# Chapter 2

## Theory and Literature Review

### 2.1 Theory

In this section, all related theories will be classified into two groups: economic theory and econometric theory.

#### 2.1.1 Economic Theory

There have been two periods of intense work on growth theory, the first in the late 1950s and the 1960s and the second, in the late 1980s and early 1990s. Research in the first period is mainly based on neoclassical growth theory. Neoclassical growth theory focuses on capital accumulation and its link to saving decisions, while endogenous growth theory focuses on the determinants of technological progress (Dornbusch et al., 2011).

##### 2.1.1.1 Neoclassical Growth Theory

In the 1950s, MIT economist Robert Solow presented a new model of economic growth which replaced the fixed-coefficients production function with a neoclassical production function. The form of the production function is as follows:

$$Y(t) = F(\ K(t), L(t)\ ) \tag{2.1}$$

which possess the three following properties:

Positive and diminishing marginal products with respect to each input:

$$\frac{\partial Y(t)}{\partial K(t)} > 0, \frac{\partial Y^2(t)}{\partial K^2(t)} < 0, \qquad \frac{\partial Y(t)}{\partial L(t)} > 0, \frac{\partial Y^2(t)}{\partial L^2(t)} < 0,$$
$$\forall K > 0 \ and\ \forall L > 0 \tag{2.2}$$

2) Constant returns to scale:

$$\lambda Y(t) = F\big(\lambda K(t), \lambda L(t)\big), \forall \lambda > 0 \tag{2.3}$$

3) Inada conditions

$$\lim_{K\to 0}(F_K) = \lim_{L\to 0}(F_L) = \infty$$

$$\lim_{K\to \infty}(F_K) = \lim_{L\to \infty}(F_L) = 0$$

(2.4)

Neoclassical growth theory starts with a simplifying assumption. In the beginning, it pretends that there is no technological progress. This implies that the economy reaches a long-run level of output and capital which called the steady-state equilibrium (where per capita economic variables are no longer changing, $\Delta y = 0$ and $\Delta k = 0$). There are three broad steps proceeded by the neoclassical growth theory. First, the theory shows how various economic variables determine the economy's steady state. Second, it shows the transition from the economy's current position to this steady state. Finally, technological progress has been added into the model, when the productivity growth happened, if there is a steady state, the steady-state growth rate of output remains exogenous. The steady-state growth rate of per capita income is determined by the rate of technical progress. While the steady-state growth rate of aggregate output is the sum of the rate of technical progress and population growth rate (Dornbusch et al., 2011).

Neoclassical growth theory concludes that long-run rate of growth does not depend on the saving rate but results from improvements in technology. An economy will always converge towards a steady state rate of growth, which depends only on the rate of technological progress and the rate of labor force growth. The limitations of the model include its failure to take account of entrepreneurship and strength of institutions. Besides, it does not explain how or why technological progress occurs. These failures lead to the development of endogenous growth theory, which endogenous technological progress and knowledge accumulation.

#### 2.1.1.2 Endogenous Growth Theory

Endogenous growth theory assumes that long-run growth rate of output is determined by variables within the model, not an exogenous rate of technological progress as in a neoclassical model (Dornbusch et al., 2011).

Endogenous growth model modified the production function in a way that allows for self-sustaining growth. The model assumes a production function with a constant marginal product of capital and with capital as the only one factor. Specifically, let

$$Y = aK \tag{2.5}$$

That is, output is proportional to the capital stock. The marginal product of capital is simply the constant $a$. Assume the saving rate is constant at s, and there is neither population growth nor depreciation of capital. Then all saving goes to increase the capital stock. Accordingly,

$$K = sY = saK \tag{2.6}$$

or

$$\Delta K/K = sa \tag{2.7}$$

The growth of capital is proportional to the saving rate. Further, since the output is proportional to capital, the growth rate of output is

$$\Delta Y/Y = sa \tag{2.8}$$

In this example, the higher the saving rate, the higher growth rate of output (Dornbusch et al., 2011).

The key to this endogenous model is the inexistence of diminishing returns to the inputs. Hence the return to investment in endogenous model is a constant. Economic growth in the most developed countries depends on the rate of technological progress. According to endogenous growth model, technological progress depends on saving, particularly investment directed towards human capital (Dornbusch et al., 2011).

**2.1.2 Econometric Theory**

In this section, panel data analysis will be reviewed. Panel unit root tests, panel cointegration tests, panel dynamic ordinary least squares (DOLS) estimation as well as panel Granger causality tests associated with vector error correction model (VECM) will be employed to test the relationship among the variables.

**2.1.2.1 Panel Data Analysis**

A longitudinal, or panel, data set is one that follows a given sample of individuals over time, and thus provides multiple observations on each individual in the sample (Hsiao, 2003). Panel data models have become increasingly popular among empirical studies due to the high capacity for capturing the complexity compared to cross-sectional or time-series data models. In other words, panel data can enrich empirical analysis in ways that may not be possible if we use only cross-sectional or time series data.

A general linear panel model can be written as follows:

$$y_{it} = \alpha_i + X'_{it}\beta_{it} + \varepsilon_{it} \qquad i = 1,\ldots,N;\ t = 1,\ldots,T \tag{2.9}$$

where the subscript *i* denotes the cross-sectional dimension whereas *t* denotes the time-series dimension. $y_{it}$ represents the dependent variable, $\alpha_i$ is a scalar, $X_{it}$ represents the independent variable, $\beta_{it}$ is the coefficient term, and $\varepsilon_{it}$ is residual term. If each cross-sectional unit has the same number of time series observations, then we call it balanced panel, if the number of observations differs among panel members, we call such a panel as unbalanced panel (Baltagi, 2008).

**2.1.2.2 Panel Unit Root Tests**

Panel unit root tests emerged from time series unit root tests. The major difference to time series unit root tests is that asymptotic behavior of time-series dimension *T* and the cross-sectional dimension *N* has to be considered. The way in which *N* and *T* converge to infinity is critical for determining the asymptotic behavior of estimators and tests used for non-stationary panel (Kunst, 2011). Recent literature suggests that panel-based unit root tests are more efficient compared with unit root tests based on individual time series. There are five types of panel unit root tests which are quite popular currently: Levin, Lin and Chu (2002) test, Breitung (2000) test, Im, Pesaran and Shin (2003) test, Fisher-type tests using ADF and PP tests (Maddala and Wu (1999) and Choi (2001)), and Hadri (2000) test.

Consider a following AR (1) process for panel data:

$$y_{it} = \rho_i y_{it-1} + X_{it}\delta_i + \epsilon_{it} \tag{2.10}$$

where $i = 1, 2, \ldots, N$ cross-section units or series, that are observed over periods $t = 1, 2, \ldots T$. The $X_{it}$ represents the exogenous variable in the model, including any fixed effects or individual trends, $\rho_i$ is the autoregressive coefficient, and $\epsilon_{it}$ is the error term which assumed to be mutually independent idiosyncratic disturbance. If $|\rho_i| < 1$, $y_{it}$ is said to be weakly (trend-) stationary. On the other hand, if $|\rho_i| = 1$ then $y_{it}$ contains a unit root (Eviews 7 Help Topic).

Fisher-type unit root tests (Maddala and Wu, 1999, and Choi, 2001) are employed in the study since they have ability to handle unbalanced panel data. Fisher-type tests have been proposed by Maddala, Wu and Choi by using Fisher's (1932) results to derive tests that combine the p-values from individual unit root tests.

Define $\pi_i$ as the *p*-value from any individual unit root test for cross-section *i*, under the null of unit root for all *N* cross-sections, we have the asymptotic result that:

$$-2\sum_{i=1}^{N}\log(\pi_i) \rightarrow \chi^2_{2N} \tag{2.11}$$

In addition, Choi demonstrates that:

$$Z = \frac{1}{\sqrt{N}}\sum_{i=1}^{N}\Phi^{-1}\,(\pi_i) \rightarrow N(0,1)$$

(2.12)

where $\Phi^{-1}$ is the inverse of the standard normal cumulative distribution function (Maddala and Wu, 1999, and Choi, 2001; Eviews 7 Help Topic).

**2.1.2.3 Panel Cointegration Tests**

The finding that many macro data may contain a unit root has spurred the development of non-stationary data analysis theory. Engle and Granger (1987) pointed out that a linear combination of two or more non-stationary data may be stationary. If such a stationary linear combination exists, these non-stationary data are said to be cointegrated. The stationary linear combination is called the cointegration equation and may be interpreted as a long-run equilibrium relationship among the variables (Eviews 7 Help Topic). The extensive interest in panel data has led to a focus on tests of cointegration in a panel setting. Two cointegration tests will be employed in this study, Pedroni (1999, 2004) tests and Kao (1999) test.

**1) Pedroni Tests**

Pedroni (2000, 2004) proposed several tests for cointegration in a panel data model that allow for heterogeneous intercepts and trend coefficients across individuals. Consider the following regression:

$$y_{it} = \alpha_i + \delta_i t + \beta_{1i}x_{1i,t} + \beta_{2i}x_{2i,t} + \ \ldots + \beta_{Mi}x_{Mi,t} + e_{i,t}$$

(2.13)

for $t = 1, \ldots, T;\ i = 1, \ldots, N;\ m = 1, \ldots, M;$ where $y$ and $x$ are assumed to be integrated of order one, e.g. I (1). The parameters $\alpha_i$ and $\delta_i$ are individual and trend effects which may be set to zero if desired.

Under the null hypothesis of no cointegration, the residuals $e_{i,t}$ will be I (1). Obtain the residual form Eq. (2.13) and test whether the residuals are I

(1) by running the auxiliary regression,

$$e_{it} = \rho_i e_{it-1} + \upsilon_{it}$$

(2.14)

or

$$e_{it} = \rho_i e_{it-1} + \sum_{j=1}^{p_i} \psi_{ij} \Delta e_{it-j} + \upsilon_{it}$$

(2.15)

for each cross-section. Pedroni describes several methods of constructing statistics for testing for null hypothesis of no cointegration ($\rho_i = 1$). There are two alternative hypotheses: the homogeneous alternative, $(\rho_i = \rho) < 1$ for all $i$ (which Pedroni terms the within-dimension test or panel statistics test), and the heterogeneous alternative, $\rho_i < 1$ for all $i$ (also referred to as the between-dimension or group statistics test).

The Pedroni panel cointegration statistic $\xi_{N,T}$ is conducted form the residuals from either Eq. (2.14) or Eq. (2.15). A total of eleven statistics with varying degree of properties (size and power for different N and T) are generated.

Pedroni showed that the standardized statistic is asymptotically normally distributed,

$$\frac{\xi_{N,T} - \mu\sqrt{N}}{\sqrt{\upsilon}} \Rightarrow N(0,1)$$

(2.16)

where $\mu$ and $\upsilon$ are Monte Carlo generated adjustment terms (Pedroni, 2000, 2004; Eviews 7 Help Topic).

**2) Kao Tests**

Consider the panel regression model

$$y_{it} = x_{it}'\beta + z_{it}' + e_{it}$$

(2.17)

where $y_{it}$ and $x_{it}$ are I (1) and noncointegrated. For $z_{it} = \{\mu_i\}$, Kao (1999) proposed DF and ADF-type unit root tests for $e_{it}$ as a test for the null of no cointegration. The DF-Type tests can be calculated from the fixed effects residuals

$$\hat{e}_{it} = \rho\hat{e}_{it-1} + v_{it} \tag{2.18}$$

where $\hat{e}_{it} = \tilde{y}_{it} - \tilde{x}_{it}\hat{\beta}$ and $\tilde{y}_{it} = y_{it} - \bar{y}_i$. In order to test the null hypothesis for no cointegration, the null can be written as $H_0 = \rho = 1$. The OLS estimate of $\rho$ and $t$-statistic are given as

$$\hat{\rho} = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T}\hat{e}_{it}\hat{e}_{it-1}}{\sum_{i=1}^{N}\sum_{t=2}^{T}\hat{e}_{it}^2} \tag{2.19}$$

and

$$t_\rho = \frac{(\hat{\rho}-1)\sqrt{\sum_{i=1}^{N}\sum_{t=2}^{T}\hat{e}_{it-1}^2}}{s_e} \tag{2.20}$$

where $s_e^2 = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=2}^{T}(\hat{e}_{it} - \hat{\rho}\hat{e}_{it-1})^2$. Kao proposed the following four DF-type tests:

$$DF_\rho = \frac{\sqrt{N}T(\hat{\rho}-1) + 3\sqrt{N}}{\sqrt{10.2}} \tag{2.21}$$

$$DF_t = \sqrt{1.25}t_\rho + \sqrt{1.875N} \tag{2.22}$$

$$DF_\rho^* = \frac{\sqrt{N}T(\hat{\rho}-1) + \frac{3\sqrt{N}\hat{\sigma}_v^2}{\hat{\sigma}_{0v}^2}}{\sqrt{3 + \frac{36\hat{\sigma}_v^4}{5\hat{\sigma}_{0v}^4}}} \tag{2.23}$$

and

$$DF_t^* = \frac{t_\rho + \dfrac{\sqrt{6N}\hat{\sigma}_v}{2\hat{\sigma}_{0v}}}{\sqrt{\dfrac{\hat{\sigma}_{0v}^2}{2\hat{\sigma}_v^2} + \dfrac{3\hat{\sigma}_v^2}{10\hat{\sigma}_{0v}^2}}}$$

(2.24)

where $\hat{\sigma}_v^2 = \hat{\Sigma}_{yy} - \hat{\Sigma}_{yx}\hat{\Sigma}_{xx}^{-1}$ and $\hat{\sigma}_{0v}^2 = \hat{\Omega}_{yy} - \hat{\Omega}_{yx}\hat{\Omega}_{xx}^{-1}$. While $DF_\rho$ and $DF_t$ are based on the strong exogeneity of the regressors and errors, $DF_\rho^*$ and $DF_t^*$ are for the cointegration with endogenous relationship between regressors and errors. For the ADF test, we can run the following regression:

$$\hat{e}_{it} = \tilde{\rho}\,\hat{e}_{it-1} + \sum_{j=1}^{p} \psi_j \Delta\,\hat{e}_{it-1} + v_{itp}$$

(2.25)

With the null hypothesis of no cointegration, the ADF test statistics can be constructed as

$$ADF = \frac{t_{ADF} + \dfrac{\sqrt{6N}\hat{\sigma}_v}{2\hat{\sigma}_{0v}}}{\sqrt{\dfrac{\hat{\sigma}_{0v}^2}{2\hat{\sigma}_v^2} + \dfrac{3\hat{\sigma}_v^2}{10\hat{\sigma}_{0v}^2}}}$$

(2.26)

where $t_{ADF}$ is the *t*-statistic of $\rho$ in Eq. (2.25). The asymptotic distributions of $DF_\rho$, $DF_t$, $DF_\rho^*$, $DF_t^*$ and ADF converge to a standard normal distribution $N$ (0,1) by sequential limit theory (Baltagi, 2008).

**2.1.2.4 Panel Dynamic Ordinary Least Squares (DOLS) Estimation**

Traditional ordinary least squares (OLS) approach may not dominate the endogeneity effects of the regressors in the presence of the cointegrated variables. For investigating the panel cointegrated relationships among the integrated variables, dynamic ordinary least squares (DOLS) method, which provided by Kao and Chiang (2000) will be employed in this study. DOLS method includes leads and lags of the independent variables as the following equation:

$$y_{i,t} = \alpha_i + \theta_i X_{i,t} + \sum_{j=-q_i}^{q_i} c_{ij}\, \Delta X_{i,t+j} + v_{it}, \quad t = 1,\ldots,T, \quad i = 1,\ldots,N \tag{2.27}$$

where $\alpha_i$ indicates the individual-specific effect and $q_i$ is the leads and lags of each independent variable in the first difference to control for endogenous feedback. $v_{it}$ denotes the disturbance terms. The panel DOLS estimation is fully parametric and offers a computationally convenient alternative to the panel FMOLS estimator proposed by Phillips and Moon (1999) and Pedroni (2004) (Lee and Chiu, 2010).

**2.1.2.5 Panel Granger Causality Tests**

To examine the causal relationships of both short-run and long-run, panel Granger causality tests associated with vector error correction model (VECM) is estimated. A panel VECM is estimated following the two-step procedure described in Engle and Granger (1987). The steps consist of first estimating the long-run equilibrium model specified in the cointegration equation in order to obtain the estimated residuals, and then using these residuals lagged one period as the error correction term (Hamit-Haggar, 2010). VECM is used for correcting disequilibrium in cointegration relationship, which captured by the error correction term. The panel based VECM is specified as follows:

$$\Delta y_{it} = \alpha_{1i} + \lambda_{1i} ECT_{i,t-1} + \sum_{k=1}^{q} \theta_{11i,k}\, \Delta y_{i,t-k} + \sum_{k=1}^{q} \theta_{12i,k}\, \Delta x_{it-k} + \mu_{1i,t} \tag{2.28}$$

$$\Delta x_{it} = \alpha_{2i} + \lambda_{2i} ECT_{i,t-1} + \sum_{k=1}^{q} \theta_{21i,k}\, \Delta y_{i,t-k} + \sum_{k=1}^{q} \theta_{22i,k}\, \Delta x_{it-k} + \mu_{2i,t} \tag{2.29}$$

where $\Delta$ is the first-difference operator; $\alpha_{ji}$ ($j$ = 1, 2) represents the fixed effect; $k$ ($k$ = 1, …, $q$) is the optimal lag length determined by the Schwarz Criterion;

$ECT_{i,t-1}$ is the estimated lagged error correction term derived from the long-run cointegration relationship; $\lambda_{ji}$ ($j$ = 1, 2) is the speed of adjustment; $\mu_{i,t}$ is the serially uncorrelated error term with mean zero. The short-run causality is determined by the statistical significance of the partial $F$-statistic associated with the corresponding right hand side variables. Long-run causality is revealed by the statistical significance of the respective error correction terms using a $t$-test (Apergis and Payne, 2009).

**2.2 Literature Review**

The relationship among FDI, human capital and economic growth has been examined extensively during the last two decades. Most of the empirical studies have employed panel data of various countries or regional groups. Some of the empirical studies are based on national level, for instance, Kottaridi and Stengos (2010) employed 25 OECD countries and 20 non-OECD countries' data from 1970 to 2004 to test the non-linear relationship among FDI, human capital and economic growth. Borensztein et al. (1998) employed 69 developing countries' data from 1970 to 1989 to examine how foreign direct investment affected economic growth. Noorbakhsh et al. (2001) employed 36 developing countries' data from Africa, Asia and Latin America from 1980 to 1994 to investigate the effect of human capital and FDI inflows in developing countries. There are also some studies based on Chinese provincial level, for example, Yao and Wei (2007) employed 29 provinces' data of China from 1979 to 2003 to test and verify the role of FDI in China's economic growth. Buckly et al. (2002) employed 29 provinces' data of China from 1989 to 1999 to test the relationship between FDI and economic growth based on the regional differences. Since different authors studied the relationship between FDI and economic growth from different perspectives, most of the empirical studies provide different results about their relationship. The literature review will be divided into two parts: positive relationship group and weak or insignificant relationship group.

Table 2.1 summarizes the empirical studies of positive effect of FDI, human capital on economic growth. Yao and Wei (2007) used ordinary least squares (OLS) and generalized method of moments (GMM) estimations to find that FDI helps to generate technological progress and shifts China's production frontier, the results indicated that both FDI and human capital positively affected the total output in China during 1979 to 2003. Zhang (2006) found positive contribution of FDI on economic growth over the period 1992 to 2004 by using the panel data regression. The results indicated that FDI brings positive externality effect such as facilitating transition and diffusing technology and contributes to China's economic growth directly through raising productivity and promoting export. Buckly et al. (2002) employed OLS regression and Granger causality tests to find the positive effect of FDI on economic growth. However, the positive effect depends on the conditions of the host economy. Hsiao and Hsiao (2006) investigated the relationship between FDI, exports and GDP in East and Southeast Asia by both time-series and panel data methods. The authors concluded that both FDI and exports caused the economic growth in the long term, and FDI caused GDP both directly and indirectly through exports. Furthermore, this study proved that panel data analysis is superior compared with traditional time-series or cross-section analysis. Tuan et al. (2009) employed OLS and two-stage least squares (2SLS) estimations to verify that FDI promoted economic growth by increasing technological productivity growth in China over the period 1987 to 2004.

Some studies have shown that although there is a positive relationship between FDI and economic growth, the extent of the positive effect depends on the human capital threshold. For instance, by employing the seemingly unrelated regressions (SUR) technique, Borensztein et al. (1998) pointed out that FDI is much more efficient than domestic investment in boosting the economic growth if the host country has a minimum threshold stock of human capital over the period 1970 to 1989. Kottaridi and Stengos (2010) employed semi-parametric partially linear regression (PLR) and semi-parametric partially linear additive regression (PLAR) as well as GMM estimation to get the empirical results that FDI benefits economic growth only for countries with a minimum threshold of absorptive capacity. Meng (2010) employed panel data regression to examine the existence of the FDI spillover effect and test the correlation between the FDI spillover effect and economic growth. The results showed that there are both crowd-out and crowd-in effects through FDI in China. FDI plays a more significant role when it interacts with human capital compared with FDI itself. In a study for 36 developing countries from Africa, Asia and Latin America during the period 1980 to 1994, Noorbakhsh et al. (2001) found the level of human capital in host countries can affect the geographical distribution of FDI. Developing countries enhance their attractiveness for FDI by raising the level of local skills and building up human resource capabilities. Fu (2010) used panel data to verify the existence of the FDI spillover effect in China over the period 1998 to 2008. The author concluded that FDI generates a spillover only when it interacts with human capital, regional development, financial marketing and openness of the economy, respectively. All these literatures proved that human capital is quite an important element when testing the relationship between FDI and economic growth.

*Table 2.1* *Summary of the literature review on positive relationship among FDI, human capital and economic growth.*

| Authors& References | Data | Dependent Variable(DV) and Independent Variables(IV) | Methodology | Results |
|---|---|---|---|---|
| E. Borensztein, J. De, Gregorio, J-W. Lee, (1998) How does foreign direct investment affect economic growth? | 69 developing countries (1970-1989) | DV = g (GDP growth rate)<br>IV = FDI (FDI ratio)<br>H (human capital)<br>FDI*H (interaction term of FDI and human capital) | Seemingly unrelated regressions technique (SUR) | 1. FDI is much efficiency than domestic investment if the host country has a minimum threshold stock of human capital.<br>2. The effect of FDI on economic growth depends on the human capital available in the host economy (a strong positive interaction FDI and human capital).<br>3. FDI is complementary to domestic investment, but not quite significant. |
| Farhad Noorbakhsh, Alberto Paloni, Ali Youssef, (2001) Human capital and FDI inflows to developing countries: new empirical evidence | 36 developing countries from Africa, Asia and Latin America (1980-1994) | DV = FDI /GDP(FDI ratio )<br>IV = $HK_1$ (secondary school enrollment ratio)<br>$HK_2$ (number of accumulated years of secondary education present in the working age population)<br>$HK_3$ (number of accumulated years of secondary and tertiary education in the working age population)<br>CV (control variables) | OLS regression Fixed-effect model | 1. Developing countries can enhance their attractiveness for FDI by raising the level of local skills and building up human resource capabilities.<br>2. The level of human capital in host country can affect the geographical distribution of FDI.<br>3. Human capital is a statistically significant determinant of FDI inflows.<br>4. Human capital is one of the most important determinants and it plays a more important role through time. |

***Table 2.1*** *Summary of the literature review on positive relationship among FDI, human capital and economic growth (con).*

| Authors& References | Data | Dependent Variable(DV) and Independent Variables(IV) | Methodology | Results |
|---|---|---|---|---|
| Peter J. Buckly, Jeremy Clegg, Chengqi Wang and Adam R. Cross, (2002) FDI, regional differences and economic growth: panel data evidence from China | 29 provinces in China (1989-1999) | DV = Y (GDP growth rate)<br>IV = $K_d$ (growth rate of domestic capital stock)<br>$K_f$ (growth rate of the stock of FDI)<br>H (human capital)<br>E (growth rate of provincial exports) | Granger-causality test<br>OLS regression | 1. FDI benefits the economically stronger provinces most.<br>2. The quality and quantity of resources such as domestic and foreign investment, labor growth and human capital are crucial to promote economic growth.<br>3. There is no evidence for showing the human capital threshold-effect for FDI.<br>4. The full benefits of FDI are realized when competition in the local market is strong from both foreign and domestic firms. |
| Frank S. T. Hsiao, Mei-Chu W. Hsiao, (2006) FDI, exports, and GDP in East and Southeast Asia --- Panel data versus time-series causality analyses | China, Korea, Taiwan, Hong Kong, Singapore, Malaysia, Philippines, and Thailand (1986-2004) | Y (real GDP)<br>F (real FDI inflows)<br>E (real exports) | Fixed effects model<br>Random effects model<br>Unit root tests<br>Cointegration tests<br>Panel data VAR model<br>Granger causality tests | 1. Both inward FDI and exports cause the economic growth.<br>2. Panel data analysis is superior comparing with traditional time-series or cross-section analysis.<br>3. Panel analysis shows that FDI causes GDP both directly and indirectly through exports. |

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***Table 2.1*** *Summary of the literature review on positive relationship among FDI, human capital and economic growth (con).*

| Authors& References | Data | Dependent Variable(DV) and Independent Variables(IV) | Methodology | Results |
|---|---|---|---|---|
| Kevin H. Zhang, (2006) Foreign direct investment and economic growth in China: A panel data study for 1992-2004 | 28 regions in China (1992-2004) | DV= $\dot{Y}$ (GDP growth rate)<br>IV = $\dot{L}$(population growth rate)<br>H (human capital)<br>I/Y (gross fixed capital formation over GDP)<br>IF/Y (FDI flows over GDP)<br>Δ(F/Y) (changes of FDI ratio)<br>D (regional dummy) | Fixed-effect estimation Regression | 1. FDI contributes to China's economic growth directly through raising productivity and promoting export.<br>2. FDI brings positive externality effect such as facilitating transition and diffusing technology.<br>3. FDI keeps increasing from 1992-2004, and to be larger in the coastal region than inland region.<br>4. Marginal product of foreign capital is larger than domestic capital. |
| Shujie Yao, Kailei Wei, (2007) Economic growth in the presence of FDI: The perspective of newly industrialising economies | 29 provinces in China (1979-2003) | DV= GDP<br>IV = K (capital stock),<br>H (human capital),<br>Fdi (FDI/(DI + FDI)),<br>Exp (Export/GDP) | Panel cointegration tests<br>OLS estimations<br>The GMM approach<br>Fixed effect model<br>Random effect model | 1. Capital, export, FDI and human capital positively affect the output.<br>2. FDI helps technological progress and shift China's production frontier over time.<br>3. FDI plays more significant role in the East and less significant role in the Central and the West. East part of China has the highest annual growth rate of technological progress among the three regions. |

***Table 2.1*** *Summary of the literature review on positive relationship among FDI, human capital and economic growth (con).*

| Authors& References | Data | Dependent Variable(DV) and Independent Variables(IV) | Methodology | Results |
|---|---|---|---|---|
| Constantina Kottaridi, Thanasis Stengos, (2010) Foreign direct investment, human capital and non-linearities in economic growth | 25 OECD countries and 20 non-OECD countries (1970-2004) | DV = Y (growth rate of GDP per capita),<br>IV = N (population growth),<br>X (GDP per capita),<br>Id/Y (domestic investment ratio),<br>If/Y (foreign direct investment ratio),<br>H (human capital),<br>If*H<br>D (region dummy) | Semi-parametric partially linear regression (PLR)<br>Semi-parametric partially linear additive regression (PLAR)<br>The least squares dummy variable model (LSDV)<br>GMM estimation | 1. Initial income and human capital have a non-linear effect on economic growth.<br>2. FDI benefits the economic growth but only for countries with a minimum threshold of absorptive capacity, such as the higher level of income.<br>3. FDI inflows have enhanced growth in developing countries.<br>4. FDI inflows have a non-linear effect on growth. |
| Chyau Tuan, Linda F. Y. Ng, Bo Zhao, (2009) China's post-economic reform growth: The role of FDI and productivity progress | Two globalized delta economics in China: Pearl River Delta and Yangtze River Delta (1978-2004) | DV = Y (GDP)<br>IV = K (capital stock)<br>FDI<br>R&D<br>HC1 (human capital of high education)<br>HC2 (human capital of secondary education)<br>HC/P (HC1+HC2) | Panel estimations with fixed effects<br>OLS estimations<br>2SLS estimations<br>Correlation analyses | 1. FDI inflows increase technological productivity growth (TFP) progressing since China's economic opening.<br>2. TFP is endogenetic and has significant impact on output growth.<br>3. FDI has positive effect on output growth and productivity progress both directly and indirectly.<br>4. Technology-and knowledge-related factors such as R&D expenses and human capital endowment are significantly in improving productivity progress and output growth. |

***Table 2.1** Summary of the literature review on positive relationship among FDI, human capital and economic growth (con).*

| Authors& References | Data | Dependent Variable(DV) and Independent Variables(IV) | Methodology | Results |
|---|---|---|---|---|
| Fu Han, (2010) Panel data study on R&D spillovers from FDI in China: Analysis on threshold effect | 30 provinces in China (1998-2008) | DV = Y (the amount of R&D authorization)<br>IV = FDI<br>$RD_P$ (the number of R&D workers)<br>$RD_F$ (the expenses of R&D)<br>PGDP (GDP per capita)<br>H (human capital)<br>OPEN (extent of openness) | Fixed-effect model<br>Hausman test<br>Panel data estimation | 1. FDI generates the spillover only when it interacts with human capital, regional development, financial market and openness of the economy.<br>2. Human capital and the efficiency of financial market are the most important factors that affect China's R&D spillover effect.<br>3. The unbalanced development in different regions is the main reason to drive the different FDI spillover effect. |
| Meng Tie, (2010) The correlation analysis of FDI spillover effect and China's economic growth | 30 provinces in China (1993-2007) | DV = GDP<br>IV = FDI/GDP<br>H (human capital )<br>H*FDI/GDP (interaction of human capital and FDI ratio) | Panel data regression | 1. There are both crowed-out and crowed-in effects through FDI affect economic growth.<br>2. FDI plays a more significant role when it interacted with human capital compared with single FDI.<br>3. There is a human capital threshold effect in China's economy, eastern China already pass the threshold then FDI can positively affect the economic growth, however, for central and western regions, human capital does not pass the threshold, the positive effect on FDI seems insignificant. |

On the contrary, there are some empirical works showing the positive effect of FDI on economic growth is insignificant or FDI even generated a negative effect on economic growth by crowding out the domestic industries. Table 2.2 summarizes the empirical studies of weak or insignificant effect of FDI, human capital on economic growth. Carkovic and Levine (2002) examined the effect of FDI in 72 countries by using OLS and GMM estimations, the authors found that there is no positive influence in economic growth. Furthermore, evidence shows that there is no causal link between FDI and economic growth. The effect of FDI on economic growth depends on the recipient country's level of educational attainment, economic development, financial development and trade openness. Katerina et al. (2004) also found the same results as Carkovic and Levine (2002) based on a Bayesian analysis. It states that FDI does not have any significant effect on economic growth for transition countries.

***Table 2.2*** *Summary of the literature review on weak or insignificant relationship between FDI and economic growth.*

| Authors& References | Data | Dependent Variable(DV) and Independent Variables(IV) | Methodology | Results |
|---|---|---|---|---|
| Maria Carkovic, Ross Levine, (2002) Does foreign direct investment accelerate economic growth? | 72 countries (1960-1995) | DV = GROWTH (growth rate of GDP per capita )<br>IV = FDI (FDI/GDP)<br>Average years of schooling<br>Inflation<br>Government size<br>Openness | OLS regression<br>GMM panel estimator | 1. FDI does not exert a robust, positive influence on economic growth.<br>2. There is no causal link between FDI and economic growth.<br>3. Growth effect of FDI depends on the recipient country's level of educational attainment, economic development, financial development and trade openness. |
| Lyroudi Katerina, Papanastasiou John, Vamvakidis Athanasios, (2004) Foreign direct investment and economic growth in transition economies | 17 transition countries (1995-1998) | DV = Y (GDP growth rate)<br>IV = X (FDI/GDP)<br>E = country's distribution term | Bayesian analysis on panel data | 1. FDI does not have any significant relationship with economic growth for transition countries.<br>2. After removing outliers' effects from the data set, FDI does not exert any robust influence on growth. |