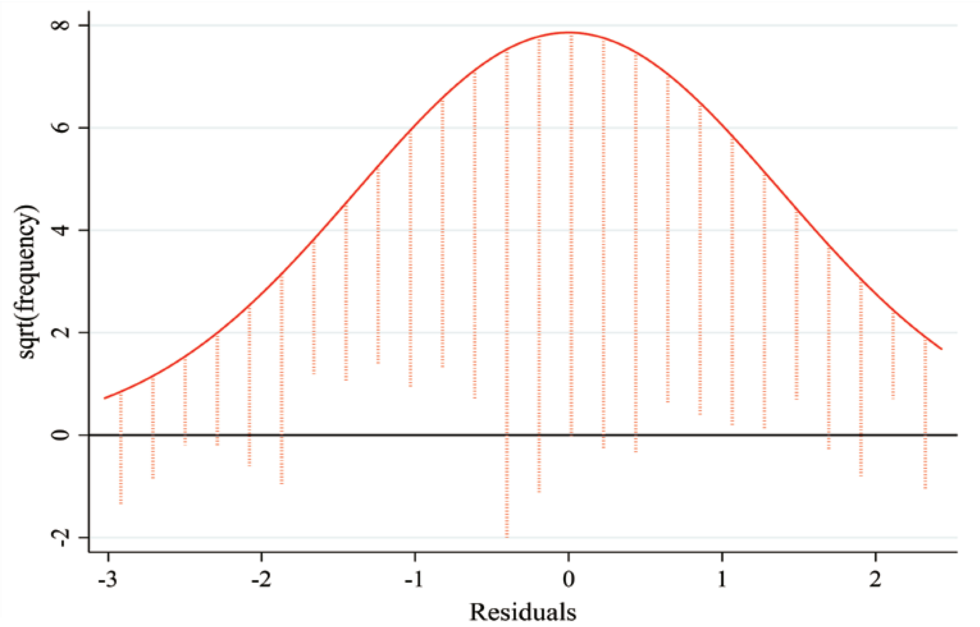


Figure 3: Hanging Rootogram



Moreover, we implement Wald tests of simple and composite linear hypotheses about the parameters of the fit models obtained by the simultaneous quantile regression with bootstrapped standard errors. The major reason to perform Wald statistical test is to control that coefficients on the human capital variable have the same value. The Wald-statistic and its corresponding p-value is represented in Table 5. The null hypothesis of coefficient equality is rejected at the 1% significance level, indicating that the coefficients vary across different quantiles.

Table 5: Wald Test of Coefficient Equality

Test Result	***p*-value**
$F\,(3, 717) = 269.25$	Prob $> F = 0.0000$

While the statistical variation of coefficients is statistically confirmed for the conditional distribution of human capital spillovers, the intra-cluster correlation should be identified in regard to data sampled from independent and identically distributed clusters by using the Parente-Santos Silva testing procedure (Parente and Silva, 2016).

To test the intra-cluster correlation, we apply quantile regression with robust and clustered standard errors method (QREG2). The results of this test show that the intra-cluster correlation is not statistically significant. Therefore, the quantile estimator could be assumed as consistent and efficient. Table 6 summarizes the QREG2 method estimations along with the results of the intra-cluster correlation test.

As represented in Table 6, the estimation results of quantile regression with robust and clustered standard errors statistically validate the previous spillover effects of human capital on investment and they are robust regarding the intra-cluster correlation. Finally, the simultaneity of decision processes leads us to examine the endogeneity problem of all the models.

Table 6: Quantile Regression with Robust and Clustered Standard Errors: QREG2 Results

	Dependent variable: lnGFC								
	τ=10th	τ=20th	τ=30th	τ=40th	τ=50th	τ=60th	τ=70th	τ=80th	τ=90th
lnHC	5.38*** (0.39)	5.98*** (0.58)	6.34*** (0.56)	5.82*** (0.51)	5.84*** (0.48)	5.56*** (0.47)	5.80*** (0.45)	2.55*** (0.84)	1.39*** (0.42)
lnCS	-1.28*** (0.30)	0.04 (0.29)	0.58** (0.28)	1.22*** (0.30)	1.68*** (0.32)	1.80*** (0.38)	2.44*** (0.31)	1.84*** (0.35)	1.42*** (0.33)
lnUNEMP	0.17*** (0.06)	0.30*** (0.05)	0.33*** (0.07)	0.34*** (0.08)	0.29*** (0.10)	0.18 (0.17)	-0.15 (0.10)	-0.17 (0.15)	-0.31** (0.13)
lnUNION	-1.12*** (0.11)	-1.03*** (0.09)	-1.09*** (0.06)	-1.15*** (0.05)	-1.17*** (0.06)	-1.15*** (0.06)	-1.13*** (0.04)	-1.41*** (0.13)	-1.49*** (0.11)
Constant	26.66*** (1.56)	20.68*** (1.30)	18.51*** (1.38)	17.03*** (1.34)	15.52*** (1.22)	15.69*** (1.25)	13.65*** (1.12)	21.29*** (2.60)	25.15*** (1.90)
Pseudo-R^2	0.4435	0.4907	0.4983	0.5045	0.5029	0.5027	0.4826	0.4687	0.4345
No. of obs.	722	722	722	722	722	722	722	722	722
Obj. function	0.1738	0.2712	0.3248	0.3578	0.3686	0.3581	0.3286	0.2585	0.1486
Intra-cluster correlation	0.111 (0.912)	0.250 (0.803)	-1.000 (0.317)	-1.000 (0.317)	-1.000 (0.317)	-1.000 (0.317)	0.429 (0.668)	0.250 (0.803)	0.111 (0.912)

Note: Robust and clustered standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10. The objective function and intra-cluster correlation test results are also integrated into the table.

Thus, we estimate the generalized quantile regression for panel data (Powell, 2014, 2016; Baker et al., 2016) in Table 7. The lagged values of the explanatory variables are implemented as instruments to solve the endogeneity problem. All in all, the empirical results of each selected quantile show that they are also coherent with the previous ones and thus imply that the robustness checks verify the human capital spillover effects on the level of investment.

Table 7: Generalized Quantile Regression: QREGPD Results

	Dependent variable: lnGFC								
	τ=10th	τ=20th	τ=30th	τ=40th	τ=50th	τ=60th	τ=70th	τ=80th	τ=90th
lnHC	5.74*** (0.76)	5.98*** (1.24)	6.33*** (0.61)	5.91*** (0.57)	6.15*** (0.52)	5.78*** (0.51)	6.17*** (0.53)	2.86*** (0.92)	1.39*** (0.50)
lnCS	-1.25*** (0.33)	9.72*** (2.40)	0.55 (0.34)	1.20*** (0.36)	1.83*** (0.35)	1.81*** (0.38)	2.45*** (0.32)	1.82*** (0.38)	1.42** (0.63)
lnUNEMP	0.21** (0.08)	0.30*** (0.11)	0.36*** (0.07)	0.28** (0.11)	0.28** (0.12)	0.19 (0.16)	-0.15 (0.14)	-0.19 (0.18)	-0.31 (0.23)
lnUNION	-1.20*** (0.15)	-1.03*** (0.21)	-1.08*** (0.07)	-1.17*** (0.06)	-1.17*** (0.06)	-1.16*** (0.06)	-1.14*** (0.05)	-1.39*** (0.15)	-1.49*** (0.18)
Constant	26.28*** (2.42)	-18.54* (10.22)	18.56*** (1.71)	17.15*** (1.55)	14.52*** (1.39)	15.44*** (1.37)	13.19*** (1.20)	20.97*** (2.99)	25.15*** (3.12)
No. of obs.	722	722	722	722	722	722	722	722	722

Note: The standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.10. Instruments are the first and second lagged values of explanatory variables: lnLHC(-1), lnLHC(-2), lnLCS(-1), lnLCS(-2), lnLUNEMP(-1), lnLUNEMP(-2), lnLUNION(-1), lnLUNION(-2).

Conclusion

In this study, an attempt is considered to test the proposition put forth by the current literature on the existence of spillovers effect of human capital on the level of gross capital formation that there might be huge differences in various quantiles. Thus, in order to carry our analysis, we implement several econometric techniques on a balanced panel of 722 observations across the selected 19 OECD member countries for the period 1980-2017. In particular, to largely account for the human capital spillover effect, we benefit from the PWT 9.1 dataset for that variable, which consists of both returns to education and years of schooling. Also, in order to test the whole structure of investment, the level of gross capital formation is used, which is obtained from the World Bank, WDI database.

In that vein, we investigate the relationship between the level of investment and human capital spillovers in consideration of applying quantile regression techniques to test whether such a relationship varies along with the human capital distribution. First, we run two close approaches: (i) a quantile regression model bootstrapped standard errors (SQREG) (Koenker, 2005) and (ii) bootstrapped quantile regression (BSQREG) (Hahn, 1995). Second, we also implement a quantile regression with asymptotically robust under heteroskedasticity and intra-cluster correlation (Machado et al., 2011; Parente and Silva, 2016). Finally, we also deal with the endogeneity problem in estimated models, by applying generalized quantile regression for panel data (Powell, 2014, 2016; Baker et al., 2016).

In order to test the given linkage among the variables, the core presumption depends on the change in the degree of bargaining power of workers. Therefore, we use two indicators to measure the effect of bargaining power, i.e., the unemployment rate and the trade union density. On the one hand, an increase in the unemployment rate might lead to an increase in the level of investment since the firms could have more power to reduce costs by repressing the workers to accept their implemented wages. On the other hand, a lower rate of unionization decreases the bargaining power of workers on the contracts and thereby reduces their fallback option against the capital. In consideration of these theoretical backgrounds, the empirical findings show that human capital spillovers have a positive impact on the gross capital formation in line with the assumptions towards the effects of bargaining power of workers. In particular, such effect has a bell-shaped pattern along with the human capital conditional distribution, suggesting that the countries whose degree of human capital ranges between the values from 10% to 40% indicating that they are more prone to acquire higher returns from human capital spillovers, whereas the returns are found to be lower from the higher quantiles. All in all, the overall results imply that the heterogeneity in human capital spillovers over the level of investment is widely accepted across the selected 19 OECD countries over the period 1980-2017, implying that the policies should be redesigned in consideration of aiming at the inclusion of a higher part of social segments for having higher attainment in education.

Declarations

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflicts of interest/Competing interests

There is no conflict of interest/Competing interests

Availability of data and material

The data that support the findings of this study are openly available in the website of World Bank (www.worldbank.org), Penn World Tables (https://www.rug.nl/ggdc/productivity/pwt/?lang=en), and OECD Statistics (https://stats.oecd.org/).

Code Availability

The computer program results are shared through the tables in the manuscript.

The author can send the codes upon request.

Authors' Contributions

Not applicable.

REFERENCES

Abbott, B., & Gallipoli, G. (2017). Human capital spillovers and the geography of intergenerational mobility. Review of Economic Dynamics, 25: 208-233.
Acemoglu, D. A. (1996). A microfoundation for social increasing returns in human capital accumulation. The Quarterly Journal of Economics, 111(3): 779-804.
Aghion, P., & Jaravel, X. (2015). Knowledge spillovers, innovation and growth. The Economic Journal, 125(583): 533-573.
Aldieri, L., & Vinci, C. P. (2017). Quantile regression for panel data: An empirical approach for knowledge spillovers endogeneity. International Journal of Economics and Finance, 9(7): 106-113.
Apergis, N., Economidou, C., & Filippidis, I. (2009). International technology spillovers, human capital and productivity linkages: Evidence from the industrial sector. Empirica, 36: 365-387.
Audretsch, D. B., & Belitski, M. (2020). The role of R&D and knowledge spillovers in innovation and productivity. European Economic Review, 123: 103391.
Badinger, H., Egger, P. H., & von Ehrlich, M. (2015). Productivity growth, human capital and technology spillovers: Nonparametric evidence for EU regions. Oxford Bulletin of Economics and Statistics, 81(4): 768-779.
Baker, M., Powell, D., & Smith, T. A. (2016). QREGPD: Stata module to perform Quantile Regression for Panel Data. Statistical Software Components S458157. Boston College Department of Economics.
Bar, T., & Leiponen, A. (2012). A measure of technological distance. Economics Letters, 116: 457-459.
Belfield, C. R., Battu, H., & Sloane, P. J. (2004). Human capital spillovers in the workplace: Evidence for the service sector in Britain. International Journal of Manpower, 25(1): 123-138.
Benos, N., & Karagiannis, S. (2016). Do education quality and spillovers matter? Evidence on human capital and productivity in Greece. Economic Modelling, 54: 563-573.
Breckling, J., & Chambers, R. (1988). M-quantiles. Biometrika, 74(4): 761-772.
Buchinsky, M. (1994). Changes in the U.S. wage structure 1963-1987: Application of quantile regression. Econometrica, 62(2): 405-458.
Cabrales, C. A. (2011). Human capital externalities and growth. Ensayos sobre Politica Economica, 29(66): 15-47.
Canay, I. A. (2011). A simple approach to quantile regression for panel data. The Econometrics Journal, 14(3): 368-386.
Ciccone, A., & Peri, G. (2006). Identifying human-capital externalities: Theory with applications. Review of Economic Studies, 73: 381-412.
Coad, A., & Rao, R. (2011). The firm-level employment effects of innovations in high-tech US manufacturing industries. Journal of Evolutionary Economics, 21: 255-283.
Damijan, J. P., Jaclič, A., & Rojec, M. (2006). Do external knowledge spillovers induce firms' innovations? Evidence from Slovenia. In: Tavares, A. T., Teixeira, A. (eds.), Multinationals, Clusters and Innovation, London: Palgrave Macmillan.
Diwakar, B., & Sorek, G. (2017). Human-capital spillover, population and R&D-based growth. The B.E. Journal of Macroeconomics, 17(1): 1-17.
Feenstra, R. C., Inklaar, R., & Timmer, M. P. (2015). The next generation of the Penn World Table. American Economic Review, 105(10): 3150-3182.

Friendly, M. (2000). Visualizing categorical data. Cary: SAS Institute.

Gelman, A., & Hill, J. (2007). Data analysis using regression and multilevel/hierarchical models. Cambridge, New York: Cambridge University Press.

Griliches, Z. (1992). The search for R&D spillovers. The Scandinavian Journal of Economics, 94: S29-S47.

Hahn, J. (1995). Bootstrapping quantile regression estimators. Econometric Theory, 11(1): 105-121.

Hamid, A., & Pichler, J. H. (2009). Human capital spillovers, productivity and growth in the manufacturing sector of Pakistan. The Pakistan Development Review, 48(2): 125-140.

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value. American Economic Review, 76: 984-1001.

Jones, C. I., & Vollrath, D. (2013). Introduction to economic growth. 3rd edition, New York and London: W. W. Norton & Company.

Jovanovic, B., & Rob, R. (1989). The growth and diffusion of knowledge. Review of Economic Studies, 56(4): 569-582.

Koenker, R. (2004). Quantile regression for longitudinal data. Journal of Multivariate Analysis, 91(1): 74-89.

Koenker, R. (2005). Quantile regression. New York: Cambridge University Press.

Koenker, R., & Bassett, G. (1978). Regression quantiles. Econometrica, 46: 33-50.

Lucas, R. (1988). On the mechanics of economic development. Journal of Monetary Economics, 22(1): 3-42.

Machado, J., Parente, P., & Silva, J. S. (2011). Qreg2: Stata module to perform quantile regression with robust and clustered standard errors. Statistical Software Components, Boston College Department of Economics.

Malley, J., & Woitek, U. (2019). Estimated human capital externalities in an endogenous growth framework. Working Papers 2019_04, Business School-Economics, University of Glasgow.

Metcalfe, R., & Sloane, P. J. (2007). Human capital spillovers and economic performance in the workplace in 2004: Some British evidence. IZA Discussion Paper Series, IZA DP No. 2774.

Moretti, E. (2002). Human capital spillovers in manufacturing: Evidence from plant-level production functions. Working Papers 02-27, Center for Economic Studies, U.S. Census Bureau.

Moretti, E. (2004). Estimating the social return to higher education: Evidence from longitudinal and repeated cross-section data. Journal of Econometrics, 121: 175-212.

Newey, W. K., & Powell, J. L. (1987). Asymmetric least squares estimation and testing. Econometrica, 55: 819-847.

O'Mahony, M. (2012). Human capital formation and continuous training: Evidence for EU countries. Review of Income and Wealth, 58(3): 531-549.

Parente, P. M. D. C., & Silva, J. M. C. S. (2016). Quantile regression with clustered data. Journal of Econometric Methods, 5: 1-15.

Park, W. (2012). Does human capital spillover beyond plant boundaries? Evidence from Korea. (Unpublished paper), Columbia University.

Powell, D. (2014). Did the economic stimulus payments of 2008 reduce labor supply? Evidence from quantile panel data estimation. RAND Labor and Population Working Paper 710-3.

Powell, D. (2016). Quantile regression with nonadditive fixed effects. RAND Labor and Population Working Paper Available online: https://pdfs.semanticscholar.org/b2be/fdf37fa0d-1faa88675e085e54584c4072e4a.pdf.

Powell, D. (2017). Quantile treatment effects in the presence of covariates. RAND Labor and Population Working Paper. Available online: https://works.bepress.com/david_powell/4/download/.

Ramos, P., Suriñach, J., & Artís, M. (2010). Human capital spillovers, productivity and regional convergence in Spain. Papers in Regional Science, 89(2): 435-447.

Rauch, J. E. (1993). Productivity gains from geographic concentration of human capital: Evidence from the cities. Journal of Urban Economics, 34(3): 380-400.

Romer, P. M. (1986). Increasing returns and long-run growth. Journal of Political Economy, 94(5): 1002-1037.

Romer, P. (1994). The origins of endogenous growth. Journal of Economic Perspectives, 8: 3-22.

Rosenthal, S., & Strange, W. (2008). The attenuation of human capital spillovers. Journal of Urban Economics, 64(2): 373-389.

Serrano, G., & Cabrer, B. (2004). The effect of knowledge spillovers on productivity growth inequalities in Spanish regions. Environment and Planning A: Economy and Space, 36(4): 731-753.

Sloane, P. J., Battu, H., & Belfield, C. (2003). Human capital spillovers within the workplace: Evidence for Great Britain. Oxford Bulletin of Economics and Statistics, 65(5): 575-594.

Thönnessen, R., & Gundlach, E. (2013). The size of human capital externalities: Cross-country evidence. Public Choice, 157(3/4): 671-689.

Tukey, J. W. (1965). The future of processes of data analysis. Reprinted in: Jones, L.V. (ed.) 1986. The collected works of John W. Tukey. Volume IV: Philosophy and principles of data analysis: 1965-1986. Monterey, CA: Wadsworth and Brooks/Cole, 517-547.

Tukey, J. W. (1972). Some graphic and semigraphic displays. In: Bancroft, T. A. and Brown, S. A. (eds.), Statistical papers in honor of George W. Snedecor, Ames: Iowa State University Press.

Verspagen, B. (1997). Measuring intersectoral technology spillovers: Estimates from the European and US patent office databases. Economic Systems Research, 9: 47-65.

Wainer, H. (1974). The suspended rootogram and other visual displays: An empirical validation. The American Statistician, 28(4): 143-145.