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A comparative analysis of research and development spending and total factor productivity growth in Hong Kong, Shenzhen, Singapore

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A B S T R A C T

In this paper, we focus on three locations in the Asia-Pacific region—Hong Kong, Shenzhen, and Singapore—to analyse the impact of variations in research and development (R&D) spending on total factor productivity (TFP) growth. In each of the three cases, we compare and contrast the role of public and private R&D in boosting TFP growth as well as the pattern of causality involving public and private R&D and the capacity of both types of R&D to generate economic spillovers. Our results show that the impact of both public and private R&D varies across the three cases, with significant but limited outcomes for TFP growth in the case of Hong Kong, no significant growth in Shenzhen, but strong and positively significant growth in Singapore.

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1. Introduction

Technical change is a key contributor to economic growth and development. Recent decades have witnessed significant increases in research and development (R&D)[1] spending among several Asian economies (Battelle, 2015; Battelle, 2016). Fig. 1, below, captures the R&D spending trends in some of the key East Asian and advanced economies, benchmarked against the OECD average of 2.34% of GDP as of 2017.

R&D can be sub-classified based on whether it is conducted in the public sector or the private sector, or based on its nature and objectives—whether it involves basic research, applied research, or experimental development.[2] While multiple studies have established the relationship whereby R&D boosts productivity by expanding resource bases and making resource utilization more efficient (Fagerberg, 1994; Jones, 1995), gaps remain regarding our understanding of the extent to which distinct types of R&D affect productivity and how they do so.

This study addresses these gaps by evaluating the relationship between R&D—sub-classified into public R&D and private R&D—and total factor productivity (TFP), a key measure of economic productivity, in three vibrant locations in Asia—Hong Kong, Shenzhen, and Singapore—that have considerable mutual reference value given their similarities in size, geography, proximity, and keenness to exploit innovation-led growth.[3] All three economies have embraced longstanding commitments to innovation-led growth, albeit by adopting distinct mechanisms for pursuing this objective. Hong Kong and Shenzhen, sovereign units of China, exhibit several characteristics which distinguish them from the rest of the Mainland.[4]

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[1] As defined by the Frascati Manual (OECD, 1994: 29), R&D "comprises creative work undertaken on a systematic basis in order to increase the stock of knowledge and the use of this stock of knowledge to devise new applications."

[2] The Frascati Manual (OECD, 2015) classifies research into three categories—*basic research* is experimental or theoretical work undertaken primarily to acquire new knowledge about observable phenomena and facts, not directed toward any particular use; *applied research* is original investigation to acquire new knowledge directed primarily towards a specific practical aim or objective; *experimental development* is a systematic effort, based on existing knowledge acquired from research or practical experience, directed toward creating novel or improved materials, products, devices, processes, systems, or services.

[3] In 2017, Hong Kong's GDP was approximately USD 340 billion for a population of 7.5 million, Shenzhen recorded a GDP of approximately USD 331 billion for a population of 12.6 million, while Singapore, the least populated of the three, achieved a GDP of approximately USD 342 billion for a population of 5.7 million (sources: For Hong Kong and Singapore—World Bank data, 2017 (https://data.worldbank.org); For Shenzhen—CEIC (2020), 'China CN: GDP: Guangdong: Shenzhen'. Retrieved on December 17, 2020, from: https://www.ceicdata.com/en/china/gross-domestic-product-prefecture-level-city/cn-gdp-guangdong-shenzhen.)

[4] Hong Kong, a former British colony now designated as a special administrative region of China under the 'one country, two systems' arrangement, has largely retained the economic and administrative systems that were in place before reunification with China in 1997. Shenzhen, which officially became a city in 1979, was designated China's first special economic zone (SEZ) in 1980.

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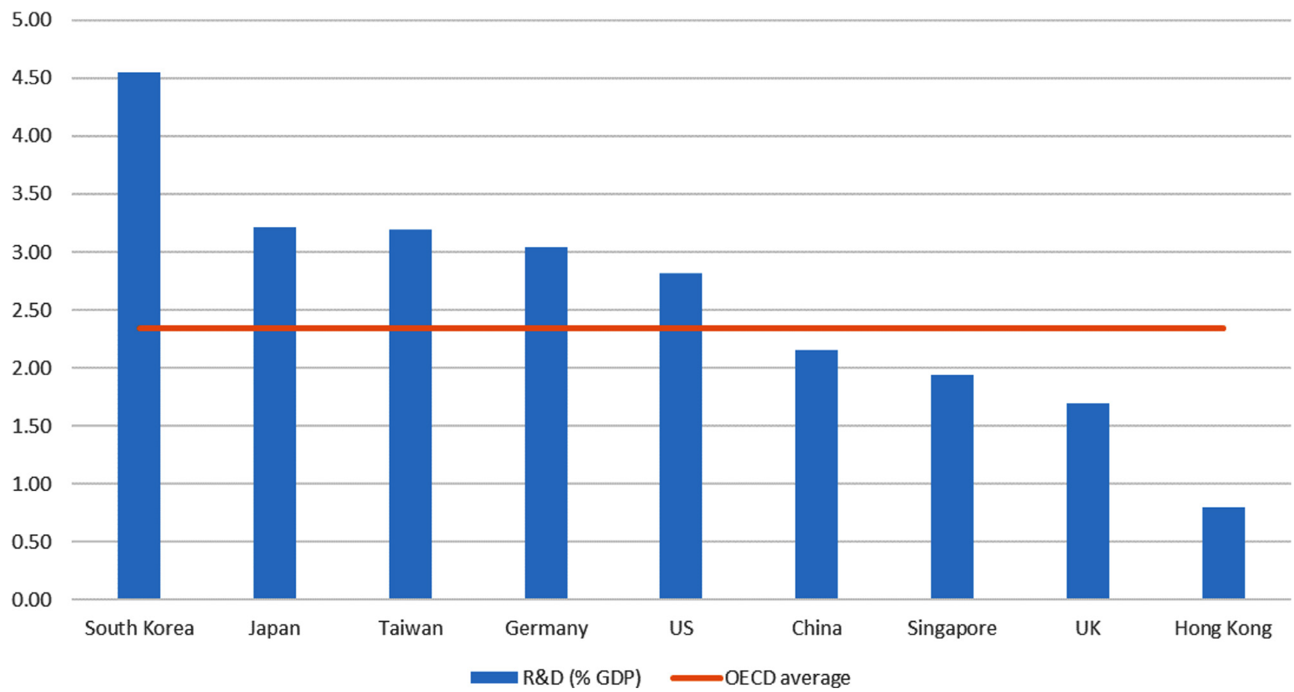

Fig. 1. R&D Spending (% GDP) by Country/Region, 2017 Sources: OECD, Hong Kong Annual Digest of Statistics, Singapore Department of Statistics.

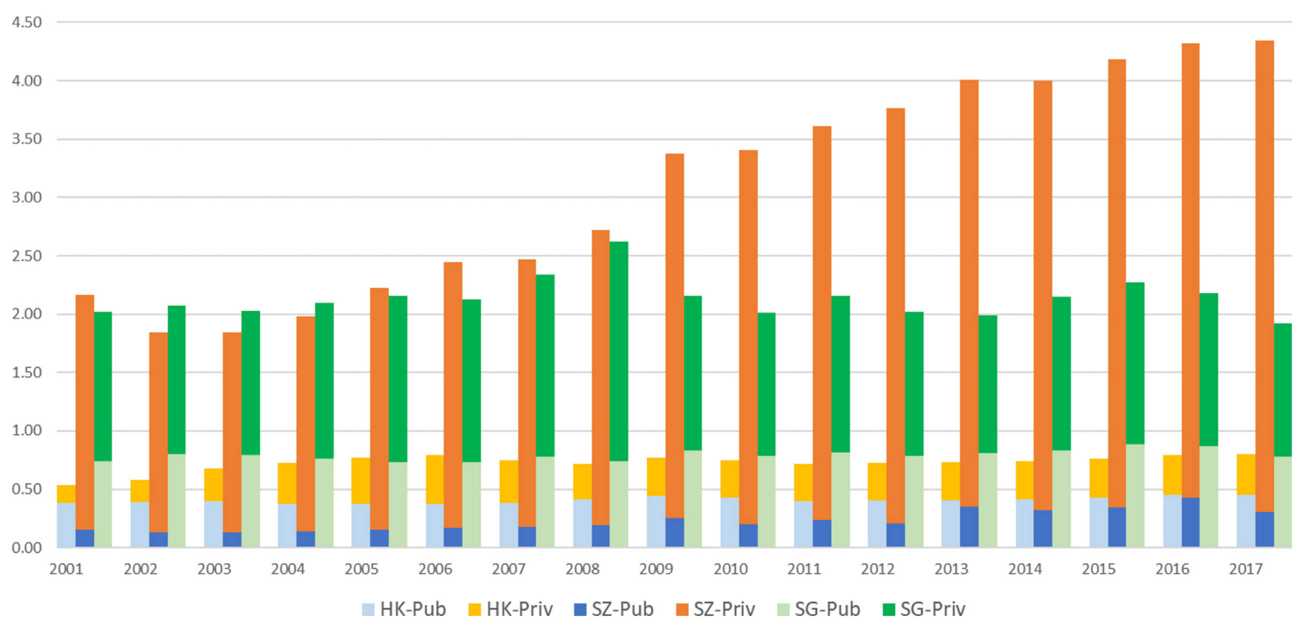

Fig. 2. Year-on-Year R&D spending (as a % of GDP) in Hong Kong, Shenzhen, and Singapore, 2001–2017 Sources: Hong Kong Annual Digest of Statistics 2019, Shenzhen Statistical Yearbook 2018, Singapore Department of Statistics (2020) Notes: HK=Hong Kong; SZ=Shenzhen; SG=Singapore; Pub=Public; Priv=Private.

Singapore, an independent island city-state, is globally recognised for its rapid economic progress.[5]

There is also substantial variation in R&D spending across these locations, as depicted in Fig. 2. We explore these variations to understand the impact of R&D on productivity in each of the three locations.

As illustrated in Fig. 2, Hong Kong's R&D-to-GDP ratio—around 0.80%—has been consistently below the OECD average of 2.34% (Fig. 1) and, in recent years, even well below the average ratio in Mainland China of around 2%. The figure for Shenzhen, on the other hand, has been above Mainland China's average, and its R&D-to-GDP ratio, at approximately 4%, is comparable to that of some of the world's most R&D-intensive countries, such as South Korea. Singapore's ratio of R&D to GDP, which stands at 2.1%, is fairly consistent throughout the period, and in line with the OECD average.

The key objective of our study is to capture significant differences in the ways in which public R&D and private R&D in-

[5] Hong Kong is broadly known for its *'laissez faire'* approach to governance, an approach that has for the most part let the market prevail, the government playing at best a 'facilitative role' in promoting infrastructure and higher education (Fuller, 2010). In Shenzhen, on the other hand, R&D takes place largely within private enterprises under the aegis of certain strategic directives from the local government (Yang, 2014; Yang, 2015). Singapore, known for its government's strong 'interventionist role,' has been more directly engaged in promoting R&D and picking winners in specific sectors (Wang, 2018).

fluence economic productivity and to understand how these interrelate with one another in building the capacity to generate sufficient and sustainable spillovers in various economic settings. Achieving these objectives carries relevance beyond the three economies of concern to the present study insofar as policymakers around the globe attempt to understand the comparative influence of public and private R&D expenditures as they seek the most effective vehicles for boosting productivity, economic growth and indeed transforming into regional and/or global innovation hubs.

TFP is used as an indicator of growth because it quantifies the portion of output—in this case GDP—that cannot be attributed to an increase in physical capital and/or labor, and is considered an important concept by economists studying the impact of technical progress on economic growth.[6]

R&D assumes any of several forms, ranging from public sector R&D, directed through public research institutes and educational institutions, to private in-house R&D carried out by businesses to develop existing or new products or processes. The impact of R&D on productivity works differently through these distinct channels, and we expect this study to generate insights for policymakers engaged in designing innovation policy when evaluating options for optimizing gains from investments in R&D.

Specifically, this study addresses the following **research questions** (RQ):

RQ 1: Is there a positive relationship between R&D and TFP in Hong Kong, Shenzhen, or Singapore?

RQ 2: Which type of R&D—public or private—has a stronger influence on TFP?

RQ 3: Does public R&D spill over to the private sector and stimulate private R&D? Is there evidence of reverse causality?

The hypotheses through which we explore these questions are:

H1: R&D has a significant, positive impact on TFP in each of the three cases under consideration.

H2: Private R&D has a more immediate and significant impact on economic productivity than public R&D.

H3: Public R&D generates spillovers that stimulate private R&D. No reverse causality is expected.

Our study manifests three significant points of departure from existing studies. First, we use the latest available data—through 2017—for Hong Kong, Shenzhen, and Singapore to capture the most recent trends in their R&D spending. Second, for each of the three locations, we differentiate between public R&D and private R&D (not least because public R&D has often been considered an important determinant of subsequent R&D investment by the private sector; cf. Coccia, 2017; Cin et al., 2017). Third, we bring Shenzhen into the comparative framework for the first time. Shenzhen, despite being modeled along the lines of fast-paced Hong Kong from its inception, has never been studied in the manner we propose, let alone compared with either Hong Kong or Singapore in the context of R&D spending and TFP.[7]

The structure of the paper is as follows. First, we present our theoretical framework, interwoven with extant literature, in the section below. Second, we explain the methodology we use to conduct our analysis. Third, we present our results. Fourth, we discuss those results, especially in terms of their broader policy significance. Finally, we conclude our paper with implications derived from our findings as well as the main limitations of the present study.

2. Theoretical framework

In this paper, we concern ourselves with the growth stimulated by the technological progress of a nation measured as *TFP*, the role of *public and private R&D* in the development of such technological progress, and the interaction between public and private R&D in the form of *spillovers*.

TFP measures residual growth in total output of a firm, an industry, or a national economy that cannot be explained by the accumulation of traditional inputs such as labor and/or capital. TFP is synonymous with enhanced productivity and competitiveness—the higher a country's TFP, the better its ability to yield higher output with the same resources and drive economic growth. Nations experience enduring economic growth when the process of technological change manifests endogenously through the generation of new technology and knowledge, through enhanced R&D efforts and economic spillovers generated by the adoption of technology. R&D efforts by nations include both increase in public spending on R&D and mechanisms to stimulate private R&D.

The earliest models of TFP, which captured the role of technology in economic growth, assumed that technology is determined exogenously. Subsequent theoretical work led to the development of the "endogenous" or "new growth" theory. This strand of work purportedly explains the enduring nature of economic growth experienced by many countries by reference to the endogenous nature of technological economic change. The endogeneity factor was incorporated into the model in the form of economic *spillovers* generated by the adoption of technology, resulting in increasing returns to scale (Romer, 1990); *human capital development*, i.e. knowledge, education, training, and experience embodied in workers; or in the form of *creative destruction*, i.e. the generation of new technology and knowledge through enhanced R&D efforts.

Thus, key determinants of TFP include manpower development through both formal education and on-the-job training; economic restructuring towards more productive sectors of the economy; demand intensity and increased capacity utilisation rates with respect to machines and equipment; the rate of adoption of new technologies; and, most significantly, investment in R&D (Griliches, 1994; Jajri, 2007).

Empirically, the relationship between *private R&D* and productivity via its impact on TFP has been studied and documented extensively (Griliches and Lichtenberg, 1984; Coccia, 2011; Coccia, 2012). Studies have shown that R&D matters, with the estimated output elasticity with respect to private R&D carried out within firms falling within the range of 10% to 30% (Nadiri, 1993). This wide variation reflects the relationship between R&D variables and TFP, which tends to be sensitive to the methodology used to calculate TFP estimates within the growth-accounting framework as well as differences in econometric specifications, data sources, the number of economic units, methods for estimating R&D and economic performance, and periods under study (Atella and Quintierri, 2001; Van Biesebroeck, 2007). Furthermore, insofar as R&D conducted by industrial actors may be either self-funded or government-funded, its effects on productivity may differ depending on the funding source, which may in turn af-

[6] TFP growth in Hong Kong and Singapore has been studied using data for the period running from 1970 through 1991 (Young, 1992), in which healthy TFP growth was found in Hong Kong but negative growth was found in Singapore. More recently, Ho, Wong and Toh (2009) and Ho and Wong (2017) have evaluated the impact of R&D on TFP in the single case of the Singaporean economy and its TFP. These studies, which (unlike Young, 1992) examine Singapore's productivity and R&D data through 2001 and 2012, respectively, find a positive and significant relationship between Singapore's R&D investment and TFP. To date, no credible studies have evaluated TFP growth in Shenzhen.

[7] Shenzhen's 40-year period of rapid development, during which it has grown from a backwater village into a large-scale manufacturing base in the Pearl River Delta and then into a burgeoning innovation hub (Chen and Ogan, 2017), represents a compelling case that is worth analyzing, particularly in light of its spectacular record GDP growth over the past two decades, averaging 13% annually.

fect research agendas and incentive structures (Bronzini and Iachini, 2014; Duguet, 2004; Guellec and van Pottelsberghe de la Potterie, 2001; Wallsten, 2000).

Fewer theoretical frameworks exist to inform the study of the impact of *public research* on economic productivity (for an exception, see Coccia, 2010). Public R&D may not have a direct impact on TFP, as its more immediate mission is contributing to the scientific knowledge base. For instance, in the context of 16 OECD countries, Guellec and van Pottelsberghe de la Potterie (2001) found a negative impact of defense-related R&D, a weak positive impact of civilian R&D (health- and environment-related)—primarily on account of spillovers into private R&D—and a much stronger contribution of government- and university-conducted research on productivity, with long-term elasticity of around 0.17. Other scholars have, however, found the impact of public R&D on TFP to be much weaker. Voutsinas and Tsamadias (2014) estimated the long-run elasticity from public R&D in Greece at 0.075, while Ho and Wong (2017), in their case study of Singapore, showed that long-run elasticity of R&D was 0.091.

Insofar as the relationship between public and private R&D holds, scholars have considered whether the two complement one another—generating spillovers that enhance productivity growth—or serve as substitutes, with public R&D crowding out private R&D (Bye et al., 2019; Cin et al., 2017; Czarnitzki and Hussinger, 2017; Duguet, 2004; Wallsten, 2000). The outcomes of these studies point in both ways depending on sensitivity to empirical realities and the econometric techniques employed (cf. David et al., 2000; Coccia, 2010; Bronzini and Iachini, 2014).

Given the wide variations in results reported by studies undertaken to compute TFP and the sensitivity of TFP to various types of R&D, we sought to empirically determine the impact of public and private R&D on TFP in our selected cases of Hong Kong, Shenzhen, and Singapore.

3. Methodology

In this paper we adopt a two-step TFP approach utilizing a Cobb-Douglas–based analysis, as explained by Nadiri (1993). We used time-series data for all three locations for this purpose. Terleckyj (1974) explained the two-step productivity approach to estimating a model that relates R&D expenditure to TFP, deriving the TFP equation from the underlying Cobb-Douglas production function. This two-step TFP approach used the model pioneered by Solow (1957), with a simple Cobb-Douglas production function, to link output to R&D investment. The TFP obtained from this method is considered an indicator of productivity.

Our method of computing TFP utilizes Cobb-Douglas based analysis to estimate the production function at the aggregate level. We use our method to gauge the macroeconomic effects of R&D investments. This method for computing TFP is suitable for our purpose as it requires time-series data on conventional inputs (labor and capital) and R&D stock for estimating the production function. As we are estimating the macroeconomic effects of R&D, these macroeconomic data were used directly in our method.

Using this approach, we are aware of the implied assumption of separability of R&D investments from conventional inputs of labor and capital and we recognize that R&D activities can be complements to labor and capital rather than substitutes for these factors. Despite this shortcoming, the main advantage of using this method is its parsimony and the ready availability of the data for running the model for our three cases. Moreover, there are concerns about the endogeneity of input factors for estimating TFP, which are normally overcome by including interaction terms in complex models. However, in our case, relatively short time-series data were available, especially for Hong Kong and Shenzhen, and constructing a complex model with interaction terms would have entailed a substantial loss of degrees of freedom.[8]

Major assumptions underlying this model include constant returns to scale (CRS) with respect to capital and labor and equilibrium in product and input markets.[9] Domar (1961: 712) has characterized TFP measured in this manner as a residual, accounting for "increases in output not accounted for by explicitly recognized inputs." This residually measured TFP, known as the "Solow residual," is then expressed as TFP growth and tested for its relationship with either R&D intensity (Griliches, 1994; Griliches and Mairesse, 1995) or R&D capital stock (Coe and Helpman, 1995).

We begin our analysis with a general Cobb-Douglas production function, explained by Solow (1957):

$$Y_t = A_t {K_t}^{\propto} {L_t}^{1-\propto} \tag{1}$$

where Y = output, A = productivity, K = physical capital stock, and L = labor employed. We then convert equation (1) into a logarithmic function. Equation (2) represents the logarithmic version of equation (1). In logarithmic form, the production function may be estimated as a linear model, providing unconstrained estimates of each of the parameters of the production function.

$$Log\ Y_t = Log\ A_t + \propto Log\ K_t + (1- \propto)\ Log\ L_t \tag{2}$$

With respect to equation (2), TFP is the increase in output (Y) that is not explained by increases in capital and labor inputs, on the assumption of CRS and perfect competition in capital and labor markets. CRS means that $\alpha + \beta = \propto + (1- \propto) = 1$ in equation (1). In estimating labor's and capital's respective shares of output, we referred to the method provided by the US Bureau of Labor Statistics (1997) in initially estimating the wage share. We define the wage share (or labor's share in output) as equal to the total amount of employee compensation (CE) divided by total output (in this case GDP) within the same year, where β_t symbolizes labor's share in year t:

$$\beta_t = 1 - \propto_t = \frac{CE_t}{GDP_t} \tag{3}$$

In estimating capital stock, we adopted the perpetual inventory method based on Griliches's approach (1980). This approach entails approximating the initial capital stock for each of the three cases in the first year of the period of analysis, or K_0. Following Ramirez-Rondan et al. (2005), we assumed that the capital stock growth rate for the preceding period equals the GDP growth rate (g). Given such an approach, we can estimate the initial capital stock using the formula shown below:

$$K_0 = \frac{GFCF_0}{g + \delta} \tag{4}$$

For subsequent years, the estimated capital stock will be:

$$K_t = (1 - \delta)K_{t-1} + GFCF_t \tag{5}$$

[8] To be sure, there are alternatives for computing productivity, including the Index Numbers, Data Envelopment Process, Ordinary Least Squares, Stochastic Frontiers, and Generalized Method of Moment (GMM-SYS) approaches. The Index Numbers and Data Envelopment Process approaches are more suitable for estimating productivity at the firm or industry level, which was not applicable in our case (Van Biesebroeck, 2007). Ordinary Least Squares faces the problem of simultaneity among inputs and unobserved productivity so we did not consider it. Stochastic Frontiers required a strong assumption that productivity differences remained constant over time and observations shared the same level of technology. These assumptions were hard to justify in our case as our data for the three locations clearly showed that productivity differences did not remain constant over time and observations did not share the same level of technology. Furthermore, GMM-SYS is more suitable for parametric methods whereas we used nonparametric estimation given the small number of observations available. Finally, the regressors may not be normally distributed, especially in the case of Shenzhen, for which we interpolated the figures for 2001–2008 backwards due to the lack of available data.

[9] While the assumption of constant returns to scale has been widely used, it is worth noting that TFP estimates might differ if inputs are no longer assumed to be optimal, or indeed in the case of non-constant returns to scale.

We assume a depreciation rate (δ) for capital stock of approximately 5%, following Ho and Wong (2017) and Karabarbounis and Neiman (2014), who provided a range of estimates falling between 4% and 8%.

We also apply the same perpetual inventory method in estimating the R&D capital stock generated from annual R&D investments. We assume a depreciation rate in this category of 10%, as shown in figures provided by Voutsinas and Tsamadias (2014), who based their approaches on Lichtenberg (1992) and Coe and Helpman (1995). The following formulas for estimating total R&D, public R&D, and private R&D capital stock are highlighted in Equations (6), (7), and (8) below:

$$\begin{aligned} S_0 &= \frac{R_0}{g+\delta} \\ S_t &= (1-\delta)S_{t-1} + R_t \end{aligned} \tag{6}$$

$$\begin{aligned} S.PUB_0 &= \frac{R.PUB_0}{g+\delta} \\ S.PUB_t &= (1-\delta)S.PUB_{t-1} + R.PUB_t \end{aligned} \tag{7}$$

$$\begin{aligned} S.PRIV_0 &= \frac{R.PRIV_0}{g+\delta} \\ S.PRIV_t &= (1-\delta)S.PRIV_{t-1} + R.PRIV_t \end{aligned} \tag{8}$$

TFP is computed from equation (2) based on available data. To derive TFP equation (9) from the Log form of the production function in equation (2), we referred to Terleckyj (1974), the Australian Industry Commission (1995), and Guellec and van Pottelsberghe de la Potterie (2001).

$$log\ Y_t - \alpha\ log\ K_t - (1-\alpha)\log L_t = \rho + \gamma \log S \tag{9}$$

The left side of equation (9) represents TFP, an increase in output *(Log Y)* which cannot be explained by changes in capital *(Log K)* or labor *(Log L)*. Capital stock for R&D is symbolized as Log S. After computing TFP, it is possible to regress it against the right-hand variables in equation (9), as shown in equation (10), this time including the lag order of 1 for TFP (TFP_{t-1}):

$$TFP = \rho + TFP_{t-1} + \gamma \log S \tag{10}$$

The effects of R&D on output are expected to occur following a time lag. Equation (10) is, therefore, treated as a long-run relationship. The residuals derived from estimating equation (10) may be tested to establish the existence of a co-integrated long-run equilibrium relationship between TFP and its R&D capital stock determinants, Log_S. The availability of data for estimating equation (10) is one of the major advantages of this equation. The implied assumption of the separation of R&D investments and the conventional inputs of labor and physical capital may, however, as pointed out by Griliches (1979) and Sterlacchini (1989), limit the generalizability of the analysis. In the real world, R&D and innovative activities do not act as substitutes for labor and capital, but in fact more likely complement those factors (Nelson, 1981). Any interactions between R&D and other factors are not adequately explained using this two-step approach.

Our primary aim is to estimate the impact of R&D—both public and private—on TFP growth, basing our approach on Ho, Wong and Toh (2009), Ho and Wong (2017), and Voutsinas and Tsamadias (2014). We conducted an augmented Dickey-Fuller (ADF) test to observe whether there is stationarity either within the variables of interest or within the first-order differencing (the rate of change, characterized by ▲) of these variables (Dickey and Fuller, 1979). The ADF test was followed by a Johansen cointegration test (Johansen, 1991; Johansen, 1995; both detailed in the Appendix) to measure whether there exists a long-run relationship between TFP and total R&D, TFP and public R&D, or TFP and private R&D.

Then, following Ho, Wong and Toh (2009) and Ho and Wong (2017), we regressed the dependent variable (TFP) separately on several independent variables, namely overall R&D, public R&D, and private R&D. This enabled us to examine, in accordance with the second research question, whether public R&D has a more positive—and significant—impact on productivity growth than private R&D does.

In addressing the third research question, we carried out the Granger causality test (Granger, 1969) to analyze the degree of causality between public and private R&D as a means of measuring whether increasing public R&D spending boosts additional investment in private R&D. We hypothesize that public R&D generates private R&D, but we believe there is no reverse causality, given that private entities have stronger incentives to protect their R&D outputs as opposed to sharing their intellectual property with the public. We chose a lag order of 2 for determining the presence of causal relationships between the R&D variables. The formula to be used in this Granger causality test is as follows:

$$\begin{aligned} LogSpriv_t = {} & \propto + \emptyset_1\ LogSpriv_{t-1} + \ldots + \emptyset_n\ LogSpriv_{t-n} \\ & + \delta_1\ LogSpub\ _{t-1} + \ldots + \delta_n LogSpub_{t-n} \end{aligned} \tag{11a}$$

$$\begin{aligned} LogSpub_t = {} & \propto + \emptyset_1\ LogSpub_{t-1} + \ldots + \emptyset_n\ LogSpub_{t-n} \\ & + \delta_1\ LogSpriv\ _{t-1} + \ldots + \delta_n LogSpriv_{t-n} \end{aligned} \tag{11b}$$

Lastly, to compute the mean lag in R&D capital stock, which is defined as the speed-of-adjustment process in output growth resulting from an increase in R&D capital stock, the following equation was used:

$$Mean\ lag = \lambda\ /\ (1-\lambda) \tag{12}$$

Here λ is derived from the coefficient of the lagged variable of interest in the regression table. In this case, we use the coefficient from the lagged TFP (TFP_{t-1}) variable for the purpose of estimating the mean and median lags.

To compute the median lag of R&D capital, which denotes the duration of the time lapse such that the proportion of the total lag effect of R&D capital on output (GDP) is equal to one-half, the following equation was used:

$$Median\ lag = \log(0.5)/\ \log(\lambda) \tag{13}$$

We relied on aggregate-level data to incorporate our model into our analysis. This is a departure from studies that use firm- and industry-level data to compute TFP (cf. Nadiri, 1993). In our case, however, such industry-level data are not uniformly available for all three of our cases. Moreover, Griliches (1992) concludes that estimates of R&D effects on productivity depend on the level of aggregation of the data used in a given model. R&D generates spillovers and its macroeconomic effects cannot be inferred directly from firm- or industry-level estimates. For precise measurement of the macroeconomic effects of R&D investments it is, therefore, necessary that macroeconomic-level data be used directly. Hall, Mairesse, and Mohnen (2010) add that aggregate R&D can be a useful measure of R&D intensity in a country/region, as disaggregating the R&D data at the firm level can be problematic.

We used a variety of sources to obtain data for our Hong Kong, Shenzhen, and Singapore cases. First, in the case of Hong Kong, we used the government's Annual Digest on Statistics, covering the period running from 1998 through 2017. We derived data primarily for GDP, gross fixed capital formation (GFCF), total workforce, and R&D expenditure from the Digest. All the values were derived in constant 2010 prices, using the GDP deflator approach.

Second, with regard to Shenzhen, our period of analysis runs from 2001 through 2017. We relied on the annual Shenzhen Statistical Yearbook, the most recent of which was the 2018 edition. Data for GDP, GFCF, the labor force, and R&D expenditures were sourced from the yearbooks. Because Shenzhen's public-sector R&D

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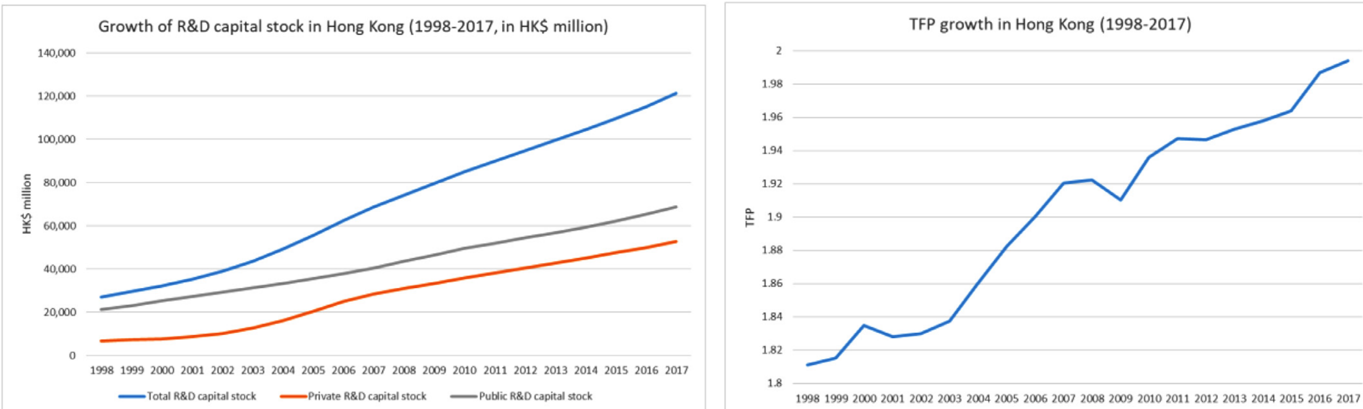

Fig. 3. Growth of R&D Capital Stock and TFP in Hong Kong.

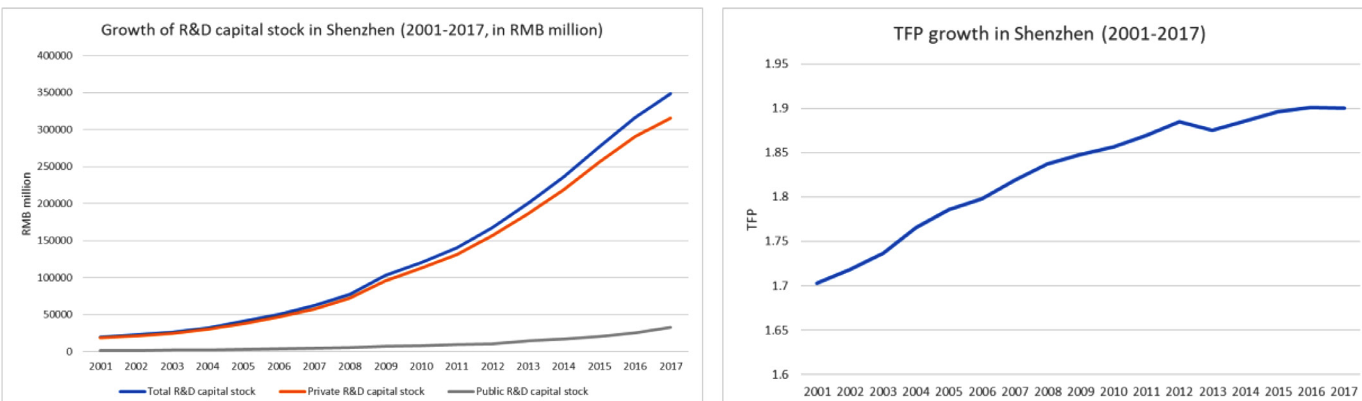

Fig. 4. Growth of R&D Capital Stock and TFP in Shenzhen.

was not mentioned in annual yearbooks prior to 2009, we interpolated from existing data points obtained for public R&D and simulated estimated values through 2001. To obtain data for earlier years, we needed to estimate the entire amount of R&D expenditure in Shenzhen for the pre-2009 period. We did so by assuming that the average weighting of private R&D for the 2009–2017 period (approximately 93% of the total expenditure) remained constant for the preceding years.

Third, for Singapore, we derived data from the Singapore Department of Statistics, spanning a 37-year period running from 1981 through 2017. Virtually all of the variables we obtained for the following analysis were sourced directly from the website of that agency (http://www.singstat.gov.sg), which provides the greatest number of interactive online databases that enable us to download the figures directly into our datasets.

4. Results

In Figs. 3, 4, and 5, we provide estimates of the growth of R&D capital stock and TFP for the three locations. In general, all the TFP figures exhibited an upward trajectory, with some variation from one case to another.

Our first research question involves identifying whether the positive—and statistically significant—relationship between R&D and TFP is generalizable for all three cases under study. The results are shown in Table 1.

Our results show that our first hypothesis is partly rejected for Hong Kong and Shenzhen. With regard to Hong Kong, we found that results for the Log_S variable (coefficient = 0.199) were significant only at p-value < 0.1, whereas the result for its lagged TFP (TFP_{t-1}) variable was not statistically significant. For Shenzhen, we found partial evidence for the hypothesis, as the coefficient for Log_S is 0.065, but not statistically significant, whereas the coefficient for TFP_{t-1} is 0.471 and significant at p-value < 0.001. For Singapore, the hypothesis is confirmed, as the short-run coefficients of Log_S (0.036; p-value < 0.01) and TFP_{t-1} (0.628; p-value < 0.001) are both positive and significant.

In Tables 2 and 3, below, we highlight the results obtained when we isolated both public R&D and private R&D capital stock in our regression on TFP. The results closely resemble what we have identified through the econometric tests reported in the Appendix: statistical significance is confirmed for the TFP–private R&D equation in Hong Kong, and for both the TFP–public R&D and TFP–private R&D equations in Singapore, but none of the results for Shenzhen was statistically significant.

Table 1
Non-Parametric Kernel Regression of TFP and Total R&D Capital Stock.

	Dependent variable: TFP		
Ind. Variables	Hong Kong	Shenzhen	Singapore
TFP_{t-1}	0.2332	0.471307***	0.62781***
	(0.5072)	(0.218951)	(0.09903)
Log_S	0.1988+	0.064728	0.03596**
	(0.1091)	(0.109465)	(0.01068)
N	19	16	36
R-squared	0.9866	0.9947	0.9234
F-statistic	58.5	24.2	203.1
Prob > F	0.00	0.00	0.00

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

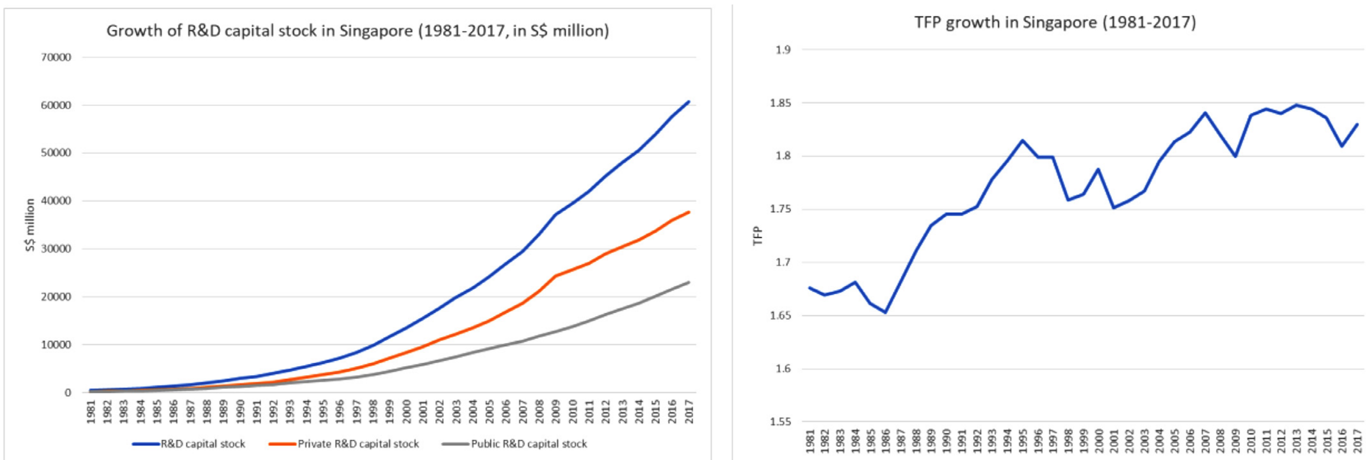

Fig. 5. Growth of R&D Capital Stock and TFP in Singapore.

Table 2
Non-Parametric Kernel Regression of TFP and Public R&D Capital Stock.

	Dependent Variable: TFP		
Ind. Variables	Hong Kong	Shenzhen	Singapore
TFP_{t-1}	0.29984	0.739533*	0.64199***
	(0.63696)	(0.180607)	(0.09769)
Log_Spub	0.20638	0.012885	0.03544**
	(0.18302)	(0.063172)	(0.01086)
N	19	16	36
R-squared	0.9866	0.9928	0.9225
F-statistic	22.5	44.0	198.7
Prob > F	0.00	0.00	0.00

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Table 3
Non-Parametric Kernel Regression of TFP and Private R&D Capital Stock.

	Dependent Variable: TFP		
Ind. Variables	Hong Kong	Shenzhen	Singapore
TFP_{t-1}	0.25270+	0.42895	0.62419***
	(0.15180)	(0.45475)	(0.09975)
Log_Spriv	0.15406***	0.07201	0.03503**
	(0.03700)	(0.10682)	(0.01021)
N	19	16	36
R-squared	0.9866	0.9947	0.9235
F-statistic	835.39	22.1	220.2
Prob > F	0.00	0.00	0.00

+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Our second research question asks whether public R&D or private R&D has a more significant impact on productivity growth in the three cases. To address this question, we estimated both the short-run and long-run elasticities based on regression results reported in the previous tables. The results are shown in Tables 4, 5, and 6.

In the case of Hong Kong, we found that, regarding overall R&D expenditure, short-run elasticity (0.199) was significant at p-value < 0.1. While the coefficients for both short-run (coefficient = 0.206) and long-run (coefficient = 0.295) elasticities from public R&D were higher than what we found in the case of private R&D (with short-run and long-run elasticity coefficients at 0.154 and 0.206, respectively), no statistical significance could be identified for public R&D (p-value > 0.1 for both short-run and long-run elasticity coefficients). Private R&D has a significant impact (coefficient = 0.154; p-value < 0.001) in the short run, but no significant impact in the long run (coefficient = 0.206; p-value > 0.1).

With regard to Shenzhen, we found that, regarding overall R&D expenditure, the short-run and long-run elasticity coefficients (0.065 and 0.122) were not significant at p-value > 0.1. Public R&D demonstrated lower short-run (coefficient = 0.013) and long-run (coefficient = 0.049) elasticities than what we observed in private R&D (short-run and long-run elasticities at 0.072 and 0.126, respectively), but once again we found no evidence of statistical significance, with their p-values exceeding 0.1.

In the case of Singapore, the short-run and long-run elasticities from total R&D were 0.036 and 0.097, with evidence of statistical significance at p-values < 0.05. The coefficients were largely similar when we observed the elasticities for public R&D (with their scores at 0.035 and 0.099, and their p-values < 0.05). We found the results on private R&D also to be fairly stable, as their short-run and long-run elasticities were 0.035 and 0.093, and also statistically significant at p-values < 0.05.

The mean and median lags shown in Tables 4, 5, and 6 suggest some interesting findings. Among the three cases, Hong Kong exhibits the shortest mean and median lags (0.30 and 0.48 years) for total R&D, with the lags associated with public R&D, 0.43 and 0.58 years, slightly longer, respectively, than those for private R&D (0.34 and 0.50 years).

Regarding Shenzhen, the mean and median lags from their total R&D were 0.89 and 0.92 years. It was in the public R&D domain that Shenzhen recorded the longest mean and median lags (at 2.84 and 2.30 years) among the three locations. The resulting figures for private R&D were close to what we observed in total R&D, with their mean and median lags at 0.75 and 0.82 years.

Singapore demonstrated the longest mean and median lags among the three cases in terms of total R&D, with these figures at 1.69 and 1.49 years, respectively. The numbers for public R&D were not considerably different (mean lag = 1.79 years; median lag = 1.56 years). The resulting mean and median lags in private R&D were not far from those of total R&D, with the figures at 1.66 and 1.47 years.

In summary, our second hypothesis is also rejected. In the case of Hong Kong, the elasticity coefficients from public R&D were higher than what we observed in private R&D, but only the short-run elasticity from private R&D demonstrated statistical significance at p-value < 0.05. With regard to Shenzhen, private R&D resulted in higher elasticities on TFP than public R&D, but we found none of the coefficients reaching statistical significance at p-values < 0.05. Finally, for Singapore, public R&D and private R&D had closely similar elasticity coefficients in the short run, but long-run elasticity from public R&D was slightly higher than that of pri-

Table 4
Short-Run and Long-Run Elasticity of Total R&D vis-à-vis TFP (based on Table 1).

	Hong Kong	Statistical significance	Shenzhen	Statistical significance	Singapore	Statistical significance
Short-run TFP elasticity	0.199	No	0.065	No	0.036	Yes
Long-run TFP elasticity	0.260	No	0.122	No	0.097	Yes
Mean lag (years)	0.30		0.89		1.69	
Median lag (years)	0.48		0.92		1.49	

Statistical significance is 'yes' if $p < 0.05$, otherwise 'no'

Table 5
Short-Run and Long-Run Elasticity of Public R&D vis-à-vis TFP (based on Table 2).

	Hong Kong	Statistical significance	Shenzhen	Statistical significance	Singapore	Statistical significance
Short-run TFP elasticity	0.206	No	0.013	No	0.035	Yes
Long-run TFP elasticity	0.295	No	0.049	No	0.099	Yes
Mean lag (years)	0.43		2.84		1.79	
Median lag (years)	0.58		2.30		1.56	

Statistical significance is 'yes' if $p < 0.05$, otherwise 'no'

Table 6
Short-Run and Long-Run Elasticity of Private R&D vis-à-vis TFP (based on Table 3).

	Hong Kong	Statistical significance	Shenzhen	Statistical significance	Singapore	Statistical significance
Short-run TFP elasticity	0.154	Yes	0.072	No	0.035	Yes
Long-run TFP elasticity	0.206	No	0.126	No	0.093	Yes
Mean lag (years)	0.34		0.75		1.66	
Median lag (years)	0.50		0.82		1.47	

Statistical significance is 'yes' if $p < 0.05$, otherwise 'no'

Table 7
Test 1—Whether Public R&D Boosts Private R&D.

	Hong Kong	Shenzhen	Singapore
Log_spriv_lag1	1.86733***	2.24743***	1.43446***
	(0.10724)	(0.28150)	(0.13384)
Log_spriv_lag2	-1.10640***	-0.99587*	-0.47939**
	(0.12515)	(0.31560)	(0.13477)
Log_spub_lag1	3.05855*	-0.25335	0.32795+
	(1.09826)	(0.22504)	(0.17974)
Log_spub_lag2	-2.49240*	-0.01005	-0.29027
	(1.00944)	(0.33292)	(0.19246)
Constant	-3.60350**	-0.17220	0.09110
	(0.94662)	(0.33292)	(0.08548)
N	18	15	35
Multiple R-squared	0.9990	0.9992	0.9998
Adjusted R-squared	0.9987	0.9989	0.9998
F-statistic	3248.9	3203.8	41198.4
Prob > F	0.00	0.00	0.00

+ $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 8
Test 2—Whether Private R&D Boosts Public R&D.

	Hong Kong	Shenzhen	Singapore
Log_spub_lag1	1.098797**	0.74859*	1.59271***
	(0.306462)	(0.32466)	(0.10980)
Log_spub_lag2	-0.182918	0.35761	-0.75773**
	(0.281678)	(0.40409)	(0.11757)
Log_spriv_lag1	-0.020171	0.06107	-0.08022
	(0.029924)	(0.40612)	(0.08176)
Log_spriv_lag2	0.044563	-0.17214	0.21163*
	(0.034922)	(0.45531)	(0.08233)
Constant	0.663485*	0.27724	0.32417***
	(0.264149)	(0.48030)	(0.05221)
N	18	15	35
Multiple R-squared	0.9997	0.9986	0.9999
Adjusted R-squared	0.9996	0.9980	0.9999
F-statistic	10232.7	1785.3	87288.3
Prob > F	0.00	0.00	0.00

+ $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

vate R&D. All coefficients demonstrated statistical significance at p-values < 0.05.

Our third research question relates to the spillover impacts of public R&D and private R&D. We wanted to examine not only whether public R&D boosts private R&D but also whether there is any reverse causality. Our proposition is that the private sector may not be incentivized to lead exploratory research activities, especially in the presence of high risks and uncertainties. Thus, the public sector would be expected to 'lead the way' by pioneering such research. We followed Ho and Wong (2017), adopting a lag order of 2 as the basis of our analysis. The results are shown in Tables 7 and 8.

Based on our analysis we found that, in Hong Kong, public R&D boosts private R&D but only at the lag order of 1 (coefficient = 3.059; p-value < 0.05). No reverse causality was identified. With regard to Shenzhen, however, neither public R&D nor private R&D boost each other. Finally, in the case of Singapore, public R&D generates spillovers to private R&D, but only at a lag order of 1 (coefficient = 0.328; p-value < 0.1). Interestingly, we found evidence of reverse causality, with private R&D resulting in an increase in public R&D at a lag order of 2 (coefficient = 0.212; p-value < 0.05).

In summary, our third hypothesis, that public R&D boosts private R&D with no reverse causality, is also partly rejected. We see public R&D generating positive spillovers to private R&D in Hong Kong and Singapore, but not in Shenzhen, and reverse causality is identified only in the Singapore case.

To recap, we addressed three research questions in our study. First, regarding the question whether the relationship between R&D and TFP remains positive and long-run, we showed that this result holds true partially for Hong Kong (as shown by its TFP–private R&D correlation). In the case of Shenzhen, we found no evidence of any positive, significant relationship between R&D and TFP in the long run. Our results for Singapore demonstrated statistical significance when regressing TFP on all R&D variables (total, public, and private).

Regarding the second research question, our results showed that the hypothesis that private R&D boosts TFP growth more significantly than public R&D does is partially rejected. While Hong Kong generated higher coefficients of short-run and long-run elasticities from public R&D, none demonstrated statistical significance. Instead, only private R&D—despite yielding lower coefficients than public R&D—has a statistically significant coefficient. We found no statistically significant results in the case of Shenzhen, but private R&D appears to perform better than public R&D in improving productivity growth. The coefficient of private R&D is higher than that of public R&D. For Singapore, public R&D is more effective than private R&D in boosting TFP.

Finally, regarding our third research question, our findings confirm that public R&D has spillover effects on private R&D in the cases of Hong Kong and Singapore. Regarding Shenzhen, we could not identify any spillover impact from either public R&D or private R&D. Contrary to our prior expectation that private R&D has no reverse spillover impact on public R&D, we found evidence of significant impact of private R&D on public R&D in Singapore.

5. Discussion

It remains to elaborate on our findings on a case-by-case basis. First, with regard to Hong Kong, the main implication of these findings is that public R&D efforts undertaken by the government have not yielded any significant, long-term boost in productivity growth. A report compiled by a University Grants Committee (UGC)–organized task force team (University Grants Committee, 2017) has 'lamented' the low degree of effectiveness of government R&D schemes, given that the projects tend to involve very short implementation periods (on average around 2–3 years). This could possibly explain the non-significance of the relationship between public R&D capital stock and TFP growth as well as the short-term impact of public R&D on boosting private R&D.

Another possible explanatory factor is that, insofar as most public R&D in Hong Kong takes the form of research activities in institutions of higher education, the results may not be best captured in terms of productivity but rather in terms of knowledge stocks or simply in scientific publications. There appears to be some degree of recognition amongst Hong Kong policymakers regarding this issue; as it seeks to expand its overall R&D spending it is channeling some of this funding towards encouraging universities to carry out more mid-stream, applied research activities.

Even though the overall commitment to R&D so far has been relatively low in Hong Kong (amounting to only 0.80% of GDP in 2017), the private sector is a major R&D performer within this pool, carrying out as much as 44% of the total R&D in 2017, and financing about 50% of it in the same year (Census and Statistics Department, 2019). Two important points to note, however, are first, that large firms in particular—constituting a mere 6% of the total number of establishments in Hong Kong—accounted for more than half (52%) of total in-house R&D expenditures as compared with 29% for medium-sized firms and 19% for small firms (Census and Statistics Department, 2018). Second, the positive relationship between private sector R&D and productivity is only significant in the short term suggesting that the effectiveness of private R&D (for producitivity) is short-lived.

Coupled with the short-term linkages between public R&D and private R&D, this implies that there is a disconnect between current research efforts and the resulting productivity outcomes. This indicates that the government needs to do more to improve linkages between the two sectors, especially in terms of university–industry linkages (Coccia, 2010). The government might also consider extending the lifecycle of its funded R&D projects, mainly to give researchers more time to conduct their activities.

Second, the Shenzhen case has shown us that maximizing R&D investment alone (as a percentage of GDP) is inadequate—there has to be a corresponding recognition of the nature and substance of the underlying R&D. While we expected the large amounts of R&D being carried out in the private sector in Shenzhen to contribute towards enhancing its productivity, our results indicate otherwise. The reason for this, we suspect, is that R&D expenditure in Shenzhen is characterized by large amounts of 'experimental development' (see Fig. 6, below).[10]

A well-established line of research on long-term productivity growthemphasizes the centrality of basic research vis-à-vis other types of R&D (Griliches, 1986; Lichtenberg and Siegel, 1991). This line of scholarship maintains that "the premium on basic research may reflect the tendency of applied and experimental development to be more effective when carried out in conjunction with some basic research activities" (Czarnitzki and Thorwarth, 2012: 1561). In their disaggregated analysis of low-technology and high-technology firms, Czarnitzki and Thorwarth (2012) find that the impact of basic research on productivity growth in high-technology firms is three times as large as the effects attributed to applied research and experimental development.

In a similar vein, Cohen and Levinthal (1990) argue in their influential paper that firms often invest in R&D not only to directly pursue new process and product innovations but also to enhance their learning capabilities as they seek to absorb external knowledge. It follows that we can expect R&D to impact TFP *indirectly* through its influence on a firm's absorptive capacity. This can justify carrying out R&D classified as 'experimental development' within a firm's boundaries. In other words, experimental research will have a meaningful impact on overall productivity only if it is embedded in basic and applied research—which enhances a firm's absorptive capacity.

As shown in Fig. 6, as recently as 2010 almost all of the R&D activities in Shenzhen were categorized as 'experimental development'—which implies that Shenzhen focused most of its R&D activity on making products that are 'improved versions from existing ones.' Basic and applied research were almost non-existent in Shenzhen until the early 2010s, after which the shares of both types began to increase gradually. The increase in basic and applied research since the early 2010s has been a welcome step taken by the Shenzhen government towards enhancing the city's R&D ecosystem, but one area to which the government may want to pay particular attention is identifying mechanisms through which firms' focus on experimental development can be more effectively, and more quickly, translated into improvements in productivity. Indeed, firms in Shenzhen would be well advised to look towards increasing collaboration with not only local institutions but also their counterparts—especially universities—in neighboring Hong Kong, given Hong Kong's relatively stronger position for conducting basic and applied research. In light of the Chinese Government's recent (February 2019) announcement of the 'Greater Bay Area (GBA) initiative' (encouraging greater innovation-related exchange between cities in Southern China), this form of collaboration between the two cities would be not only especially timely (i.e. supported strongly by both local governments) but also a fruitful research direction to pursue.

[10] In our analysis, the impact of private R&D on total TFP in Hong Kong is more significant than that reported in Shenzhen. Hong Kong also reports stronger commitments to basic and applied research than Shenzhen does. In the business sector in 2016, 70% of in-house R&D was devoted to experimental development, 26% was devoted to applied research, and 4% was devoted to basic research (Census and Statistics Department, 2017).

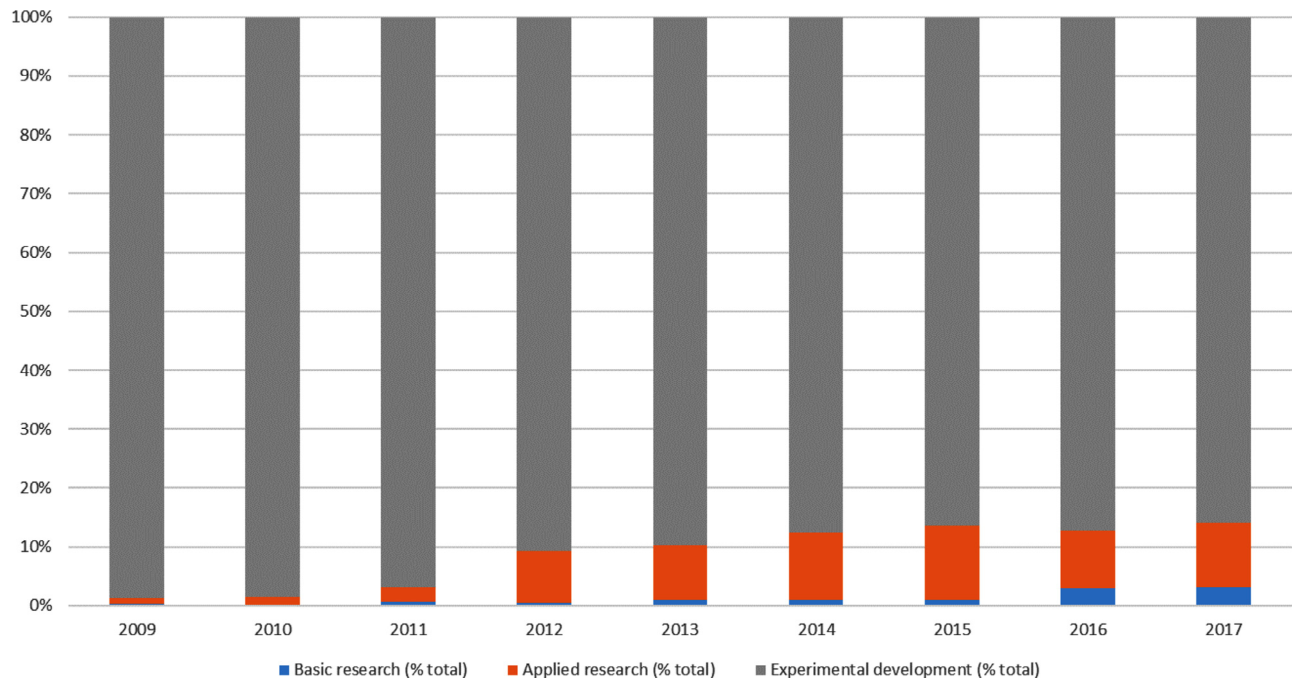

Fig. 6. Breakdown of R&D Expenditure by Type of Activity, Shenzhen, 2009–2017Source: Shenzhen Statistical Yearbook, 2018 Edition.

In comparison with Hong Kong and Shenzhen, Singapore has performed fairly well, as both public R&D and private R&D have contributed positively to boosting productivity growth in the city-state.

Despite this relative success, the long-run elasticity of private R&D to TFP in Singapore still remains below the OECD average range of 0.13 to 0.17 (Guellec and van Pottelsberghe de la Potterie, 2001). Two reasons might explain Singapore's better—but not exceptionally strong—performance in comparison with that of OECD countries. First, in Singapore, R&D runs mostly downstream, and R&D activities there diverge in nature from those conducted in OECD countries (Ho and Wong, 2017). Second, Singapore's industrial landscape has been dominated by multinational corporations (MNCs) for a long time, and local firms have not been able to absorb research to produce products that can be commercialized despite the rapid technological catching-up it has achieved.

These findings suggest that Singapore's government needs to focus on developing absorptive capacities in domestic firms so that they are able to commercialize new inventions. Linkages between these firms and larger enterprises and universities needs to be strengthened to properly exploit basic research. Singapore is known for its heavy military and public-sector R&D and efforts to transfer technology from these sectors to local firms in Singapore should be accelerated. This is important in Singapore's case, as it has a relatively small domestic market and an open economy. Its local industries can target overseas markets only if enterprises are competitive and use cutting-edge research and technologies to develop their products and services.

6. Conclusion

Our study's policy implications begin with our finding that the impact of R&D—particularly public R&D—on productivity growth is not always universally positive, even within such vibrant and dynamic economies as Hong Kong, Shenzhen, and Singapore.

On the one hand, our findings are closely aligned with economists' past observation that private R&D, or stimulation of private R&D by government support (i.e. public R&D subsidies), raises productivity in the long run (Coccia, 2010; Coccia, 2012; Cin et al., 2017). On the other, our analysis also provides some striking insights into the nature of the R&D–TFP link. The impact of private R&D on TFP growth as well as stimulation of private R&D by public R&D funding happen to be short-lived in Hong Kong, and this could be attributed to the ad hoc nature of government support for innovation development in the city (Sharif, 2006; Fuller, 2010; Zhang, 2020). Nonetheless, a strongly interventionist-state approach is hardly a guarantee of better linkages in this respect (Coccia, 2010; Coccia, 2012; Bye et al., 2019), particularly when we observe contrasting results in Shenzhen and Singapore. The former has invested more than 4% of its GDP annually on R&D activities, but the evidence on productivity growth and added private R&D activity is largely inconclusive. Singapore demonstrates results that resemble findings reported by Coccia (2017) that a country's TFP growth is best predicted when its R&D-to-GDP ratio ranges between 2.3% and 2.6% (as is the case for Singapore).

More broadly, our findings suggest that policymakers should strike a careful balance between laissez-faire and state-led attitudes. Private-sector participation in innovative activities can be induced through funding schemes, grants, or joint collaborations with public research organizations, especially in developing regions where public R&D intensity is more likely to be higher than in private R&D (Coccia, 2010). The role of the state needs to be invoked to influence the direction of change of innovation-led growth, the evaluation of mission orientation based on the specific needs of the nation, and fostering system-wide linkages to strengthen the innovation system (Mazzuccato, 2016). Furthermore, our analysis suggests that—provided that the optimal R&D-to-GDP ratio is accompanied by incentives for enterprises—private R&D is strongly likely to induce positive changes in productivity growth (Coccia, 2012), which in turn enables widespread structural transformation at the national level (De Vries et al., 2012; Foster-McGregor and Verspagen, 2016; Timmer and Szirmai, 2000).

It behooves us to acknowledge that this study is subject to several limitations. This paper considers productivity growth only at an aggregate, whole-of-economy level, but it has not delved deeper into more micro-level aspects of analysis, e.g. firm-level performance (Berube and Mohnen, 2009). In particular, we have not fully considered whether—and how—targeted public R&D subsidies subsequently enhance supported firms' innovation performance (Berube and Mohnen, 2009; Cin et al., 2017; Czarnitzki and Hussinger, 2017; Bye et al., 2019). Furthermore, other economic studies have demonstrated that whether public R&D subsidies positively boost private-sector investments in R&D depends on the types of firms being supported (Bronzini and Iachini, 2014). This analysis has also not accounted for differences in industry-level performance, especially given the fact that manufacturing has been a major explanatory factor behind rapid productivity growth in Asian economies (Timmer and Szirmai, 2000).

We acknowledge that, apart from R&D conducted locally in firms, higher education institutions, or public research institutes, knowledge and technology may influence TFP through various other channels. There may be spillovers from foreign sources through collaborative linkages between business partners, networks along the supply chain, or engagement with foreign scientists and engineers. A few studies (cf. Coe and Helpman, 1995; Guellec and van Pottelsberghe de la Potterie, 2001) have estimated the effects of foreign R&D on productivity by analyzing foreign R&D capital stock using proxy computational measures based on foreign trade structures. At present, our paper is unable to consider these factors given data limitations. For our part, however, we have worked towards building a parsimonious model, limiting the focus of our study to the impact of locally conducted R&D in all three cases, primarily since neither Hong Kong (a special administrative region) nor Shenzhen (a city) is an independent country and no separate statistics on import/export activities are available for Shenzhen prior to 2014.

Finally, it is helpful to remind ourselves that Hong Kong's economy is predominantly service-oriented, with sectors such as finance and banking, logistics, real estate, and professional services accounting for over 90% of its GDP in 2017 (Hong Kong Annual Digest of Statistics, 2019). Singapore is increasingly becoming service-based as well (accounting for around 70% of its GDP as of 2016; Singapore Department of Statistics), while Shenzhen continues to be dominated by traditional manufacturing, accounting for over 30% of its GDP as of 2017 (Shenzhen Statistical Yearbook, 2018). What do these differences imply for our study of the impact of R&D on TFP? Both manufacturing and service sectors employ labor, capital, and technology and the R&D impacts on TFP then depend on the type or nature of R&D being conducted to be classified as productivity- or efficiency-enhancing activity. While it would be interesting to explore the impact of these varying patterns of economic structures on TFP systematically, the absence of disaggregated data on R&D spending separated by manufacturing and services limits the generalizability of such analyses, which suggests future research directions.

Declaration of Competing Interest

There is no actual or potential conflict of interest including any financial, personal or other relationships with other people or organizations within three years of beginning the submitted work that could inappropriately influence, or be perceived to influence, our work.

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Appendix

Econometric Test 1: Stationarity Test

To avoid spurious outcomes when regressing TFP on R&D, we must first determine whether the variables themselves—or the first-order differencing (rate of change) for the values within these variables—are stationary across the time series. In this case, we run the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) to measure the stationarity (or its absence) of these variables. The ADF test is also known as a unit root test. The results of the ADF test for the three locations are reported in Table A1.

The null hypothesis for this test is the non-stationarity of the variable, indicated by the presence of a unit root. The alternative hypothesis (when t-statistics exceed the values at the 5% level of significance), on the other hand, implies the rejection of the non-stationarity of the variable; in other words, the variable (or its first-order differencing) is stationary.

In Table A1 we report surprising results regarding the stationarity of the variables in these three localities. Only with regard to Singapore did the tests demonstrate the existence of stationarity in terms of the first-order differences for the TFP and R&D variables. In Hong Kong's case, only the private R&D variable demonstrates stationarity, in both values and the first-order difference. The remaining variables, on the other hand, display no stationarity. Lastly, for Shenzhen, stationarity can be detected only in the first-order difference for the TFP variable.

Given the above-reported results for Hong Kong and Shenzhen, and the non-stationary nature of these variables (TFP, total R&D, and private R&D for Hong Kong as well as all R&D-related variables for Shenzhen), it is possible that other effects not captured in this paper (such as workforce skill levels, foreign investments, etc.) may affect the rate of change in these variables.

Econometric Test 2: Johansen Cointegration Test

We also conducted a test by examining the relationship between TFP and each of the R&D variables: total R&D capital stock (Log_S), total public R&D capital stock (Log_Spub), and total private R&D capital stock (Log_Spriv). Following Voutsinas and Tsamadias (2014), we limited our lag selection to one lag, in accordance with Schwarz (1978) and Akaike (1987). To determine the long-run relationships between TFP and each of the R&D variables, we sought to analyze whether the resulting trace-test results surpass the 5% threshold; any trace test that exceeds the threshold implies the rejection of the null hypothesis of no long-run relationship. In Tables A2—A4, below, we display the results of the Johansen cointegration test.

Table A1
Results of ADF Tests for TFP and R&D Variables in Hong Kong, Shenzhen and Singapore.

	Hong Kong	Shenzhen	Singapore
TFP	-0.9761	-1.6722	-2.2981
▲TFP	-3.0387	-5.4635*	-4.4809*
Log_S	-3.8844*	1.6115	-0.9680
▲ Log_S	-2.7937	-0.2130	-5.0487**
Log_Spub	-0.4721	-1.8540	-0.2429
▲ Log_Spub	-2.8015	-2.9283	-4.4945**
Log_Spriv	-4.8389**	1.6916	-2.5538
▲ Log_Spriv	-4.1491*	0.0024	-4.6703**

* indicates rejection of the null hypothesis at the 5% level of significance;
** indicates rejection of the null hypothesis at the 1% level of significance

Table A2
Results of Johansen Cointegration Test (Hong Kong).

Variables	Number of cointegrating equations	Trace test	5% critical value	1% critical value
TFP and Log_S	0	50.54**	17.95	23.52
	1	13.49*	8.18	11.65
TFP and Log_Spub	0	8.23	17.95	23.52
	1	2.93	8.18	11.65
TFP and Log_Spriv	0	60.44**	17.95	23.52
	1	14.74**	8.18	11.65

* indicates rejection of the null hypothesis at the 5% level of significance;
** indicates rejection of the null hypothesis at the 1% level of significance

Table A3
Results of Johansen Cointegration Test (Shenzhen).

Variables	Number of cointegrating equations	Trace test	5% critical value	1% critical value
TFP and Log_S	0	18.96*	17.95	23.52
	1	4.06	8.18	11.65
TFP and Log_Spub	0	16.42	17.95	23.52
	1	0.21	8.18	11.65
TFP and Log_Spriv	0	17.12	17.95	23.52
	1	2.30	8.18	11.65

* indicates rejection of the null hypothesis at the 5% level of significance;
** indicates rejection of the null hypothesis at the 1% level of significance

Table A4
Results of Johansen Cointegration Test (Singapore).

Variables	Number of cointegrating equations	Trace test	5% critical value	1% critical value
TFP and Log_S	0	28.83**	17.95	23.52
	1	7.00	8.18	11.65
TFP and Log_Spub	0	38.36**	17.95	23.52
	1	10.17*	8.18	11.65
TFP and Log_Spriv	0	22.31*	17.95	23.52
	1	6.49	8.18	11.65

* indicates rejection of the null hypothesis at the 5% level of significance;
** indicates rejection of the null hypothesis at the 1% level of significance

Some observations can be inferred from the cointegration test results reported in Tables A2—A4. In the Singapore case, a long-run equilibrium can be confirmed in the relationship between TFP and both components of R&D (public and private R&D). The pattern appears to be statistically more significant in the relationship between TFP and private R&D. Regarding Hong Kong, we find long-run relationships only between TFP and Log_S and between TFP and Log_Spriv. The relationship between TFP and Log_Spub appears, in this regard, to be only a short-run relationship. The result for Shenzhen appears to be anomalous, quite likely because of the non-stationary nature of all R&D-related variables in the Shenzhen case. A long-run relationship is established between TFP and Log_S, but not when disaggregated into both Log_Spub and Log_Spriv.

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