# *An Analysis of the Determinants of Total Factor Productivity in China*

CLAUDIO TOCCO

# AN ANALYSIS OF THE DETERMINANTS OF TOTAL FACTOR PRODUCTIVITY IN CHINA


by

Claudio Tocco


Doctor of Philosophy in Economics


Durham University Business School

Durham University


December 2015


Abstract

In this study, I analyse total factor productivity (TFP) and its determinants in Chinese industrial firms. The results from the system-GMM estimation indicate the existence of increasing returns to scale and a positive impact on firms' TFP arising from technological change. Moreover, the following factors were found to be determinants of higher TFP levels in most industries: lack of political affiliation, paid-in capital share owned by investors other than the State, Marshallian and Jacobian spillovers, age, marketing capabilities, internal liquidity and industrial competition. The results from the TFP growth decomposition indicate an annual average TFP growth of 9.68% across Chinese industrial firms during the period of 1998-2007. This was largely determined by the reallocation of resources across existing firms. From a policymaking perspective, measures targeting the previously mentioned determinants are likely to spur firms' TFP and consequently drive national long-run economic growth.

## Statement of Copyright

**Acknowledgements**

*I am deeply indebted to Prof Richard Harris and Dr Rebecca Stratling for their guidance in writing this dissertation. The conversations I had with them have been a valuable source of inspiration and insight into this topic.*

## Dedication

*This thesis is dedicated to my parents, Giancarlo and Luciana, and my brother Michele.*

## 1. Introduction

Total factor productivity (TFP) growth refers to growth in output that is not attributable to factor inputs. This can be further decomposed into efficiency increases and technological changes. TFP is important because it generates benefits, both within a firm and beyond.

Firstly, from the firm's perspective, TFP growth enables the firm to become more competitive and to increase people's living standards. Beckman and Buzzell (1958) describe a connection between productivity and living standards delivered through the wage and price channels. On the one hand, a more productive firm can afford to pay higher wages to its workers, hence increasing the employees' living standards through increased consumption ability. At the same time, productivity can lower the firm's output prices or allow the firm to provide greater value to consumers at a given price, hence increasing their products' utility.

Secondly, TFP growth also generates benefits that go beyond the firm, as suggested by the following quote: "In the long run, living standards depend on the efficiency with which our economic resources are utilized" (Beckman and Buzzell, 1958, p. 26). At the national level, TFP plays a major role in raising living standards and spurring economic growth. Besides the accumulation of factor inputs, TFP is the main driver behind differences in long-run within- and cross-country economic growth. This has been suggested by the empirical results of Easterly and Levine (2001), Klenow and Rodriguez-Clare (1997), and Benhabib and Spiegel (1994).

Analysing TFP and its determinants enables the understanding of which factors policymakers should target in order to achieve TFP growth, leading to long-run national economic growth and higher living standards for citizens. "In models that emphasize TFP growth, national policies that enhance the efficiency of capital and labour or alter the endogenous rate of technological change, can boost productivity growth and thereby accelerate long-run economic growth" (Easterly and Levine, 2001, p. 180). This quote indicates that sustainable, long-run economic growth can be achieved through national policies aimed at efficiency improvements and technological upgrades, the sub-components of TFP. Macro-level analyses of TFP, such as the ones mentioned above, are particularly important in cross-country studies. Despite this importance, such analyses often ignore the fact that firms are heterogeneous in many respects, TFP being one of them.

A micro-level analysis of TFP, on the other hand, would enable to infer what determines TFP levels and growth rates across firms, thus providing information on how policymakers and firm managers can target such determinants to improve TFP. Since they are more targeted, micro-level measures are more likely to lead to more successful results than macro-level ones, which would tend to adopt a "one size fits all" approach. Thus, the use of micro-level measures would potentially contribute to more competitive firms, the raising of citizens' living standards and sustainable long-run economic growth.

The Chinese economy is an important area of study, as its performance has been relatively strong over the last three decades. Firstly, figures from the Chinese Statistical Yearbook (2012), expressed in constant prices, report an average annual output growth rate of about 9% since 1978, while IMF (2013) figures suggest a global output growth of about 3% since 1980. Secondly, according to World Bank figures (World Bank, 2013), China has become the second largest contributor, after the United States, to global economic output, contributing with a 14.25% share as of 2012. Thirdly, the country constitutes an exceptional case in terms of its slow and gradual reform path undertaken as it has moved from a socially planned economic system to a market-oriented one.

The achievement of strong economic growth in China has resulted in an improvement in living standards for its citizens. According to figures from the World Bank (2013), real GDP per capita has increased from $523.95 in 1980 to $7,957.62 in 2012, representing a 15-fold increase. However, the gap between China and the high-income countries remains high, as these record an average real GDP per capita of $32,166 as of 2012. According to the World Bank (2013), China is still classified as an upper-middle income country, since its income per capita lies within the $4,086 to $12,615 band. The move to a high-income country status could be achieved by adopting national policies aimed at raising TFP.

Considering the importance of TFP for the Chinese economy, the study conducted in this thesis aims to answer the following research questions:

- What factors determine TFP levels and TFP growth in Chinese industrial firms during the period of 1998-2007?
- How does TFP growth differ across firms differentiated by industry, province and ownership/political affiliation?

The study therefore belongs to the literature analysing TFP and its determinants in China at the firm level. There are four important studies on this topic (Yao et al., 2007; Li et al., 2010; Brandt et al., 2012; Shen and Song, 2013) that are similar to this one, as they analyse multiple determinants of productivity. However, the current study differs from these in four respects.

Firstly, compared to most existing studies, this study adopts a more comprehensive set of TFP level determinants in the estimation. The following determinants are included: political affiliation, ownership, exporting activity, competition, Marshallian (or MAR) spillovers, Jacobian (or Jacob) spillovers, city spillovers, liquidity, firm age, R&D, time trend, and marketing capabilities. The inclusion of such variables is important because omitting them would generate biased estimates of the production function, and of TFP as a result. The choice of determinants is also motivated by the empirical results from the literature and the information available in the Chinese National Bureau of Statistics (NBS) dataset from which the sample is sourced. A more detailed discussion of the motivation for their inclusion, their measurement and their expected effects on TFP is presented in Section 3.3.

Secondly, the set of industries analysed from the sample taken from the Chinese NBS is wider than in most existing studies, as it includes 26 industries belonging to the mining, manufacturing and public utilities sectors. This allows for differences in technology between firms, avoiding the assumption that all firms operate using a standard technology. The sample adopted in this study includes both State-owned and non-State-owned firms with at least RMB 5mn in annual sales. Firms are located in 31 provinces, or province-equivalent municipal cities. This unbalanced sample comprises 2,183,709 firm-year observations, corresponding to a wide number of firms ranging from 148,474 in 1998 to 331,453 in 2007.

Thirdly, while most existing studies have relied on the semiparametric methodologies of Olley and Pakes (1996) or Levinsohn and Petrin (2003) to analyse the determinants of TFP levels, this study adopts SYS-GMM. The major advantage of this methodology, in comparison with the previously mentioned semiparametric ones, is the allowance for firms' fixed effects. Previous studies have indicated that firms have unmeasured productivity advantages that remain constant over time and that need to be captured. Moreover, SYS-GMM has the advantage of tackling endogeneity in the right-hand-side variables (including the lagged dependent variable) as well as selection bias by using lagged values of the endogenous variables as instruments in the first differences equation and first-differences of the same variables as instruments in the levels equation (Blundell and Bond, 1998). SYS-GMM is particularly preferable over the semiparametric methodologies of Olley and Pakes (1996) and Levinsohn and Petrin (2003) because the latter do not allow for fixed effects and are based on strong and unintuitive assumptions that generate collinearity problems in the first stage of estimation (Ackerberg et al., 2006).

Fourthly, compared to most existing studies, this study analyses the determinants of TFP growth by using the Haltiwanger (1997) decomposition approach. Such an approach decomposes aggregate TFP growth into the contributions provided by the following: a within-firm component representing the impact of the resource reallocation within existing firms, according to their initial shares of output in their related industries; a between-firm component indicating a change in the output share of firms, weighted by the deviation of the firm's initial productivity from the initial industry index; a covariance component, measuring whether a firm's increasing productivity corresponds to an increasing market share; an entering component indicating the contribution of entrant firms to their related industry's TFP growth, measured with respect to the initial industry index; an exiting component indicating the contribution of exiting firms to their related industry's TFP, measured with respect to the initial industry index. Since Melitz and Polanec (2012) find this decomposition to be characterized by biases, their methodology is also adopted in order to understand which set of results is the most appropriate.

This study has been built by taking these four distinctions into account, which distinguishes it from existing studies on firm-level TFP estimation in China.

The results of the SYS-GMM estimation indicate the existence of increasing returns to scale in most industries, suggesting that firms produce a higher proportion of output from a given proportion of factor inputs. Moreover there is a positive impact on firms' TFP arising from technological change. In terms of political affiliation/ownership, a lack of politically affiliation with any level of government and a lack of State paid-in capital ownership share positively affect TFP. Such factors are likely to enable the firms to undertake decisions aimed at maximising TFP rather than satisfying political motives. Regarding spatial variables, there is evidence of positive effects on TFP from both Marshallian and Jacobian spillovers. Despite such benefits, TFP tends to be hampered by the high costs incurred when firms are based in large urban areas. In terms of knowledge variables, the results indicate that younger firms tend to be more productive than their older counterparts, suggesting that the former are likely to be more dynamic and to use the latest technology available. Moreover, in contrast with the initial expectations, R&D expenditures do not seem to lead to higher TFP levels. Likewise, export activity does not seem to lead to higher TFP in most industries, suggesting that most exporting firms are engaged in processing trade activities. As initially expected, industrial competition is found to result in higher TFP, as it pushes firms' managers to increase their efforts and to reduce slack. Firms' marketing capabilities are also found to be beneficial to TFP, indicating that firms are able to differentiate products from their competitors and build successful brands. The positive relationship between firms' liquidity and their TFP indicates that Chinese firms are financially constrained and that they must rely on their internal liquidity to undertake productive investment activities.

Results obtained using the SYS-GMM estimation are found to be more valid than results from the semiparametric estimation following Levinsohn and Petrin (2003), since the latter are characterized by inconsistencies in some relationships (e.g. in the case of political affiliation), low coefficients on both the capital and labour inputs, and the indication of decreasing returns to scale in most industries, which are unlikely for the dynamic and fast growing Chinese economy.

The analysis of the relative importance of the determinants of TFP levels indicates that exogenous technological improvements have the largest positive effect on firms' TFP levels. The effect of an increasing proportion of firms' paid-in capital owned by either individuals or corporates is also found to be large. In contrast, large negative effects on TFP levels are found for an increasing proportion of firms' paid-in capital owned by the State, and firms' high level of political affiliation with either the central or local government. This indicates that State influence on firms, through either ownership of paid-in capital or political affiliation, is not conducive to higher TFP. In addition, the large negative effect for the variable representing city spillovers indicates that the advantages that firms enjoy from being based in cities are outweighed by the disadvantages.

The results from the Kolmogorov-Smirnov tests and the related cumulative empirical TFP distributions are in line with the SYS-GMM results, since they indicate that TFP distribution differs across firms with different political affiliations, paid-in capital share ownership, R&D and export activities. These also emphasize the importance of estimating TFP separately for each industry and taking into account geographical differences. Moreover, they point to the existence of TFP growth between 1998 and 2007.

Chinese firms have recorded an annual average TFP growth of 9.68%, based on the Haltiwanger (1997) and the Melitz and Polanec (2012) decompositions. The former decomposition indicates that such growth is mainly due to the net entry of more productive firms, in line with the findings of Brandt et al. (2012). The latter decomposition, which is more appropriate because it addresses the measurement biases included in the former, indicates that TFP growth largely results from a between-firm effect representing the reallocation of resources through the contraction and expansion of output shares between firms characterized by different productivity levels.

The structure of the paper is as follows. Chapter 2 covers total factor productivity. The first section discusses what TFP is and its importance. The second section reviews the main methods for measuring TFP at the firm level. The third section discusses the determinants of TFP and reviews the related studies in the literature. The fourth section discusses how the current study contributes to the literature.

Chapter 3 analyses the determinants of TFP levels in the Chinese industrial sector. The first section presents the dataset utilized. The second section introduces the SYS-GMM methodology for analysing TFP levels, and briefly mentions the Levinsohn and Petrin semiparametric methodology. The third section introduces the Kolmogorov-Smirnov methodology for testing the equality of empirical cumulative TFP distributions across firms. The fourth section explains the variables utilised, discusses the related descriptive statistics, and formulates the hypotheses underlying the estimation of TFP levels. The fifth section discusses the results from the SYS-GMM estimation. This is followed in the sixth section by a discussion of the results from the semiparametric estimation following Levinsohn and Petrin (2003). In the seventh section, an analysis of the relative importance of determinants of TFP is conducted. Finally, the results of the Kolmogorov-Smirnov test are discussed.

Chapter 4 analyses the determinants of TFP growth across firms in the Chinese industrial sector. The first section introduces the methodology developed by Haltiwanger (1997), which decomposes TFP growth, and discusses the related results. Since Melitz and Polanec (2012) find that Haltiwanger's (1997) methodology generates biases that lead to over-measurement of the contribution of entering and exiting firms to aggregate TFP growth, their methodology is introduced in the second section. This is followed by a discussion of the related results.

Chapter 5 concludes the thesis by summarizing the findings and discussing the related policy implications.

## 2. Total Factor Productivity

The previous chapter introduced the thesis. This chapter discusses total factor productivity and its importance, followed by a discussion of the main TFP measurement methods and its determinants.

### 2.1. An Introduction to Total Factor Productivity

In a firm's production process, factor inputs, such as labour and capital, are used in order to produce output. In other words: "The production function describes the technical relationship between the inputs and outputs of a production process" (Coelli et al., 1998, p. 12). A typical production function can be represented by the following equation:

$$Y_{it} = A_{it}\, f(L_{it}, C_{it},) \quad (1)$$

In (1), $Y_{it}$ is the output of firm $i$ at time $t$, $L_{it}$ is the labour input, and $C_{it}$ is the capital input. $A_{it}$ is the level of output not attributable to factor inputs, also known as total factor productivity (TFP), which can also be represented as an index:

$$TFP_{it} \equiv A_{it} = \frac{Y_{it}}{f(L_{it}, C_{it},)} \tag{2}$$

TFP, as expressed in (2), is the ratio of output produced to inputs utilised in the production process. Graphically, a production function can be represented by an isoquant. Nishimizu and Page (1982) decomposed the TFP change into technological change and technical efficiency change. Taking the best production function frontier, which is the maximum output attainable based on a given level of input, technological change represents the shift in the best frontier resulting from technological progress. A change in technical efficiency, on the other hand, represents the effect of actions undertaken by the firm, such as an improvement in managerial practices in order to "catch up" with industry best practices. Firms having a relatively high TFP will produce higher amounts of output with the same set of inputs than firms with a relatively low TFP.

TFP represents the most suitable definition for productivity, compared to, for example, partial factor productivity. The latter is given by the ratio of output to a specific factor input such as labour, capital, or intermediate materials. The most used among partial factor productivity indices has been labour productivity. This is because it has a prominent position in organisational debates between labour unions and management concerning changes in employment conditions like wage increases. Stigler (1947) argues that attributing changes in output to just one input is likely to lead to a limited understanding of productivity and a consequent misuse of economic resources. Productivity within a firm is determined by a combination of more than one input and the interactions between them. In addition, a partial factor productivity index can be affected by the intensity of input use. For example, two similar firms adopting the same production processes and the same technology may record different labour productivities if one of them uses its capital input more intensively. Therefore, considering the limitations of the partial factor productivity measure, productivity can be better expressed by a broader definition that encompasses all inputs and outputs involved in the production process. Moreover, such a definition is not affected by the usage intensity of factor inputs (e.g. capital), which is ignored in a partial productivity measure such as labour productivity. TFP, also referred to as multi-factor productivity, is given by the ratio of gross firm output to all inputs adopted in the production process. This is because "only by relating output to all tangible inputs can it be determined whether there has been a net saving in real costs per unit of output, or conversely, a gain in productivity" (Kendrick, 1956, p. 2). TFP is the most suitable definition of productivity for this study, as it can be used to analyse firms that combine various different inputs to produce a certain amount of output. In this thesis, when the terms "productivity" and "TFP" are used, they refer interchangeably to total factor productivity.

## 2.2. A Discussion of the Importance of TFP

Having analysed what productivity is, the next step is to understand its importance. Productivity is a widely discussed concept, not only in the academic literature but also among political leaders, trade unions and industry leaders. In other words, "productivity isn't everything, but in the long run is almost everything" (Krugman, 1997, p.9). This is because increased productivity generates benefits for firms, individuals and, consequently, the overall economy. It can also be said "it is only in the long term that productivity growth makes a large difference to the welfare of a country, and it is only in the long term that the rate of productivity growth is subject to fundamental change" (Wolff, 2014, p.12). Within a firm, an increase in TFP generates a higher level of output based on a given level of input. Therefore, it allows a firm to achieve better economic performance by reducing unit costs. As a consequence, the firm becomes more competitive. This idea suggests that increased productivity leads to better firm performance. In addition, productivity has benefits that go beyond the firm. For example, "in the long run, living standards depend on the efficiency with which our economic resources are utilized" (Beckman and Buzzell, 1958, p. 26). Beckman and Buzzell (1958) suggest a connection between productivity and living standards that is delivered through the wage and price channels. A more productive firm is likely to pay its employees better wages in order to reward them for their performance, thus enabling the employees to increase their living standards by spending more. Concerning the price channel, a more productive firm can lower the prices of its products, making the products more affordable to consumers. The consumers can thus receive higher utility by consuming more. Therefore, higher productivity is a key factor in improving levels of consumption and, hence, standards of living. In addition, productivity is not only related to better firm performance and living standards, but also to overall benefits to the public. "At the national level, productivity growth has been of paramount importance in raising levels of living, in strengthening potential national security, and in the provision for future economic growth" (Kendrick, 1956, p. 1). When it is more productive, a firm has a greater ability to compete internationally, leading to increased exports. The earnings obtained by selling products both locally and internationally are likely to be reinvested or paid out to shareholders. In summary, higher TFP leads to a combination of higher exports, investments and consumption, which are likely to generate a positive effect on a country's national income and living standards.

## 2.3. A Review of the Main TFP Measurement Methods

In the first section of this chapter, TFP was defined within the context of a production function, explaining the relationship between output and factor inputs in a firm's production process. TFP was expressed as the level of output produced based on a given level of factor inputs. The second section discussed the importance of TFP, not only as a measure of a firm's economic performance but also for national living standards and the nation's economic growth and prosperity. This section describes how TFP is measured.

Methods for measuring TFP can be categorised into macro-level and micro-level methods. Macro-level methodologies measure aggregates that relate to country-, region- or industry-level productivity. Micro-level methodologies, in contrast, measure firm- or plant-level productivity. While it is not in the scope of this analysis to review all methodologies for micro-level productivity measurement in depth, Van Beveren (2012) and Del Gatto et al. (2011) have provided comprehensive surveys of such methodologies. For the set of micro panel data that will be adopted in this work, macro methodologies are not suitable. This is because in a macro-level analysis, an economy is viewed as being constituted by only one aggregate sector. However, such is not the case in an economy that can be disentangled into different sectors, which can then be decomposed further into firms. Each firm is characterised by different characteristics, such as different production processes, outputs, inputs, and TFP. Therefore, macro-level analyses of production functions do not take into account the heterogeneity existing across firms. Micro-level methodologies, on the other hand, analyse TFP differences among firms having different characteristics. This enables us to understand what determines this heterogeneity and, therefore, how productivity can be improved through targeted microeconomic policy measures that are likely to be more successful than their macro-level counterparts. Among the micro-level measures of TFP, the first presented in this section is ordinary least squares (OLS). The description of OLS is accompanied by a discussion of the main methodological issues arising in TFP estimation. This is followed by a review of the main methodologies aimed at addressing the endogeneity issue: fixed effects (FE), instrumental variables (IV), generalised method of moments (GMM) and system-GMM

(SYS-GMM), as well as the semi-parametric estimations developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003).

### 2.3.1. Ordinary Least Squares (OLS)

The following explanation is adopted from the work of Van Beveren (2012). The estimation of TFP through OLS is performed using the following production function:

$$Y_{it} = A_{it}K_{it}^{\beta_k}L_{it}^{\beta_l}M_{it}^{\beta_m} \tag{3}$$

In the above function, $Y_{it}$ represents the output of firm *i* at time *t*, $K_{it}$ represents the capital input, $L_{it}$ represents the labour input, $M_{it}$ represents the intermediate input, and $A_{it}$ represents total factor productivity. $\beta_k$, $\beta_l$ and $\beta_m$ represent the elasticity of output with respect to capital, labour and intermediate inputs, respectively. After applying natural logarithms to both sides of the equation (3), it becomes:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \varepsilon_{it} \tag{4}$$

In (4), TFP is given by:

$$\ln A_{it} = \beta_0 + \varepsilon_{it} \tag{5}$$

The function has been disentangled into $\beta_0$, representing the average firm efficiency level, and $\varepsilon_{it}$, representing the firm's deviation from this average. When the deviation from the average firm efficiency level is negative, it indicates inefficiency. $\varepsilon_{it}$ can be further decomposed into two elements: $v_{it}$ and $u_{it}$. $v_{it}$ is a TFP component that is observable or predictable when a firm makes its choice of inputs, or when it decides to enter or exit an industry. It can represent the part of TFP resulting from different managerial practices, machine breakdowns or workers' strikes. $u_{it}$ is an unobservable component that represents a measurement error or an unexpected productivity shock. It is not observable by a firm when it makes its choice of inputs or when it decides to enter or exit an industry. By applying the decomposition of $\varepsilon_{it}$ into $v_{it}$ and $u_{it}$, the previous function becomes:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + v_{it} + u_{it} \tag{6}$$

Where:

$$\ln A_{it} = \beta_0 + v_{it} + u_{it} \tag{7}$$

A firm's observed TFP is given by the average firm efficiency level $\beta_0$ and the observed component $v_{it}$ of the deviation $\varepsilon_{it}$ from this average:

$$TFP \equiv \omega_{it} = \beta_0 + v_{it} \tag{8}$$

This is estimated through OLS and calculated as a residual representing the level of output not attributable to the capital, labour and material inputs:

$$TFP = \widehat{\omega}_{it} = \hat{\beta}_0 + \hat{v}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} \tag{9}$$

The TFP level can be obtained by solving for $\exp(\widehat{\omega}_{it})$. OLS estimation is adopted because of its practical and theoretical advantages, its ease of implementation in various statistical and econometric software applications, and its numerous desirable properties, such as unbiasedness, consistency, homoscedasticity and efficiency.

However, in the context of a production function, the OLS estimation has one main issue. In principle, OLS should only work when the inputs are assumed to be exogenous. This means that inputs in the production process are chosen independently of a firm's TFP. Since the decision makers within a firm make the choice of inputs according to various factors, among them being the observable part of TFP, the assumption of the inputs' exogeneity is too strong. Marschak and Andrews (1944) argue that factor inputs are determined within a firm rather than exogenously. This means that the levels of input into the production process are also determined according to the observable part of TFP, which itself is also influenced by the inputs chosen. Therefore, there is a two-way relationship between factor inputs and productivity, generating a simultaneity or endogeneity issue. Such endogeneity is given by the inputs' correlation with $\widehat{\omega}_{it}$. Ignoring this issue in the OLS estimation leads to estimates that are biased and inconsistent. In this specific case, the bias is known as "endogeneity bias" or "simultaneity bias."

In the context of TFP estimation, three other issues need to be considered. One concerns the unavailability of data regarding physical inputs and outputs and their respective prices at the firm level. If one assumes the existence of perfect competition, where all firms are subject to the same input and output prices, and considering that individual firms' prices are not available, output quantities can be substituted for by sales deflated by an industry price index. At the same time, input quantities can be proxied by their deflated values. However, firm-level prices are likely to differ from those proxied using the industry deflators. If markets are assumed to be imperfectly competitive and individual firms' prices are not available, the use of firm level prices as instruments is likely to cause an omitted price bias. De Loecker (2007) argues that if inputs and outputs are positively correlated while output and price are negatively correlated, a negative correlation might be generated between variable inputs and firm-level prices. The ultimate result of these relationships is bias in the factor input coefficients.

For the Colombian manufacturing sector, Foster et al. (2008) found TFP to be underestimated when deflated values of sales were used as a proxy for output. This was particularly true for entering firms, which are likely to charge lower prices than existing firms within the industry. Therefore, if a firm's output is represented by deflated sales, it will be underestimated, as will TFP. At the same time, if a firm charges higher prices than its industry competitors, output will be overestimated, as will TFP (Van Beveren 2012). Van Beveren (2012) furthermore suggests that no explicit solution exists for addressing the bias caused by the absence of specific firm-level price data.

A second issue concerns firms belonging to the same industry but producing multiple different products, as they are likely to differ in production technology and the nature of the demand. Bernard et al. (2009) suggest that biased estimates of TFP are likely to result from the assumption that firms use the same technology and have the same nature of demand for their products. Therefore, in order to generate consistent estimates of TFP, data on single inputs and outputs is needed. This enables the accounting for technological differences across firms that produce various outputs (Bernard et al., 2009). Van Beveren (2012) argues that the assumption that a firm produces only a single output it is likely to lead to the underestimation of TFP, as the synergies generated in producing multiple outputs are likely to be ignored.

A third issue in the estimation of TFP concerns the self-selection of firms into and out of an industry, an issue that was first discussed by Wedervang (1965). Firms are also likely to make the decision to enter or exit an industry according to their TFP. Ackerberg et al. (2007) argue that if firms know their productivity before exiting an industry, there should be a correlation between productivity and the capital stock, as firms with higher capital but lower productivity are more likely to survive than firms with a lower capital stock. Such a selection bias is likely to generate a downward bias in the capital input coefficient due to the negative correlation between productivity and capital stock. Van Beveren (2012) furthermore argues that ignoring this issue or coping with it using a balanced sample that excludes entering and exiting firms is likely to cause TFP estimates to be biased upwards.

This section has introduced the measurement of productivity and the main issues arising from it. The discussion has suggested that, in estimating productivity, the following potential biases must be taken into account: the endogeneity of inputs in the production process; the unavailability of firm output and input prices; the unavailability of data on single inputs and outputs; and the self-selection of firms into and out of an industry. Among these issues the simultaneity issue has been most widely discussed within the methodological literature (Van Beveren 2012). The methodologies reviewed in the following sections mainly focus on addressing this issue. The methodologies include the following: the fixed effects (FE) approach; the instrumental variables (IV) approach; the generalised method of moments (GMM) methodology; the system-GMM (SYS-GMM) approach; and the semi-parametric estimation methods developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003).

### 2.3.2. Fixed Effects (FE)

The simultaneity issue arising from the estimation of TFP through OLS can be addressed by adopting the fixed-effects (FE) estimation methodology proposed by Mundlak (1961) and Hoch (1962). One may consider a fixed effects regression model where the $v_{it}$ component of TFP observed by the firm varies across firms but does not change over time (*firm fixed-effect regression model*). The constancy of $v_{it}$ over time represents the main assumption of this estimation methodology. Since the time index is removed by $v_{it}$, the production function becomes:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + v_i + u_{it} \tag{10}$$

Another assumption used in fixed effects estimation is the strict exogeneity of the factor inputs included within the vector $x_{it}$, which is thus uncorrelated with $u_{it}$:

$$E[x_{it}|u_{it}] = 0 \tag{11}$$

One can apply the fixed effects regression model the firm: first-differencing, mean-differencing, or least squares dummy variables (LSDV) estimations. In the case of the mean-differencing estimation:

$$(y_{it} - \overline{y_\iota}) = \beta_k(k_{it} - \overline{k_\iota}) + \beta_l(l_{it} - \overline{l_\iota}) + (v_i - \overline{v_\iota}) + (u_{it} - \overline{u_\iota}) \tag{12}$$

In equation (12), $v_i - \overline{v_\iota} = 0$ because $v_i = \overline{v_\iota}$. The equation thus becomes:

$$(y_{it} - \overline{y_\iota}) = \beta_k(k_{it} - \overline{k_\iota}) + \beta_l(l_{it} - \overline{l_\iota}) + (u_{it} - \overline{u_\iota}) \tag{13}$$

In the second step, an OLS regression is performed in order to obtain estimates of the input coefficients. Ackerberg et al. (2007) suggest that the fixed effects estimation has the advantage of addressing the simultaneity bias by considering just the time invariant productivity. Van Beveren (2012) furthermore argues that as long as the decision to enter or exit an industry is made according to the time invariant productivity, firms' self-selection bias is addressed. However, despite being useful for addressing both the simultaneity and self-selection biases, the fixed effects estimation methodology is characterised by four main weaknesses. First, as Griliches and Mairesse (1995) note, the method yields low and insignificant capital coefficients, as well as low estimates of returns to scale. Second, according to Del Gatto et al. (2011), the assumption of constant unobserved TFP over time does not rest on strong theoretical grounds. The authors suggest that such an assumption is more suitable when analysing a short sample period. Thirdly, Del Gatto et al. (2011) also argue that the fixed effects methodology only exploits the variation of TFP across time and does not consider the cross-sectional information. Fourth, according to Wooldridge (2009), the fixed effects estimation requires a strong assumption of strict exogeneity of inputs in order to achieve unbiased and consistent estimates. Strict exogeneity means that the current and future input choices are not affected by TFP. This is a strong assumption, as TFP can affect the decisions of a firm regarding the quality and quantity of inputs to process, and the decisions to enter or exit an industry. Fifth, Olley and Pakes (1996) found that fixed effects estimation leads to widely different estimates when applied to a balanced and an unbalanced sample. For these five reasons, the fixed effects estimation is unsatisfactory for addressing the simultaneity issue.

### 2.3.3. Instrumental Variables (IV)

The simultaneity issue can also be addressed by applying the instrumental variables (IV) estimation. Compared to the fixed effects estimation, this methodology can be performed without the assumption of the strict exogeneity of inputs, which Wooldridge (2009) regards as too strong. In the instrumental variables estimation, the variation of each input variable can be decomposed into two different parts: one, whose correlation with the TFP component $v_{it}$ generates the simultaneity bias as well as inconsistent estimates, and another that is uncorrelated with $v_{it}$. Understanding the variation of each input variable that is uncorrelated with $v_{it}$ enables us to ignore the variation that generates biased estimates. Such information can be obtained through instrumental variables estimation, which simulates the variation in the independent variables that is uncorrelated with the $u_{it}$. It must be stressed that instruments should not enter directly into the production function (Van Beveren, 2012).

The instrumental variables approach tends to produce consistent and unbiased estimators. However, it must also be stressed that a valid IV estimation must satisfy two conditions. One is the *instrument relevance* condition, according to which the instrument $Z_{it}$ must be correlated with the independent variable $X_{it}$ that it represents:

$$corr(Z_{it}, X_{it}) \neq 0 \tag{14}$$

The more of the correlation that is explained by the instrument, the more information provided to explain the independent variable. An instrument explaining only a small part of the variation in $X_{it}$ is considered weak. The power of an instrument is represented by the *F*-statistic obtained in the first-stage regression, whereby the instrument is regressed on the related instrumented variable. In this case, the higher the value of the *F*-statistic, the more information regarding the independent variable that is provided by the instrument. Following the instrument relevance condition, a valid IV estimation must also satisfy the *instrument exogeneity condition*, according to which the instrument must be uncorrelated with the disturbance term:

$$corr(Z_{it}, u_{it}) = 0 \tag{15}$$

When the instruments adopted are endogenous, the IV approach fails, leading to inconsistent estimators. If the previous two conditions are met and the instruments do not enter the production function directly, IV estimators can be obtained by applying the two-stage least squares (*2SLS*) approach, whereby estimates are calculated in two stages. In the first stage, the IV are decomposed into two: one part that is uncorrelated with the error and another that is correlated. In the second stage, the uncorrelated parts of the independent variables are used to determine the regressors. Therefore, each independent variable is represented by the following:

$$X_{it} = \pi_{0t} + \pi_{1t}Z_{1t} + v_{it} \tag{16}$$

In this function, $\pi_{0t} + \pi_{1t}Z_{1t}$ represents the part of the independent variable that is uncorrelated with the disturbance $u_{it}$, while $v_{it}$ represents the part of the independent variable that is correlated with the disturbance $u_{it}$. In the 2SLS approach, only the first part of the independent variable is used, while the second one is ignored. In the first stage, an OLS regression is applied for each endogenous variable. Eventual exogenous variables, $W_{it}$, are included in the regression. However, since the values of $\pi_{0t}$ and $\pi_{1t}$ are unknown, they are estimated in the first stage. In the second stage, the predicted values of the previous regression are used:

$$\hat{X}_{it} = \hat{\pi}_{0t} + \hat{\pi}_{1t} Z_{1t} \tag{17}$$

The $Y_{it}$ is then regressed on the predicted values of the $\widehat{X}_{it}$:

$$Y_{it} = \beta_0 + \beta \hat{X}_{it} + u_{it} \tag{18}$$

This process enables us to obtain estimators that are unbiased and consistent. Despite this, the difficulty of the IV approach lies in finding the right instruments. Ackerberg et al. (2007) do not recommend using input prices as instruments, since they claim it could potentially generate four issues. The first is related to the competitive nature of both the input and output markets in which the firm operates. In the case of inputs, when markets are perfectly competitive, input prices are uncorrelated with TFP because the firm has no power to set prices. In that case, input prices can be used as instrumental variables. However, when a firm has market power, input prices are likely to be set according to input quantities and the firm’s productivity (van Beveren, 2012). In such a case, the input prices would be endogenous variables correlated with TFP, thus resulting in biased and inconsistent estimates. Based on the arguments presented above, it can be inferred that input prices are a valid instrument only when one assumes that firms operate in perfectly competitive markets.

The second issue is related to the lack of reporting of input prices by firms. It is difficult to find firms that report prices and who report them with a high level of precision. The third issue arises when input prices are reported. In this case, prices must vary across firms in order to reflect the different input market conditions faced by each firm in particular, rather than reflecting different input qualities. This is because input qualities are likely to enter the production function through the unobservable $u_{it}$ (representing TFP) and are, therefore, likely to be correlated with the instruments used. Ackerberg et al. (2007), for example, argue that if wages are related to the quality of employees’ work rather than labour market conditions, this would be reflected in productivity, generating a correlation with instruments and resulting in inconsistent and biased estimates. The fourth issue is related to the assumption of the exogenous evolution of TFP across time (Ackerberg et al., 2007). This is a strong assumption, since the choice of inputs within a firm affects TFP. In summary, the existence of the above four issues does not seem to support the use of input prices as instruments for estimating TFP. Other than input prices, the instruments that have been suggested in the literature include output prices and variables affecting the output demand or supply of inputs. Such instruments might have greater validity according to the competitive structure of the relative market, although they tend to be more difficult to find in comparison to other instruments.

### 2.3.4. Generalised Method of Moments (GMM) and SYS-GMM

Apart from the ordinary least squares, fixed effects and instrumental variables methodologies, an alternative proposed for addressing the issue of simultaneity is the use of lagged input levels as instruments for input changes, after applying a first-differentiation to the production function. Such a methodology is adopted, for example, by Mairesse and Hall (1996) in their GMM estimation, in which they control for both the endogeneity of inputs and heterogeneity across firms. GMM does not require the assumptions of zero autocorrelation of the error term across years and homoscedasticity across firms in order to obtain efficient estimates. Moreover, the standard error estimates arising from the GMM estimation are robust in the presence of correlation across equations and heteroscedasticity conditions. The explanation of the GMM estimator methodology provided here follows Blundell and Bond (1998). Taking an individual effect autoregressive model with unobserved firm-specific effects,

$$y_{it} = \alpha y_{i,t-1} + \eta_i + v_{it} \qquad (19)$$

$$where\ i = 1, \dots, N\ and\ t = 2, \dots, T$$

In (19), $\alpha$ is the parameter of interest, and $\eta_i$ is the firm fixed effect, which is potentially correlated with $x_{it}$. Following Mairesse and Hall (1996), lagged levels of the 3-year variables are used as instruments for the labour, capital and R&D capital variables in the first-differenced equation.

Mairesse and Hall (1996) subsequently impose $\frac{(T-1)(T-2)}{2}$ orthogonality conditions, which are:

$$E\left[y_{i,t-s}, \Delta v_{it}\right] = 0 \qquad (20)$$

Where:

$$t = 3, \dots, T$$

$$s = 2, \dots, T$$

The moment restriction imposed is:

$$E[Z_i' \, \hat{u}_i] = 0 \qquad (21)$$

Where $Z_i$ is the $(T-2) \times m$ matrix of instruments, omitting the $i$ subscripts, and $\hat{u}_i$ is the $(T-2)$ vector. The GMM estimator based on the moment conditions minimises the quadratic distance $\hat{u}_i' Z A_N Z_i' \, \hat{u}_i$ for the metric $A_N$, where $Z'$ is the $N(T-2) \times m$ matrix and $\hat{u}_i'$ is the $N(T-2)$ vector. This provides the following GMM estimator for $\alpha$:

$$\hat{\alpha}_{dif} = (\hat{y}_{-1}' Z A_N Z' \, \hat{y}_{-1})^{-1} \hat{y}_{-1}' Z A_N Z' \hat{y} \qquad (22)$$

Where $y_i'$ is a $(T-2)$ vector, $\hat{y}_{i,-1}'$ is the $(T-2)$ vector and $\hat{y}$ and $\hat{y}_{-1}$ are stacked across individuals in the same way as $\hat{u}$. If alternative choices are taken for the weights $A_N$, this provides a set of GMM estimators that are consistent for large $N$ and finite $T$, but which differ in their asymptotic efficiency. The weights are given by:

$$A_N = \left( N^{-1} \sum_{i=1}^{N} Z_i' \, \hat{u}_i \hat{u}_i' Z_i \right) \qquad (23)$$

This is the two-step estimator that is asymptotically efficient in the class of estimators based on the linear moment conditions.

Despite the advantages of the first-differenced GMM estimator, Blundell and Bond (1998) found its instruments to be weak. Thus, there is not enough information about the endogenous variables represented when the value of $\alpha$ increases towards 1, or when there is an increase in the variance of the fixed effect $\eta_i$ in relation to the variance of the effect $v_{it}$ This is due to the persistency of the instruments representing the independent variables, therefore suggesting that their lagged levels, which are used as instruments, have a weak correlation with their first-differences, which represent the independent variables. Moreover, the authors found that using the standard first-differenced GMM estimator leads to a low and insignificant capital coefficient, resulting in decreasing returns to scale and imprecise estimates.

Blundell and Bond (1998) suggest that such issues cause finite sample biases. They propose that such biases can be reduced by also using the lagged first-differences of $y_{it}$ as instruments for the equation in levels, in addition to the lagged levels as instruments for the equation in the first differences. The authors thus introduce the following additional moment conditions:

$$E\left(u_{it}, \Delta y_{i,t-1}\right) = 0 \; for \; t = 4,5, \dots, T \tag{24}$$

And

$$E\left(u_{i3}, \Delta_{yi2}\right) = 0 \tag{25}$$

The new GMM estimator, called system-GMM (SYS-GMM), is based on the previous conditions, which themselves are based on a stacked system comprising the $(T-2)$ equations in first differences and the $(T-2)$ equations in levels, corresponding to the periods $3, \dots, T$ for which the instruments are observed. As in the previous case, the GMM estimator deteriorates as $\alpha$ moves towards 1. However, since $|\alpha| < 1$, the moment condition provides information about the endogenous variables it represents. The two-step estimator is calculated in the same way as previously defined. Blundell and Bond's (1998) framework differs from the standard first-differenced GMM in that it allows for an autoregressive (AR(1)) component in the production function error term, enabling serial correlation in order to obtain valid lagged internal instruments for equations in first-differences or equations in levels.

Using a panel of 509 US manufacturing firms, Blundell and Bond (2000) found that there are finite sample biases in the first-differenced GMM estimator resulting from the existence of weak instruments and that these biases diminish with the imposition of constant returns to scale. The authors also report higher and more significant capital coefficients resulting from the SYS-GMM approach, in comparison with the first-differenced GMM estimator, with no rejection of the assumption of constant returns to scale. Moreover, compared to the instruments in the standard first-differenced GMM estimator, the new instruments are not rejected, thus suggesting that they are informative for the endogenous variables in levels that they represent, with the imposition of constant returns to scale generating even better results. Performing a Monte Carlo simulation, Blundell and Bond (1998) demonstrate that the SYS-GMM has better finite sample properties and is more efficient than the standard first-differenced GMM estimator, which was characterised by large finite sample bias and low precision. Van Biesebroeck (2007) found SYS-GMM to be the most suitable parametric methodology when there is measurement error or technological heterogeneity among firms, compared to the following methodologies: index numbers, data envelopment analysis, instrumental variables estimation, stochastic frontiers and semiparametric estimation. This is because SYS-GMM was found to generate the most robust estimates for both total factor productivity levels and growth rates compared to other estimators. Van Biesebroeck (2007) also argues that when technological heterogeneity between firms is absent but there are constant productivity differences over time, SYS-GMM provides the most reliable results.

### 2.3.5. Olley and Pakes' (1996) Semi-parametric Estimation

The explanation of this methodology follows Olley and Pakes (1996). The achievement of consistent and unbiased estimates by this approach relies on three main assumptions. The first is the assumption of the existence of only one unobserved state variable at the firm level, evolving according to a first-order Markov process. This variable is productivity. The second is the assumption of monotonicity for the investment variable, meaning that investment increases in productivity and only positive values of investment are used in the analysis. The third is the assumption that all firms belonging to the same industry are subject to the same input and output prices, meaning that they operate in perfectly competitive markets. Therefore industry deflators are used for both inputs and outputs.

In the Olley and Pakes (1996) estimation methodology, since a firm maximises the expected discounted value of future cash flows at the beginning of each period, the firm will compare its sale (or liquidation) value with the expected return it can generate by continuing to operate. If it is not worth operating, the firm will liquidate. Otherwise, the firm will decide to pursue a positive investment, a choice that is also based on the perception of future market structure and input factor prices.

These decisions can be expressed by an exit rule and an investment demand function, respectively:

$$\chi_t = \left\{1 \; if \; \omega_t \geq \underbrace{\omega_t}\,(a_t, k_t), 0 \; otherwise\right\} \tag{26}$$

$$i_t = i_t(\omega_t, a_t, k_t) \tag{27}$$

Where $i_t$ is the investment, $\omega_t$ is TFP, $a_t$ is the age of the firm and $k_t$ is the capital stock. In (27), investment is a function of productivity, age and the capital stock. Here, the production function is represented by the following:

$$y_{it} = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it} \tag{28}$$

In this equation, $\eta_{it}$ represents measurement error or an unexpected productivity shock. In Olley and Pakes' (1996) estimation algorithm, labour is the only variable factor, and is hence affected by the current $\omega_{it}$ value, while the other inputs, $k_t$ and $a_t$, are relatively fixed and are affected by the distribution of $\omega_{it}$ depending on the information at time $t-1$ and past values of $\omega_{it}$. Olley and Pakes (1996) impose a strict monotonicity condition for investment, which means it increases in $\omega_t$ when $\omega_t$ is not equal to zero. A positive productivity shock is thus likely to result in a positive shock in the future, hence leading to an accumulation of capital. The previous two assumptions enable the inversion of the unobservable term $\omega_t$ thus addressing the endogeneity issue by controlling for $\omega_{it}$. Investment is thus used as a proxy to control for the correlation between input levels and the unobserved firm-specific productivity shock, hence addressing the simultaneity bias. With investment increasing in $\omega_{it}$, the previous investment function can be inverted to become:

$$\omega_{it} = h_t(i_t, a_t, k_t) \tag{29}$$

By substituting the inverted investment function into the production function, it becomes:

$$y_{it} = \beta_l l_{it} + \phi_t(i_{it}, a_{it}, k_{it}) + \eta_{it} \tag{30}$$

Where:

$$\phi_t(i_{it}, a_{it}, k_{it}) = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + h_t(i_{it}, a_{it}, k_{it}) \tag{31}$$

The equation is estimated with OLS, resulting in consistent estimates for $\beta_l$ but not for $\beta_a$ or $\beta_k$, thus not allowing the measurement of their effect on a firm's investment decision. In order to estimate, $\beta_a$ and $\beta_k$, the following relation on productivity at time $t + 1$ is taken:

$$\omega_{i,t+1} = E\left[\omega_{i,t+1} | \omega_{it}\right] + \xi_{t+1} \tag{32}$$

Where $\xi_{t+1}$ represents the innovation component in $\omega_{it+1}$. The relation means that TFP at $t + 1$ follows a first-Markov process given by the expected value of productivity at $t + 1$, conditional on the information on TFP at time $t$, plus the innovation component at $t + 1$. Firms will decide to operate if:

$$\chi_t = 1 \; if \; \omega_t \geq \underbrace{\omega_t}\,(a_t, k_t) \tag{33}$$

Since the innovation component $\xi_{t+1}$ is correlated with the variable inputs $\beta_l l_{it}$, this is subtracted from the output:

$$y_{it} - \beta_l l_{it} = \phi_t(i_{it}, a_{it}, k_{it}) + \eta_{it} \tag{34}$$

The TFP expectation at time $t + 1$ now becomes:

$$E[\omega_{it+1} | k_{it+1}, \chi_{t+1} = 1] = \beta_0 + \beta_k k_{it+1} + E[\omega_{it+1} | \omega_{it+1}, \chi_{t+1} = 1] \tag{35}$$

The second stage of the estimation algorithm is:

$$y_{it+1} - \beta_l l_{it+1} = \beta_a a_{it+1} + \beta_k k_{it+1} + g(P_t, \phi_t - \beta_a a_t - \beta_k k_t) + \xi_{t+1} + \eta_{t+1} \quad (36)$$

In this function, $E[\omega_{it+1}|\omega_{it+1}, \chi_{t+1} = 1] = g(P_t, \phi_t - \beta_a a_t - \beta_k k_t)$ is the firm's expectation of productivity at time $t+1$, $P_t = Pr\left[\chi_{t+1} = 1|\underbrace{\omega_{t+1}}(a_{t+1}, k_{t+1}), J_t\right]$ is the probability of the firm's survival at time $t$, and $\xi_{t+1} = \omega_{t+1} - E[\omega_{t+1}|\omega_t, \chi_{t+1} = 1]$ is the innovation component. The coefficients for the capital and age inputs can be obtained by executing a non-linear least squares regression on the previous equation. Because $\xi_{t+1}$ and $\eta_{t+1}$ are not correlated with $k_{i,t+1}$ and $a_{i,t+1}$, this estimation leads to unbiased and consistent estimates of $\beta_a$ and $\beta_k$.

### 2.3.6. Levinsohn and Petrin's (2003) Semiparametric Estimation

The explanation of this methodology follows the structure of Levinsohn and Petrin (2003). The previous section demonstrated how Olley and Pakes (1996) use investment as a proxy to control for the simultaneity between the input choice and productivity. Although investment seems to represent a valuable proxy, Levinsohn and Petrin (2003) indicate that intermediate inputs constitute a better proxy. This is mainly because of the monotonicity condition imposed in Olley and Pakes's (1996) methodology, which results in the consideration of only positive investment observations. Since firms do not always invest, such a condition is likely to cause an efficiency loss in the estimation, since observations in which investment is equal to zero would not be considered in the methodology. Firstly, Levinsohn and Petrin (2003) suggest that since firms always report a positive value for their use of intermediate inputs, it constitutes a better proxy. Secondly, when non-convex adjustment costs lead to twists in the investment demand function, plants might not properly respond to shocks by adjusting investment, leaving the correlation between endogenous variables and the unobservable term. This is because investment is costly and relatively difficult for firms to adjust in response to a shock. In contrast, intermediate inputs are likely to be easier to adjust. This consideration provides further support for the use of intermediate inputs as a proxy. Levinsohn and Petrin (2003) adopt intermediate inputs as a proxy rather than investment because it is less susceptible to zero values and due to efficiency losses arising in the estimation using investment as a proxy. The monotonicity condition is more likely to hold than in the Olley and Pakes (1996) method. Moreover, intermediate inputs can be adjusted at a lower cost than investments when productivity shocks occur, hence removing the correlation between the independent variables and the disturbance. As in the case of Olley and Pakes's (1996) method, $\omega_t$ is the only unobservable term that enters into the function for intermediate inputs $m_t$. The intermediate inputs (e.g. materials and energy) are added into the production function:

$$y_{it} = \beta_0 + \beta_k k_t + \beta_s l_t^s + \beta_u l_t^u + \beta_e e_t + \beta_f f_t + \beta_m m_t + \omega_t + \eta_t \tag{37}$$

In this function, $l_t^s$ is the log of skilled labour input, $l_t^u$ is the log of unskilled labour, $e_t$ is the log of electricity input, $f_t$ is the log of fuel inputs, and $m_t$ is the log of material inputs. A firm index is not adopted in the function because both input and output prices are assumed to be the same across all firms. Because of the monotonicity condition, the material input demand function can be inverted as follows:

$$\omega_t = \omega_t(m_t, k_t) \tag{38}$$

Therefore:

$$\phi_t(m_t, k_t) = \beta_0 + \beta_k k_t + \beta_m m_t + \omega_t(m_t, k_t) \tag{39}$$

This equation can be estimated by OLS, as Olley and Pakes (1996) have done. However, Levinsohn and Petrin (2003) also use a different approach. By regressing output on capital and material input, the authors estimate the following conditional moments:

- $E(y_t | m_t, k_t)$,
- $E(l_t^s | m_t, k_t)$,
- $E(l_t^u | m_t, k_t)$,
- $E(e_t | m_t, k_t)$,
- $E(f_t | m_t, k_t)$.

These are then subtracted from the production function, where no intercept is used to obtain the first stage estimates:

$$\begin{aligned} y_{it} - E(y_t | m_t, k_t) \\ &= \beta_s(l_t^s - E(l_t^s | m_t, k_t)) + \beta_u(l_t^u - E(l_t^u | m_t, k_t)) + \beta_e\big(e_t - E(e_t | m_t, k_t)\big) \\ &+ \beta_f(f_t - E(f_t | m_t, k_t)) + \eta_t \end{aligned} \tag{40}$$

In the second stage of the estimation algorithm, it is assumed that capital and the innovation component of productivity are uncorrelated:

$$E[k_t \eta_t^*] = 0 \quad (41)$$

In addition, innovation in productivity at time t is uncorrelated with the choice of material inputs at time $t-1$:

$$E[m_{t-1} \eta_t^*] = 0 \quad (42)$$

The residual is obtained by the following:

$$\xi_t + \eta_t(\beta^*) = y_t - \beta_s l_t^s - \beta_u l_t^u - \beta_e e_t - \beta_f f_t - \beta_m^* m_t - \beta_k^* k_t - E[\omega_t | \omega_{t-1}] \quad (43)$$

In this function, $\beta^* = (\beta_m^*, \beta_k^*)$, $E[\omega_t | \omega_{t-1}]$ is estimated by using the estimates of $\omega_t$ obtained from the results of the first stage estimation and the $(\beta_m^*, \beta_k^*)$.

The authors, by adding six over-identifying conditions to the two already existing ones, arrive at the following expectation vector:

$$E[(\xi_t + \eta_t) Z_t] \quad (44)$$

Where $Z_t$ is a vector:

$$Z_t = \{k_t, m_{t-1}, l_{t-1}^s, l_{t-1}^u, e_{t-1}, f_{t-1}, k_{t-1}, m_{t-2}\} \quad (45)$$

Estimates of $(\hat{\beta}_k, \hat{\beta}_m)$ are obtained by minimising the following function with the GMM approach, which uses $t-1$ values of the materials variable as instruments for the *t* variable:

$$Q(\beta^*) = min_{\beta^*} \sum_{h=1}^{8} (\sum_i \sum_{t=T_{i0}}^{T_{i1}} (\xi_{i,t} + \eta_{i,t}(\beta^*)) Z_{i,ht})^2 \quad (46)$$

In this function, $i$ represents the firm index, $h$ represents the instrument index, $T_i$ represents the time index.

According to the above explanation, Levinsohn and Petrin's (2003) semiparametric approach differs from Olley and Pakes's (1996) in four respects. Firstly, Levinsohn and Petrin (2003) adopt intermediate inputs rather than investment to control for the simultaneity between input choice and productivity. Secondly, Levinsohn and Petrin (2003) obtain the coefficient for the intermediate inputs' proxy variable in the second stage of the estimation, rather than in the first stage. Thirdly, while Olley and Pakes (1996) adopt an unbalanced panel and consider the survival probability in the second stage of the estimation, Levinsohn and Petrin (2003) do not include it since Olley and Pakes's (1996) results showed very small efficiency gains (Van Beveren, 2012). Fourth, when a revenue production function is estimated instead of a value-added function, an additional moment condition is needed to obtain the estimate for intermediate inputs. Therefore, the second stage of estimation in Levinsohn and Petrin's (2003) methodology utilises the GMM approach.

In order to demonstrate the usefulness of the intermediate input proxy, Levinsohn and Petrin (2003) adopt plant-level annual data from manufacturing firms in the period of 1979-1986, focusing on metals, textiles, food products and wood products. As described above, their methodology uses intermediate inputs to control for the correlation between input levels and unobserved firm-specific productivity shocks (i.e. the simultaneity issue). The addition of these inputs brings some relevant benefits. Firstly, the investment proxy can only be used for firms reporting a positive level of capital investment. As many firms report zero or negative capital investment, this leads to an efficiency loss. In comparison, the intermediate input proxy allows this problem to be avoided, as firms almost always report positive intermediate inputs. Secondly, when a productivity shock occurs, it is costly for a firm to respond by changing its capital investment. This maintains the correlation between the firm-specific productivity shocks and the regressors. Intermediate inputs are less costly to adjust than investment when a productivity shock occurs, thus leading to a weakening correlation between inputs and TFP. Thirdly, as intermediate inputs are not state variables, the use of intermediate inputs creates a better link between the economic theory and the strategy of estimation than does capital investment.

Despite representing a step forward compared to the Olley and Pakes (1996) model, Levinsohn and Petrin's (2003) approach has its shortcomings. Ackerberg et al. (2006) argue that, as with Olley and Pakes's (1996) method, the approach suffers from serious collinearity problems arising in the first stage of estimation and given this condition, the method requires strong and unintuitive assumptions to be made in order for it to be correctly identified. The following discussion of such assumptions is based on Ackerberg et al. (2006).

The first assumption is strict monotonicity. While for Olley and Pakes (1996), investment must be strictly monotonic in $\omega_{it}$, Levinsohn and Petrin (2003) also require that intermediate inputs be strictly monotonic in $\omega_{it}$. This condition is necessary for the non-parametric inversion of $\omega_{it}$, since the endogeneity issue would otherwise not be addressed.

The second assumption states that $\omega_{it}$ is the only unobservable term in the functions for investment, as carried out by Olley and Pakes (1996), and those for intermediate inputs, as carried out by Levinsohn and Petrin (2003). Like the previous assumption, this condition is required in order to invert $\omega_{it}$.

The third assumption regards the timing of input choices in the two methodologies. In the Olley and Pakes (1996) methodology, $k_{it}$ is decided at $t-1$, while in the Levinsohn and Petrin (2003) methodology, it is decided at or before $t-1$. If such were not the case, the moment condition would be violated, as $k_{it}$ would not be orthogonal to $\xi_{it}$. In Olley and Pakes's (1996) approach, the first-stage estimation would be complicated by a choice of $k_{it}$ earlier than $t-1$, as $i_{it-1}$ could not be used to invert $\omega_{it-1}$ thus complicating the estimation in the first stage.

The fourth assumption regards the use of the labour input in the two methodologies. For example, in Olley and Pakes's (1996) method, $l_{it}$ cannot have dynamic implications, while in Levinsohn and Petrin's (2003) approach, it can. Moreover, in Levinsohn and Petrin's (1996) model, $l_{it}$ and $m_{it}$ are assumed to be perfectly variable inputs, meaning that they are defined when $\omega_{it}$ is observed by the firm's decision maker. If $m_{it}$ was chosen before knowing $\omega_{it}$, then $m_{it}$ cannot be used for the inversion in the first stage of $\omega_{it}$. If $l_{it}$ was chosen before knowing $\omega_{it}$, then $l_{it}$ would be chosen before $m_{it}$, and thus its choice would be based on $l_{it}$, which would not enable us to identify the labour coefficient in the first stage by entering into the function.

Ackerberg et al. (2006) argue that these four assumptions, upon which the semiparametric methods are based, are strong and unintuitive, therefore generating serious collinearity issues in the first stage of estimation. Based on the ideas of Olley and Pakes (1996) and Levinsohn and Petrin (2003), Ackerberg et al. (2006) presented a new estimator that has the advantage of not suffering from collinearity issues. In addition, it can be compared with dynamic panel data estimators. On the one hand, this is similar to estimators developed by Olley and Pakes (1996), as well as Levinsohn and Petrin (2003), as it uses investment or intermediate inputs, respectively, in order to control for productivity shocks. On the other hand, it estimates the labour coefficient in the second stage. While it is not the aim of this section to review this methodology, it is important to note that by using the same dataset as the one used by Levinsohn and Petrin (2003), Ackerberg et al. (2006) demonstrate that their method is more stable across various potential variables. Other methodologies have recently been developed by Wooldridge (2009), De Loecker (2007) and Katayama et al. (2009). Despite their usefulness, discussing them is beyond the scope of this thesis.

### 2.3.7. Choosing the Right TFP Estimator

The previous sections analysed how TFP is measured and the main issues arising from such measurements. Following that analysis, it is important to highlight which method constitutes the most valuable estimator for analysing TFP determinants at the firm level. Van Beveren (2012) reviewed various issues in the estimation of TFP at the firm level, such as the endogeneity of input choices (also known as simultaneity bias), the omitted variable bias (due to the lack of available data on physical inputs and outputs and their respective prices), the sample selection bias (which results from not allowing for firm entry and exit), and the production of multiple products by a firm (resulting in differences in production technology across products produced by single firm). In tackling such issues, the author compares the performance of different estimators, such as fixed effects, GMM, and the semi-parametric estimators of Olley and Pakes (1996) and Levinsohn and Petrin (2003). Based on the results obtained, Van Beveren (2012) argues that the choice of a specific TFP estimator should be based on the data utilised and the related assumptions imposed.

SYS-GMM represents the most suitable estimator for analysing TFP determinants at the firm level, especially compared to the widely used semiparametric approaches, since it has the advantage of allowing for firms' fixed effects. As previous studies have indicated that firms have unmeasured productivity advantages that remain constant over time and that need to be captured, the SYS-GMM approach enables the consideration of such fixed effects. Moreover, SYS-GMM has the advantage of addressing the endogeneity of the right-hand-side variables (including the lagged dependent variable) as well as selection bias by using lagged values of the endogenous variables as instruments in the first differences equation, and first-differences of the same variables as instruments in the levels equation (Blundell and Bond, 1998). SYS-GMM is particularly preferable to the semiparametric methodologies of Olley and Pakes (1996) and Levinsohn and Petrin (2003), as these do not allow for fixed effects and are based on strong and unintuitive assumptions, which generate collinearity problems in the first stage of estimation (Ackerberg et al., 2006). Van Biesebroeck (2007) compared the sensitivity of five different productivity estimators (index numbers, data envelopment analysis, stochastic frontiers, GMM, and semi-parametric estimation) using a Monte-Carlo simulation. Although each method has its own advantages and disadvantages, the system GMM estimator was found to be the most robust technique in presence of measurement errors and technological heterogeneity.

In summary, the main total factor productivity estimation methodologies have been discussed in this section: ordinary least squares, fixed effects, instrumental variables, GMM and its variation, SYS-GMM, and the semiparametric methodologies of Olley and Pakes (1996) and Levinsohn and Petrin (2003). The conditions in which each of them is most suitable approach have also been discussed. The next section presents the main determinants of total factor productivity.

## 2.4. A Review of the Determinants of TFP

The first section of the chapter reviewed TFP in the context of the production function. The second section discussed the importance of TFP for a firm's economic performance, people's standards of living and national economic growth. The third section analysed how TFP is measured and explained why micro-level measures are more valuable than macro-level ones. This section will review the determinants of TFP at the micro level. A micro-level analysis of TFP enables us to understand what determines the differences in TFP across firms. As a result, it offers a better understanding of TFP than that attainable with aggregate data. The determinants of TFP examined in this section are the following: internal and external knowledge, political affiliation, foreign direct investment, economies of scale, competition, spatial spillovers, city location, export activity, managerial ability and marketing capabilities. This is followed by a review of studies analysing multiple determinants of TFP and a discussion of the contribution of the study in this thesis.

### 2.4.1. Internal and External Knowledge

"Knowledge can be defined as a dynamic framework or structure from which information can be stored, processed and understood" (Howells, 2002, p. 872). This definition suggests that knowledge is taken up and accumulated, and that rather than being static, it increases as a result of new knowledge gained. According to Polanyi (1962), knowledge can be explicit or tacit. Explicit knowledge can be transmitted in a direct and explicit way. For example, when new machinery is installed, workers are provided with instructions on how it functions. Workers then acquire tacit knowledge by learning processes and procedures, that are not directly or explicitly communicated. For example, a worker who learns a firm's processes, routines, ideals and values without having been provided with any explicit guidance on the topics develops tacit knowledge. The importance of knowledge can be exemplified by the following quote: "Knowledge is crucial in helping to create innovation which in turn stimulates economic growth and development. It also plays a more specific role in establishing and sustaining the long-term capabilities and performance of firms and organisations and in enhancing the success and well-being of individuals and communities" (Howells, 2002, p. 871). This description suggests that knowledge is crucial in order for firms to flourish, while also having effects that go far beyond a firm's boundaries. Harris and Moffat (2013) argue that knowledge is part of a firm's intangible assets. "Intangible assets are a firm's dynamic capability created by core competence and knowledge resources, including organizational structure, employee expert skills, employment centripetal force, R&D innovation capability, customer size, recognizable brand, and market share" (Tsai et al., 2012, p. 67). This definition suggests that intangible assets comprise knowledge that can be disentangled into various components, including R&D. These assets are seen as critical drivers for knowledge creation, innovation and, consequently, economic growth (Kramer et al., 2011, p. 447).

From the above definitions and descriptions of knowledge, one might infer that, ceteris paribus, a firm with a high relative level of knowledge is likely to show greater productivity compared to a firm with a relatively low level. However, this is not always the case, as the firm must be able to use its knowledge for productive purposes by developing absorptive capacity. Absorptive capacity can be explained as follows: "The ability of a firm to recognise the value of new, external information, assimilate it, and apply it to commercial ends is critical to its innovative capabilities. We label this capability a firm's absorptive capacity and suggest that is largely a function of the firm's level of prior related knowledge" (Cohen and Levinthal, 1990, p.128). Although this definition provides an insight into what absorptive capacity is, a more comprehensive definition might also include the ability of the firm to use internal knowledge. Eustace (2000, p. 6) suggests that "increasingly, the capacity to combine external and internal sources of knowledge to exploit commercial opportunities has become a distinctive competency." Therefore, it is important to develop knowledge and to use it for productive purposes, the extent of which is determined by a firm's absorptive capacity.

Additional insight into the importance of knowledge for productivity is provided by the resource-based theory, of which Barney (1991) is a proponent. He argues that a firm is made up of resources, among them knowledge, which are used to implement strategies aimed at improving a firm's efficiency. This suggests that knowledge can contribute to higher TFP within a firm. According to Barney (1991), such resources can constitute a source of sustainable competitive advantage when they are valuable, rare, imperfectly imitable, and without substitute. Thus, knowledge can add further value when it is a source of competitive advantage, hence improving a firm's position with respect to its competitors. In addition, Teece et al. (1997) state that a competence can constitute a competitive advantage and thus be a source of higher TFP only when it is difficult to replicate by competitors and when it can be applied from one setting to another.

The resource-based view of the firm, despite providing a valuable insight into the nature of the firm, does not consider the external environment where the firm operates. As discussed earlier, the external environment can constitute an additional source of knowledge. In addition, "few firms possess all the inputs required for successful and continuous technological development" (Almeida et al., 2003, p. 302). For example, a firm can have specific relationships with suppliers, with whom it collaborates in improving inputs, or customers, with whom it collaborates in improving its products. Rosenkopf and Nerkar (2001) decompose knowledge into two parts. The first is the knowledge developed by a firm using its own resources. The authors call this first-order competence and suggest that it can constitute a source of competitive advantage but can also result in rigidity. The other is called second-order competence, or knowledge acquired outside the firm's boundaries. In summary, both internal and external knowledge can be determinants of TFP when a firm possesses absorptive capacity and when the knowledge is a source of competitive advantage.

Having stressed the importance of knowledge, it is important to discuss how knowledge is measured. As described above, one approach is to focus on absorptive capacity. Eustace (2000) suggests that absorptive capacity comprises R&D, know-how, intellectual property, workforce skills, world-class supply networks and brands. Some of these, such as R&D expenditure, can be quantified. Others, such as workforce skills, supply network and brands, are not easily quantifiable. Romijn and Albaladejo (2002) and Vinding (2006) propose the use of human capital measures, while Schmidt (2005) created a knowledge measure that combines R&D activities, related prior knowledge, individuals' skills, organisational structure, and human resources management practices. Among the potential measures suggested in the literature, one may wonder which is the most valuable. Most studies seem to have followed the suggestion of Cohen and Levinthal (1989), in which R&D is used as a proxy for absorptive capacity. The authors describe a dual role for R&D. Firstly, it develops absorptive capacity, which enables the firm to identify, absorb and exploit external knowledge for productive purposes, which are likely to indirectly result in higher TFP. Secondly, R&D generates products and process improvements within a firm, which are likely to directly lead to higher TFP. This dual role suggests that R&D is the most valuable proxy for absorptive capacity because it has both a direct and indirect effect on TFP.

However, some R&D investment is unsuccessful and is thus unlikely to result in higher TFP. Some R&D expenditures can result in TFP-improving innovations, while others may be a waste of resources. In their subsequent paper, Cohen and Levinthal (1990) suggest that absorptive capacity is path-dependent, or mostly a function of the prior knowledge that a firm has accumulated. This means that by already having a certain level of knowledge, a firm is able to better process and exploit new knowledge for innovative purposes, compared to firms without that level of knowledge. In contrast to Cohen and Levinthal (1990), Schmidt (2005) argues that R&D does not represent a valuable proxy for absorptive capacity because of its path-dependent characteristics. In response to this issue, Harris and Li (2009) measured absorptive capacity through a factor analysis on 36 variables representing the following: the firm's ability to exploit external knowledge, the knowledge generated by its networking relationships with external bodies, the implementation of new organisational structures and human resource management strategies, partnerships built with enterprises or institutions at the international level, and the acquisition and absorption of codified scientific knowledge from research partners. Harris and Li (2009) argue that their measure of absorptive capacity is the most direct and comprehensive. However, the difficulty in using such a measure lies in having access to the entire set of 36 variables. Harris and Li (2009) constructed this measure for firms based in the UK, for which information is more likely to be available than for those in developing countries such as China. Thus, despite the path-dependency issue suggested by Schmidt (2005), R&D constitutes the most reliable measure of absorptive capacity.

Empirically, the positive effect of R&D investment on TFP has been demonstrated by various studies. Lokshin et al. (2008) examined the impact of internal and external R&D on labour productivity in a sample of 301 Dutch firms during the period of 1996-2001. The change in knowledge stock was measured as a function of the investment into both internal and external R&D, where internal R&D represented absorptive capacity and external R&D represented the acquisition of external technology. The authors' results prove that both internal and external R&D positively affect labour productivity. Their most interesting finding, however, is that external R&D only has a positive impact when there is an adequate level of internal R&D. This suggests that a firm may particularly benefit from knowledge acquired externally when it has a strong level of absorptive capacity, which would enable it to exploit external knowledge for productive purposes. Other studies have analysed the relationship between R&D and productivity but without separating the two channels by which R&D impacts productivity.

Griliches (1986), for example, analysed the relationship between R&D expenditures and TFP growth in a sample of 1,000 large US manufacturing firms during the period of 1957-1977. A knowledge variable was inserted into a standard production function as a factor of production. This was measured with the variable $\mathrm{K} = \sum \mathrm{w_i R_{t-i}}$, where $\mathrm{R_{t-i}}$ represents the lagged effect of real gross investment in R&D on TFP. Griliches's findings suggest a positive and significant contribution of R&D to TFP growth, and this was found to last over time. In addition, a larger effect on TFP was found for company-financed research compared to federally funded research, and for basic research compared to other types of research.

In line with Griliches's (1986) study, Lichtenberg and Siegel (1991) analysed the relationship between R&D and TFP growth by comparing company-financed research with federally-funded research. The analysis looked at over 2,000 US firms during three different periods between 1972 and 1985. In the study, R&D was measured in terms of its intensity, given by the ratio of R&D expenditure to sales. Consistent with Griliches's (1986) findings, Lichtenberg and Siegel's (1991) results demonstrate a positive contribution of R&D investment to TFP growth. In particular, company-financed research was found to provide a higher return in terms of TFP than federally funded research. On the one hand, this suggests that firms benefit more from internally generated knowledge rather than externally generated knowledge. On the other hand, this points to a likely low level of absorptive capacity in the firms within the sample.

As with Lichtenberg and Siegel (1991), Griliches and Mairesse (1991) used an R&D intensity variable. However, instead of measuring the variable's contribution to TFP growth, they adopted labour productivity growth as a dependent variable. Although this is a valuable proxy, a more valuable one would have been TFP, as it considers all inputs utilized within the production process. In their study, Griliches and Mairesse (1991) assessed the contribution of R&D to labour productivity growth in both the United States and Japan by using firm-level data for the period of 1973-1980. In contrast to previous studies, the data only comprised company-financed R&D. Despite being minor, R&D contribution was found to be similar in the US and Japan. Moreover, the findings suggest that R&D contributed 0.4-0.6% to labour productivity growth during the period analysed. However, as Griliches and Mairesse (1991) point out, the Japanese R&D data is characterized by missing and inaccurate values, suggesting that the results should be interpreted cautiously.

Regarding the Chinese context, two studies have examined the effect of R&D on productivity at the firm level. Hu (2001) analysed the relationship between R&D spending and the productivity of 813 high-tech Chinese firms in the Haidian District of Beijing in 1995. The impact of R&D was measured in terms of its share of sales, thus representing its intensity. On the one hand, the results indicate the existence of a positive effect of privately financed R&D on Chinese firms' productivity. On the other hand, the results indicate the existence of a negative relationship between government financed R&D and firms' productivity. Despite this, the results also suggest that government financed R&D indirectly affects firms' productivity in a positive manner, as it stimulates private R&D expenditure.

While Hu's (2001) study focused on high-tech firms, Wu et al. (2007) examined 145 firms belonging to the watch and clock manufacturing industry in Southern China. Apart from R&D intensity, knowledge was also examined in terms of capital intensity (the ratio of a firm's capital expenditure to its number of employees) and level of product differentiation (the ratio of a firm's advertising expenditure to its gross output). The results suggest that technical efficiency is positively affected by knowledge expressed as R&D and capital intensity, but negatively by knowledge expressed as product differentiation.

Based on the above discussion and empirical results from the literature, knowledge creation in the form of R&D investment is likely to have a positive effect on firms' TFP. This positive effect is likely to be exerted through two channels: a direct channel, as R&D expenditure is undertaken for product and process improvements, and an indirect channel, as R&D develops absorptive capacity, which enables firms to absorb external knowledge and use it for productive purposes. The empirical literature analysing Chinese firms indicates that privately financed R&D directly and positively affects TFP. Government financed R&D, on the other hand, directly and negatively affects TFP but provides an indirect positive effect by promoting private R&D expenditure.

Other than through R&D investment, knowledge can be also obtained through experience. This is because a firm is expected to become more productive as it ages, according to the so-called "survival effect." As it matures, a firm accumulates knowledge according to a process defined by Arrow (1962) as "learning by doing," which is likely to generate improvements in TFP. "Learning is the product of experience. Learning can only take place through the attempt to solve a problem and therefore only takes place during activity" (Arrow, 1962, p.155). This suggests that a firm's acquisition of knowledge does not just occur through mere repetition in production, but also through solving the problems encountered. In addition, "as plants age, managers accumulate experience, gain from learning by doing, undertake new investments, or achieve economies of scale, all of which can improve plant-level productivity" (Jensen et al., 2001, p. 323). Moreover, over time, firms become more knowledgeable about the market in which they operate, and learn how to better satisfy their customers' needs, source inputs and process them. These developments are likely to result in higher TFP. Jensen et al. (2001) also suggest another aspect of the relationship between TFP and firm age. The authors argue that new firms entering an industry might have higher productivity than existing ones. This is because the new firms might utilize more recent and innovative capital that represents technological best practices. Thus, older firms are expected to be less productive than younger firms because of the so-called "vintage effect." Marshall (1890) also suggests that older firms might be subject to inertia, rendering them unable to adjust as quickly to the dynamic market environment as their younger counterparts. Hannan and Freeman (1984) also argue that a firm's negative performance is often due to the so-called "inertia effect," by which firms are unable to adjust their structures and strategies to the dynamic environment, making them unable to exploit the opportunities the environment offers. In summary, the above arguments suggest there is no unilateral relationship between firm age and TFP. There can be a positive relationship due to the "survival effect," or a negative relationship due to either the "vintage" or "inertia" effects.

Jensen et al. (2001) studied the evolution of US labour productivity in manufacturing plants from 1963 to 1992. The vintage effect was measured as the change in labour productivity of newer plants compared with older ones when entering their respective industry. The survival effect was measured as the change in labour productivity of existing plants over time. Both effects were found to contribute to the overall growth in manufacturing industry labour productivity. In particular, the higher productivity of newer plants compared to older plants suggests that newer plants bring with them the latest best practice technology, pointing to the existence of the vintage effect. At the same time, Jensen et al. (2001) also demonstrate the existence of the survival effect, as plants that were already in an industry became more productive over time.

Majumdar (1997) looked at a sample of 1,020 Indian firms to analyse the impact of firm size and age on productivity and profitability over the period of 1998-1994. Firm age was measured as the number of years that a firm's data had been recorded in the database. The findings suggest that older firms are more productive than younger ones, while being less profitable. From these results, one would infer that the more a firm matures, the more productive it becomes. This suggests that older firms learn by doing as they become more experienced. Consistent with Jensen et al.'s (2001) study, this suggests the existence of a survival effect. However, India has a different institutional setting than the US that is characterised by greater barriers to entry and exit.

In another study in a developing country, Fernandes (2008) looked at 575 large manufacturing firms in Bangladesh belonging to five different manufacturing industries and found a non-linear relationship between firm age and TFP. This finding suggests that firms are likely to start at a low productivity level that then increases over time as the firms "learn" by undertaking investments, entering into new markets, and updating their technology. At a certain age, the firms reach a "maturity stage," from which their productivity decreases as their stock of knowledge erodes and becomes obsolete.

In the developed country context, and using a much wider sample than the above studies, Coad et al. (2013) analysed the relationship between firm age and various measures of performance. This was done with a sample of 62,259 Spanish manufacturing firms over the years of 1998-2006. Similar to Fernandes (2008), Coad et al. (2013) find that as firms age, they improve their productivity level in addition to experiencing increased profits, growth in size and lower leverage. On the other hand, at a certain age, firms start to experience worsening performance in terms of productivity growth, sales, and profitability.

Within the Chinese context, only two studies have examined the relationship between firm age and TFP. Zheng et al. (2003) analysed the technical efficiency performance of 600 State-owned enterprises belonging to 17 two-digit industries located in four provinces during the period of 1990-1994. The estimation was conducted using both a Data Envelopment Analysis approach and a Malmquist index of productivity growth. Among the explanatory variables analysed, firm age was included. This was found to significantly and positively affect firms' technical efficiency.

While Zheng et al. (2003) focused only on Chinese firms, Hsieh and Klenow (2009) compared Chinese and Indian firms to US firms. In examining the impact of resource misallocation on firms' TFP, the impact of firm age on productivity was also considered. Their results indicate an inverted U-shaped relationship between firm age and productivity, as productivity rose in the youngest 10% of Chinese firms and then remained flat before falling for the oldest 10% of Chinese firms.

The above empirical evidence on the relationship between firm age and TFP suggests that firms enter an industry with the best practice technology available, which is likely to result in higher productivity. Then, up to a certain point, the effect of age on TFP is likely to be positive as firms learn by experience. By solving issues in the production process, and learning from them, firms are likely to experience enhanced TFP. In addition, a firm is likely to better understand the market environment in which it operates over time. Such understanding enables the firm to better satisfy customer needs and to source better inputs, both of which are likely to result in higher TFP. However, as firms mature, the effect of age on TFP becomes negative due to struggles in adapting to the dynamic and uncertain external environment and keeping up with both industry best practices and new technologies. While the literature related to China is scant, it indicates the existence of a positive relationship between age and TFP for State-owned enterprises, and a non-linear relationship for firms with other kinds of ownership structures.

Until now, knowledge has been represented by R&D expenditure and age. Alternatively, knowledge can be also represented by a time trend, or Hicks-neutral technical change. This refers to the positive impact on TFP arising from an exogenous technological change that affects all firms at the same time. Such a situation generates an increase in TFP while the ratio of the marginal product of capital to the marginal product of labour remains constant for a given capital to labour ratio. The Hicks-neutral technical change must not be confused with either the Harrod or Solow-neutral changes. A Harrod-neutral technical change is labour augmenting, where relative factor shares are constant for any capital to output ratio. A Solow-neutral technical change is capital augmenting, whereby relative factor shares are constant for any labour to output ratio.

In summary, the above discussion suggests that knowledge is a valuable determinant of total factor productivity. Knowledge can be represented in various ways. Firstly, a firm can commit funds to R&D, which would result in higher TFP in two distinctive ways. One is through product and process improvements. The second is through the development of absorptive capacity, which enables a firm to exploit external knowledge for productive purposes. The empirical literature analysing Chinese firms indicates that privately financed R&D directly affects TFP in a positive manner, while government financed R&D directly affects TFP negatively but indirectly affects it positively by promoting private R&D expenditure. Secondly, a firm is expected to acquire more knowledge and therefore become more productive over time through experience. This is according to the process of "learning by doing," whereby a firm becomes better at production by solving issues encountered in the process. In addition, the firm becomes more knowledgeable about the market in which it operates, enabling it to better satisfy its customers' needs and to source better inputs, both of which are likely to result in higher TFP. However, a positive effect of a firm age on TFP is not always present. An older firm might become slower to adapt its characteristics and strategies to the market or to keep its technology up to date with industry best practices. Such conditions are likely to result in lower TFP. Moreover, new industry entrants are more likely to utilize the latest technology available, thus making them more productive than firms already established within an industry and forcing the older firms to exit. This suggests that the relationship between age and TFP can also be negative. In the Chinese context, the literature is still scant but it indicates the existence of a positive relationship between age and TFP for State-owned enterprises, and a non-linear relationship for firms with other kinds of ownership structures. In addition to R&D and age, knowledge can be also represented by the time trend, or the Hicks-neutral technical change, which is the impact on TFP of exogenous technology that affects all firms at the same time.

This section has discussed knowledge as a determinant of firms' total factor productivity. The next section discusses firms' political affiliation.

### 2.4.2. Political Affiliation

"A company is connected with a politician if one of the company's large shareholders or top officers is: a member of parliament, a minister or the head of state, or closely related to a top official" (Faccio, 2006, p. 370). In the literature, politically affiliated firms have been found to enjoy significant advantages over non-politically affiliated ones.

Firstly, politically connected firms tend to benefit in terms of preferential access to credit. Such was suggested by Johnson and Mitton (2003), who looked at a sample of 424 Malaysian firms over the period of 1997-1998 and found that the imposition of capital controls following the onset of the Asian financial crisis largely benefited firms linked to the country's then prime minister. Dinç (2005) compared the actions of government-owned banks with those of private banks in 43 major emerging markets during general elections in the years of 1994-2000. The results suggest that government-owned banks increase their lending during election years compared to private banks. Such increases were mainly attributed to political motivations.

Secondly, politically affiliated firms tend to benefit from government contracts. Goldman et al. (2013) examined the importance of political connections in the United States by analysing a sample of companies belonging to the S&P500 before and after the 1994 midterm and 2000 general US elections. Their results show that companies with connections to the winning party tend to experience an increase in procurement contracts.

Thirdly, politically connected firms also benefit in terms of regulatory protection. This is suggested by the results of Kroszner and Stratmann (1998), who investigated the relationship between competition among three rival interests groups and its effect on contributions made to legislators from the US financial services industry. While abovementioned studies are focused on single countries, Faccio (2010) analysed the differences between politically connected and non-politically connected firms in a sample of 16,191 companies across 47 countries. Her findings suggest that politically connected firms, in comparison with non-connected ones, have higher leverage, lower taxation, poorer accounting, greater market power, lower ROA and lower market valuation. Moreover, differences with non-politically corrected firms were found to be wider when the firms are based in countries characterised by high corruption, and when political connections are closer, as it is the case for connections with company owners and ministers.

The above empirical results suggest that politically connected firms are likely to benefit from preferential access to credit, government contracts, regulatory protection, and lower taxation. Since such benefits make it easier for a firm to operate, political connections are likely to result in higher TFP levels.

China can be distinguished from other transition economies due to its continuous Communist Party leadership, whose membership includes connections with key figures, both political and economic (Li et al., 2008). In the Chinese context, a political affiliation is a *lishu* relationship between a firm and any level of government (Li, 2004; Tan et al., 2007; Xia et al., 2009). The empirical evidence is mixed, suggesting that political affiliations have both positive and negative effects on Chinese firms' performance.

Li et al. (2008) studied more than 2,000 private Chinese firms to examine whether Communist Party membership positively affects firms' profitability. Their results indicate that membership in the Communist Party positively affects private firms' profitability, particularly in regions with less developed markets and legal systems. Political affiliation enables private firms to overcome the legal, institutional and ideological barriers that are set up against private ownership in China. Moreover, the results suggest that politically connected private firms benefit in terms of higher availability of loans. Although this study provides an insight into the effect on of political connections firm performance, it is limited to private firms. A following study might also consider analysing such an effect on other kinds of firms, such as State-owned firms. In addition, the study only analysed the effect of political connections on firms' profitability measures, not considering TFP.

While the above study focused only on private enterprises, Wu et al. (2012) also analysed State-owned enterprises (SOEs). Specifically, they examined the effect of political affiliation on the performance of both SOEs and private firms (as measured by Tobin's Q and ROA) for 1,408 firms between 1999 and 2007. In their study, a firm's political connectedness was represented by a dummy variable taking the value of 1. A firm was regarded as politically connected if either the Chairman or CEO had worked in the Chinese government or the military. The results indicate that private firms with politically connected managers tend to record better performance than firms without such connections. In contrast, local SOEs with connected managers recorded worse performances than those with non-connected managers. In addition, private firms with connected managers tend to benefit from tax incentives, while local SOEs with connected managers tend to be subject to overinvestment issues.

Although the two measures of performance adopted in the previous two studies are valuable, TFP could have also been considered, as it indicates the extent to which inputs are transformed into valuable output. Du and Girma (2010) evaluated the effect of political connections on the survival and growth prospects, as well as the TFP growth, of 106,000 private Chinese enterprises. The authors represented the extent of political connectedness through a vector of three binary variables representing affiliation with local, prefecture or town level, and regional or central government agencies. Their findings suggest that politically connected Chinese firms have a higher chance of survival and higher employment growth. Moreover, firms associated with local and high levels of government, and which belong to capital-intensive industries, seem to benefit most from political connections. However, firms without political affiliation seem to display better productivity growth. This suggests that there might be cases in which political connections are not beneficial to a firm's performance. It might be that a political affiliation makes a firm less likely to focus on maximising productivity than pursuing objectives that are politically motivated.

This section has discussed political affiliation as a determinant of a firm's TFP. The discussion indicates that politically affiliated firms tend to enjoy substantial benefits over non-politically affiliated ones. The empirical results from the literature suggest that politically connected firms are likely to benefit through preferential access to credit, government contracts, regulatory protection, and lower taxation. Such benefits make it easier for a firm to operate, likely resulting in higher TFP. For Chinese firms in particular, the empirical evidence is mixed, suggesting that political affiliation has both positive and negative effects on performance. The only study concerning the effect of political affiliation on Chinese firms' TFP documents a negative relationship, although the analysis was limited to private firms. While the consideration of firms with other kinds of ownership structures would provide additional insights into this relationship, the study points that political affiliation might not be beneficial to a firm's productivity.

### 2.4.3. Foreign Direct Investment

While the previous two sections reviewed the importance of knowledge and political affiliation as determinants of TFP, this section discusses a firm's ownership and focuses on foreign direct investment (FDI). A foreign-owned firm is expected to have a higher TFP than firms with other kinds of ownership. According to the internalisation or transaction cost theory developed by Coase (1937) and Williamson (1981), foreign-owned firms enter into new markets when they have firm-specific advantages to exploit. A foreign-owned firm will be likely to make such a decision if it expects the future benefits to outweigh the related costs of entry. Suyanto et al. (2009) argue that domestic firms have a better performance within their domestic markets than foreign-owned firms. Thus, foreign-owned firms require a comparative advantage in order to compensate for the lack of experience within a new market and the sunk costs of entry. Such advantages can include better technology, know-how, superior managerial practices, and innovative marketing techniques, among others. For example, a foreign-owned firm may use more innovative machinery than local firms, or have managers who are able to select a better combination of factor inputs. For these reasons, foreign-owned firms are likely to be more productive than local ones.

For example, a foreign-owned firm's investment into a domestic firm is likely to either directly or indirectly lead to higher productivity in the domestic firm. The effect is direct when the local plant or firm in which the foreign-owned firm has invested benefits directly from the comparative advantage brought by the foreign owner. One instance is when a local plant benefits from the adoption of more advanced technology that the foreign owner has brought as part of the investment contract.

Caves (1974) suggests that, in addition to its direct effects, FDI can also indirectly affect domestic firms' TFP. This occurs when there are spillovers from foreign-owned plants to domestically owned ones. Regarding the channels through which FDI is transmitted indirectly through spillovers, Crespo and Fontoura (2007) mention five: imitation/demonstration, labour mobility, exports, competition and linkages with domestic firms. Firstly, imitation/demonstration concerns local firms' adoption of the innovations used by foreign firms. These innovations can take various forms, such as innovative machinery, better managerial practices or improved input allocation. Such improvements enable a local firm to reduce costs and produce more and better output, which might ultimately result in higher TFP. Secondly, labour mobility concerns the development of a highly-skilled labour force by a foreign owner, which will improve TFP through the spread knowledge to other parts of the business. Thirdly, local plants can also benefit from the export activity that a foreign owner brings, as it is most likely to be a multinational firm. Since a foreign-owned firm has knowledge of international markets, local firms can follow its lead, for example, in learning about trading strategies or setting up new trading ventures. Fourthly, competitiveness increases for a plant or firm, as managers undertake measures to address threats from both potential and actual competitors. Moreover, the entrance of a new firm causes a reallocation of output shares within an industry. This is because the least productive firms will exit an industry, while the most productive ones will survive and even capture higher market share. This could result in increased TFP for the entire industry. Lastly, spillovers can also be transmitted through the development of commercial relationships, or linkages, between foreign-owned and local firms. Such relationships can include backward linkages, where the local firms are suppliers to the foreign-owned ones. Local firms, for example, can benefit in terms of learning from the feedback provided by foreign customers concerning the products supplied. Commercial relationships can also involve forward linkages in which foreign-owned firms are suppliers to the local firms. In this example, the local firms can benefit from the higher quality of inputs supplied. In addition, in any commercial relationship, foreign-owned and local firms can share both tangible and intangible assets, such as know-how and R&D efforts, in order to improve not just their products but also their work processes and techniques.

Based on the above discussion, it seems that FDI is likely to benefit firms in terms of higher TFP levels. In some cases, this benefit can be direct, for example, in those firms that a foreign owner has invested in. In other cases, the benefit can be indirect through spillovers, which manifest themselves through different channels such as imitation/demonstration, labour mobility, exports, competition, and backward or forward linkages.

The empirical research has provided mixed results. Some studies suggest that FDI positively affects productivity. For example, Harris (2002) studied the direct effect of foreign ownership on the TFP of firms belonging to the motor vehicle industry and four other British manufacturing industries (Pharmaceuticals, Electronic Data and Processing Equipment, Aircraft Equipment Manufacture and Repair, and Miscellaneous Foods) for the years 1980-1992, using both plant and establishment data. In the study, foreign ownership was measured as a vector of dummies, each taking a value of 1 according to the geographical origin of each firm's owner (US, EU, or Old Commonwealth Enterprise). The results indicate that foreign-owned plants are more productive than UK-owned plants. In particular, at both the establishment and plant levels, plants owned by US and EU firms were more productive than local ones within the motor vehicles sector. In the other four industries, plants owned by US firms were found to be more productive than local plants, while those owned by EU firms were not found to be more productive than local plants.

Harris and Robinson (2002) analysed plants in the UK manufacturing sector during the period of 1987-1992. They looked at the difference in TFP performance between plants that had changed ownership and plants that had not, and particularly at the difference in TFP performance between foreign-owned and domestic-owned plants. In the estimation methodology used, foreign ownership was indicated by a dummy variable that took the value 1 if a firm was foreign-owned and 0 otherwise. Surprisingly, the findings indicate that foreign owners acquired the most productive domestic plants, whose TFP subsequently decreased after the acquisition. The authors suggest that this decline in TFP might be due to post-acquisition organisational difficulties. From this study, one can infer that foreign ownership of a plant may not always result in higher TFP. Foreign firms might acquire plants that have higher efficiency and better technology than their own plants, which will likely benefit the foreign owner. However, it might prove difficult for foreign owners to integrate their operations, organisation, and culture with those of the new plant, likely resulting in a decrease in TFP.

A more general study was done by Harris and Robinson (2003), where they analysed the direct effects of foreign ownership on TFP using plant-level data from firms belonging to 20 UK manufacturing industries in the period of 1974-1995. In general, foreign-owned plants were found to be more productive than UK-owned ones. Foreign-owned plants were found to positively impact TFP within the UK manufacturing sector by pushing local plants to “catch up” with best practices. While plants owned by US firms were found to be more productive than local ones in most sectors, this productivity advantage seemed to decline over time. EU-owned plants were found to record better performance than UK-owned ones in some industries, while showing poorer performance in others. In addition, the TFP of EU-owned plants was found to decline over time, suggesting that they do not necessarily have better performance than UK-owned ones. Mixed effects were found for plants owned by Old Commonwealth and South East Asian countries. These results suggest that foreign-owned firms bring with them a comparative advantage that enables them to become more productive than local firms.

Regarding the Chinese context, Zhou et al. (2002) analysed the direct effect of FDI on Chinese firms’ productivity during the period of 1992-1995. The sample was taken from the NBS and comprised 450,000 firms representing 90% of China’s total national industrial output. However, the sample only included medium and large firms. Firm performance was measured as value added per employee. Despite the usefulness of this measure, a more valuable measure would have been TFP, as it considers all inputs utilized within a firm's production processes. Using OLS estimation, their results suggest that firms based in geographical regions characterised by higher levels and a longer presence of FDI tend to have higher productivity than firms in areas with lower levels and a shorter existence of FDI. On the other hand, firms belonging to industries characterised by high levels and a longer existence of FDI tend to have lower productivity. Based on these results, FDI seems to exert opposing effects on domestic firms, depending on whether they belong to a high-FDI region or a high-FDI industry.

Zhang et al. (2001) compared productivity levels between SOEs and firms with other ownership structures in a sample of 2,000 firms from 22 industries during the period of 1996-1998. The empirical analysis was conducted using the data envelopment analysis (DEA) methodology, which computes firms' efficiency scores and compares them with the best practice in each related industry. Their results indicate that foreign-owned firms and firms owned by investors based in Hong Kong, Macao and Taiwan recorded the highest efficiency scores, while State-owned firms recorded the lowest. The effect of ownership on changes in efficiency was also analysed using the Malmquist index, with the results showing that State-owned firms recorded faster efficiency growth than both collectively-owned firms and firms owned by investors from Hong Kong, Macao and Taiwan.

Jefferson et al. (2003) analysed the changing profile, in terms of composition and performance, of a sample of 22,000 Chinese industrial large and medium-size firms during the 5-year period between 1994 and 1999. In terms of productivity growth, the statistical results indicate that State-owned shareholding firms recorded the lowest performance, followed by overseas, other domestically owned, collectively owned, foreign owned and privately owned firms. In terms of TFP levels, at the end of 1999, the least efficient firms were SOEs, followed by shareholding, privately owned, collectively owned, overseas and foreign owned firms.

Zhang et al. (2003) examined the effect of ownership on the R&D efficiency of 8,341 Chinese industrial firms. Ownership was found to play an important role in both R&D and production efficiency. The findings indicate that foreign owned firms are the most efficient, while SOEs are the least efficient. Foreign owned firms and firms owned by investors from Hong-Kong, Macao and Taiwan seemed to record both higher technical efficiency and productive efficiency than collectively owned and joint-stock owned firms. The higher R&D

efficiency that characterises foreign-owned firms seems to be due to higher R&D intensity, and tends to result in higher firm productivity.

The above literature review has suggested that FDI has a positive effect on firms' TFP. This means that foreign-owned firms are more productive than domestically owned firms due to the advantages brought to the firm by the foreign owner, such as better technology, know-how, superior managerial practices, and innovative marketing techniques. While the abovementioned studies have analysed the direct effect of FDI on firms' TFP, other studies have analysed the indirect effects that occur through spillovers from foreign-owned plants to the local ones. Crespo and Fontoura (2007) suggest that FDI spillovers can be transmitted through five channels: imitation/demonstration, labour mobility, exports, competition, and through commercial relationships, or linkages, with domestic firms. In general, the empirical research seems to provide support for the existence of an indirect effect of FDI on TFP.

Harris and Robinson (2004) used the same dataset as in their previous study (Harris and Robinson, 2003) to analyse the indirect effect of FDI on the TFP of firms belonging to 20 UK manufacturing industries. They considered both intra-industry effects through competition, inter-industry effects through forward and backward linkages, and spatial agglomeration effects. Their results suggest that for most industries, there are no effects of FDI on TFP through spatial agglomeration spillovers. In the industries where the effect does exist, it is both positive and negative, suggesting the existence of both economies and diseconomies of scale. Inter-industry indirect FDI spillover effects due to backward and forward linkages were positive for some industries and negative for others. Regarding intra-industry indirect FDI spillover effects, no significant impact was seen in more than a third of industries. Where an impact did exist, it was in some cases positive and in other cases negative. These results seem to question the impact of indirect FDI spillovers on firm TFP, as there is no clear effect seen. Further analysis is needed to confirm these results.

Girma and Wakelin (2007) analysed the indirect effect of FDI on TFP in the UK electronics sector in 1980 and 1992. They separated FDI by the nationality of the multinational firm, which was either American or Japanese. Moreover, they evaluated the different effects of FDI in regions where government assistance was available compared to those where it was not. The type of FDI was denoted by a variable with three variants: one denoting regional intra-industry spillovers; one denoting inter-regional intra-industry spillovers; and one denoting local inter-industry spillovers. Their findings suggest a generally positive indirect effect of FDI on TFP through regional spillovers, both intra-industry and inter-industry. However, they did not find any evidence of inter-regional spillovers on plants belonging to the same sector. In addition, plants located in areas where government assistance was provided were not found to particularly benefit from FDI, suggesting that the domestic plants do not possess adequate absorptive capacity to benefit from FDI spillovers.

In addition to horizontal FDI spillovers, Suyanto et al. (2009) considered the effect of the competition channel in their investigation of the indirect effect of FDI spillovers for 568 firms belonging to the Indonesian chemical and pharmaceutical sectors from 1988 to 2000. FDI was represented by a dummy variable that was equal to 0 when there was no foreign ownership share and 1 if there was a positive share of foreign ownership. Their results suggest the presence of intra-industry spillovers, which benefit firm TFP. Moreover, firms that commit funds to R&D expenditures were found to benefit more so than those who do not. This suggests that a firm with a relatively high level of absorptive capacity, as measured by the stock of R&D, is likely to benefit more from spillovers than a firm with a relatively low level. In addition, productivity spillovers were found to be higher in the presence of competition, which was measured by an index representing the concentration of sales among producers. These results suggest that competition stimulates firm managers to undertake TFP-enhancing actions in response to threats from both actual and potential competitors.

Concerning the imitation/demonstration channel of FDI, Ben Hamida and Gugler (2009) analysed the intra-industry spillovers from FDI using Swiss firm-level data on manufacturing and services firms' productivity in 1998 and 2001. Their focus was mainly on analysing the effect of the demonstration channel of FDI spillovers on productivity, which was measured by foreign firms' sales share within an industry. In particular, how these shares of sales varied according to the firm's level of absorptive capacity was analysed. When the heterogeneity of the firms in terms of absorptive capacity was not considered, the results did not suggest the existence of spillovers. However, when this heterogeneity was taken into account, FDI spillovers were shown to manifest themselves through the demonstration channel for firms investing in R&D, which builds up absorptive capacity. This underlines the idea that in order to benefit from FDI spillovers through the demonstration channel, firms should aim to build high levels of absorptive capacity, for example, through R&D investments.

Concerning the FDI spillover effect on productivity through the labour mobility channel, Todo et al. (2009) analysed how multinational enterprises' (MNEs) employment of workers determined the spillover of knowledge to local firms. The analysis was conducted in a Chinese high tech cluster using panel data for 798 manufacturing firms during the period of 2000-2003. The knowledge spillovers from MNEs were measured in two ways: the MNEs' total labour force, and the number of educated workers. The results indicate the existence of within-industry FDI spillovers through a labour-mobility channel, represented by the employment of educated workers. The results suggest that labourers can learn by working for technologically advanced MNEs, and when these workers move to domestic firms or set up their own firms, they can apply their innovative knowledge and skills, resulting in higher TFP. Despite providing interesting results, the analysis in this paper only concerned a technology cluster, thus offering limited insight into the overall effect of FDI spillovers on TFP through the labour mobility channel.

Also in the Chinese context, Liu (2008) examined the effect of FDI spillovers on the TFP of medium and large Chinese manufacturing firms. *Intra-industry* spillovers were measured as the sum of the average foreign equity share owned by foreign investors in each firm, weighted by the firm's share of sectorial output. *Inter-industry* spillovers were divided into backward and forward linkages. *Backward* linkages were measured as the sum of firms' FDI within a sector, weighted by the share of intermediate output in another sector *from* which the firms source their inputs. *Forward* linkages were given by the sum of firms' FDI within a sector, weighted by the share of intermediate output in another sector *to* which the firms sell their inputs. The results of the study suggest that both intra-industry and inter-industry spillovers have a positive effect on TFP. In particular, backward linkages were found to have the strongest positive effect on firms' TFP. This suggests that local firms can learn by supplying foreign-owned firms with intermediate inputs, about which they might be asked to provide very detailed specifications, and about which they will receive important feedback from which to learn.

Xu and Sheng (2012) analysed how FDI spillovers affect the productivity of Chinese manufacturing firms during the period of 2000-2003. Spillovers were divided into three categories: horizontal (arising from firms within the same industry), backward (generated when a firm supplies a multinational firm) and forward (generated when a firm sources its inputs from a foreign supplier firm). Results from the estimation suggest that forward FDI spillovers have a positive effect on firm productivity through the import of qualitative intermediate goods and equipment by foreign firms belonging to the upstream sectors. However, horizontal and backward FDI spillovers were found to negatively affect TFP. Therefore, the overall results were not as positive as one might expect. Interestingly, the firms that benefitted the most from a foreign presence were the large and medium-sized firms not belonging to the state sector, and which were engaged in export activities. It would be interesting to extend the time period of study, as firms might require more time to assimilate knowledge gained from FDI.

A different approach to studying the effect of FDI spillovers was adopted by Fu and Gong (2009). They included in their model R&D spillovers from innovation activities undertaken by foreign-invested firms, measured by the industry average R&D intensity according to ownership type, and international R&D spillovers, measured as the world R&D stock. FDI intensity was measured at both the firm and industry levels. As in previous studies, the dataset was taken from the Chinese National Bureau of Statistics. However, in this case, the sample was much smaller, comprising 53,981 firms, while considering a wider period, from 2001 to 2005. The study's results show that TFP grew at about 4.8% per year during the period, mainly driven by technical change rather than changes in efficiency. Such growth confirms the findings of previous studies. Moreover, the strong technical change occurred particularly in industries dominated by domestic firms, suggesting that foreign-owned firms possess advantages, such as better managerial practices and knowledge, that result in higher TFP. In terms of R&D, investment activities undertaken by foreign-invested firms were found to negatively affect TFP, while those by domestic firms at the industry level were found to positively affect technical change.

In a later study, Wei and Liu (2006) adopted a much different approach. The effect of FDI on productivity was measured together with spillovers from R&D and exports, which represent valuable sources of knowledge. FDI spillovers were measured as the share of foreign-owned firms' capital in the total capital in an industry, region, or industry within a region. Secondly, the authors only focused on the impact of spillovers on domestic firms, rather than combining firms with different origins. The sample comprised 9,900 Chinese manufacturing firms during the period of 1998-2001, with the data taken from the Chinese National Bureau of Statistics. In order to address the issue of endogeneity, the authors adopted one-year lags of potential endogenous variables as instruments. In addition, the estimation was corrected for both heteroskedasticity and autocorrelation. Interestingly, their results suggest a positive effect on productivity of inter-industry spillovers from R&D and exports, and a positive effect on productivity of both inter- and intra-industry spillovers from the presence of foreign firms. Moreover, firms in which investors from OECD countries were major shareholders were found to have higher productivity than those in which the investors were from Hong Kong, Macao and Taiwan. This suggests that Chinese firms benefit in terms of spillovers from firms in which investors from developed countries are the major shareholders, as these firms are likely to have more advanced technology and up-to-date knowledge.

A study that found differing results from the previous ones was conducted by Hale and Long (2011). They used a data set of Chinese domestic firms taken from a 2001 World Bank survey that provides information on 1,500 firms located in 5 cities and 10 industries for the year 2000. The presence of FDI within a specific city or industry was measured as the average of foreign ownership share in the same city-industry as the domestic firm, weighted by firm employment. Upstream FDI spillovers were measured as the sum of FDI presence in all other industries in the same city, weighted by the input coefficients corresponding to the firm's industry. Downstream FDI presence was computed as the sum of FDI presence in all other industries, weighted by the output coefficients of the firm's industry to these other industries. The results suggest that foreign-owned firms tend to be more productive than domestically owned ones. The study represents a step forward from past studies analysing the impact of FDI spillovers on productivity since it adopts different methodologies. However, its limitation lies in not having a time dimension. It only provides a snapshot of productivity performance at a specific point in time, rather than analysing a trend. Therefore, it would have been better to extend the study over more years.

Another study by Wei et al. (2008) differs from the previous study in that it examined the effect of reverse productivity spillovers in China, which refer to the positive effect of knowledge from domestic firms on the productivity of multinational firm. The investigation consisted of an econometric analysis of more than 10,000 firms belonging to 193 industries, including both domestic and foreign-invested firms, during the period of 1998-2001. To measure spillovers, the authors used R&D, capital investment and employment. Moreover, the firms were differentiated according to their origin: Chinese domestic firms; Hong Kong, Macau and Taiwan-invested firms; and OECD-invested firms. The results from the econometric estimation suggest that foreign-invested firms exert a positive but diminishing spillover effect on the productivity of local Chinese firms. These local firms, in turn, tend to exert a positive but diminishing spillover effect on the productivity of foreign-invested firms. Therefore, the results suggest that domestic and foreign-invested firms complement one other. Although the study provides an innovative insight into reverse spillovers in a developing country by using a wide sample, the time period considered seems short, as firms might need more time to learn and productively implement the knowledge acquired.

While the abovementioned studies have looked at the spillover effect arising in a variety of industries, Motohashi and Yuan (2010) analysed the spillover effects arising from the innovative activities of multinational firms in two industries: automobiles and electronics. Data from 22,000 firms was taken from the annual Survey of Science and Technology

Activities, which includes medium and large firms from 1995 to 2004. Spillovers were measured using four variables: (i) the sum of technology stock of multinational firms in the assembly sector of each province in a specific year; (ii) the sum of technology stock of local firms in the assembly sector of each province in a specific year; (iii) the sum of technology stock of multinational firms in the supply sector of each province in a specific year, excluding one of the firms considered; and (iv) the sum of the technology stock of local firms in the supply sector of each province in a specific year, excluding one of the firms considered. The automobile industry showed vertical spillovers from multinational and local firms in the assembly industry to local suppliers. In the electronics industry, on the other hand, vertical spillover effects were only seen only from local firms in the assembly industry to local suppliers. The presence of horizontal spillovers was not detected. Among the control variables, the import of technology and research collaboration were found to positively affect the value of firms. This study, like previous ones, suggests a mixed effect of vertical spillovers. However, in contrast to the previous studies, it does not suggest the existence of horizontal spillovers. This finding may an anomaly due to the study limiting its analysis to two industries.

Li et al. (2001) analysed the indirect effect of FDI spillovers and competition arising from the presence of foreign firms on labour productivity. Data for the manufacturing sector was taken from the 1995 Industrial Census of the National Bureau of Statistics. Since labour productivity is not an ideal measure, it would have been better to adopt TFP. In the equation, FDI spillovers from demonstration and contagion effects were represented by two variables measuring the ratio of the foreign firms' employment to total employment, and the ratio of foreign firms' assets to total assets. Moreover, FDI spillovers through competition were measured by the labour productivity of the other firms in the sample. The study's results suggest that spillovers have different positive effects on firms. Spillovers positively affect SOEs through competition effects, and positively affect the other local firms through demonstration and contagion effects.

Lin et al. (2009) studied the effects of both horizontal and vertical FDI spillovers through backward and forward linkages on Chinese manufacturing firms' TFP during the period of 1998-2005. Horizontal spillovers were measured as the foreign share in the total output of each industry. Backward spillovers were measured by the proportion of the output of one industry purchased by another industry. Forward spillovers were measured as the foreign share of an industry's intermediate input that was supplied by another industry. The results support the existence of vertical forward spillovers, meaning that local firms are likely to benefit indirectly in terms of higher TFP from FDI spillovers through relationships with foreign-owned suppliers. However, vertical backward spillovers seemed only to exist for firms whose foreign owners were not from Hong Kong, Macao or Taiwan. This result suggests that local firms are likely to benefit indirectly from FDI spillovers in terms of higher TFP by supplying foreign-owned firms. Moreover, foreign-owned firms from countries belonging to the Organisation and Economic Co-operation Development (OECD) are likely to have higher requirements for products supplied, pushing local firms to improve their products and processes and thus increasing TFP. Regarding horizontal spillovers, FDI spillovers generated by owners from Hong Kong, Macao or Taiwan negatively affected TFP, while spillovers generated by owners from OECD countries positively affected TFP. The results indicate that Chinese firms learn from OECD foreign-owned firms belonging to the same industry, which are likely to be more advanced technologically.

The studies described above, from both outside and within the Chinese context, suggest that FDI indirectly contributes to TFP through intra-industry and inter-industry spillovers, R&D and other innovative activities, and competition. The empirical evidence complements previous evidence suggesting a positive direct contribution of FDI to firms' TFP. It could thus be inferred that FDI is a positive determinant of TFP. However, this does not seem to always be the case. According to Driffield and Love (2007), FDI might result in lower productivity for the following reasons.

Firstly, FDI might be aimed at accessing technology owned by local firms belonging to R&D-intensive sectors or to research centres through a process of technology sourcing. This suggests that a foreign firm may extract local technology through FDI, transferring it to its home country and thus not generating any direct or indirect benefits to local firms in terms of TFP. Secondly, a foreign-owned firm might undertake FDI in a particular country due to location advantages such as low taxes. Thirdly, a foreign-owned firm might undertake FDI to seek efficiency by exploiting cheaper local factor inputs, through an "efficiency seeking" process. For example, a firm might invest in a firm based in a developing country because of low labour costs. Fourthly, FDI could also result in lower TFP due to the "market stealing" effect discussed by Aitken and Harrison (1999). This occurs when a foreign firm generates higher TFP in its related industry through positive spillovers effects, but which is negatively offset when the foreign firm steals market share from local competitors, leading to lower industry TFP. Fifthly, Harris and Robinson (2003) argue that in the short run, difficulties can be caused by cultural differences between foreign owners and local workers. For example, a foreign firm that acquires a plant is likely to bring a new culture and management practices that contrast with the existing ones, which might negatively impact TFP in the short run. Harris and Moffat (2011) also argue that TFP performance might differ according to the form of investment the foreign firm undertakes, which can be through a “greenfield” or a “brownfield” plant. Greenfield plants provide the firm with the freedom to bring its own management practices, culture and production techniques, among the various factors. However, they do not enable a firm to source any technology. Brownfield plants, on the other hand, provide a firm with local technology. However, a foreign owner will bring a new culture that is likely to contrast with the existing one. Lastly, when a firm acquires new technology, it must devote its resources to assimilating the technology and learning to use it productively. For example, when a local automotive firm adopts the working processes of a foreign-owned firm, these processes are not likely to be implemented immediately. There might be a period of adjustment in which all of the parties involved learn about the new procedure. Moreover, even when a new technology is implemented, it might take additional time for workers to become familiar with it. Thus, in the short term, FDI can have a negative effect on firms’ TFP. This idea is supported by some results in the empirical literature.

Driffield and Love (2007) analysed this topic using a dataset of FDI flows from 30 different countries to 11 manufacturing sectors over the period of 1987-1997. A lagged measure of FDI was used to represent the effect of FDI externalities on TFP. This was then combined with four binary dummy variables, each representing a different motivation for undertaking the FDI. The findings indicate that inward FDI in the UK manufacturing industry has a positive effect on firms’ TFP, but only when the motive for undertaking the FDI is the ownership advantage. Inward FDI motivated by local technology sourcing or efficiency seeking was found to have a negative impact on TFP.

Other empirical results indicate the existence in some cases of the previously mentioned “market stealing” effect, according to which the positive spillover effect exerted by FDI is negatively counterbalanced by the foreign firm stealing market share from local competitors. This might ultimately lead to decreased TFP. Aitken and Harrison (1999) looked at a sample of 4000 Venezuelan firms over the years of 1976-1989 and analysed whether foreign-owned firms display higher productivity than local firms and whether FDI spillovers to other firms occur. The direct effect of FDI was measured as the share of foreign equity at the plant level. The indirect spillover effect was measured as the average share of foreign equity for all the plants within each sector, weighted by each plant’s contribution to employment in the sector. In addition, the authors included a variable combining FDI at the plant and sectorial levels in order to measure the effect of FDI on joint ventures. A positive direct effect of FDI was found only for small firms, while a negative indirect effect was found for large firms, suggesting that foreign firms invest in the most productive local firms. It seems that the higher the FDI, the lower the productivity of domestic firms, suggesting the existence of a market-stealing effect. Since they are more productive, foreign-owned firms might gain market share at the expense of local firms, thus “stealing” customers and causing a decrease in the productivity of the overall industry.

FDI also negatively affects firms’ TFP when it takes time to assimilate foreign-brought technology and to use it productively. This idea is supported by the study of Liu (2008), which analysed the effect of FDI spillovers through the imitation channel on Chinese manufacturing firms’ rate of growth and level of TFP. Liu’s findings suggest a positive indirect effect of FDI on firms’ TFP level in the long run and a negative effect on TFP growth in the short run. These results indicate that there are cases in which firms take time to assimilate a new technology and use it productively.

In summary, this section has analysed the importance of ownership, and especially FDI, for firms’ productivity. The results from the empirical literature suggest that FDI has both direct and indirect effects. The effect is direct when a local firm in which a foreign firm has invested benefits from the technology brought, superior know-how, or innovative managerial practices and machinery. The effect is indirect when a local firm in which a foreign firm has not invested but is based in the same geographical area benefit from technology spillovers. These seem to occur through five different channels: imitation/demonstration, labour mobility, exports, competition, and commercial relationships, or backward and forward linkages, with domestic firms. It has also been suggested that in order for a firm to receive the greatest benefit from the indirect effects of FDI, it must have absorptive capacity, or the ability to absorb and utilise knowledge for productive purposes. A firm with a higher level of absorptive capacity is likely to be more productive than a firm with a lower level.

However, there are cases in which FDI does not generate a positive effect on TFP. For example, such is the case when a foreign firm is more interested in sourcing superior local technology, seeking efficiency from low input costs or placing its plants in an advantageous low-tax location. In addition, it has been suggested that FDI might have short-term negative effects on productivity due to the “market stealing” and “technology learning” effects. Moreover, a clash of cultures between a foreign owner and local foreign-invested firm might hinder improvements in productivity.

### 2.4.4. Economies of Scale

In general, a firm can achieve economies of scale by increasing the quantity of output produced while decreasing the cost per unit of output. Differing from economies of scale are economies of scope. These are achieved by a firm when, by jointly producing a range of different products, the costs per unit of output are lower than would be if each kind of output was produced individually. Economies of scale can be distinguished between internal (related to a firm having an individual plant) and external (related to a firm having multiple plants).

Internal economies of scale do not directly affect TFP, but rather do so indirectly. In equation (2), TFP is expressed as the ratio of output produced to inputs utilised in the production process. TFP is not affected directly by internal returns to scale ($\beta_l + \beta_c$) because any change in the denominator on the right-hand side of (2), which represents a change in factor inputs utilised, is reflected by a change in the related numerator, which represents a change in output produced, maintaining $A_{it}$ unchanged.

Internal economies of scale mainly arise from indivisibilities, specialisation, and greater efficiency of large machines. Indivisibilities refer to the fact that a minimum quantity of indivisible inputs is required for a plant to function. These constitute fixed costs because, regardless of the input level, the plant must pay for them in order to operate. When a plant increases the amount of output it produces, these fixed costs can be spread over more output, thus reducing the cost per unit of output. Specialisation concerns the role of workers within a plant. When a plant has a relatively low scale, a worker is likely to undertake many different tasks, reducing his or her efficiency and leading to higher costs per unit of output. For example, in a small plant, the director is likely to perform both manual and administrative tasks. When a plant's scale increases, the director might focus on just the administration while delegating the manual tasks to a deputy. This is likely to result in higher efficiency and, therefore, lower costs per unit of output. Economies of scale can arise from the greater efficiency of large machines because they can transform inputs into more outputs. This allows the plant to operate at higher capacity, reducing the costs per unit of output. For example, if an automotive plant increases its scale by raising the number of vehicles it produces, the increased output of its large machinery will lower the costs per units of output.

However, a plant can also experience diseconomies of scale if increasing the quantity of output produced causes the costs per unit of output to rise. When they occur within a specific plant, diseconomies of scale are internal. They might be due, for example, to the inability of managers to lead a plant that has become either too large or complex, indirectly causing a decrease in productivity.

External economies of scale can arise when a firm has multiple plants. According to Baldwin et al. (2010), "multi-establishment firms may be better able to collect and analyse information that can improve management practices and thus raise productivity" (p. 921). Harris and Moffat (2011) suggest five other additional reasons why multiple plants lead to economies of scale. Firstly, a multi-plant firm has plants located in its clients' markets; thus, by being closer to clients, transportation costs are reduced. A multi-plant firm is also likely to adapt more quickly to the market in which it operates and to better respond to client needs, compared to single-plant firms. Secondly, central services such as human resources, research and development, marketing, and sales are likely to be shared across plants, thus providing the benefit of spreading fixed costs across plants. Thirdly, the burden of excess capacity is likely to be spread across plants rather than being concentrated within a single plant, thus benefiting the firm as a whole. Fourth, as they are more geographically diversified, multi-plant firms are likely to have access to less costly sources of funding than single-plant ones. Lastly, as Harris and Moffat (2011) argue, Jarmin's (1999) "Government Technical Assistance Programs and Plant Survival: The Role of Plant Ownership Type" suggests that multi-plant firms have easier access to information compared to single-plant ones since technology is shared among multiple plants. For example, a technological advancement achieved in one plant might be successfully applied in another plant.

However, there are also reasons why multi-plant firms may be at a disadvantage with respect to single-plant firms. Firstly, since single-plant firms concentrate production in one geographical location, they are likely to have higher productivity than multi-plant firms. Secondly, as argued by Leibenstein (1966), managers of multi-plant firms might face difficulties in allocating resources among plants. For example, resources that would otherwise be used more effectively by the most productive plants might instead be allocated to the least productive ones. Thirdly, as multi-plant firms are likely to be multinational enterprises (MNEs) in which ownership and control is separated, managers might not have the right motivations in terms of remuneration and incentives, making them less likely to make decisions aimed at improving productivity. Managers of single-plant firms, on the other hand, are more likely to also be owners who bear more risk, and thus their decisions would be aimed at improving productivity. Fourth, the greater complexity of multi-plant firms makes them more difficult to manage. Such can be the case when a firm has plants based in different markets, or produces a wide product range. Fifth, since they are less complex from an organisational point of view, single-plant firms are likely to be faster in decision making and adjusting production to client needs, resulting in higher productivity.

Productivity is one of the factors that managers must take into account when considering whether to enter, thrive within or exit an industry. This is because "efficient firms grow and survive; inefficient firms decline and fail" (Jovanovic, 1982, p. 649). Concerning exiting, the empirical research has looked at differences in the probability of survival between single and multi-plant firms. Bernard and Jensen (2007), for example, studied the impact of firm structure on the probability of plant closure in two panels of about 170,000 US manufacturing plants during the periods of 1987-1992 and 1992-1997. A dummy variable was used to represent whether a plant was part of a multi-plant firm. A plant was deemed part of a multi-plant firm if there was at least one other plant with the same ownership in the sample. The study's results suggest that the probability of shutting down is the lowest for plants belonging to multi-plant firms, those owned by US multinationals (compared to plants owned by domestic firms), and those having changed ownership. These plants were also found to have a range of characteristics (larger, older, more productive, more likely to export, more capital intensive, employing more highly skilled workers and operating in industries characterised by lower probability of shutdown). Once these characteristics were controlled for, the results were the opposite. Thus, the study concludes that the probability of shutting down is higher for plants belonging to multi-plant firms compared to single-plant firms.

The above results differ from those of Dunne et al. (1989). Using a larger US sample (about 200,000 plants) and an "older" time period (1967-1977), the authors analysed the relationships between plant characteristics and its employment growth and failure rate. Plants were differentiated according to two ownership categories, single-unit plants and multi-unit plants, to which the estimation methodology was applied separately. The relationship between age and failure rate was found to be negative and did not seem to differ between the two kinds of plants. The relationship between size and failure rates was also negative, particularly for plants that belonged to multi-plant firms. Accounting for the failure rate, plants owned by single-plant firms were characterized by a negative effect of size on employment growth. Plants owned by multi-plant firms, on the other hand, showed a positive effect of size on employment growth. The results suggest that plants owned by multi-plant firms are less likely to fail and more likely to employ more people as they increase the scale of their operations, compared to plants owned by single-plant firms.

Lieberman (1990) studied how divestment occurs within the chemical industry by analysing US data on 30 different chemical products and different forms of divestment, such as cutting capacity or exiting. To analyse the effect of a plant's scale and size on its closure, a dummy variable was included that took the value of zero if the firm operated with a single plant and a value of one if a firm had multiple plants. The results show that during industry decline, multi-plant firms that represent a large share of industry capacity are more likely to close individual plants than single-plant firms. This suggests that during a downturn, multi-plant firms might decide to close their least productive plant rather than keeping it alive and reducing the support provided to the other plants.

Disney et al. (2003) studied establishment entry and exit in UK manufacturing. By applying an exit hazard function separately to single and group establishments, they found the single establishments to have a higher hazard exit rate in comparison with group establishments. However, when single establishments were conditioned on the average characteristics of the group establishments, they were found to have a lower hazard exit rate than group establishments conditioned on the average characteristics of the single ones. This implies that the hazard exit rate is determined by an establishment's characteristics rather than by its organisational structure. Based on this study and that of Bernard and Jensen (2007), it thus seems that single and multi-plant firm structures do not directly determine plant failure rate. However, there are other characteristics that play a role in this relationship, such as a firm's size and age.

Using the same database as Disney et al. (2003), Harris and Hassaszadeh (2002) adopted a large number of explanatory variables and conducted their analysis at the plant level (rather than the establishment level) to analyse the effect of plant ownership and age on the probability of plant closure, using a hazard function. Plants were differentiated using a dummy variable that indicated whether they belonged to a single-plant or multi-plant firm. Their findings contrast with those of Disney et al. (2003), suggesting that single-plant firms are much less likely to fail compared to multi-plant firms. This likelihood was found to increase with plant age.

This section has reviewed the importance of economies of scale as a determinant of higher TFP. Economies of scale are achieved by an economic unit if the costs per unit of output decrease when the quantity of output produced is increased. Internal economies of scale are related to an individual plant and external ones are related to firms with multiple plants. In contrast to economies of scale, economies of scope are obtained when different outputs are produced and costs per unit of output are lower than would be by producing each kind of output individually. Internal economies of scale mainly arise due to indivisibilities, specialisation, and greater efficiency of large machines. However, a plant can also experience diseconomies of scale, both internal and external, if its costs per unit of output rise when it increases the quantity of output produced. Concerning external economies of scale, Harris and Moffat (2011) suggest five reasons why they arise in a multi-plant context: reduction in transportation costs; ease in adapting to client markets and needs; spread of costs such as R&D, human resources and marketing across different plants; spread of excess capacity across plants; access to less costly funding sources due to the diversified structure; and easier access to information, as technology is shared across plants. However, such benefits are not always the case: single-plant firms have more concentrated production and are thus likely to be more productive; managers of multi-plant firms might misallocate resources; in multi-plant firms, managers might not be provided with the right motivation in terms of remuneration and incentives; multi-plant firms are likely to be more complex and thus more difficult to manage than single-plant firms; and single-plant firms are likely to have a more flexible organisational structure and thus respond more quickly to changes in the market environment. The empirical research has looked at the difference in the probability of survival between single and multi-plant firms. Productivity is one of the factors that determine whether a firm enters, thrives within or exits an industry. The empirical findings do not clearly suggest a specific relationship between whether a plant is from a single-plant or multi-plant firm and its probability of survival. Some studies have documented that single-plant firms are more likely to survive than multi-plant ones. Others have documented an opposite effect. However, in this relationship, certain plant characteristics, such as size and age, need to be considered, as these play a critical role in the achievement of economies of scale.

### 2.4.5. Competition

A fifth determinant of TFP is the competitive structure of the market in which a firm operates. Nickell (1996) suggests that an industry is more competitive if there are less monopoly rents. In this case, a firm's managers are likely to increase their efforts and to reduce slack, thus leading to an increase in productivity. It is also because the higher the competition, the more likely a firm is to exit an industry if its productivity is relatively low. In addition, Nickell (1996) argues that monopoly rents benefit workers in the form of higher wages and reduced efforts. In this case, higher competition would lead to reduced wages within an industry, consequently lowering labour costs and increasing workers' efforts, resulting in higher productivity. Meyers and Vickers (1997) argue that since firms within an industry can be compared to one another, investors reward the relatively high-performing ones by providing them with a lower cost of capital while withdrawing capital from or increasing its cost for the relatively low-performing ones. This pushes firms to improve their productivity. Tang and Wang (2005) state that an increase in product market competition leads to higher demand elasticity, which is likely to result in higher potential profits and thus increased managerial efforts. Lastly, a firm not only responds to increased competition by increasing its "efforts" in order to improve productivity; it might also pursue the opportunity to innovate by upgrading its technology to match industry best practices.

One would therefore infer that competition benefits a firm's total factor productivity. However, this does not seem to always be the case. Hermalin (1992) argues that increased competition is likely to diminish a firm's profits and a manager's income, which might result in a reduction in effort (Schumpeterian effect) due to a risk-adjustment effect, changing the risk profile of different kinds of actions and resulting in lower productivity. In addition, Horn et al. (1994) argue that there exists a negative relationship between competition and the effort incentives provided to managers by their working contract. By examining three different settings, each characterised by a different level of competition, the authors argue that managerial effort is the greatest when the extent of competition is the lowest. Moreover, according to Tang and Wang (2005), Kamien and Schwartz (1982) suggest in *Market Structure and Innovation* that a firm in a monopoly position is more able to finance innovative projects and dominate its market than a firm without such power. From the above discussion, it appears that the relationship between competition and productivity has two different directions.

One of the first studies to consider the effect of competition on TFP was done by Nickell et al. (1992). The authors analysed the connection between product, labour and financial market effects, and the change in TFP for 100 UK manufacturing companies for the period of 1972-1986. Competition, or the product market structure, was represented by three variables: market share, or the share of a company's sales in the three-digit industry sales; concentration, or the five-firm concentration ratio in the industry according to domestic sales; and import penetration, given by imports as a proportion of industry production. An increase in market share was found to cause a long-run reduction in TFP levels. This suggests that, as a firm increases its monopoly power, the managers and workers do not improve their "efforts" because they are enjoying monopoly rents. On the other hand, increased market share was found to result in higher TFP growth, suggesting that firms with a relatively large market share have a higher TFP than those with a small market share, and indicating that large firms are more incentivised or have a higher capacity to innovate.

In a subsequent study, Nickell (1996) looked at 670 UK manufacturing companies to examine the relationship between competition and productivity. The effect of competition on productivity was measured using a variable to indicate a firm's market share within an industry. The effect of competition on productivity growth was proxied by two dummy variables, the first taking the value of 1 when the manager stated that there were more than five competitors in the product's market, and 0 otherwise; and the second measuring rents, as given by the average of profits minus capital costs during the sample period, divided by the value added. Two-digit industry dummies, namely average firm size, industry concentration and industry import penetration, were included to measure the effect of competition on productivity growth. Consistent with the findings of Nickell et al. (1992), the higher a firm's market share, the lower its productivity level. Moreover, higher competition, represented by a higher number of competitors and lower rents, was found to be beneficial to productivity growth. From these results, one could infer that higher competition pushes managers and workers to reduce slack and improve their efforts in order to survive, thus stimulating higher productivity.

Sjöholm (1999) analysed the effects of regional characteristics, among them competition, on labour productivity growth for Indonesian manufacturing plants in 1980 and 1991. The variable representing competition was constructed using the Herfindahl index. High values of this index suggest that a high level of concentration and thus a low level of competition characterize an industry, while the opposite is the case for low index values. The results indicate that the effect of competition on labour productivity growth is insignificant, not affecting productivity growth. However, its effect on the labour productivity level was found to be positive and statistically significant. This means that as competition increases, productivity decreases.

Inui et al. (2008) measured the effect of market competition, represented by the inverted-Herfindahl and inverted-Lerner indices, on TFP growth and R&D intensity for Japanese manufacturing firms during the period of 1997-2003. Here, the inverted-Herfindahl index measures a firm's share of sales in its industry at a given time. As this refers only to domestic competition, the import ratio, or the percentage of the import of the total production in a specific industry, was also adopted as a proxy for international competition. The results show a positive effect of competition in terms of the inverted-Herfindahl index, the inverted-Lerner index and the import ratio on firms' TFP. This suggests that as competition increases, firms are more likely to improve their efficiency and undertake innovations, both of which are TFP-enhancing actions. An inverted U-shaped relationship was found between competition, as measured by the inverted-Herfindahl index, and productivity. Subsequently, the authors added the square terms of the competition measures in order to understand whether competition and productivity were characterised by an inverted-U relationship. The existence of such a relationship was only supported when the inverted-Herfindahl index was used as the competition measure. This would suggest that productivity increases as competition increases, thus pushing firms to improve their efficiency as well as to innovate. This effect occurs up to a certain point, after which increased competition causes firms' incentive to innovate to decline. This study provides a valuable insight into the relationship between the Herfindahl index and TFP. However, the insight is limited since the authors perform the estimation using the index method. Although the authors acknowledge that using the Olley and Pakes' (1996) semiparametric methodology takes into account both the simultaneity issue and the selection bias due to firm entry and exit, the methodology does not consider fixed effects and is based on strong assumptions.

Tang and Wang (2005) studied the effect of competition and skill shortages on labour productivity for 5,320 Canadian firms in the manufacturing sector, using a survey covering the years of 1997-1999. Innovation was represented by the firms' perception of their competitive environment, both domestic and international, upon which their effort and innovation activities would depend. The perception of the competitive environment was based on four different factors: easy substitution of products, constant arrival of competing products and competitors, and obsolescence of products. These seem to provide a better indicator of competition compared to those used in the previously-mentioned studies. The existence of high competition, measured in terms of market share or number of competitors, does not mean that competition poses a threat to a firm's performance. However, a survey providing such detailed information might not be possible in every country; one would consequently need to rely on standard measures of competition. The study's results suggest that the higher the degree of competition perceived by a firm, the higher the productivity level achieved, an effect that is likely to occur through higher innovation or improved efforts.

Further evidence regarding the effect of competition on TFP is provided by Griffith (2001), who studied how changes in competitive pressures affect managers' and workers' efforts in UK manufacturing firms during the period of 1980-1996, and how these pressures affect both TFP levels and growth rates. Here, managerial firms, which are characterised by the separation of ownership and control and, consequently, by agency costs, were compared to single or entrepreneurial firms, in which owners and managers are the same person and which are thus not characterised by agency costs. The results suggest that as a consequence of the increase in product market competition, increased TFP is only found for managerial firms but not entrepreneurial ones. This suggests that an increase in competition arising from product market reforms is likely to lead to reduced agency costs for firms in which there is a separation of ownership and control, ultimately resulting in higher TFP.

In the Chinese context, Perkins (1996) examined the effect of enterprise, market and ownership reforms on the productivity of 300 State-owned, collective and foreign funded Chinese firms based in three coastal provinces in 1993. Among the determinants of TFP considered in the analysis, the firm's exposure to international competition, measured as the ratio of exports to output for each firm, was used. The results suggest that firms that are more exposed to international competition are 22-34% more productive than firms that are not exposed.

Zhang et al. (2001) analysed the effect of both ownership and competition on the productive efficiency of 1,989 Chinese industrial firms located in Shanghai. In contrast with Perkins's (1996) approach, the authors decomposed competition into international and domestic. The extent of the firms' exposure to international competition was measured as the ratio of the firm's export revenue to its total assets. The extent of domestic market competition was measured using the Herfindahl index of industrial concentration. The results suggest a positive effect of international competition on firm productivity. Moreover, it seems that firms belonging to industries characterised by higher concentration, as suggested by the Herfindahl index, have higher efficiency scores, indicating that they are more productive.

In estimating the effect of productivity spillovers from FDI to between 124,944 and 143,974 domestic Chinese firms during 1998-2005, Lin et al. (2009) included in their model a variable representing the intensity of domestic industrial concentration within each industry. This was found to have a significant and negative coefficient, suggesting that a higher extent of domestic competition within an industry positively affects firms' TFP.

This section has reviewed the importance of competition as a determinant of higher total factor productivity. The findings from the empirical research suggest that competition is a positive determinant of productivity. Firstly, competition is likely to reduce monopoly rents, resulting in reduced slack and higher managerial efforts. Secondly, it lowers the wages within an industry, reducing the cost of labour and improving firms' TFP. Thirdly, it represents a threat, causing least productive firms to exit while the most productive firms thrive and survive. Fourth, it enables the most productive firms to be rewarded with a lower cost of capital from investors, compared to the least productive ones. Lastly, higher competition leads to higher demand elasticity, which is likely to result in higher potential profits and thus increased managerial efforts. Theoretically, a manager would be incentivised by these reasons not just to increase his or her efforts and reduce slack, but also to innovate, thus improving the firm's productivity. However, there are some reasons why higher competition might not lead to productivity improvements. This is because competition might reduce a firm's profits and the manager's income, thus reducing the manager's efforts and propensity to innovate. In contrast, a firm in a monopoly position might be more able to finance innovative projects that could ultimately result in higher TFP. Therefore, from a theoretical perspective, the effect of competition on TFP might have different directions. Despite this, the empirical results indicate that competition has positive effects. It seems that the higher a firm's market share, the lower is its TFP, as managers enjoy the rents provided by the monopoly condition. In addition, the higher the number of competitors, the higher the firms' productivity, as managers feel threatened, and thus pushed, to increase their efforts and pursue innovative projects. In the empirical studies discussed above, the managers' perception of competition seems to be more representative variable than the actual competition itself, as represented by the market share, import penetration and industry concentration. This is because the potential TFP-enhancing measures undertaken by managers in a situation of increased competition are likely to depend on their perceptions of the competition. In addition, an increase in product market competition has been found to increase TFP, particularly for managerial firms characterised by agency costs, as a result of the separation between ownership and control. Overall, the results from the empirical research indicate the existence of a positive effect of competition on firms' productivity.

### 2.4.6. Spatial Spillovers

Ornaghi (2006) defines spillovers, or technological externalities, as the pool of general knowledge to which a firm has access. A firm can obtain this knowledge in the following ways: by being based in a particular location (spatial spillovers); from its industrial relations (intra and inter-industry spillovers); from its export activities (export spillovers); from R&D activities (R&D spillovers); and from FDI (FDI spillovers). In order to obtain a higher benefit from spillovers, a firm needs to have absorptive capacity, or "the ability of a firm to recognise the value of new, external information, assimilate it, and apply it to commercial ends" (Cohen and Levinthal, 1990, p.128). Therefore, in order to further improve its TFP, a firm must be able to use the knowledge available for the most productive purposes.

"Spatial spillovers or agglomeration externalities are benefits that accrue to plants from being located in the vicinity of a large concentration of other plants" (Harris and Moffat, 2012a, p. 763). In general, such spillovers can be classified as either Marshallian or Jacobian. In addition, spillovers can also manifest differently according to whether a firm is based in a city, or not. City spillovers will be discussed in the following section (2.4.7.), while this section will focus on Marshallian and Jacobian spillovers.

Marshallian spillovers, also known as agglomeration, location or specialisation externalities, were first suggested by Marshall (1890), who described them as a range of benefits for a firm arising from being in close proximity to industry peers. This effect occurs because "if one man starts a new idea, it is taken up by others and combined with suggestions of their own; and thus it becomes the source of further new ideas" (Marshall 1890, p. 271). Marshall's statement suggests that these externalities manifest themselves through imitation and adoption of ideas among firms. Subsequently, Glaeser et al. (1992) combined the ideas of Marshall (1890) with those of Arrow (1962) and Romer (1986) in the Marshall-Arrow-Romer model, which proposes the existence of knowledge spillovers across firms that ultimately benefit intra-industry growth. Therefore, as suggested by Marshall (1890), if a firm develops an TFP-enhancing innovation such as a new working practice or an innovative product, other firms are likely to imitate and adopt it. A contagion thus develops from one firm to another, which is likely to result in higher TFP growth for the industry as a whole. Other than imitation/demonstration, Marshallian spillovers can manifest themselves in other ways. The close geographical distance of firms belonging to the same industry fosters cooperation, potentially resulting in higher industry TFP. Firstly, firms can exploit synergies, for example, by collaborating on R&D projects to improve products and processes. Secondly, firms located at different levels within an industry supply chain can develop commercial relationships. In this case, spillovers manifest themselves through backward and forward linkages. In backward linkages, a supplier firm obtains knowledge by learning from its customers through feedback concerning the products it provides. In forward linkages, customer firms obtain knowledge by using innovative products from their suppliers. Thirdly, firms based in the same geographical area can benefit from sharing assets. For example, two firms can reduce their input transportation costs by jointly leasing or renting trucks. Fourth, as Marshall (1890) suggests, externalities can be manifested through the development of an industry-related labour market pool. This means that in an industry-specific geographical area, workers will develop industry-specific skills. This provides two benefits. On the one hand, workers benefit in terms of the ease of mobility from one firm to another. On the other hand, firms benefit from the opportunity to more easily hire specialised workers than in the case of a more industry-diverse geographical area. These four cases represent the ways in which Marshallian externalities manifest themselves among firms based in a specific location and belonging to a specific industry. These spillovers are likely to result in higher TFP for the industry as a whole. It must be stressed that spatial spillovers and FDI spillovers are not mutually exclusive, but rather are complementary. This means that they can interact with each other to facilitate the transmission of knowledge among firms, thus contributing to TFP growth.

Different from Marshallian spillovers are Jacobian spillovers, also known as diversification or urbanisation externalities. According to Harris and Moffat (2011), these occur when plants located in an industry-diverse area benefit from the economies of scope such a location provides. Compared to Marshallian externalities, Jacobian externalities manifest themselves across economic units belonging to different industries. As Jacob (1970) states: “The greater the sheer numbers and varieties of divisions of labour already achieved in an economy, the greater the economy’s inherent capacity for adding still more kinds of goods and services” (p. 59). Therefore, it seems that plants with different knowledge and capabilities can complement each other’s skills sets, resulting in mutual benefits. Moreover, Jacob (1970) suggests that the diversity in terms of industry and occupation that characterises urban economies favours the spillover of innovations across different industries. For example, an automotive firm can benefit from knowledge acquired by interacting with scientists from a university’s mechanical engineering research department. This interaction generates knowledge spillovers from the research department to the firm, bringing benefits in terms of product or process improvements and ultimately being likely to result in higher TFP. Jacobian externalities can also occur, for example, when a firm involved in the production of aluminium, absorbs knowledge from a food production firm located nearby. This example suggests that by being located in the same geographical area, firms belonging to different industries can obtain mutually benefits that are likely to result in higher TFP.

The above discussion suggests that spillovers, both Marshallian and Jacobian, are likely to be positive determinants of a firm’s TFP. Micro-level empirical results seem to support the existence of Marshallian externalities, while no significant evidence has been found for Jacobian externalities.

López and Südekum (2009) looked at data on 4,911 plants belonging to the Chilean manufacturing sector during the period of 1990-1999 to examine the impact of spatial spillovers on TFP. Attention was also paid to the spillovers that might arise from the vertical relationships between suppliers and customers. Intra-industry spillovers were measured by the number of plants belonging to a firm’s industry and region at the same time. Moreover, as intra-industry spillovers are not necessarily localised, a variable representing the number of plants from the same sector but based in different regions was included. Inter-industry spillovers were represented by the number of firms belonging to different industries based in the same region. While no effect was found for Jacobian spillovers on plants' TFP, Marshallian spillovers were found to exert a positive impact on plants' TFP. It might be that plants do not productively exploit, or do not find worth exploiting, the knowledge pool created by plants located in the same area but belonging to different industries. However, the plants were found to benefit from the presence of suppliers. Therefore, it seems that plants benefit from forward linkages, through which spillovers can manifest themselves.

Cingano and Schivardi (2010) provide further evidence from Italian manufacturing firms belonging to 784 local labour systems. In their study, localisation economies in a local labour system were measured as the share of the sectorial city employment in the total manufacturing employment. Urbanisation economies were measured by the Hirschman-Herfindahl index. The results indicate a positive effect of Marshallian externalities and city size on local TFP growth, while no evidence for an impact of Jacobian externalities was found, thus confirming the results of the previous study.

Baldwin et al. (2010) used plant-level data for the Canadian manufacturing sector over the period of 1989-1999. In order to measure localisation economies, they adopted the following multiple variables: a variable representing the industry mix in a metropolitan area (as a proxy for industry labour pool); an upstream supplier-weighted location quotient (as a proxy for the density of upstream suppliers in a specific location); and the density of plants in a geographical area (as a proxy for intra-industry knowledge spillovers). Urbanisation economies were measured as the population of the metropolitan area or agglomeration where the plant was located. On the one hand, their findings suggest a positive effect of localisation economies on productivity. On the other hand, urbanisation economies were found to have a negative effect on productivity, suggesting that firms do not benefit from Jacobian externalities.

In the case of France, Martin et al. (2011) analysed the effect of geographical spillovers on manufacturing plant and firm-level TFP over the period of 1996-2004. Marshallian spillovers were measured for each plant as the number of other workers employed in the same industry and in the same area. Jacobian spillovers for a plant were calculated as the difference between the numbers of workers in other industries based in the same area as the plant. The study's results support the existence of Marshallian externalities that make a positive contribution to TFP in the short run. A 10% increase in the number of plant workers from the same industry was found to increase firms' TFP by 0.55%. Therefore, one would infer that having firms belonging to the same industry in the same area would be beneficial in terms of TFP.

However, this relationship was found to be bell-shaped, meaning that when a plant is based in an area with a high number of workers (i.e. the area is overcrowded), TFP is likely to suffer. In addition, the results do not indicate the existence of Jacobian externalities, at least in the short run. However, since Jacobian externalities manifest themselves across plants belonging to different industries, it might take longer for them to spread and for the related knowledge to be applied productively than with Marshallian externalities because the plants need to complement their diverse set of skills and knowledge.

Within the Chinese context, Lin et al. (2011) examined the effect of spatial agglomeration, measured in terms of concentration of manufacturing activity, on firms' labour productivity. The firms analysed belonged to the textile industry, during the period of 2000-2005. The dataset comprised 22,152 firms taken from the National Bureau of Statistics, including all SOEs and large and medium-sized non-State-owned textile enterprises having sales higher than RMB 5mn. Although this was a highly representative sample, small firms were not included. In the estimation, the spatial agglomeration variable was measured using the Ellison and Glaeser (1997) index, which compares the actual geographical distribution of firms and their expected distribution in the absence of agglomeration in a city. The index figures suggest that spatial agglomeration has an increasing trend and differs among sub-industries. Estimation was conducted using both fixed and random effects and their validity was tested using the Hausman test, which tends to favour the fixed effects model. Overall, the findings suggest that industrial agglomeration has a significant positive impact on productivity. The relationship between industrial agglomeration and productivity showed an inverted U-shape: the higher the concentration of firms, the higher the firms' productivity through positive externalities, although this effect declines if the extent of agglomeration is excessively high.

Li (2004) analysed the effect of agglomeration and privatisation on the labour productivity of 80,000 foreign-owned firms between 1994 and 1996. Output per employee was used as a measure of productivity, despite not being as valuable as TFP. The advantage of having access to the labour force and product markets was represented by an index measured at the provincial level. Moreover, agglomeration economies were measured through two variables representing the concentration of foreign firms and the industry concentration of domestic firms, respectively. Results from a multiple linear regression model suggest that foreign firms benefit from location advantages such as infrastructure and factor inputs. The concentration of foreign firms and the effect of reforms were found to positively affect firms' productivity. In contrast, concentration of domestic firms was found to negatively affect firms' productivity. This study provides interesting insights into the effects of location and agglomeration externalities on foreign firms' productivity. However, it would have been interesting for this study to consider other kinds of firms.

Yang et al. (2013) examined the effect of spatial concentration of manufacturing and R&D activities on a price-adjusted measure of labour productivity for Chinese firms belonging to the electronics industry during the years of 2005-2007. As a measure of spatial concentration, the Ellison and Glaeser (1997) index was adopted. The index values obtained suggest that both production and R&D activities are highly concentrated, particularly R&D. The effect of spatial concentration was examined through fixed and random effects techniques. These do not take into account the simultaneity issue, suggesting that the estimates may be biased and inconsistent. Despite the presence of this issue, production agglomeration was found to be positively related with firm productivity, particularly for smaller firms, while R&D agglomeration seemed to have a negative relationship, suggesting the overcrowding of R&D activity.

This above paragraph examined spatial spillovers or agglomeration externalities, which are benefits that a plant obtains by being geographically close to other plants. These are differentiated between Marshallian and Jacobian spillovers. Marshallian spillovers relate to firms that are in close proximity to their industry peers. They are manifest through the channels of imitation/demonstration, synergies, commercial relationships, asset sharing, and labour pooling. Other than Marshallian, externalities can also be Jacobian, which occur when plants are located in an area characterised by different industrial activities, allowing the plants to benefit from the economies of scope this provides. For example, a firm in one industry can absorb and exploit knowledge from a firm in another industry, likely resulting in higher TFP. Therefore, compared to Marshallian externalities, Jacobian externalities manifest themselves across economic units belonging to different industries. Based on the above discussion, one would expect both Marshallian and Jacobian externalities to be positive determinants of firm TFP. Some of the most recent studies concerning agglomeration externalities have been examined. While Marshallian externalities have been found to exert a positive effect on firms' TFP, Jacobian externalities have not. Therefore, one would infer that by placing firms belonging to the same industry in the same geographical area, TFP will improve as a result of positive mechanisms (imitation/demonstration, synergies, commercial relationships, asset sharing, and labour pooling). However, locating firms belonging to different industries in the same area might not lead to higher firm TFP. It may take longer for Jacobian spillovers to be transmitted within a geographical area because of the firm diversity and the greater difficulty of applying the diverse knowledge productively compared to Marshallian spillovers. In addition, plants might not find it worthwhile to explore the knowledge of plants from different industries, or they may not even be able to exploit such knowledge productively. Regarding the Chinese context, empirical evidence is still scant. The evidence available points to the existence of location and agglomeration economies, although the relationship does not seem to be linear. Another study suggests that firms owned by foreign investors benefit from a higher concentration of foreign firms but suffer from a higher concentration of domestic firms. Although these represent valuable results, further investigation is required to both extend and confirm the findings.

### 2.4.7. City Location

Knowledge spillovers can also manifest differently depending on whether a firm is based in a city, as cities are likely to have a higher population density than other locations such as towns or villages. "By facilitating face-to-face contact, the concentration of people in a particular area will facilitate the transfer of knowledge. In addition, workers will find it easier to move from one firm to another. This process will cause the transfer of knowledge across firms. The same diffusion of knowledge will occur when plants are better able to learn from their customers and suppliers when they are located in cross proximity" (Harris and Moffat, 2012a, p.764).

By being based in a city, a firm is likely to reap benefits for four different reasons. Firstly, a firm benefits in terms of knowledge spillovers, which are likely to be higher in comparison to smaller locations. This is because, in such a location, people are likely to interact more with each other, thus enabling a faster transfer of knowledge than would be possible elsewhere. Moreover, as Borowiecki (2013) argues, the cost of transmitting knowledge rises with distance. A city is therefore an environment where knowledge can be spread relatively quickly and where new ideas are constantly created. "The new impressions and new ideas that are the heart of technological progress are probably most likely to occur in such a setting" (Sveikauskas, 1975, p.394). Using a 2007 survey of 6000 French workers concerning workplace communication, Charlot and Duranton (2004) suggest that city size and urban schooling positively impact workplace communication. Therefore, the larger the city, the higher the workplace communication is likely to be. If a firm's workers live within the city and interact with fellow citizens, they are likely to bring outside knowledge to the firm, likely resulting in higher TFP. Secondly, when a firm is based in a city, it is more able to obtain important insights into its customer base. In this way, it can better adapt its products to customer needs. Moreover, since the customers are in close proximity, the firm has the opportunity to reduce transportation costs and respond more quickly to customer feedback and to any issue that might arise from product sales. Thus, the closer level of interaction of a firm with its customers would enable the firm to undertake TFP-enhancing actions such as product improvements. Thirdly, another benefit that a firm might reap by being based within a city is the availability of a wider labour pool. A firm would therefore have to struggle less to find an employee with the right skills for a specific job. In addition, the larger the city, the higher the availability of a more skilled labour force than in a smaller city. This was found by Bacolod et al. (2009) for a sample of US cities. In addition, using a survey of US establishments, Elvery (2010) demonstrated that companies based in large metropolitan statistical areas (MSAs) have a more skill-intensive workforce than those based in small MSAs. Therefore, the availability of a large and more highly skilled labour pool in a city is likely to benefit a firm in terms of higher TFP. Fourth, another advantage a city might provide to local firms is the high availability of business services such as accounting, legal and financial services.

Despite the abovementioned benefits, companies might face other issues from being based in a city. Carlino (1987) argues that in a city, the time and cost of transporting goods and commuting are likely to be high, along with the high commercial and residential rents. The extra time and costs of commuting experienced by a firm’s workers is likely to result in a demand for higher salaries. In addition, the relatively high rent paid by a firm to be located in a city results in additional costs. These two aspects are, therefore, likely to negatively impact a firm’s TFP.

From the above analysis, it seems that being based in a city is likely to bring firms more advantages than disadvantages. The empirical evidence on this matter is mostly at the aggregate level, while the research at the micro-level remains scant.

In one of the first micro-level studies on the topic Mitra (1999) analysed how the size of a city impacted the efficiency index of Indian firms belonging to the electric machinery (212 firms) and cotton textiles (294 firms) industries, using a cross-sectional sample for the year 1992-1993. The estimation was performed using both a production function and a stochastic frontier analysis (SFA). In the production function, the impact of city agglomeration economies was measured through a function representing the total city population, or its total workforce. In the SFA, agglomeration economies were measured as the difference in efficiency between firms based in large cities and firms based in small ones, followed by an examination of the relationship between efficiency and agglomeration externalities. The results obtained using the production function were not highly significant. However, the SFA analysis suggests a positive impact of city size and workforce size on firm efficiency, although this effect declines for very large cities. These results imply that firms might generally benefit in terms of higher efficiency from being located in a city. However, after a city reaches a certain size, it might not have a sufficient infrastructure to support firms' activities, thus making it costly for firms to be based there. Although these results provide a useful insight into city spillovers, they should be interpreted with caution. Firstly, the sample size was very small. Secondly, the analysis was limited to two sectors. Thus, the results represent a specific case in point that cannot be extended to other sectors or countries.

Pan and Zhang (2002) studied the relationship between urban productivity and city size using data on 119,790 firms across 28 Chinese industries and 224 cities. Thus, they used a larger sample and considered a wider industrial base than Mitra (1999). For the study's urban production function, a shift function for city size was used to proxy the urban population. By using OLS, the authors found evidence of significant positive agglomeration effects across 19 out of 28 industries. The elasticity of agglomeration was 0.051, suggesting that as a city size doubles, the corresponding increase in productivity is 3.6%. Thus, one would infer that firms located in a city are likely to become more productive as city size increases. In addition, these agglomeration gains were found to derive from localisation economies. Therefore, the benefits that a firm gains by being located in a city come mainly from the presence of firms belonging to the same industry. While the authors did take into account the effects of ownership and geography on firm performance, they ignored other issues that compromise their results, such as the endogeneity of inputs, and firm fixed effects.

Harris and Moffat (2012a) measured the determinants of TFP using a UK plant-level panel dataset for the years 1997-2006 for almost all industries in both the manufacturing and service sectors. City spillovers were measured using a dummy variable that took the value of 1 if the plant was located in a major city and 0 otherwise. In addition, they used the SYS-GMM estimation methodology, which accounts for firms' fixed effects. Their results suggest that plants based in cities have higher TFP than plants based in the same region, but outside of cities.

In the Chinese context, Pan and Zhang (2002) examined the effect of city size on the productivity of 119,970 firms spread across 28 industries in 224 cities. The city's size was proxied by its urban population. The results suggest that as the city size doubles, a firm's productivity increases by 3.6%. When this effect was decomposed, it was found that the productivity increase was mainly due to the concentration of firms belonging to the same industry, as measured by the total district industry sales, rather than urban development, as measured by the urban population. Although this study is the only one that has been done at the firm level for China, it suggests that being based in a city brings firms a wide range of benefits that will likely result in higher TFP. In summary, despite being scant at this stage, this empirical evidence suggests that a plant or a firm based in a city is likely to benefit in terms of higher TFP.

This section has analysed the benefits gained by plants or firms based in cities that are likely to result in higher TFP. Firms seem to enjoy four main benefits that cities provide. One is the relatively high transfer of knowledge that occurs among people and workers, and the creation of new ideas arising from their interactions. This knowledge is likely to result in TFP-enhancing actions, such as product and process improvements. The second is the insight into its customers that a firm can obtain through close proximity to them, enabling it to adapt its products and respond more quickly to customers' needs, as well as reducing transportation costs. The third is the availability of a wide labour pool and, specifically, a skilled labour force, from which a firm can hire those employees who are likely to contribute the most to the firm. The fourth is the relatively high availability of business services, such as legal, accounting and financial services, which might not be as available elsewhere, thus providing the firm with support for its needs.

Based on the empirical results from the literature, it seems that being located in a city is likely to positively impact firms' TFP. However, the benefits of cities might be counterbalanced by high costs, such as transportation of goods, building rentals or purchasing, and the costs to workers of commuting or living in the city. Despite these negative aspects, the benefits of cities seem to prevail. Regarding the Chinese context, although the empirical evidence is scant, the available findings suggest that cities positively impact firms' TFP.

### 2.4.8. Export Activities

Another factor that is expected to be a determinant of TFP is export activities. Regarding this relationship, there seems to be two contrasting views. One suggests that TFP is likely to determine a firm's decision to export and hence to self-select into a new market. This is because only the most productive firms might be able to afford the sunk costs that entering into an export market entails. Roberts and Tybout (1997) analysed the entry and exit of plants in four industries in the Colombian manufacturing sector during the years 1981-1989, using a model in which a plant's current exporting status was a function of its prior export experience (a proxy for sunk costs), its observable characteristics (age, capital stock and corporate ownership, which influence its profits from export activities), and unobserved serially correlated shocks. The study's results suggest that a plant's decision to export in the current year is influenced by whether it exported in the past year. Specifically, a plant has a 60% higher probability to export in the current year if it exported in the past year, compared to a plant that has never exported. This suggests that after a firm has overcome the cost of entry, it is more likely to keep exporting than a firm that still is facing such costs. In addition, the authors found that once a plant exits from foreign markets, its costs for re-entering are not much different from those faced by new exporters. The study suggests that sunk costs constitute a hurdle that a firm must overcome in order to enter into foreign markets. Only the most productive firms are able to overcome such a hurdle and thus they self-select into the export market. In making the decision of whether to export, a firm is likely to consider different factors, among them TFP. Therefore, TFP might determine whether or not a firm self-selects into a new market.

In contrast to the "self-selection" view is "learning by exporting." According to this view, a firm learns how to become more productive and competitive through actually exporting. The more a firm exports, the more it is able to increase its productivity. This is because by participating in foreign markets in addition to the domestic market, a firm faces a larger number of competitors. In order to survive in such an environment, the firm would need to constantly improve its productivity by undertaking TFP-enhancing measures. Moreover, exporters are likely to benefit from the commercial interactions that exporting entails, as suggested by Grossman and Helpman (1991). For example, an entrepreneur that trades internationally has the opportunity to increase his stock of knowledge by interacting with foreign economic agents, learning from customer feedback, and observing more innovative technologies, more advanced products and better working practices. This knowledge might be adopted and exploited by the entrepreneur to increase the firm's TFP. Among the many possible actions an exporter can undertake, improving products and processes and adopting innovative machinery are likely to increase the firm's TFP. Therefore, according to the learning by exporting view, a firm learns how to improve its productivity by engaging in exporting activities.

After having examined both the self-selection and the learning by exporting views, it is reasonable to ask which one prevails, or whether both occur and to what extent. Do firms self-select into export markets after they have improved their productivity? Or do firms become more productive by actually exporting? Alternatively, do both effects coexist and to what extent? The empirical results from the literature seem to support the self-selection view, which indicates that the most productive firms are more capable of affording the sunk costs that entering into an export market entails.

Clerides et al. (1998) provided support for this view by looking at plant-level data for firms belonging to export-oriented industries in Colombia, Mexico and Morocco over the period of 1984-1991. The authors analysed whether the firms' productivity growth improved after exporting and whether this led to positive spillovers to domestic industry non-exporters. To do this, they built a system of two equations: one testing a firm's self-selection into an export market, and  the other testing whether exporting determines learning. The authors found that prior to exporting, firms had relatively low average variable costs, while those who stopped exporting had relatively high average variable costs. At the same time, the firms were found to have relatively high labour productivity prior to exporting, while those who stopped exporting had relatively low labour productivity. Apart from Colombian firms' labour productivity, these figures did not improve after the firms started exporting. Therefore, these findings support the self-selection of the most productive firms into export markets.

Bernard and Jensen (2004) analysed the role of export activities in determining US TFP growth rates in the manufacturing sector for the period of 1983-1992 at the plant and industry levels. The independent export variable was represented by the export status of a firm at time $t$, which was expected to affect productivity growth at time $t+1$. The authors adopted a different methodology than Clerides et al. (1998), a cross-sectional regression of the TFP growth rate to some independent variables, among them a variable representing exporting. At the aggregate and industry levels, export growth was found to result from higher productivity, while the opposite was not the case. At the plant level, no strong evidence was found for the existence of a "learning by exporting" effect, thus confirming the results of the previous study. In addition, the TFP of plants was found to increase before entering into an export market and during its entry. This suggests that the most productive plants self-select into the export market. Employment and output growth rates were found to be much higher for exporters, and this process continued after exporting started. Therefore, it seems that export activity supports the TFP growth of exporting firms. In addition, at the industry level, it was found that 42% of TFP growth during the years 1983-1992 was due to reallocation of output across plants, as relatively high-TFP exporters had grown at faster rates in terms of employment and output than relatively low-TFP non-exporters. Therefore, a reallocation effect occurred whereby exporting firms contributed more to their industry aggregate TFP growth than non-exporting firms. In the results of Bernard and Jensen (2004), exporting did not seem to affect TFP directly. Since exporting firms had higher employment and output growth, the reallocation of output shares from less productive plants to more productive ones led to a higher aggregate TFP, where exporters provided the largest share of the contribution. Thus, there seems to be an indirect effect of exporting on TFP at the industry level. It can be inferred that exporting benefits productive plants the most, enabling them to grow in terms of output and employment.

Another study by Arnold and Hussinger (2009) used firm-level data for 389 German manufacturing firms over the years 1992-2000. In the study, export activity was represented by a firm’s export status. The findings suggest that larger, more R&D intensive, and more productive firms are more likely to become exporters. Thus, firms with a relatively high TFP are more likely to start exporting than those with a relatively low TFP. Using both a Granger causality test and a matching technique, exporting was not found to improve the firms’ TFP and there were no evident differences in terms of TFP between exporting and non-exporting firms. Thus, it seems that the “learning by exporting” effect does not exist, thus providing additional support for the existence of only the “self-selection” view.

In comparison with the relatively small sample used by Arnold and Hussinger (2009), Kim et al. (2009) examined the relationship between exporting and TFP for 1,335 Korean manufacturing firms belonging to eight industries during the years 1997-2003. Exporting was represented by a firm’s exporting status. Using the same method as Clerides et al. (1998), they found that exporting did not lead to higher productivity, except for in the machinery and equipment industry. Therefore, the effect of “learning by exporting” was almost non-existent. The self-selection effect was measured following Roberts and Tybout (1997), with the finding that productivity led to exporting for just three industries out of eight, namely machinery and equipment, computers and office machinery, and electronic components. Since they were limited to these industries, the existence of these relationships cannot be extended to the manufacturing sector as a whole.

This section has thus far discussed the possibly two-sided relationship between exporting and TFP. On the one hand, there may be a self-selection effect, whereby more productive firms self-select into new markets and start exporting. On the other hand, there may be “a learning by exporting” effect, whereby firms learn how to increase their productivity by getting involved in export activities. The studies analysed above were focused on gaining a better understanding of these effects in both developed and developing countries. Most of the studies document the existence of a self-selection effect and the absence of a “learning by exporting” effect. One study found that both effects are irrelevant, while two others suggest that exporting has an indirect effect on aggregate industry productivity. This is because exporting firms have a higher employment and output growth and the reallocation of output shares from the least productive plants to those that are the most productive leads to a higher aggregate TFP, where exporters provide the largest share of the contribution. Thus, there seems to be an indirect effect of exporting on TFP at the industry level. It can be inferred that, in some cases, exporting benefits the most productive plants, enabling them to grow in terms of output and employment. In general, one can infer from the literature reviewed that exporting does not determine higher productivity at the firm level.

However, there have also been studies demonstrating the existence of a positive effect of export activity on TFP, supporting the idea that firms "learn by exporting." Castellani (2002) argues that most studies supporting the self-selection view have adopted variables that are not representative of export behaviour. This is because they all use a variable where export behaviour can either take a value of 1 or 0, which does not represent the intensity of a firm's involvement in export activities. Thus, he uses the ratio of a firm's foreign to total sales as a measure of export intensity. Using firm-level data for about 5,000 Italian manufacturing firms in the years 1989-1994, Castellani (2002) found that export intensity has a positive effect on labour productivity. Therefore, the higher the export intensity, as measured by the ratio of foreign to total sales, the higher a firm's labour productivity growth. "Learning requires experience of foreign markets, which comes with time and specific investments, and can be very much correlated with the share of foreign exports" (Castellani, 2002, p.625).

Blalock and Gertler (2004) take a different view from Castellani concerning the prevalence of findings supporting the self-selection thesis. They argue that the previous studies documenting the existence of a self-selection effect mainly focused on developed countries, which are likely to be as productive as their trading counterparts. In contrast, firms in developing countries might still have room for learning from their trading partners and experiencing technological transfers, that give them a greater opportunity to improve their TFP. By adopting a dichotomous variable for exporting in a sample of 20,000 Indonesian manufacturing plants during the period of 1990-1996, they found that plants experienced a 2-5% gain in productivity after starting export activities. Their findings thus support the view that firms learn by exporting.

De Loecker (2007) introduced the destinations where firms export their goods by splitting the sample into destination markets. He also used a dichotomous dummy variable as proxy for the firm's probability to start exporting. By using firm-level data for 7,915 Slovenian manufacturing firms during the period of 1994-2000, he found that firms experienced productivity increases after starting to export, an effect that increased in the following years.

Exporting firms were found to be 8.8% more productive on average and to learn by exporting in 13 out of 16 sectors. In particular, firms that exported to regions characterised by high income, such as Western Europe and North America, were found to achieve the largest improvements in productivity. Therefore, it seems that firms achieve a higher TFP as a result of learning and technology transfers by exporting to developed countries. Moreover, consistent with Blalock and Gertler (2004), firms in developing countries might still have room for learning from their trading partners and experiencing technological transfers, which improve their capacity to increase TFP. De Loecker (2007) also suggests that the existence of the learning effect in Slovenia was motivated by the country's economic transition from socialist to market-oriented, and by the fall in 1990 of the CMEA trading system, which provided firms with the opportunity to export towards developed regions.

Greenaway and Kneller (2007) analysed the effect of learning by exporting in a sample of UK manufacturing firms during the period of 1989-1998. The authors compares TFP between exporters with non-exporters having similar observable characteristics, focusing on whether it differed according to firms' existing level of exposure to foreign firms within their domestic market. The rationale is that firms, by operating in export markets, are likely to benefit in terms of TFP growth from competition and technology transfers arising from the presence of foreign firms. In the analysis, exporters were differentiated from non-exporters using dummy variables. The exposure to foreign firms was expressed by three measures, two representing international competition and one knowledge: one was the Grubel and Lloyd index, representing the extent of the similarity between imported and exported products; the second was a combination of the share of industry exports in the related output and the Grubel and Lloyd index; and the third was the ratio of industry R&D expenditure to related industry output. The results suggest the existence of a learning-by-exporting effect. However, this effect was found to be lower for those industries whose firms already had a high exposure to foreign firms through international competition. From these results, it seems that firms learn and increase their TFP once they start exporting. However, firms that have already been exposed to foreign firms, and thus whose TFP has already increased as a result of competition and technology transfers, are likely to experience less of a "learning by exporting" effect and lower TFP growth as a result.

García et al. (2012) took a different approach from the previous studies by considering how firms with different levels of absorptive capacity, measured as R&D expenditure, benefit from learning by exporting. The measure of exporting used was the export status, which took the value of 1 if a firm was exporting and 0 otherwise. From a sample of 1,534 Spanish manufacturing firms during the period of 1990-2002, the results indicate that firms learn by exporting. In particular, the firms benefiting the most from learning by exporting, in terms of both labour productivity and TFP, were those with a relatively high level of absorptive capacity, measured in terms of R&D and, hence, technological advancement. Firms having relatively high levels of R&D investment were found to have better performance than those having relatively low levels.

The findings of the above-mentioned studies suggest that firms that engage in exporting benefit in terms of higher TFP, supporting the learning by exporting view.

In the Chinese context, Sun and Hong (2011) analysed how exporting affects productivity by looking at a firm-level dataset spanning 2001-2005. Exporting was represented by a measure of export intensity. The data came from the National Bureau of Statistics of China (NBS) and considered about 70,000 SOEs and non-SOEs with at least RMB 5mn of sales. In order to analyse how various ownership types interact with the export premium, the export variable was combined with ownership variables. In addition, in order to analyse how firms belonging to different industries are exposed to export markets, an industrial export intensity variable was included. The authors subsequently investigated the learning-by-exporting effect by adding a variable representing experience (the number of years since a firm started exporting) and another representing the interaction between experience and export intensity. The results from their fixed effects' estimation suggest the existence of a positive effect of export intensity on firm productivity. However, since this analysis was likely to be characterised by the presence of the endogeneity issue, they also adopted an instrumental variable approach. The coefficients for ownership variables suggest that SOEs are less productive, while foreign-owned companies are the most productive. However, it appears that as the share of foreign ownership increases, the positive effect of exporting decreases. When the variables representing export experience and its interaction with export intensity were added to the model, exporting experience was found to have a positive effect on productivity, while the interaction variable had a negative effect. These results suggest that firms with longer exporting experience are more productive. However, the positive effect decreases with the length of export experience. When the instrumental variables approach was adopted, the effect of export intensity became insignificant.

Yu (2010) examined the effect of exporting on Chinese firms' TFP in terms of processing trade and import competition through tariff reduction policies. Firm-level production data for 2000-2006 was taken from China's National Bureau of Statistics of manufacturing enterprises, which covers both SOEs and non-SOEs. The number of firms studied ranged from 162,885 in 2000 to 301,961 in 2006. TFP was estimated using the Olley and Pakes (1996) approach. As this approach tends to overestimate the coefficient on capital, the author also adopted the system-GMM developed in Blundell and Bond (1998). A 10% tariff decrease was found to generate a 12% productivity gain.

Du et al. (2012b) examined how Chinese firms' TFP is impacted by entry into and exit from export markets. In contrast with previous studies on the effect of exporting on productivity, the study separated exporting firms into domestic and foreign-owned. The number of firms studied varied from about 150,000 at the end of the 1990s to over 240,000 in 2005. In order to deal with the potential endogeneity issue, the authors adopted the OP (1996) approach and some variants, while the matching technique was adopted to isolate the impact of export participation on firm productivity. The results suggest that domestic firms achieve productivity gains once they start exporting, an effect that increases in the following years. Foreign firms, on the other hand, do not show any significant productivity increase once they start exporting or when they continue to export. When domestic firms exit from export markets, their productivity slows, while the same effect is not seen in foreign-owned firms. Interestingly, after classifying firms according to their technology level, it appears that the productivity gains achieved by firms that were starting to export were more significant in industries characterised by high and medium technology levels than for firms with low technology levels. It might be that foreign-owned firms do not need significantly improve their efficiency or innovate by exporting. Domestically owned firms might have more room for productivity improvements. Based on above results, it seems that exporting has a positive effect on firms' TFP.

This section has analysed the relationship between a firm's engagement in export activities and its TFP. In this regard, there exist two main contrasting views. One suggests that TFP is likely to determine a firm's decision to export, and hence to self-select into a new market. This is because only the most productive firms are able to afford the sunk costs that exporting activity entails (e.g. spending time collecting information on export markets, structuring a platform to support potential exporting activities, sustaining distribution and marketing costs). Therefore, the benefits gained from the export activity should outweigh its costs. In such a decision, a firm will consider various factors, among them TFP, which is a measure of the firm's economic performance and competitiveness. Therefore, TFP is likely to determine whether a firm self-selects into the export market.

In contrast to the "self-selection" view is the "learning by exporting" view. According to this view, a firm learns by engaging in exporting how to become more productive and thus more competitive. The more a firm exports, the higher its productivity becomes. This is because by participating in foreign as well as domestic markets, the firm faces a larger number of competitors. In order to survive in such an environment, the firm would have to constantly improve its productivity by undertaking TFP-enhancing measures. Moreover, exporters are likely to benefit from the commercial interactions that exporting entails (e.g. interacting with foreign economic agents, learning from customer feedback, and observing innovative technologies, competing products and competitors' working practices). However, the learning by exporting effect is likely to be lower in those industries whose firms have already had high exposure to foreign firms through international competition. The knowledge of international markets and competition is adopted by the entrepreneur and can be exploited to increase the firm's TFP through product and process improvements and the adoption of innovative machinery. Therefore, according to the learning by exporting view, a firm learns how to improve its productivity the more it exports. Some studies support the self-selection view, in which the most productive firms enter into the export markets. Most of these studies document the existence of a self-selection effect along with the absence of a "learning by exporting" effect. However, by focusing on developing countries and using different proxies, other studies have found that once firms start exporting, they learn how to improve their productivity. The empirical results indicate that exporting has a positive effect on TFP.

### 2.4.9. Managerial Ability

Managerial ability can be defined as "the knowledge, skills and experience, which is often tacit, residing with and utilized by managers" (Holcomb et al., 2009, p.459). Managerial ability represents the combination of manager characteristics that, through interaction, results in decisions that shape how a firm operates. It can be further decomposed into general, firm-specific and industry-specific managerial ability, leading to differences among decision makers. Since all managers are unlikely to possess the same characteristics, some might be more skilled than others. Holcomb et al. (2009) suggest that managerial ability results from domain and resource expertise. Domain expertise is the ability of managers to understand their industry and the main components of their firms, such as products, markets and strategies. Resource expertise represents the ability of managers to best use the resources they possess, such as labour and capital. Concerning domain expertise, a manager at an automotive firm might be more knowledgeable than his competitors regarding consumer preferences, and thus more capable of adapting the company's products accordingly. Moreover, concerning resource expertise, the same manager might be more capable than others of devising strategies to match the firm's workforce with its physical assets. In particular, it is crucial for managers to foster creativity and innovation among employees, which is likely to result in higher TFP. Managers with higher managerial ability are expected to achieve superior firm performance, which can be seen in terms of TFP growth. Managers play a prominent role within firms. "Managers are conductors of an input orchestra. They coordinate the application of labour, capital, and intermediate inputs. Just as a poor conductor can lead to a cacophony rather than a symphony, one might expect poor management to lead to discordant production operations" (Syverson, 2011, p.336). Although a firm may possess qualitative inputs, employ the most highly-skilled employees, and possess the best production techniques and most innovative machinery, managers have the ultimate power to combine the available resources in the best possible way for productive purposes. Koprowski (1981) argues that good management practice occurs when the management is focused on increasing productivity. For example, rewarding or promoting high performing employees within a firm is likely to generate TFP growth. If this does not occur, such employees are likely to leave the firm, possibly resulting in a TFP decrease. A manager has the opportunity to make the best use of the available resources to achieve TFP growth. The manager's decisions can also allow the firm to simply survive, or, in the worst case, lead the firm to exit its industry due to low TFP. The empirical results from the literature seem to support a positive effect of good managerial practices on TFP.

For example, Ichinowski et al. (1997) studied the effect of human resource management (HRM) variables on the productivity of 36 finishing lines owned by 17 different steel companies. Productivity was measured as the percentage of the operating time that a production line was running. In this study, the HRM variables provide a measure of the work practices adopted by steel firms in their management of personnel: incentive pay, recruiting and selection, teamwork, employment security, flexible job assignments, skills training and communication. As the authors acknowledge, examining the impact of a single practice on productivity would produce biased estimates since practices interact and form synergies. Therefore, the practices were grouped into four different combinations, or "systems", based on their level of innovation. The study's results provide an interesting insight, as HRM systems were found to be determinants of productivity. However, the effects on productivity of single HRM practices were found to be small. This suggests that within a firm, the introduction of a single HRM practice is not likely to cause a significant TFP improvement. However, its effect is more likely to be significant when combined with other complementary practices due to the creation of synergies. From these results, one would infer that the introduction of HRM systems leads to productivity improvements. However, the results should be interpreted with caution since the study only looked at steel companies. Therefore, such an analysis should be extended to more sectors. Moreover, the size of the sample adopted was small, with only 36 production lines examined.

Lazear (2000) analysed improvements in productivity due to a change in pay practices by examining the output produced by 3,000 workers within an auto glass company over a period of 19 months. Rather than analysing many practices or systems of practices as did Ichinowski et al. (1997), the study focused on just the pay practice. When it was switched from an hourly wage to piece-rate pay, the output per worker was found to improve by 44%. This was due to the incentive effects associated with the new pay practice, which pushed workers to increase their efforts and increased the ability of the firm to hire and retain the most productive workers. Although there was a strong increase in productivity, it would be interesting to see whether this was accompanied by a decrease in quality as workers shifted their focus to output quantities. Since the observed unit was the worker, the study had a much larger sample than Ichinowski et al.'s (1997). In addition, it focused on a specific management practice. Although the pay practice had a positive effect on productivity, it does not mean that other potential management practices are likely to be successful in raising productivity. Moreover, since the results are focused on a specific activity in a firm, the results cannot be extended to other industries.

A more comprehensive study than the above two was done by Bloom and Van Reenen (2007), who examined 18 management practices through a survey of 732 medium-sized manufacturing firms across the US, France, Germany and the UK. Management practices were measured using answers provided by firm managers regarding five different categories concerning operations monitoring, targets and incentives. The study found the measures of management practice to be positively associated with measures of firm performance, among them TFP, for all the countries. Therefore, it seems that good management practices are positively associated with productivity. Poorly managed firms were found to be mainly family-owned and to operate in environments characterised by low competition. The former effect might be because family-owned firms, which often choose their CEOs from among their primogeniture, are less likely to be well managed. In the latter effect, an environment characterised by low competition would enable the least productive firms to survive and disincentivise managers to upgrade their practices by reducing slack and pursuing innovation, which are supposed to increase TFP. In a more competitive environment, on the other hand, the least productive firms are likely to exit the industry while allowing the most productive firms to thrive and gain market share. It must be noted that the authors of the study measured the correlations between management practices and the various measures of firm performance and not the causal effects of management practice changes on firm performance. In a subsequent study, Bloom and Van Reenen (2010) extended the same methodology to a larger sample of 5,850 firms across 17 countries. Their results suggest that the US, Japan and Germany have the highest management scores, while countries such as China, Brazil and India have the lowest scores. By measuring the correlation between measures of firm performance, among them productivity, and management practices, their results suggest a positive association. However, being correlations, the results could indicate that good management practices result in high productivity, or that high productivity results in the adoption of good management practices.

The studies by Ichinowski et al. (1997) and Lazear (2000) suggest that when firms adopt good managerial practices, productivity is likely to improve. However, since these analyses were limited to one sector each, the results cannot be extended to other industries. The studies by Bloom and Van Reenen (2007; 2010), on the other hand, cover more firms, sectors and countries. They suggest that there is a positive association between management practices and productivity. However, since the relationship is represented by a correlation, no direction of causality from one factor to the other can be inferred.

In this section, the relationship between managerial ability and productivity has been discussed. Managerial ability represents the combination of a manager's characteristics, which, by interacting with one another, result in decisions that shape how a firm operates. The term can be further decomposed into general, firm specific and industry specific. Managers might differ in their abilities because of different domain and resource expertise. In particular, within resource expertise, it is crucial for managers to foster creativity and innovation among employees, which is ultimately likely to result in higher TFP. Managers with greater abilities are expected to achieve superior firm performance, which can be measured in terms of TFP growth. Thus, managers have a prominent role within firms. Although a firm may use qualitative inputs, employ the most skilled employees, possess the best production techniques and the use most innovative machinery, managers have the ultimate power and responsibility to combine the available resources in the best possible way. Koprowski (1981) argues that good management practice occurs when the management is focused on increasing productivity. The empirical results from the literature support a positive effect of good managerial practices on TFP, although the studies are focused on specific sectors and small samples. Other studies that have extended the analysis to a large number of firms, sectors and countries suggest a positive correlation between managerial practices and productivity. However, since these studies do not look at the direction of causality, further investigation is needed.

### 2.4.10. Marketing Capabilities

Barney (1991), a proponent of the resource-based view of the firm, argues that firms within an industry differ according to the resources they possess. This suggests that each firm has a set of resources that are unique. A resource can, therefore, represent a firm-specific advantage (FSA), that is "a unique capability proprietary to the organization. It may be built upon product or process technology, marketing or distributional skills. The FSAs are based ultimately on a firm's internalization of an asset, such as production, knowledge, managerial, or marketing capabilities over which the firm has proprietary control" (Rugman, 2005, p.34). According to this definition, among the various firm-specific advantages are the firm's marketing capabilities. Vorhies and Morgan (2005) argue that these represent the capacity of a firm to transition resources into valuable output. It can also be said that the "marketing capability of a firm is reflected in its ability to differentiate products and services from competitors and build successful brands. Thus, a firm that spends money on advertising and promoting its products can increase sales both by expanding the sales of the product category and by getting customers to switch to their brands. Firms with strong brand names can charge premium prices in foreign markets to enhance their profitability as well" (Kotabe et al., 2002, p.82). Vorhies and Morgan (2005) identify the following marketing capabilities: product development, pricing, channel management, marketing communications, selling, market information management, marketing planning, and marketing implementation. These may therefore constitute a crucial determinant of a firm's performance. The findings from the literature seem to support this view.

Morgan et al. (2009) analysed a cross-industry sample of 114 US firms to examine the effect of three marketing capabilities (market sensing, brand management, and customer relationship management) on the firms' revenue and margin growth rates. The three marketing measures were assessed through a survey, using a point scale. Market-sensing capabilities had a significant positive effect on the revenue growth rate, while having a negative effect on the margin growth rate. Customer relationship management capabilities had a significant negative effect on revenue growth rate and a positive effect on margin growth rate. Brand management capabilities were found to have a significant positive effect on revenue growth rate and a negative effect on margin growth rate. Therefore, the results point to the different effects of each capability on the various measures of firm performance. Although the results of this study provide an insight into the relationship between marketing capabilities and firm performance, the measurement of capabilities might be too subjective, as it is scored from questions asked to firms' managers. The use of a more objective measure of marketing capabilities would have been preferred.

For the UK, Nath et al. (2010) examined the impact of firms' functional capabilities (marketing and operations) and diversification strategies (product/service and international diversification) on financial performance. The sample comprised 102 UK-based logistics companies over the period of 2005-2006. Given the importance of marketing and operational capabilities and diversification strategies in logistics, the industry is valuable for analysing the effect of these factors on financial performance. However, it would have been preferable to extend the analysis to many other sectors. Despite this limitation, the authors adopted a valuable measure of marketing capabilities, with the variables being marketing expenditures, intangible resources, relationship expenditures and installed customer base. The result of the estimation, conducted through a Data Envelopment Analysis (DEA), indicate that marketing capabilities strongly affect the financial performance of firms.

Yu et al. (2014) examined the impact of marketing capabilities and operational capabilities on firms' financial performance. This relationship was studied by applying an input-oriented constant return to scale DEA model on a sample comprising 186 retail firms in the UK during 2010. To measure marketing capabilities, they followed Nath et al.'s (2010) approach, whereby sales were used as an output measure of marketing activity, while marketing resources were measured by the following three inputs: stock of marketing expenditure, intangible resources and relationship expenditure. Their results suggest that marketing capabilities have a significant positive effect on operational capability, consequently improving efficiency in the financial sector.

While the above studies looked at firms based in developed markets, Wu (2013) looked at 19,653 firms spread across 73 emerging economies to examine the effect of the firms' marketing capabilities on their performance. The geographic breadth of the sample enabled the author to shed light on the overall effect of marketing capabilities on firm performance in emerging economies. In the study, marketing capabilities were proxied by an indicator that averaged the following three items: the number of months the firm took to plan its product mix and target markets; the number of months it took for the firm to allocate the necessary human resources; and the number of months in which the investment was made. Although the proxy for marketing capabilities was comprehensive, adopting time measures does not seem ideal, as time might not indicate the true extent of firms' marketing capabilities. Despite this shortcoming, the results suggest that marketing capabilities positively affect firm performance. It also appears that marketing capabilities have a stronger effect on firm performance in countries with higher levels of economic development, individualistic societies and weak legislative systems.

Also in the developing country context, Lee and Rugman (2012) analysed the impact of firms' specific advantages on performance by looking at a sample of 150 Korean multinational enterprises for the year 2004. The firm-specific advantages considered were innovation capabilities measured by R&D, and marketing capabilities measured by selling, general and administrative expenses. Specifically, a firm's marketing capabilities were measured as the total amount of selling, general, and administrative expenses divided by the number of employees. The extent of the relationships was examined using a two-stage feasible generalised least square regression model. The results suggest that both marketing and innovation capabilities affect the performance of firms in a non-linear, U-shaped manner. Moreover, it seems that Korean firms can exploit their firm-specific advantages when they attract FDI from the Asian Pacific region, enabling them to strengthen these advantages.

The empirical results from research at firm level seem to suggest that marketing capabilities positively affect a firm's performance. However, the studies have not considered the impact of marketing capabilities on any specific productivity measure. Despite this, the relationship between marketing capabilities and productivity is expected to be negative.

### 2.4.11. Other Studies

This section differs from the previous sections in that it covers different determinants rather a single specific determinant. Since significant research on these determinants has not been done for Chinese firms, they are discussed together in this section.

Chen and Guariglia (2013) looked at the relationship between Chinese firms' financial factors and productivity. In particular, they analysed the link between the availability of internal finance and productivity by examining this relationship from different perspectives: ownership, liquidity level and involvement in exporting. Firms in the sample belonged to the manufacturing sector, according to annual accounting reports filed with the National Bureau of Statistics during the period of 2001-2007. The sample included 130,840 SOEs and non-SOEs from 31 provinces, and which had at least RMB 5mn sales. The empirical analysis of TFP was conducted using the SYS-GMM approach. The results show that the firms' TFP was positively affected by their cash flow, suggesting that the firms were financially constrained and mainly relied on internal funds. In terms of ownership, private and foreign-owned firms' TFP was positively affected by their cash flow, while SOEs' TFP was not, suggesting that only the first two categories of firms were financially constrained. For both private and foreign firms, the effect was found to be worse for those firms characterized by negative liquidity. This suggests that firms use their liquidity in order to pursue productivity-enhancing activities when there are fluctuations in their internal finance. In terms of exporting, foreign-owned firms that did not export had a higher sensitivity of TFP to cash flows than those who did, although the difference in sensitivity with private firms was not significant.

Zhang and Liu (2013) examined the relationship between wages and labour productivity in the manufacturing sector. This was analysed using a dataset of manufacturing enterprises for the period of 1998-2007 taken from the Chinese National Bureau of Statistics. The sample covered both SOEs and non-SOEs having sales of more than RMB 5mn. Therefore, the sample was the same as used by Chen and Guariglia (2013). Two labour productivity variables were used as measures of performance. The main difference with the previous studies in the area was the use of productivity as an independent variable, while previous ones used it as a dependent variable. The results suggest a positive correlation between wages and labour productivity, although this effect decreases over time.

This section has reviewed studies on different determinants of productivity. For each determinant, significant research at the firm level for the Chinese context is still lacking. Thus, further evidence is needed to confirm the extent of the relationship of the main determinants discussed (liquidity and wages) with productivity. The studies discussed in the following section consider multiple determinants of productivity.

### 2.4.12. Studies Analysing Multiple Determinants

The studies discussed in the previous sections focused on analyzing how firm-level productivity was affected by one or a few determinants. Although they provide a valuable insight, they suffer from one major limitation. Productivity has many more determinants that interact together and generate synergies. Ignoring the other important determinants of productivity would generate biased estimates of the production function and of productivity. Moreover, productivity-enhancing actions undertaken by a firm according to such results are likely to be limited. A few studies have addressed this issue by considering multiple determinants of productivity. A firm can implement better TFP-enhancing decisions by considering a wider range of potential factors determining TFP. Only four studies have analysed TFP at the firm level in China by considering multiple determinants. These studies differ in terms of their estimation methodologies, the samples adopted, and the determinants analysed.

For example, Yao et al. (2007) considered the following determinants of TFP: size, ownership, direct sales, and human capital. In order to calculate the efficiency scores of firms, they adopted a Data Envelopment Analysis approach. TFP growth was subsequently measured using the Malmquist index, while a Tobit regression was adopted to estimate the effects of TFP determinants. The sample size was small, comprising a panel of only 22 firms belonging to the insurance industry during the period of 1999-2004. Despite the small sample size, the empirical results suggest that size, direct sales and human capital have a positive effect on firms' productivity. Interestingly, in contrast to what has been suggested by previous studies regarding ownership, State-owned firms showed better performance than non-State-owned ones. The authors suggest that such performance is the result of the dominance of State-owned enterprises within the industry, as the firms are backed by the government, and by the characteristics of the industry itself, in which customers emphasize brand name, trust and reliability.

Li et al. (2010) looked at effect of the following institutional factors on firms' productivity: regional differences in commercialisation and the existence of market segmentation. They also considered the following determinants of productivity: exporting, R&D, interest payments, age, size, management level, and ownership. Moreover, they analysed the relationship between TFP, exporting, financing and innovation. This study was conducted using a sample of 647,987 firms belonging to 30 industries over the period of 1999-2007. This data was taken from the Chinese NBS, and included medium and large-sized firms having at least RMB 5mn in sales. Although the sample seems to be representative of the Chinese industrial sector, it would have been better to also consider smaller firms, as this would have provided additional insight into the determinants of small firms' TFP. In the study, TFP was estimated using a translog production function and the Levinsohn and Petrin (2003) semi-parametric approach. The results suggest that firms based in regions characterized by a faster commercialisation process record higher productivity. On the other hand, firms based in more segmented regions tended to record lower productivity. Overall, the results of the study indicate that regional imbalances and differences in commercialisation and market segmentation have different effects on productivity.

Brandt et al. (2012) analysed TFP growth for a panel of firms representing 90% of Chinese manufacturing output during the period spanning 1998-2007. The number of firms studied ranged from 148,685 in 1998 to 313,048 in 2007. The dataset was obtained from the National Bureau of Statistics, and included SOEs and non-SOEs having sales above RMB 5mn. In comparison with other studies using the same dataset, the analysis also included industry deflators, industry agreements and programmes to match firms over time and capital stock series. In the estimation, productivity growth was measured using the Tornqvist index number. Productivity levels were measured using a Caves' index, which allows the comparison of a firm's productivity to the industry average. In order to confirm the robustness of their results, the authors also estimated productivity using the Olley and Pakes (1996) and Ackerberg et al. (2006) approaches. According to the estimation results, TFP growth was 2.85% on average when a gross output production function was utilized, and 7.96% when a value added production function was utilized. In comparison with the previous studies, productivity growth was decomposed following the methodology developed by Foster et al. (2001), enabling an understanding of the extent to which TFP growth is determined by "within-firm" productivity growth, "between-firm" productivity growth, the entrance of relatively high productive firms or the exit of low productive ones. The empirical results indicate that the entry of relatively high productive firms contributed to two-thirds of the productivity growth in the Chinese industrial sector during the period. Moreover, the results indicate that the growth of value added in the Chinese industrial sector was largely due to improvements in existing firms and the entry of relatively high productive firms. Despite providing valuable findings, the methodologies adopted by Brandt et al. (2012) did not allow for fixed effects, and did not include the vector $X_{it}$ of TFP determinants, making them unable to explain what determines TFP levels.

While the above two studies analysed TFP across a wide range of industries, Shen and Song (2013) focused only on the iron and steel industry during the period of 1998-2007. In the study, the following determinants of TFP were considered: capital intensity, the share of total revenues generated by new products, the market share within the iron and steel industry, the Herfindahl index of industrial concentration, firm scale, a marketization index, and the share of exports in total revenue. While the sample source was the same as in previous studies, its size was considerably smaller, with the number of firms ranging from 1,654 in 1998 to 4,929 in 2007. In order to estimate TFP, the authors adopted the one-step Wooldridge (2009) GMM method and tested the robustness of their results using the Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2007) methodologies. Their results showed that TFP increased during the period analysed and was positively affected by R&D investment, firm size, market share and marketization reform. On the other hand, TFP was negatively affected by market monopoly power and capital intensity. Moreover, determinants of productivity varied across firms having different characteristics, such as size, ownership and location. It seems that, for small firms, productivity is positively affected by market share, while R&D negatively affects it. In contrast, for large SOEs, productivity is not sensitive to market share or R&D. For large private firms, productivity is determined by their intensity of export activities, measured as the share of exports in total revenue.

This section has reviewed firm-level productivity studies, which, compared to those presented in the previous sections, consider the effect of multiple determinants on TFP rather than focusing on only one determinant. This approach is important because TFP is determined jointly by a combination of factors rather than just one. By interacting with one another, these factors are likely to generate a different effect on productivity than when they are considered individually. For this reason, these studies provide better insight into the potential determinants of productivity at the firm level. The next section discusses how the study conducted in this thesis differs from the previous ones, and how it contributes to the existing literature.

### 2.4.13. The Contribution of this Study

The study conducted for this thesis belongs to the literature analysing TFP and its determinants in China at the firm level. Previous studies in this area differ from one another in terms of their aims, estimation methodologies, datasets, determinants and the time periods considered. There are four important studies that analyse Chinese TFP at the firm level (Yao et al., 2007; Li et al., 2010; Brandt et al., 2012; Shen and Song, 2013). The study conducted for this thesis differs from them in four respects.

The first distinction is the use of a more comprehensive set of determinants of TFP in the estimation, providing a better and broader understanding of the potential determinants of total factor productivity in China. Such determinants are included in the estimation of TFP because their omission would produce biased estimates of the production function, and hence biased estimates of TFP. The choice of determinants is also motivated by the empirical results from the literature and the information available in the Chinese National Bureau of Statistics (NBS) dataset from which the sample used in this study has been sourced. Thus, although the previous studies have provided valuable insights, the current study has extended the set of TFP determinants studied to include the following: political affiliation, ownership structure, engagement in exporting, extent of competition, Marshallian (or MAR) spillovers, Jacobian (or Jacob) spillovers, city spillovers, liquidity, age, R&D expenditure, time trend, and marketing capabilities.

The second major distinction from the studies reviewed above is the analysis of a wider set of 26 industries. In this study, the sample is taken from the yearly accounting reports filed by industrial firms to the Chinese National Bureau of Statistics. Such a sample considers all industrial medium- and large-sized firms, both State-owned and non-State-owned, having annual sales above RMB 5mn. These belong to the entire manufacturing and mining sectors and are located in 31 provinces or municipalities. The estimation of TFP determinants across a wide range of industries allows the accounting for differences in technology, thus avoiding the assumption that firms operate using a standard technology shared across all industries.

While most previous studies have used the Olley and Pakes (1996) or Levinsohn and Petrin (2003) methodologies to analyse the determinants of TFP at the firm-level in China, this study adopts SYS-GMM, an approach developed by Arellano and Bond (1991) and Blundell and Bond (1998), and subsequently applied in a production function by Blundell and Bond (2000). SYS-GMM is a system of estimated equations, comprising an equation in first-differences, instrumented by its lagged levels, and an equation in levels, instrumented by its lagged first-differences. The major advantage of this methodology, compared to the widely used semiparametric approaches, is the allowance for firms' fixed effects. As previous studies have indicated that firms have unmeasured productivity advantages that remain constant over time and that need to be captured, the SYS-GMM approach enables the consideration of such fixed effects. Moreover, SYS-GMM has the advantage of addressing the endogeneity of the right-hand-side variables (including the lagged dependent variable) as well as selection bias by using lagged values of the endogenous variables as instruments in the first differences equation, and first-differences of the same variables as instruments in the levels equation (Blundell and Bond, 1998). SYS-GMM is particularly preferable to the semiparametric methodologies of Olley and Pakes (1996) and Levinsohn and Petrin (2003), as these do not allow for fixed effects and are based on strong and unintuitive assumptions, which generate collinearity problems in the first stage of estimation (Ackerberg et al., 2006). Van Biesebroeck (2007) compared the sensitivity of five different productivity estimators (index numbers, data envelopment analysis, stochastic frontiers, GMM, and semi-parametric estimation) using a Monte-Carlo simulation. Although each method has its own advantages and disadvantages, the system GMM estimator was found to be the most robust technique in presence of measurement errors and technological heterogeneity.

The fourth major distinction from most of the previously mentioned studies is the decomposition of TFP growth using the approach developed by Haltiwanger (1997). These methods separate TFP growth into the contribution provided by the following: a within-firm component representing the impact of the resource reallocation within existing firms, according to their initial shares of output in their related industries; a between-firm component indicating a change in the output share of firms, weighted by the deviation of the firm's initial productivity from the initial industry index; a covariance component, measuring whether a firm's increasing productivity corresponds to an increasing market share; an entering component indicating the contribution of entrant firms to their related industry's TFP growth, measured with respect to the initial industry index; an exiting component indicating the contribution of exiting firms to their related industry's TFP, measured with respect to the initial industry index. In order to gain an additional understanding into the determinants of TFP growth, this decomposition is also performed at the industry, province and political affiliation/ownership levels. Since Melitz and Polanec (2012) have found this decomposition to be characterized by biases, their approach is also adopted in order to understand which set of results is the most appropriate.

In summary, most of the existing studies on this topic do not use multiple covariates in their models to explain what determines TFP in China, do not include firm-level fixed effects, do not cover the broad range of industries studied in the present paper, and do not decompose TFP growth. Therefore, this study builds on the existing literature by taking these four issues into account, thus distinguishing this study from previous studies on firm-level TFP estimation in China and contributing to the literature in that way. Overall, this study aims to understand what has determined TFP levels and growth rates across Chinese firms during the period of 1998-2007, and how total TFP growth has differed across firms belonging to different industries, based in different provinces, and characterised by different combinations of ownership structures and political affiliations. The results can be used to infer potential microeconomic productivity-enhancing reforms targeting the most relevant determinants of TFP.

# 3. An Analysis of the Determinants of TFP Levels

Chapter 1 introduced the thesis. Chapter 2 discussed TFP, its importance, its measurement and its determinants. It also reviewed the existing studies on Chinese firm-level TFP and proposed the contribution provided by the current study. This chapter analyses what determines TFP levels across Chinese industrial firms.

Section 3.1 describes the dataset adopted, while Section 3.2 describes the SYS-GMM estimator. Section 3.3 introduces the two-sample Kolmogorov-Smirnov test. Section 3.4 describes the variables adopted, the related descriptive statistics and the hypotheses to be tested. Section 3.5 presents the results of the SYS-GMM estimation. In order to check which set of results is the most valid, the Levinsohn and Petrin (2003) semiparametric estimation is also applied, and its results are discussed in Section 3.6. Section 3.7 analyses the relative importance of the determinants of TFP levels. The results of the Kolmogorov-Smirnov tests are discussed in Section 3.8.

### 3.1. Dataset

The dataset adopted in this study is taken from the yearly accounting reports filed by industrial firms with the Chinese National Bureau of Statistics. In this dataset, the unit observed is the firm, which is defined as a legal unit and identified by a unique ID. Brandt et al. (2012) point out that large Chinese firms might include many subsidiaries that would be represented as additional firms if they were registered as legal units. Moreover, a firm receives a new ID any time it changes its legal registration, for example, after a restructuring, merger or acquisition. In order to address this issue, Brandt et al. developed an algorithm that makes possible to match firms' IDs over time using both their code and other identifying information. The same algorithm is adopted in this study and is available online.[1] Where possible, Brandt et al. (2012) tracked firms using other types of information, such as their name, industry and address. 95.9% of firms' matches were performed using their IDs, while 4.1% using other identifying information. The sample adopted in the current study includes both State-owned firms and non-State-owned firms with at least RMB 5mn in annual sales. The firms are located in 31 provinces, or province-equivalent municipal cities, and belong to the mining, manufacturing and public utilities sectors. The related industries are classified according to two-digit Chinese Industrial Classification (CIC) codes. A firm's membership in an industry is defined according to the sales generated by its major product. The industries are the following: Other Mining (SIC10+80), Food Production (SIC14), Tobacco (SIC16), Textile (SIC17), Apparel & Footwear (SIC18), Leather (SIC19), Timber (SIC20), Furniture (SIC21), Papermaking (SIC22), Printing (SIC23), Cultural (SIC24), Petroleum Processing (SIC25+70), Chemical (SIC26+28), Medical (SIC27), Rubber (SIC29), Plastic (SIC30), Non-metal Products (SIC31), Metal Products (SIC32+33+34), Machinery & Equipment

[1] The complementary information needed to use the NBS dataset developed by Brandt et al. (2012) can be downloaded from the following link: http://www.econ.kuleuven.be/public/N07057/CHINA/appendix/

(SIC35+36), Transport Equipment (SIC37), Measuring Instruments (SIC41), Other Manufacturing (SIC42+43), Electronic Power (SIC44), Gas Production (SIC45), Water Production (SIC46) and Coal Mining (SIC60).

Since the National Bureau of Statistics dataset does not consider firms having annual sales lower than RMB 5mn, 80% of industrial firms are excluded from the sample. Despite this exclusion, Brandt et al. (2012) found that by using the full census of firms periodically carried out in China, the omitted firms only accounted for about 9.9% of output and 2.5% of exports. In addition, Brandt et al.'s (2012) comparison between the 1995 National Bureau of Statistics dataset and the 2004 census indicate that the former has similar coverage, which enabled them to argue that the exclusion of small firms with annual sales lower than RMB 5mn in the NBS dataset did not generate systematic bias in their estimates.

The unbalanced sample adopted in this study comprises 2,183,709 firm-year observations, which correspond to a wide number of firms, ranging from 148,474 in 1998 to 331,453 in 2007. The sample's structure can be seen in Table A of the appendix. Only 5.4% of firms, corresponding to 14.8% of firm-year observations, are included in the accounting information for the entire sample period. 14% of firms, corresponding to 16.7% of firm-year observations, have data for one to two years before exiting from the sample. Brandt et al. (2012) suggest that this is due to ownership restructuring caused by the economic reforms implemented during the 1990s. Some firms also do not have information on variables used to calculate TFP. According to Brandt et al. (2012), this is because the information was not originally reported, or because variables such as real capital stock or value added have negative values. Moreover, firms with less than eight employees are not considered because they fall into a different legal regime. This implies that 17% of the original number of firms is removed from the sample in 1998, and the ratio falls by 6% each year after 2001.

### 3.2. System-GMM Estimation

Total factor productivity is the level of output that is not attributable to the level of factor inputs, and is thus measured as a residual. Section 2.3 discussed the estimation of TFP through different approaches: ordinary least squares, fixed effects, instrumental variables, GMM and system-GMM, and the semiparametric methods developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003).

Each of these approaches adopts different statistical analyses and is based on different assumptions. Moreover, each is appropriate under specific circumstances. Van Beveren (2012) compared the following estimators: fixed effects, instrumental variables and SYS-

GMM, and the semiparametric methods of Olley and Pakes (1996) and Levinsohn and Petrin (2003). These were evaluated under the existence of the following estimation issues: endogeneity of inputs, omitted variable bias, sample selection bias, and multiple-output producing firms. Based on the results obtained, Van Beveren (2012) argues that the choice of a specific TFP estimator should be based on the data utilised and the related assumptions imposed.

The estimation approach adopted in this study is the SYS-GMM. Roodman (2006) suggests that this estimator is designed for panel data analyses, such as the one conducted in this study, having the following characteristics:

- A relatively short time period and many units considered. In this study, the time period spans 1998-2007 and the sample ranges from 148,474 firms in 1998 to 331,453 in 2007.
- A linear functional relationship. In the production function adopted in this study, there is a functional relationship between outputs produced, factor inputs adopted, and TFP.
- A left-hand side variable dependent on its own past realisations. In this study, this is the case for firm output, since decision makers are likely to choose each year's output according to the previous year's output.
- Independent variables that are not strictly exogenous. This indicates that independent variables can be correlated with the past and possibly current realisations of the error. In this study, output, employment, capital, intermediate inputs, the R&D dummy and the exporting dummy are treated as endogenous, since firm managers are likely to make decisions according to both the past and current realisations of the error, in this case TFP. Because it seems that causality runs in both directions, from endogenous variables to productivity and vice versa, the independent variables might be correlated with the error term, represented by TFP.
- Fixed individual time-invariant effects, also known as fixed effects. Such a consideration in this study is based on the findings of Baily (1992), Bartelsman and Dhrymes (1998), Haskel (2000) and Martin (2008), who demonstrated that firms are heterogeneous in terms of productivity and tend to spend long periods of time in the same area of the productivity distribution. This suggests that firms tend to have fixed characteristics that do not change significantly over time. As explained earlier, productivity is likely to be correlated with the explanatory variables, potentially generating biased and inconsistent estimates.

- Idiosyncratic errors, except for fixed effects, that are characterised by heteroskedasticity and autocorrelation within firms but not across them. In this study, productivity shocks represented by $\varepsilon_{it}$ are serially correlated, and relative factor inputs are likely to respond to these shocks.

In this study, TFP is measured through a log-linear Cobb-Douglas firm production function, which includes fixed effects:

$$y_{it} = \alpha_i + \alpha_E e_{it} + \alpha_M m_{it} + \alpha_K k_{it} + \alpha_X X_{it} + \alpha_T t + \varepsilon_{it} \tag{47}$$

Here, *y*, *e*, *m* and *k* are the natural logarithms of real gross output, employment, intermediate inputs and the capital stock, respectively, for each firm $i$ at time $t$ (whereby $i = 1, \dots, N$ and $t = 1, \dots T$). $X_{it}$ is a vector that includes all the variables determining TFP: political affiliation, ownership, exporting, competition, Marshallian spillovers, Jacobian Spillovers, city spillovers, liquidity, age, R&D and marketing capabilities. All of these variables are included in the model because the empirical results from the literature indicate that they either positively or negatively affect TFP. Although some of these variables might be correlated, not including them would generate the issue of omitted variable bias, which results in biased and inconsistent estimates. In equation (47), $t$ is a time trend representing exogenous gains in TFP over time. $\alpha_i$ is a time-invariable, unobserved, firm-specific fixed-effect, and $\varepsilon_{it}$ is an observation-specific error term.

Measuring TFP requires the adoption of price deflators for both inputs and outputs. Since deflators at the firm level are not available in the dataset adopted, industry deflators are taken from various Chinese statistical yearbooks, while the investment, or capital stock, deflator is adopted from Brandt et al. (2012). The deflator is built through a procedure that converts the estimates at original purchase prices into real values that are comparable across both time and firms.

Once TFP is estimated according to equation (47) for each industry, the elasticity of output with respect to each of the three inputs (employment, intermediate inputs and capital stock) is obtained. This enables the measurement of TFP as a residual, or the level of output that is not attributable to the level of factor inputs:

$$lnT\hat{F}P_{it} = y_{it} - \hat{\alpha}_E e_{it} - \hat{\alpha}_M m_{it} - \hat{\alpha}_K k_{it} = \hat{\alpha}_i + \hat{\alpha}_X X_{it} + \hat{\alpha}_T t + \hat{\varepsilon}_{it} \tag{48}$$

In measuring TFP as a residual, the above approach should be the preferred one. Harris and Moffat (2013) argue that a common mistake in existing TFP studies lies in excluding the vector $X_{it}$ as a regressor when estimating the equation (47) and subsequently using (48) in order to measure TFP. In such a case, the vector $X_{it}$ would become part of the error term $\hat{\varepsilon}_{it}$. TFP tends to be subsequently regressed on the vector $X_{it}$ in order to obtain the determinants through a two-stage estimation. Since $X_{it}$ is initially omitted, this would cause estimates to be biased, generating an "omitted-variable" bias. This is the reason why the former approach for measuring TFP is preferred to the latter.

The initial equation (47) is estimated through SYS-GMM. In comparison with other approaches, SYS-GMM allows for the presence of fixed effects. Moreover, SYS-GMM addresses the endogeneity and selection bias issues by using lagged first-differences as instruments for the equation in levels, in addition to lagged levels as instruments for the equation in first-differences[2]. The use of additional instruments enables the efficiency of the estimation to be increased. Moreover, SYS-GMM allows for both endogenous regressors and a first-order autoregressive error term, and also provides results for three additional diagnostic tests: the Hansen test regarding the validity of the set of instruments used, and the tests for autocorrelation, namely AR(1) and AR(2).

SYS-GMM exploits more moment conditions than other GMM approaches and can still face the issue of weak instruments. This suggests that the parameter estimates and the related diagnostic tests are sensitive to the instrument set adopted. An important assumption for the validity of SYS-GMM is the joint exogeneity of instruments. The Hansen test of overidentifying restrictions tests the null hypothesis that the instruments are distributed independently of the production function and are uncorrelated with the residuals. Thus, a strong rejection of the null hypothesis of the test would strongly counter the estimates' validity.

The Arellano and Bond (1991) test for autocorrelation has the null hypothesis of zero autocorrelation in the $\varepsilon_{it}$ disturbances. The test for AR(1) in the first differences usually rejects the null hypothesis. This is because the $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i,t-1}$ is likely to be correlated with $\Delta\varepsilon_{i,t-1} = \varepsilon_{i,t-1} - \varepsilon_{i,t-2}$, as the two equations share the same $\varepsilon_{i,t-1}$ item. One should pay greater attention to the test for AR(2) in the first-differenced residuals $\varepsilon_{it}$, as this potentially detects autocorrelation in levels. This test analyses the relationship between $\varepsilon_{i,t-1}$ in

[2] A lagged value of the dependent variable is included for SIC30, SIC32 and SIC44. For these industries, the short-run coefficients are transformed into long-run coefficients.

the $\Delta\varepsilon_{it}$ and $\varepsilon_{i,t-2}$in the $\Delta\varepsilon_{i,t-2}$. According to Arellano and Bond (1991), the presence of first-order autocorrelation does not imply that the estimates are inconsistent, while the presence of second-order autocorrelation does.

Since the validity of lagged levels dated $t-2$ in the first-differenced equations tends to be rejected by the Hansen test, lagged levels dated $t-3$ (and earlier) are used, as these tend to be accepted. This is combined with lagged first-differences dated $t-2$, which are used as instruments in the levels equations, and tend to be accepted by the Hansen test.

In the set of variables adopted in the estimation conducted in this study, year, industry and province dummies are included in order to control for year, industry and location effects, respectively.

SYS-GMM is applied using Stata by performing the command *xtabond2* developed by Roodman (2006).

In order to check whether the SYS-GMM results are the most appropriate, the Levinsohn and Petrin (2003) semiparametric approach is also used to analyse the relationship between TFP and its determinants. Its choice is based on its widespread use in previous studies on TFP estimation.

This section has discussed the SYS-GMM estimation approach adopted in this study to analyse what determines TFP levels in Chinese industrial firms. The following section discusses the two-sample Kolmogorov-Smirnov test.

### 3.3. Two-sample Kolmogorov-Smirnov (KS) Test

This section discusses how the Kolmogorov-Smirnov (KS) tests of equality of empirical cumulative distributions of TFP levels are conducted and the related distributions plotted.

In the KS test, the calculated two-sample case D-statistic represents the highest horizontal distance, or highest difference, between the empirical cumulative distributions of TFP levels, representing the two groups compared. In the test, a binary variable with two distinctive values is taken. Subsequently, the empirical cumulative distribution of a random variable, in this case the natural logarithm of TFP, is compared for the first value of the group variable with the empirical cumulative distribution of TFP level for the second value of the group variable. Thus, the Kolmogorov-Smirnov test D-statistic is based on the maximum horizontal deviation between two plotted curves representing the two groups’ empirical cumulative distributions of TFP levels.

In the Kolmogorov-Smirnov test, the null hypothesis (*H0*) states that two groups have the same empirical cumulative TFP distributions. The *p*-value indicates whether the maximum horizontal deviation, or gap, between the two empirical cumulative distributions of TFP levels is statistically significant. Therefore, a relatively small *p*-value is preferred to a relatively high one, since this would reject the null hypothesis of equality of empirical cumulative distributions of TFP levels.

Calculating a two-sided KS statistic and plotting the related empirical cumulative distributions of TFP levels enables to test whether the distribution for one sub-group of firms lies to the right of the distribution for another sub-group. In such case, there is first-order stochastic dominance between such (random) variables.

One of the advantages of using the two-sample Kolmogorov-Smirnov test is that it does not assume that the analysed data has a specific distribution. Compared to the *t*-statistic, the value of the *D*-statistic and the related *p*-value cannot be influenced by scale changes such as logged values or reciprocal ones. This means that its results do not differ when the data values are transformed. A transformation only modifies the distribution's frequency, represented on the *x*-axis, while keeping the maximum distance between the two empirical cumulative TFP distributions unchanged. Therefore, the Kolmogorov-Smirnov test focuses on the relative distribution of data, and is thus robust to outliers.

In this section, KS tests are implemented and empirical cumulative distributions of TFP levels are plotted for Chinese manufacturing firms according to the following determinants: industry, time, political affiliation, paid-in capital ownership, province, R&D expenditure, and exporting.

This section has introduced the Kolmogorov-Smirnov test of equality of empirical cumulative TFP distributions. The next section describes the variables adopted, the related descriptive statistics, and the underlying hypotheses.

### 3.4. Variables, Descriptive Statistics and Hypotheses

In the empirical analysis conducted in this study, different sets of variables are used. Nominal variables, except for capital stock, are transformed to enable their comparison over the sample period. They are thus expressed in constant year prices by adopting the industry-specific price deflators developed by Brandt et al. (2012). As part of the production function, the following determinants of TFP are included within the vector of variable $X_{it}$: political affiliation, ownership, exporting, competition, MAR spillovers, Jacobian spillovers, city spillovers, liquidity, age, R&D expenditure, time trend and marketing capabilities. A more detailed motivation for their inclusion, their measurement and the expected effects on productivity are discussed in this section.

### 3.4.1. Ownership

Various major firm shareholders might be driven by different motivations, which would be reflected in decisions impacting firm performance, and hence TFP. The consideration of political affiliation also considers the potential political impact that State influence might have on a firm performance through ownership of paid in capital. Forms of ownership other than State ownership are likely to be characterised by a relatively low impact of political influence arising from an affiliation. This suggests that firms whose major owners differ from the State are likely to record higher TFP. In the set of variables comprising vector $X_{it}$ in equation (48), a determinant representing firm ownership structure is included. The National Bureau of Statistics database, from which the dataset used in this study is sourced, includes a measure of firm ownership based on the fraction of paid-in capital contributed by the following owners: the State (*p_capstate*), collective firms[3] (*p_capcoll*), legal entities[4] or corporate investors (*p_capcorporate*), individual investors (*p_capindividual*), foreign investors from Hong Kong, Macao and Taiwan (*p_caphkmactai*), and all other foreign investors excluding those from Hong Kong, Macao and Taiwan (*p_capforeign*). Following Ding et al. (2013), investors from Hong Kong, Macao and Taiwan are separated from other foreign investors in order to take into account the "round-tripping" FDI effect described in Huang (2003). According to Ding et al. (2013), Huang's (2003) "*Selling China: Foreign Direct Investment During the Reform Era"* points out that domestic Chinese firms might register as foreign entities in nearby regions in order to exploit various benefits, such as tax and legal benefits, which are provided by the Chinese government to foreign entities.

The descriptive statistics in Table 1 suggest that the majority of sample firm's paid-in capital over the entire time period is owned by individuals (37.9%). This is followed by corporations/legal entities (20.9%), the State (14.5%), collective firms (12.5%), foreigners (6.9%) and investors from Hong Kong, Macao and Taiwan (7.4%). The figures point to a decreasing role of the State over the sample period, since the proportion of paid-in capital owned diminishes from 33.5% in 1998 to 3.7% in 2007. The same trend occurs for the

[3] Collective firms are typically owned by communities in either urban or rural areas. Those in rural areas are also commonly known as township and village enterprises (TVEs).
[4] Legal entities refer to industrial enterprises, construction and real estate firms, development companies, transportation and power companies, security companies, trust and investment companies, foundations and funds, banks, technology and research institutions, and so on.

proportion of paid-in capital owned by collective firms, which decreases from 28.4% in 1998 to 4.6% in 2007. In comparison, the trend moves in the opposite direction for corporations/legal entities (from 12% in 1998 to 26.9% in 2007), individuals (from 14.2% in 1998 to 49.4% in 2007), investors from Hong Kong, Macao and Taiwan (from 6.5% in 1998 to 7.5% in 2007) and foreigners (from 5.4% in 1998 to 7.9% in 2007). Overall, the figures point to a decreasing role of the State in the manufacturing sector, accompanied by an increasing role of other forms of owners, including individuals, corporations/legal entities, and foreign investors.

Based on the empirical results of Zhang et al. (2001), Jefferson et al. (2003) and Zhang et al. (2003), an increasing share of State-owned paid-in capital is expected to have a negative effect on firms' TFP. At the same time, an increasing share of firms' paid-in capital owned by other investors, such as collective firms, legal entities or corporations, individuals and foreign investors, is expected to have a positive impact on firms' TFP.

### 3.4.2. Political Affiliation

As was discussed in Section 2.4.2, politically connected firms are likely to benefit through preferential access to credit, government contracts, regulatory protection, and lower taxation. As these benefits would make it easier for a firm to operate, they are likely to result in higher TFP. However, there are cases in which political affiliation might not be beneficial to firms' TFP, since a firm's managers might make decisions that are politically motivated, which might negatively affect TFP.

The vector of variables $X_{it}$ in equation (48) include a determinant representing the extent of a firm's political affiliation. Firms are classified as highly politically affiliated when the affiliation is with the central or provincial governments (*high_politics*); medium politically affiliated when the affiliation is with the local government (*medium_politics*); and not politically affiliated when there is no affiliation with any level of government (*no_politics*). A firm's political affiliation is proxied by a dummy variable that takes the value of 1 when it belongs to one of the previous groups and 0 otherwise.

Table 1 presents the descriptive statistics for political affiliation. It is interesting to note that during the sample period, 51.6% of firms on average are not politically affiliated. Strikingly, only 15.5% of firms were not politically affiliated in 1998, while 75.8% of firms were not politically affiliated in 2007. While 71.5% of firms had a political affiliation with local governments in 1998, only 21% had such a relationship in 2007. At the same time, only 3.2% of firms were affiliated with a central or provincial government in 2007, while 13% were affiliated in 1998. Overall, these figures point to a declining trend in the political affiliation of firms. Based on the empirical results of Li et al. (2008) and Du and Girma (2010), a negative relationship between *high_politics* and firms' TFP is expected. Moreover, a positive relationship between *no_politics* and firms' TFP is expected.

### 3.4.3. Exporting

A variable representing a firm's exporting activity is included in the vector of variables $X_{it}$ in equation (48). This variable captures the "learning by exporting" effect discussed in Section 2.4.8. By exporting, a firm is expected to become more productive since it faces a larger number of competitors, which will push it to undertake TFP-enhancing measures. Moreover, the firm is also likely to benefit in terms of higher TFP from the commercial interactions that exporting entails. Such interactions include contact with foreign economic agents, learning from customer feedback, and observing competitors' innovative technologies, products and working practices.

In order to measure the effect of exporting on TFP, a firm's exporting status is proxied by a dummy variable (*no_exporter*). This takes the value of 1 when a firm does not export abroad and 0 otherwise.

Table 1 presents the descriptive statistics for the two exporting variables used as determinants of exporting. Interestingly, it seems that the share of non-exporting firms does not change significantly over the years, as it was 78.4% in 1998 and 76.3% in 2007. Based on the empirical results obtained by Sun and Hong (2011) and Du et al. (2012b), *no_exporter* is expected to have a negative effect on firms' TFP, which would suggest that Chinese firms are likely to benefit in terms of higher TFP from exporting.

### 3.4.4. Competition

Section 2.4.5 discussed how competition can positively affect productivity. This is because by facing an increasing number of competitors, managers are incentivised not just to increase their efforts but also to innovate, hence increasing firms' TFP.

The vector of variables $X_{it}$ in equation (48) includes a variable representing the extent of competition faced by the firm within its industry. In this study, the extent of competition is proxied by the natural logarithm of the Herfindahl index (*lherf*). This measures the extent of industrial concentration by the two-digit industry Standard Industrial Classification (SIC). Since it is important to look at the percentage change in competition resulting in a change in productivity, or elasticity between the two variables, the natural logarithm is applied to the value of the index. Based on the empirical results discussed in Section 2.4.2, *lherf* is expected to have a negative coefficient, meaning that a higher extent of industrial concentration is expected to have a negative impact on firms' TFP.

The descriptive statistics for the Herfindahl index presented in Table 1 show that industrial concentration diminishes over the sample period, pointing to increased competition in the market. This is suggested by the decrease in the Herfindahl index from 0.004 in 1998 to 0.002 in 2007. Overall, markets do not seem to be concentrated, since the average Herfindahl index during the period of 1998-2007 is 0.003. Based on the empirical results obtained by Zhang et al. (2001) and Lin et al. (2009) in the literature for Chinese firms, *lherf* is expected to negatively affect firms' TFP, suggesting that Chinese firms are not likely to benefit from a high level of industrial concentrations. In other words, they are likely to benefit from the presence of industrial competition.

### 3.4.5. Marshallian (or MAR) Spillovers

The vector of variables $X_{it}$ in equation (48) includes a determinant representing Marshallian spillovers (*lagglom*). This is because, as discussed in Section 2.4.6, Marshallian spillovers provide a wide range of benefits to firms arising from being in close proximity to its industry peers, and these benefits are likely to result in higher firm TFP levels. Such spillovers can manifest through the channels of imitation/demonstration, synergies, commercial relationships, asset sharing, and labour pooling.

In this study, Marshallian spillovers are measured by the percentage share of industry output in the province where a firm is based. Since we are looking at the percentage change in MAR spillovers resulting in a change in productivity, or the elasticity between the two variables, the natural logarithm is applied to their values.

As seen in Table 1, Marshallian or MAR spillovers increase from 1998 to 2007. This is shown by the increase in the percentage of industry output for each province, which was 7.98% in 1998 and 10.06% in 2007, while having an average of 9.31% over the sample period. Based on the empirical results obtained by Lin et al. (2011) and Yang et al. (2013), a positive relationship between *lagglom* and firm TFP is expected.

### 3.4.6. Jacobian Spillovers

In contrast to Marshallian spillovers, Section 2.4.6 discussed how Jacobian spillovers occur when plants are located in an area characterised by different industrial activities and benefit from the economies of scope this provides. Firms are likely to benefit in terms of higher TFP from the industrial diversity because it favours the transmission of innovations across different industries.

A variable representing Jacobian spillovers, also known as diversification or urbanisation externalities, is included in the vector of variables $X_{it}$ in equation (48). In this study, Jacobian spillovers (*ldivers*) are measured as the natural logarithm of the proportion of three-digit industries (maximum 226) located in 208 city areas where the firms are based. Since we are looking at the percentage change in Jacobian spillovers resulting in a change in productivity, or the elasticity between the two variables, the natural logarithm is applied to their values.

Jacobian spillovers seem to decrease over the sample period, as seen in the descriptive statistics in Table 1. The proportion of three-digit industries located in the city areas where a firm is based is, on average, 55.3% over the entire period, decreasing from 66% in 1998 to 54.6% in 2007. Based on the discussion in this section, *ldivers* is expected to have a positive effect on firms' TFP, meaning that Chinese firms are expected to benefit in terms of higher TFP from being based in areas characterized by industrial diversity.

### 3.4.7. City Location Spillovers

The discussion in Section 2.4.7 suggested that firms are likely to benefit in terms of higher TFP by being based in a major city, as this can potentially provide firms with the following benefits: high transfer of knowledge among workers and city residents; deeper insight into the customer base; availability of a large, skilled labour pool; and high availability of business services, such as legal, accounting and financial services. These positive aspects conferred by cities are likely to positively impact TFP. Despite this, there are cases in which the benefits might be counterbalanced by the high costs of being in a city, including the costs of transporting goods and renting or purchasing buildings, and commuting or living in the city, which would result in lower TFP. In this study, a dummy variable representing city location spillovers is included in the vector of variables $X_{it}$ within the equation (48). City location spillovers are proxied by a dummy variable (*city200*) that is equal to 1 if a firm is located in the largest 200 cities according to population size, and 0 otherwise.

The descriptive statistics presented in Table 1 show that firms have increasingly located themselves within the major Chinese cities. In 2007, 87.4% of firms were based in the top 200 cities, compared to 27.1% in 1998. Based on the empirical results of Pan and Zhang (2002), *city200* is expected to have a positive effect on TFP, suggesting that Chinese firms are expected to benefit in terms of higher TFP levels by being based in a major city.

### 3.4.8. Liquidity

Following Chen and Guariglia (2013), two variables representing liquidity as a determinant of TFP are included in the vector of variables $X_{it}$ in equation (48). The first variable (*lliquid*) is the ratio of working capital divided by total assets. This variable is used as an indicator of internal sources of finance. This is because if firms are facing difficulties in obtaining external financing, they must rely on their own internal funds. Such a situation would constrain firms' ability to pursue productivity-enhancing projects such as R&D expenditures and capital investments. Therefore, the higher the availability of internal funds, the more likely a firm is to purse productivity-enhancing projects and thus to achieve higher TFP levels.

The second variable (*neg_liquid*) is a dummy variable that is equal to 1 if a firm has a negative liquidity, and 0 otherwise. It is expressed as the natural logarithm of working capital, or the difference between current assets and current liabilities divided by total assets. Since we are looking at the percentage change in liquidity resulting in a change in productivity, or the elasticity between the two variables, the natural logarithm is applied to their values. Moreover, the constant 1 is added to each firm's liquidity value, expressed in RMB billions, in order to handle related values between 0 and 1 that, if naturally logged, would become negative. Hence, adding 1 enables us to obtain positive values from the natural logarithm. This variable is adopted because negative liquidity could make it difficult for firms to raise external funds, as it increases the cost of bankruptcy. Thus, firms with negative liquidity are likely to be more dependent on their cash flow to finance productivity-enhancing activities. This suggests that the higher the level of liquidity recorded by firms, the higher TFP is expected to be.

The descriptive statistics presented in Table 1 show that the share of firms having a negative working capital to total assets ratio (*neg_liquid*) decreases from 51.7% in 1998 to 37.9% in 2007, while averaging 42.6% during the sample period. At the same time, the ratio of working capital to total assets (*lliquid*) increases from 11.2% in 1998 to 16.2% in 2007. The figures suggest that firms have become more liquid over the sample period.

Based on the empirical results of Chen and Guariglia (2013), *neg_liquid* is expected to be significant and to have a negative effect on TFP, while *lliquid* is expected to be significant and to have a positive effect.

### 3.4.9. Age

As was discussed in Section 2.4.1, a firm is expected to acquire more knowledge and therefore become more productive over the years as a product of experience, according to a "learning by doing" process. However, as a firm becomes older, it can also become slower to adapt its characteristics and strategies to the markets in which it operates and to keep its technology up to date with the industry best practices, likely resulting in lower TFP. In this study, a variable representing the age of the firm (*lage*), measured as the natural logarithm of the firm's age based on its year of inception, is included in the vector of variables $X_{it}$ in equation (48).

Since we are looking at the percentage change in age resulting in a change in productivity, or the elasticity between the two variables, the natural logarithm is applied to the variables' value.

As seen in the descriptive statistics in Table 1, the age of the firms in the sample decreases over the time period considered. Firm age, calculated according to the year it was founded, is, on average, 15 years during the sample period, decreasing from 19 in 1998 to 12 in 2007. The figures suggest that new firms might have entered the market, thus reducing the average age of firms in the sample. According to the empirical results of Zheng et al. (2003) and Hsieh and Klenow (2009), *lage* is expected to have a negative effect on firms' TFP.

#### 3.4.10. R&D Spending as a Source of Knowledge

Section 2.4.1 discussed how R&D expenditure enables a firm to build up absorptive capacity, or the ability to absorb and utilize knowledge for productive purposes. Moreover, it enables a firm to undertake both product and process improvements. Those are two channels through which R&D expenditure can result in higher firm TFP.

In the vector of variables $X_{it}$ in equation (48), a dummy variable proxying the firm's R&D expenditure is included. The variable takes the value of 1 if the firm has undertaken any R&D spending, and 0 otherwise.

The descriptive statistics in Table 1 show that only 10.9% of firms in the sample have undertaken R&D expenditure during the sample period, although the share increases from 9.5% in 1998 to 10.6% in 2007. Based on the discussion in Section 2.4.1 and the empirical results of Hu (2001) and Wu et al. (2007), R&D spending is expected to have a positive effect on Chinese firms' TFP.

#### 3.4.11. Time Trend or Hicks-neutral Technical Change

It was stressed in Section 2.4.1 that, other than age, intangible assets and R&D, knowledge can be represented by a time trend, or a Hicks-neutral technical change. In the vector of variables $X_{it}$ in equation (48), a variable representing the time trend or the Hicks-neutral technical change (*t_trend*) is included. This represents the impact on TFP resulting from exogenous technological improvements affecting all firms over time. Based on the discussion in Section 2.4.1, *t_trend* is expected to have a positive impact on firms' TFP. In other words, firms are expected to become more productive over time as a result of Hicks-neutral technical change.

### 3.4.12. Marketing Capabilities

Section 2.4.10 argued that marketing capabilities represent a firm's ability to distinguish its products and services from competitors and to build successful brands, enabling the firm to charge higher prices and increase its productivity as a result.

In this study, in the vector of variables $X_{it}$ in equation (48), a variable representing the firm's marketing capabilities is included. The availability of data does not enable us to construct broad measures of marketing capabilities such as those used by Nath et al. (2010) and Yu et al. (2014). Therefore, marketing capabilities are proxied by the value of selling and distribution costs as a share of sales. The resulting variable ($lfc$) is similar to the one adopted by Lee and Rugman (2012). Since we are looking at the percentage change in marketing capabilities resulting in a change in productivity, or the elasticity between the two variables, the natural logarithm is applied to their values.

As shown by the descriptive statistics in Table 1, the firms improve their marketing capabilities during the sample period. This is indicated by the decrease in selling and distribution costs as a percentage of sales from 5.6% in 1998 to 3.9% in 2007. More efficient firms are expected to have a lower ratio of selling and distribution costs as a percentage of sales, meaning that they are more able to transform their resources into valuable output, to distinguish their products and services from the competition, and to forge successful brands. Although there is no empirical evidence for China at the firm level, the discussion and the empirical results presented in Section 2.4.11 lead us to expect a negative relationship between $lfc$ and firms' TFP.

This section has discussed the variables adopted in the empirical analysis of this study, the related descriptive statistics, and the underlying hypotheses. The next section discusses the results of the SYS-GMM estimation.

Table 1: Descriptive statistics for variables used in TFP estimation, China 1998-2007

| | | 1998-2007 | | 1998 | | 2007 | |
|---|---|---|---|---|---|---|---|
| Variable | Definition | Mean | SD | Mean | SD | Mean | SD |
| y | Sales (billion RMB 2002 prices) | 0.074 | 0.716 | 0.042 | 0.386 | 0.107 | 1.017 |
| m | Intermediate inputs (billion RMB 2002 prices) | 0.050 | 0.448 | 0.034 | 0.241 | 0.065 | 0.607 |
| e | Employment | 286.482 | 1331.806 | 405.083 | 1891.556 | 235.527 | 1149.528 |
| k | Real net tangible fixed assets (billion RMB 2002 prices) | 0.031 | 0.442 | 0.027 | 0.275 | 0.033 | 0.538 |
| age | Firm age (based on year-of-inception) | 15.858 | 68.807 | 19.952 | 85.590 | 12.141 | 44.387 |
| no_politics | Proportion of firms with no political affiliation | 0.516 | 0.500 | 0.155 | 0.362 | 0.758 | 0.428 |
| med_politics | Proportion of firms with medium political affiliation with local governments | 0.421 | 0.494 | 0.715 | 0.451 | 0.210 | 0.407 |
| high_politics | Proportion of firms with high political affiliation with central or provincial governments | 0.063 | 0.243 | 0.130 | 0.336 | 0.032 | 0.175 |
| p_capstate | Proportion of paid-in capital owned by the State | 0.145 | 0.341 | 0.335 | 0.456 | 0.037 | 0.181 |
| p_capcoll | Proportion of paid-in capital owned by collective firms | 0.125 | 0.314 | 0.284 | 0.421 | 0.046 | 0.200 |
| p_capcorporate | Proportion of paid-in capital owned by corporations/legal entities | 0.209 | 1.179 | 0.120 | 0.289 | 0.269 | 2.892 |
| p_capindividual | Proportion of paid-in capital owned by individuals | 0.379 | 1.209 | 0.142 | 0.318 | 0.494 | 2.902 |
| p_caphkmactai | Proportion of paid-in capital owned by HK/Macao/Taiwan | 0.074 | 0.247 | 0.065 | 0.223 | 0.075 | 0.251 |
| p_capforeign | Proportion of paid-in capital owned by foreigners | 0.069 | 0.235 | 0.054 | 0.200 | 0.079 | 0.255 |
| no_exporter | Dummy variable for non-exporting firms | 0.749 | 0.434 | 0.784 | 0.411 | 0.763 | 0.425 |
| herf | Herfindahl index of industrial concentration (by 2-digit SIC) | 0.003 | 0.005 | 0.004 | 0.006 | 0.002 | 0.004 |
| divers | % of 3-digit industries (max 226) in city areas where a firm is based (Jacob) | 0.553 | 0.158 | 0.660 | 0.198 | 0.546 | 0.128 |
| agglom | % of industry output (2-digit SIC) in the province where a firm is based (MAR) | 9.307 | 8.101 | 7.975 | 7.513 | 10.060 | 8.210 |
| rd | Dummy variable for firm undertaking R&D spending | 0.109 | 0.311 | 0.095 | 0.293 | 0.106 | 0.307 |
| lfc | Selling & distribution costs as % of sales | 4.729 | 6.588 | 5.561 | 8.084 | 3.924 | 4.814 |
| neg_liquid | Dummy variable for negative working capital to total assets | 0.426 | 0.494 | 0.517 | 0.500 | 0.379 | 0.485 |
| lliquid | Ratio of working capital to total assets | 0.144 | 0.195 | 0.112 | 0.177 | 0.162 | 0.203 |
| city200 | Dummy variable for firm located in top 200 cities according to population size | 0.780 | 0.414 | 0.271 | 0.445 | 0.874 | 0.331 |
| N | No. of observations | 2,183,709 | | 148,474 | | 331,453 | |

### 3.5. Results of the SYS-GMM Estimation

Table 2 presents the results of the SYS-GMM estimation of the determinants of total factor productivity levels for 26 industries. The table also includes the diagnostic tests associated with each estimated equation: the Hansen test of the validity of the instrument set used, and two Arellano and Bond (1991) tests for autocorrelation in differenced residuals (AR(1) and AR(2)).

The results of the test for AR(1) in first differences reject the null hypothesis of zero autocorrelation in differenced residuals since there is a negative first-order serial correlation in the first-differenced residuals for all models. The results of the test for AR(2) point to the existence of second-order serial correlation in first-differenced residuals for most models. Despite this issue of autocorrelation, the models pass (at the 5% level or better) the Hansen test of over-identification and this provides the basis for treating the models estimated as adequate.

The elasticities of output with respect to labour, intermediate inputs and capital vary across industries, but they are positive and significant for most. The results also indicate the existence of increasing returns to scale for most industries (18 out of 26), with an average sum of output elasticities equal to 1.2, suggesting that firms produce a higher proportion of output from a given proportion of inputs utilised.

The results for the parameter estimates associated with $X_{it}$ will be discussed by grouping them into variables related to political affiliation/ownership, spatial variables (Marshallian, Jacobian and city spillovers), internal and external knowledge variables (age, R&D and time trend), and all other variables (exporting, competition, liquidity and marketing capabilities).

Regarding the political affiliation/ownership variables, for most industries the coefficients for the “high level of political affiliation” variable (*high_politics*) are statistically significant and negative, while the coefficients of the “no political affiliation” variable (*no_politics*) are statistically significant and positive. Such is the case for typically competitive industries, such as metal and non-metal products, machinery and equipment, and furniture. These results suggest that a high level of political affiliation has a negative effect on firm TFP while the lack of political affiliation has a positive effect. Consistent with the initial expectations, Chinese industrial firms do not seem to benefit in terms of a higher TFP level from a political affiliation with the central or provincial governments. This could be because politically affiliated firms are unlikely to focus on maximising TFP, but rather on pursuing politically motivated objectives. The finding suggests that an increasing role of the markets, and a decreasing influence of the government, both central and provincial, on firms’ activities, is conducive to increased firm TFP. These findings are similar to those of Du and Girma (2010), who found that politically unaffiliated firms perform better in terms of TFP growth than politically affiliated ones. However, in industries typically characterized by a high level of industrial concentration, such as gas and water production, a high level of political affiliation positively affects TFP. A potential explanation for this finding could be that, in sectors with national strategic importance, political affiliation would provide firms with benefits such as ease in access to credit, regulatory protection, lower taxation and greater market power, resulting in higher TFP.

The consideration of political affiliation also involves the potential political impact that State influence might have on firms' TFP by being a major shareholder. The results suggest that forms of ownership other than the State one are likely to be characterised by a relatively low impact of political affiliation. In general, the coefficients for the variable representing the proportion of paid-in capital owned by the State (*p_capstate*) are statistically significant and negative, while the coefficients of the variables representing the proportion of paid-in capital owned by collective investors (*p_capcoll*), corporations (*p_capcorporate*), individuals (*p_capindividual*) and foreigners (*p_capforeign*) are positive for most industries. As initially expected, firms do not seem to benefit in terms of higher TFP from an increasing proportion of paid-in capital owned by the State, but rather from an increasing proportion of paid-in capital possessed by other types of owners. It can be inferred that decreases in State ownership and increases of other forms of ownership in Chinese industrial firms is conducive to higher firm TFP. Different types of paid-in capital owners might have different motivations for their ownership, which is ultimately reflected in decisions that impact the firms' TFP. Compared to other owners of paid-in capital, the State might be driven by political motivations, such as maximising employment, which in some cases might be inconsistent with maximising TFP levels. However, the findings are different for the medical, electronic power and water production sectors, in which an increasing share of paid-in capital owned by private investors is associated with a decrease in TFP, and an increasing share of paid-in capital owned by the State is associated with increased TFP. This suggests that in strategic or monopolistic sectors, State ownership is conducive to higher TFP. In a large number of sectors, Chinese industrial firms seem to positively benefit from a higher proportion of paid-in capital owned by foreigners (*p_capforeign)*. In line with the view of Hymer (1976), this finding suggests that foreign owners are likely to have more favourable characteristics than domestic owners, such as more advanced managerial practices, highly innovative technology and better marketing capabilities, which would lead to higher TFP levels. In summary, the findings for the relationship between firms' TFP levels and ownership variables indicate that private forms of ownership are more conducive to higher TFP levels than State forms of ownership. These results are similar to those of Zhang et al. (2001), Jefferson et al. (2003) and Zhang et al. (2003), who found that State-owned enterprises are the least efficient and have achieved the lowest rate of TFP growth.

Spatial variables are included in the vector $X_{it}$ in order to measure whether firms benefit in terms of higher TFP levels from the spillovers arising from the location where they are based. These spatial variables are Marshallian spillovers (*lagglom*), Jacobian spillovers (*ldivers*) and city spillovers (*city200*). For 16 out of the 26 industries, the coefficients for the variable representing Marshallian spillovers (*lagglom*) are statistically significant and positive. The effects are particularly strong in the non-metal products, other mining and medical industries. In line with the arguments of Marshall (1890), the existence of positive Marshallian spillovers indicates that firms are likely to benefit in terms of higher TFP levels from the externalities arising from being geographically close to industry peers. In such a situation, firms are likely to undertake TFP-enhancing actions, such as imitating and adopting ideas from other firms, cooperating through sharing assets, pursuing joint R&D projects or engaging in joint ventures. Moreover, by being based in the same area, firms are likely to develop commercial relationships with suppliers and customers and to enjoy the higher availability of an industry-specialised labour pool, enabling them to improve their productivity. From these results, it can be inferred that policy measures aimed at increasing industrial agglomeration within specific geographical areas are conducive to higher firm TFP. These findings are in line with those of Lin et al. (2011) and Yang et al. (2013), who found that industrial agglomeration has a significant and positive impact on firms' TFP.

The coefficients for the variable representing Jacobian spillovers (*ldivers*) are statistically significant and positive for 23 out of 26 industries. The effects are the strongest in the machinery & equipment, other manufacturing, and apparel & footwear industries. These results suggest that Chinese industrial firms are likely to benefit in terms of higher TFP from the spillovers arising by being located in an area characterised by different industrial activities. This is in line with Jacob's (1970) argument that plants having different knowledge and capabilities can complement each others' skills sets, resulting in mutual benefits, and that the industrial and occupational diversity that characterises urban economies favours the spillover of innovations across different industries, ultimately resulting in higher TFP. The results indicate that policy measures aimed at increasing industrial diversity within specific geographical areas are likely to result in higher firm TFP. These findings are similar to those of Liu (2002) and Batisse (2002), who found a positive effect of Jacobian spillovers on firms' TFP.

While Chinese industrial firms based in geographical areas where they are close to their industry peers, or which are characterized by industrial diversity, seem to benefit in terms of higher TFP, they do not seem to benefit from being based in the major Chinese cities. This is suggested by the statistically significant and negative coefficients for the variable representing city spillovers (*city200)* for 17 out of 26 industries. A city was expected to provide several benefits to firms, such as insight into the customer base, the availability of a wide labour pool, and plenty of business services, which would have resulted in higher TFP. However, in most industries, other aspects of cities probably dominate these, hence hampering TFP. For example, as argued by Carlino (1987), the time and cost of transporting goods and commuting are likely to be high in cities, as well as both the commercial and residential rents, which would result in higher costs and thus lower TFP levels. Based on these results, it can be inferred that policy measures aimed at increasing firms' presence within cities are not likely to result in higher TFP. This suggests that it might be better to locate firms outside cities, in areas characterised by industrial agglomeration or diversity, where firms are more likely to benefit in terms of higher TFP. These results contrast with those of Pan and Zhang (2002), who found that firms based in larger cities have higher TFP.

In order to measure both internal and external knowledge, which a firm can take advantage of in order to become more productive, three variables are included in the vector $X_{it}$: a firm's age (*lage*), an R&D dummy (*rd_dum*) indicating whether a firm invests in R&D, and a time trend (*t_trend*). Chinese industrial firms are expected to acquire more knowledge and, therefore, to become more productive over the years as a product of experience according to a "learning by doing" process. However, for most industries, it seems that this is not the case, as suggested by the statistically significant and negative coefficients for the age variable in 17 out of 26 industries. A potential explanation for this negative relationship is that older firms are likely to be overtaken by more productive younger firms, which adopt more innovative technology, according to what Jensen et al. (2001) describe as the "vintage effect." Another potential explanation is that older firms are slower to adjust to the dynamic environment in which they operate than their younger peers, as a result of the "inertia effect" postulated by Hannan and Freeman (1984). From these results, it can be inferred that policy measures aimed at favouring the entrance of younger and more dynamic firms into their respective industries, are likely to result in higher TFP. These results contrast with those of Zheng et al.

(2003) and Hsieh and Klenow (2009), who found a positive effect of firms' age on their total factor productivity.

In only 6 industries out of 26, the results indicate that productivity improves by undertaking R&D expenditures, as indicated by the statistically significant and positive coefficients for those industries. This positive finding might be explained by the ability of R&D expenditures to positively and directly affect firms' TFP levels by allowing both product and process improvements. In line with the arguments of Cohen and Levinthal (1989), R&D expenditure might also have a positive and indirect effect on firms' TFP levels through the development of absorptive capacity, or a firm's ability to identify, absorb and exploit external knowledge for productive purposes. For these 6 industries, the results indicate that policy measures aimed at incentivizing firms' R&D expenditure, for example, via tax cuts or subsidised funding, are likely to generate higher firm TFP. However, there is only limited evidence for the positive effect of R&D and TFP, hence suggesting that Chinese firms do not make a productive use of their R&D expenditure.

In addition to R&D expenditures and age, knowledge is represented by the time trend, or Hicks-neutral technical change. The results indicate that Chinese firms are likely to become more productive over time as they are affected by positive exogenous technological improvements. This is indicated by the statistically significant and positive coefficients for the variable (*t_trend*) in 24 out of 26 industries. The effect is particularly strong in industries such as the non-metal and metal products, and transport equipment, as these tend to be more dynamic and closer to the technological frontier.

In summary, regarding internal and external knowledge variables, Chinese firms in most industries seem to benefit from the positive effect on TFP of the time trend, while they tend to become less productive as they age. Furthermore, R&D does not seem to result in higher firm TFP.

In addition to ownership/political affiliation, spatial and knowledge variables, other variables are included in the vector $X_{it}$ as potential determinants of TFP in Chinese industrial firms. These are variables proxying for firms' export activity, industrial competition, liquidity and marketing capabilities.

For only 6 out of 26 industries, the results indicate that Chinese firms engaged in export activities are likely to be more productive than those not engaged, as suggested by the statistically significant and negative coefficients on the variable representing a non-exporting firm (*no_exporter*). A potential explanation for the positive relationship is that, by participating in foreign markets in addition to the domestic market, firms are likely to face a larger number of competitors. In order to survive in such a competitive environment, firms would need to constantly increase their efficiency and undertake technological improvements, both of which are TFP-enhancing measures. Moreover, in line with the arguments of Grossman and Helpman (1991), firms are also likely to benefit from the commercial interactions that exporting entails, including interacting with foreign economic agents, learning from customer feedback, and observing the innovative technologies, products and working practices of competitors – all activities that would stimulate firms to undertake additional TFP-enhancing actions. However, this view is not supported by the data. This could potentially be explained by the "processing trade" argument. According to Wang and Yu (2011), between 2000 and 2006, 60% of Chinese exports were in the form of "processing trade." Jarreau and Poncet (2012) argue that exporting is beneficial to firm performance only when it is in the form of ordinary exports and not in the form of "processing trade." The empirical results of Dai et al. (2011) indicate that Chinese firms that only engage in processing trade are 4% to 30% less productive than non-exporters. When processing exporters are removed from the sample, Dai et al.'s (2011) findings indicate that exporters record higher productivity than non-exporters. From these results, it can be inferred that policy measures supporting firms' export activities, such as tax incentives, government subsidies, or the provision of market intelligence, are likely to be successful only when firms are not processing exporters.

For 14 out of 26 industries, the statistically significant and negative coefficients for the variable representing the Herfindahl index of industrial concentration (*lherf*) indicate that the higher an industry's concentration is, the lower the related firms' TFP. This effect is the strongest in the petroleum processing, coal mining and medical industries. For these industries, the findings indicate that policy measures aimed at increasing the level of industrial competition can augment firms' TFP levels. These results are in line with the view of Nickell (1996), who suggests that by facing an increasing number of competitors in their industries, firms might be more inclined to undertake measures aimed at improving their TFP in order to survive. Moreover, a higher level of competition is also likely to reduce monopoly rents, which would result in increased managerial efforts. Competition can also lower the wages within an industry, thus reducing the cost of labour and improving firms' TFP. However, in this study, a higher level of competition does not result in higher firm TFP for 9 industries. The negative effect of competition on TFP is especially strong for the cultural, textile and gas production industries. This might be explained by Hermalin's (1992) argument that increased competition is likely to diminish a firm's profits and managers' income, resulting in reduced managerial effort and lower TFP. In general, for the majority of industries, the findings are similar to those of Zhang et al. (2001), who found a negative effect of industrial concentration on firms' productivity, although that analysis was limited to firms based in Shanghai. The findings are also similar to those of Lin et al. (2009), who found that industrial concentration negatively affects firms' productivity, although that study adopted a smaller sample over a shorter time period.

Among the variables included in the vector $X_{it}$ as potential determinants of TFP in Chinese industrial firms, two variables measure firms' liquidity. The first variable is the negative working capital to total assets dummy (*neg_liquid*), for which the coefficients are statistically significant and negative for all industries, except for tobacco and coal mining. The effect is particularly strong for the metal products, non-metal products and measuring instruments industries. The second variable is the natural logarithm of the working capital to total assets ratio (*lliquid*), for which the coefficients are statistically significant and positive for all industries, except for electronic power. The effect is the strongest for the non-metal products, metal products and tobacco industries. These results indicate that firms with a higher level of liquidity tend to record higher TFP. In line with the arguments of Chen and Guariglia (2013), when firms experience difficulties in raising external funds, they must rely on internal funds. Such funds might be vital for pursuing productivity-enhancing projects. Hence, the availability of liquid internal assets is likely to improve the firms' capacity to obtain cash on short notice to be used to finance highly productive investments. Moreover, liquidity might also be used to finance activities such as product and process improvements, which are likely to cause a shift in firms' efficiency frontier, or best practice technology, resulting in higher TFP. From these findings, it can be inferred that policy measures aimed at facilitating Chinese firms' access to external sources of liquidity, would enable them to pursue investments and improve their productivity. The results are consistent with those of Chen and Guariglia (2013), who found that Chinese firms' TFP is positively and significantly affected by the availability of internal liquid assets.

The statistically significant and negative coefficients for the variable representing firms' marketing capabilities (*lfc*) in 23 out of 26 industries suggest that firms with lower selling and distribution costs as a percentage of sales tend to be more productive. A potential explanation for this finding might be that such firms are more able to transform their resources into valuable output, to distinguish their products from competitors, and to build brands that allow them to charge higher prices, all of which would lead to higher TFP levels. These results are in line with those of Morgan et al. (2009), Nath et al. (2010), Lee and Rugman (2012) and Yu et al. (2014).

In summary, although the Arellano and Bond (1991) tests point to the issue of autocorrelation, the SYS-GMM results indicate that the estimates obtained are economically sensible since they pass the Hansen test, pointing to the validity of the instrument set adopted, and providing the basis for treating the models estimated as adequate. The elasticity of output with respect to labour, intermediate inputs and capital vary across industries, but are positive and significant for most. The results also indicate the existence of increasing returns to scale, suggesting that firms produce a higher proportion of output from a given proportion of inputs. In addition, these indicate that the inclusion of multiple determinants of TFP in the vector $X_{it}$ does not generate a multicollinearity issue, since there are not insignificant small parameters estimates and not large standard errors. The SYS-GMM results suggest that Chinese industrial firms tend to benefit in terms of higher TFP levels from a lack of political affiliation, an increasing proportion of paid-in capital owned by shareholders other than the State, the presence of Marshallian and Jacobian spillovers, age, time trend, industrial competition, the availability of internal liquid assets and marketing capabilities. Policy measures aimed at targeting positive determinants of TFP are likely to result in higher TFP levels across Chinese industrial firms.

Following the above discussion of the results of the SYS-GMM estimation, the next section will review the results from the estimation done using the semiparametric approach of Levinsohn and Petrin (2003).

Table 2: Two-step System-GMM Production Function, Various Industries, China 1998-2007

| Dependent variable: *ln* sales | Other Mining (SIC10+80) | Food Production (SIC14) | Tobacco (SIC16) | Textile (SIC17) | Apparel & Footwear (SIC18) | Leather (SIC19) |
|---|---|---|---|---|---|---|
| lr_input | 0.308*** | 0.366** | 0.386*** | 0.853*** | 0.653*** | 0.763*** |
| | (0.074) | (0.157) | (0.082) | (0.019) | (0.049) | (0.058) |
| Lemp | 0.505*** | 0.311* | 0.613** | 0.153*** | 0.294*** | 0.095* |
| | (0.064) | (0.174) | (0.287) | (0.033) | (0.041) | (0.053) |
| lr_capital | 0.225*** | 0.357* | 0.387** | 0.037** | 0.085** | 0.143* |
| | (0.065) | (0.196) | (0.161) | (0.019) | (0.038) | (0.073) |
| t_trend | 0.067*** | 0.040*** | 0.042*** | -0.020*** | 0.045*** | 0.024*** |
| | (0.005) | (0.007) | (0.015) | (0.002) | (0.002) | (0.005) |
| lage | -0.014 | -0.011 | -0.045 | -0.026*** | -0.031*** | -0.034* |
| | (0.011) | (0.013) | (0.082) | (0.006) | (0.008) | (0.019) |
| no_politics | 0.047*** | 0.038*** | 0.184* | 0.036*** | 0.016*** | -0.002 |
| | (0.011) | (0.011) | (0.097) | (0.004) | (0.005) | (0.006) |
| high_politics | -0.233*** | 0.017 | -0.072 | 0.016 | 0.023 | -0.105 |
| | (0.050) | (0.029) | (0.159) | (0.015) | (0.025) | (0.065) |
| p_capstate | -0.361*** | -0.119*** | 0.429 | -0.101*** | -0.097*** | -0.282*** |
| | (0.086) | (0.040) | (0.389) | (0.015) | (0.027) | (0.081) |
| p_capcoll | 0.131* | 0.066 | 0.561 | 0.050*** | 0.024* | 0.004 |
| | (0.074) | (0.047) | (0.399) | (0.011) | (0.014) | (0.037) |
| p_capcorporate | 0.002 | 0.035 | 0.391 | 0.031*** | 0.036*** | 0.002 |
| | (0.058) | (0.036) | (0.396) | (0.008) | (0.013) | (0.034) |
| p_capindividual | 0.014 | 0.052 | 0.814* | 0.034*** | 0.044*** | 0.020 |
| | (0.062) | (0.045) | (0.436) | (0.010) | (0.016) | (0.041) |
| p_capforeign | -0.056 | -0.031 | 0.015 | 0.029*** | 0.012* | 0.008 |
| | (0.062) | (0.035) | (0.528) | (0.006) | (0.006) | (0.011) |
| no_exporter | -0.268 | -0.003 | -0.310* | -0.014*** | -0.018** | 0.053 |
| | (0.243) | (0.015) | (0.163) | (0.005) | (0.009) | (0.127) |
| rd_dum | 0.036 | 0.015 | -0.242 | 0.015** | 0.027** | 0.142 |
| | (0.116) | (0.019) | (0.168) | (0.006) | (0.011) | (0.204) |
| lagglom | 0.157*** | 0.060*** | 0.140** | -0.017* | 0.057*** | 0.051*** |
| | (0.020) | (0.020) | (0.062) | (0.010) | (0.015) | (0.018) |
| lherf | -0.157*** | -0.147*** | 0.110 | 0.303*** | 0.062*** | -0.051** |
| | (0.018) | (0.028) | (0.082) | (0.011) | (0.022) | (0.021) |
| ldivers | 0.058*** | 0.083*** | 0.068 | 0.131*** | 0.198*** | 0.108*** |
| | (0.017) | (0.016) | (0.052) | (0.009) | (0.015) | (0.020) |
| lfc | -0.053*** | -0.067*** | -0.057** | -0.017*** | -0.000 | -0.038*** |
| | (0.007) | (0.018) | (0.026) | (0.003) | (0.005) | (0.012) |
| neg_liquid | -0.038*** | -0.049*** | -0.035 | -0.024*** | -0.050*** | -0.041*** |
| | (0.008) | (0.012) | (0.053) | (0.004) | (0.009) | (0.014) |
| lliquid | 0.617*** | 0.451** | 0.865*** | 0.168*** | 0.220*** | 0.236** |
| | (0.111) | (0.187) | (0.220) | (0.027) | (0.047) | (0.092) |
| city200 | 0.005 | -0.028* | -0.054 | -0.073*** | -0.068*** | -0.084*** |
| | (0.015) | (0.016) | (0.054) | (0.006) | (0.006) | (0.011) |
| Constant | -4.557*** | -3.007** | -2.435 | 1.357*** | -1.862*** | -0.352 |
| | (0.679) | (1.462) | (2.129) | (0.232) | (0.462) | (0.566) |
| Province Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 37,858 | 25,785 | 2,244 | 165,590 | 94,106 | 46,267 |
| Number of Firms | 13,060 | 9,455 | 483 | 46,533 | 27,447 | 13,223 |
| AR(1) z-statistic | -10.48 | -4.951 | -4.743 | -18.55 | -15.22 | -11.62 |
| AR(1) z-statistic p-value | 0 | 0 | 0 | 0 | 0 | 0 |
| AR(2) z-statistic | -2.362 | -1.585 | 0.449 | -4.815 | -3.019 | -3.735 |
| AR(2) z-statistic p-value | 0.0182 | 0.113 | 0.653 | 0 | 0.00254 | 0.000188 |
| Hansen Test | 7.585 | 4.648 | 10.63 | 10.90 | 7.298 | 12.97 |
| Hansen Test p-value | 0.270 | 0.325 | 0.474 | 0.0916 | 0.199 | 0.0729 |
| Returns to Scale (-1) | 0.0374 | 0.0346 | 0.386** | 0.0432*** | 0.0323* | 0.00117 |
| z-statistic RTS | 1.020 | 0.490 | 2.075 | 2.700 | 1.696 | 0.0468 |

Standard Errors in Parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2: PANEL B

| Dependent variable: *ln* sales | Timber (SIC20) | Furniture (SIC21) | Papermaking (SIC22) | Printing (SIC23) | Cultural (SIC24) | Petroleum Processing (SIC25+70) |
|---|---|---|---|---|---|---|
| lr_input | 0.493*** | 0.494*** | 0.843*** | 0.634*** | 0.754*** | 0.265* |
| | (0.118) | (0.068) | (0.032) | (0.046) | (0.051) | (0.145) |
| lemp | 0.483*** | 0.446*** | 0.166*** | 0.230** | 0.239*** | 0.743*** |
| | (0.114) | (0.078) | (0.045) | (0.104) | (0.067) | (0.145) |
| lr_capital | 0.130* | 0.169*** | 0.040*** | 0.174*** | 0.059* | 0.245** |
| | (0.076) | (0.046) | (0.009) | (0.049) | (0.031) | (0.100) |
| t_trend | 0.054*** | 0.030*** | 0.034*** | 0.051*** | 0.074*** | -0.005 |
| | (0.009) | (0.004) | (0.004) | (0.006) | (0.005) | (0.008) |
| lage | -0.022** | -0.058*** | -0.018** | -0.105*** | -0.005 | -0.080*** |
| | (0.011) | (0.013) | (0.008) | (0.027) | (0.013) | (0.027) |
| no_politics | 0.025* | 0.018 | 0.014*** | 0.035*** | 0.004 | 0.053*** |
| | (0.013) | (0.012) | (0.005) | (0.008) | (0.008) | (0.020) |
| high_politics | -0.223*** | -0.093* | -0.000 | 0.064*** | -0.008 | -0.034 |
| | (0.085) | (0.050) | (0.019) | (0.019) | (0.035) | (0.070) |
| p_capstate | -0.160* | -0.219*** | -0.114** | 0.080 | -0.164** | -0.214** |
| | (0.085) | (0.065) | (0.050) | (0.065) | (0.078) | (0.087) |
| p_capcoll | 0.181*** | 0.202*** | -0.042 | 0.259*** | -0.054 | -0.031 |
| | (0.050) | (0.047) | (0.047) | (0.069) | (0.047) | (0.089) |
| p_capcorporate | 0.126*** | 0.223*** | -0.048 | 0.215*** | -0.041 | -0.018 |
| | (0.035) | (0.041) | (0.045) | (0.062) | (0.039) | (0.077) |
| p_capindividual | 0.124*** | 0.201*** | -0.045 | 0.222*** | -0.030 | 0.011 |
| | (0.040) | (0.043) | (0.046) | (0.065) | (0.041) | (0.082) |
| p_capforeign | 0.050** | 0.059*** | 0.016 | 0.051* | 0.023* | 0.185** |
| | (0.025) | (0.017) | (0.015) | (0.027) | (0.013) | (0.086) |
| no_exporter | -0.091 | -0.074 | 0.169 | -0.339** | 0.261 | -0.563*** |
| | (0.057) | (0.064) | (0.127) | (0.148) | (0.160) | (0.185) |
| rd_dum | 0.592* | -0.008 | 0.168** | 0.106** | 0.023 | 0.005 |
| | (0.348) | (0.018) | (0.072) | (0.042) | (0.015) | (0.046) |
| lagglom | 0.133*** | 0.119*** | 0.076*** | 0.091*** | -0.005 | 0.106*** |
| | (0.034) | (0.024) | (0.014) | (0.020) | (0.021) | (0.032) |
| lherf | 0.036 | -0.174*** | -0.141*** | 0.092*** | 0.347*** | -0.323*** |
| | (0.025) | (0.036) | (0.012) | (0.026) | (0.059) | (0.078) |
| ldivers | 0.207*** | 0.223*** | 0.200*** | 0.264*** | 0.127*** | 0.147*** |
| | (0.034) | (0.030) | (0.014) | (0.018) | (0.024) | (0.054) |
| lfc | -0.058*** | -0.061*** | -0.019*** | -0.037*** | -0.010 | -0.045*** |
| | (0.013) | (0.011) | (0.005) | (0.006) | (0.006) | (0.013) |
| neg_liquid | -0.042*** | -0.052*** | -0.023*** | -0.062*** | -0.026*** | -0.078*** |
| | (0.013) | (0.011) | (0.005) | (0.009) | (0.009) | (0.023) |
| lliquid | 0.348** | 0.408*** | 0.195*** | 0.465*** | 0.197*** | 0.740*** |
| | (0.136) | (0.075) | (0.027) | (0.087) | (0.056) | (0.179) |
| city200 | -0.034* | -0.073*** | -0.096*** | -0.149*** | 0.002 | 0.019 |
| | (0.020) | (0.014) | (0.008) | (0.016) | (0.013) | (0.029) |
| Constant | -3.128*** | -4.049*** | -1.707*** | -0.546 | 0.107 | -5.308*** |
| | (0.841) | (0.779) | (0.297) | (0.821) | (0.743) | (1.121) |
| Province Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 38,762 | 22,234 | 57,792 | 39,503 | 24,427 | 12,378 |
| Number of Firms | 12,942 | 6,980 | 15,111 | 10,452 | 6,963 | 4,129 |
| AR(1) z-statistic | -10.55 | -5.504 | -13.63 | -14.05 | -9.141 | -5.800 |
| AR(1) z-statistic p-value | 0 | 0 | 0 | 0 | 0 | 0 |
| AR(2) z-statistic | -1.765 | -2.385 | -4.454 | -2.994 | -1.081 | -2.379 |
| AR(2) z-statistic p-value | 0.0776 | 0.0171 | 0 | 0.00275 | 0.280 | 0.0174 |
| Hansen Test | 12.84 | 13.83 | 6.341 | 22.17 | 12.47 | 11.79 |
| Hansen Test p-value | 0.117 | 0.129 | 0.386 | 0.0752 | 0.188 | 0.108 |
| Returns to Scale (-1) | 0.106* | 0.109*** | 0.0496*** | 0.0383 | 0.0526* | 0.253*** |
| z-statistic RTS | 1.702 | 3.263 | 2.244 | 0.699 | 1.741 | 3.745 |

Standard Errors in Parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2: PANEL C

| Dependent variable: *ln* sales | Chemical (SIC26+28) | Medical (SIC27) | Rubber (SIC29) | Plastic (SIC30) | Nonmetal Products (SIC31) | Metal Products (SIC32+33+34) |
|---|---|---|---|---|---|---|
| lr_input | 0.850*** | 0.550*** | 0.555*** | 1.039*** | 0.191*** | 0.752*** |
| | (0.022) | (0.040) | (0.112) | (0.054) | (0.040) | (0.067) |
| lemp | 0.203*** | 0.768*** | 0.249* | 0.133** | 0.700*** | 0.587*** |
| | (0.052) | (0.102) | (0.146) | (0.059) | (0.182) | (0.070) |
| lr_capital | 0.016** | 0.065** | 0.153* | 0.079*** | 0.449*** | 0.788*** |
| | (0.006) | (0.027) | (0.080) | (0.031) | (0.133) | (0.114) |
| t_trend | 0.017*** | 0.047*** | 0.051*** | 0.028*** | 0.098*** | 0.137*** |
| | (0.003) | (0.005) | (0.013) | (0.005) | (0.013) | (0.008) |
| lage | -0.040*** | -0.162*** | -0.052* | -0.014 | -0.132*** | -0.251*** |
| | (0.014) | (0.027) | (0.026) | (0.014) | (0.027) | (0.024) |
| no_politics | 0.031*** | 0.071*** | 0.030*** | 0.002 | 0.068*** | 0.077*** |
| | (0.005) | (0.013) | (0.011) | (0.006) | (0.009) | (0.013) |
| high_politics | 0.001 | -0.015 | -0.005 | -0.021 | -0.130*** | -0.541*** |
| | (0.020) | (0.018) | (0.053) | (0.024) | (0.034) | (0.074) |
| p_capstate | -0.131*** | -0.219*** | -0.150* | -0.054 | -0.296*** | -0.029 |
| | (0.028) | (0.037) | (0.083) | (0.036) | (0.061) | (0.070) |
| p_capcoll | -0.015 | -0.028 | 0.121 | 0.034 | 0.168* | 0.749*** |
| | (0.014) | (0.033) | (0.099) | (0.042) | (0.093) | (0.098) |
| p_capcorporate | -0.035** | -0.077*** | 0.099 | 0.031 | 0.136* | 0.601*** |
| | (0.014) | (0.029) | (0.089) | (0.038) | (0.072) | (0.080) |
| p_capindividual | -0.030** | -0.023 | 0.100 | 0.027 | 0.175** | 0.725*** |
| | (0.013) | (0.029) | (0.095) | (0.041) | (0.088) | (0.093) |
| p_capforeign | 0.051*** | 0.079** | 0.025 | 0.028*** | 0.091 | 0.043 |
| | (0.010) | (0.032) | (0.028) | (0.009) | (0.055) | (0.039) |
| no_exporter | -0.027 | 0.079 | -0.149 | 0.042 | 0.221 | 0.089 |
| | (0.037) | (0.110) | (0.173) | (0.066) | (0.145) | (0.147) |
| rd_dum | 0.043 | 0.222* | 0.261 | 0.163* | -0.247*** | 0.002 |
| | (0.061) | (0.129) | (0.196) | (0.097) | (0.062) | (0.021) |
| lagglom | 0.025*** | 0.155*** | -0.011 | 0.041* | 0.203*** | 0.005 |
| | (0.006) | (0.024) | (0.025) | (0.022) | (0.017) | (0.035) |
| lherf | -0.051*** | -0.234*** | -0.201*** | -0.041** | -0.187*** | 0.200*** |
| | (0.008) | (0.029) | (0.068) | (0.017) | (0.020) | (0.028) |
| ldivers | 0.138*** | 0.165*** | 0.198*** | 0.163*** | 0.266*** | 0.407*** |
| | (0.008) | (0.018) | (0.030) | (0.020) | (0.022) | (0.030) |
| lfc | -0.028*** | -0.129*** | -0.046*** | -0.022** | -0.059*** | -0.157*** |
| | (0.005) | (0.015) | (0.012) | (0.009) | (0.008) | (0.015) |
| neg_liquid | -0.028*** | -0.046*** | -0.053*** | -0.021** | -0.100*** | -0.183*** |
| | (0.004) | (0.010) | (0.018) | (0.009) | (0.008) | (0.022) |
| lliquid | 0.194*** | 0.495*** | 0.337*** | 0.317*** | 1.192*** | 1.610*** |
| | (0.026) | (0.055) | (0.096) | (0.052) | (0.215) | (0.172) |
| city200 | -0.092*** | -0.094*** | -0.114*** | -0.129*** | -0.047*** | -0.153*** |
| | (0.006) | (0.015) | (0.018) | (0.013) | (0.011) | (0.018) |
| Constant | -1.259*** | -5.495*** | -3.005*** | -0.768* | -6.030*** | -1.590*** |
| | (0.347) | (0.468) | (1.042) | (0.426) | (1.407) | (0.592) |
| Province Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 154,348 | 33,367 | 22,894 | 55,225 | 173,374 | 93,059 |
| Number of Firms | 42,297 | 8,952 | 6,611 | 18,323 | 47,034 | 32,965 |
| AR(1) z-statistic | -21.29 | -12.44 | -5.941 | -8.279 | -16.28 | -11.34 |
| AR(1) z-statistic p-value | 0 | 0 | 0 | 0 | 0 | 0 |
| AR(2) z-statistic | -2.047 | -3.147 | -1.431 | -2.315 | -7.577 | -5.068 |
| AR(2) z-statistic p-value | 0.0406 | 0.00165 | 0.152 | 0.0206 | 0 | 0 |
| Hansen Test | 7.224 | 13.92 | 14.18 | 10.33 | 12.06 | 15.98 |
| Hansen Test p-value | 0.614 | 0.0838 | 0.116 | 0.412 | 0.0606 | 0.100 |
| Returns to Scale (-1) | 0.0686** | 0.383*** | -0.0432 | 0.0352* | 0.340*** | 0.247*** |
| z-statistic RTS | 2.140 | 4.584 | -0.767 | 1.778 | 4.592 | 9.940 |

Standard Errors in Parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2: PANEL D

| Dependent variable: *ln* sales | Machinery & Equipment (SIC35+36) | Transport Equipment (SIC37) | Measuring Instruments (SIC41) | Other Manufacturing (SIC42+43) | Electronic Power (SIC44) | Gas Production (SIC45) |
|---|---|---|---|---|---|---|
| lr_input | 0.626*** | 0.640*** | 0.562*** | 0.649*** | 0.169*** | 0.265*** |
| | (0.035) | (0.071) | (0.142) | (0.045) | (0.044) | (0.092) |
| lemp | 0.450*** | 0.383*** | 0.460** | 0.162*** | 0.392** | 0.348*** |
| | (0.065) | (0.104) | (0.197) | (0.053) | (0.153) | (0.110) |
| lr_capital | 0.104** | 0.094* | 0.202* | 0.135*** | 0.086 | 0.461*** |
| | (0.046) | (0.050) | (0.117) | (0.030) | (0.052) | (0.117) |
| t_trend | 0.078*** | 0.068*** | 0.072*** | 0.024*** | 0.032*** | 0.081*** |
| | (0.006) | (0.007) | (0.008) | (0.005) | (0.009) | (0.012) |
| lage | -0.109*** | -0.076*** | -0.186** | -0.073*** | -0.062 | -0.042 |
| | (0.011) | (0.017) | (0.078) | (0.016) | (0.039) | (0.052) |
| no_politics | 0.031*** | 0.012** | 0.040** | -0.015*** | 0.090*** | 0.140** |
| | (0.004) | (0.005) | (0.018) | (0.006) | (0.027) | (0.059) |
| high_politics | -0.063*** | -0.030 | -0.046 | 0.034 | 0.031 | 0.324*** |
| | (0.016) | (0.028) | (0.042) | (0.026) | (0.044) | (0.121) |
| p_capstate | -0.208*** | -0.049 | -0.333* | -0.050 | -0.155* | -0.226** |
| | (0.032) | (0.047) | (0.193) | (0.062) | (0.092) | (0.092) |
| p_capcoll | 0.116*** | 0.059 | -0.001 | 0.170*** | -0.057 | 0.297** |
| | (0.034) | (0.047) | (0.152) | (0.049) | (0.074) | (0.132) |
| p_capcorporate | 0.075*** | 0.065 | -0.040 | 0.164*** | -0.067 | 0.088 |
| | (0.026) | (0.041) | (0.144) | (0.042) | (0.064) | (0.085) |
| p_capindividual | 0.098*** | 0.067 | 0.010 | 0.166*** | -0.095 | 0.206* |
| | (0.029) | (0.044) | (0.156) | (0.042) | (0.074) | (0.113) |
| p_capforeign | 0.084*** | 0.037* | 0.096** | 0.045*** | -0.025 | 0.062 |
| | (0.016) | (0.020) | (0.042) | (0.014) | (0.038) | (0.094) |
| no_exporter | -0.039 | -0.116* | 0.622 | -0.361** | -0.519* | -0.578 |
| | (0.052) | (0.069) | (0.428) | (0.180) | (0.275) | (0.580) |
| rd_dum | 0.000 | -0.308* | 0.076 | 0.009 | 0.085*** | 0.005 |
| | (0.051) | (0.177) | (0.242) | (0.012) | (0.025) | (0.078) |
| lagglom | -0.016 | -0.003 | -0.061** | -0.007 | 0.046*** | 0.138*** |
| | (0.014) | (0.011) | (0.028) | (0.016) | (0.015) | (0.043) |
| lherf | -0.054*** | -0.080*** | 0.061*** | 0.062*** | -0.028 | 0.205** |
| | (0.015) | (0.021) | (0.021) | (0.015) | (0.033) | (0.089) |
| ldivers | 0.241*** | 0.166*** | 0.181*** | 0.223*** | 0.006 | 0.188*** |
| | (0.010) | (0.017) | (0.041) | (0.022) | (0.015) | (0.065) |
| lfc | -0.057*** | -0.033*** | -0.069*** | -0.034*** | -0.019*** | -0.100*** |
| | (0.006) | (0.009) | (0.026) | (0.006) | (0.007) | (0.023) |
| neg_liquid | -0.052*** | -0.043*** | -0.117*** | -0.072*** | -0.046*** | -0.022 |
| | (0.006) | (0.008) | (0.029) | (0.010) | (0.014) | (0.035) |
| lliquid | 0.437*** | 0.301*** | 0.613** | 0.351*** | 0.236 | 0.789*** |
| | (0.053) | (0.053) | (0.250) | (0.055) | (0.163) | (0.238) |
| city200 | -0.119*** | -0.084*** | -0.057** | -0.072*** | -0.002 | 0.057 |
| | (0.009) | (0.012) | (0.024) | (0.008) | (0.015) | (0.057) |
| Constant | -3.431*** | -2.785*** | -2.631* | -0.854** | -2.084** | -1.198 |
| | (0.569) | (0.798) | (1.407) | (0.427) | (0.879) | (0.886) |
| Province Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 276,450 | 72,401 | 42,265 | 60,473 | 36,854 | 2,238 |
| Number of Firms | 84,449 | 22,159 | 14,731 | 19,250 | 7,845 | 695 |
| AR(1) z-statistic | -29.24 | -10.37 | -10.01 | -15.56 | -6.976 | -3.176 |
| AR(1) z-statistic p-value | 0 | 0 | 0 | 0 | 0 | 0.00149 |
| AR(2) z-statistic | -5.363 | -2.587 | -2.118 | -2.329 | 2.312 | -1.438 |
| AR(2) z-statistic p-value | 0 | 0.00968 | 0.0341 | 0.0199 | 0.0208 | 0.150 |
| Hansen Test | 18.33 | 13.40 | 6.520 | 6.529 | 12.67 | 27.83 |
| Hansen Test p-value | 0.106 | 0.0629 | 0.480 | 0.367 | 0.0806 | 0.114 |
| Returns to Scale (-1) | 0.181*** | 0.117** | 0.224* | -0.0547 | 0.437** | 0.0739 |
| z-statistic RTS | 8.258 | 2.556 | 1.710 | -1.420 | 2.227 | 0.710 |

Standard Errors in Parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2: PANEL E

| Dependent variable: *ln* sales | Water Production (SIC46) | Coal Mining (SIC60) |
|---|---|---|
| lr_input | 0.142* | 0.568*** |
| | (0.082) | (0.027) |
| lemp | 1.220*** | 0.391*** |
| | (0.161) | (0.062) |
| lr_capital | 0.216** | 0.083* |
| | (0.092) | (0.044) |
| t_trend | 0.051*** | 0.034*** |
| | (0.006) | (0.004) |
| lage | -0.221*** | -0.079*** |
| | (0.046) | (0.016) |
| no_politics | 0.174*** | 0.061*** |
| | (0.040) | (0.011) |
| high_politics | 0.239*** | -0.015 |
| | (0.064) | (0.032) |
| p_capstate | -0.474*** | -0.212*** |
| | (0.157) | (0.081) |
| p_capcoll | 0.136 | -0.051 |
| | (0.146) | (0.078) |
| p_capcorporate | -0.191 | 0.001 |
| | (0.140) | (0.078) |
| p_capindividual | -0.138 | -0.012 |
| | (0.149) | (0.078) |
| p_capforeign | -0.099 | -0.234 |
| | (0.145) | (0.146) |
| no_exporter | -0.009 | -0.103*** |
| | (0.360) | (0.027) |
| rd_dum | -0.020 | 0.238*** |
| | (0.184) | (0.085) |
| lagglom | 0.032 | 0.103*** |
| | (0.033) | (0.013) |
| lherf | 0.055** | -0.247*** |
| | (0.023) | (0.023) |
| ldivers | 0.071*** | 0.019* |
| | (0.023) | (0.011) |
| lfc | -0.049*** | -0.000 |
| | (0.008) | (0.003) |
| neg_liquid | -0.041*** | -0.044*** |
| | (0.014) | (0.007) |
| lliquid | 0.305** | 0.376*** |
| | (0.134) | (0.062) |
| city200 | -0.033 | -0.059*** |
| | (0.024) | (0.009) |
| Constant | -8.343*** | -4.078*** |
| | (1.278) | (0.534) |
| Province Dummies | Yes | Yes |
| Observations | 19,451 | 32,920 |
| Number of Firms | 3,183 | 10,866 |
| AR(1) z-statistic | -8.935 | -17.74 |
| AR(1) z-statistic p-value | 0 | 0 |
| AR(2) z-statistic | -0.642 | -3.644 |
| AR(2) z-statistic p-value | 0.521 | 0.000268 |
| Hansen Test | 11.26 | 6.614 |
| Hansen Test p-value | 0.258 | 0.251 |
| Returns to Scale (-1) | 0.578*** | 0.0417 |
| z-statistic RTS | 6.065 | 1.080 |

Standard Errors in Parentheses, *** p<0.01, ** p<0.05, * p<0.1

### 3.6. Results of the Semiparametric Estimation

Table 3 presents the results of the estimation of the determinants of TFP levels for 26 industries according to the Levinsohn and Petrin (2003) semiparametric methodology.

The results suggest that for the majority of industries, the coefficients for employment (*lemp*) and capital (*lr_capital*) are higher in the SYS-GMM estimation results than in the results from the Levinsohn and Petrin (2003) semiparametric estimation. However, the coefficients for intermediate inputs (*lr_input*) are lower in the SYS-GMM results than with the Levinsohn and Petrin (2003) estimation. Moreover, the results based on the Levinsohn and Petrin (2003) estimation indicate the existence of increasing returns to scale for 4 out of 26 industries, and decreasing returns to scale for 10 out of 26 industries, with the average sum of output elasticities equalling 0.95. In contrast, the results based on the SYS-GMM estimation indicate the existence of increasing returns to scale for 18 out of 26 industries, since the average sum of output elasticities equals 1.2. Increasing returns to scale are more likely for the fast growing Chinese economy than decreasing ones. This suggests that the results based on the SYS-GMM estimation are more plausible than the ones based on the semiparametric estimation following Levinsohn and Petrin (2003).

As with the SYS-GMM results, the results of the semiparametric estimation can be summarized by grouping the variables included in the vector $X_{it}$ into categories: political affiliation/foreign ownership variables, spatial variables (Marshallian, Jacobian and city spillovers), knowledge variables (age, R&D and time trend), and all other variables (exporting, competition, liquidity and marketing capabilities).

Regarding political affiliation/ownership variables, the statistically significant and positive coefficients of the "high level of political affiliation" variable (*high_politics*) for 13 out of 26 industries indicate that a high level of political affiliation has a positive effect on firms' TFP levels. This effect is strongest for the tobacco, apparel & footwear and water production industries. Only the timber industry showed a negative effect of a high level of political affiliation on firms' TFP levels. The results suggest that Chinese industrial firms benefit in terms of higher TFP from being affiliated with the central or provincial governments. Moreover, the statistically significant and positive coefficients for the "no political affiliation" variable (*no_politics*) for 20 out of 26 industries indicate that a lack of political affiliation also has a positive effect on firms' TFP levels. Here, firms appear to benefit in terms of higher TFP from not being politically affiliated with any level of government. The industries in which this effect is the strongest are the tobacco, electronic power and water production industries. Based on these results, a high level of political affiliation with the central or provincial governments and the lack of a political affiliation are both conducive to higher firm TFP levels. These results are inconsistent, and also partly differ from the initial expectations and the results of the SYS-GMM estimation, in which the coefficients of the "high level of political affiliation" variable are mostly statistically significant and negative and those on the "no political affiliation" are mostly statistically significant and positive. These findings also differ from those of Du and Girma (2010), which indicate that, conditional on survival, politically unaffiliated firms perform better in terms of TFP growth than politically affiliated ones.

The consideration of political affiliation also takes into account the potential political impact that State influence might have on a firm's performance by being a major shareholder. This is because forms of ownership other than the State ownership are likely to be characterised by a relatively low impact of political influence from an affiliation. In the semiparametric results, the coefficients for the variable representing the proportion of paid-in capital owned by the State (*p_capstate*) are statistically significant and negative in 21 out of 26 industries (this effect is the highest in the leather, furniture and water production industries), while the variables representing the proportion of paid-in capital owned by collective investors (*p_capcoll*), corporations (*p_capcorporate*), individuals (*p_capindividual*) and foreigners (*p_capforeign*) are statistically significant and positive for most industries. These results indicate that a higher proportion of paid-in capital owned by the State results in lower firm TFP levels, while a higher proportion of paid-in capital owned by collective investors, corporations, individuals and foreign investors is conducive to higher firm TFP levels. These findings are consistent with the results from the SYS-GMM estimation and with initial expectations. They are also similar to the findings of Zhang et al. (2001), Jefferson et al. (2003) and Zhang et al. (2003), who found that State-owned enterprises were the least efficient and had achieved the lowest rate of TFP growth, although the studies looked at smaller samples and shorter time periods.

Regarding spatial variables, the coefficients for the variable representing Marshallian spillovers (*lagglom*) are statistically significant and positive for 13 out of 26 industries, but negative in 4 industries. The positive effect is the strongest in the electronic power, tobacco and plastics industries. The coefficients for the variable representing Jacobian spillovers (*ldivers*) are statistically significant and positive in 22 out of 26 industries, with the highest effect seen in the machinery & equipment, other manufacturing, and apparel & footwear industries. The coefficients for the variable representing city spillovers (*city200*) are negative for 18 out of 26 industries, with the strongest negative effect seen in the leather, transport equipment and measuring instruments industries. These results indicate that firms are likely to benefit in terms of higher TFP from the externalities arising by being geographically close to their industrial peers, and by being located in an area characterised by different industrial activities. The results also indicate that firms do not benefit in terms of higher TFP levels from being based in a major city. The positive relationship between Marshallian spillovers and TFP levels is consistent with the results of the SYS-GMM estimation and similar to those of Lin et al. (2011), who found that industrial agglomeration has a significant positive impact on the productivity of firms, although the relationship takes an inverted U-shape and only the textile industry was examined. The findings are also similar to those of Yang et al. (2013), who found that production agglomeration has a positive relationship with firms' productivity, although their analysis is limited to the electronics industry. The positive relationship between Jacobian spillovers and TFP is consistent with the SYS-GMM results and similar to the findings of Liu (2002), who found that Jacobian spillovers positively affect the productivity of 29 manufacturing industries based in Shenzhen. The results are also similar to those of Batisse (2002), who found Jacobian spillovers to positively affect firms' added value in 30 industrial sectors across 29 Chinese provinces. The negative relationship between firms' TFP levels and city spillovers is consistent with the SYS-GMM estimation, but contrasts with the results of Pan and Zhang (2002), who found that for firms spread across 28 industries in 224 Chinese cities, firms' productivity increases as the city size doubles. In summary, in line with the results of the SYS-GMM estimation presented in the previous section, firms benefit in terms of higher TFP from being based in areas characterized by industrial agglomeration and diversity, while not benefiting from being based in cities.

Among the three knowledge variables examined, the coefficients for the variable representing firms' age (*lage*), are statistically significant and negative in 13 out of 26 industries, indicating that firms tend to become less productive as they age. These results are consistent with those of the SYS-GMM estimation but contrast with those of Zheng et al. (2003) who found a significant and positive effect of age on firms' technical efficiency for 600 SOEs during 1980-1994, and Hsieh and Klenow (2009), who found that the productivity of Chinese and Indian firms rises through the youngest tenth of firms and then remains flat before falling for the oldest tenth of firms. In contrast to the previous finding, the coefficients for the variable representing firms' R&D expenditures are statistically significant and positive for most industries, indicating that firms benefit in terms of higher TFP levels by undertaking R&D. These results are consistent with those from the SYS-GMM estimation and those of Wu et al. (2007), who found that R&D positively affected the technical efficiency of 145 firms belonging to the watch and clock manufacturing industry. The results also support those of Hu (2001), who found a positive relationship between both firm and government R&D and the productivity of 813 firms. The coefficients for the variable representing the time trend (*t_trend*), or Hicks-neutral technical change, are statistically significant and positive for 20 out of 26 industries, suggesting that Chinese firms benefit in terms of TFP level increases over time as they are affected by positive exogenous technological improvements. In summary, among knowledge variables, R&D expenditure and the time trend positively affect firms' TFP, while age negatively affects TFP. These results differ from the SYS-GMM results, in which a higher level of R&D expenditure resulted in lower TFP levels for most industries.

In addition to ownership/political affiliation, spatial and knowledge variables, others variables are included in the vector $X_{it}$: exporting, competition, liquidity and marketing capabilities.

For 14 out of 26 industries, the statistically significant and negative coefficients for the variable representing a non-exporting firm (*no_exporter*) indicate that exporting has a positive effect on firms' TFP levels. The results thus suggest that firms benefit from exporting. These findings are not consistent with those from the SYS-GMM estimation, although they are consistent with those of Sun and Hong (2011), who found a positive effect of exporting on Chinese firms' TFP, and Du et al. (2012b), who found that domestic firms achieve productivity gains by exporting while foreign firms do not.

The statistically significant coefficients for the variable representing the Herfindahl index of industrial concentration (*lherf*) indicate that the higher the industrial concentration, the worse the firm TFP level. This was the case for 15 out of 26 industries, including non-metal products, chemical and food production, but was not the case for 10 out of 26 industries, including the water production, gas production and tobacco industries. In other words, most industries' firms benefit in terms of higher TFP levels from an increased level of competition. These results are consistent with those of the SYS-GMM estimation and similar to those of Zhang et al. (2001), who found a negative effect of industrial concentration on firms' productivity, although their analysis was limited to firms based in Shanghai. The results are also similar to those of Lin et al. (2009), who found that industrial concentration negatively affects firms' productivity, although they looked at a smaller sample over a shorter time period.

In terms of liquidity, the coefficients for the negative working capital to total assets dummy (*neg_liquid*) are statistically significant for all industries except tobacco. The coefficients for the natural logarithm of the working capital to total assets ratio (*lliquid*) variable are statistically significant and positive for all industries except for gas production. These results are consistent with those of the SYS-GMM estimation and those of Chen and Guariglia (2013), who found that a firm's productivity is positively and significantly affected by the level of internal liquidity.

For 18 out of 26 industries, the coefficients for the variable representing marketing capabilities (*lfc*) are statistically significant and negative, indicating that firms having lower selling and distribution costs as a percentage of sales tend to be more productive. Such firms are likely to be more able to transform their resources into valuable output, to better distinguish their products from competitors, and to build brands that enable them to charge higher prices, thus increasing their TFP level. These findings are consistent with those of the SYS-GMM estimation but contrast with those of Morgan et al. (2009), Nath et al. (2010), Lee and Rugman (2012) and Yu et al. (2014).

In summary, the empirical analyses in this study suggest that the SYS-GMM estimation results are more valid than those from the Levinsohn and Petrin's (2003) semiparametric estimation. Firstly, coefficients for the political affiliation variables based on the semiparametric estimation indicate that Chinese firms benefit from having both a high level of political affiliation and no political affiliation at all. This is somewhat inconsistent and contrasts with the results obtained using the SYS-GMM estimation, as well as with the empirical results reported in the literature. Secondly, elasticities with respect to output are much lower for capital and labour but higher for intermediate inputs when the Levinsohn and Petrin (2003) semiparametric estimation methodology is adopted. Thirdly, the evidence based on the Levinsohn and Petrin's (2003) semiparametric approach suggests the existence of decreasing returns to scale, which are unlikely for the dynamic and fast growing Chinese economy. In contrast, the results based on the SYS-GMM methodology indicate the existence of increasing returns to scale. In summary, the empirical results based on the SYS-GMM estimation seem to be more valid than those based on Levinsohn and Petrin's (2003) methodology, strengthening the case for using SYS-GMM as the preferred estimator of TFP in this study.

Table 3: Long-run Levinsohn and Petrin Semi Production Function, Various Industries, China 1998-2007

| Dependent variable: *ln* sales | Other (SIC10+80) | Food-Production (SIC14) | Tobacco (SIC16) | Textile (SIC17) | Apparel & Footwear (SIC18) | Leather (SIC19) |
|---|---|---|---|---|---|---|
| lr_input | 1.000*** | 0.810*** | 0.328*** | 0.675*** | 0.861*** | 0.881*** |
| | (0.008) | (0.011) | (0.084) | (0.012) | (0.005) | (0.086) |
| lr_capital | 0.007* | 0.168*** | 0.784*** | 0.057*** | 0.019*** | 0.033*** |
| | (0.004) | (0.011) | (0.124) | (0.004) | (0.002) | (0.009) |
| lemp | 0.040*** | 0.102*** | 0.220*** | 0.079*** | 0.118*** | 0.086*** |
| | (0.002) | (0.005) | (0.039) | (0.002) | (0.004) | (0.004) |
| t_trend | 0.031*** | 0.027*** | 0.026*** | -0.037*** | 0.038*** | 0.015*** |
| | (0.001) | (0.002) | (0.006) | (0.002) | (0.001) | (0.001) |
| lage | 0.007*** | -0.018*** | -0.000 | -0.007*** | -0.007*** | -0.009*** |
| | (0.002) | (0.004) | (0.027) | (0.002) | (0.003) | (0.004) |
| no_politics | 0.007** | 0.024*** | 0.118* | 0.028*** | 0.016*** | 0.005 |
| | (0.003) | (0.006) | (0.066) | (0.003) | (0.004) | (0.006) |
| high_politics | 0.016** | 0.034** | 0.099* | 0.010 | 0.074*** | -0.062 |
| | (0.008) | (0.016) | (0.056) | (0.014) | (0.023) | -0.062 |
| p_capstate | -0.023 | -0.190*** | -0.056 | -0.197*** | -0.211*** | -0.433*** |
| | (0.020) | (0.021) | (0.310) | (0.012) | (0.017) | (0.044) |
| p_capcoll | -0.000 | -0.020 | -0.062 | 0.017*** | -0.015** | -0.017 |
| | (0.018) | (0.013) | (0.299) | (0.006) | (0.007) | (0.013) |
| p_capcorporate | -0.000 | -0.018 | -0.150 | 0.015*** | -0.007 | 0.002 |
| | (0.018) | (0.013) | (0.302) | (0.004) | (0.005) | (0.008) |
| p_capindividual | -0.011 | -0.016 | 0.134 | 0.010*** | -0.012*** | 0.008 |
| | (0.018) | (0.011) | (0.312) | (0.004) | (0.004) | (0.007) |
| p_capforeign | -0.010 | -0.004 | -0.021 | 0.021*** | 0.016*** | 0.007 |
| | (0.022) | (0.014) | (0.399) | (0.004) | (0.005) | (0.007) |
| no_exporter | -0.009* | -0.017*** | -0.067* | -0.025*** | -0.009*** | -0.019*** |
| | (0.005) | (0.006) | (0.036) | (0.002) | (0.003) | (0.005) |
| rd_dum | 0.017* | 0.041*** | 0.130*** | 0.037*** | 0.042*** | 0.024*** |
| | (0.010) | (0.007) | (0.028) | (0.004) | (0.005) | (0.007) |
| lagglom | 0.023*** | 0.023** | 0.093 | -0.026*** | 0.019* | 0.025** |
| | (0.003) | (0.010) | (0.062) | (0.009) | (0.011) | (0.011) |
| lherf | -0.135*** | -0.517*** | 0.441*** | 0.382*** | 0.217*** | -0.077*** |
| | (0.005) | (0.023) | (0.060) | (0.010) | (0.017) | (0.011) |
| ldivers | -0.010* | 0.088*** | 0.010 | 0.055*** | 0.154*** | 0.087*** |
| | (0.006) | (0.010) | (0.036) | (0.005) | (0.012) | (0.015) |
| lfc | -0.006*** | -0.010*** | -0.045** | -0.009*** | 0.008*** | -0.015*** |
| | (0.001) | (0.003) | (0.021) | (0.002) | (0.003) | (0.004) |
| neg_liquid | -0.014*** | -0.042*** | -0.007 | -0.030*** | -0.032*** | -0.032*** |
| | (0.004) | (0.008) | (0.053) | (0.003) | (0.003) | (0.006) |
| lliquid | 0.100*** | 0.242*** | 0.607*** | 0.131*** | 0.121*** | 0.114*** |
| | (0.011) | (0.024) | (0.178) | (0.012) | (0.009) | (0.015) |
| city200 | -0.002 | -0.050*** | -0.050 | -0.033*** | -0.054*** | -0.077*** |
| | (0.004) | (0.009) | (0.035) | (0.004) | (0.006) | (0.009) |
| Province dummies | yes | yes | yes | yes | yes | yes |
| | | | | | | |
| Observations | 37,858 | 47,250 | 2,244 | 165,590 | 94,106 | 46,267 |
| Returns to Scale (-1) | 0.047*** | 0.081*** | 0.332*** | -0.189*** | -0.002 | -0.001 |
| z-statistic RTS | 8.252 | 7.485 | 2.938 | -15.41 | -0.787 | -0.00813 |

Standard Errors in Parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3: PANEL B

| Dependent variable: *ln* sales | Timber (SIC20) | Furniture (SIC21) | Paper-Making (SIC22) | Printing (SIC23) | Cultural (SIC24) | Petroleum-Processing (SIC25+70) |
|---|---|---|---|---|---|---|
| lr_input | 0.880*** | 0.657*** | 0.632*** | 0.972*** | 0.852*** | 0.913*** |
| | (0.007) | (0.049) | (0.013) | (0.008) | (0.109) | (0.013) |
| lr_capital | 0.035*** | 0.045*** | 0.063*** | 0.006 | 0.035*** | 0.051*** |
| | (0.004) | (0.007) | (0.006) | (0.005) | (0.008) | (0.009) |
| lemp | 0.083*** | 0.107*** | 0.094*** | 0.052*** | 0.102*** | 0.024*** |
| | (0.004) | (0.005) | (0.004) | (0.002) | (0.005) | (0.003) |
| t_trend | 0.024*** | 0.013*** | 0.034*** | 0.015*** | 0.084*** | -0.019*** |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.003) | (0.001) |
| lage | 0.000 | -0.010* | -0.004 | -0.007*** | 0.001 | 0.006** |
| | (0.003) | (0.005) | (0.003) | (0.002) | (0.005) | (0.003) |
| no_politics | 0.010* | 0.010 | 0.013*** | 0.003 | 0.014** | 0.004 |
| | (0.006) | (0.011) | (0.005) | (0.003) | (0.007) | (0.005) |
| high_politics | -0.060* | 0.023 | -0.001 | 0.040*** | 0.017 | 0.007 |
| | (0.033) | (0.050) | (0.017) | (0.006) | (0.035) | (0.011) |
| p_capstate | -0.136*** | -0.355*** | -0.145*** | 0.001 | -0.224*** | -0.049** |
| | (0.019) | (0.035) | (0.015) | (0.008) | (0.036) | (0.021) |
| p_capcoll | 0.042*** | 0.008 | -0.002 | 0.015* | -0.019 | -0.014 |
| | (0.013) | (0.022) | (0.009) | (0.008) | (0.015) | (0.018) |
| p_capcorporate | 0.024** | 0.047*** | 0.003 | 0.001 | -0.020** | -0.010 |
| | (0.010) | (0.010) | (0.009) | (0.007) | (0.009) | (0.019) |
| p_capindividual | 0.017* | 0.013 | 0.000 | -0.004 | -0.011 | -0.012 |
| | (0.010) | (0.009) | (0.008) | (0.007) | (0.007) | (0.018) |
| p_capforeign | 0.013 | 0.011 | 0.051*** | 0.026** | 0.005 | 0.034 |
| | (0.011) | (0.010) | (0.012) | (0.011) | (0.009) | (0.028) |
| no_exporter | -0.019*** | -0.014* | -0.003 | 0.010** | -0.007 | 0.005 |
| | (0.006) | (0.007) | (0.006) | (0.005) | (0.006) | (0.011) |
| rd_dum | 0.037*** | 0.029*** | 0.052*** | 0.023*** | 0.034*** | 0.023*** |
| | (0.008) | (0.010) | (0.008) | (0.006) | (0.011) | (0.007) |
| lagglom | 0.006 | 0.044*** | 0.034*** | 0.034*** | -0.012 | -0.011** |
| | (0.009) | (0.017) | (0.012) | (0.008) | (0.015) | (0.005) |
| lherf | 0.086*** | -0.086*** | -0.283*** | -0.080*** | 0.479*** | -0.001 |
| | (0.019) | (0.021) | (0.010) | (0.013) | (0.045) | (0.008) |
| ldivers | 0.065*** | 0.135*** | 0.110*** | 0.063*** | 0.102*** | -0.061*** |
| | (0.011) | (0.022) | (0.010) | (0.007) | (0.021) | (0.008) |
| lfc | -0.014*** | -0.012* | -0.010*** | -0.005*** | -0.001 | 0.005* |
| | (0.004) | (0.006) | (0.003) | (0.002) | (0.004) | (0.003) |
| neg_liquid | -0.028*** | -0.025*** | -0.037*** | -0.022*** | -0.033*** | -0.015*** |
| | (0.006) | (0.008) | (0.005) | (0.003) | (0.006) | (0.005) |
| lliquid | 0.088*** | 0.137*** | 0.146*** | 0.127*** | 0.158*** | 0.081*** |
| | (0.020) | (0.027) | (0.017) | (0.011) | (0.023) | (0.020) |
| city200 | -0.045*** | -0.046*** | -0.038*** | -0.056*** | 0.006 | 0.017** |
| | (0.007) | (0.014) | (0.006) | (0.004) | (0.013) | (0.007) |
| Province dummies | yes | yes | yes | yes | yes | yes |
| Observations | 38,762 | 22,234 | 57,792 | 31,177 | 24,427 | 12,378 |
| Returns to Scale (-1) | -0.002 | -0.191*** | -0.210*** | 0.030*** | -0.012 | -0.012* |
| z-statistic RTS | -0.581 | -3.664 | -15.29 | 8.746 | -0.115 | -1.894 |

Standard Errors in Parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3: PANEL C

| Dependent variable: *ln* sales | Chemical (SIC26+28) | Medical (SIC27) | Rubber (SIC29) | Plastic (SIC30) | Nonmetal-Products (SIC31) | Metal-Products (SIC32+33+ |
|---|---|---|---|---|---|---|
| lr_input | 0.984*** | 0.884*** | 0.874*** | 0.868*** | 0.542*** | 0.922*** |
| | (0.018) | (0.011) | (0.045) | (0.004) | (0.010) | (0.045) |
| lr_capital | 0.000 | 0.051*** | 0.030*** | 0.041*** | 0.080*** | 0.019*** |
| | (0.008) | (0.006) | (0.011) | (0.003) | (0.002) | (0.005) |
| lemp | 0.025*** | 0.042*** | 0.110*** | 0.089*** | 0.120*** | 0.085*** |
| | (0.001) | (0.003) | (0.006) | (0.002) | (0.003) | (0.003) |
| t_trend | 0.005*** | -0.006*** | 0.026*** | 0.014*** | 0.037*** | 0.057*** |
| | (0.000) | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) |
| lage | -0.001 | -0.004 | -0.020*** | -0.007** | -0.008*** | -0.015*** |
| | (0.001) | (0.003) | (0.005) | (0.003) | (0.001) | (0.002) |
| no_politics | 0.011*** | 0.009** | 0.039*** | 0.015*** | 0.008*** | 0.034*** |
| | (0.002) | (0.004) | (0.008) | (0.004) | (0.002) | (0.003) |
| high_politics | 0.019*** | 0.006 | 0.015 | 0.011 | 0.040*** | 0.011 |
| | (0.004) | (0.009) | (0.033) | (0.015) | (0.010) | (0.013) |
| p_capstate | -0.043*** | -0.057*** | -0.213*** | -0.205*** | -0.115*** | -0.132*** |
| | (0.004) | (0.014) | (0.034) | (0.012) | (0.010) | (0.012) |
| p_capcoll | -0.004 | -0.027** | 0.015 | 0.015** | 0.036*** | 0.039*** |
| | (0.003) | (0.013) | (0.016) | (0.007) | (0.007) | (0.008) |
| p_capcorporate | -0.007** | -0.012 | 0.011 | 0.022*** | 0.039*** | 0.025*** |
| | (0.003) | (0.011) | (0.013) | (0.006) | (0.006) | (0.006) |
| p_capindividual | -0.009*** | -0.011 | -0.001 | 0.014** | 0.028*** | 0.015*** |
| | (0.003) | (0.011) | (0.013) | (0.006) | (0.006) | (0.005) |
| p_capforeign | 0.019*** | 0.017 | 0.023* | 0.046*** | 0.063*** | 0.043*** |
| | (0.004) | (0.012) | (0.014) | (0.007) | (0.008) | (0.007) |
| no_exporter | -0.004*** | -0.016*** | -0.001 | 0.001 | -0.019*** | -0.021*** |
| | (0.001) | (0.005) | (0.009) | (0.003) | (0.004) | (0.003) |
| rd_dum | 0.012*** | 0.023*** | 0.053*** | 0.041*** | 0.021*** | 0.030*** |
| | (0.002) | (0.003) | (0.012) | (0.004) | (0.005) | (0.005) |
| lagglom | 0.002 | 0.045*** | -0.052** | 0.074*** | 0.017*** | 0.015* |
| | (0.002) | (0.011) | (0.022) | (0.017) | (0.006) | (0.009) |
| lherf | -0.019*** | -0.526*** | -0.304*** | -0.164*** | -0.514*** | 0.352*** |
| | (0.001) | (0.016) | (0.035) | (0.011) | (0.008) | (0.013) |
| ldivers | 0.014*** | 0.052*** | 0.137*** | 0.094*** | 0.137*** | 0.108*** |
| | (0.003) | (0.009) | (0.017) | (0.009) | (0.007) | (0.007) |
| lfc | -0.001 | -0.008*** | -0.000 | -0.014*** | -0.009*** | -0.021*** |
| | (0.001) | (0.002) | (0.005) | (0.002) | (0.002) | (0.003) |
| neg_liquid | -0.016*** | -0.035*** | -0.045*** | -0.037*** | -0.030*** | -0.042*** |
| | (0.001) | (0.004) | (0.008) | (0.004) | (0.004) | (0.003) |
| lliquid | 0.086*** | 0.199*** | 0.174*** | 0.190*** | 0.202*** | 0.150*** |
| | (0.005) | (0.016) | (0.026) | (0.016) | (0.013) | (0.011) |
| city200 | -0.017*** | -0.010 | -0.084*** | -0.042*** | -0.081*** | -0.091*** |
| | (0.002) | (0.006) | (0.010) | (0.006) | (0.004) | (0.004) |
| Province dummies | yes | yes | yes | yes | yes | yes |
| Observations | 129,000 | 33,367 | 22,894 | 80,982 | 173,374 | 139,488 |
| Returns to Scale (-1) | 0.009 | -0.023** | 0.013 | -0.002 | -0.259*** | 0.027 |
| z-statistic RTS | 0.904 | -2.156 | 0.346 | -0.722 | -25.46 | 0.641 |

Standard Errors in Parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3: PANEL D

| Dependent variable: *ln* sales | Machinery Equipment (SIC35+36) | Transport-Equipment (SIC37) | Measuring-Instrument (SIC41) | Other-Manufacturi (SIC42+43) | Electronic-Power (SIC44) | Gas Production (SIC45) |
|---|---|---|---|---|---|---|
| lr_input | 0.861*** | 0.907*** | 0.886*** | 0.858*** | 0.357*** | 0.825*** |
| | (0.104) | (0.003) | (0.007) | (0.121) | (0.015) | (0.060) |
| lr_capital | 0.036** | 0.050*** | 0.049*** | 0.036*** | 0.194*** | 0.093* |
| | (0.016) | (0.003) | (0.004) | (0.008) | (0.015) | (0.052) |
| lemp | 0.106*** | 0.041*** | 0.054*** | 0.101*** | 0.242*** | 0.032*** |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.008) | (0.012) |
| t_trend | 0.046*** | 0.041*** | 0.056*** | 0.009*** | 0.046*** | 0.072*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.009) |
| lage | -0.018*** | -0.003*** | -0.002 | -0.019*** | 0.071*** | -0.011 |
| | (0.001) | (0.001) | (0.002) | (0.003) | (0.006) | (0.010) |
| no_politics | 0.027*** | 0.006*** | 0.007* | -0.009 | 0.085*** | 0.018 |
| | (0.002) | (0.002) | (0.004) | (0.006) | (0.011) | (0.024) |
| high_politics | 0.059*** | 0.024*** | 0.017** | 0.051** | 0.137*** | 0.027 |
| | (0.008) | (0.005) | (0.008) | (0.020) | (0.014) | (0.031) |
| p_capstate | -0.239*** | -0.040*** | -0.007 | -0.248*** | -0.148*** | -0.094*** |
| | (0.008) | (0.006) | (0.008) | (0.024) | (0.031) | (0.031) |
| p_capcoll | 0.029*** | 0.003 | 0.027*** | 0.016* | -0.066** | -0.014 |
| | (0.005) | (0.005) | (0.006) | (0.009) | (0.032) | (0.039) |
| p_capcorporate | 0.005 | -0.005 | 0.033*** | 0.034*** | -0.091*** | -0.009 |
| | (0.004) | (0.005) | (0.005) | (0.007) | (0.030) | (0.032) |
| p_capindividual | 0.001 | -0.008* | 0.018*** | 0.022*** | -0.074** | -0.008 |
| | (0.004) | (0.004) | (0.005) | (0.007) | (0.031) | (0.037) |
| p_capforeign | 0.065*** | 0.025*** | 0.030*** | 0.047*** | -0.050 | 0.052 |
| | (0.005) | (0.006) | (0.005) | (0.009) | (0.045) | (0.046) |
| no_exporter | -0.020*** | 0.003 | 0.005 | 0.001 | -0.080** | -0.032 |
| | (0.002) | (0.002) | (0.003) | (0.004) | (0.033) | (0.055) |
| rd_dum | 0.054*** | 0.015*** | 0.027*** | 0.067*** | 0.112*** | -0.004 |
| | (0.003) | (0.002) | (0.003) | (0.005) | (0.020) | (0.039) |
| lagglom | -0.001 | 0.003 | -0.007 | -0.051*** | 0.102*** | 0.001 |
| | (0.008) | (0.007) | (0.005) | (0.010) | (0.013) | (0.025) |
| lherf | -0.108*** | -0.150*** | 0.017*** | 0.040*** | -0.232*** | 0.306*** |
| | (0.006) | (0.005) | (0.005) | (0.009) | (0.036) | (0.089) |
| ldivers | 0.193*** | 0.096*** | 0.066*** | 0.176*** | 0.034*** | 0.074*** |
| | (0.006) | (0.005) | (0.009) | (0.014) | (0.011) | (0.026) |
| lfc | -0.013*** | -0.009*** | -0.001 | -0.009*** | -0.021*** | -0.010 |
| | (0.002) | (0.001) | (0.002) | (0.003) | (0.007) | (0.008) |
| neg_liquid | -0.047*** | -0.019*** | -0.023*** | -0.051*** | -0.038*** | -0.032** |
| | (0.002) | (0.002) | (0.004) | (0.005) | (0.010) | (0.014) |
| lliquid | 0.188*** | 0.134*** | 0.177*** | 0.174*** | 0.781*** | 0.053 |
| | (0.007) | (0.006) | (0.011) | (0.016) | (0.061) | (0.064) |
| city200 | -0.105*** | -0.077*** | -0.063*** | -0.057*** | 0.025** | 0.003 |
| | (0.003) | (0.003) | (0.004) | (0.007) | (0.011) | (0.021) |
| Province dummies | yes | yes | yes | yes | yes | yes |
| Observations | 276,450 | 72,401 | 35,460 | 60,473 | 46,033 | 2,238 |
| Returns to Scale (-1) | 0.003 | -0.002 | -0.012** | -0.005 | -0.207*** | -0.050 |
| z-statistic RTS | 0.0312 | -0.886 | -1.976 | -0.0457 | -8.118 | -0.927 |

Standard Errors in Parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3: PANEL E

| Dependent variable: *ln* sales | Water-Production (SIC46) | Coal Mining (SIC60) |
|---|---|---|
| lr_input | 0.463*** | 0.834*** |
| | (0.034) | (0.012) |
| lr_capital | 0.258*** | 0.041*** |
| | (0.010) | (0.005) |
| lemp | 0.207*** | 0.087*** |
| | (0.007) | (0.003) |
| t_trend | 0.052*** | 0.009*** |
| | (0.001) | (0.001) |
| lage | 0.019*** | 0.000 |
| | (0.006) | (0.003) |
| no_politics | 0.046** | 0.009* |
| | (0.018) | (0.005) |
| high_politics | 0.068*** | 0.003 |
| | (0.022) | (0.011) |
| p_capstate | -0.265*** | -0.058 |
| | (0.049) | (0.044) |
| p_capcoll | -0.059 | -0.006 |
| | (0.053) | (0.044) |
| p_capcorporate | -0.168*** | 0.013 |
| | (0.052) | (0.045) |
| p_capindividual | -0.122** | 0.005 |
| | (0.055) | (0.045) |
| p_capforeign | -0.022 | -0.156** |
| | (0.078) | (0.073) |
| no_exporter | -0.059** | -0.033*** |
| | (0.025) | (0.009) |
| rd_dum | 0.001 | 0.043*** |
| | (0.029) | (0.012) |
| lagglom | 0.010 | 0.072*** |
| | (0.013) | (0.006) |
| lherf | 0.200*** | -0.181*** |
| | (0.010) | (0.014) |
| ldivers | 0.029*** | -0.012* |
| | (0.009) | (0.006) |
| lfc | -0.014*** | 0.005** |
| | (0.003) | (0.002) |
| neg_liquid | -0.039*** | -0.030*** |
| | (0.008) | (0.004) |
| lliquid | 0.188*** | 0.112*** |
| | (0.043) | (0.015) |
| city200 | 0.001 | -0.019*** |
| | (0.010) | (0.004) |
| Province dummies | yes | yes |
| Observations | 19,451 | 32,920 |
| Returns to Scale (-1) | -0.072** | -0.038*** |
| z-statistic RTS | -2.404 | -3.722 |

Standard Errors in Parentheses, *** p<0.01, ** p<0.05, * p<0.1

### 3.7. Relative importance of TFP determinants

After having analysed what determines higher TFP levels across Chinese industrial firms, it is important to underline which determinants are likely to exert the largest impact on TFP. This would enable policymakers to understand which determinants they should focus on in order to achieve higher TFP levels.

In order to measure such impacts, the parameter estimates resulting from the SYS-GMM estimation are taken. The weighted mean of the parameter estimates is calculated for each variable. In this case, the weight is measured as the number of firms in each industry as a proportion of the total number of firms in all industries. The weighted mean of the parameter estimates for each variable is standardized by multiplying it by the respective variable standard deviation. This is then divided by the dependent variable standard deviation. In all the calculations, only the parameter estimates of the industries that were statistically significant in the SYS-GMM estimation are included.

In table 4, the figures are ordered in a decreasing order, according to the extent of the impact on TFP levels. For some variables, in order to measure their positive impact on TFP, the weighted mean of parameter estimates is multiplied by the negative value of the respective independent variable standard deviation. These are the variables representing: exporting (*no_exporter*), age (*lage*), competition (*lherf*), liquidity (*neg_liquid*) and marketing capabilities (*lfc*).

Based on these results, it can be seen that the time trend (*t_trend*), or Hicks-neutral technical change, has the largest impact on TFP levels. In other words, firms largely increase their productivity over time as a result of exogenous technological improvements.

The figures in table 4 also indicate that a significant positive impact on TFP levels comes from the share of Chinese industrial firms' proportion of paid-in capital owned by either individuals (*p_capindividual*) or corporations (*p_capcorporate*). At the same time, a significant negative impact on TFP levels comes from the proportion of paid-in capital owned by the State (*p_capstate*). In comparison with other owners, such as the State, individuals or corporates are more likely to influence firms' decision towards the maximization of TFP, rather than the pursuit of politically motivated objectives, such as maximum employment. This is also indicated by the variable representing the political affiliation of a firm with either the central or provincial government (*high_politics*), which has a large negative effect on TFP. It can be therefore inferred that policy measures aimed at decreasing State influence on Chinese firms, in terms of both ownership and political affiliation, and at increasing private forms of ownership, could have a large positive impact on firms' TFP.

Among the negative effects on TFP, the second worst has been recorded by the variable representing city spillovers (*city200*). Although firms seem to benefit from being based in areas characterized by industrial agglomeration and diversity, as indicated by the positive values for the variables representing Marshallian (*lagglom*) and Jacobian (*ldivers*) spillovers, they do not seem to benefit from being based in cities. While cities are likely to provide firms with many positive advantages, such as access to a wide customer base, these are likely to be dominated by other disadvantages, such as higher rent and transportation costs, which might hamper their TFP. This suggests that policy measures incentivizing firms to be based in areas characterized by industrial agglomeration and diversity other than cities are likely to have a large positive effect on firms' TFP.

Table 4: Relative importance of different TFP effects based on equation (47)

| Variable | Impact |
|---|---:|
| t_trend | 0.103 |
| p_capindividual | 0.086 |
| p_capcorporate | 0.068 |
| lliquid | 0.053 |
| lage | 0.050 |
| ldivers | 0.050 |
| lagglom | 0.037 |
| lfc | 0.029 |
| p_capcoll | 0.025 |
| neg_liquid | 0.020 |
| no_exporter | 0.013 |
| no_politics | 0.012 |
| lherf | 0.007 |
| p_capforeign | 0.006 |
| rd_dum | 0.001 |
| high_politics | -0.012 |
| city200 | -0.023 |
| p_capstate | -0.035 |

## 3.8. Results of the KS Testing

Tables 5 through 7 present the results of the two-sample Kolmogorov and Smirnov (KS) tests of equality of TFP distribution functions. Figures 1 through 15 complements the tables by plotting the related empirical cumulative TFP distributions.

Table 5: Two-Sample Kolmogorov-Smirnov Statistics for Equality of Distribution Functions

| Industry | | | | Year | | | |
|---|---|---|---|---|---|---|---|
| | *Group* | *D* | *p-Value* | | *Group* | *D* | *p-Value* |
| *0* | *Apparel & Footwear* | 0 | 1 | *0* | *1998* | 0.0005 | 0.945 |
| *1* | *Machinery & Equipment* | -0.5476 | 0 | *1* | *2007* | -0.262 | 0 |
| **Political Affiliation** | | | | **Political Affiliation** | | | |
| | *Group* | *D* | *p-Value* | | *Group* | *D* | *p-Value* |
| *0* | *No Political Affiliation* | 0.0005 | 0.945 | *0* | *No High Political Affiliation* | 0.0071 | 0 |
| *1* | *High Political Affiliation* | -0.262 | 0 | *1* | *High Political Affiliation* | -0.1879 | 0 |
| **Political Affiliation** | | | | **State Ownership** | | | |
| | *Group* | *D* | *p-Value* | | *Group* | *D* | *p-Value* |
| *0* | *Political Affiliation* | 0.1814 | 0 | *0* | *State Ownership<0.25* | 0 | 1 |
| *1* | *No Political Affiliation* | 0 | 0.999 | *1* | *State Ownership>0.25* | -0.3428 | 0 |
| **Province** | | | | **R&D** | | | |
| | *Group* | *D* | *p-Value* | | *Group* | *D* | *p-Value* |
| *0* | *Guizhou* | 0.4121 | 0 | *0* | *No R&D* | 0.0158 | 0 |
| *1* | *Shanghai* | 0 | 1 | *1* | *R&D* | -0.0917 | 0 |
| **Exporting** | | | | | | | |
| | *Group* | *D* | *p-Value* | | | | |
| *0* | *Non Exporter* | 0.0069 | 0 | | | | |
| *1* | *Exporter* | -0.1391 | 0 | | | | |

The first line represents a hypothesis test that TFP for group 0 has smaller values than for group 1. The related D-statistic indicates the largest difference between the distribution functions in this direction. The second line represents a hypothesis test that TFP for group 0 has larger values than for group 1. The related D-statistic indicates the largest difference between the distribution functions in this direction.

Figure 1 compares the productivity distribution between firms belonging to the “Apparel and Footwear” and “Machinery and Equipment” industries. Firms belonging to the “Apparel &

Footwear" industry have a productivity distribution to the right of those belonging to the "Machinery & Equipment" industry, indicating that the former stochastically dominate the latter in terms of its TFP distribution (KS tests in Table 5 indicate that the maximum gap between the distribution for firms belonging to the Apparel & Footwear industry and firms belonging to the Machinery and Equipment industry has a value of 0.55, and is significant at the 1% level). Based on the same rationale, Figures 12 and 13 indicate that the productivity distribution of firms belonging to the "Leather" industry stochastically dominates the one of the firms belonging to the "Other Manufacturing" industry, for both 1998 and 2007. Moreover, Figures 14 and 15 indicate that the productivity distribution of firms belonging to the "Other Manufacturing" industry stochastically dominates the productivity distribution of firms belonging to the "Apparel & Footwear" industry in both 1998 and 2007. In Figures 14 and 15, there is some evidence of significant crossover in terms of TFP distribution between the two sub-groups at high values of the empirical cumulative distributions. These results point to the existence of heterogeneity in empirical cumulative distributions of TFP levels for groups of firms according to their industry, suggesting that it is important to estimate TFP levels separately for each of them.

Figure 2 compares the empirical cumulative distributions of TFP levels between firms operating in 1998 and firms operating in 2007. Consistent with the results presented in Table 2, firms operating in 2007 have a productivity distribution to the right of those operating in 1998, indicating that the former stochastically dominate the latter in terms of their TFP distribution (a KS test shows that the maximum gap between the distribution for firms operating in 1998 and firms operating in 2007 has a value of 0.26, and is significant at the 1% level). This points to the existence of TFP growth between 1998 and 2007.

Figure 3 indicates the existence of heterogeneity between the productivity distributions of non-politically affiliated firms and politically affiliated ones. Firms with no political affiliation have a productivity distribution to the right of those with high political affiliation and medium political affiliation, indicating that the former distribution stochastically dominates the other two (a KS test shows that the maximum gap between the distribution for firms with no affiliation and firms having high political affiliation is 0.18, and is significant at the 1% level). There is also evidence of some significant crossover in the figures representing the sub-groups at high values of the empirical cumulative distributions. These findings suggest that non-politically affiliated firms are more productive than politically affiliated ones, consistent with the findings in Table 2.

Figure 4 compares the TFP distribution between firms in which the State owns more than 25% of paid-in capital and those in which the State owns less than 25%. The figure shows that the productivity distribution for firms in which the State owns less than 25% of paid-in capital is on the right of the distribution for firms in which the State owns more than 25% of paid-in capital, suggesting that the former stochastically dominates the latter. The KS test indicates that the maximum gap between the two distributions is 0.34 and is statistically significant at the 1% level. These findings indicate that firms having a share of State paid-in capital ownership lower than 25% have higher TFP levels than firms in which the share is higher, and are again in line with the findings in Table 2.

Figure 5 compares the TFP distribution for firms based in the Shanghai province to those based in the Guizhou province. The distribution for firms based in Shanghai is on the right of the distribution for firms based in Guizhou, suggesting that firms based in Shanghai are more productive than firms based in Guizhou (the value of the KS test statistic is 0.41 and is statistically significant at the 1% level). Moreover, Figures 8 and 9 indicate that firms based in Guizhou are more productive than firms based in Guangdong both in 1998 and 2007. Figures 10 and 11 indicate that firms based in Guangdong are more productive than firms based in Yunnan both in 1998 and 2007. These results, which are in line with those presented in Section 3.5, point to the existence of heterogeneity in TFP levels across groups of firms based in different provinces, and suggest that it is important to take geographical differences into account when estimating TFP.

Figure 6 compares the empirical cumulative productivity distributions between firms undertaking R&D and those not doing so. The figure indicates that the former dominates the latter (a KS test shows that the maximum gap between the distribution for firms undertaking R&D and firms not doing so has a value of 0.09 and is significant at the 1% level). These results indicate that firms undertaking R&D have higher TFP levels than firms not doing so.

Figure 7 compares the productivity distribution between exporting firms and non-exporting ones. The first group has a productivity distribution to the right of the second group, indicating that the empirical cumulative distribution of TFP levels for exporting firms dominates that of the non-exporting firms. KS tests show that the maximum gap between the two distributions has a value of 0.14, and is statistically significant at the 1% level. These results indicate that firms engaged in exporting activities have higher TFP levels than non-exporting firms.

In summary, the results of the KS tests and the related empirical cumulative TFP distributions are in line with the findings represented in Table 2. The results indicate that empirical cumulative distributions of TFP levels differ across groups of firms having different characteristics in terms of political affiliation, paid-in capital share ownership, R&D expenditure and exporting. The results also point to the existence of heterogeneity in TFP levels across groups of firms belonging to different industries and based in different provinces, thus suggesting that it is important to estimate TFP separately for each industry, and to take into account the geographical differences across firms when estimating TFP levels. Moreover, the KS tests and empirical cumulative distributions indicate the existence of TFP growth between 1998 and 2007.

Table 6: Industry Two-sample Kolmogorov-Smirnov Test for Equality of Distribution Functions

| Group | SIC | Industry | D | P-value | SIC | Industry | D | P-value |
|---|---|---|---|---|---|---|---|---|
| 0 | 42 | Other Manufacturing | 0 | 1 | 42 | Other Manufacturing | 0 | 1 |
| 1 | 10 | Other Mining | -0.9534 | 0 | 14 | Food Production | -0.5538 | 0 |
| 0 | 42 | Other Manufacturing | 0 | 1 | 42 | Other Manufacturing | 0.5213 | 0 |
| 1 | 16 | Tobacco | -0.9347 | 0 | 17 | Textile | -0.0001 | 1 |
| 0 | 42 | Other Manufacturing | 0 | 1 | 42 | Other Manufacturing | 0.8617 | 0 |
| 1 | 18 | Apparel & Footwear | -0.807 | 0 | 19 | Leather | 0 | 1 |
| 0 | 42 | Other Manufacturing | 0 | 1 | 42 | Other Manufacturing | 0 | 1 |
| 1 | 20 | Timber | -0.9617 | 0 | 21 | Furniture | -0.9348 | 0 |
| 0 | 42 | Other Manufacturing | 0.4861 | 0 | 42 | Other Manufacturing | 0 | 1 |
| 1 | 22 | Papermaking | 0 | 1 | 23 | Printing | -0.219 | 0 |
| 0 | 42 | Other Manufacturing | 0.0023 | 0.83 | 42 | Other Manufacturing | 0 | 1 |
| 1 | 24 | Cultural | -0.3644 | 0 | 25 | Petroleum | -0.9767 | 0 |
| 0 | 42 | Other Manufacturing | 0.1454 | 0 | 42 | Other Manufacturing | 0 | 1 |
| 1 | 26 | Chemical | -0.0155 | 0 | 27 | Medical | -0.9853 | 0 |
| 0 | 42 | Other Manufacturing | 0 | 1 | 42 | Other Manufacturing | 0.8326 | 0 |
| 1 | 29 | Rubber | -0.6539 | 0 | 30 | Plastic | 0 | 1 |
| 0 | 42 | Other Manufacturing | 0 | 1 | 42 | Other Manufacturing | 0.3321 | 0 |
| 1 | 31 | Non-metal Products | -0.9492 | 0 | 32 | Metal Products | -0.0768 | 0 |
| 0 | 42 | Other Manufacturing | 0 | 1 | 42 | Other Manufacturing | 0 | 1 |
| 1 | 35 | Machinery & | -0.8969 | 0 | 37 | Transport & | -0.8393 | 0 |
| 0 | 42 | Other Manufacturing | 0 | 1 | 42 | Other Manufacturing | 0 | 1 |
| 1 | 41 | Measuring | -0.7885 | 0 | 44 | Electric & Heat | -0.9892 | 0 |
| 0 | 42 | Other Manufacturing | 0.0179 | 0.102 | 42 | Other Manufacturing | 0 | 1 |
| 1 | 45 | Gas Production | -0.6643 | 0 | 46 | Water Production | -0.9988 | 0 |
| 0 | 42 | Other Manufacturing | 0 | 1 | | | | |
| 1 | 60 | Coal Mining | -0.9195 | 0 | | | | |

The first line represents a hypothesis test that TFP for group 0 has smaller values than for group 1. The related D indicates the largest difference between the distribution functions in this direction. The second line represents a hypothesis test that TFP for group 0 has larger values than for group 1. The related D indicates the largest difference between the distribution functions in this direction.

Table 6: Province Two-sample Kolmogorov-Smirnov Test for Equality of Distribution Functions

| Group | Code | Province | D | P-value | Code | Province | D | P-value |
|---|---|---|---|---|---|---|---|---|
| 0 | 44 | Guangdong | 0.0111 | 0 | 44 | Guangdong | 0.0396 | 0 |
| 1 | 11 | Beijing | -0.0875 | 0 | 12 | Tianjin | -0.0269 | 0 |
| 0 | 44 | Guangdong | 0.0019 | 0.675 | 44 | Guangdong | 0 | 1 |
| 1 | 13 | Hebei | -0.141 | 0 | 14 | Shanxi | -0.3555 | 0 |
| 0 | 44 | Guangdong | 0.0019 | 0.904 | 44 | Guangdong | 0.0037 | 0.23 |
| 1 | 15 | Inner Mongolia | -0.2411 | 0 | 21 | Liaoning | -0.1563 | 0 |
| 0 | 44 | Guangdong | 0.0003 | 0.997 | 44 | Guangdong | 0 | 1 |
| 1 | 22 | Jilin | -0.2959 | 0 | 23 | Heilongjiang | -0.3087 | 0 |
| 0 | 44 | Guangdong | 0.0788 | 0 | 44 | Guangdong | 0.0423 | 0 |
| 1 | 31 | Shanghai | -0.0096 | 0 | 32 | Jiangsu | -0.0317 | 0 |
| 0 | 44 | Guangdong | 0.0708 | 0 | 44 | Guangdong | 0.0006 | 0.976 |
| 1 | 33 | Zheijiang | -0.0173 | 0 | 34 | Anhui | -0.1501 | 0 |
| 0 | 44 | Guangdong | 0.0004 | 0.983 | 44 | Guangdong | 0.0027 | 0.678 |
| 1 | 35 | Fujian | -0.0707 | 0 | 36 | Jiangxi | -0.2454 | 0 |
| 0 | 44 | Guangdong | 0.0022 | 0.415 | 44 | Guangdong | 0.0028 | 0.395 |
| 1 | 37 | Shandong | -0.0562 | 0 | 41 | Henan | -0.1789 | 0 |
| 0 | 44 | Guangdong | 0.0037 | 0.313 | 44 | Guangdong | 0 | 1 |
| 1 | 42 | Hubei | -0.1593 | 0 | 43 | Hunan | -0.2045 | 0 |
| 0 | 44 | Guangdong | 0.0024 | 0.753 | 44 | Guangdong | 0 | 1 |
| 1 | 45 | Guanxi | -0.2671 | 0 | 46 | Hainan | -0.2996 | 0 |
| 0 | 44 | Guangdong | 0.0023 | 0.814 | 44 | Guangdong | 0.0004 | 0.985 |
| 1 | 50 | Chongqing | -0.2054 | 0 | 51 | Sichuan | -0.204 | 0 |
| 0 | 44 | Guangdong | 0.0035 | 0.686 | 44 | Guangdong | 0.0002 | 0.999 |
| 1 | 52 | Guizhou | -0.3337 | 0 | 53 | Yunnan | -0.3107 | 0 |
| 0 | 44 | Guangdong | 0.0009 | 0.997 | 44 | Guangdong | 0 | 1 |
| 1 | 54 | Tibet | -0.506 | 0 | 61 | Shaanxi | -0.3108 | 0 |
| 0 | 44 | Guangdong | 0.0003 | 0.997 | 44 | Guangdong | 0.0014 | 0.987 |
| 1 | 62 | Gansu | -0.3594 | 0 | 63 | Qinghai | -0.3846 | 0 |
| 0 | 44 | Guangdong | 0.0002 | 1 | 44 | Guangdong | 0 | 1 |
| 1 | 64 | Ningxia | -0.1785 | 0 | 65 | Xinjiang | -0.3033 | 0 |

The first line represents a hypothesis test that TFP for group 0 has smaller values than for group 1. The related D indicates the largest difference between the distribution functions in this direction. The second line represents a hypothesis test that TFP for group 0 has larger values than for group 1. The related D indicates the largest difference between the distribution functions in this direction.

Figure 1: Empirical cumulative TFP distributions for firms belonging to the Apparel & Footwear and Machinery & Equipment Industries

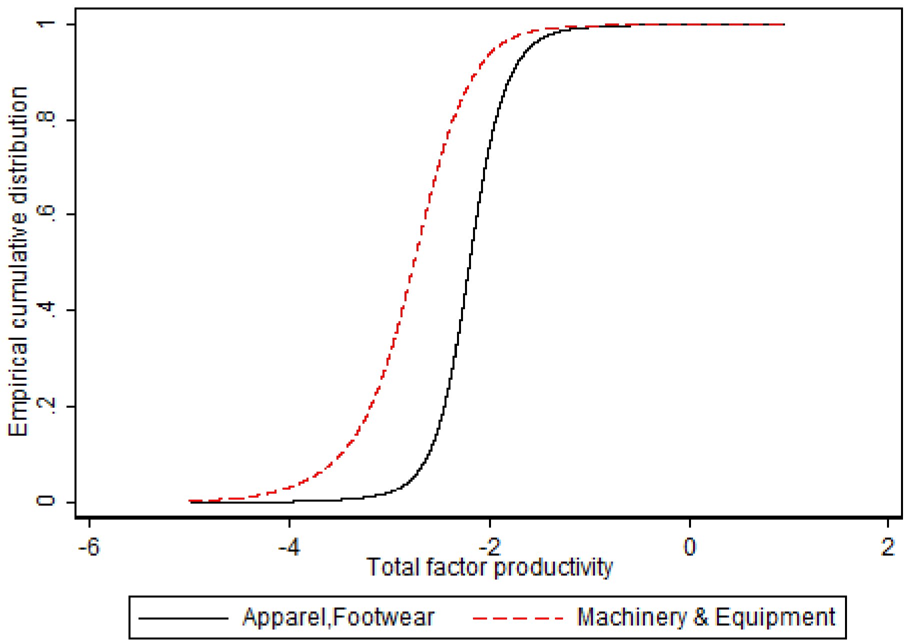



Figure 2: Empirical cumulative TFP distributions for firms operating in 1998 and 2007

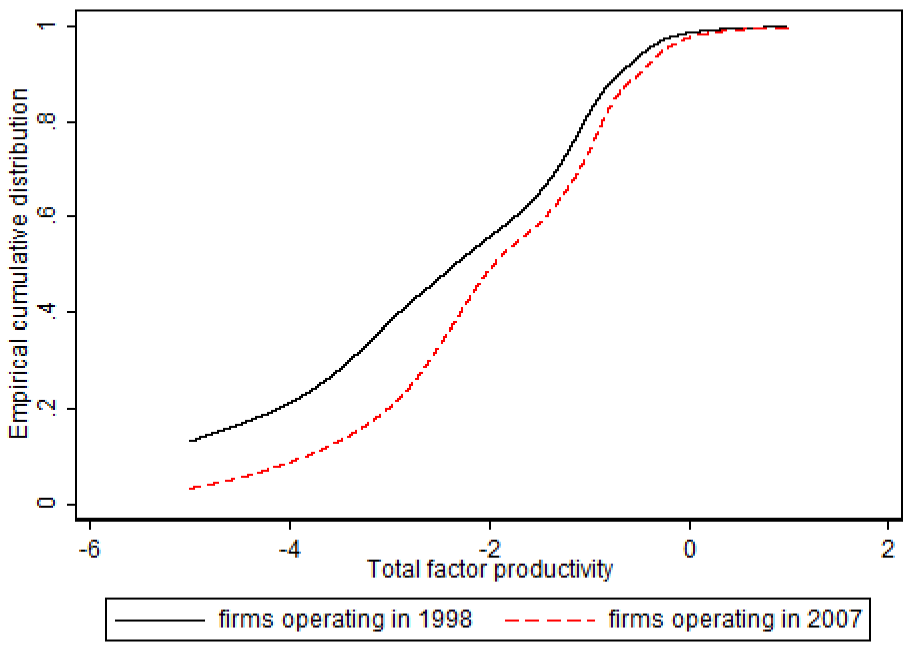


Figure 3: Empirical cumulative TFP distributions for firms according to their political affiliation

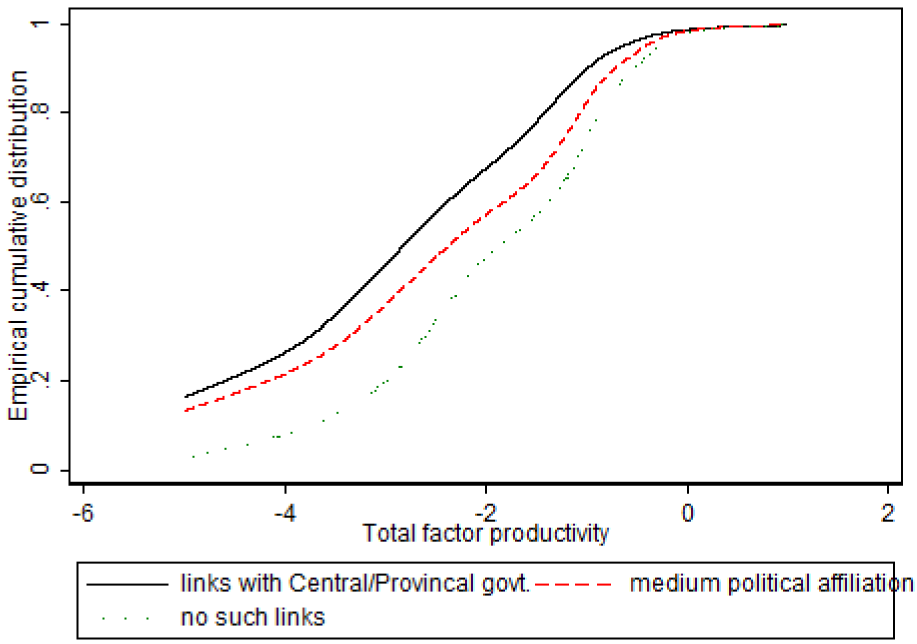



Figure 4: Empirical cumulative TFP distributions for firms according to their State paid-in capital ownership share

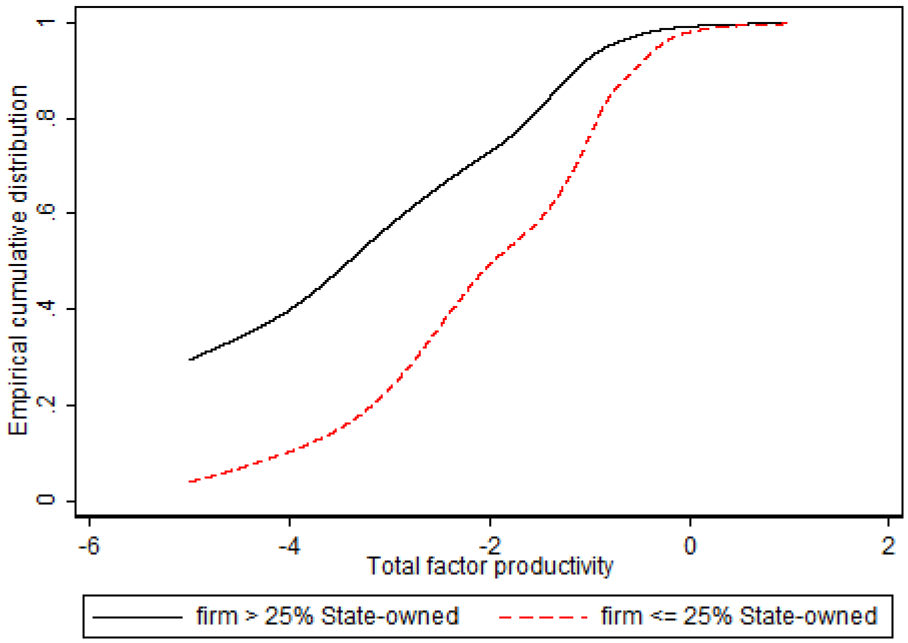


Figure 5: Empirical cumulative TFP distributions for firms based in the Guizhou and Shanghai provinces

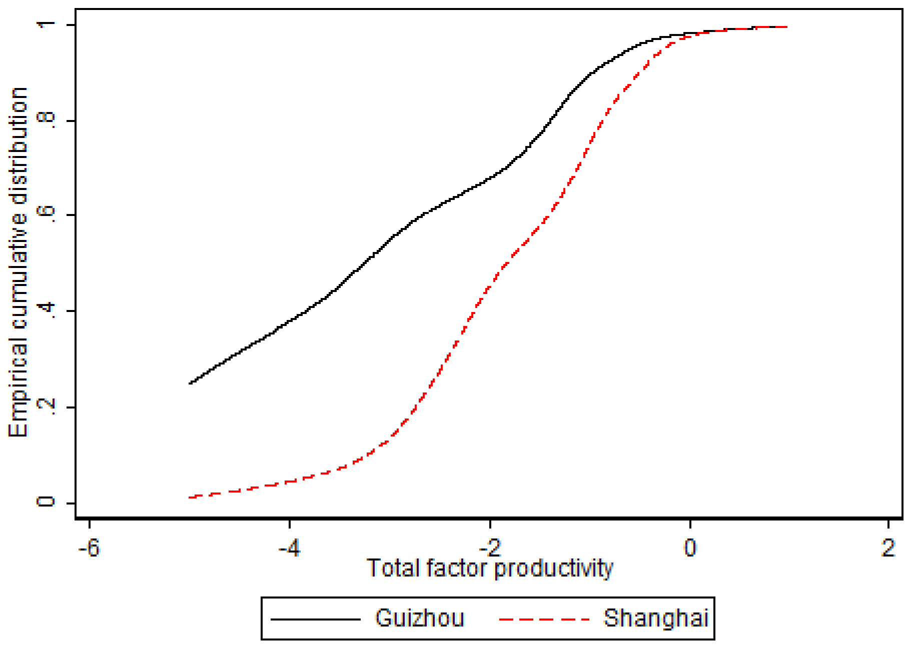



Figure 6: Empirical cumulative TFP distributions for firms undertaking R&D and those not doing so

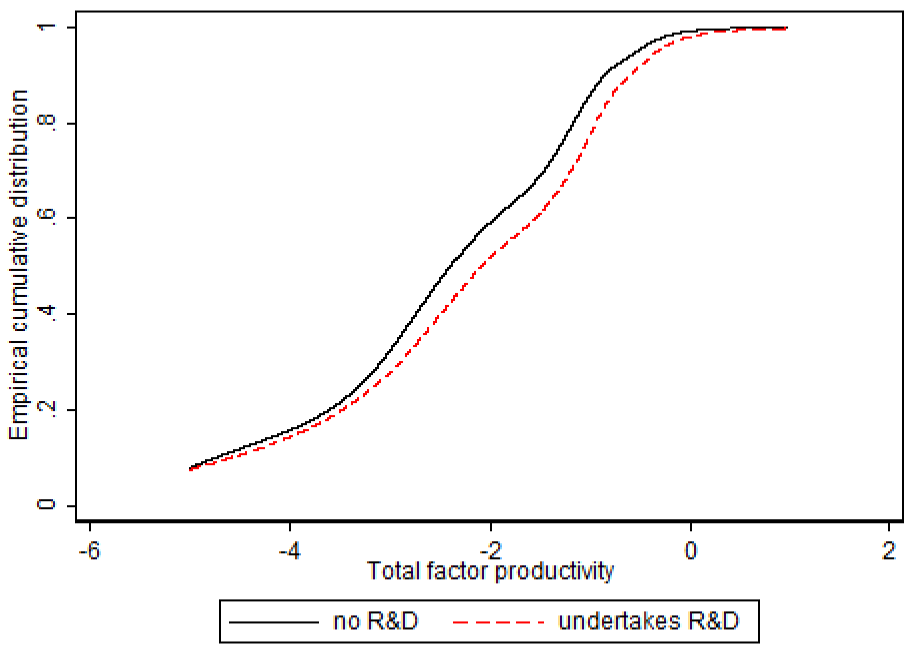


Figure 7: Empirical cumulative TFP distributions for exporting firms vs. non-exporting ones

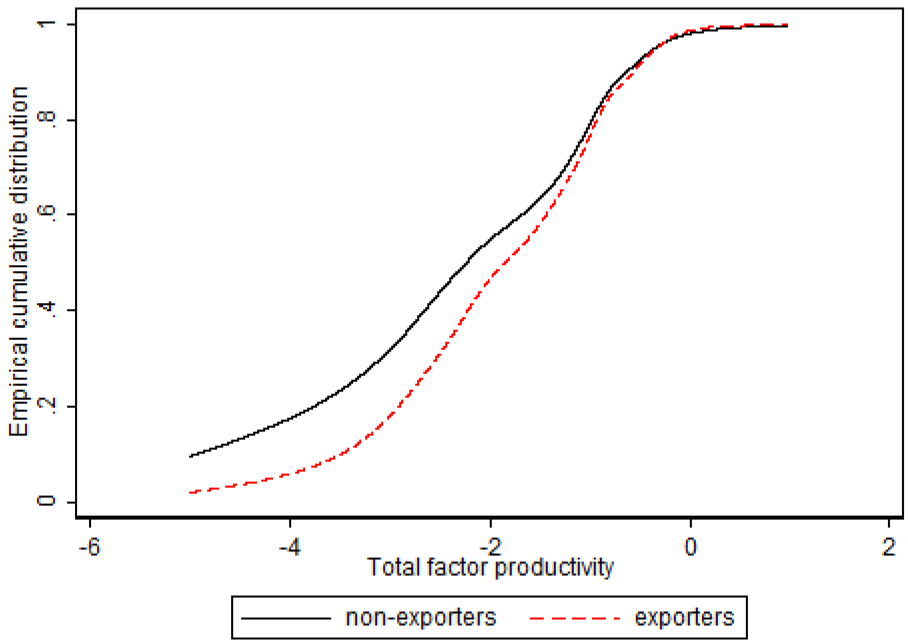



Figure 8: Empirical cumulative TFP distributions for firms based in Guangdong and Guizhou in 1998

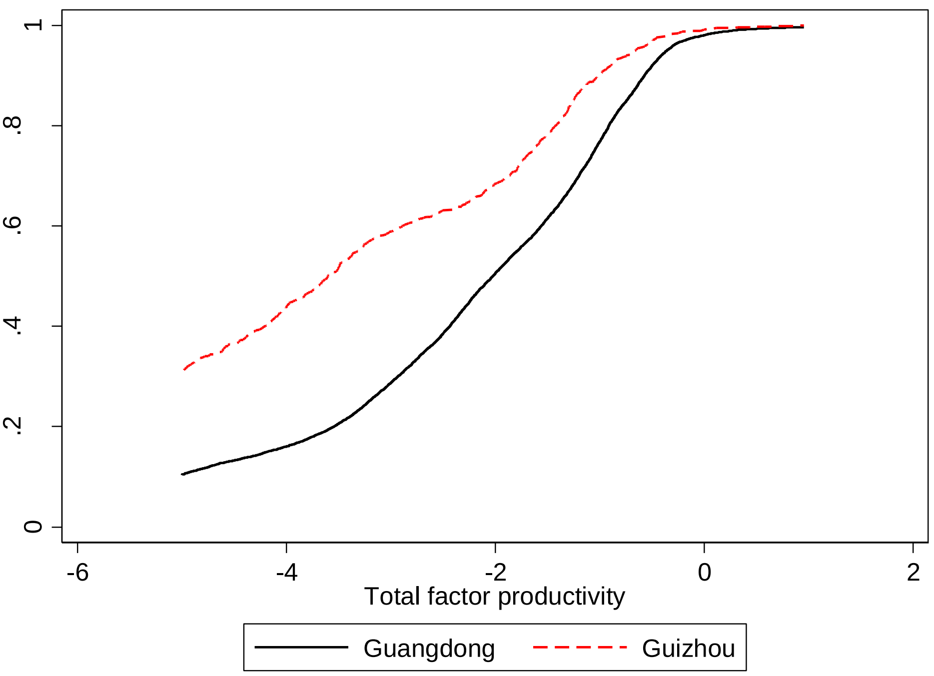


Figure 9: Empirical cumulative TFP distributions for firms based in Guangdong and Guizhou in 2007

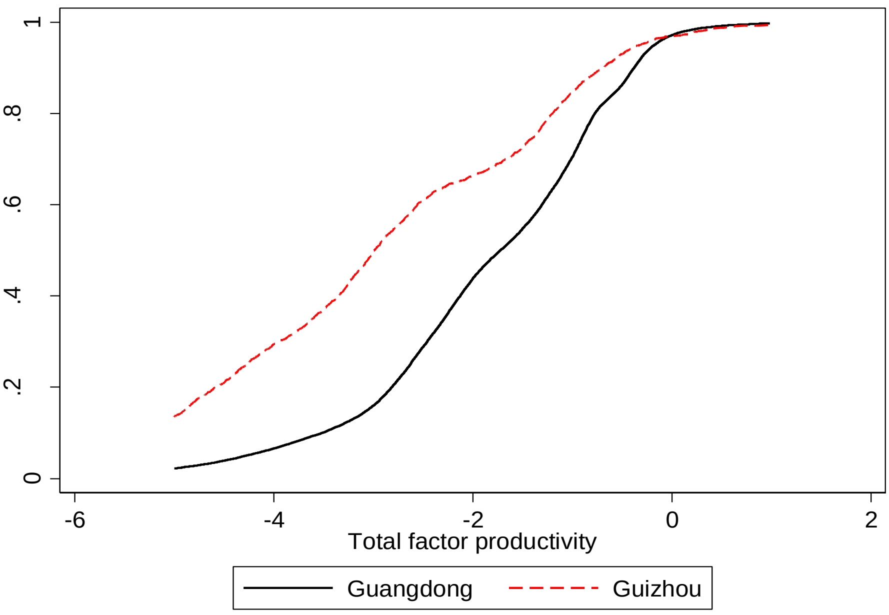



Figure 10: Empirical cumulative TFP distributions for firms based in Guangdong and Yunnan in 1998

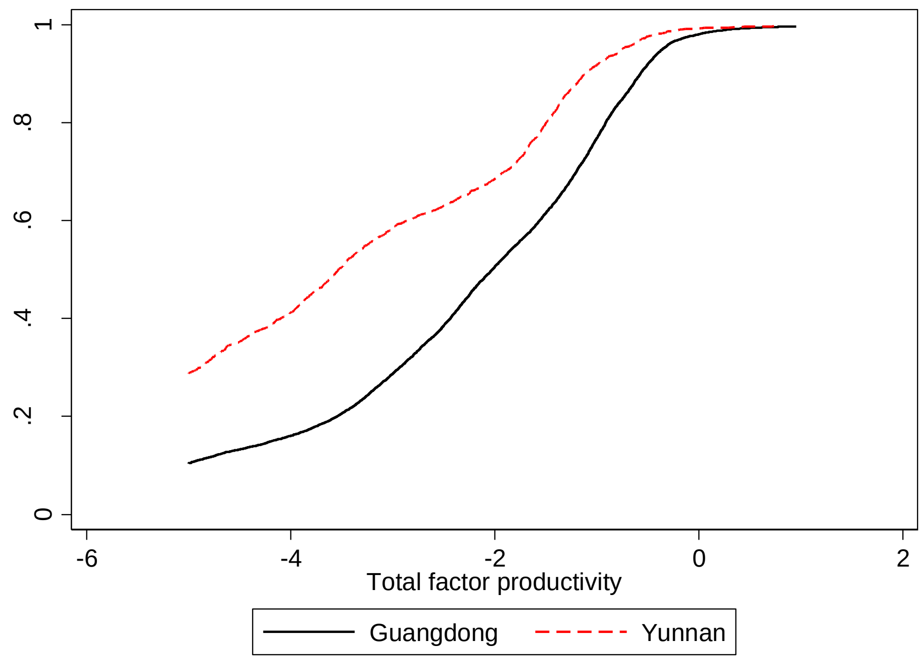


Figure 11: Empirical cumulative TFP distributions for firms based in Guangdong and Yunnan in 2007

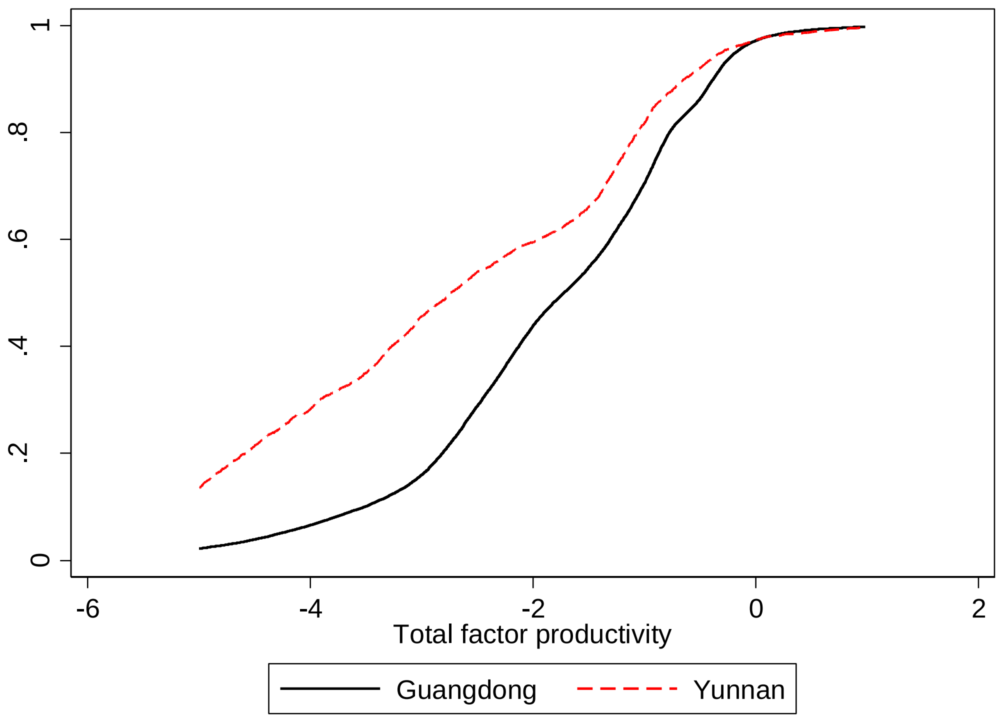



Figure 12: Empirical cumulative TFP distributions for firms belonging to the Other Manufacturing and Leather industries in 1998

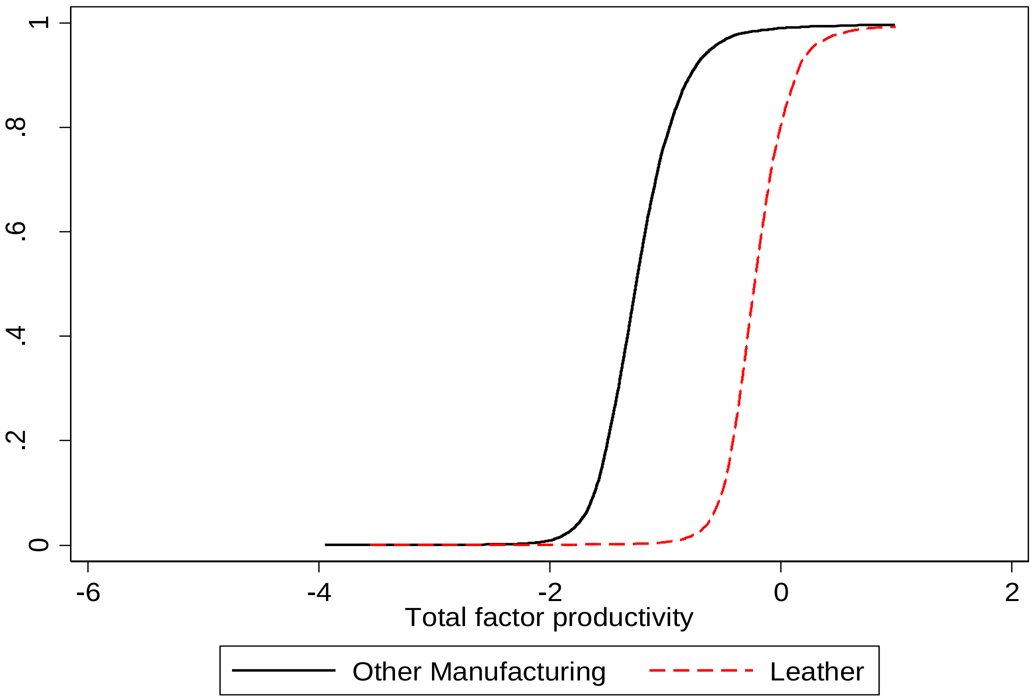


Figure 13: Empirical cumulative TFP distributions for firms belonging to the Other Manufacturing and Leather industries in 2007

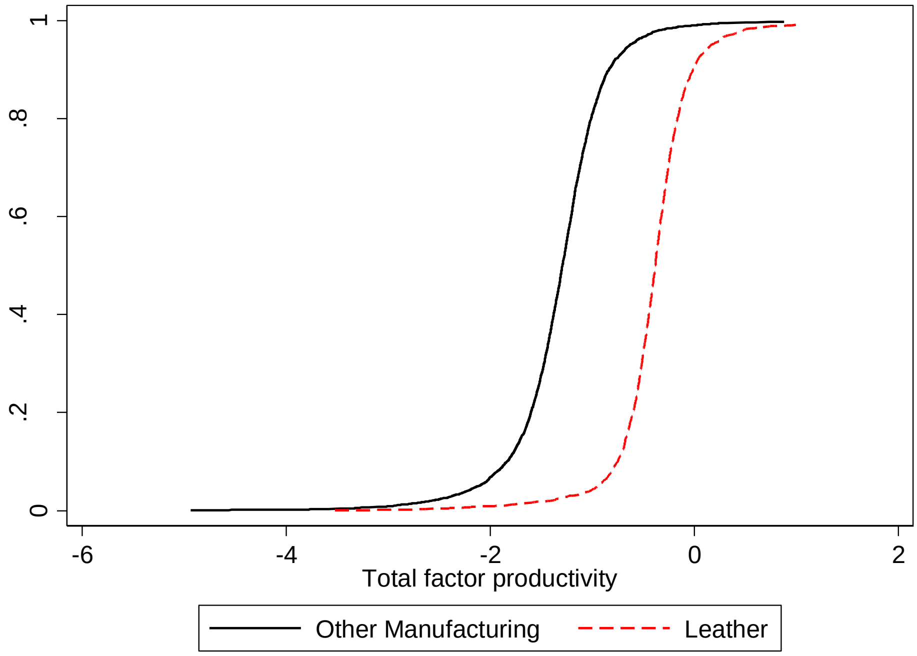



Figure 14: Empirical cumulative TFP distributions for firms belonging to the Other Manufacturing and Apparel & Footwear industries in 1998

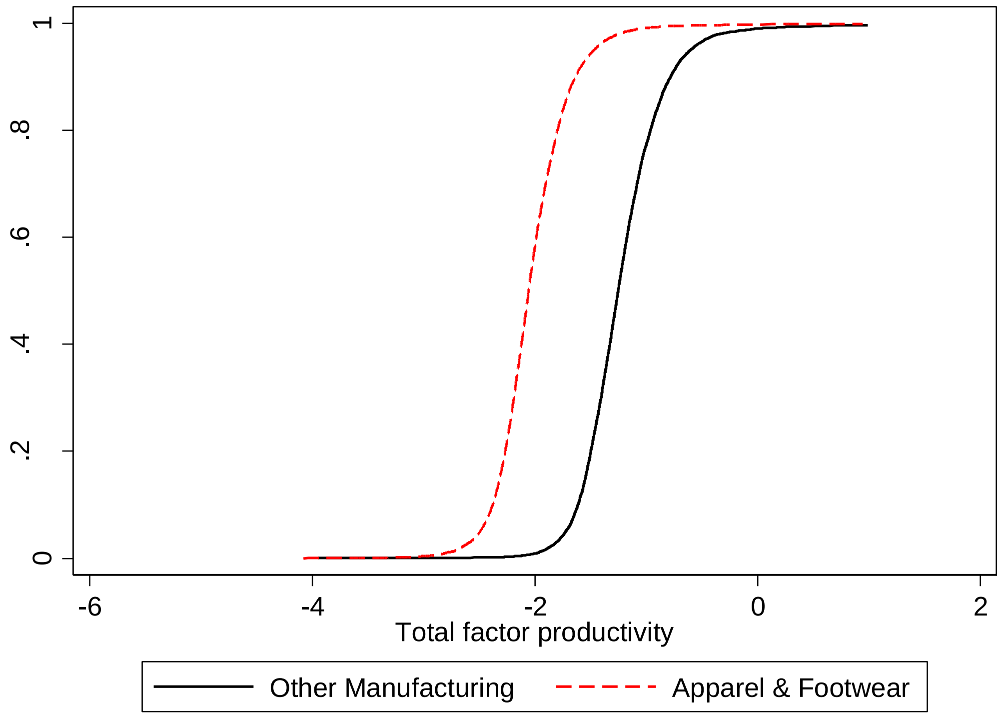
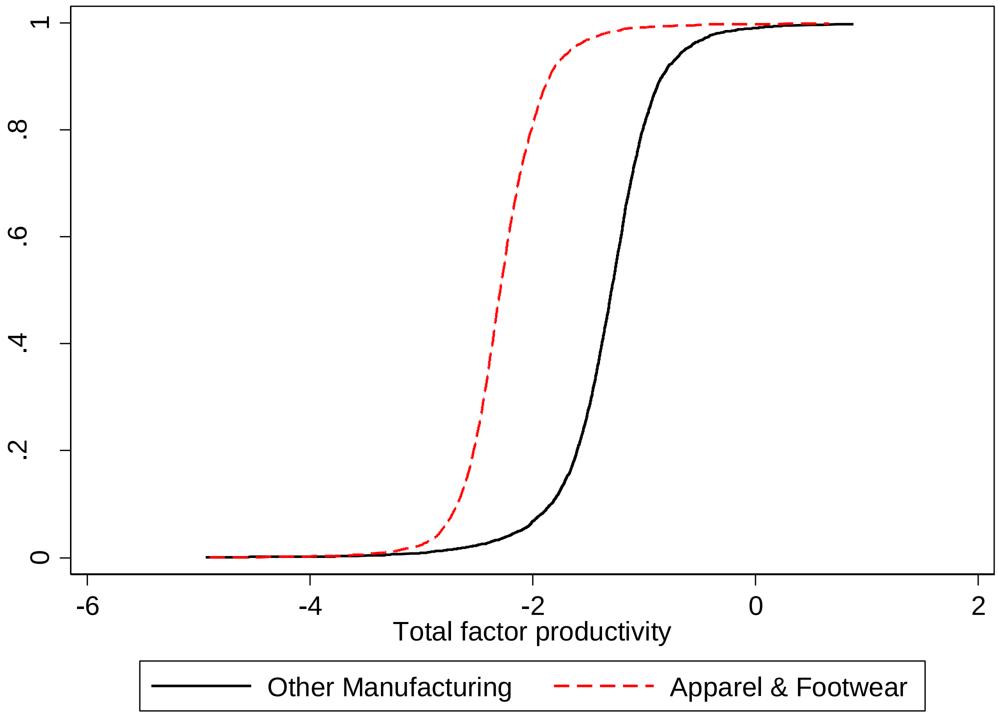


Figure 15: Empirical cumulative TFP distributions for firms belonging to the Other Manufacturing and Apparel & Footwear industries in 2007



## 4. An Analysis of the Determinants of TFP Growth

Chapter 3 analysed the determinants of TFP levels across Chinese firms during the period of 1998-2007. This chapter analyses the determinants of TFP growth during the same period. A decomposition of TFP growth can provide policymakers with an understanding of the underlying determinants. Policy measures targeting them would spur TFP growth and consequently drive national economic growth.

The decomposition of TFP growth is performed in Section 4.1 using the Haltiwanger (1997) approach, which breaks down aggregate TFP growth into the contributions provided by the following: firms becoming more productive over time, the reallocation of resources through contraction and expansion of output shares between firms characterized by different TFP levels, the entrance of relatively high productive firms, and the exit of relatively low productive firms. In order to gain an additional understanding of the determinants of TFP growth, the decomposition is also performed at the industry, province and political affiliation/ownership levels.

Melitz and Polanec (2012) have found that the Haltiwanger (1997) decomposition methodology generates biases in the measurement of the contribution to TFP growth from entering and exiting firms. Thus, their methodology is also adopted in Section 4.2 in order to check which set of results is the most appropriate.

### 4.1. Haltiwanger's (1997) Decomposition

In this study, a decomposition of aggregate TFP growth is applied using following the methodology of Haltiwanger (1997), which represents a modified version of Baily et al.'s (1992) approach. In this section, the description of the methodology follows that of Haltiwanger (1997). Using the firm-level TFP estimates resulting from the application of SYS-GMM, an industry index of aggregate productivity in year $t$ is determined as a weighted average of individual firm-level productivity:

$$\ln P_t = \sum_i \theta_{it} \ln P_{it} \tag{58}$$

Its growth rate between year $t$ and $t-k$ is then calculated as follows:

$$\Delta \ln P_t = \ln P_t - \ln P_{t-k} \tag{59}$$

In (58), $\theta_{it}$ represents the share of gross output for firm $i$ in period $t$ in its industry (using 1998 prices), while $P_{it}$ represents TFP for firm $i$ in period $t$.

In general, the Haltiwanger (1997) decomposition approach disentangles TFP growth into the contributions provided by the following: firms that continue to operate between time $t$ and $t-k$; firms that enter into their related industry at time $t$; and firms that exit from their related industries at time $t-k$.

The productivity growth between time $t$ and $t-k$, expressed in (59) as $\Delta \ln P_t$, can be further decomposed into the following terms:

$$\sum \theta_{it-k} \Delta \ln P_{it} + \sum (\ln P_{it-k} - \ln P_{t-k}) \Delta\theta_{it} + \sum \Delta \ln P_{it} \Delta\theta_{it} + \sum \theta_{it} (\ln P_{it} - \ln P_{t-k}) - \sum \theta_{it-k} (\ln P_{it-k} - \ln P_{t-k}) \tag{60}$$

The first term represents the impact on TFP of the resource reallocation within firms operating both at times $t$ and $t-k$, according to their initial shares of output in their related industries. The second term represents a between-firm component indicating a change in output share, weighted by the deviation of the firm's initial productivity from the initial industry index. The third term represents the covariance effect, which measures whether a firm's increasing productivity corresponds to an increasing market share. The fourth term describes the contribution of entrant firms to their related industry's TFP growth, measured with respect to the initial industry index. The fifth term measures the contribution of exiting firms to their related industry's TFP, measured with respect to the initial industry index.

The between-firm, the entry and exit components are expressed in terms of their deviation from the overall industry productivity index $\ln P_{t-k}$. Therefore, the second term suggests that an existing firm contributes positively to the between-firm productivity component only if its productivity is higher than the initial industry average aggregate productivity. The fourth term suggests that an entering firm contributes positively to the entry component only if it has a higher productivity than the initial industry average aggregate productivity. The fifth term suggests that an exiting firm contributes positively to the exit component only if it has lower productivity than the initial industry average aggregate productivity. If exiting firms record a lower productivity than the initial industry average, the fifth term is expected to be negative. In (60), the fifth term takes a negative sign in order for it to contribute positively to TFP growth.

One issue that may arise in the TFP growth decompositions is selection bias. In this study, “entering” not only refers to a firm joining its respective industry but can also mean becoming large enough to be part of the NBS sample. At the same time, “exiting” not only refers to a firm leaving the industry, but can also indicate that a firm becomes too small to be part of the NBS sample. While one might conclude that the exclusion of small firms could generate a selection bias, the empirical results in the literature suggest that most firms that decline and become small in size usually close (Baldwin and Gorecki, 1991; Bernard and Jensen, 2002; Disney et al., 2003; Dunne et al., 1998). Moreover, by adopting the full census of firms carried out for China in 2004, Brandt et al. (2012) found that the firms omitted from the National Bureau of Statistics sample (80% of total) only accounted for about 9.9% of output and 2.5% of exports in 2004. This indicates that even if firms that become small do not close, their importance is minimal, suggesting that such exclusion is not likely to have a significant impact on the results of the TFP growth decompositions, thus not generating a selection bias.

In summary, the Haltiwanger (1997) approach disentangles TFP growth into within-firm increases, between-firm increases[5] and the contribution provided by entering and exiting firms. It therefore provides a complete overview of what drives TFP growth within the Chinese industrial sector. Moreover, in order to gain an additional understanding of the determinants of TFP growth, the decomposition is also performed at the industry, province and political affiliation/ownership levels. The Haltiwanger approach is a more informative measure, as it allows for output reallocation across sub-groups. It must be stressed that when a large number of sub-groups are considered, or when these have different shares in the total aggregate output, the results can be difficult to interpret. This is because the results are determined by the importance of each group (e.g. industry) within the economy, which is measured in terms of its share of total output, in addition to what is happening to TFP within each group. Therefore, in order to better interpret the Haltiwanger (1997) approach results, the figures from the decomposition are weighted to take into account the relative size of each group.[6] A standard TFP index for each sub group is also produced.

[5] The between-firm and cross-firm effects obtained through the Haltiwanger (1997) approach are combined into a unique ‘between firm’ effect. Although the separate information provided by each component is relevant, the main focus in this study is the change in annual TFP growth within firms, between firms, or through entry and exit.

[6] When results are produced for all industries or all provinces, the weighted and actual figures are the same. When firms are then sub-divided into single industries or single provinces, the results differ since there are differences in the relative size of each sub-group within the whole economy.

Although the Haltiwanger (1997) approach is a valuable methodology for decomposing TFP growth, Melitz and Polanec (2012) found that it generates biases in the measurement of the contribution to TFP growth from entering and exiting firms. By decomposing TFP growth for a sample of Slovenian firms for the years 1995-2000, they compared the Haltiwanger (1997) approach with other methodologies, and argue that it suffers from an over-measurement of the contribution of entering and exiting firms to TFP growth. They also compared their own TFP decomposition methodology, which represents an extension of that developed by Olley and Pakes (1996), with those of Griliches and Regev (1995) and Foster et al. (2001), who adopt the Haltiwanger (1997) approach. Melitz and Polanec's (2012) results show a large positive contribution of entering firms when the Griliches and Regev (1995) and Foster et al. (2001) methodologies are adopted, an effect that increases over the sample period. Their decomposition, in contrast, indicates that entry provides an almost null contribution to aggregate productivity growth, as entering firms have, on average, nearly the same TFP level as existing firms for each time period. These results highlight that the TFP dynamic decomposition developed by Melitz and Polanec (2012) provides a more suitable measure than Haltiwanger's (1997) because it utilises different TFP reference levels to measure the contribution of surviving, entering and exiting firms to aggregate TFP, thus eliminating the measurement biases that characterise the Griliches and Regev (1995) and Foster et al. (2001) methodologies. In order to confirm this finding, and to verify which set of results is the most appropriate, the Melitz and Polanec (2012) decomposition methodology is also adopted.

### 4.1.1. Results of the Haltiwanger (1997) Decomposition

Table 8: Firm-level TFP Growth (average % p.a.) in Chinese Industrial Sector (1998-2007)

| | *China* |
|---|---|
| *Haltiwanger Approach* | SYS-GMM |
| Actual TFP Growth | 9.68 |
| | |
| Decomposition of TFP Growth | |
| Within Firm | 2.13 |
| Between Firm | 2.42 |
| Entering Firms | 7.03 |
| Exiting Firms | -1.90 |
| | |
| TFP Index | |
| 1998 | 1.00 |
| 2007 | 2.39 |

The second and third terms of equation (60) have been combined into the "between" component of TFP growth.

Table 8 reports the main results from the decomposition of TFP growth for the Chinese industrial sector according to the Haltiwanger (1997) approach. The annual average TFP growth recorded between 1998 and 2007 by Chinese firms is 9.68%. The figures suggest that this growth is mainly due to the entrance of new firms having higher TFP than existing ones, with the former contributing 7.03% to the aggregate annual average TFP growth. This finding is in line with the results of Brandt et al. (2012), who found that the net entry of firms accounts for more than two-thirds of annual average growth in TFP. The exit of more productive firms contributes negatively to the overall figure, with -1.9%. Moreover, the contribution to the overall annual average TFP growth resulting from existing firms becoming more productive over time is just 2.13%. There is also a small positive contribution of 2.42% to the aggregate TFP growth resulting from the between-firm effect, or the reallocation of resources through the contraction and expansion of output shares between firms characterized by different productivity levels. The TFP index for the whole sample increases from 1.00 in 1998 to 2.39 to 2007.

The approach used to decompose the aggregate annual average TFP growth can also be used to measure the contributions from related sub-groups according to industry, province and political affiliation/ownership levels. These groups can be also decomposed, hence indicating the impact of intra- and inter-resource reallocations, and the impact of firms' entry and exit from their industries.

### 4.1.2. Results for Industry, Province and Political Affiliation/Ownership Decompositions

Table 9: Firm-level TFP Growth (average per annum) in Industry Sub-sectors, 1998-2007, China

| | TFP Growth (% p.a.) | | Decomposition of Weighted TFP Growth | | | | Output Share (%) | |
|---|---|---|---|---|---|---|---|---|
| | | | Within | Between | Entering | Exiting | | |
| | Actual | Weighted | Firm | Firm | Firms | Firms | 1998 | 2007 |
| *Sector* | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Water Production | 0.24 | 45.05 | 2.86 | 26.89 | -7.09 | 22.39 | 0.53 | 0.24 |
| Petroleum Processing | 2.56 | 26.22 | 3.93 | 18.70 | -4.00 | 7.59 | 9.77 | 3.39 |
| Machinery & Equipment | 1.08 | 15.82 | 4.23 | 1.42 | 9.09 | 1.08 | 6.84 | 11.52 |
| Nonmetal Products | 0.81 | 15.34 | 4.01 | 2.66 | -2.94 | 11.61 | 5.30 | 5.18 |
| Metal Products | 2.03 | 14.32 | 1.85 | 2.37 | 16.68 | -6.57 | 14.16 | 18.29 |
| Transport Equipment | 0.94 | 13.92 | 4.51 | 0.66 | 9.65 | -0.90 | 6.75 | 9.02 |
| Other Mining | 0.20 | 13.41 | 5.01 | 1.61 | 1.28 | 5.50 | 1.50 | 1.78 |
| Gas Production | 0.04 | 13.21 | 1.99 | 0.21 | 13.31 | -2.31 | 0.31 | 0.31 |
| Electric power and heating | 1.02 | 12.65 | 6.77 | 5.00 | -9.93 | 10.80 | 8.09 | 6.75 |
| Medical | 0.28 | 12.20 | 2.64 | 4.98 | -5.92 | 10.51 | 2.33 | 1.83 |
| Measuring instrument | 0.50 | 11.30 | 1.39 | 1.54 | 11.42 | -3.06 | 4.41 | 7.30 |
| Food Production | 0.14 | 8.06 | 1.95 | -1.60 | 14.06 | -6.34 | 1.75 | 1.83 |
| Coal Mining | 0.21 | 7.89 | 3.34 | 0.71 | 2.89 | 0.95 | 2.62 | 2.31 |
| Tobacco | 0.18 | 7.24 | 3.06 | 0.35 | -0.57 | 4.41 | 2.45 | 1.16 |
| Furniture | 0.03 | 5.98 | 0.40 | -0.07 | 6.12 | -0.47 | 0.47 | 0.74 |
| Timber | 0.04 | 5.58 | 1.21 | 0.22 | 1.83 | 2.32 | 0.80 | 1.16 |
| Apparel & Footwear | 0.08 | 2.58 | 2.32 | -1.96 | 8.05 | -5.82 | 3.10 | 2.81 |
| Rubber | 0.02 | 1.86 | 1.39 | -0.09 | 6.70 | -6.14 | 1.30 | 1.12 |
| Papermaking | 0.01 | 0.29 | 0.04 | -1.43 | 14.90 | -13.21 | 2.10 | 1.96 |
| Chemical | -0.07 | -0.75 | -2.03 | -1.54 | 11.84 | -9.02 | 9.61 | 8.40 |
| Cultural | -0.01 | -1.01 | 2.44 | -5.80 | 9.22 | -6.87 | 0.88 | 0.66 |
| Plastic | -0.04 | -1.68 | -2.74 | -3.17 | 19.96 | -15.74 | 2.44 | 2.38 |
| Printing | -0.02 | -2.51 | 0.72 | -5.11 | 9.76 | -7.87 | 0.88 | 0.63 |
| Textile | -0.25 | -3.44 | -0.28 | -2.72 | 13.74 | -14.18 | 7.30 | 6.08 |
| Leather | -0.07 | -3.45 | -0.16 | -5.56 | 19.18 | -16.90 | 1.89 | 1.61 |
| Other manufacturing | -0.27 | -11.14 | -5.16 | -2.54 | 8.05 | -11.49 | 2.42 | 1.56 |
| *All Sectors* | 9.68 | 9.68 | 2.13 | 2.42 | 7.03 | -1.90 | 100.00 | 100.00 |

The second and third terms of equation (60) have been combined into the "between" component of TFP growth.

Table 9 reports the results for the industry-level decomposition of actual annual average growth in TFP according to the Haltiwanger (1997) approach. Column (1) reports the average percentage per annum TFP growth according to equation (60). However, these figures do not account for the differences in the relative size of each sub-group, measured in terms of the output shares indicated in columns (7) and (8), which correspond to 1998 and 2007, respectively. In column (2), the values from column (1) are weighted by the base year output shares shown in column (7). Columns (3), (4), (5) and (6) represent the decomposition of the annual weighted average TFP growth, with the rows summing to make the numbers in column (2).

In terms of absolute annual average TFP growth, as represented by the actual figures in column (1), the highest growth is recorded by the petroleum processing, metal products and machinery & equipment industries, while the lowest growth is recorded by the other manufacturing, textile and chemical industries. The figures in column (2) take into account the relative size of each sector in the base year. Here, the water production industry records the strongest annual weighted average TFP growth, followed by the petroleum processing and machinery & equipment industries. The lowest annual weighted average TFP growth is recorded by the other manufacturing, leather and textile industries.

In terms of the TFP growth decomposition, the figures in columns (3), (4), (5) and (6) show that the highest performing industries are characterised by a strong effect from the entry of new firms, which is the case for the machinery & equipment, metal products and transport equipment industries. The high performing industries also show a strong effect from the exit of firms, which is the case for the water production, petroleum processing and non-metal products industries. The worst performing industries are characterized by a strong effect from both the entry and exit of more productive firms, as is the case in the other manufacturing, leather and textile industries.

Table 10: Firm-level TFP Growth (average per annum) in Provinces, 1998-2007, China

| | TFP Growth (% p.a.) | | Decomposition of Weighted TFP Growth | | | | Output Share (%) | |
|---|---|---|---|---|---|---|---|---|
| | Actual | Weighted | Within Firm | Between Firm | Entering Firms | Exiting Firms | 1998 | 2007 |
| *Province* | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Jiangxi | 0.32 | 26.46 | 5.50 | 2.30 | 16.79 | 1.87 | 1.22 | 1.99 |
| Inner Mongolia | 0.20 | 23.13 | 5.33 | -0.37 | 16.98 | 1.18 | 0.84 | 1.54 |
| Xinjiang | 0.27 | 20.21 | 3.95 | 15.40 | -0.98 | 1.84 | 1.33 | -0.06 |
| Heilongjiang | 0.65 | 19.63 | -7.32 | 25.61 | 0.27 | 1.07 | 3.33 | 0.91 |
| Shandong | 1.57 | 17.76 | 3.90 | 2.85 | 10.60 | 0.42 | 8.83 | 12.59 |
| Qinghai | 0.04 | 17.68 | 2.03 | 1.85 | -1.37 | 15.17 | 0.25 | 2.37 |
| Gansu | 0.15 | 15.30 | 3.94 | 4.78 | 0.53 | 6.05 | 0.99 | 0.78 |
| Hunan | 0.25 | 14.33 | 1.99 | 1.47 | 10.86 | 0.01 | 1.75 | 1.88 |
| Chongqing | 0.16 | 12.82 | 2.19 | -0.02 | 6.85 | 3.80 | 1.23 | 1.16 |
| Liaoning | 0.66 | 12.44 | 4.30 | 5.00 | 3.49 | -0.35 | 5.34 | 4.40 |
| Sichuan | 0.31 | 12.41 | 3.43 | 3.69 | 6.07 | -0.78 | 2.49 | 2.37 |
| Anhui | 0.27 | 12.38 | 4.63 | 4.83 | 5.14 | -2.22 | 2.22 | 2.08 |
| Beijing | 0.28 | 10.67 | 3.89 | 2.60 | 5.43 | -1.25 | 2.59 | 3.14 |
| Henan | 0.51 | 10.63 | 2.55 | 4.14 | 6.18 | -2.24 | 4.76 | 4.99 |
| Hebei | 0.51 | 10.38 | 1.73 | 4.87 | 6.75 | -2.98 | 4.92 | 4.70 |
| Zhejiang | 0.67 | 10.14 | 0.84 | 0.37 | 14.93 | -6.00 | 6.60 | 9.09 |
| Shanxi | 0.17 | 9.65 | 2.69 | 2.32 | 2.32 | 2.32 | 1.72 | 1.93 |
| Yunnan | 0.18 | 9.56 | 1.69 | 0.43 | 3.45 | 3.98 | 1.86 | 1.16 |
| Jilin | 0.18 | 9.48 | 3.79 | -0.35 | 2.94 | 3.10 | 1.90 | 1.31 |
| Guangxi | 0.12 | 9.45 | 3.46 | 0.90 | 5.48 | -0.40 | 1.26 | 1.09 |
| Shaanxi | 0.10 | 9.25 | 3.55 | 4.26 | 0.18 | 1.26 | 1.11 | 1.09 |
| Fujian | 0.21 | 8.14 | 1.66 | -0.84 | 10.57 | -3.25 | 2.64 | 3.17 |
| Ningxia | 0.03 | 7.82 | 0.22 | 0.16 | 4.16 | 3.29 | 0.36 | 0.31 |
| Hainan | 0.02 | 7.39 | 3.58 | -4.60 | 7.25 | 1.16 | 0.24 | 0.22 |
| Jiangsu | 0.85 | 7.02 | 1.76 | 0.58 | 10.16 | -5.48 | 12.15 | 13.25 |
| Tianjin | 0.21 | 6.89 | 2.85 | 2.96 | 6.00 | -4.92 | 3.00 | 2.50 |
| Guizhou | 0.05 | 6.88 | 3.53 | -0.67 | 1.96 | 2.05 | 0.71 | 0.56 |
| Hubei | 0.17 | 4.61 | 1.44 | 3.02 | 3.83 | -3.68 | 3.60 | 2.43 |
| Shanghai | 0.24 | 2.88 | 2.64 | -2.16 | 6.14 | -3.74 | 8.19 | 6.72 |
| Guangdong | 0.35 | 2.79 | 0.85 | -1.09 | 5.27 | -2.24 | 12.68 | 11.96 |
| *All Provinces* | 9.69 | 9.68 | 2.13 | 2.42 | 7.03 | -1.90 | 100.00 | 100.00 |

The second and third terms of equation (60) have been combined into the "between" component of TFP growth.

Table 10 reports the Haltiwanger (1997) sub-decomposition of annual average TFP growth for Chinese provinces. As represented in column (1), the highest actual TFP growths are recorded by Shandong, Jiangsu and Liaoning, while Hainan, Ningxia and Qinghai record the lowest growth. The figures in column (2) take into account the relative size of each province in the base year. In this case, the provinces of Jiangxi, Inner Mongolia and Xinjiang provinces record the highest annual weighted average TFP growth, while the provinces of Guangdong, Shanghai and Hubei record the lowest annual weighted average TFP growth. The fact that Western provinces such as Inner Mongolia and Xinjiang record high TFP growth while coastal provinces such as Shanghai and Guangdong record low TFP growth might reflect a "catch up" effect of less developed provinces with more developed ones, which are typically located on the coast.

In terms of the TFP growth decomposition, the figures in columns (3), (4), (5) and (6) indicate that provinces with high TFP growth show a strong effect of firms' entry, such as in Jiangxi, Inner Mongolia and Shandong, and a strong between-firm effect, such as in Xinjiang and Heilongjiang. Provinces characterized by low TFP growth, such as Hubei, Shanghai and Guangdong, show a strong contribution from the effects of both firms' entry and exit.

Table 11: Firm-level TFP Growth (average per annum) by Group 1998-2007, China

| | TFP Growth (% p.a.) | | Decomposition of Weighted TFP Growth | | | | Output Share (%) | |
|---|---|---|---|---|---|---|---|---|
| | | | Within | Between | Entering | Exiting | | |
| | Actual | Weighted | Firm | Firm | Firms | Firms | 1998 | 2007 |
| *Group* | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| State<25%/No Politics | 5.86 | 50.39 | 2.33 | -0.12 | 52.69 | -4.51 | 11.62 | 54.33 |
| State<25%/High Politics | 1.97 | 18.46 | 7.62 | 10.37 | -2.00 | 2.47 | 10.67 | 11.78 |
| State>=50%/High Politics | 2.30 | 8.95 | 2.31 | 3.83 | -0.69 | 3.51 | 25.67 | 10.70 |
| State>=50%/No Politics | 0.07 | 8.48 | 0.27 | 1.63 | 6.86 | -0.28 | 0.82 | 0.63 |
| 25<State<50%/No Politics | 0.02 | 3.52 | 1.05 | -1.54 | 5.65 | -1.63 | 0.48 | 0.40 |
| State>=50%/Medium Politics | 0.20 | 1.26 | 0.97 | 0.86 | 0.19 | -0.75 | 15.80 | 3.66 |
| 25<State<50%/Medium Politics | 0.00 | 0.05 | 1.21 | 0.78 | 0.60 | -2.55 | 2.45 | 0.72 |
| 25<State<50%/High Politics | -0.02 | -1.21 | 1.94 | 2.13 | -2.55 | -2.74 | 1.29 | 0.74 |
| State<25%/Medium Politics | -0.71 | -2.28 | 0.78 | 0.50 | 3.85 | -7.41 | 31.21 | 17.04 |
| *All Groups* | 9.68 | 9.68 | 2.13 | 2.42 | 7.03 | -1.90 | 100.00 | 100.00 |

The second and third terms of equation (60) have been combined into the "between" component of TFP growth.

Table 11 reports the Haltiwanger (1997) decomposition of annual average TFP growth for groups of firms according to their political affiliation and State share ownership of paid-in capital. In terms of absolute annual average TFP growth, as represented in column (1), the highest is recorded by non-politically affiliated firms whose paid-in capital State share ownership is lower than 25%, while firms having medium political affiliation and whose paid-in capital State share ownership is smaller than 25% record the lowest annual average TFP growth. The figures in column (2) take into account the relative size of each group during the base year. Of these, non-politically affiliated firms whose paid-in capital State share ownership is lower than 25% record the highest annual weighted average TFP growth, while medium politically affiliated firms whose paid-in capital State share ownership is below 25% record the lowest weighted annual average TFP growth per annum. These figures indicate that Chinese industrial firms benefit in terms of high TFP growth from a lack of government influence in terms of both political affiliation and paid-in capital share ownership.

In terms of TFP growth decomposition, the figures in columns (3), (4), (5) and (6) indicate that the entry of new firms underlies the strong TFP growth recorded by non-politically affiliated firms whose paid-in capital State share ownership is less than 25%. At the same time, there is a strong negative effect on TFP growth of the exit of firms that are more productive than the existing average for medium and highly politically affiliated firms whose paid-in capital State share ownership is less than 50%.

In summary, the results from using the Haltiwanger (1997) approach show an annual average TFP growth of 9.68% during the period of 1998-2007 for the Chinese firms in the sample. The figures suggest that this growth is mainly due to the entrance of new firms having a relatively high TFP, with these firms contributing 7.03% to the overall annual average TFP growth. The contributions of the other components are mild: -1.9% due to the exit of more productive firms; 2.13% contribution from TFP improvements within existing firms; and 2.42% resulting from the between-firm effect, which represents the reallocation of resources through the contraction and expansion of output shares between firms characterized by different productivity levels. The TFP index for the entire sample increases from 1.00 in 1998 to 2.39 to 2007. These results suggest that policy measures favouring the entrance of new, dynamic and innovative firms would be conducive to TFP growth within the Chinese industrial sector. Among industries, water production records the strongest annual weighted average TFP growth, while the other manufacturing industry records the lowest annual weighted average TFP growth.

Among provinces, Jiangxi, Inner Mongolia and Xinjiang record the highest annual weighted average TFP growth, while Guangdong, Shanghai and Hubei record the lowest TFP growth. Such results suggest the existence of a “catch-up” effect of less developed Western provinces to the highly developed Eastern ones.

Firms that are not politically affiliated and whose State paid-in capital share ownership is below 25% record the highest annual weighted average TFP growth, while medium politically affiliated firms whose State paid-in capital ownership is less than 25% record the lowest TFP growth. These results indicate that policy measures aimed at decreasing the role of the State in the Chinese industrial sector, both in terms of political affiliation and paid-in capital share ownership, are conducive to higher TFP growth.

This section has introduced the Haltiwanger (1997) approach for decomposing TFP growth and discussed the results based on its application in the Chinese industrial sector. The next section introduces the Melitz and Polanec (2012) approach and discusses the related results.

## 4.2. Melitz and Polanec (2012) Decomposition

This section describes the TFP decomposition methodology of Melitz and Polanec (2012). Firms' aggregate productivity is calculated as:

$$\Phi_t = \bar{\varphi}_t + \sum_i (s_{it} - \bar{s}_t)(\varphi_{it} - \bar{\varphi}_t) \tag{61}$$

Here, $\bar{\varphi}_t = \frac{1}{n_t}\sum_{i=1}^{n_t} \varphi_{it}$ is the unweighted firm productivity mean and $\bar{s}_t = \frac{1}{n_t}$ is the mean market share. Melitz and Polanec (2012) use the following Olley and Pakes (1996) decomposition:

$$\Delta\Phi = \Delta\bar{\varphi}_S + \Delta cov_S \tag{62}$$

In this case, the change in aggregate TFP is given by the sum of the change in weighted average TFP across firms and the covariance between firms' productivity and market share.

Equation (62) is subsequently decomposed into:

$$\begin{aligned} \Delta\Phi &= (\Phi_{S2} - \Phi_{S1}) + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{S1} - \Phi_{X1}) \\ &= \Delta\bar{\varphi}_S + \Delta cov_S + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{S1} - \Phi_{X1}) \end{aligned} \tag{63}$$

In the first line of equation (63), aggregate productivity growth is decomposed into the contribution provided by existing firms, entering firms and exiting firms. In the second line, the contribution of existing firms is further decomposed into the contribution provided by a shift in productivity, represented by the un-weighted mean growth in the productivity of existing firms $\Delta\bar{\varphi}_S$, and the contribution provided by market share $\Delta cov_S$ across existing firms. This represents the covariance between existing firms' market share and TFP.

The Haltiwanger (1997) approach adopts the same TFP reference level to measure the contributions to aggregate TFP growth provided by existing firms, entering firms, and exiting firms. The TFP reference level is represented by the aggregate TFP for the period $t = 1$, and is adopted because existing firms are tracked over time. In contrast, Melitz and Polanec (2012) adopt three different TFP reference levels for existing, entering, and exiting firms. In the case of existing firms, the TFP reference level is represented by their aggregate productivity at time $t = 1$. In the case of entering firms, it is the aggregate productivity of existing firms at time $t = 2$. In the case of exiting firms, it is the aggregate productivity of existing firms at time $t = 1$. Such TFP reference levels indicate that existing firms make a positive contribution to the aggregate figure if their productivity at time $t = 2$ is higher than at time $t = 1$. Entering firms make a positive contribution to the aggregate figure if their productivity when they enter at time $t = 2$ is higher than the productivity of existing firms. Exiting firms make a positive contribution to the aggregate figure if their productivity when they exit at time $t = 1$ is lower than the productivity of existing firms.

Based on a sample of Slovenian manufacturing firms operating during 1995-2000, Melitz and Polanec's (2012) results suggest that their decomposition approach, as well as those of Griliches and Regev (1995) and Foster et al. (2001), are characterised by almost the same contribution of existing, entering and exiting firms when a one-year sample interval is considered. However, the components' contributions seem to differ as the time interval is widened. The results indicate the existence of an over-measurement of the positive contribution of both entering and exiting firms to aggregate TFP when the Griliches and Regev (1995) and Foster et al. (2001) methodologies are adopted. Such contributions also seem to increase over time. This is because entering firms have almost the same productivity as existing ones in each year, hence lowering the TFP reference level in the Griliches and Regev (1995) and Foster et al. (2001) decomposition approaches, and increasing the entering firms' contribution over time. The TFP reference level in these decomposition approaches seems to be below $\Phi_{S2}$. At the same time, the TFP reference level for exiting firms seems to be above $\Phi_{S1}$, thus increasing the contribution of exiting firms to aggregate TFP growth.

The above discussion suggests the existence of an over-measurement of the contribution of entering and exiting firms when the Foster et al. (2001) decomposition, which follows the approach of Haltiwanger (1997), is adopted. Melitz and Polanec (2012) found that this corresponds to an under-measurement of 7-10% over five years of the contribution provided by existing firms. Among sub-components, this effect seems to be mainly attributable to the between-firm effect, or the reallocation of resources. According to the results of Melitz and Polanec's (2012) methodology, the contribution from the reallocation of resources is 5% over five years, or double that found using the Griliches and Regev (1995) and Foster et al. (2001) methodologies. Moreover, the results of Melitz and Polanec's (2012) TFP decomposition approach indicate that the contribution of entering firms to aggregate productivity is about zero and does not increase over time, thus suggesting the existence of an over-measurement issue in the other two methodologies particularly in the Foster et al. (2001) approach.

These results highlight that the TFP dynamic decomposition of Melitz and Polanec (2012) represents a more suitable measure than the one used by Haltiwanger (1997), as it utilises different TFP reference levels to measure the contribution of surviving, entering and exiting firms to aggregate TFP, thus eliminating measurement biases that characterise Haltiwanger's methodology. In order to confirm this, and to verify which set of results are the most appropriate, Melitz and Polanec's (2012) methodology is also adopted in this study and its results discussed in the following subsection.

### 4.2.1. Results of the Melitz and Polanec (2012) Decomposition.

Table 12: Firm-level TFP Growth (average % p.a.) in the Chinese Industrial Sector (1998-2007)

| | *China* |
|---|---|
| *Melitz and Polanec (2012) Approach* | SYS-GMM |
| Actual TFP Growth | 9.68 |
| | |
| Decomposition of TFP Growth | |
| Within Firm | 3.15 |
| Between Firm | 6.47 |
| Entering Firms | 3.51 |
| Exiting Firms | -3.45 |
| | |
| TFP Index | |
| 1998 | 1.00 |
| 2007 | 2.39 |

The second and third terms of equation (60) have been combined into the "between" component of TFP growth.

Table 12 reports the main results of the decomposition of productivity growth according to the Melitz and Polanec (2012) approach. The annual average TFP growth of Chinese firms recorded during the period of 1998-2007 is 9.68%. The figures indicate that such growth mainly results from the between-firm effect, which contributes 6.47% to the aggregate annual average TFP growth, a much larger contribution than the 2.42% seen in the results from the Haltiwanger decomposition. While in the results of the Haltiwanger decomposition approach, the entrance of new firms contributes 7.03% to the annual average TFP growth, this figure is just 3.15% with the Melitz and Polanec (2012) approach. This finding confirms the results of Melitz and Polanec (2012) and provides further evidence for the existence of an over-measurement issue of the “entering firms” component of TFP growth when the Haltiwanger (1997) decomposition methodology is adopted. Consistent with the -1.9% TFP growth obtained with the application of the Haltiwanger (1997) decomposition, the results suggest a productivity decrease due to the exit of more productive firms, although in this case, the effect is stronger, with a -3.45% contribution to the overall figure. Moreover, the contribution resulting from existing firms becoming more productive over time is just 3.15%, slightly larger than the 2.13% found with the Haltiwanger decomposition. As with the results from the application of the Haltiwanger approach, the TFP index for the entire sample increases from 1.00 in 1998 to 2.39 to 2007.

### 4.2.2. Results for Industry Sub-sectors, Provinces and Ownership/Political Affiliation

Table 13: Firm-level TFP Growth (average per annum) in Industry Sub-sectors, 1998-2007, China

| | TFP Growth (% p.a.) | | Decomposition of Weighted TFP Growth | | | | Output Share (%) | |
|---|---|---|---|---|---|---|---|---|
| | | | Within | Between | | | | |
| | Actual | Weighted | Firm | Firm | Enterers | Exitors | 1998 | 2007 |
| *Sector* | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Water Production | 0.38 | 71.90 | 23.38 | 35.25 | -7.98 | 21.25 | 0.53 | 0.24 |
| Petroleum Processing | 4.36 | 44.68 | 0.82 | 42.46 | -5.36 | 6.76 | 9.77 | 3.39 |
| Machinery & Equipment | 0.97 | 14.12 | 14.54 | -2.52 | 2.59 | -0.49 | 6.84 | 11.52 |
| Nonmetal Products | 0.91 | 17.21 | 20.03 | -5.34 | -7.09 | 9.61 | 5.30 | 5.18 |
| Metal Products | 1.67 | 11.78 | -2.71 | 9.92 | 12.73 | -8.15 | 14.16 | 18.29 |
| Transport Equipment | 0.84 | 12.48 | 5.33 | 3.90 | 5.39 | -2.13 | 6.75 | 9.02 |
| Other Mining | 0.22 | 14.37 | 15.59 | -1.39 | -3.47 | 3.64 | 1.50 | 1.78 |
| Gas Production | 0.04 | 12.52 | 8.22 | -0.67 | 9.09 | -4.12 | 0.31 | 0.31 |
| Electric power and heat power | 0.79 | 9.81 | 4.64 | 7.53 | -12.06 | 9.70 | 8.09 | 6.75 |
| Medical | 0.29 | 12.24 | 6.20 | 5.28 | -8.37 | 9.14 | 2.33 | 1.83 |
| Measuring instruments | 0.13 | 2.95 | 1.83 | 1.76 | 4.33 | -4.97 | 4.41 | 7.30 |
| Food Production | 0.12 | 6.94 | 5.83 | -0.53 | 9.75 | -8.11 | 1.75 | 1.83 |
| Coal Mining | 0.19 | 7.32 | 4.10 | 2.21 | 1.10 | -0.09 | 2.62 | 2.31 |
| Tobacco | 0.14 | 5.74 | 0.78 | 3.66 | -1.25 | 2.54 | 2.45 | 1.16 |
| Furniture | 0.00 | -0.24 | 4.94 | -0.64 | -1.99 | -2.55 | 0.47 | 0.74 |
| Timber | 0.00 | -0.55 | 7.18 | -2.01 | -5.70 | -0.01 | 0.80 | 1.16 |
| Apparel and Footwear | 0.10 | 3.35 | 8.51 | -2.04 | 4.52 | -7.64 | 3.10 | 2.81 |
| Rubber | 0.03 | 2.51 | 4.60 | 1.26 | 4.46 | -7.81 | 1.30 | 1.12 |
| Papermaking | 0.00 | 0.20 | -0.23 | 4.17 | 11.42 | -15.17 | 2.10 | 1.96 |
| Chemical | -0.39 | -4.07 | -0.56 | -1.62 | 8.72 | -10.62 | 9.61 | 8.40 |
| Cultural | 0.00 | -0.36 | 5.97 | -4.48 | 6.44 | -8.29 | 0.88 | 0.66 |
| Plastic | -0.12 | -4.84 | -12.00 | 8.68 | 16.05 | -17.57 | 2.44 | 2.38 |
| Printing | 0.00 | -0.29 | 4.13 | -2.25 | 7.19 | -9.36 | 0.88 | 0.63 |
| Textile | -0.48 | -6.52 | -0.98 | 0.23 | 10.45 | -16.22 | 7.30 | 6.08 |
| Leather | -0.13 | -6.64 | -1.07 | -2.49 | 15.67 | -18.75 | 1.89 | 1.61 |
| Other manufacturing | -0.38 | -15.68 | -9.29 | 0.72 | 6.08 | -13.19 | 2.42 | 1.56 |
| *All Sectors* | 9.68 | 9.68 | 3.15 | 6.47 | 3.51 | -3.45 | 100.00 | 100.00 |

The second and third terms of equation (60) have been combined into the "between" component of TFP growth.

The results from the industry sub-decomposition represented in Table 13 suggest that, in terms of actual annual average TFP growth, as represented by the figures in column (1), the highest growth is seen for the petroleum processing, metal products, and machinery & equipment industries, while the lowest growth is seen for the other manufacturing, chemical and textile industries. These results are similar to those obtained from the Haltiwanger (1997) decomposition. When the relative size of each industry during the base year is taken into account, resulting in the figures in column (2), the water production, petroleum processing and non-metal products industries record the highest annual weighted average TFP growth, while the textile, leather and other manufacturing industries record the lowest performance. These results are similar to those obtained from the Haltiwanger (1997) decomposition.

Looking at the figures in columns (3), (4), (5), (6), which are decomposed for each industry, the industries that have experienced rapid TFP growth are characterized by a strong impact of the within-firm effect, including the water production, non-metal products and other mining industries. These also show a strong impact of the between-firm effect, such as in the water production and petroleum processing industries. On the other hand, the industries recording the lowest growth see a strong impact of the exit of more productive firms and the entrance of new ones. This is the case for the other manufacturing, leather and textile industries.

Table 14: Firm-level TFP Growth (average per annum) in Provinces, 1998-2007, China

| | TFP Growth (% p.a.) | | Decomposition of Weighted TFP Growth | | | | Output Share (%) | |
|---|---|---|---|---|---|---|---|---|
| | Actual | Weighted | Within Firm | Between Firm | Enterers | Exitors | 1998 | 2007 |
| *Province* | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Jiangxi | 0.27 | 22.16 | 6.88 | 4.31 | 10.71 | 0.26 | 1.22 | 1.99 |
| Inner Mongolia | 0.16 | 18.95 | 7.35 | 3.37 | 8.39 | -0.16 | 0.84 | 1.54 |
| Xinjiang | 0.47 | 35.85 | 2.04 | 36.10 | -2.97 | 0.67 | 1.33 | 0.59 |
| Heilongjiang | 1.20 | 36.11 | 1.45 | 34.98 | -0.55 | 0.23 | 3.33 | 0.91 |
| Shandong | 1.47 | 16.66 | 4.22 | 7.76 | 5.81 | -1.13 | 8.83 | 12.59 |
| Qinghai | 0.03 | 13.28 | 1.60 | 3.17 | -4.45 | 12.96 | 0.25 | 0.20 |
| Gansu | 0.16 | 15.80 | 4.03 | 8.35 | -0.71 | 4.13 | 0.99 | 0.78 |
| Hunan | 0.22 | 12.64 | 7.62 | 1.05 | 6.17 | -2.20 | 1.75 | 1.88 |
| Chongqing | 0.14 | 11.10 | 4.09 | 1.67 | 3.38 | 1.96 | 1.23 | 1.16 |
| Liaoning | 0.90 | 16.95 | 3.00 | 15.22 | 0.39 | -1.66 | 5.34 | 4.40 |
| Sichuan | 0.33 | 13.20 | 8.27 | 4.27 | 2.96 | -2.31 | 2.49 | 2.37 |
| Anhui | 0.36 | 16.42 | 3.12 | 14.92 | 2.07 | -3.69 | 2.22 | 2.08 |
| Beijing | 0.20 | 7.69 | 1.58 | 6.47 | 2.16 | -2.52 | 2.59 | 3.14 |
| Henan | 0.48 | 10.12 | 5.84 | 4.65 | 3.31 | -3.68 | 4.76 | 4.99 |
| Hebei | 0.51 | 10.31 | 2.90 | 8.26 | 3.71 | -4.56 | 4.92 | 4.70 |
| Zhejiang | 0.52 | 7.86 | 1.82 | 4.43 | 9.41 | -7.81 | 6.60 | 9.09 |
| Shaanxi | 0.10 | 9.14 | 4.57 | 7.33 | -2.61 | -0.15 | 1.11 | 1.09 |
| Yunnan | 0.19 | 10.41 | 3.85 | 2.19 | 1.81 | 2.56 | 1.86 | 1.16 |
| Jilin | 0.19 | 10.02 | 3.09 | 4.27 | 0.87 | 1.79 | 1.90 | 1.31 |
| Guangxi | 0.13 | 9.94 | 7.04 | 2.65 | 2.49 | -2.23 | 1.26 | 1.09 |
| Shanxi | 0.12 | 6.88 | 3.13 | 3.43 | -0.59 | 0.91 | 1.72 | 1.93 |
| Fujian | 0.16 | 6.19 | 1.33 | 3.23 | 6.15 | -4.53 | 2.64 | 3.17 |
| Ningxia | -0.003 | -0.84 | 2.04 | -5.28 | 1.15 | 1.24 | 0.36 | 0.31 |
| Hainan | 0.01 | 4.92 | 4.23 | -1.95 | 2.84 | -0.19 | 0.24 | 0.22 |
| Jiangsu | 0.81 | 6.76 | 3.50 | 3.99 | 6.36 | -7.09 | 12.05 | 13.15 |
| Tianjin | 0.27 | 9.14 | 2.34 | 10.02 | 3.14 | -6.37 | 3.00 | 2.50 |
| Guizhou | 0.06 | 9.03 | 9.25 | -0.06 | -0.76 | 0.61 | 0.71 | 0.56 |
| Hubei | 0.19 | 5.17 | 2.89 | 5.65 | 2.03 | -5.41 | 3.60 | 2.43 |
| Shanghai | 0.08 | 1.03 | 1.80 | 1.12 | 3.25 | -5.14 | 8.19 | 6.72 |
| Guangdong | -0.07 | -0.55 | 0.98 | 1.29 | 1.22 | -4.03 | 12.68 | 11.96 |
| | 9.68 | 9.68 | 3.15 | 6.47 | 3.51 | -3.45 | 100.00 | 100.00 |

The second and third terms of equation (60) have been combined into the “between” component of TFP growth.

Table 14 reports the Melitz and Polanec (2012) sub-decomposition of annual average TFP growth for Chinese provinces. In terms of actual annual average TFP growth, as represented in column (1), the highest is recorded by Shandong, Heilongjiang and Liaoning, while Hainan, Ningxia and Guangdong provinces record the lowest. These results partly contrast those obtained from the Haltiwanger (1997) decomposition, in which the best performing provinces were Shandong, Jiangsu and Liaoning, while Hainan, Ningxia and Qinghai were the worst performing. In terms of annual weighted average TFP growth, Heilongjiang, Xinjiang and Jiangxi record the best performance, while Shanghai, Guangdong and Ningxia record the worst. These results differ from those from the Haltiwanger decomposition, in which the best performing provinces were Jiangxi, Inner Mongolia and Xinjiang, while Hubei, Shanghai and Guangdong had the worst performance.

The figures in columns (3), (4), (5) and (6), which represent the decomposition of annual weighted average TFP growth, indicate that the fastest growing provinces are characterized by a strong positive contribution from the between-firm effect, as is the case for the Heilongjiang, Xinjiang and Liaoning provinces. Moreover, the slowest growing provinces are characterised by a strong negative contribution from the exit of more productive firms, such as in the Guangdong and Shanghai provinces.

Table 15: Firm-level TFP Growth (average per annum) in Groups 1998-2007, China

| | TFP Growth (% p.a.) | | Decomposition of Weighted TFP Growth | | | | Output Share (%) | |
|---|---|---|---|---|---|---|---|---|
| | Actual | Weighted | Wirhin Firm | Between Firm | Enterers | Exitors | 1998 | 2007 |
| *Group* | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| State<25%/No Politics | -2.92 | -25.15 | -52.63 | 1.61 | 31.50 | -5.64 | 11.62 | 54.33 |
| State<25%/High Politics | 0.99 | 9.30 | -6.04 | 18.43 | -4.74 | 1.64 | 10.67 | 11.78 |
| State>=50%/High Politics | 4.45 | 17.35 | 4.59 | 11.85 | -1.29 | 2.20 | 25.67 | 10.70 |
| State>=50%/No Politics | 0.22 | 27.33 | 24.85 | 0.30 | 3.84 | -1.66 | 0.82 | 0.63 |
| 25<State<50%/No Politics | -0.03 | -6.56 | 2.34 | -9.59 | 2.94 | -2.24 | 0.48 | 0.40 |
| State>=50%/Medium Politics | 3.26 | 20.64 | 26.36 | -3.18 | -0.10 | -2.44 | 15.80 | 3.66 |
| 25<State<50%/Medium Politics | 0.27 | 11.10 | 15.87 | -0.62 | 0.09 | -4.23 | 2.45 | 0.72 |
| 25<State<50%/High Politics | 0.22 | 17.06 | 1.30 | 24.00 | -3.87 | -4.36 | 1.29 | 0.74 |
| State<25%/Medium Politics | 3.22 | 10.30 | 12.64 | 4.90 | 2.25 | -9.49 | 31.21 | 17.04 |
| *All Groups* | 9.68 | 9.68 | 3.15 | 6.47 | 3.51 | -3.45 | 100.00 | 100.00 |

The second and third terms of equation (60) have been combined into the “between” component of TFP growth.

Table 15 reports the Melitz and Polanec (2012) decomposition of annual average TFP growth for groups of firms according to their extent of political affiliation and State ownership of paid-in capital. Column (1) indicates that non-politically affiliated firms in which the State has a paid-in capital share larger than 50% record the highest actual TFP growth. On the other hand, non-politically affiliated firms with a State paid-in capital share ownership smaller than 25% record the lowest performance. These results contrast with those obtained from the Haltiwanger (1997) decomposition, in which non-politically affiliated firms with a State paid-in capital ownership smaller than 25% recorded the highest growth, while medium politically affiliated firms with a State paid-in capital share ownership smaller than 25% recorded the lowest growth.

The figures in columns (3), (4), (5) and (6) indicate an important role for within-firm TFP improvements for the best performing group of firms, such as those whose State paid-in capital ownership is larger than 50% and which are characterized by either a lack of political affiliation or a medium affiliation (with either the central or provincial governments).

In summary, the results of the Melitz and Polanec (2012) decomposition approach show an annual average growth in TFP of 9.68% during 1998-2007 for the Chinese firms in the sample. The figures indicate this is mainly due to the between-firm effect, while the contribution from the other components is small. The TFP index for the entire sample increases from 1.00 in 1998 to 2.39 to 2007. Across industries, the water production, petroleum processing and non-metal industries record the highest annual weighted average TFP growth, followed by the petroleum processing and non-metal products industries, while the other manufacturing, leather and textile industries record the lowest growth. Across provinces, the Heilongjiang, Xinjiang and Jiangxi provinces record the highest annual weighted average TFP growth, while Ningxia, Guangdong and Shanghai record the lowest growth. When firms are grouped according to the extent of their political affiliation and the share of paid-in capital owned by the State, the firms whose State capital share ownership is larger than 50% and that lack political affiliation record the highest TFP growth, while firms having a state ownership smaller than 25% and no political affiliation record the lowest TFP growth.

## 5. Conclusion and Policy Implications

Total factor productivity is important because it generates benefits both within firms, largely by increasing efficiency and technological change, and beyond, by being the main driver of national long-run economic growth and higher living standards. Analysing TFP and its determinants enables an understanding of which factors policymakers can target in order to achieve higher TFP. While macro-level analyses are important for multi-country studies, they ignore the fact that firms are heterogeneous in many respects, among them TFP. A micro-level analysis, on the other hand, enables us to infer what determines TFP levels and growth rates across firms, providing guidance for policymakers on how to target such determinants to improve TFP. Because they tend to be more targeted, micro-level analyses are more likely to be successful than macro-level ones, which tend to adopt a "one size fits all" approach. Micro-level analyses could therefore contribute to the creation of more competitive firms, increased living standards for citizens and sustainable long-run economic growth.

The Chinese economy has recorded a very strong economic performance over the last three decades, significantly outpacing the global growth rate. Moreover, it is the second largest contributor to global output, after the United States. Surprisingly, the shift from a socially planned to a market-oriented economic system has been achieved through a slow and gradual approach to reform. This shift has enabled China to become an upper middle-income country according to the World Bank (2013) classification. The next step in China's economic development would be the move to high-income country status. Such a shift could be achieved by pursuing policies aimed at increasing total factor productivity.

In light of this, the study conducted in this thesis has aimed to answer the following research questions:

- What factors determine TFP levels and TFP growth in Chinese industrial firms during the period of 1998-2007?
- How does TFP growth differ across firms differentiated by industry, province and ownership/political affiliation?

Four other studies have analysed multiple determinants of TFP in China at the firm level (Yao et al., 2007; Li et al., 2010; Brandt et al., 2012; Shen and Song, 2013). However, the current study distinguishes itself in four main respects. Firstly, the set of TFP determinants analysed is more comprehensive. These include political affiliation, ownership, exporting, competition, Marshallian (or MAR) spillovers, Jacobian (or Jacob) spillovers, city spillovers, liquidity, age, R&D, time trend, and marketing capabilities. It is important to include all of these determinants of TFP, since omitting any would produce biased estimates of the production function, leading to biased estimates of TFP. The choice of determinants is also motivated by the empirical results in the literature and the information available in the Chinese National Bureau of Statistics (NBS) database. Secondly, the set of industries analysed is wider than in most previous studies, with 26 industries belonging to the mining, manufacturing and public utilities sectors. This allows for differences in technology among firms, thus avoiding the assumption that all firms operate using a standard technology. The sample adopted in this study includes both State-owned and non-State-owned firms having annual sales of at least RMB 5mn. The firms are located in 31 provinces, or province-equivalent municipal cities. This unbalanced sample comprises 2,183,709 firm-year observations, which correspond to a large number of firms, ranging from 148,474 in 1998 to 331,453 in 2007. Thirdly, the analysis of the determinants of TFP levels adopts the SYS-GMM methodology, which contrasts with the semiparametric methodologies of Olley and Pakes (1996) and Levinsohn and Petrin (2003) used in previous studies. The major advantage of this methodology, compared to the semiparametric ones, is the allowance for firms' fixed effects, since previous studies have indicated that firms have unmeasured productivity advantages that remain constant over time and that need to be captured. Moreover SYS-GMM has the advantage of tackling both endogeneity of the right-hand-side variables (including the lagged dependent variable) and selection bias by using lagged values of the endogenous variables as instruments in the first differences equation, and first-differences of the same variables as instruments in the levels equation (Blundell and Bond, 1998). SYS-GMM is particularly preferable to the semiparametric methodologies of Olley and Pakes (1996) and Levinsohn and Petrin (2003), as these do not allow for fixed effects and are based on strong and unintuitive assumptions, which generate collinearity problems in the first stage of estimation (Ackerberg et al., 2006). Fourth, the analysis of the determinants of TFP growth is conducted using the Haltiwanger (1997) decomposition approach, which separates TFP growth into the contributions provided by the following: a within-firm component representing the impact of the resource reallocation within existing firms, according to their initial shares of output in their related industries; a between-firm component indicating a change in the output share of firms, weighted by the deviation of the firm's initial productivity from the initial industry index; a covariance component, measuring whether a firm's increasing productivity corresponds to an increasing market share; an entering component indicating the contribution of entrant firms to their related industry's TFP growth, measured with respect to the initial industry index; an exiting component indicating the contribution of exiting firms to their related industry's TFP, measured with respect to the initial industry index. In order to gain an additional understanding of how the determinants of TFP growth differ across firms having different characteristics, the decomposition is also performed at the industry, province and political affiliation/ownership levels. Since Melitz and Polanec (2012) find the approach developed in Haltiwanger (1997) to be characterized by biases, their methodology is also adopted in order to understand which set of results is the most appropriate. The combination of these four features distinguishes this study from existing studies on firm-level TFP estimation in China.

The results of the SYS-GMM estimation of the determinants of TFP levels indicate the existence of increasing returns to scale in most industries, suggesting that firms produce a higher proportion of output from a given proportion of factor inputs. Moreover, the findings suggest that firms are subject to exogenous technological change.

Various factors are found to be important in determining higher TFP levels across Chinese industrial firms. Firstly, the lack of State influence on firms in terms of both paid-in capital share ownership and political affiliation results in higher TFP. This may be due to the greater ability of non-politically influenced firms to enjoy the freedom to undertake decisions in their best interest, rather than politically motivated ones. While this is the case in most sectors, strategic or monopolistic sectors such as the medical, electronic power and water production industries obtain benefits to TFP from State influence. Despite this special case, the evidence indicates that policy measures aimed at decreasing the role of the State in the economy while increasing the role of private actors is conducive to higher total factor productivity.

Secondly, there is evidence of a positive effect on firms' TFP from being based in areas characterized by either industrial agglomeration or industrial diversity, although large city areas tend to generate high costs for firms that hamper their productivity. Policy measures favouring industrial agglomeration, such as the creation of geographic industrial clusters, would result in higher TFP, as firms would benefit from knowledge spillovers manifested through the channels of imitation/demonstration, synergies, commercial relationships, asset sharing, and labour pooling. Also, measures favouring industrial diversity would be beneficial to firms, since such a diverse environment would facilitate the transmission of innovation across industries.

Thirdly, the findings indicate that younger firms tend to be more productive than their older counterparts. This might be explained by the ability of younger firms to adapt their business processes and strategies to the dynamic markets in which they operate and keep their technology up to date with industry best practices. Thus, policy measures aimed at facilitating the entrance of younger firms into the market, for example, by lowering the regulatory barriers to entry and offsetting initial business costs through tax cuts or subsidies, would be beneficial for firms' TFP.

Fourth, increased levels of competition within industries are found to result in higher firm TFP. This is because in a competitive environment, firms are likely to be motivated to undertake TFP-enhancing decisions such as increasing their efficiency and undertaking technological change. Such a positive effect suggests that policy measures aimed at increasing competition within Chinese industries, such as the disbanding of cartels and the liberalization of both monopolistic and strategic sectors, would generate higher TFP levels.

Chinese industrial firms are found to benefit in terms of higher TFP levels from the possession of marketing capabilities. Such capabilities enable firms to transform their resources into valuable output, to better distinguish their products from competitors, and to build successful brands so that they can charge a premium to customers. A higher TFP level can therefore be achieved by pursuing policy measures that support firms' marketing capabilities, such as the provision of business consulting so that firms can better target their consumers.

The positive relationship between firms' liquidity and TFP indicates the existence of financial constraints, suggesting that Chinese firms have difficulties in raising external finance and must therefore rely on their internal liquidity to finance productive investments. A shortage of internal liquidity pushes firms to either postpone or cancel productive investments. Since the existence of financial constraints distorts the allocation of capital and thus hampers firms' TFP, policy steps aimed at addressing this issue, such as the development of the bond market, would be beneficial.

There are also factors that, contrary to initial expectations, do not determine higher TFP levels: R&D expenditure and exporting. Although R&D expenditure was expected to have both direct and indirect positive effects on TFP, this is not the case in most industries. It might be that such expenditure is focusing on the wrong areas. For example, R&D might be focused on improving low-priority products and processes. The findings also indicate that exporting does not seem to lead to higher TFP. Chinese firms were expected to learn by exporting how to become more productive, since they would face a larger number of competitors with more innovative technologies, working practices and products. However, this is not the case in most industries. This finding can potentially be explained by the "processing trade" argument of Jarreau and Poncet (2012), which suggests that exporting is beneficial to firms' performance only when it is in form of ordinary exports rather than "processing trade." Empirical evidence from Wang and Yu (2011) and Dai et al. (2011) supports this idea.

Following an analysis of the determinants of TFP levels, it has been assessed which determinants have the largest impact on TFP levels. The findings indicate that exogenous technological improvements have the largest positive effect on firms' TFP levels.

The results also indicate a large positive effect of an increasing proportion of firms' paid-in capital owned by either individuals or corporates, and large negative effects from an increasing proportion of firms' paid-in capital owned by the State, and firms' high level of political affiliation with either the central or local government. From this result, it can be inferred that policy measures aiming at reducing the State influence on firms, through either ownership or political affiliation, are likely to have the largest positive effect on Chinese firms' TFP.

The large negative effect for the variable representing city spillovers, and the positive effects for the variables representing Marshallian and Jacobian spillovers, indicate that policy measures favoring industrial agglomeration and diversity in areas other than cities are also likely to have a large positive effect on firms' TFP.

The results of Kolmogorov-Smirnov tests and the related empirical cumulative TFP distributions are in line with the SYS-GMM findings, since they indicate that TFP differs across firms having diverse characteristics such as political affiliation, paid-in capital share ownership, R&D and exporting. The KS test results also stress the importance of estimating TFP separately for each industry and taking into account the geographical differences between firms. Moreover, the results indicate the existence of TFP growth between 1998 and 2007.

The application of the methodologies of Haltiwanger (1997) and Melitz and Polanec (2012) indicate that Chinese industrial firms have recorded an aggregate annual average TFP growth of 9.68% between 1998-2007. The latter methodology, whose results are more appropriate since the method addresses the measurement biases characterizing the former, indicates that such growth largely results from a between-firm effect, which represents the reallocation of resources through the contraction and expansion of output shares between firms characterized by different productivity levels. The results indicate a small contribution to aggregate TFP growth from within-firm TFP improvements and the entrance of new firms, and a negative contribution from the exit of more productive firms. High growth industries are characterized by a strong impact from the within-firm effect (e.g. in the water production, non-metal products and other mining industries) and the between-firm effect (e.g. in the water production and petroleum processing industries). TFP growth across provinces is characterized by a strong contribution from the between-firm effect (e.g. in Heilongjiang, Xinjiang and Liaoning). When firms are grouped according to their political affiliation and State ownership share of paid-in capital, non-politically affiliated firms in which the State has a paid-in capital share larger than 50% record the highest actual TFP growth, while non-politically affiliated firms with a State paid-in capital share ownership smaller than 25% have record the lowest performance. Within-firm TFP improvements drive the strong performance of the former. The results of the aggregate TFP decomposition indicate that policy measures favouring the entry of more productive firms, within-firm TFP improvements, and especially the reallocation of resources across existing firms, are conducive to higher TFP growth.

Since this study has only considered medium and large-sized firms, future research should also consider small firms, thus offering a more comprehensive understanding of the determinants of TFP in the Chinese industrial sector. Such research would indicate whether the determinants of TFP vary across firms of different sizes. It would also indicate whether small or medium-to-large firms are the main drivers of aggregate TFP growth.

As the industrial sector has been the main focus of this study, an extension to the research should include the service sector. Such research would indicate whether one sector or the other largely drives national aggregate TFP and whether TFP is differentially determined in each. Since China is undergoing a shift from the dominance of the industrial sector towards the service sector, the inclusion of the latter would help determine whether such a shift is beneficial to national aggregate TFP growth.

In light of the major role of total factor productivity in raising living standards and in driving national long-run within- and cross-country economic growth (Easterly and Levine, 2001; Klenow and Rodriguez-Clare, 1997; Benhabib and Spiegel, 1994), policy measures targeting the determinants of TFP levels and TFP growth would enable Chinese firms to become more competitive and allow the achievement of sustainable long-run economic growth and higher living standards in China, enabling the country to raise its status to a high-income economy.

## References

Ackerberg, D.A. Benkard, C.L. Berry, S. and Pakes, A. (2007) Econometric Tools for Analyzing Market Outcomes. In: Heckman, J.J. and Leamer E.E. (1st edition) *Handbook of Econometrics.* Amsterdam: North-Holland, pp. 4171-4276

Aitken, B.J. Harrison, A.E. (1999) Do Domestic Firms Benefit from Foreign Direct Investment? Evidence from Venezuela. *The American Economic Review,* 89(3): 605-618

Allen, F. Qian, J. and Qian, M. (2005) Law, Finance and Economic Growth in China. *Journal of Financial Economics,* 77(1): 57-116

Almeida, P. Dokko, G. Rosenkopf L. (2003) Startup Size and the Mechanisms of External Learning: Increasing Opportunity and Decreasing Ability? *Research Policy,* 32(2): 301-315

Arellano, M. and Bond, S. (1991) Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economics Studies,* 58(2): 277-298

Arnold, J.M. and Hussinger, K. (2005) Export Behaviour and Firm Productivity in German Manufacturing: A Firm-Level Analysis. *Review of World Economics,* 141(2): 219-243

Arrow, K.J. (1962) The Economic Implications of Learning by Doing. *The Review of Economic Studies*, 29(3): 155-173

Bacolod, M. Blum, B.S. and Strange, W.G. (2009) Skills in the City. *Journal of Urban Economics,* 65(2009): 136-153

Baily, M.N. Hulten, C. Campbell, D. Bresnahan, T. and Caves, R.E. (1992) Productivity Dynamics in Manufacturing Plants. *Brookings Papers on Economic Activity. Microeconomics,* 1992: 187-267

Baldwin, J.R. and Gorecki, P.K. (1991) Firm Entry and Exit in the Canadian Manufacturing Sector, 1970-1982. *The Canadian Journal of Economics*, 24(2): 300-323

Baldwin, J.R. Mark Brown, W. and Rigby, D.L. (2010) Agglomeration Economies: Microdata Panel Estimates from Canadian Manufacturing. *Journal of Regional Science,* 50(5), pp. 915-934

Barney, J. (1991) Firm Resources and Sustained Competitive Advantage. *Journal of Management*, 17(1): 99-120

Bartelsman, E.J. and Dhrymes, P.J. (1998) Productivity Dynamics: U.S. Manufacturing Plants, 1972-1986. *Journal of Productivity Analysis,* 9(1998): 5-34

Basant, R. and Fikkert, B. (1996) The Effects of R&D, Foreign Technology Purchase, and Domestic and International Spillovers on Productivity in Indian Firms. *The Review of Economics and Statistics*, 78(2): 187-199

Batisse, C. (2002) Dynamic Externalities and Local Growth: A Panel Data Analysis Applied to Chinese Provinces. *China Economic Review,* 13(2-3): 231-251

Beckman, T.N. and Buzzell, R.D. (1958) Productivity: Facts and Fiction. *Business Horizon,* 1 (1): 24-38

Bell, C.R. (1988) Economies of, versus Returns to, Scale: A Clarification. *The Journal of Economic Education*, 19(4): 331-335

Benhabib, J. and Spiegel, M.M. (1994) The Role of Human Capital in Economic Development: Evidence from Aggregate Cross-country Data. *Journal of Monetary Economics*, 34(1994): 143-173

Ben Hamida, L. and Gugler, P. (2009) Are There Demonstration-related Spillovers from FDI? Evidence from Switzerland. *International Business Review*, 18(2009): 494-508

Berger, A.N. Hasan, I. and Zhou, M. (2009) Bank Ownership and Efficiency in China: What Will Happen in the World's Largest Nation? *Journal of Banking & Finance,* 33(2009): 113-130

Bernard, A.B. and Jensen J.B. (2002) The Deaths of Manufacturing Plants. NBER Working Papers Series, No. 9026. Available from: http://www.nber.org/papers/w9026.pdf [29/06/2015]

Bernard, A.B. and Jensen J.B. (2004) Exporting and Productivity in the USA. *Oxford Review of Economic Policy, Oxford University Press,* 20(3): 343-357

Bernard, A.B. and Jensen J.B. (2007) Firm Structure, Multinationals, and Manufacturing Plant Deaths. *The Review of Economics and Statistics,* 89(2): 193-204

Bernard, A.B., Redding, S.J. and Schott, P.K. (2009) Products and Productivity. *Scandinavian Journal of Economics*, 111(4): 681-709

Bilgin, M.H. Lau, C.K.M. and Karabulut, G. (2012) Technology Transfer and Enterprise Performance: A Firm-Level Analysis in China. *Journal of Business Economics and Management,* 13(3): 489-498

Blalock, G. and Gertler, P.J. (2004) Learning from Exporting Revisited in a Less Developed Setting. *Journal of Development Economics*, 75(2004): 397-416

Blalock, G. and Veloso, F.M. (2007) Imports, Productivity Growth, and Supply Chain Learning. *World Development,* 35(7): 1134-1151

Bloom, D.E. and Canning, D. (2004) Global Demographic Change: Dimensions and Economic Significance. *Proceedings, Federal Reserve Bank of Kansas City,* 8 (2004): 9-56

Bloom, D.E. and Finlay, J.E. (2009) Demographic Change and Economic Growth in Asia. *Asian Economic Policy Review*, 4(2009): 45-64

Bloom, N. and Van Reenen, J. (2007) Measuring and Explaining Management Practices Across Firms and Countries, *Quarterly Journal of Economics,* 122(4): 1351-1408

Bloom, N. and Van Reenen, J. (2010) Why do Management Practices Differ Across Firms and Countries? *Journal of Economic Perspectives*, 24(1): 203-224

Bloom, N. Draca, M. and Van Reenen, J. (2011) Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. NBER Working Papers Series, No. 16717. Available from: http://www.nber.org/papers/w16717 [31/08/2013]

Blundell, R. and Bond, S. (1998) Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics,* 87(1998): 115-143

Blundell, R. and Bond, S. (2000) GMM Estimation with Persistent Panel Data: an Application to Production Functions. *Econometric Reviews,* 19(3): 321-340

Borowiecki, K.J. (2013) Geographic Clustering and Productivity: An Instrumental Variable Approach for Classical Composers. *Journal of Urban Economics,* 73(1): 94-110

Bowles, P. (2012) Rebalancing China's Growth: Some Unsettled Questions. *Canadian Journal of Development Studies*, 33(1): 1-13

Bramall, C. (2009) *Chinese Economic Development*. New York: Routledge

Brandt, L. and Li, H. (2003) Bank Discrimination in Transition Economies: ideology, information, or incentives? *Journal of Comparative Economics,* 31(2003): 387-413

Brandt, L. and Rawski, T. (2008) *China's Great Economic Transformation*. 1st Edition. Cambridge: Cambridge University Press

Brandt, L. Van Biesebroeck, J. and Zhang, Y. (2012) Creative Accounting or Creative Distruction? Firm-Level Productivity Growth in Chinese Manufacturing. *Journal of Development Economics,* 97(2): 339-351

Branstetter, L.G. (2001) Are Knowledge Spillovers International or Intranational in Scope? Microeconometric Evidence from the US and Japan. *Journal of International Economics,* 53(2001): 53-79

Breth, R.M. (1977) *Mao's China: A Study of Socialist Economic Development*. Melbourne: Longman Cheshire Pty

Bridgham, P. (1967) Mao's "Cultural Revolution": Origin and Development. *The China Quarterly*, 29(1967): 1-35

Buck, T. Filatotchev, I. Nolan, P. and Wright, M. (2000) Different Paths to Economic Reform in Russia and China: Causes and Consequences. *Journal of World Business,* 35(4): 370-400

Carlino G.A. (1987) Productivity in Cities: Does City Size Matter? *Business Review, Federal Reserve Bank of Philadelphia*, 11 (1987): 3-12

Castellani, D. (2002) Export Behavior and Productivity Growth: Evidence from Italian Manufacturing Firms. *Review of World Economics/Weltwirtschaftliches Archiv*, 38(4): 605-628

Cavallo, E.A. and Frankel, J.A. (2008) Does Openness to Trade Make Countries More Vulnerable to Sudden Stops, or Less? Using Gravity to Establish Causality. *Journal of International Money and Finance*, 27(8): 1430-1452

Caves, R. (1974) Multinational Firms, Competition, and Productivity in Host-Country Markets. *Economica,* 41(162): 176-193

Caves, R. (1996) *Multinational Enterprise and Economic Analysis*. 2nd Edition. Cambridge: Cambridge University Press

Caves, D.W. Christensen, L.R. and Swanson J.A. (1981) Productivity Growth, Scale Economies, and Capacity Utilization in U.S. Railroads, 1955-4. *The American Economic Review*, 71(5): 994-1002

Chai, J.C.H. (1998) *China Transition to a Market Economy*. Oxford: Clarendon Press

Chan, K.S. Dang, V.Q.T. and Yan, I.K.M. (2012) Financial Reform and Financing Constraints: Some Evidence from Listed Chinese Firms. *China Economic Review,* 23(2): 482-497

Che, J. and Qian, Y. (1998) Insecure Property Rights and Government Ownership of Firms. *The Quarterly Journal of Economics,* 113(2): 467-496

Chen, C.H. (1992) Modernization in Mainland China: Self-Reliance and Dependence. *American Journal of Economics and Sociology,* 51(1): 57-98

Chen, G. Firth, M and Xu, L. (2009) Does the Type of Ownership Control Matter? Evidence from China's Listed Companies. *Journal of Banking and Finance,* 33(1): 171-181

Chen, M. and Guariglia, A. (2013) Internal Financial Constraints and Firm Productivity in China: Do Liquidity and Export Behavior Make a Difference? *Journal of Comparative Economics,* 41(4): 1123-1140

Chen, Z. (2003) Capital Markets and Legal Development: The China Case. *China Economic Review,* 14: 451-472

Chen, K. Huang Y.J., and Yang, C.H. (2009) Analysis of Regional Productivity Growth in China: A Generalized Metafrontier MPI Approach. *China Economic Review,* 20(4): 777-792

Chen, K. Jefferson, G.H. and Singh I. (1992) Lessons from China's Economic Reform. *Journal of Comparative Economics*, 16(2): 201-225

National Bureau of Statistics (2012): China Statistical Yearbook. Available from: http://www.stats.gov.cn/tjsj/ndsj/2012/indexeh.htm [22/12/2013]

Chong, T.T. Lu, L. Ongena, S. (2013) Does Banking Competition Alleviate or Worsen Credit Constraints Faced by Small- and Medium-sized Enterprises? Evidence from China. *Journal of Banking & Finance,* 37(9): 3412-3424

Chow, G.C. (1987) *The Chinese Economy.* 2nd Edition. Singapore: World Scientific Publishing

Chow, G.C. (1993) How and Why China Succeeded in Her Economic Reform. *China Economic Review,* 4(2): 117-128

Chow, G.C. (2007) *China's Economic Transformation.* 2nd Edition. Oxford: Blackwell Publishing

Cingano, F. and Pinotti, P. (2013) Politicians at Work: The Private Returns and Social Costs of Political Connections. *Journal of the European Economic Association,* 11(2): 433-465

Cingano, F. and Schivardi, F. (2010) Identifying the Sources of Local Productivity Growth. *Journal of the European Economic Association,* 2(4): 720-742

Clark, P.B. and Wilson, J.Q. (1961) Incentive Systems: a Theory of Organizations. *Administrative Science Quarterly,* 6(2): 129-166

Clerides, S.K. Lach, S. and Tybout J.R. (1998) Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico and Morocco. *The Quarterly Journal of Economics*, 113(3): 903-947

Coad, A. Segarra, A. and Teruel, M. (2013) Like Milk or Wine: Does Firm Performance Improve with Age? *Structural Change and Economic Dynamics,* 24(2013): 173-189

Coase, R.H. (1937) The Nature of the Firm. *Economica,* 4(16): 386-405

Coe, D.T. Helpman, E. (1995) International R&D Spillovers. *European Economic Review,* 39(1995): 859-887

Coelli, T. Prasada Rao, D.S. and Battese G.E. (1998) *An Introduction to Efficiency and Productivity Analysis.* 2nd edition. Boston: Kluwer Academic Press

Cohen, W.M. Levinthal D.A. (1989) Innovation and Learning: The Two Faces of R&D. *The Economic Journal,* 99(397): 569-596

Cohen, W.M. Levinthal D.A. (1990) Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly,* 35(1): 128-152

Crespo, N. Fontoura, M.P. (2007) Determinant Factors of FDI Spillovers – What Do We Really Know? *World Development* 35(3): 410-425

Dai, M., Maitra, M., & Yu, M. (2011). Unexceptional exporter performance in China? The role of processing trade. Peking University, Mimeograph.

Daniel III, C. (2001) The Impact on China of its Ascension into the WTO. *The Social Science Journal*, 41(3): 363-374

Dekle R. (2002) Concentration and Regional Growth: Evidence from the Prefectures. *The Review of Economics and Statistics,* 84(2): 310-315

De Loecker, J. (2007) Do Exports Generate Higher Productivity? Evidence from Slovenia. *Journal of International Economics,* 73(2007): 69-98

Del Gatto, M. Di Liberto, A. and Petraglia, C. (2011) Measuring Productivity. *Journal of Economic Surveys,* 25(5): 952-1008

Deng, K. (2012) *China's Political Economy in Modern Times. Changes and Economic Consequences, 1800-2000.* New York: Routledge

Didier, T. and Schmukler, S.L. (2013) The Financing and Growth of Firms in China and India: Evidence From Capital Markets. *Journal of International Money and Finance,* 39(2013): 111-137

Dinç, I.S. (2005) Politicians and Banks: Political Influences on Government-owned Banks in Emerging Markets. *Journal of Financial Economics*, 77(2): 453-479

Ding, S. Guariglia, A. and Knight, J. (2013) Investment and Financing Constraints: Does Working Capital Management Make a Difference? *Journal of Banking & Finance*, 37(5): 1490-1507

Disney, R. Haskel, J. and Heden, Y. (2003) Entry, Exit and Establishment Survival in UK Manufacturing. *The Journal of Industrial Economics,* 51(1): 91-112

Dollar, D. Wolff, E.N. (1993) *Competitiveness, Convergence and International Specialization*, MIT Press, Cambridge, MA

Dong, X.Y. and Putterman, L. (1997) Productivity and Organziation in China's Rural Industries: A Stochastic Frontier Analysis. *Journal of Comparative Economics,* 24(2): 181-201

Dong, X.Y. and Putterman, L. (2003) Soft Budget Constraints, Social Burdens, and Labor Redundancy in China's State Industry. *Journal of Comparative Economics,* 31(2003): 110-133

Doraszelski, U. and Jaumandreu, J. (2008) R&D and Productivity: Estimating Production Functions when Productivity is Endogenous. CEPR Discussion Paper Series, No. 6636, Available from: http://www.cepr.org/pubs/dps/DP6636.asp [22/06/2013]

Dosi, G. Lei, J. and Yu, X. (2013) Institutional Change and Productivity Growth in China's Manufacturing: The Microeconomics of Creative Restructuring. *LEM Working Paper Series,* No. 7, Available from: http://www.lem.sssup.it/WPLem/2013-07.html [21/12/2013]

Dougherty, S. Herd, R. and He, P. (2007) Has a Private Sector Emerged in China's Industry? Evidence from a Quarter of a Million Chinese Firms. *China Economic Review,* 18(3): 309-334

Driffield, N. and Love, J.H. (2007) Linking FDI Motivation and Host Economy Productivity Effects: Conceptual and Empirical Analysis. *Journal of International Business Studies,* 38(2007): 460-473

Driffield, N. and Du, J. (2007) Privatization, State Ownership and Productivity: Evidence from China. *International Journal of the Economics of Business,* 14(2): 215-239

Du, J. and Girma, S. (2010) Red Capitalists: Political Connections and Firm Performance in China. *KYKLOS,* 63(4): 530-545

Du, J. and Girma, S. (2012a) Firm Size, Source of Finance, and Growth – Evidence from China. *International Journal of the Economics of Business,* 19(13): 397-419

Du, J. Lu, Y. Tao, Z. and Yu, L. (2012b) Do Domestic and Foreign Exporters Differ in Learning by Exporting? Evidence from China. *China Economic Review,* 23(2): 296-315

Dunne, T. Roberts, M.J. and Samuelson, L. (1998) Patterns of Firm Entry and Exit in US Manufacturing Industries. *Rand Journal of Economics,* 19(4): 495-515

Eckstein, A. (1966) *Communist China's Economic Growth and Foreign Trade*: *Implications for U.S. Policy*. New York: McGraw-Hill Book Company

Eckstein, A. (1976) *China's Economic Development.* Michigan: The University of Michigan Press

Eckstein, A. (1977) *China's Economic Revolution*. Cambridge: Cambridge University Press

Elvery, J.A. (2010) City Size and Skill Intensity. *Regional Science and Urban Economics,* 40(2010): 367-379

Easterly, W. and Levine, R. (2001) It's Not Factor Accumulation: Stylized Facts and Growth Models. *The World Bank Economic Review*, 15(2): 177-219

European Commission 2013: Eurostat. Available at: http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/themes [22/12/2013]

Eustace, C. (2000) The Intangible Economy: Impact and Policy Issues. *Report of the European High Level Expert Group on the Intangible Economy*, European Commission.

Evans, D.S. (1987) The Relationship Between Firm Growth, Size, and Age: Estimates for 100 Manufacturing Industries. *The Journal of Industrial Economics,* 35(4): 567-581

Faccio, M. (2006) Politically Connected Firms. *The American Economic Review,* 96(1): 369-386

Faccio, M. (2010) Differences between Politically Connected and Nonconnected Firms: A Cross-Country Analysis. *Financial Management*, 39(3): 905-928

Farinas, J.C. and Ruano, S. (2005) Firm Productivity, Heterogeneity, Sunk Costs and Market Selection. *International Journal of Industrial Organization*, 23(7-8): 505-534

Farrell, M.J. (1947) The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society. Series A (General).* 120(3): 253-290

Fazzari, S.M. Hubbard, R.G. and Petersen, B.C. (1998) Financing Constraints and Corporate Investment. *Brookings Papers on Economic Activity*, 1998(1): 141-195

Fernandes, A.M. (2008) Firm Productivity in Bangladesh Manufacturing Industries. *World Development*. 36(10): 1725-1744

Fischer, S. (1993) Socialist Economic Reform: Lessons of the First Three Years. *The American Economic Review,* 83(2): 390-395

Forbes, S.J. and Lederman, M. (2010) Does Vertical Integration Affect Firm Performance? Evidence from the Airline Industry. *RAND Journal of Economics,* 41(4): 765-790

Foster, L. Haltiwanger, J.C. and Krizan, C.J. (2001) Aggregate Productivity Growth. Lessons from Microeconomic Evidence. In: Hulten, C.R. Dean, E.R. Harper, M.J. (eds.) *New Developments in Productivity Analysis*. Chicago: University of Chicago Press, pp. 303-372

Foster, L. Haltiwanger, J.C. and Syverson, C. (2008) Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability? *American Economic Review,* 98(1): 394-425

Frantzen, D. (2002) Intersectoral and International R&D Knowledge Spillovers and Total Factor Productivity. *Scottish Journal of Political Economy,* 49(3): 280-303

Fu, F. Vijverberg, C.C. and Chen, Y.S. (2008) Productivity and Efficiency of State-Owned Enterprises in China. *Journal of Productivity Analysis,* 29(3): 249-259

Fu, X. and Gong, Y. (2009) International and Intranational Technological Spillovers and Productivity Growth in China. *Asian Economic Papers,* 8(2): 1-23

Fu, X. and Gong, Y. (2011) Indigenous and Foreign Innovation Efforts and Drivers of Technological Upgrading: Evidence from China. *World Development,* 39(7): 1213-1225

Fu, X. and Heffernan, S. (2007) Cost X-efficiency in China's Banking Sector. *China Economic Review,* 18(2007): 35-53

Fu, X. and Heffernan, S. (2009) The Effects of Reform on China's Bank Structure and Performance. *Journal of Banking & Finance*, 33(2009): 39-52

Gang, F. (1994) Incremental Changes and Dual-Track Transition: Understanding the Case of China. *Economic Policy,* 9(19): 99-122

García, F. Avella, L. and Fernández L. (2012) Learning from Exporting: The Moderating Effect of Technological Capabilities. *International Business Review,* 21(6): 1099-1111

Ge, W. (1999) Special Economic Zones and the Opening of the Chinese Economy: Some Lessons for Economic Liberalization. *World Development*, 27(7): 1267-1285

Geng, X. and Weiss, J. (2007) Development in North East People's Republic of China: An Analysis of Enterprise Performance 1995-2002. *China Economic Review,* 18(2): 170-189

Ghosh, S. (2013) Do Economic Reforms Matter for Manufacturing Productivity? Evidence from the Indian Experience. *Economic Modelling,* 31(2013):723-733

Girma, S. and Gong, Y. (2008) FDI, Linkages and the Efficiency of State-Owned Enterprises in China. *The Journal of Development Studies,* 44(5): 728-749

Girma, S. and Wakelin, K. (2007) Local Productivity Spillovers from Foreign Direct Investment in the U.K. Electronics Industry. *Regional Science and Urban Economics,* 37(3): 399-412

Goldman, E. Rocholl, J. and So, J. (2013) Politically Connected Boards of Directors and The Allocation of Procurement Contracts. *Review of Finance,* 17(5): 1-32

Gordon, R.H. and Li, W. (1995) The Change in Productivity of Chinese State Enterprises, 1983-1987. *Journal of Productivity Analysis,* 6(1): 5-26

Greenhalgh, S. (2003) Science, Modernity, and the Making of China's One-Child Policy. *Population and Development Review,* 29(2): 163-196

Griffith, R. (2001) Product Market Competition, Efficiency, and Agency Costs: An Empirical Analysis, The Institute for Fiscal Studies, Working Paper W01/12. Available from: http://eprints.ucl.ac.uk/3840/1/3840.pdf [25/06/2013]

Griffith, R. Harrison, R. and van Reenen, J. (2006) How Special Is the Special Relationship? Using the Impact of U.S. R&D Spillovers on U.K. Firms as a Test of Technology Sourcing. *The American Economic Review,* 96(5): 1859-1875

Griliches, Z. and Regev, H. (1995) Firm Productivity in Israeli Industry: 1978-1988. *Journal of Econometrics,* 65(1995): 175-203

Grossman, G.M. and Helpman, E. (1991) Trade, Knowledge Spillovers, and Growth. *European Economic Review,* 35(2-3): 517-526

Groves, T. Hong, Y. McMillan, J. and Naughton, B. (1994) Autonomy and Incentives in Chinese State Enterprises. *The Quarterly Journal of Economics,* 109(1): 183-209

Guariglia, A. Liu, X. and Song, L. (2011) Internal Finance and Growth: Microeconomic Evidence on Chinese Firms. *Journal of Development Economics*, 96(1): 79-94

Glaeser, E.L. Kallal, H.D. Scheinkman, J.A. Shleifer A. (1992) Growth in Cities. *Journal of Political Economy,* 100(6): 1126-1152

Greenaway, D. and Kneller, R. (2007) Industry Differences in the Effect of Export Market Entry: Learning by Exporting? *Review of World Economics*, 143(3): 416-432

Griliches, Z (1986) Productivity, R&D, and Basic Research at the Firm Level in the 1970s. *American Economic Review*, 76(1): 141-154

Griliches, Z. and Mairesse, J. (1991) R&D and Productivity Growth: Comparing Japanese and U.S. Manufacturing Firms. In: Hulten, C.R. *Productivity Growth in Japan and the United States*. Chicago: University of Chicago Press, pp. 317-348

Griliches, Z. and Mairesse, J. (1995) Production Functions: The Search for Identification. NBER Working Papers Series, No. 5067, Available from: http://www.nber.org/papers/w5067.pdf [15/04/2013]

Guariglia, A. Liu, X. and Song, L. (2011) Internal Finance and Growth: Microeconomic Evidence on Chinese Firms. *Journal of Development Economics*, 96(1): 79-94

Gurley, J.G. (1976) *China's Economy and the Maoist Strategy*. New York: Monthly Review Press

Hale, G. and Long, C. (2011) Are there Productivity Spillovers from Foreign Direct Investment in China? *Pacific Economic Review,* 16(2): 135-153

Hall, R. and Jones, C.I. (1999) Why do Some Countries Produce so Much More Output per Worker than Others? *The Quarterly Journal of Economics*, 114(1): 83-116

Haltiwanger, J. (1997) Measuring and Analyzing Aggregate Fluctuations: The Importance of Building from Microeconomic Evidence. *Review of the Federal Reserve Bank of St. Louis,* 79(1997): 55-77

Han, J. Liu, R. and Zhang J. (2012) Globalization and Wage Inequality: Evidence from Urban China. *Journal of International Economics,* 87(2012): 288-297

Hannan, M.T Freeman J. (1984) Structural Inertia and Organizational Change. *American Sociological Review*. 49(2): 149-164

Harris, R. (2002) Foreign Ownership and Productivity in the United Kingdom – Some Issues When Using the ARD Establishment Level Data. *Scottish Journal of Political Economy,* 49(3): 318-335

Harris, R. (2005) Economics of the Workplace: Special Issue Editorial. *Scottish Journal of Political Economy*, 52(3): 323-343

Harris, R. and Hassaszadeh, P. (2002) The Impact of Ownership Changes and Age Effects on Plant Exits in UK Manufacturing, 1974-1995. *Economics Letters* 75(3): 309-317

Harris, R. and Li, Q.C. (2009) Exporting, R&D, and Absorptive Capacity in UK Establishments. *Oxford Economic Papers*, 61(1): 74-103

Harris, R. Moffat, J. (2011) Plant-level Determinants of Total Factor Productivity in Great Britain, 1997-2006. SERC Discussion Paper, No. 64, Available from: http://www.spatialeconomics.ac.uk/textonly/SERC/publications/download/sercdp0064.pdf [16/05/2013]

Harris, R. and Moffat, J. (2012a) Is Productivity Higher in British Cities? *Journal of Regional Science*, 52(5): 762-786

Harris, R. and Moffat, J. (2012b) R&D, Innovation and Exporting in Britain: An Empirical Analysis. Available at: http://www.cppr.ac.uk/media/media_232346_en.pdf [17/5/2013]

Harris, R. and Moffat, J. (2013) Intangible Assets, Absorbing Knowledge and Its Impact on Firm Performance: Theory, Measurement and Policy Implications. *Contemporary Social Science: Journal of the Academy of Social Sciences*, 8(3): 1-16

Harris, R. and Robinson, C. (2002) The Effect of Foreign Acquisitions on Total Factor Productivity: Plant-Level Evidence from U.K. Manufacturing, 1987-1992. *The Review of Economics and Statistics*, 84(3): 562-568

Harris, R. and Robinson, C. (2003) Foreign Ownership and Productivity in the United Kingdom Estimates for U.K. Manufacturing Using the ARD. *Review of Industrial Organization*, 22(3): 207-223

Harris, R. and Robinson, C. (2004) Productivity Impacts and Spillovers from Foreign Ownership in the United Kingdom. *National Institute Economic Review*, 187(1): 58-75

Haskel, J. (2000) What Raises Productivity? The Microeconomics of UK Productivity Growth, Queen Mary, University of London Research Paper.

He, Z. (2000) Corruption and Anti-corruption in Reform China. *Communist and Post-Communist Studies*, 33(2000): 243-270

Hermalin, B.E. (1992) The Effects of Competition on Executive Behavior. *The RAND Journal of Economics,* 23(3): 350-365

Higón, D.A. (2007) The impact of R&D Manufacturing Spillovers on UK Manufacturing TFP:A Dynamic Panel Approach. *Research Policy,* 36(7): 964-979

Hoch, I. (1962) Estimation of Production Function Parameters Combining Time-Series and Cross-Section Data, *Econometrica*, 30(1): 34-53

Holcomb, T.R. Holmes Jr., R.M. and Connelly, B.L. (2009) Making the Most of What You Have: Managerial Ability as a Source of Value Creation. *Strategic Management Journal*, 30(5): 457-485

Holmstrom, B. and Milgrom, P. (2004) The Firm as an Incentive System. *The American Economic Review*, 84(4): 972-991

Horn, H. Lang, H. and Lundgren, S. (1994) Competition, Long Run Contracts and Internal Inefficiencies in Firms. *European Economic Review*, 38(2): 213-233

Hortacsu, A. and Syverson C. (2007) Cementing Relationships: Vertical Integration, Foreclosure, Productivity and Prices. NBER Working Papers Series, No. 12894, Available from: http://www.nber.org/papers/w12894 [23/06/2013]

Hou, J.W. (2011) Economic Reform of China: Cause and Effects. *The Social Science Journal*, 48(3): 419-434

Hou, C.C. and Hou, J.W. (2001) Evolution of Economic Institutions and China's Economic Reform. *The Social Science Journal*, 39(3): 363-379

Howe, C. Kueh, Y.Y. and Ash, R. (2003). *China's Economic Reform: A Study with Documents.* London: Routledge Curzon

Howells, J.R.L. (2002) Tacit Knowledge, Innovation and Economic Geography. *Urban Studies*, 39(5-6): 871-884

Howitt, P. (2000), Endogenous Growth and Cross-country Income Differences. *American Economic Review,* 90(4): 829-846

Hsieh, C.T. and Klenow, P.J. (2009) Misallocation and Manufacturing TFP in China and India. *Quarterly Journal of Economics*, 124(4): 1403-1448

Hu, A.G. (2001) Ownership, Government R&D, Private R&D, and Productivity in Chinese Industry. *Journal of Comparative Economics,* 29: 136-157

Huang, J. (2008) Spillovers from Taiwan, Hong Kong, and Macau Investment and from Other Foreign Investment in Chinese Industries. *Contemporary Economic Policy,* 22(1): 13-25

Huang, Y. (2003) *Selling China: Foreign Direct Investment during the Reform Era*. New York: Cambridge University Press

Huang, Y. and Duncan, R. (1997) How Successful Were China's State Sector Reforms? *Journal of Comparative Economics,* 24(1): 65-78

Hymer, S. (1976) *The International Operations of National Firms: a Study of Direct Foreign Investment.* Cambridge, Massachusetts; London: MIT Press

Ichinowski, C. Shaw, K. and Prennuschi, G. (1997) The Effects of Human Resource Management Practices on Productivity: A Study of Steel Finishing Lines. *The American Economic Review,* 87(3): 291-313

International Monetary Fund (2013): World Economic Outlook Database. Available from: http://www.imf.org/external/pubs/ft/weo/2013/01/weodata/index.aspx [31/05/2013]

Inui, T. Kawakami, A. and Miyagawa, T. (2008) Do Competitive Markets Stimulate Innovation? An Empirical Analysis Based on Japanese Manufacturing Industry Data. RIETI Discussion Paper Series, No. 08-E-012, Available from: www.rieti.go.jp/jp/publications/dp/08e012.pdf [28/08/2013]

Ishikawa, (1983) China's Economic System Reform: Underlying Factors and Prospects. *World Development*, 11(8): 647-658

Jacob, J. (1970) *The Economy of Cities*. New York: Random Hause

Jarreau, J. and Poncet, S. (2012) Export Sophistication and Economic Growth: Evidence from China. *Journal of Development Economics,* 97(2): 281-292

Jefferson, G. and Jian, S. (2006) Privatization and Restructuring in china: Evidence from Shareholding Ownership, 1995-2001. *Journal of Comparative Economics,* 34(1): 146-166

Jefferson, G.H. Rawski, T.G. Li, W. and Yuxin, Z. (2000) Ownership, Productivity Change, and Financial Performance in Chinese Industry. *Journal of Comparative Economics*, 28(4): 768-813

Jefferson, G. Zhu, A.G.Z., Guan, X. and Xu, X. (2003) Ownership, Performance, and Innovation in China's Large- and Medium-size Industrial Enterprise Sector. *China Economic Review,* 14(1): 89-113

Jensen, J.B. McGuckin, R.H. and Stiroh, K.J. (2001) The Impact of Vintage and Survival on Productivity: Evidence from Cohorts of U.S. Manufacturing Plants. *The Review of Economics and Statistics,* 83(2): 323-332

Jiang, B.B. Laurenceson, J. and Tang, K.K. (2008) Share Reform and The Performance of China's Listed Companies. *China Economic Review,* 19(3): 489-501

Johnson, S. and Mitton, T. (2003) Cronyism and Capital Controls: Evidence from Malaysia. *Journal of Financial Economics,* 67(2): 351-382

Katayama, H. Lu, S. and Tybout, J.R. (2009) Firm-level Productivity Studies: Illusion and a Solution. *International Journal of Industrial Organization,* 27(3): 403-413

Keller, W. (1998) Are international R&D Spillovers Trade-related? Analyzing spillovers Among Randomly Matched Trade Partners, *European Economic Review*, 42(8): 1469-1481

Kendrick, J.W. (1956) *Productivity Trends: Capital and Labour*. Cambridge: National Bureau of Economic Research

Kennett, D. (2001) *A New View of Comparative Economic Systems.* London: Harcourt

Kerr, D. (2007) Has China Abandoned Self-reliance? *Review of International Political Economy*, 14(1): 77-104

Kim, S. Gopinath, M. and Kim, H. (2009) High Productivity Before or After Exports? An Empirical Analysis of Korean Manufacturing Firms. *Journal of Asian Economics,* 20(4): 410-418

King, F.H.H. (1968) *A Concise Economic History of Modern China.* New York: Praeger, Pall Mall.

Klenow, P. and Rodriguez-Clare, A. (1997) The Neo-classical Revival in Growth Economics: Has It Gone Too Far? In Bernanke, B., Rotemberg, J. (Eds.), NBER Macroeconomics Annual. MIT Press, Cambridge, MA: 73-102

Klenow, P. and Rodriguez-Clare, A. (2005) Externalities and Economic Growth. In: Aghion, P., Durlauf, P. (Eds.) Handbook of Economic Growth, Elsevier Science: 817-861

Klette, T.J. (1999) Market Power, Scale Economies and Productivity: Estimates from a Panel of Establishment Data. *The Journal of Industrial Economics,* 47(4): 451-476

Knight, J. and Wang W. (2011) China's Macroeconomic Imbalances: Causes and Consequences. *The World Economy*, (2011): 1476-1506

Kolmogorov, A.N. (1933) Sulla Determinazione Empirica di una Legge di Distribuzione. *Giornale dell'Istituto Italiano degli Attuari,* 4(1933): 83-91

Kong, X. Marks, R.E. and Wan, G.H. (1999) Technical Efficiency, Technological Change and Total Factor Productivity Growth in Chinese State-Owned Enterprises in the Early 1990s. *Asia Economic Journal,* 13(3): 267-281

Koprowski, E.J. (1981) Exploring the Meaning of "Good" Management. *The Academy of Management Review,* 6(3): 459-467

Kornai, J. (1980) The Soft Budget Constraint. *Kyklos*, 39(1): 3-30

Kotabe, M. Srinivasan, S.S. and Aulakh, P.S. (2002) Multinationality and Firm Performance: The Moderating Role of R&D and Marketing Capabilities. *Journal of International Business Studies*, 33(1): 79-97

Kramer, J.P. Marinelli, E. Iammarino, S. Revilla Diez, J. (2011). Intangible Assets as Drivers of Innovation: Empirical Evidence on Multinational Enterprises in German and UK Regional Systems of Innovation. *Technovation*, 31(9): 447-458

Krasnikov, A. and Jayachandran, S. (2008) The Relative Impact of Marketing, Research and Development, and Operations Capabilities on Firm Performance. *Journal of Marketing,* 72(4): 1-11

Kroszner, R.S. and Stratmann, T. (1998) Interest-Group Competition and the Organization of Congress: Theory and Evidence from Financial Services' Political Action Committees. *The American Economic Review,* 88(5): 1163-1187

Krugman, P. (1990) *The Age of Diminished Expectations: US Economic Policy in the 1990s.* Cambridge and London: The MIT Press

Krusekopf, C.C. (2002) Diversity in Land-tenure Arrangements Under the Household Responsibility System in China. *China Economic Review,* 13(2-3): 297-312

Kung, J.K. (1994) Egalitarianism, Subsistence Provision, and Work Incentives in China's Agricultural Collectives. *World Development,* 22(2): 175-187

Kung, J.K. and Lin, J.Y. (2003) The Causes of China's Great Leap Famine, 1959-1961. *Economic Development and Cultural Change,* 52(1): 51-73

Kwon, J.K. (1986) Capital Utilization, Economies of Scale and Technical Change in the Growth of Total Factor Productivity: An Explanation of South Korean Manufacturing Growth. *Journal of Development Economics,* 24(1): 75-89

Lai, H.H. (2002) China's Western Development Programme: Its Rationale, Implementation, and Prospects. *Modern China*, 28(4): 432-466

Lazear, E.P. (2000) Performance Pay and Productivity. *The American Economic Review,* 90(5): 1346-1361

Lee, H. and Rugman, A.M. (2012) Firm-specific Advantages, Inward FDI Origins, and Performance of Multinational Enterprises. *Journal of International Management*, 18(2012): 132-146

Leibenstein, H. (1966) Allocative Efficiency vs. "X-Efficiency". *The American Economic Review*, 56(3): 392-415

Levinsohn, J. and Petrin, A. (2003) Estimating Production Functions Using Inputs to Control

Li, D.D. (1996) A Theory of Ambiguous Property Rights in Transition Economies: The Case of the Chinese Non-State Sector. *Journal of Comparative Economics*, 23(40): 1-19

Li, H. (2012) The Impact of China's Stock Market Reforms on its International Stock Market Linkages. *The Quarterly Review of Economics and Finance*, 52(4): 358-368

Li, H. Meng, L. Wang, Q. and Zhou, L.A. (2008) Political Connections, Financing and Firm Performance: Evidence from Chinese Private Firms. *Journal of Development Economics*, 87(2): 283-299

Li, H. and Zhang, J. (2007) Do High Birth Rates Hamper Economic Growth? *The Review of Economics and Statistics*, 89(1): 110-117

Li, J. (1995) China's One Child Policy: How and How Well Has It Worked? A Case Study of Hebei Province, 1979-88. *Population and Development Review*, 21(3): 563-585

Li, J. Lam, K. and Qiam, G. (2001) Does Culture Affect Behaviour and Performance of Firms? The Case of Joint Ventures in China. *Journal of International Business Studies*, 32(1): 115-131

Li, K. Liu, Z. Yu, Y. and Zhang, J. (2010) Does Market-oriented Economic Transition Enhance Enterprise Productivity? Evidence From China's Enterprises. *Pacific Economic Review*, 15(5): 719-742

Li, S. (2004) Location and Performance of Foreign Firms in China. *Management International Review*, 44(2): 151-169

Li, S. (2004) The Puzzle of Firm Performance in China: an Institutional Explanation. *Economics of Planning*, 37(1): 47-68

Li, S. and Xia, J. (2008) The Roles and Performance of State Firms and Non-State Firms in China's Economic Transition. *World Development*, 36(1): 39-54

Li, X. Liu, X. and Parker, D. (2001) Foreign Direct Investment and Productivity Spillovers in the Chinese Manufacturing Sector. *Economics Systems*, 25(4): 305-321

Li, W. and Tang, D.T. (2005) The Great Leap Forward: Anatomy of a Central Planning Disaster. *Journal of Political Economy*, 113(4): 840-877

Lichtenberg, F.R. (1992) Industrial De-diversification and Its Consequences for Productivity. *Journal of Economic Behavior and Organization*, 18(1992): 427-438

Lichtenberg, F.R. and Siegel, D. (1991) The Impact of R&D Investment on Productivity – New Evidence Using Linked R&D Data. *Economic Enquiry,* 29(2): 203-229

Lieberman, M.B. (1990) Exit from Declining Industries: "Shakeout" or "Stakeout"? *The RAND Journal of Economics,* 21(4): 538-554

Lin, H. Li, H. and Yang, C. (2011) Agglomeration and Productivity: Firm-Level Evidence from China's Textile Industry. *China Economic Review,* 22(3): 313-329

Lin, J.Y. (1988) The Household Responsibility System in China's Agricultural Reform: A theoretical and Empirical Study. *Economic Development and Cultural Change*, 36(3): 199-224

Lin, J.Y. (1990) Collectivization and China' Agricultural Crisis in 1959-1961. *Journal of Political Economy,* 98(6): 1128-1252

Lin, J.Y. (1992) Rural Reforms and Agricultural Growth in China. *The American Economic Review,* 82(1): 34-51

Lin, J.Y. and Liu, Z. (2000) Fiscal Decentralization and Economic Growth in China. *Economic Development and Cultural Change,* 49(1): 1-21

Lin, J.Y. and Yang, D.T. (1998) On the Causes of China's Agricultural Crisis and the Great Leap Famine. *China Economic Review,* 9(2): 125-140

Lin, J.L. (1988) The Household Responsibility System in China's Agricultural Reform: A Theoretical and Empirical Study. *Economic Development and Cultural Change*, 36(3): 199-224

Lin, J.L. (1990) Collectivization and China's Agricultural Crisis in 1959-1961. *Journal of Political Economy,* 98(6): 1228-1252

Lin, P. Liu, Z. and Zhang, Y. (2009) Do Chinese Domestic Firms Benefit from FDI Inflow? Evidence of Horizontal and Vertical Spillovers? *China Economic Review,* 20(4): 677-691

Liou, K.T. (2012) Incentive Policies and China's Economic Development: Change and Challenge. *Journal of Public Budgeting, Accounting & Financial Management,* 24(1): 114-135

Liu, Z. (2002) Foreign Direct Investment and Technology Spillover: Evidence from China. *Journal of Comparative Economics,* 30(2002): 579-602

Liu, Z. (2008) Foreign Direct Investment and Technology Spillovers: Theory and Evidence. *Journal of Development Economics,* 85(2008): 176-193

Liu, X. and Buck, T. (2007) Innovation Performance and Channels for International Technology Spillovers: Evidence from Chinese High-tech Industries. *Research Policy,* 36(2007): 355-366

Lokshin, B. Belderbos, R. and Carree M. (2008) The Productivity Effects of Internal and External R&D: Evidence from a Dynamic Panel Data Model. *Oxford Bulletin of Economics and Statistics,* 70(3): 399-413

Lööf, H. and Andersson, M. (2010) Imports, Productivity and Origin Markets: The Role of Knowledge Intensive Economies. *The World Economy,*

López, R.A. and Südekum, J. (2009) Vertical Industry Relations, Spillovers, and Productivity: Evidence from Chilean Plants. *Journal of Regional Science,* 49(4): 721-747

Luo, X. (2004) The Role of Infrastructure Investment Location in China's Western Development. World Bank Working Paper, No. 3345, Available from: http://elibrary.worldbank.org/doi/book/10.1596/1813-9450-3345 [10/12/2013]

Ma, G. and Yi, W. (2010) China's High Saving Rate: Myth and Reality. BIS Working Papers, No. 312, Available from: Available from: http://www.bis.org/publ/work312.htm [18/08/2013]

Ma, J. Evans, D.G. Fuller, R.J. and Stewart, D.F. (2002) Technical Efficiency and Productivity Change of China's Iron and Steel Industry. *International Journal of Production Economics,* 76(3): 293-312

Mairesse, J. and Hall, B.H. (1996) Explorating the Productivity of Research and Development: an Exploration of the GMM Methods Using Data on French and United States

Manufacturing Firms. NBER Working Papers Series, No. 5501, Available from: http://www.nber.org/papers/w5501.pdf [15/04/2013]

Majumdar, S.K. (1997) The Impact of Size and Age on Firm-Level Performance: Some Evidence from India. *Review of Industrial Organization*, 12(2): 231-241

Marrocu, E. Paci, R. and Usai S. (2012) Productivity Growth in the Old and New Europe: The Role of Agglomeration Externalities. *Journal of Regional Science*, 53(3): 418-442

Marschak, J. and Andrews W.H. Jr. (1954) Random Simultaneous Equations and the Theory of Production. *Econometrica*, 12 (3/4): 143-205

Marshall, A. (1922) *Principles of Economics: An Introductory Volume.* 8th edition. London: Macmillan & Co., Limited.

Martin, R. (2008) Productivity Dispersion, Competition and Productivity Measurement. CEP Discussion Paper, No. 692, Available from: http://eprints.lse.ac.uk/19573/ [03/09/2013]

Martin, P. Mayer, T. and Mayneris F. (2011) Spatial Concentration and Plant-level Productivity in France. *Journal of Urban Economics*, 69(2011): 182-195

Melitz, M.J. and Polanec, S. (2012) Dynamic Olley-Pakes Productivity Decomposition With Entry and Exit. NBER Working Papers Series, No. 18182, Available from: http://www.nber.org/papers/w18182 [29/06/2014]

Mertha, A.C. (2009) From 'Rustless Screws' to 'Nail Houses': The Evolution of Property Rights in China. *Orbis*, 53(2): 233-249

Meyer, M.A. and Vickers, J. (1997) Performance Comparisons and Dynamic Incentives. *Journal of Political Economy*, 105(3): 547-581

Mitra, A. (1999) Agglomeration Economies as Manifested in Technical Efficiency at the Firm Level. *Journal of Urban Economics*, 45 490-500

Morgan, N.A. Slotegraaf, R.J. and Vorhies, D.W. (2009) Linking Marketing Capabilities with Profit Growth. *International Journal of Research in Marketing*, 26(4): 284-293

Motohashi, K. and Yuan, Y. (2010) Productivity Impact of Technology Spillover from Multinationals to Local Firms: Comparing China's Automobile and Electronics Industries. *Research Policy:* 39(6): 790-798.

Movshuk, O. (2004) Restructuring, productivity and technical efficiency in China's Iron and Steel Industry, 1988-2000. *Journal of Asian Economics*, 15(1): 135-151

Mundlak, Y. (1961) Empirical Production Function Free of Management Bias. *Journal of Farm Economics*, 43(1): 44-56

Nakajima, T. Nakamura, M. and Yoshioka K. (1998) An Index Number Method for Estimating Scale Economies and Technical Progress Using Time-Series of Cross-Section Data: Sources of Total Factor Productivity. *The Japanese Economic Review*, 49(3): 310-334

Nath, P. Nachiappan, S. and Ramanathan R. (2010) The Impact of Marketing Capability, Operations Capability and Diversification Strategy on Performance: A Resource-Based View. *Industrial Marketing Management,* 39(2010): 317-329

Naughton, B.J. (2004) The Western Development Program. In: Naughton, B.J. and Yang, D.L. (*ed*) *Holding China Together.* Cambridge: Cambridge University Press, pp. 253-295

Nelson, R.A. and Wohar, M.E. (1983) Regulation, Scale Economies, and Productivity in Steam-Electric Generation. *International Economic Review,* 24(1): 57-79

Nickell, S.J. (1996) Competition and Corporate Performance. *Journal of Political Economy,* 104(4): 724-746

Nickell, S.J. and Nicolitsas, D. (1999) How Does Financial Pressure Affect Firms? *European Economic Review,* 43(8): 1435-1456

Nickell, S.J. Wadhwani, S. and Wall M. (1992) Productivity Growth in UK Companies, 1975-1986. *European Economic Review,* 36(5): 1055-1085

Nishimizu, M. and Page J.M. Jr. (1982) Total Factor Productivity Growth, Technological Progress and Technical Efficiency Change: Dimensions of Productivity Change in Yugoslavia, 1965-78. *The Economic Journal*, 92(368): 920-936

Nishitateno, S. (1983) China's Special Economic Zones: Experimental Units for Economic Reform. *International and Comparative Law Quarterly*, 32(1): 175-185

North, D.C. (2000) Big-Bang Transformations of Economic Systems: An Introductory Note. *Journal of Institutional and Theoretical Economics*, 156(1): 3-8

Olley, G.S. and Pakes, A. (1996) The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*, 64(6): 1263-1297

Ornaghi, C. (2006) Spillovers in Product and Process Innovation: Evidence from Manufacturing Firms. *International Journal of Industrial Organization*, 24(2): 349-380

Overman, H. Gibbons, S. and Tucci, A. (2009) The Case for Agglomeration Economies. *Manchester Independent Economics Review.* Manchester. Available at: http://www.manchester-review.org.uk/projects/view/?id=718

Pan, Z. and Zhang F. (2002) Urban Productivity in China. *Urban Studies,* 39(12): 2267-2281

Park, B.S. (2009) China's Corporate Reform and its Economic Effect. *SERI Quarterly,* 7(2009): 11-21

Park, S.H. Li, S. and Tse, D.K. (2006) Market Liberalization and Firm Performance during China's Economic Transition. *Journal of International Business Studies,* 37(1): 127-147

Polanyi, M. (2005) Tacit Knowing: Its Bearing on Some Problems of Philosophy. *Review of Modern Physics,* 34(4): 601-616

Peng, X. (2011) China's Demographic History and Future Challenges. *Science*, 333(581): 581-587

Perkins, F.C. (1996) Productivity Performance and Priorities for the Reform of China's State-Owned Enterprises. *Journal of Development Studies,* 32(3): 414-444

Petrin, A. Poi, B.P. and Levinsohn, J. (2004) Production Function Estimation in Stata Using Inputs to Control for Unobservables. *The Stata Journal,* 4(2): 113-123

Putterman, L. (1987) The Incentive Problem in the Demise of Team Farming in China. *Journal of Development Economics,* 26(1): 103-127

Putterman, L. (1990) Effort, Productivity, and Incentives in a 1970s Chinese People's Commune. *Journal of Comparative Economics,* 14(1): 88-104

Pyle, D.J. (1997) *China's Economy.* Basingstoke: MacMillan Press Ltd

Qian, Y. (2000) The Process of China's Market Transition (1978-1998): The Evolutionary, Historical, and Comparative Perspectives. *Journal of Institutional and Theoretical Economics,* 156(1): 151-171

Rajan, S.I. (1994) China's One-Child Policy: Implication for Population Aging. *Economic and Political Weekly,* 29(38): 2502-2506

Rasiah, R. Miao, Z. and Xin, K.X. (2013) Can China's Miraculous Economic Growth Continue? *Journal of Contemporary Asia*, 43(2): 295-313

Rawski, T.G. (1975) The Growth of Producer Industries, 1900-1971 In: D.H. Perkins (ed). *China's Modern Economy in Historical Perspective*. Stanford: Stanford University Press, pp. 203-234

Rawski, T.G. (1980) *China's Transition to Industrialism: Producer Goods and Economic Development in the Twentieth Century.* Ann Arbor: University of Michigan Press

Rawski, T.G. (1995) Implications of China's Reform Experience. *The China Quarterly*, 144(12): 1150-1173

Reinhart, C.M. and Rogoff, K.S. (2009) *This Time is Different: Eight Centuries of Financial Folly*. Princeton: Princeton University Press

Riskin, C. (1998) Seven Questions About the Chinese Famine of 1951-61. *China Economic Review*, 9(2): 111-124

Roberts, M.J. and Tybout, J.R. (1997) The Decision to Export in Colombia. An Empirical Model of Entry with Sunk Costs. *The American Economic Review,* 87(4): 545-564

Roland, G. (2000) *Transition and Economics: Politics, Markets and Firms*. Cambridge, Massachusetts: The MIT Press

Romer, P.M. (1986) Increasing Returns and Long-run Growth. *Journal of Political Economy,* 94(5): 1002-1037

Romijn, H. and Albaladejo, M. (2002) Determinants of Innovative Capacity in Small Electronics and Software Firms in Southeast England. *Research Policy,* 31(7): 1053-1067

Roodman, D. (2006) How to do xtabond2: An Introduction to Difference and System GMM in Stata. *The Stata Journal*, 9(1): 86-136

Rosenkopf, L. and Nerkar, A. (2001) Beyond Local Search: Boundary-Spanning, Exploration, and Impact in the Optical Disk Industry. *Strategic Management Journal*, 22(4): 387-306

Rugman, A.M. (2005) *The Regional Multinationals: MNEs and 'Global' Strategic Management.* Cambridge University Press, Cambridge, UK

Schmidt, T. (2005) What Determines Absorptive Capacity? *Working Paper*

Schoar, A. (2002) Effects of Corporate Diversification on Productivity. *Journal of Finance,* 57(6): 2379-2403

Shangquan, G. (1993) Taking a Market Oriented Direction and Pushing Forward in a Gradual Way – The Basic Experience of China's Economic Reform. *China Economic Review,* 4(2): 129-136

Shen, C. Jin, J. and Zou, H. (2012) Fiscal Decentralization in China: History, Impact, Challenges and Next Steps. *Annals of Economics and Finance,* 13(1): 1-51

Shen, Y. and Song, (2013) Re-estimation of firms' total factor productivity in China's iron and steel industry. *China Economic Review,* 24(1): 177-188

Shirley, M.M. and Xu, L.C. (2001) Empirical Effects of Performance Contracts: Evidence from China. *The Journal of Law, Economics & Organization,* 17(1): 168-200

Sjöholm, F. (1999a) Productivity Growth in Indonesia: The Role of Regional Characteristics and Direct Foreign Investment. *Economic Development and Cultural Change,* 47(3): 559-584

Sjöholm, F. (1999b) Exports, Imports and Productivity: Results from Indonesian Establishment Data. *World Development,* 27(4): 705-715

Smirnov, N.V. (1939) Estimate of Deviation between Empirical Distribution Functions in Two Independent Samples. *Bulletin Moscow University,* 2(1): 3-16

Solow, R.M. (1957) Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics.* 39(3): 312-320

Stigler, G.J. (1947) *Trends in Output and Employment.* Cambridge: National Bureau of Economic Research

Sun, J. Harimaya, K. and Yamori, N. (2013) Regional Economic Development, Strategic Investors, and Efficiency of Chinese City Commercial Banks. *Journal of Banking & Finance*, 37(5): 1602-1611

Sun, X. and Hong, J. (2011) Exports, Ownership and Firm Productivity: Evidence from China. *The World Economy*, 34(7): 1199-1215

Suyanto, Salim, R.A. and Bloch H. (2012) Does Foreign Direct Investment Lead to Productivity Spillovers? Firm Level Evidence from Indonesia. *World Development*, (37)12: 1861-1876

Sveikauskas, L. (1975) The Productivity of Cities. *Quarterly Journal of Economics*, 89(3), 393-413

Syverson, C. (2011) What Determines Productivity? *Journal of Economic Literature*, 49(2): 326-365

Tan, J. Li, S. and Xia, J. (2007) When Iron Fist, Visible Hand, and Invisible Hand Meet: Fir-Level Effects of Varying Institutional Environments in China. *Journal of Business Research,* 60(7): 786-794

Tang, J. and Wang, W. (2005) Product Market Competition, Skill Shortages and Productivity: Evidence from Canadian Manufacturing Firms. *Journal of Productivity Analysis*, 23(3): 317-339

Teece, D.J. Pisano, G. Shuen, A. (1997) Dynamic Capabilitites and Strategic Management. *Strategic Management Journal*, 18(7): 509-533

Todo, Y. Zhang, W. Zhou L. (2009) Knowledge Spillovers from FDI in China: The Role of Educated Labor in Multinational Enterprises. *Journal of Asian Economics*, (20) 2009: 626-639

Tondkar, R.H. Peng, S. and Hodgdon, C. (2003) The Chinese Securities Regulatory Commission and The Regulation of Capital Markets in China. *Advances in International Accounting*, 16(1): 153-174

Transparency International (2011): Corruption Perceptions Index. Available from: http://www.transparency.org/cpi2011/results [14/02/2014]

Trefler, D. (1993) International Factor Price Differences: Leontief Was Right! *Journal of Political Economy,* 101(6): 961-987

Trefler, D. (1995) The Case of Missing Trade and Other Mysteries. *American Economic Review,* 85(5): 1029-1046

Tsai, C.F. Lu, Y.H. Chen, D.C. (2012) Determinants of Intangible Assets Value: The Data Mining Approach. *Knowledge Based Systems,* 31(1): 67-77

U.S. Congress, Joint Economic Committee (1967). *An Economic Profile of Mainland China.* Washington: GPO

Van Bart, A. (1993) Comparative Levels of Manufacturing Productivity in Postwar Europe: Measurement and Comparisons. *Oxford Bulletin of Economics and Statistics*, 52(4): 343-374

Van Bart, A. and Pilat, D. (1993) Productivity Levels in Germany, Japan and the United States: Differences and Causes. *Brookings Paper on Economic Activity,* 2(1): 1-69

Van Beveren, I. (2012) Total Factor Productivity Estimation: A Practical Review. *Journal of Economic Surveys,* 12(1): 98-128

Van Biesebroeck, J. (2007) Robustness of Productivity Estimates. *The Journal of Industrial Economics,* 55(3): 529-569

van der Panne, G. (2004) Agglomeration Externalities: Marshall versus Jacobs. *Journal of Evolutionary Economics,* 14(5): 593-604

Vinding, A.L. (2006) Absorptive Capacity and Innovative Performance: A Human Capital Approach. *Economics of Innovation and New Technology,* 15(4-5): 507-517

Vogel, A. and Wagner J. (2010) Higher Productivity in Importing German Manufacturing Firms: Self-Selection, Learning From Importing, or both? *Review of World Economics,* 145(4): 641-665

Vorhies, D.W. and Morgan, N.A. (2005) Benchmarking Marketing Capabilities for Sustainable Competitive Advantage. *Journal of Marketing,* 69(1): 80-94

Wang, J. (2013) The Economic Impact of Special Economic Zones: Evidence from Chinese Municipalities. *Journal of Development Economics,* 101(1): 133-147

Wang, Z. and Yu, Z. (2011) Trade Partners, Trade Products, and Firm Performance: Evidence from China's Exporter-Importers, *GEP Working Paper Series, the University of Nottingham*

Wedervang, F. (1965) *Development of a Population of Industrial Firms.* Oslo: Scandinavian University Books

Wei, Y. and Liu, X. (2006) Productivity Spillovers from R&D, Exports and FDI in China's Manufacturing Sector. *Journal of International Business Studies,* 37(4): 544-577

Wei, Y. Liu, X. and Wang, C. (2008) Mutual Productivity Spillovers between Foreign and Local Firms in China. *Cambridge Journal of Economics,* 32(4): 609-631

Wei, Z. Varela, O. and Hassan, M.K. (2002) Ownership and Performance in Chinese Manufacturing Industry. *Journal of Financial Management,* 12(1): 61-78

Williamson, O.E. (1981) The Economics of Organization: The Transaction Cost Approach. *American Journal of Sociology,* 87(3): 548-577

Wills, I. and Yang, X. (2006) The Importance of Property Rights for Economic Growth: The Case of Rural China, 1979-1987. *Economic Papers,* 25(2): 117-124

Windmeijer, F. (2005) A Finite Sample Correction for the Variance of Linear Efficient Two-step GMM Estimators. *Journal of Econometrics,* 126(1): 25-51

Wolff, E.N. (2014) *Productivity Convergence: Theory and Evidence.* Cambridge: Cambridge University Press

Wooldridge, J.M. (2009) On Estimating Firm-level Production Functions Using Proxy Variables to Control for Unobservables. *Economic Letters,* 104(3): 112-114

World Bank (2013) World Development Indicators. [online] Available at: http://data.worldbank.org/ [22/12/2013]

World Trade Organization (2001) 2001 Press releases. [online] Available at: http://www.wto.org/english/news_e/pres01_e/pr243_e.htm [26/12/2013].

World Trade Organization (2013): Trade Profiles: China. [online] Available at: http://stat.wto.org/CountryProfile/WSDBCountryPFView.aspx?Country=CN& [28/12/2013].

Wu, F.W.Y. (1981) From Self-reliance to Interdependence? Developmental Strategy and Foreign Economic Policy in Post-Mao China. *Modern China*, 7(4): 445-482

Wu, H.L. and Chen, C.H. (2010) Operational Performance of Commercial Banks in the Chinese Transitional Economy. *Journal of Developing Areas,* 44(1): 1-15

Wu, J. (2013) Marketing Capabilities, Institutional Development, and the Performance of Emerging Market Firms: A Multinational Study. *International Journal of Research in Marketing,* 30(1): 36-45

Wu, W. Wu, C. Zhou, C. and Wu, J. (2012) Political Connections, Tax Benefits and Firm Performance: Evidence from China. *Journal of Accounting and Public Policy,* 31(3): 277-300

Wu, Y. (2003) Has Productivity Contributed to China's Growth? *Pacific Economic Review,* 8(1): 15-30

Wu, Z.B. Yeung, G. Mok, V. and Han, Z. (2007) Firm-Specific Knowledge and Technical Efficiency of Watch and Clock Manufacturing Firms in China. *International Journal of Production Economics,* 107(2): 317-332

Yang, C.H., Lin, H.L. and Li, H.Y. (2013) Influences of Production and R&D Agglomeration on Productivity: Evidence from Chinese Electronics Firms. *China Economic Review,* 27(1): 162-178

Yang, D.T. Zhang, J. and Zhou, S. (2011) Why Are Saving Rates so High in China? NBER Working Papers Series, No. 16771, Available from: http://www.nber.org/papers/w16771 [18/08/2013]

Yanikkaya, H. (2003) Trade Openness and Economic Growth: A Cross-Country Empirical Investigation. *Journal of Development Economics,* 72(2003): 57-89

Yao, S. Han, Z. and Feng, G. (2007) On technical Efficiency of China's Insurance Industry after WTO Accession. *China Economic Review,* 18(1): 66-86

Yu, M. (2010) Processing Trade, Firm's Productivity, and Tariff Reductions: Evidence from Chinese Products. CCER Working Paper Series, No. E2010007, Available from: http://www.eaber.org/sites/default/files/documents/CCER_Yu_2010.pdf [12/01/2014]

Yu, W. Ramanathan, R. and Nath, P. (2014) The Impacts of M and Operations Capabilities on Financial Performance in the UK Retail Sector: A Resource-based Perspective. *Industrial Marketing Management*, 43(2014): 25-31

Yu, X. and Sheng, Y. (2012) Productivity Spillovers from Foreign Direct Investment: Firm-level Evidence from China. *World Development,* 40(1): 62-74

Xia, J. Li, S. and Long, C. (2009) The Transformation of Collectively Owned Enterprises and its Outcomes in China, 2001-2005. *World Development,* 37(10): 1651-1662

Xiwei, Z. and Xiangdong, Y. (2007) Science and Technology Policy Reform and Its Impact on China's National Innovation System. *Technology in Society,* 29: 317-325

Xu, L.C. (2000) Control, Incentives and Competition. The Impact of Reform on Chinese State-owned Enterprises. *Economics of Transition,* 8(1): 151-173

Zhang, L. (2012) Do Imports of Technology Facilitate Technological Progress? Evidence from China. *Procedia Engineering,* 29(3): 2826-2831

Zhang, J. and Liu, X. (2013) The Evolving Pattern of the Wage-labor Productivity Nexus in China: Evidence from Manufacturing Firm-Level Data. *Economic Systems,* 37(3): 354-368

Zhang, A. Zhang Y. and Zhao, R. (2001) Impact of Ownership and Competition on the Productivity of Chinese Enterprises. *Journal of Comparative Economics,* 29(2): 327-346

Zhang, A. Zhang Y. and Zhao, R. (2002) Profitability and Productivity of Chinese Industrial Firms: Measurement and Ownership Implications. *China Economic Review,* 13(1): 65-68

Zhang, A. Zhang Y. and Zhao, R. (2003) A Study of the R&D Efficiency and Productivity of Chinese Firms. *Journal of Comparative Economics,* 31(2003): 444-464

Zhang, J. Wang, L. and Wang, S. (2012) Financial Development and Economic Growth: Recent Evidence from China. *Journal of Comparative Economics,* 40(3): 393-412

Zhao, S. (1993) Deng Xiaoping's Southern Tour: Elite Politics in Post-Tianmen China. *Asian Survey,* 33(8): 739-756

Zheng, J. Liu, X. and Bigsten (1998) Ownership Structure and Determinants of Technical Efficiency: An Application of Data Envelopment Analysis to Chinese Enterprises (1986-1990) *Journal of Comparative Economics,* 26(3): 465-484

Zheng, J. Liu, X. and Bigsten, A. (2003) Efficiency, technical progress, and best practice in Chinese state enterprises (1980-1994). *Journal of Comparative Economics,* 31(1): 134-152

Zhou, D. Li, S. and Tse, D.K. (2002) The Impact of FDI on the Productivity of Domestic Firms: The Case of China. *International Business Review,* 11(4): 465-484

Zhou, Q. (2010) The Institutional Foundation of China’s Economic Growth. *China Economic Journal*, 3(1): 25-32

Zhu, X. Li, L. and Xue, Y. (2012) Banking System Reform, Earnings Quality and Credit Allocation. *China Journal of Accounting Research,* 5(3): 217-22

**Appendix**

Table A1. Structure of the unbalanced panel

Panel I.

| *Year* | *Number of observations* | *Percent* | *Cumulative* |
|---|---|---|---|
| *1998* | 148,474 | 6.8 | 6.8 |
| *1999* | 148,474 | 6.8 | 13.6 |
| *2000* | 162,004 | 7.4 | 21.0 |
| *2001* | 168,275 | 7.7 | 28.7 |
| *2002* | 180,751 | 8.3 | 37.0 |
| *2003* | 195,389 | 9.0 | 46.0 |
| *2004* | 277,827 | 12.7 | 58.7 |
| *2005* | 270,564 | 12.4 | 71.1 |
| *2006* | 300,498 | 13.8 | 84.8 |
| *2007* | 331,453 | 15.2 | 100 |
| *Total* | 2,183,709 | 100 | |

Panel II.

| *Number of observations per firm* | *Number of firms* | *Percent* | *Cumulative* | *Number of firm-year observations* | *Percent* | *Cumulative* |
|---|---|---|---|---|---|---|
| 1 | 109,513 | 19.6 | 19.6 | 109,513 | 5.0 | 5.0 |
| 2 | 103,878 | 18.6 | 38.1 | 207,756 | 9.5 | 14.5 |
| 3 | 74,800 | 13.4 | 51.5 | 224,400 | 10.3 | 24.8 |
| 4 | 98,547 | 17.6 | 69.1 | 394,188 | 18.1 | 42.9 |
| 5 | 41,828 | 7.5 | 76.6 | 209,140 | 9.6 | 52.4 |
| 6 | 36,373 | 6.5 | 83.1 | 218,238 | 10.0 | 62.4 |
| 7 | 26,356 | 4.7 | 87.8 | 184,492 | 8.4 | 70.9 |
| 8 | 19,746 | 3.5 | 91.3 | 157,968 | 7.2 | 78.1 |
| 9 | 8,616 | 1.5 | 92.8 | 77,544 | 3.6 | 81.7 |
| 10 | 40,047 | 7.2 | 100 | 400,470 | 18.3 | 100.0 |
| Total | 559,704 | 100 | | 2,183,709 | 100 | |