

Policy Research Working Paper 2857¹
Markups, Returns to Scale, and Productivity: A Case Study of
Singapore's Manufacturing Sector

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Abstract

We derive the dual approach of Hall (1988). We show that both primal and dual TFP growth underestimate true productivity growth if there is imperfect competition or decreasing returns to scale. Contradicting Roeger (1995), we show that imperfect competition alone could not explain the differences between primal and dual TFP growth if factor shares remain constant. Correcting for input endogeneity and selection bias, we estimate industry markups and scale coefficients of Singapore's manufacturing sector with both the primal and dual approaches. Results indicate that all industries violate one or both of the neoclassical assumptions. Controlling for imperfect competition and non-constant returns to scale, the estimated growth rate of productivity of the sector doubles the conventional growth accounting measures.

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Nontechnical Summary

The results of this paper challenge the conventional wisdom in the literature that productivity plays no role in the economic development of Singapore. Properly accounting for market power and returns to scale technology, the estimated average productivity growth is twice as large as the conventional total factor productivity (TFP) measures.

Using a standard growth accounting (production function) technique, Young (1992, 1995) finds no sign of TFP growth in the aggregate economy and the manufacturing sector of Singapore. Based on Young's results, Krugman (1994) claims that there is no East Asia miracle as all of the economic growth in Singapore could be attributed to its capital accumulation in the past three decades. Citing evidence of non-diminishing market rate of returns to capital investment in Singapore during the period of fast growth as an indication of high productivity growth, Hsieh (1999) challenges Young's findings using the dual approach. All of these papers however maintain the assumptions of perfect competition and constant returns to scale and use only aggregate macro-level data.

This paper uses industry level data and focuses on Singapore's manufacturing sector. We develop an empirical methodology to estimate industry productivity growth in the presence of market power and non-constant returns to scale. The estimation of industry markups and returns to scale in this paper combines both the production function (primal) and the cost function (dual) approaches while controlling for input endogeneity and selection bias.

The results of a fixed effect panel regression show that all industries in the manufacturing sector violate at least one of the two assumptions. Relaxing the assumptions leads to an estimated productivity growth that is on average twice as large as the conventional TFP calculation. We conclude that productivity growth plays a nontrivial role in the manufacturing sector.

1. Introduction

Hall (1988, 1990) shows that when the assumptions of perfect competition and constant returns to scale are violated, the growth rate of primal total factor productivity (TFP) no longer reflects the true productivity growth. The growth rate of primal TFP, which is also referred to as the Solow residuals in the literature, is defined as the growth rate of output minus the revenue share-weighted average of the growth rates of inputs. Employing industry data of the U.S. manufacturing sector, Hall finds that the primal TFP is correlated with some exogenous macroeconomic variables, which suggests the existence of increasing returns to scale and imperfect competition in the manufacturing sector.

Hall's findings have generated a series of related studies. It has become a standard technique in the literature to apply the primal "Hall regression" to determine the nature of returns to scale and the competitiveness of an industry. For example, using a similar technique, Caballero and Lyons (1990, 1992); Bartelsman, Caballero, and Lyons (1994); and Basu and Fernald (1997) show the empirical importance of non-constant returns to scale in explaining the procyclical movement of Solow residuals in both U.S. and European industries. Levinsohn (1993) and Harrison (1994) also apply the primal "Hall regression" to show the effect of trade liberalization on the monopoly power of domestic firms.

Focusing on the price-cost side of the production theory and applying the cost function as the dual equivalent of the production function, Roeger (1995) shows that the presence of market power not only causes the dual TFP to underestimate real productivity growth, it also creates a wedge between primal and dual TFP growth. The growth rate of dual TFP is defined as the revenue share-weighted average of the growth rate of input prices minus the growth rate of output price. In other words, while maintaining the assumption of constant returns to scale, he relaxes the assumption of perfect competition and shows that markup greater than one could explain the difference between the primal and dual productivity

measures using U.S. manufacturing data.

In this paper we relax both the assumption of perfect competition and that of constant returns to scale at the same time.³ Complementary to the results of Hall (1988, 1990), we show that in the presence of market imperfections or non-constant returns to scale, dual TFP growth rates no longer reflect actual productivity growth. In particular, imperfect competition or decreasing returns to scale technology will result in a downward bias of both of the conventional TFP measures. In addition, this paper derives the theoretical difference between the primal and dual TFP measures without both assumptions and shows that the wedge between the two productivity measures depends on the growth rates of factor shares in revenue. Thus, as long as factor shares in revenue remain constant, which is one of the stylized facts in the empirical data, the difference between the growth rates of primal and dual TFP vanishes, even in the presence of imperfect competition or non-constant returns to scale. In other words, in contradiction to the results of Roeger (1995), we show that the difference between primal and dual TFP should not be attributed to the presence of imperfect competition while maintaining the assumption of constant returns to scale.

Empirical equivalence of primal and dual TFP is tested using industry panel data of the Singapore manufacturing sector. The productivity growth of Singapore has been studied previously by Young (1992, 1995) and Hsieh (1999). In a famous and surprising study, Young (1992) finds little evidence of primal TFP growth in the aggregate Singapore economy – virtually all Singapore’s growth from the 1970s to the 1990s is attributed to its factor accumulation. Similar poor performance of primal TFP is also documented in Young (1995) when the manufacturing sector data is studied. Citing evidence of non-diminishing market rate of returns to capital investment in Singapore during the period of fast growth as an indication of high productivity growth, Hsieh (1999) challenges Young’s finding using the

³ Similar to Hall’s approach, we maintain the assumptions that factor markets are perfectly competitive and production functions are non-joint.

dual approach. While acknowledging that the primal and dual TFP should be equal, Hsieh advocates that if the national account data on the capital endowment of Singapore is flawed, then the dual approach would provide a better measurement of productivity.

The empirical section of this paper is an attempt to adjudicate between Young and Hsieh at an industry level by estimating the industry productivity growth in the presence of imperfect competition and non-constant returns to scale. We first run a panel regression that embraces both primal and dual approaches to estimate industry-specific markups and returns to scale. Given that the primal and dual approaches are theoretically equivalent, combining them in the empirical specification allows us to double the sample size of the regressions. We then apply an Olley and Pakes (1996) type correction for input endogeneity and selection bias at an industry level to estimate the average industry markup and returns to scale. We also address the concern raised by Basu and Fernald (1997) regarding the differences between value added and output functions.

Results of a panel regression on the combined data set pass a specification test on the equivalence of the primal and dual regressions with flying colors. The results also indicate that all of the industries in the sector violate at least one of the assumptions of perfect competition and constant returns to scale. This implies that, in order to determine the actual productivity growth, conventional growth accounting techniques, which are based on the two assumptions, are not appropriate for the Singapore manufacturing sector. Controlling for input endogeneity and survival probability of firms in the industries, the estimated markup of an average industry in the sector is around 1.4, while production technique is best characterized as decreasing returns to scale. After correcting for imperfect competition and decreasing returns to scale, the estimated productivity growth in the sector doubles the conventional TFP measures. Thus, the results of this paper favor Hsieh's finding at the aggregate level that the productivity growth of Singapore could in fact be quite high.

How sensible are the estimates on markup and returns to scale? While various authors

have found markups greater than one in U.S. and European industries, decreasing returns to scale technology has been regarded as less acceptable in the literature. Basu and Fernald (1997) argue that decreasing returns to scale makes no economic sense at a firm level as it implies that firms consistently price output below marginal cost. They also show that the degree of decreasing returns to scale diminishes at a higher level of aggregation. They explain the observed puzzles as aggregation bias due to firm heterogeneity in the industries. For our current data set, even after controlling for firm heterogeneity using an Olley and Pakes type correction, we still obtain an estimated scale coefficient that is significantly less than one. Thus, we argue that for the case of Singapore’s manufacturing sector, decreasing returns to scale is a result of the limited supply of industrial land and buildings in the tiny city-state rather than aggregation bias due to firm’s heterogeneity. In fact, in recent years, Singapore’s government has been actively encouraging firms to relocate production plants to Malaysia, Indonesia and China while keeping the headquarter’s activities in the island, to slow rising business costs due to limited supply of land and labor in the economy.

This paper is organized as follows. Section 2 presents a theoretical model detailing the relationship between primal and dual TFP and true productivity growth in the presence of imperfect competition and non-constant returns to scale. Section 3 develops the empirical strategy to estimate industry markup and scale coefficient, utilizing both the primal and dual Hall regressions. Section 4 describes the data set, and Section 5 presents the regression results. Section 6 discusses various econometric and specification issues, and Section 7 concludes the paper.

2. Theory: The Relationship between Primal and Dual TFP

2.1 The Neoclassical Model

The standard assumptions of a neoclassical model of production are constant returns to scale, non-joint production, and perfectly competitive markets for inputs and outputs. Under these

assumptions, let i be the industry index and t be the time index; the relationship between the growth rate of output, \widehat{Y}_{it} , the growth rate of labor input, \widehat{L}_{it} , and capital input, \widehat{K}_{it} , can be represented by Equation (1),

$$\widehat{Y}_{it} = \widehat{A}_{it} + \theta_{iL}\widehat{L}_{it} + \theta_{iK}\widehat{K}_{it}, \quad (1)$$

where A_{it} is the growth rate of Hicks neutral productivity, θ_{iX} is the share of input X in total revenue, and $\theta_{iL} + \theta_{iK} = 1$. Thus,

$$\widehat{A}_{it} = \left(\frac{\widehat{Y}_{it}}{\widehat{K}_{it}} \right) - \theta_{iL} \left(\frac{\widehat{L}_{it}}{\widehat{K}_{it}} \right). \quad (2)$$

Using the dual approach of production theory, a similar relationship also exists between the growth rate of output price, \widehat{p}_{it} , the growth rate of wages, \widehat{w}_{it} , and rental price, \widehat{r}_{it} :

$$\widehat{p}_{it} = \theta_{iL}\widehat{w}_{it} + \theta_{iK}\widehat{r}_{it} - \widehat{A}_{it} \Rightarrow \quad (3)$$

$$\widehat{A}_{it} = \theta_{iL} \left(\frac{\widehat{w}_{it}}{\widehat{r}_{it}} \right) - \left(\frac{\widehat{p}_{it}}{\widehat{r}_{it}} \right). \quad (4)$$

Thus it is straightforward to define the growth rate of primal TFP, which is also known as the Solow residual, and the growth rate of dual TFP:

Definition 1 Let \widehat{TFP}_{it}^P be the growth rate of primal TFP, and \widehat{TFP}_{it}^D be the growth rate of dual TFP, then

$$\widehat{TFP}_{it}^P = \left(\frac{\widehat{Y}_{it}}{\widehat{K}_{it}} \right) - \theta_{iL} \left(\frac{\widehat{L}_{it}}{\widehat{K}_{it}} \right) \quad (5)$$

$$\widehat{TFP}_{it}^D = \theta_{iL} \left(\frac{\widehat{w}_{it}}{\widehat{r}_{it}} \right) - \left(\frac{\widehat{p}_{it}}{\widehat{r}_{it}} \right). \quad (6)$$

Notice that under the assumption of constant returns to scale and perfect competition, the growth rates of the two TFP measures are theoretically identical, and they measure the true productivity growth, \widehat{A}_{it} , exactly.

2.2 Departure from the Neoclassical Model

2.2.1 The Primal Analysis

Let the production function of industry i in period t be

$$Y_{it} = A_{it}F_i(L_{it}, K_{it}). \quad (7)$$

Taking the logarithm and then differentiating Equation (7) with respect to time will give us

$$\frac{\partial Y_{it}/\partial t}{Y_{it}} = \frac{\partial A_{it}/\partial t}{A_{it}} + \frac{\partial L_{it}/\partial t}{L_{it}} \frac{L_{it}}{F_i} \frac{\partial F_i}{\partial L_i} + \frac{\partial K_{it}/\partial t}{K_{it}} \frac{K_{it}}{F_i} \frac{\partial F_i}{\partial K_i}. \quad (8)$$

Let $\hat{X}_t = \frac{\partial X/\partial t}{X}$, and let $\frac{X}{F} \frac{\partial F}{\partial X} = \frac{X}{Y} \frac{\partial Y}{\partial X} = \alpha_X$, the elasticity of output with respect to input X . Equation (8) can be simplified to

$$\hat{Y}_{it} = \hat{A}_{it} + \alpha_{iL} \hat{L}_{it} + \alpha_{iK} \hat{K}_{it}. \quad (9)$$

For each industry i , assume that the production function F_i is homogeneous of degree S_i . The size of S_i relative to 1 tells us the degree of returns to scale of the industry. Returns to scale are increasing, constant, or decreasing as S_i is greater than, equal to, or less than unity.

Using Euler's theorem for homogeneous functions:

$$\alpha_{iL} + \alpha_{iK} = S_i, \quad (10)$$

we can re-express Equation (9) with the convention that $x = \frac{X}{K}$:

$$\hat{Y}_{it} - \hat{K}_{it} = \hat{A}_{it} + \alpha_{iL} (\hat{L}_{it} - \hat{K}_{it}) + (S_i - 1) \hat{K}_{it} \Rightarrow \quad (11)$$

$$\hat{y}_{it} = \hat{A}_{it} + \alpha_{iL} \hat{l}_{it} + (S_i - 1) \hat{K}_{it}. \quad (12)$$

Let the price markup of firm over marginal cost of firm i be

$$\mu_i = \frac{p_{it}}{m_{it}}, \quad (13)$$

and recall that θ_{iL} is the share of labor in total revenue.⁴ According to Proposition (A2) in the Appendix, $\alpha_{iL} = \mu_i \theta_{iL}$, Equation (12) can be simplified to

$$\hat{y}_{it} = \hat{A}_{it} + \mu_i \theta_{iL} \hat{l}_{it} + (S_i - 1) \hat{K}_{it}. \quad (14)$$

Thus, in the presence of imperfect competition ($\mu \neq 1$) and non-constant returns to scale ($S \neq 1$), the relationship between the growth rate of primal TFP and \hat{A}_{it} , the growth rate of actual productivity, is

$$\begin{aligned} \widehat{TFP}_{it}^P &\equiv \hat{y}_{it} - \theta_{iL} \hat{l}_{it}, \text{ by definition} \\ &= \hat{A}_{it} + (\mu_i - 1) \theta_{iL} \hat{l}_{it} + (S_i - 1) \hat{K}_{it}, \end{aligned} \quad (15)$$

which leads us to the following proposition:

Proposition 2 *Let $0 < \hat{L}_{it} < \hat{K}_{it}$. The growth rate of primal TFP will be less than the growth rate of true productivity if markup is greater than one and technology is decreasing returns to scale.*

Proof. Given $0 < \hat{L}_{it} < \hat{K}_{it} \Rightarrow \hat{l}_{it} < 0$.

Then $\mu_i > 1$ and $S_i < 1 \Rightarrow \widehat{TFP}_{it}^P < \hat{A}_{it}$, by Equation (15). ■

Thus, in a world in which capital deepening is rapid relative to employment growth, market power and decreasing returns to scale imply that the growth rate of primal TFP falls short of actual productivity growth. The above proposition restates the results of Hall (1988, 1990), where he shows that imperfect competition may cause the Solow residual to be procyclical and correlated with some aggregate demand variables.

2.2.2 The Dual Analysis

Let $C(w_{it}, r_{it}, F_i(L_{it}, K_{it}))$ be a general cost function,

$$C(w_{it}, r_{it}, F_i(L_{it}, K_{it})) = w_{it}L_{it} + r_{it}K_{it}. \quad (16)$$

⁴ By omitting the time subscript from μ_i , we are assuming that firms in each industry follow some fixed markup rules that is constant over time. Alternatively, we could interpretate μ_i as the average markup of industry i over time.

Obviously C is homogeneous of degree 1 in L_{it} and K_{it} . As shown in the Appendix, since $F_i(L_{it}, K_{it})$ is homogeneous of degree S_i , C_i is homogeneous of degree $\frac{1}{S_i}$ in $F_i(L_{it}, K_{it})$.

Homogeneity of C_i enables us to simplify the function further:

$$\begin{aligned} C(w_{it}, r_{it}, F_i(L_{it}, K_{it})) &= (F_i(L_{it}, K_{it}))^{\frac{1}{S_i}} G_i(w_{it}, r_{it}) \\ &= \left(\frac{Y_{it}}{A_{it}}\right)^{\frac{1}{S_i}} G_i(w_{it}, r_{it}), \end{aligned} \quad (17)$$

where $G(w, r) = C(w, r, 1)$ is the unit cost function, which depends only on input prices. Thus, given unchanged input prices, the more the firm produces, or the less efficient the firm is, the higher the total cost of production.

To find the marginal cost function, m_{it} , differentiate Equation (17) with respect to Y_{it} :

$$\begin{aligned} m_{it} &= \frac{\partial C_{it}}{\partial Y_{it}} = \frac{1}{S_i} \frac{Y_{it}^{\frac{1}{S_i}-1}}{A_{it}^{\frac{1}{S_i}}} G_i(w_{it}, r_{it}) \Rightarrow \\ \ln m_{it} &= -\ln S_i + \left(\frac{1}{S_i} - 1\right) \ln Y_{it} - \frac{1}{S_i} \ln A_{it} + \ln G_i(w_{it}, r_{it}). \end{aligned} \quad (18)$$

Differentiate Equation (18) with respect to time:

$$\begin{aligned} \hat{m}_{it} &= \left(\frac{1}{S_i} - 1\right) \hat{Y}_{it} - \frac{1}{S_i} \hat{A}_{it} + \frac{w_{it}}{G_{it}} \frac{\partial G_i}{\partial w_{it}} \hat{w}_{it} + \frac{r_{it}}{G_{it}} \frac{\partial G_i}{\partial r_{it}} \hat{r}_{it} \\ &= \left(\frac{1}{S_i} - 1\right) \hat{Y}_{it} - \frac{1}{S_i} \hat{A}_{it} + \frac{w_{it} L_{it}}{C_{it}} \hat{w}_{it} + \frac{r_{it} K_{it}}{C_{it}} \hat{r}_{it}. \end{aligned} \quad (19)$$

From Equations (17) and (19), we derive

$$\left(\frac{\widehat{m}_{it}}{\widehat{r}_{it}}\right) = \left(\frac{1}{S_i} - 1\right) \hat{Y}_{it} - \frac{1}{S_i} \hat{A}_{it} + \frac{w_{it} L_{it}}{C_{it}} \left(\frac{\widehat{w}_{it}}{\widehat{r}_{it}}\right), \quad (20)$$

where $\frac{w}{G} \frac{\partial G}{\partial w} = \frac{wL}{G} \left(\frac{A}{Y}\right)^{\frac{1}{S}} = \frac{wL}{C}$ is obtained from the definition of $G(w, r)$.

Let $c_{iX} = \frac{w_i X_i}{C_i}$, the payment share of input X in total cost of industry i . Assume that the markup coefficient, μ_i , is constant over time, such that

$$\hat{p}_{it} = \hat{m}_{it}.$$

With this simplification, multiply both sides of Equation (19) by $-S_i$ and rearrange the terms:

$$\widehat{\left(\frac{r_{it}}{p_{it}}\right)} = \hat{A}_{it} - S_i c_{iL} \widehat{\left(\frac{w_{it}}{r_{it}}\right)} + (S_i - 1) \widehat{\left(\frac{p_{it} Y_{it}}{r_{it}}\right)}. \quad (21)$$

Using the property that $S_i c_{iL} = \mu_i \theta_{iL}$ (by Proposition (A2) in the Appendix), we can further simplify Equation (21) to

$$\widehat{\left(\frac{r_{it}}{p_{it}}\right)} = \hat{A}_{it} + \mu_i \theta_{iL} \widehat{\left(\frac{r_{it}}{w_{it}}\right)} + (S_i - 1) \widehat{\left(\frac{p_{it} Y_{it}}{r_{it}}\right)}, \quad (22)$$

where $\theta_{iL} = \frac{w_i L_i}{p_i Y_i}$, the payment share of input L in total revenue of industry i .

Thus, in the presence of imperfect competition ($\mu \neq 1$) and non-constant returns to scale ($S \neq 1$), the relationship between the growth rate of dual TFP and \hat{A}_{it} , the growth rate of actual productivity is

$$\begin{aligned} \widehat{TFP}_{it}^D &= \theta_{iL} \widehat{\left(\frac{w_{it}}{r_{it}}\right)} - \widehat{\left(\frac{p_{it}}{r_{it}}\right)}, \text{ by definition} \\ &= \hat{A}_{it} + (\mu_i - 1) \theta_{iL} \widehat{\left(\frac{r_{it}}{w_{it}}\right)} + (S_i - 1) \widehat{\left(\frac{p_{it} Y_{it}}{r_{it}}\right)}. \end{aligned} \quad (23)$$

Proposition 3 *Let $0 < \hat{r}_{it} < \hat{w}_{it}$, and $\hat{r}_{it} < \widehat{p_{it} Y_{it}}$. The growth rate of dual TFP will be less than the growth rate of true productivity if markup is greater than one and technology is decreasing returns to scale.*

Proof. Given $0 < \hat{r}_{it} < \hat{w}_{it}$, and $\hat{r}_{it} < \widehat{p_{it} Y_{it}} \Rightarrow \widehat{\left(\frac{r_{it}}{w_{it}}\right)} < 0$ and $\widehat{\left(\frac{p_{it} Y_{it}}{r_{it}}\right)} > 0$.

Then $\mu_i > 1$ and $S_i < 1 \Rightarrow \widehat{TFP}_{it}^D < \hat{A}_{it}$, by Equation (23). ■

The above proposition shows that, with the right conditions, both imperfect competition and decreasing returns to scale may result in dual TFP underestimating true productivity growth. Notice that by maintaining the assumption of constant returns to scale, that is setting $S_i = 1$, Roeger (1995) shows that imperfect competition causes the dual TFP to underestimate true productivity growth. In other words, Roeger considers only one of the scenarios of the above proposition.

2.2.3 The Difference

It is clear that if $\mu \neq 1$ or $S \neq 1$, then neither the growth rate of primal nor that of dual TFP will reflect the true growth rate of productivity. The difference between the two measured growth rates of TFP can be derived by subtracting Equation (23) from Equation (15):

$$\widehat{TFP}_{it}^P - \widehat{TFP}_{it}^D = (\mu_i - 1)\theta_{iL} \left(\frac{\widehat{w_{it}L_{it}}}{\widehat{r_{it}K_{it}}} \right) + (S_i - 1) \left(\frac{\widehat{r_{it}K_{it}}}{\widehat{p_{it}Y_{it}}} \right). \quad (24)$$

Thus, in theory, the presence of imperfect competition and non-constant returns to scale creates a possible wedge between the two measures. However, given that the shares of input in total revenue are mostly constant in the real world, the right-hand side of Equation (24) is practically nil even when competition is imperfect and returns to scale are not constant.

Proposition 4 *If the shares of labor and capital in total revenue are constant, then the growth rate of primal TFP equals the growth rate of dual TFP.*

Proof. Constant input shares $\Rightarrow \left(\frac{\widehat{r_{it}K_{it}}}{\widehat{p_{it}Y_{it}}} \right) = \left(\frac{\widehat{w_{it}L_{it}}}{\widehat{p_{it}Y_{it}}} \right) = 0 \Rightarrow \left(\frac{\widehat{w_{it}L_{it}}}{\widehat{r_{it}K_{it}}} \right) = 0$.

Then $\widehat{TFP}_{it}^P - \widehat{TFP}_{it}^D = 0$, by Equation (24). ■

3. Empirical Strategy

To estimate productivity growth in the presence of imperfect competition and non-constant returns to scale, we would first have to estimate markup and scale coefficient according to Equations (14) and (22), which we shall call the *primal* and *dual Hall regressions*:

$$\hat{y}_{it} = \hat{A}_{i1} + \beta_{i2}\theta_{iL}\hat{l}_{it} + \beta_{i3}\hat{K}_{it}. \quad (25)$$

$$\left(\frac{\widehat{r_{it}}}{\widehat{p_{it}}} \right) = \hat{A}_{i1} + \gamma_{i2}\theta_{iL} \left(\frac{\widehat{r_{it}}}{\widehat{w_{it}}} \right) + \gamma_{i3} \left(\frac{\widehat{p_{it}Y_{it}}}{\widehat{r_{it}}} \right). \quad (26)$$

The estimated values of β_{i2} and γ_{i2} will be the industry-specific markups, and 1 plus the estimated values of β_{i3} or γ_{i3} will be the industry-specific returns to scale coefficients.⁵ In

⁵ In other words, we consider μ_i and S_i as the structural parameters of the model that can be estimated.

other words, the following restrictions hold if the primal and dual regressions are equivalent:

$$\begin{aligned}
 \beta_1 &= \gamma_1 \\
 \beta_2 &= \gamma_2 \\
 \beta_3 &= \gamma_3.
 \end{aligned}
 \tag{27}$$

With consistent estimates of markup and scale coefficient, we can then infer the industry productivity growth from Equations (14) and (22).

However, it is obvious that Equations (25) and (26) have serious endogeneity problems. Growth rate of technological progress, \hat{A}_{it} , enters a firm's first-order conditions for profit maximization (as well as that of cost minimization), which determine the input demand and also output of the firm. Thus, without controlling for \hat{A}_{it} , the least squares estimates for the coefficients of the growth rate of labor per unit of capital and the growth rate of capital will be biased upward.

Moreover, there is selection bias in the above specification due to firm's entry/exit behavior, as shown in Olley and Pakes (1996). Given that while only productive firms choose to stay in business and unproductive firms choose to exit, larger firms, especially those that have invested heavily, would be able to survive a short period of low productivity. Without controlling for survival probability of firms in the industry, least squares estimates for capital growth would be biased downwards.

To address the problems of endogeneity and selection bias, we first try a simple fixed effect approach by modelling productivity growth as the sum of industry fixed effect and year fixed effect. We then apply an Olley and Pakes (1996) type correction to estimate the average industry markup and returns to scale.

3.1 Fixed Effect Correction

Without loss of generality, assume that the Hicks neutral technological progress parameter is a random variable of the following form:

$$\begin{aligned} A_{it} &= A_{i0}e^{\phi_{it}t} \\ \hat{A}_{it} &= \phi_{it} = a_i + \lambda_t + u_{it}, \end{aligned} \quad (28)$$

where A_{i0} is the technological level of industry i at the beginning, period 0, and ϕ_{it} is the growth rate of technological progress. Thus, the growth rate of the technological progress of industry i in period t consists of an industry-specific growth rate, a_i , and a period-specific growth rate, λ_t , which captures the macroeconomic shock that is common across industries in the same period, plus a white noise, u_{it} , which is a classical random error term with zero mean and σ^2 variance.

Substitute Equation (28) into Equations (12) and (22) and we will get

$$\hat{y}_{it} = a_i + \lambda_t + \mu_i \theta_{iL} \hat{l}_{it} + (S_i - 1) \hat{K}_{it} + u_{it}. \quad (29)$$

$$\left(\frac{\hat{r}_{it}}{\hat{p}_{it}} \right) = a_i + \lambda_t + \mu_i \theta_{iL} \left(\frac{\hat{r}_{it}}{\hat{w}_{it}} \right) + (S_i - 1) \left(\frac{\hat{p}_{it} \hat{Y}_{it}}{\hat{r}_{it}} \right) + u_{it}. \quad (30)$$

Using the cross equation restrictions, Equations (29) and (30) may be stacked to give

$$\begin{pmatrix} \hat{y}_{i1} \\ \vdots \\ \hat{y}_{iT} \\ \left(\frac{\hat{r}_{i1}}{\hat{p}_{i1}} \right) \\ \vdots \\ \left(\frac{\hat{r}_{iT}}{\hat{p}_{iT}} \right) \end{pmatrix} = \alpha_i \mathbf{1} + \sum_{t=2}^T \lambda_t \mathbf{D}_t + \mu_i \begin{pmatrix} \theta_i \hat{l}_{i1} \\ \vdots \\ \theta_i \hat{l}_{iT} \\ \theta_i \left(\frac{\hat{r}_{i1}}{\hat{w}_{i1}} \right) \\ \vdots \\ \theta_i \left(\frac{\hat{r}_{iT}}{\hat{w}_{iT}} \right) \end{pmatrix} + (S_i - 1) \begin{pmatrix} \hat{K}_{i1} \\ \vdots \\ \hat{K}_{iT} \\ \left(\frac{\hat{P}_{i1} \hat{Y}_{i1}}{\hat{r}_{i1}} \right) \\ \vdots \\ \left(\frac{\hat{P}_{iT} \hat{Y}_{iT}}{\hat{r}_{iT}} \right) \end{pmatrix} + \mathbf{u}_i$$

or, $\mathbf{YHAT}_i = \alpha_i \mathbf{1} + \sum_{t=2}^T \lambda_t \mathbf{D}_t + \mu_i \mathbf{LKCON}_i + (S_i - 1) \mathbf{KGRW}_i + \mathbf{u}_i, \quad (31)$

where bold characters denote vectors. \mathbf{D}_t is a $2T \times 1$ indicator vector that has an entry equal to one for period t , and zero otherwise. We will discuss the validity of stacking the two equations in detail in section 6 below.

There are two obvious advantages to stacking the two equations. The first is that the sample size is doubled, which is desirable given the small sample. The second advantage is that we can use the existing theory on panel regression on a single equation to estimate Equation (31), avoiding the complications of estimating a system of panel equations.

3.2 Olley and Pakes (1996) Type Correction

Olley and Pakes (1996) assume that at the beginning of every period, firms observe their productivity and, based on the observed productivity, they decide to stay in business or to quit the market. Providing that all surviving firms have positive investment, they can therefore use investment as a control for productivity, which is observed by the firms but not by researchers.⁶ In other words, they assume that those firms that have higher investment are those that observe higher productivity growth. By introducing a polynomial of investment and capital stock as the control of productivity in the estimation of the production function, they show that upward bias on the coefficient of labor input is reduced.

In addition, to control for survival probability, Olley and Pakes estimate a probit regression where survival is modelled as a polynomial of investment and capital. A consistent estimated coefficient on capital is obtained by imposing the consistent estimate of the coefficient on labor input in the production function, with the estimated survival probability and the control of productivity introduced in both series estimation and kernel estimation.

To adopt Olley and Pakes' correction on our industry-level data set, we would need to proxy firms' survival probability by the change in total number of firms in the industry. In

⁶ Levinsohn and Petrin (1999, 2000) show that instead of investment, intermediate input could be a good instrument for productivity growth, especially for those firms that are staying in business but do not have positive investment every year.

other words, if there is an increase in the number of firms in the current period, we would assume that the survival probability is high. Firms' turnover rate is not a perfect proxy for an individual firm's entry and exit choice. However, to capture industry productivity, which is unobservable for researchers but is observable for firms in the industry, turnover rate may nevertheless be a good proxy. When an industry on average has high productivity growth, we should observe net entry of firms and increases in the number of firms in the industry. On the other hand, when the average productivity of the industry is low, we should observe net exit of firms and decreases in the total number of firms in the industry.⁷

Our correction procedure is as follows:⁸

1. We estimate Equation (31) by pooling all industries and years and introducing a 3rd order polynomial of the growth rates of investment and capital stock as a control for productivity, controlling for industry and year fixed effects. Provided that the growth rate of investment is positively correlated with the growth rate of productivity, the estimated coefficient on labor input, which represents industry markup, would be consistent. The estimated polynomial is hence a consistent estimate of productivity.⁹
2. We regress the ratio of number of firms in each industry across two years on a 3rd order polynomial of the growth rates of investment and capital stock, controlling for industry and year fixed effects. The fitted value of regression gives us a consistent estimate of survival probability due to productivity growth.
3. We impose the consistent estimate on the industry markup from step 1, and re-run

⁷ For detailed treatment of how turnover of firms affects industry productivity, please refer to Roberts and Tybout (1996, 1997), and Aw, Chen, and Roberts (2001).

⁸ Notice that Olley and Pakes (1996) directly estimate the elasticity of value added with respect to labor and capital, α_L and α_K , by regressing the log of value added on the log of labor and capital, controlling for productivity and selection bias. Given that we are interested in industry markups and returns to scale, we rearrange the equation by regressing the growth rate of value added to capital ratio on the growth rate of labor to capital ratio multiplied by revenue share of labor input and the growth rate of capital input. In other words, our model is equivalent to the first difference of Olley and Pakes (1996).

⁹ Recall that Olley and Pakes (1996) show that the level of productivity is a 4th order polynomial of the level of investment and capital stock. Thus in the first difference, the polynomial would be reduced to 3rd order. We also tested a 4th order polynomial in the estimation, but it makes no difference.

Equation (31) with a polynomial of survival probability and productivity as controls to get a consistent estimate of the coefficient of capital growth, which represents the industry scale coefficient.

4. With the consistent estimates of markup and scale coefficient, we derive the growth rate of industry productivity according to Equations (14) and (22).

4. Data

Table 1 presents the mean values of the main variables used in the regressions in our data set. Output of an industry is defined as the value added of the industry deflated by the manufactured products price index of that industry. Manufactured products price series can be obtained from the *Yearbook of Statistics of Singapore*.

The total number of workers of an industry in a year is used as a measure of labor input of the industry. Wages of workers are constructed by dividing the total remuneration of an industry by the total number of workers.

Capital input is generated by the standard perpetual inventory method with constant depreciation rate. Since data are not available before 1960, 1960 is taken as the benchmark year, and the capital stock prior to 1960 is assumed to be zero. Given that our regression analysis only starts in 1974, any bias due to the underestimation of the initial capital stock should be minimal. There are four kinds of capital asset, and each has a different depreciation rate. Because there are no published depreciation rate data for Singapore, we used the depreciation rates calculated for the different capital goods of the U.S. by Jorgenson and Sullivan (1981). The depreciation rate for Plant and Buildings is 0.0361; for Machinery and Equipment, 0.1047; for Transport Equipment, 0.2935; and for Office Equipment, 0.2729. The Tornqvist growth rate of the aggregate capital input is constructed as a weighted average of the growth rate of each of the capital assets.

Rental prices for the four types of capital input are constructed according to the internal

nominal rate of return specification model developed by Jorgenson, Gollop, and Fraumeni (1987), which is also known as the *ex post* rental price.¹⁰

Unless otherwise stated, most of the data needed for the regression are obtained from various years of the *Report on the Census of Industrial Production*.

5. Results

5.1 Fixed Effects Correction

Equation (31) is estimated by fixed effect panel regression using both primal and dual data from 1975 to 1992 on the 31 (3-digit SIC level) industries of Singapore's manufacturing sector. Due to some missing value in rental prices, the total number of unbalanced panel observations is 1115. The result of the regression is presented in Table 2, which reports the estimated industry markups and scale coefficients and their robust standard errors.¹¹

According to Table 2, 27 out of 31 industries have an estimated markup greater than one. And out of the 27 industries, 15 are significantly greater than one at 95% confidence level. A joint test on the perfect competition hypothesis for all the industries is performed and rejected with more than a 99% confidence level. On the other hand, 24 out of the 31 industries in the manufacturing sector have an estimated scale coefficient of less than one. Out of the 26 industries, 12 are significantly decreasing returns to scale at a 95% confidence level. A joint test of constant returns to scale against decreasing returns to scale of all the industries is performed and rejected at more than a 99% confidence level in favor of the decreasing returns to scale hypothesis.

Thus, both the industry joint tests suggest that the Singapore manufacturing sector as a whole has violated both the assumptions of perfect competition and constant returns to scale technology. In addition, when the hypotheses of perfect competition and constant returns to

¹⁰For details regarding the adjustments of taxes and allowances of Singapore, please refer to Wong and Gan (1994).

¹¹We report the estimated returns to scale by adding one to the estimated coefficients on capital input.

scale are jointly tested within each industry, they are rejected by all of the 31 industries at more than a 99% confidence level.

Finally, we perform a specification test on the equivalent of the primal and dual regressions. The result of the testing overwhelmingly supports the hypothesis that the estimated coefficients from the primal regression are not statistically different from the estimated coefficients from the dual regression. We conclude that our result supports Proposition 3, that the primal and dual approaches are equivalent, even in the presence of imperfect competition and non-constant returns to scale.¹²

Given the rather compelling results of the above tests, we feel comfortable concluding that all industries in Singapore's manufacturing sector violate either constant returns to scale or perfect competition or both assumptions. Hence, conventional growth accounting exercises will unavoidably underestimate the true productivity growth.

5.2 Olley-Pakes Type Correction

Given that an Olley and Pakes correction requires a large sample for consistent estimates, we pool all industries and years to estimate the average industry markup and scale coefficient of the manufacturing sector. Table 3 presents the estimation procedure.

Column (1) shows the estimated industry markup and scale coefficient in the pooled data set without correcting for input endogeneity and firms' selection bias. Given that labor demand is positively correlated with unobserved productivity growth, the estimate of industry markup would have an upward bias, while the bias on scale coefficient is unclear, as selection bias would introduce an opposing downward bias on the coefficient on capital input. We introduce investment growth as a control for productivity in Column (2). Even though investment growth is not a good control, the upward bias on industry markup is nevertheless reduced, as predicted by the theory. On the other hand, controlling for investment reduces

¹²Detailed results of the hypothesis testing are available from the author upon request.

the downward bias on scale coefficient, as firms' survival rate is positively correlated with investment.

Column (3) introduces a 3rd order polynomial of investment and capital stock growth to control for productivity growth. As long as productivity growth is positively correlated with investment growth and surviving firms tend to have larger capital stock, the estimated industry markup of 1.44 would be consistent. Given the robust standard error, the estimated industry markup is significantly greater than one with a 99% confidence level.

We estimate the survival rate of firms in the industries in Column (4), where firms' turnover rate is used as the dependent variable. We regress turnover rate on a 4th order polynomial of investment and capital stock growth to control for selection bias that is correlated with capital stock.

We impose the consistent estimate of industry markup from Columns (5) to (7). In Column (5), only the powers of the estimated productivity are introduced. This reduces the upward bias froms Column (1) and (2). The powers of the estimated survival rate are introduced in Column (6), further reducing the size of the bias. Finally, in Column (7), when the full polynomial of the estimated productivity and survival rate is included, the consistent estimate of industry scale coefficient is 0.57. The scale coefficient is significantly estimated and is also significantly less than one at a 99% confidence level.

In summary, correcting for endogeneity and selection bias does not change the qualitative results of the fixed effect regressions. Overall, industries in the manufacturing sector are still characterized as imperfect competition with decreasing returns to scale technology.

5.3 Estimated Industry Productivity

To illustrate the size of underestimation of both primal and dual TFP in the presence of imperfect competition and non-constant returns to scale, we plot the average growth rate of industry primal and dual TFP and the estimated primal and dual productivity growth

in Figure 4. The growth rates of the estimated industry productivity are constructed using the consistent estimates on industry markup and returns to scale according to Column (7) of Table 3.

The first observation from Figure 4 is that the difference between industry primal and dual TFP growth rate is almost negligible, which is evident from our Proposition 3, since factor shares have been relatively constant.

Moreover, controlling for imperfect competition and non-constant returns to scale, the estimated growth rates of primal and dual productivity are consistently higher than the growth rates of primal and dual TFP. The differences are most prominent for industries that have high capital input growth such as the electronics industry.

The simple average of the annual growth rate of productivity of all the industries from 1974 to 1992 is more than 7%, whereas the corresponding simple average of the growth rates of industry TFP is less than 3%. In other words, by correcting for imperfect competition and non-constant returns to scale, the underlying true productivity growth of the industries in the Singapore manufacturing sector is shown to be more than double what could be measured by the conventional growth accounting techniques.

6. Robustness Checks

6.1 Real Value Added as Real Output

There may be a concern about the data because the growth rate of real value added was used instead of the growth rate of real output in the regression. As pointed out in Basu and Fernald (1995, 1997), because of the construction of the value added statistics, the growth rate of real value added will not be independent of the growth rate of intermediate input if the market is not perfectly competitive, even if the production function is weakly separable. Thus, using growth rate of real value added as the dependent variable may omit an important

variable.¹³

In order to control for this omitted variable problem, the growth rate of nominal intermediate input is included in the regression. For reasons of data availability, the growth rate of *nominal* intermediate input is included in the regression instead of the growth rate of *real* intermediate input *and* the growth rate of *relative prices*, which are suggested by the theory (see Appendix). Thus, we are implicitly imposing the assumption that both regressors have the same coefficient. But since prices of intermediate input are not easily available, growth rate of nominal intermediate input is the second best alternative. The results are reported in Table 5.

We perform a likelihood ratio test to verify the explanatory power of the growth rate of intermediate input in the regression. We are happy to find that even though the growth rate of intermediate input as a whole has significant explanatory power according to the test, the point estimates of industry markups and returns to scale are not statistically different from those listed in Table 2. In fact, only two industries have an even lower estimate of the returns to scale coefficients when the growth rate of intermediate input is included. This could be because growth rates of labor-capital ratio and capital input are not statistically correlated with the growth rate of intermediate input in the data.

6.2 Efficiency Labor Input

Data on the growth rate of labor input are constructed from the growth rate of number of workers in the industry. Thus, implicitly, the assumption of homogeneous labor input is imposed. But it is reasonable to believe that one unit of labor input in the 1990s should have higher productivity than one unit of labor input in the 1970s due to the accumulation of human capital of the economy. The homogeneous labor input assumption may bias the estimated coefficient due to the problem of error in measurement.

¹³For a detailed exposition of the claim, please refer to the Appendix.

More specifically, let L_{it} denote unit of physical labor and L_{it}^e denote unit of efficient labor,

$$L_{it}^e = e_{it}L_{it}, \quad (32)$$

where e_{it} indicates the level of efficiency of labor input in industry i in period t .

We can modify our production function to incorporate labor efficiency:

$$Y_{it} = A_{it}F(L_{it}^e, K_{it}). \quad (33)$$

Thus Equation (9) can be adjusted to

$$\hat{Y}_{it} = \hat{A}_{it} + \alpha_{iL}\hat{L}_{it}^e + \alpha_{iK}\hat{K}_{it} \quad (34)$$

$$= \hat{A}_{it} + \alpha_{iL}(\hat{L}_{it} + \hat{e}_{it}) + \alpha_{iK}\hat{K}_{it} \quad (35)$$

or

$$\hat{Y}_{it} = \hat{A}_{it} + \alpha_{iL}\hat{e}_{it} + \alpha_{iL}\hat{l}_{it} + S_i\hat{K}_{it}. \quad (36)$$

Hence, there may be an omitted variable problem in our regression due to the mismeasurement of labor input. The resulting estimates of the regression may be biased. However, if the increase in human capital is homogeneous across industries, then the effect of \hat{e}_{it} will be captured in our period-specific effect, λ_t . Similarly, if the increase in efficiency is industry specific, then omitting \hat{e}_{it} will not be problematic as it will be explained by the industry-specific effect, a_i .

Thus, the inclusions of period-specific effect and industry-specific effect will reduce the potential bias of the estimates due to the mismeasurement of labor input.

6.3 Capacity Utilization of Capital Input

In the regression, the growth rate of the *service* of capital input is proxied by the growth rate of capital input of the industries. In other words, full capacity utilization of capital input is assumed in the model. However, it is well known in the literature that the capacity

utilization of capital input may fluctuate over the business cycle. Thus, without adjustment on the rate of utilization of capital input, there may be an error in variable problem in the regression.

To illustrate this point, let K_{it} be the physical capital input and σ_{it} be the rate of utilization of the capital input. Thus, the service of the capital input is

$$K_{it}^s = \sigma_{it}K_{it}. \quad (37)$$

The production function can again be modified:

$$Y_{it} = A_{it}F(L_{it}, K_{it}^s). \quad (38)$$

Thus, Equation (9) can be adjusted to

$$\hat{Y}_{it} = \hat{A}_{it} + \alpha_{iL}\hat{L}_{it} + \alpha_{iK}\hat{K}_{it}^s \quad (39)$$

$$= \hat{A}_{it} + \alpha_{iL}\hat{L}_{it} + \alpha_{iK}(\hat{K}_{it} + \hat{\sigma}_{it}) \quad (40)$$

or

$$\hat{Y}_{it} = \hat{A}_{it} + \alpha_{iK}\hat{\sigma}_{it} + \alpha_{iL}\hat{l}_{it} + S_i\hat{K}_{it}, \quad (41)$$

with $cov(\hat{A}_{it}, \hat{\sigma}_{it}) > 0$ due to business cycle fluctuation.

Hence, without adjusting for capacity utilization, we again introduce an omitted variable problem in the regression, which may result in bias in estimation of the regression.

One way to correct for the variability of the utilization of capital input is to use an instrument to proxy its rate. Harrison (1994) uses a measure of total energy used as the instrument. However, not all capital is electrical machinery and not all electricity consumption is due to the use of capital. The inclusion of total energy used in the regression may in turn introduce some extra noise into the estimation.

Fortunately, the inclusion of the period-specific effect, λ_t , takes care of the business cycle fluctuation that is common across industries. Shocks that are specific to an industry will be

captured by the industry-specific dummies. Thus, without introducing any extra variable, we are able to control for the capacity utilization of capital input.

7. Conclusion

The dual equivalence of Hall's (1988) technique is derived and tested. This paper shows that, theoretically, the presence of either imperfect competition or decreasing returns to scale technology will cause both primal and dual TFP growth rates to underestimate actual productivity growth. The size of bias depends on the degree of deviation from perfect competition and constant returns to scale.

On the other hand, the difference between the growth rates of primal and dual TFP depends on the change in factor shares in revenue. Given that, in general, factor shares are relatively constant, the difference between the two TFP measures is close to zero, even if imperfect competition or non-constant returns to scale exist. These are the main theoretical findings of the paper, and it can be viewed as a complement to Hall (1988, 1990) and a contradiction to the results of Roeger (1995).

The empirical section of this paper focuses on establishing a procedure that is capable of estimating actual productivity growth, even in the presence of imperfection competition and non-constant returns to scale technology. A panel regression that embraces both the primal and dual approaches is proposed to fully utilize information derived from both the quantity and price sides of the data. We also present an empirical model that follows an Olley and Pakes (1996) type correction for input endogeneity and selection bias at an industry level to estimate the average industry markup and returns to scale.

Using Singapore's manufacturing sector as a case study, the empirical result of this paper shows that both the primal and dual regressions are empirically equivalent. In addition, all industries in the sector violated at least one of the assumptions of perfect competition and constant returns to scale. Controlling for input endogeneity and selection bias, the estimated

average annual growth rate of productivity of the sector is more than 7%, which far exceeds both conventional measures. Thus, the regression result casts doubt on Young's (1992, 1995) findings, as it suggests that the productivity growth of Singapore may be much higher than what can be measured using the conventional growth accounting technique. In other words, without testing the two assumptions of perfect competition and constant returns to scale, one should exercise caution when using conventional TFP measures.

A Homogeneity of the Cost Function

Proposition 5 (A1) Let $C(w, r, F(L, K)) = wL + rK$, and $Y = AF(L, K)$. If F is homogeneous of degree S in (L, K) , then

1. C is homogeneous of degree $\frac{1}{S}$ in F
2. C is homogeneous of degree $\frac{1}{S}$ in Y
3. Let $m = \frac{\partial C}{\partial Y}$, then $m = \frac{1}{S} \frac{C}{Y}$.

Proof.

1. Increase both L and K by $\delta^{\frac{1}{S}}$ times, $\delta > 0$:

$$C\left(w, r, F\left(\delta^{\frac{1}{S}}L, \delta^{\frac{1}{S}}K\right)\right) = C(w, r, \delta F(L, K)), \text{ by homogeneity of } F(L, K).$$

Since C is homogeneous of degree 1 in (L, K) , the left-hand side of the above equation can be reduced to $\delta^{\frac{1}{S}}C(w, p, F(L, K))$. Thus, $C(w, p, \delta F(L, K)) = \delta^{\frac{1}{S}}C(w, p, F(L, K))$ implies that $C(w, p, F(L, K))$ is homogeneous of degree $\frac{1}{S}$ in $F(L, K)$.

2. Notice that Y is homogeneous of degree 1 in F . Thus, C is homogeneous of degree $\frac{1}{S}$ in $F \Rightarrow C$ is homogeneous of degree $\frac{1}{S}$ in Y .
3. By Euler equation of homogeneous function, C is homogeneous of degree $\frac{1}{S}$ in $Y \Rightarrow \frac{\partial C}{\partial Y}Y = \frac{1}{S}C \Rightarrow m = \frac{1}{S} \frac{C}{Y}$.

■

B Input Elasticity, Revenue Share, and Cost Share

Definition 6 Let

$$\begin{aligned} \alpha_X &= \frac{\partial F}{\partial X} \frac{X}{F}, \text{ the elasticity of output with respect to input } X; \\ \theta_X &= \frac{wX}{pY}, \text{ the payment share of input } X \text{ in total revenue;} \\ c_X &= \frac{wX}{C}, \text{ the payment share of input } X \text{ in total cost.} \end{aligned}$$

Proposition 7 (A2) Let $Y = AF(L, K)$ be the production function of a firm, and F be homogeneous of degree S in L and K . Let μ be the price over marginal cost markup. Let firm minimize cost. Then

1. $\alpha_X = \mu\theta_X$, $X = L, K$
2. $c_X = \frac{1}{S}\alpha_X = \frac{\mu}{S}\theta_X$, $X = L, K$
3. $c_L + c_K = 1$
4. $\alpha_L + \alpha_K = S$
5. $\theta_L + \theta_K = \frac{S}{\mu}$.

Proof.

1. Firm facing given w and r , minimize the following program:

$$\begin{aligned} \min C &= wL + rK \\ \text{s.t. } Y &= AF(L, K) \end{aligned}$$

$$\Rightarrow \mathcal{L} = wL + rK - \lambda(AF(L, K) - Y)$$

F.O.C.:

$$w = \lambda A \frac{\partial F}{\partial L}$$

By Envelope Theorem, $m = \frac{\partial C}{\partial Y} = \lambda$, the marginal cost of production. Thus,

$$\frac{w}{mA} = \frac{\partial F}{\partial L} \Rightarrow \alpha_L = \frac{wL}{mY} = \mu\theta_L.$$

Similarly, $\alpha_K = \mu\theta_K$.

2. By Proposition (A1), $m = \frac{1}{S} \frac{C}{Y} \Rightarrow C = SmY$. Thus,

$$c_L = \frac{wL}{C} = \frac{wL}{SmY} = \frac{1}{S} \alpha_L = \frac{1}{S} \mu\theta_L.$$

Similarly, $c_K = \frac{1}{S} \alpha_K = \frac{1}{S} \mu\theta_K$.

3. $c_L + c_K = \frac{wL}{C} + \frac{rK}{C} = 1$, by the definition of C .
4. $\alpha_L + \alpha_K = \frac{\partial F}{\partial L} \frac{L}{F} + \frac{\partial F}{\partial K} \frac{K}{F} = S$, by Euler equation for homogenous function.
5. $\theta_L + \theta_K = c_L \frac{S}{\mu} + c_K \frac{S}{\mu}$, by 2.
 $\Rightarrow \theta_L + \theta_K = (c_L + c_K) \frac{S}{\mu} = \frac{S}{\mu}$, by 3.

■

C Real Value Added vs. Real Output

To understand this problem, we need to go back to the construction of the real value added statistics. According to the *Report on the Census of Industrial Production* of Singapore, the nominal value added statistic is generated by subtracting the cost of intermediate input, including materials, utilities, and operating cost, from the value of output. Formally, let v_t denote the real value added in period t , $p_t Y_t$ be the value of output, and $p_{Mt} M_t$ be the cost of intermediate input. Then the nominal value added is defined as

$$p_t v_t = p_t Y_t - p_{Mt} M_t. \quad (42)$$

To find the growth rate of real value added, differentiate Equation (42) with respect to time:

$$\frac{\partial p_t}{\partial t} v_t + \frac{\partial v_t}{\partial t} p_t = \frac{\partial p_t}{\partial t} Y_t + \frac{\partial Y_t}{\partial t} p_t - \frac{\partial p_{Mt}}{\partial t} M_t - \frac{\partial M_t}{\partial t} p_{Mt}. \quad (43)$$

Using the notation of growth rate, we can simplify Equation (43) to

$$p_t v_t \hat{p}_t + p_t v_t \hat{v}_t = p_t Y_t \hat{p}_t + p_t Y_t \hat{Y}_t - p_{Mt} M_t \hat{p}_{Mt} - p_{Mt} M_t \hat{M}_t. \quad (44)$$

Let $s_M = \frac{p_{Mt} M_t}{p_t Y_t}$, the share of intermediate input in total output. Dividing both sides of Equation (44) by $p_t Y_t$ and rearranging the terms, we can get

$$(1 - s_M) \hat{v}_t = \hat{Y}_t - s_M (\hat{p}_{Mt} + \hat{M}_t - \hat{p}_t)$$

or

$$\hat{v}_t = \frac{1}{1 - s_M} \hat{Y}_t - \frac{s_M}{1 - s_M} \hat{M}_t - \frac{s_M}{1 - s_M} \left(\widehat{\frac{p_{Mt}}{p_t}} \right). \quad (45)$$

Thus, the growth rate of real value added is a weighted average of the growth rate of output and intermediate input (deflated by price of output).

To link this with our earlier regression, we need to define a production function that

includes intermediate input. Let

$$\begin{aligned} Y_t &= A_t F(L_t, K_t, M_t) \\ \hat{Y}_t &= \hat{A}_t + \alpha_L \hat{L}_t + \alpha_K \hat{K}_t + \alpha_M \hat{M}_t, \end{aligned} \quad (46)$$

where $\alpha_M = \frac{\partial F}{\partial M} \frac{M}{F}$, the elasticity of intermediate input with respect to output.

Substituting Equation (46) into Equation (45), we will get

$$\hat{v}_t = \frac{1}{1-s_M} \hat{A}_t + \frac{\alpha_L}{1-s_M} \hat{L}_t + \frac{\alpha_K}{1-s_M} \hat{K}_t + \frac{\alpha_M - s_M}{1-s_M} \hat{M}_t - \frac{s_M}{1-s_M} \widehat{\left(\frac{pMt}{p_t}\right)}. \quad (47)$$

Recall that $\alpha_M = \mu s_M$, and $\alpha_L + \alpha_K = S$, the degree of returns to scale, and $1-s_M = \frac{p_t v_t}{p_t Y_t}$.

Equation (47) can be simplified further to

$$\begin{aligned} \hat{v}_t &= \frac{1}{1-s_M} \hat{A}_t + \frac{\mu \frac{w_t L_t}{p_t Y_t}}{\frac{p_t v_t}{p_t Y_t}} \hat{l}_t + \frac{S}{1-s_M} \hat{K}_t + (\mu - 1) \frac{s_M}{1-s_M} \hat{M}_t - \frac{s_M}{1-s_M} \widehat{\left(\frac{pMt}{p_t}\right)} \\ &= \frac{1}{1-s_M} \hat{A}_t + \mu \theta_L \hat{l}_t + \frac{S}{1-s_M} \hat{K}_t + (\mu - 1) \frac{s_M}{1-s_M} \hat{M}_t - \frac{s_M}{1-s_M} \widehat{\left(\frac{pMt}{p_t}\right)}. \end{aligned} \quad (48)$$

So when we regress the growth rate of real value added, \hat{v}_t , on the growth rate of labor per capital weighted by the share of labor in value added, $\theta_L \hat{l}_t$, and the growth rate of capital, \hat{K}_t , in order to estimate the markup coefficient, μ , and the scale coefficient, S , we need to worry about a few things.

First, the growth rate of intermediate input must be included together with the growth rate of relative prices in order to avoid the problem of omitted variables. If \hat{M}_t and $\widehat{\left(\frac{pMt}{p_t}\right)}$ are omitted, then the estimated mark-up and scale coefficient will be biased, since \hat{l}_t and \hat{K}_t are correlated with M_t and $\widehat{\left(\frac{pMt}{p_t}\right)}$.

Second, even if both M_t and $\widehat{\left(\frac{pMt}{p_t}\right)}$ are included in the regression, the estimated scale coefficient, S , as well as \hat{A}_t , will be overestimated, as $1-s_M$ is less than one. In the data, the size of s_M ranges from 40% to 90%. Thus, we need to take this into account when we interpret the regression.

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Table 1: Data at a Glance, 1974-1992

SSIC	Industry Name	Average Annual Growth Rates of									Average Firms' Turnover Rate ⁴
		Output Capital Ratio	Real Rental Price	Labor Capital Ratio ¹	Rental Wage Ratio ¹	Revenue Capital Input	Revenue Rental Ratio	Primal TFP ²	Dual TFP ³	Real Investment	
311/312	Food	-0.070	-1.239	-2.458	-3.190	8.235	8.965	2.388	1.951	9.434	101.553
313	Beverage	-10.564	-9.149	-4.345	-3.034	15.304	13.889	-6.219	-6.115	5.421	99.172
314	Tobacco	-9.956	-9.824	-3.605	-3.483	12.049	11.918	-6.351	-6.341	8.127	95.725
321	Textiles	0.496	1.190	-4.168	-3.525	0.211	-0.483	4.665	4.715	-10.219	99.974
322	Apparel	1.615	1.680	-3.502	-3.435	6.770	6.704	5.117	5.115	-2.808	102.707
323	Leather	-4.187	-5.891	-5.960	-7.660	11.429	13.132	1.773	1.769	13.029	99.326
324	Footwear	-6.344	-3.992	-8.314	-5.972	7.383	5.031	1.969	1.980	-2.413	99.220
331	Wood	-1.512	-1.855	-4.618	-4.963	-0.169	0.174	3.105	3.108	-9.001	96.051
332	Furniture	0.088	0.750	-3.381	-2.720	10.699	10.037	3.469	3.470	8.772	105.952
341	Paper	-0.841	-1.037	-3.831	-4.028	12.218	12.414	2.991	2.991	10.523	102.096
342	Printing	-0.951	-1.146	-3.485	-3.681	11.973	12.168	2.535	2.534	10.682	103.676
351	Industrial Chemicals	1.015	0.879	-1.695	-1.828	13.326	13.462	2.710	2.707	8.436	108.026
352	Chemical Products	0.311	0.696	-1.726	-1.339	12.127	11.742	2.036	2.035	9.963	101.197
353/354	Petroleum	0.245	-0.202	-0.168	-0.634	2.871	3.319	0.413	0.432	11.574	103.222
355	Natural Rubber	2.796	1.937	-2.527	-3.395	-1.797	-0.939	5.323	5.332	-3.469	96.230
356	Rubber Products	-0.325	-1.573	-2.362	-3.612	5.666	6.914	2.038	2.040	6.556	99.798
357	Plastic Products	0.806	0.063	-2.269	-3.017	12.209	12.953	3.075	3.080	8.388	106.002
361/362	Glass	-4.702	-2.709	-6.935	-4.881	14.155	12.162	2.233	2.172	17.494	101.502
363	Clay	-4.265	-3.363	-5.505	-4.637	7.467	6.565	1.240	1.274	-3.408	97.185
364	Cement	2.807	2.678	-0.930	-1.112	4.899	5.029	3.737	3.790	0.577	103.426
365	Concrete Products	-1.126	-1.152	-2.834	-2.878	14.505	14.531	1.708	1.726	17.745	103.769
369	Mineral Products	-4.200	-5.769	-2.778	-4.341	7.266	8.834	-1.422	-1.427	-4.684	101.898
371	Basic Metal	-4.502	-5.692	-2.004	-3.228	7.117	8.307	-2.498	-2.464	2.217	100.197
372	Non-Ferrous Metal	5.330	4.906	-0.496	-0.973	3.288	3.711	5.825	5.880	14.306	107.849
381	Fabricated Metal	-0.873	-1.089	-2.968	-3.184	12.930	13.147	2.095	2.094	9.806	105.384
382	Machinery	1.322	0.020	-2.554	-3.873	10.426	11.727	3.876	3.893	7.105	106.164
383	Electrical	1.704	1.686	-4.024	-4.038	9.958	9.976	5.728	5.724	6.827	103.546
384	Electronics	1.805	1.982	-3.067	-2.886	16.888	16.710	4.872	4.868	14.543	108.995
385	Transport Equipment	3.100	2.985	-2.801	-2.908	7.290	7.406	5.902	5.893	3.228	104.171
386	Scientific Instruments	4.750	4.809	-1.876	-1.038	3.453	3.273	6.626	5.847	1.460	104.267
390	Other	-4.832	-5.572	-4.982	-5.721	13.211	13.952	0.150	0.149	6.206	102.788
300	Industry Average	-1.002	-1.129	-3.296	-3.394	8.818	8.927	2.294	2.265	5.691	102.293

Notes: Unless otherwise stated, all values represent the average annual growth rates from 1974 to 1992 in percentage terms.

1. Variable is multiplied by the share of labor in total revenue according to the specification of the model.

2. The growth rate of primal TFP is obtained by subtracting the growth rate of output-capital ratio from the growth rate of labor-capital ratio.

3. The growth rate of dual TFP is obtained by subtracting the growth rate of real rental price from the growth rate of rental-wage ratio.

4. Firms' turnover rate is defined as the ratio of the number of firms across two consecutive years.

Table 2: Dependent Variables – Growth Rates of Real Output and Rental Price

Method: Fixed Effect Panel Regression

Included observations: 36

Included cross sections: 31

Total panel (unbalanced) observations: 1115

Industry	Estimated Markups	Robust S.E.	Estimated Scale Coefficients	Robust S.E.
Food	1.70**	(0.73)	0.62	(0.53)
Beverage	1.09*	(0.63)	0.15	(0.22)
Tobacco	-0.01	(0.79)	-0.52*	(0.31)
Textiles	1.50***	(0.18)	0.64***	(0.19)
Apparel	1.78***	(0.21)	1.25***	(0.23)
Leather	1.21***	(0.21)	0.51***	(0.16)
Footwear	1.23***	(0.28)	0.74***	(0.25)
Wood	0.90***	(0.26)	0.33	(0.27)
Furniture	1.15***	(0.15)	0.79***	(0.07)
Paper	1.26*	(0.60)	0.59**	(0.34)
Printing	1.55***	(0.32)	1.00***	(0.22)
Industrial Chemicals	3.75***	(0.54)	1.31***	(0.31)
Chemical Products	4.57***	(1.40)	1.10**	(0.51)
Petroleum	5.92***	(1.30)	0.2	(0.49)
Natural Rubber	0.86***	(0.27)	-0.05	(0.21)
Rubber Products	1.37***	(0.20)	0.55**	(0.16)
Plastic Products	1.91***	(0.17)	0.81***	(0.17)
Glass	1.68***	(0.11)	1.13***	(0.09)
Clay	2.03***	(0.25)	0.98***	(0.14)
Cement	3.43***	(0.6)	0.01	(0.28)
Concrete Products	2.98***	(0.23)	0.96***	(0.10)
Mineral Products	1.12***	(0.19)	0.4**	(0.16)
Basic Metal	-0.79	(1.03)	-1.47***	(0.56)
Non-Ferrous Metal	1.85***	(0.21)	0.77**	(0.34)
Fabricated Metal	1.58***	(0.27)	0.98***	(0.21)
Machinery	2.97***	(0.23)	1.47***	(0.18)
Electrical	1.12***	(0.17)	0.40**	(0.20)
Electronics	2.16***	(0.23)	0.73***	(0.19)
Transport Equipment	1.5***	(0.29)	0.63***	(0.19)
Scientific Instruments	1.11	(0.74)	0.23	(0.51)
Other	1.64***	(0.21)	0.74***	(0.19)
R-squared	0.782142	Mean dependent var		-0.01
Adjusted R-squared	0.758514	S.D. dependent var		0.243
S.E. of regression	0.119426	Sum squared resid		14.334
Log likelihood	845.2303	F-statistic		46.258
Durbin-Watson stat	1.843607	Prob(F-statistic)		0

Notes: *, **, and *** indicate significance at 90%, 95%, and 99% confidence levels, respectively.

Industry and year fixed effects are included but not reported.

Table 3: Olley-Pakes Correction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Growth Rate of Output per Capital			Firms' Turover Rate	Growth Rate of Output per Capital - 1.44*Growth Rate of Labor per Capital		
Estimated industry markup	1.52*** (0.08)	1.47*** (0.08)	1.44*** (0.09)		1.44*** (0.09)	1.44*** (0.09)	1.44*** (0.09)
Estimated industry scale coefficient	0.62*** (0.10)	0.64*** (0.10)			0.60*** (0.03)	0.58*** (0.08)	0.57*** (0.08)
Investment growth		0.03*** (0.01)					
Polynomial of investment and capital stock growth			3rd order	4th order			
Powers of the estimated lagged productivity growth					3rd order		
Powers of the estimated lagged survival probability						3rd order	
Polynomial of estimated lagged productivity and survival rate							3rd order
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	1115	1115	1115	1115	1083	1083	1083

Notes: Robust standard errors in parentheses.

*, **, and *** indicate significance at 90%, 95%, and 99% confidence levels, respectively.

Estimated productivity growth is obtained from the fitted value of the polynomial of investment and capital growth from Column (3).

Estimated survival rate is the fitted value of Column (4).

Table 4: TFP vs. Estimated Productivity Growth

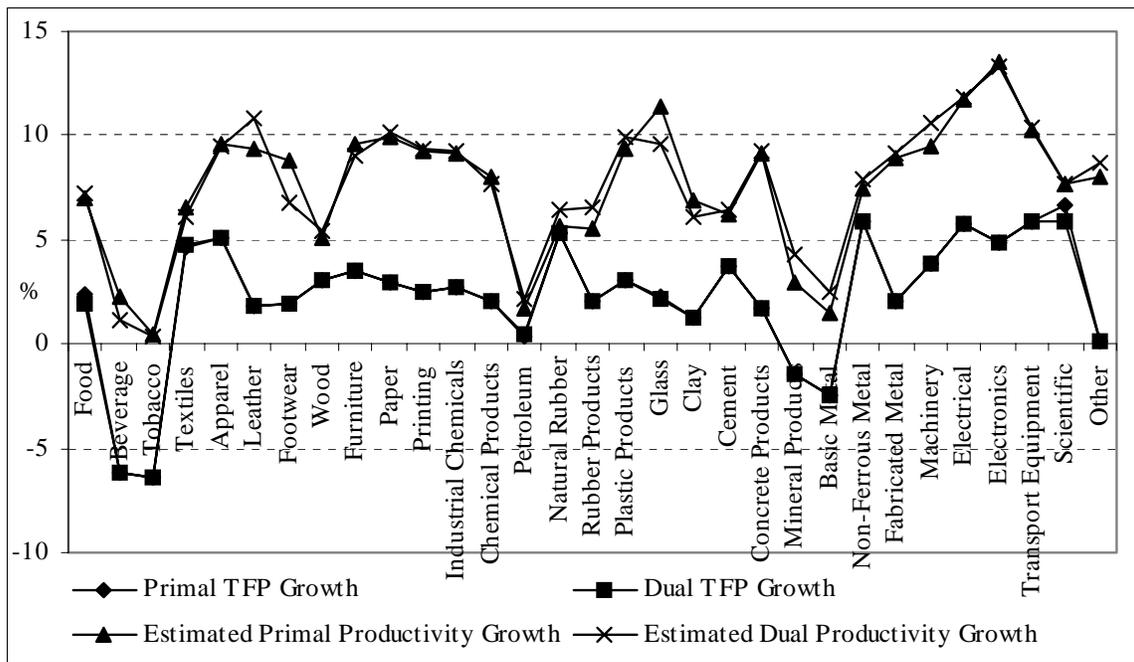


Table 5: Dependent Variables: Growth Rates of Real Output and Rental Price (controlling for the growth rate of intermediate input cost)

Method: Fixed Effect Panel Regression

Included observations: 36

Included cross sections: 31

Total panel (unbalanced) observations: 1115

Industry	Estimated Markups	Robust S.E.	Estimated Scale Coefficients	Robust S.E.
Food	2.09***	(0.84)	0.84	(0.66)
Beverage	0.96	(0.64)	0.15	(0.25)
Tobacco	-0.17	(0.82)	-0.59	(0.31)
Textiles	0.23	(0.26)	0	(0.17)
Apparel	1.49***	(0.25)	1.17***	(0.27)
Leather	0.69**	(0.29)	0.18	(0.20)
Footwear	1.10***	(0.27)	0.71***	(0.24)
Wood	0.86	(0.65)	0.33	(0.54)
Furniture	0.45**	(0.19)	0.36***	(0.11)
Paper	0.4	(0.77)	0.24	(0.40)
Printing	1.50***	(0.32)	1.01**	(0.21)
Industrial Chemicals	3.42***	(0.51)	1.2***	(0.33)
Chemical Products	5.15***	(1.10)	1.08***	(0.43)
Petroleum	7.24***	(1.37)	0.74***	(0.35)
Natural Rubber	0.86***	(0.25)	-0.03	(0.20)
Rubber Products	0.81**	(0.39)	0.35*	(0.18)
Plastic Products	1.01**	(0.50)	0.37	(0.33)
Glass	1.91***	(0.21)	1.24***	(0.12)
Clay	1.18***	(0.31)	0.57***	(0.16)
Cement	2.30***	(0.74)	-0.04	(0.27)
Concrete Products	2.12***	(0.37)	0.72***	(0.11)
Mineral Products	1.00***	(0.17)	0.28***	(0.13)
Basic Metal	-0.5	(1.05)	-1.38**	(0.57)
Non-Ferrous Metal	1.82***	(0.24)	0.71***	(0.31)
Fabricated Metal	1.10**	(0.53)	0.73***	(0.33)
Machinery	2.04***	(0.36)	1.21***	(0.22)
Electrical	0.76***	(0.22)	0.28	(0.22)
Electronics	1.50***	(0.50)	0.48*	(0.28)
Transport Equipment	1.21***	(0.42)	0.48**	(0.22)
Scientific Instruments	0.86	(0.92)	0.01	(0.69)
Other	1.03***	(0.30)	0.38*	(0.22)
R-squared	0.812598	Mean dependent var	-0.010013	
Adjusted R-squared	0.785661	S.D. dependent var	0.243026	
S.E. of regression	0.112513	Sum squared resid	12.33006	
Log likelihood	929.1809	F-statistic	38.74653	
Durbin-Watson stat	1.901742	Prob(F-statistic)	0.000000	

Notes: *, **, and *** indicate significance at 90%, 95%, and 99% confidence levels, respectively.

Industry and year fixed effects are included but not reported.

Growth rate of intermediate input is included but not reported.