Resource Misallocation, R&D Spillover and Productivity: A Study of Chinese and UK Manufacturing Firms

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December 2022

A Thesis Submitted in Fulfilment of the Requirements for the Degree of Doctor of Philosophy of Cardiff University

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Abstract

This thesis investigates the resource misallocation in the presence of the externality of R&D spillover in the Chinese and the UK manufacturing sector. It takes capital, labour, as well as the R&D input as production factors and measure the output loss caused by the resource misallocation. This thesis extends the resource misallocation model proposed by Hsieh and Klenow (2009) by considering the externality of R&D input. We find that the output loss computed from the approach suggested by the literature is overestimated when they do not consider any externality. The externality of R&D spillover can alleviate resource misallocation. We then propose an improved allocation that is a weighted sum of the solution maximizing the industry output and the solution maximizing the industry R&D spillover. This allocation generates a larger output, implying that the allocative efficiency is increased. We also decompose the industry productivity and output in an approximation to gauge the individual contribution of each input misallocation to the output loss. The results show that the largest contribution in Chinese manufacturing sector is from labour misallocation, while capital misallocation explains most of the output loss in the UK manufacturing sector. In the end, we estimate the effect of firm's own R&D effort and intra-industry and inter-industry R&D spillover for Chinese listed firms. The firm's own R&D effort has positive effect on the productivity in the manufacturing sector. The intra-industry R&D spillover is negative in the manufacturing sector suggesting innovative rivalry between firms. The positive inter-industry R&D spillover in the non-manufacturing sector implies that non-manufacturing firms are more likely to communicate and cooperate rather than compete in R&D activities.

Acknowledgement

It is a precious five-year's experience for me to complete my PhD programme at Cardiff University. This work would not have been done without many people's support.

I would like to express my gratitude to my first supervisor, Professor Kul Luintel for his great guidance at the beginning of my PhD. He guided me patiently through my empirical research and provided concise comments in writing my thesis.

I would like to express my appreciation to my secondary supervisor, Dr Helmuts Azacis, for his kind, patience, and encourage in my studies. He has provided me with great academic advice and technical skills in my research, helping me to solve many problems with my research ideas and detailed calculations. He also provided me with valuable advice on my writing. Thanks to his guidance, my PhD has been able to proceed smoothly.

Special thanks to my parents for their constant support and encouragement. Their trusting and warm companionship helped me to dispel the anxiety of a difficult study and always calmed me down.

Thanks also to my colleagues and friends who have always kept me cheered up and warm throughout my studies.

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Chapter 1 Introduction

Since the financial crisis of 2008, economic growth has continued to slow in most countries. Many believe that the primary source of the slowdown in economic growth is the slowdown in productivity growth. Exploring the reasons for the slowdown in productivity growth has become an essential topic in economic research today. As an important part of the world economy, China's economic performance is affected by the world economic environment and influences other countries and economies. China's economic growth has also slowed down significantly in recent years compared to the period before the financial crisis. Therefore, exploring what has caused this poor economic performance and what can be done to improve the situation is necessary for economic development.

Many studies have attributed the slowdown in economic growth to productivity growth. China's previous economic growth relied heavily on low-end manufacturing and massive input investment in production, which allowed the economy to reach a high growth rate but could not sustain the economy in the long run (Eichengreen et al. 2011). Therefore, in order to promote sustainable economic development, many studies have explored the determinants of total factor productivity (TFP) in the hope of increasing productivity.

There are two mainstreams of literature that discusses what causes the slowdown in the productivity. The first direction emphasises the role of R&D in boosting productivity (Griliches, 1979; Cuneo and Mairesse, 1984; Griliches and Mairesse, 1985; Wakelin, 2001). However, China's economic growth in the past heavily relied on low-end manufacturing, where economic growth comes from increased inputs. As the economy developed, the marginal revenue products of input factors gradually decreased ((Shi et al., 2017)), which caused a slowdown in economic growth. R&D activities, instead, can increase output by increasing productivity rather than by increasing the number of inputs. In recent years, it has become a pivotal point in exploring R&D's role in increasing productivity and promoting long-term economic development. Literature provides abundant empirical evidence suggesting that R&D activities have a positive role in boosting productivity growth in many countries and economies, such as France, Japan, the US, UK and Germany and other OECD countries (Griliches and Mairesse, 1985; Wakelin, 2001; O'Mahony and Vecchi, 2009; Ortega-Argilés, 2011; Kancs, et al., 2016). Yang et al. (2020) point out that the R&D input has been continuously increasing from 2000 to 2015 in China. Moreover, there are studies suggesting that a firm's productivity is not only influenced by the R&D input itself, but also by the R&D spillover from other firms (Romer, 1990; Grossman and Helpman, 1991; Sena, 2004; Ugur, et al., 2016).

In order to promote R&D activities by firms, the government both in developed and emerging countries have implemented various policies. In general, policies consist of subsidies and R&D tax incentives. The latter is more market-oriented and can reduce asymmetric information associated with R&D (Arrow, 1962; Peneder, 2008; Xiao and Zhuang, 2022). R&D tax incentives often include R&D tax credit, tax deduction of R&D expenses, etc. Since the innovation achievements created by R&D activities can generate higher productivity and therefore strengthen a country's competitiveness, most OECD countries encourage firms' R&D by R&D tax incentives (Appelt et al., 2016). Literature suggests that R&D tax incentives have a positive and significant effect on firms' R&D in developed countries, for instance, the US (Wu, 2005), France (Bozio et al., 2015), Canada (Baghana and Mohnen, 2009), the Netherlands (Lokshin and Mohnen 2012) and the UK (Sterlacchini and Venturini, 2019).

The Chinese tax policies adopt two kinds of incentives for enterprises' R&D activity: the super deduction for R&D expenditure and a concessional tax rate of 15% for High and New Technology Enterprises (HNTEs) (Jia and Ma, 2017). The R&D tax incentives in China have developed over time. In 1996, only state-owned firms (SOE) and collective industrial firms (COE) could deduct an additional 50% of the R&D

expenditure from taxable income. In 2003, the tax reform eliminated discrimination between SOEs and private firms, and R&D tax policies are now applied to all types of firms (Liu et al., 2023). Moreover, the types of R&D expense that can be deducted, have expanded and the deduction rate has also increased from 50% in 1999 to 100% for manufacturing firms and 75% for non-manufacturing firms in 2021 (Xiao and Zhuang, 2022). At the same time, the Chinese tax authority is increasingly simplifying the process for enterprises to claim R&D tax benefits (Tian et al., 2020). With the help of these R&D tax incentives, China’s R&D to GDP ratio has increased from 0.56% in 2001 to 2.13% in 2017. And the R&D investment has reached a level close to that of the US in 2016 (Liu et al., 2023).

The UK government also encourages R&D activities with tax incentives. While the R&D intensity (business R&D as a percentage of GDP) in other G7 countries has been increasing during the 1980s and 1990s, the UK shows a downward trend in the R&D intensity (Bond and Guceri, 2012). Less R&D investment leads to less new technology and invention, which further slows down productivity growth. To address this, the UK government promulgated the R&D tax credit to promote enterprises’ R&D investment in 2000. In fact, the UK government had already introduced tax deduction for R&D expenditure in the 1980s. The tax relief of 2000 was initially for the SMEs, which is subsequently extended to all firms. Under this scheme, the R&D expenditure can be deducted from the firm’s taxable income, which reduces the firm’s tax burden. SMEs can enjoy an extra 50% deduction of their R&D expenditure. And, loss-making SMEs can also apply for refundable tax credits to deduct against future profits or profits in the last accounting year (Firoz, 2021). Compared to SMEs, large firms can deduct their R&D expenditure with a lower rate of 25%, but they cannot apply for any tax credits if they are loss-making.

Evidence shows that the R&D tax policy did promote real innovation (Bond and Guceri, 2012). Sterlacchini and Venturini (2019) provide empirical evidence that the R&D

intensity in the UK significantly increased due to the R&D tax incentives of 2007 to 2009. But this effect only exists in SMEs while large companies are not influenced by these incentives.

However, although the government did a lot on incentives to promote R&D of firms, there is still a problem of misallocation of R&D resources. In addition to R&D activities, another possible way to increase productivity is to eliminate resource misallocation. Several types of input misallocation (capital, labour, R&D, energy) have been analysed in the literature (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Jones, 2011; Song et al., 2015). Resource misallocation theory considers resource allocation inefficient when the input distortion, measured by the marginal revenue product of each input factor, differs across firms. This indicates that firms with higher productivity have to pay extra "tax" to buy input. In contrast, the input price for less productive firms is lower than the efficient level, leading to a loss in productivity and output. The literature suggests that when the input price for more productive firms decreases to allow them to purchase more inputs, the marginal revenue product of the input will decrease until it is equalised for all firms.

In the thesis, we combine the two aspects of productivity improvement mentioned above. It is known that R&D input and the R&D spillover effect are essential sources of productivity improvement. Therefore, it is necessary to ensure that its allocation across firms is efficient. However, there is little literature on resource misallocation that has considered both the R&D input allocation efficiency and the effect of R&D spillover. In order to fill this gap, we consider both R&D allocation and the externality of R&D spillover in the resource misallocation model to identify the efficient resource misallocation.

The second chapter evaluates the output loss caused by resource misallocation in the Chinese manufacturing sector. We adopt a resource misallocation model proposed by

Hsieh and Klenow (2009) to build the relationship between the firm's productivity and the input price wedges. This model is widely accepted in the literature. Our study measures the output loss caused by the misallocation of capital, labour, and R&D input. Since the externality of R&D spillover is a distinctive characteristic of R&D input, we also include an R&D spillover term in the model to gauge its impact on the output. This is the main difference between our study and the literature: we consider the externality in the allocation and the literature does not. We firstly derive the allocation solution to the maximisation problem of the industry output in the case with the assumption that there does not exist any type of externality and in the case with the assumption of the externality of R&D spillover. The solution from the case with no externality suggests that the optimum is achieved when all firms face the same actual input price. However, when R&D spillover takes a role in the output, the optimal allocation would not require equalised input distortions for all input types. Instead, the efficient allocation should leave a certain level of dispersion in R&D distortion. Therefore, while the actual capital and labour prices should remain equalised for firms within an industry, the actual R&D price should be proportional to its productivity. We then compute the output gain from the above allocation approaches. Comparing the results implies that the output gain is larger from the reallocation of inputs when the R&D spillover effect is taken into account. This improves the allocation approach suggested in the literature and increases allocative efficiency. In addition, we also notice that the output loss from input misallocation could be overestimated when the R&D spillover effect is ignored. In order to gauge the output loss caused by each type of input misallocation, we compute the output gain from eliminating one type of input misallocation at a time. The results show that labour misallocation is the most significant cause of output loss in the Chinese manufacturing sector.

Chapter 3 applies the same allocation approach to measure resource misallocation in the UK manufacturing sector. The empirical results also support the conclusion derived in chapter 2: The optimal solution to the industry output maximisation problem comes from the allocation that considers the effect of R&D spillover and sustains a certain level of dispersion in R&D distortion. In this chapter, we extend the study by deriving an output decomposition to measure the individual contribution to the output loss caused by each type of misallocation. Using the UK firm-level data in the manufacturing sector, we find that capital misallocation contributes the largest to generating output loss, which is different from the Chinese case in the previous chapter. The contribution of labour misallocation is much smaller. Although the R&D misallocation contributes the least to the output loss, there is still a point worth discussing: In our model, the output is influenced by both the industry productivity and the R&D spillover. There is a trade-off between maximising the industry productivity and maximising the industry R&D spillover. Since the literature does not consider any externality, the solution in the literature only maximises industry productivity. Therefore, their solution is not an optimal one in our model. We use an approximation in decomposing the output. The approximate industry output is expressed in terms of variances and covariances of the input distortions. The optimal solution to the maximisation problem of the approximate industry output requires the capital distortion and labour distortion to be equalised across firms in the industry, in other words, zero dispersion in capital and labour distortions. However, the variance and covariance terms of R&D distortion are not zero in the optimal solution. This requires that the R&D allocation is efficient when more productive firms pay a higher actual R&D price, while the actual price for less productive firms is lower.

The previous two chapters mainly discuss how resource misallocation and R&D spillover affect productivity and output at the industry level. In chapter 4, we discuss how the industry-level R&D spillover and the firm's own R&D effort would affect the firm's productivity and output. The fourth chapter follows the basic framework proposed by Griliches (1979). It mainly discusses the empirical results of the effect of a firm's own R&D input, the R&D spillover within the industry, and the R&D spillover from other industries on productivity. From the empirical results, a firm's R&D

investment significantly increases its productivity in the manufacturing sector, while the effect of R&D in the non-manufacturing sector is not significant. Regarding the R&D spillover, the manufacturing sector has a negative correlation between the R&D spillover and productivity, indicating intense competition and technology rivalry among firms. The non-manufacturing sector, on the contrary, has positive R&D spillover, but only from other industries. The type of ownership also matters for R&D and spillover effect: The R&D effect on productivity is the most significant in jointly owned firms. Foreign-owned and jointly-owned firms have larger R&D spillover effects than other types of firms. State-owned firms can better receive inter-industry R&D spillover. These empirical observations provide policy implications: As manufacturing firms are good at transferring R&D investment to increase productivity, the government should encourage them to conduct R&D activities. The possible policy includes easing financial constraints for R&D activities and subsidising firms' R&D activities. However, as there is a negative correlation between government subsidies and productivity in our study, regulating the use of funds for R&D projects and evaluating the R&D results are required to increase R&D efficiency and avoid resource misallocation. The communication and cooperation between domestic and foreign firms can increase the R&D spillover, further promoting productivity.

Chapter 5 contains the conclusion and relevant policy suggestions.

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Chapter 2 The resource misallocation in Chinese manufacturing industries in the presence of R&D externality

2.1 Introduction

Over the past few decades, China's economic development has been characterized by the low-end manufacturing and processing industries and the massive consumption of energy resources. However, this development model has led to a steady slowdown in economic growth, as well as to problems such as waste of resources and environmental pollution. In order to achieve the sustainable development in the long term, China is now exploring new ways of economic development, which include industrial upgrading and increased investment in research and development. The question of how to improve productivity, rather than expanding production, has become a key topic of economic development.

A widely accepted view of productivity improvement is to eliminate the misallocation of resources in production. Several important misallocated input resources include capital, labour and energy. Hsieh and Klenow (2009) and subsequent related literature (e.g., Dias et al., 2016) have found that the misallocation of capital and labour is an important cause of productivity and output losses. While encouraging R&D activities is an important way to increase productivity (Griliches, 1979; Cuneo and Mairesse, 1984; Griliches and Mairesse, 1991; Wakelin, 2001), blindly increasing R&D investment or misallocating R&D resources across firms can also hinder productivity gains. Yang et al. (2020) note that the R&D input has been continuously increasing at an average rate of around 19% from 2000 to 2015. But the R&D resource is misallocated between firms, which causes inefficiency in innovation (Song et al., 2015; Boeing, 2016). Therefore, we also take R&D resources as one of the several misallocated input factors. At the same time, when thinking about how to allocate R&D resources more efficiently, we also need to consider the externalities of R&D activities

(Arrow, 1962; Nelson, 1959), as they affect the aggregate productivity in a sector and the firm's own R&D activities.

We adopt Hsieh and Klenow (2009) model to build a linkage between resource misallocation and output but extend their basic model by using R&D human capital as a third input factor as well as the externality of R&D in the production function. We quantify the aggregate output loss caused by all the three input factors. According to the explanation by Hsieh and Klenow (2009), when all firms have the same level of input distortions, the resource allocation is efficient. Following Hsieh and Klenow (2009), we introduce the concept of "tax" or "wedge" to express the input factor allocation distortion. It is measured by marginal revenue product of each input factor. The literature suggests that resources are misallocated when firms pay different amount of "tax" to hire input factors in their production. Generally, it is related to policy distortion in China (Brandt. et al. 2013), where the policy favours state-owned firms so they pay less tax than private firms. Similar interpretation also applies to firms in different regions. When the distortions are equalized across firms, a higher output means that the allocative efficiency has been increased. The gap between the output after reallocation and the initial output is the allocative efficiency gain from eliminating the resource misallocation.

One distinctive characteristic of knowledge capital is its externality (Arrow, 1962; Nelson, 1959). When a firm successfully creates a new technology or invention, it cannot keep all the benefits from this invention to itself. Other firms can also benefit from the innovation achievement (Schumpeter, 1942). Therefore, we expect the R&D spillover externality to play a role across the firms that conduct R&D activities, which later has an impact on their productivity and, consequently, on their output.

This study contributes to existing literature in the following two aspects. Firstly, we measure the impact of externality of R&D on the resource allocative efficiency in the resource misallocation model. Literature (Dias, et al. 2014; Benkovskis, 2015; Chen, 2017; Choi, 2020) shows that the allocation efficiency can be increased when equalizing all input distortions across firms in the same industry. However, there is no externality in their models and this might bias in the results of resource reallocation. Although Ayerst (2021) consider the externality of R&D activities, he applies this in a different dynamic model which is initially brought up by Klette and Kortum (2004). There are few studies quantifying the R&D externality in Hsieh and Klenow (2009) resource misallocation model. We fill the gap by including the R&D spillover factor in the production function and it is defined as the geometric average of all firms' R&D input. Also, since we have the externality of R&D in the model, the reallocated inputs when all distortions are equalized across firms are not the optimal ones anymore, though they would still increase the allocation efficiency to some extent.

The second contribution is that we bring up an alternative resource allocation approach that could generate higher allocative efficiency by considering the R&D spillover effect in firms' R&D input decision, which improves one drawback in Hsieh and Klenow (2009) methodology. That is, they assume that eliminating distortions is a good thing. However, distortions in some industries should not be completely eliminated. For example, capital rent should differ across firms when they have different default risk (Dias, et al., 2016). Therefore, in this chapter, it is also possible that the output with equalized distortions is lower than the initial output. This implies that equalizing all distortions might not increase the allocation efficiency for some industries, while it would increase the efficiency for the majority of industries.

The remainder of the Chapter proceeds as follows. Section 2 offers a brief review of the relevant literature. Section 3 describes the methodology to measure the effect of input resource misallocation on the output. Section 4 introduces the data used in the measurement. Section 5 discusses the results by comparing the estimated allocative efficiency loss with and without the presence of the externality of R&D. Then it discusses the comparison of the results of the output gain from the traditional allocation and those from our alternative allocation approach. Section 6 is devoted to robustness checks. Section 7 concludes.

2.2 Literature review

2.2.1 Economic growth, productivity and resource misallocation

In recent years, China's economic growth has shown a significant slowdown. Zhang Yong et al. (2008) indicate that investment in input factors can only promote economic growth in the short term. But in the long run, this will cause overcapacity and is not conducive to long-term economic development. Solow (1957) shows that besides the accumulation of physical capital and human capital, the improvement of total factor productivity is the other source of economic growth. The differences in the productivity across countries explains their differences in per capita income. Bai and Zhang (2014) point out that the slowdown in China's total factor productivity growth has also contributed to the slowdown in economic growth.

There are various studies exploring the reasons causing the difference in the total factor productivity among countries or the productivity slowdown in a certain country, where one of the main opinion attributes this to input factor resource misallocation (Restuccia and Rogerson 2013). Hsieh and Klenow (2009) brought up a well-known theoretical model that links the aggregate productivity to input factor allocative efficiency. They explain that when all producers have the same level of factor productivity, the input factor allocation reaches its optimal level and thus aggregate productivity and output is increased. Initially, the marginal revenue product of input factor across firms varies. Restuccia and Rogerson (2008) note that firms' input factor distortions are positively related to their own productivity. This is because as firms grow, they must incur cost to get the access to a larger proportion in the market. Therefore, only firms that are more productive are willing to pay taxes in order to expand the firm size and earn more profit, while low-productivity firms tend to remain small so they can avoid paying taxes (Roger Gordon and Wei Li, 2005). Scarpetta (2013) found that the relationship between firm size and productivity is stronger in developed economies, which suggests a more efficient resource allocation between firms within an industry. In the resource reallocation process, more input resources are moved from less productive firms to more productive firms. As more productivity firms hire more and more factor inputs, their productivity gradually decreases. At the same time, the productivity of the less productive firm gradually increases as it reducing the amount of hired inputs. This reallocation process continues until all producers reach the same level of productivity.

The resource misallocation is measured by the deviation of the productivity across firms. Hsieh and Klenow (2009) measure the capital and labour resource misallocation in Chinese and Indian manufacturing sector. They found that when capital and labour resource are reallocated to the efficient level observed in the US, the productivity is increased by 30%-50% in China and 40%-60% in India. However, Brandt et al. (2013) shed further light on the causes of resource misallocation in China. Due to a number of institutional constraints, factor markets (such as capital, labour, energy, land, etc.) in China are less marketed than those in developed countries. This results in resource misallocation between firms at different levels, including the misallocation across different regions or across firms with different ownership types. Du et al. (2014) report similar findings of significant resource misallocation between the state and private sectors.

2.2.2 Misallocation type

2.2.2.1 Capital resource misallocation

Misallocation from capital markets is a prevailing problem. Jeong and Townsend (2006) find that financial market development brought about a 70% increase in aggregate total factor productivity in Thailand between 1976 and 1996, without considering exogenous technological progress. Midrigan and Xu (2014) use a dynamic model to compare the total factor productivity loss from resource misalignment in Korea and Colombia, where the credit market development in these two countries is different. They find that the estimated total factor productivity losses from misallocation in their dynamic model is very small in both countries. Their results seem to be contradictory with those in Hsieh and Klenow (2009). They explain the different results as, in their model, firms have the ability to accumulate internal funds as they grow. Therefore, whether or not micro-level financial information is taken into account can make a large difference in the model's predictions. Brandt et al. (2012) also find very limited gains from improved input factor allocation over the period 1998-2007. Gong and Hu (2016) extend Hsieh and Klenow's (2009) model with the assumption of heterogenous product and find that the allocative efficiency loss from resource misallocation is overestimated in China. In addition, capital factor miasallocation in China is more associated with firm ownership. State-owned firms have easier access to finance, while privately owned firms have more difficulty in obtaining finance support and pay higher financial costs (Wei et al., 2016). The resource misallocation level may vary in different sectors. Dias et al. (2016) measure the allocative efficiency in agricultural, manufacturing and service sectors in Portugal. They find that the most significant misallocation comes from the service sector, which accounts for about 70% of misallocation in all sectors. At the same time, capital factor distortions are the largest source of resource misallocation in service sector.

2.2.2.2 Labour resource misallocation

There is other literature that suggests that labour factor misallocation also contributes to the loss of aggregate TFP. In earlier studies of labour misallocation in China, the literature focused on labour market distortions caused by low labour mobility (Yang and Zhou, 1999; Cai et al., 2002; Knight and Li, 2005). Labour in rural areas with low productivity cannot move to more productive urban sector, which results in larger output losses. Yang (2004) finds that the development of education in rural areas can increase labour mobility. More labour working in more productive non-agricultural activities increases the efficiency of labour allocation. In recent years, labour mobility has increased with subsequent reforms in relevant institutions such as the household registration system in China (Bai and Chen, 2016). Hertel and Zhai (2005) also suggest that the large-scale movement of labour from the low-productivity rural sector to the high-productivity urban sector significantly reduced labour misallocation in China, leading to increased economic efficiency and inequality. However, this does not guarantee that labour misallocation will completely disappear or decline over time. Chen (2019) shows that China's human capital misallocation is closely related to the undergoing industrial upgrading, which involves the distribution of general labour and human capital engaged in R&D activities across industries with different levels of technology. He conducted a counterfactual experiment to measure the impact of the human capital misallocation on productivity with the provincial panel data covering 15 years. The results show that total TFP increases by 41% when labour mismatches between industries are completely eliminated. This suggests that hiring more human capital in high-tech firms plays an important role in promoting economic development. Li and Zhang (2015) suggest that since China's manufacturing industry has been saturated, resources have begun to move to the service sector. But the productivity in China's service sector is lower than that in the manufacturing sector and this would result in the lower productivity growth. Apart from this, consistent with Brandt et al.'s (2013) view on ownership and productivity, Fleisher et al. (2011) point out that since one of the policy objectives that Chinese state-owned enterprises (SOEs) have is to stabilise employment, SOEs have an advantage such as subsidy in hiring employees. This leads to lower labour productivity in SOEs.

2.2.2.3 R&D resource misallocation

Most of the studies focus only on the misallocation of capital, labour or energy inputs. However, quantifying R&D and innovation resource misallocation has gradually gained attention. There are two main classic development theories that build the relationship between innovation and economic growth. One says that economic growth is driven by the development of new products, which is known as the variety-expanding growth model (Romer, 1990). The other is the quality-ladder growth model. It was initially brought up by Schumpeter (1942) and later developed by Grossman and Helpman (1991) and Aghion and Howitt (1992) and others. In this theory, innovation activities improve the quality of products, which further drives the economic growth.

Li et al. (2017) point out the importance of analysing the misallocation of innovation-related factor resources such as human capital and technology for the long-term development of emerging economies, as innovation is an important factor for long-term economic growth. Jovanovic (2014) estimates the impact of human capital misallocation on economic growth with the assumption of heterogeneous workers and firms. He finds that a more efficient allocation of human capital can promote long-term economic growth. Uras and Wang (2016) measure the capital and technical misallocation on TFP by setting up heterogenous firms that vary in technological and capital conditions. They use firm-level data from the US manufacturing sector and find that the technical misallocation causes more TFP losses than capital misallocation. Therefore, it is important to eliminate technology misallocation in industries that rely more on technique to increase the aggregate. Acemoglu et al. (2018) construct a model of innovation and productivity growth at the firm level. They classify firms into high type and low type based on their R&D capabilities. They find that reallocating R&D resources through taxation raises welfare by 1.4%. In addition, preferential government subsidies could be another reason that leads to R&D resource misallocation in China (Li et al., 2017), which makes state owned firms and foreign-owned firms easier in getting access to credit. However, if subsidized SOEs and foreign-owned enterprises do not undertake the relevant R&D activities, resources are misallocated.

2.2.3 The externality of R&D activities

When studying R&D resource misallocation, the spillover effect of R&D activities needs to be taken into account, because the externality is one distinctive characteristic of innovation activities. It may have an impact on R&D resource allocation efficiency and even affect firms' R&D input decision. Ayerst (2021) shows that R&D resource misallocation comes from the different goals of firms and social planner. Firms decide their R&D investment with the objective of maximising profits, while the social planner's goal is to acquire public return from the R&D spillover effect. If the R&D input required by these two goals do not coincide, then the R&D resource misallocation would occur. Using US patent data, he finds that R&D misallocation reduces productivity growth by 22%. Xiao et al. (2021) find that the effect of R&D input on TFP is also influenced by external technological environment. With a better external technological environment, the effect of a firm's own R&D activities on its productivity would be reduced. Conversely, a firm's own R&D input such as human capital stock facilitates the firm's ability to exploit technology spillovers to increase its own productivity (Su and Liu, 2016).

In the empirical evidence, the effect of knowledge or technological spillovers on TFP differs in different studies. Ujimori and Sato (2015) and Huang et al. (2019) find that knowledge spillovers can facilitate the diffusion of advanced technologies and the aggregate productivity can be increased by measuring technology spillovers through FDI (foreign direct investment). Ugur et al. (2020) find that if firms rely too much on external technology, they will invest insufficiently in their own innovation activities. This implies that knowledge spillovers do not necessarily have a positive effect on firm's R&D activities.

2.3 Model

This section describes the methodology of resource misallocation resulting from the input factor distortions at the firm level. This model allows us to measure the output gain from reducing or even eliminating resource misallocation, and consider the impact of R&D spillover externality on the size of this output gain. In the first and second part, we extend the basic framework of Hsieh and Klenow (2009) by considering the externality of R&D spillover as well as the physical capital, labour and R&D human capital in the production function. In the absence of externalities, inputs are reallocated to the optimal use when the input distortions are equalized for the firms in the same industry. With the externalities, equalizing input distortions can still generate a more efficient result, though it is not the most efficient. The gap between the output with reallocated inputs and the initial output is the efficiency gain from eliminating misallocation. In the third part, we explain the relationship between output gain, dispersions of input factors and the R&D spillover effect. The fourth part is to measure the contribution of eliminating the distortion of each input factor separately. We follow Dias et al. (2016)'s method by adjusting one input when its input factor price is equalized and keep the other inputs fixed. In the last part, we also provide an alternative solution where reallocated R&D is a weighted average of allocations that maximize two different objective functions: one is to maximize the output where there is no R&D spillover and the other is to maximize only the R&D spillover. It increases the efficiency of the input allocation to generate a better competitive outcome.

2.3.1 Theoretical framework

Similar to Hsieh and Klenow (2009), we assume a representative firm that combines the output of S manufacturing industries to produce a single homogenous final good in a perfectly competitive market. It uses a Cobb-Douglas production technology:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s} \tag{1}$$

, where Y is a single final good, and Y_s is the output of industry s. θ_s is the industry s share that satisfies $\sum_{s=1}^{S} \theta_s = 1$ and $\theta_s = \frac{P_s Y_s}{PY}$ holds in equilibrium. P_s and P represent the industry output price and final good price, respectively.

There are m_s firms in industry s. The industry output Y_s is an aggregate of m_s differentiated products Y_{si} using a CES technology:

$$Y_s = \left[\sum_{i=1}^{m_s} (Y_{si})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

, where Y_{si} is the output of firm si.

The assumption of free entry and monopolistic competition implies the relation between firm-specific output price and industry-level output price (Hsieh and Klenow, 2009; Dias et al., 2016):

$$P_{si} = P_s(\frac{Y_s}{Y_{si}})^{\frac{1}{\sigma}} \tag{3}$$

Since we will only consider resource reallocations within industries and not allow any resource reallocation across industries, we impose a normalization that $P_s Y_s^{1/\sigma} = 1$. The differentiated product of firm si is produced using a Cobb-Douglas production function:

$$Y_{si} = B_{si} K_{si}{}^{\alpha_s} L_{si}{}^{\beta_s} H_{si}{}^{\gamma_s} X_s{}^{\delta_s} \tag{4}$$

, where B_{si}, K_{si}, L_{si} and H_{si} represent firm si's TFP (total factor productivity), physical capital stock, labour and R&D human capital, respectively. All the firms in the same industry face the same R&D spillover X_s. α_s, β_s and γ_s are the industry-specific shares of physical capital, labour and R&D human capital, respectively. We assume that the sum of these three input shares equals to one: $\alpha_s + \beta_s + \gamma_s = 1$. These three input shares α_s, β_s and γ_s, in the interval (0, 1), are the same for all the firms in the same industry but vary across industries. The parameter δ_s is measuring the impact of R&D spillover externality on firm si's output and is also assumed to be the same for all firms in the same industry.

Due to the distinctive characteristic of the externality of knowledge and R&D activities, all the firms can benefit from the results of innovation to increase their productivity or output even if they do not conduct R&D activities themselves. Firms do not recognize that the industry R&D spillover depends on their choice of R&D effort so they treat the spillover as an exogenous constant. We assume that all the firms in the same industry evenly enjoy the result of other firms' R&D effort and set the R&D spillover X_s as a geometric average of the R&D stock in the industry. The amount of R&D spillover is

$$X_s = \prod_{j=1}^{m_s} H_{sj}^{\frac{1}{m_s}} \tag{5}$$

We introduce exogenous firm-specific distortions (or wedges) for each of the three input factors: physical capital distortion ($\tau_{K_{si}}$), labour distortion ($\tau_{L_{si}}$) and R&D human capital distortion ($\tau_{H_{si}}$). The firm si maximises its profits by choosing the optimal inputs subject to the inverse demand function (3) and the production function (4):

$$\pi_{si} = P_{si}Y_{si} - r_s(1+\tau_{K_{si}})K_{si} - \omega_{L_s}(1+\tau_{L_{si}})L_{si} - \omega_{H_s}(1+\tau_{H_{si}})H_{si} \tag{6}$$

, where π_{si} is firm si's profit, r_s is the rental rate for physical capital, ω_{L_s} is the wage for labour, ω_{H_s} is the wage for R&D employment. All the input factor costs are industry-specific.

The first order conditions of profit maximization imply the firm's initial input allocation:

$$I_{si} = \frac{\sigma-1}{\sigma} P_{si}Y_{si} \frac{\varphi_s}{(1+\tau_{I_{si}})c_s} \tag{7}$$

, where I_{si} is the firm's initial input allocation and there are 3 input factors represented by I_{si}: K_{si}, L_{si} and H_{si}. $\tau_{I_{si}}$ is the input distortion for the three input factors respectively. The input share of φ_s and input cost c_s are:

$$\varphi_s = \begin{cases} \alpha_s & for\ I = K \\ \beta_s & for\ I = L \\ r_s & for\ I = H \end{cases}$$

$$c_s = \begin{cases} r_s & for\ I = K \\ \omega_{L_s} & for\ I = L \\ \omega_{H_s} & for\ I = H \end{cases}$$

We can use the first order condition (7) to recover the firm-specific input distortions:

$$(1+\tau_{I_{si}}) = \frac{\sigma-1}{\sigma} P_{si}Y_{si} \frac{\varphi_s}{c_s I_{si}} \tag{8}$$

, in which a high ratio of output to input cost implies a high input factor distortion.

2.3.2 Resource reallocation and output gain

Substitute the first order condition (7) back into production function (4) and it becomes

$$Y_{si} =$$

$$B_{si}{X_s}^{\delta_s}[\frac{\sigma-1}{\sigma}P_{si}Y_{si}\frac{\alpha_s}{(1+\tau_{K_{si}})r_s}]^{\alpha_s}[\frac{\sigma-1}{\sigma}P_{si}Y_{si}\frac{\beta_s}{(1+\tau_{L_{si}})\omega_{L_s}}]^{\beta_s}[\frac{\sigma-1}{\sigma}P_{si}Y_{si}\frac{\gamma_s}{(1+\tau_{H_{si}})\omega_{H_s}}]^{\gamma_s} =$$

$$B_{si}{X_s}^{\delta_s}[\frac{\alpha_s}{(1+\tau_{K_{si}})r_s}]^{\alpha_s}[\frac{\beta_s}{(1+\tau_{L_{si}})\omega_{L_s}}]^{\beta_s}[\frac{\gamma_s}{(1+\tau_{H_{si}})\omega_{H_s}}]^{\gamma_s}(\frac{\sigma-1}{\sigma}P_{si}Y_{si})^{\alpha_s+\beta_s+\gamma_s} \quad (9)$$

Since we assume $\alpha_s + \beta_s + \gamma_s = 1$, above equation becomes

$$1 = B_{si}{X_s}^{\delta_s}[\frac{\alpha_s}{(1+\tau_{K_{si}})r_s}]^{\alpha_s}[\frac{\beta_s}{(1+\tau_{L_{si}})\omega_{L_s}}]^{\beta_s}[\frac{\gamma_s}{(1+\tau_{H_{si}})\omega_{H_s}}]^{\gamma_s}(\frac{\sigma-1}{\sigma}P_{si}) \quad (10)$$

Following the approach adopted in the literature (Hsieh and Klenow, 2009; Dias, et al. 2014; Benkovskis, 2015; Chen, 2017; Choi, 2020), firms can reallocate their inputs more efficiently (achieve a larger output) when the firm-specific distortions they face are adjusted to the same industry level: τ_{K_s}, τ_{L_s} and τ_{Hs}. We will perform the same exercise here, although later we will argue that because of spillovers, the output can be increased if in fact the distortions are not equalized across the firms. Thus, we now find τ_{K_s}, τ_{L_s} and τ_{Hs} for each s, such that the aggregate industry use of inputs does not change. Also, we will denote the new firm level variables for equalized distortions with an asterisk.

Using (3) and equalizing distortions, the input factors with equalized distortions for firm si are

$$I_{si}^{*} = \frac{\sigma-1}{\sigma}{P_{si}^{*}}^{1-\sigma}\frac{\varphi_s}{(1+\tau_{I_s})c_s} \quad (11)$$

, where I_{si}^{*} is the reallocated input of firm si after equalizing all distortions for the three input factors K_{si}^{*}, L_{si}^{*} and H_{si}^{*}. P_{si}^{*} is the output price of firm si when the distortions it faces are equalized to the industry level.

Then the output price is obtained from equation (10):

$$P_{si}^{*} = \frac{1}{B_{si}}{X_s^{*}}^{-\delta_s}(\frac{\sigma}{\sigma-1})[\frac{(1+\tau_{K_s})r_s}{\alpha_s}]^{\alpha_s}[\frac{(1+\tau_{L_s})\omega_{L_s}}{\beta_s}]^{\beta_s}[\frac{(1+\tau_{Hs})\omega_{H_s}}{\gamma_s}]^{\gamma_s} \quad (12)$$

, where X_s^* is the R&D spillover for all firms in the industry s when firm-level distortions $\tau_{K_{si}}$, $\tau_{L_{si}}$ and $\tau_{H_{si}}$ are equalized to the industry level of τ_{K_s}, τ_{L_s} and τ_{H_s}. It is the geometric average of all firms R&D human capital stock H_{si}^*.

To eliminate the output price, we substitute (12) into the input allocation with equalized distortions in (11):

$$I_{si}^* = {B_{si}}^{\sigma-1}(\frac{\sigma-1}{\sigma})^{\sigma} {X_s^*}^{\delta_s(\sigma-1)} \frac{\varphi_s}{(1+\tau_{I_s})c_s} [\frac{(1+\tau_{K_s})r_s}{\alpha_s}]^{\alpha_s(1-\sigma)} [\frac{(1+\tau_{L_s})\omega_{L_s}}{\beta_s}]^{\beta_s(1-\sigma)} [\frac{(1+\tau_{H_s})\omega_{H_s}}{\gamma_s}]^{\gamma_s(1-\sigma)} \tag{13}$$

We assume that the total physical capital, labour supply and R&D human capital supply of an industry does not change. Therefore, the aggregate industry inputs stay fixed before and after the resource reallocation from equalizing the input distortions of all firms. The initial firm level input is

$$I_{si} = {B_{si}}^{\sigma-1}(\frac{\sigma-1}{\sigma})^{\sigma} {X_s}^{\delta_s(\sigma-1)} \frac{\varphi_s}{(1+\tau_{I_{si}})c_s} [\frac{(1+\tau_{K_{si}})r_s}{\alpha_s}]^{\alpha_s(1-\sigma)} [\frac{(1+\tau_{L_{si}})\omega_{L_s}}{\beta_s}]^{\beta_s(1-\sigma)} [\frac{(1+\tau_{H_{si}})\omega_{H_s}}{\gamma_s}]^{\gamma_s(1-\sigma)} \tag{14}$$

And the aggregate industry input is the sum of all firms' input (13) in the same industry:

$$I_s = \sum_i {B_{si}}^{\sigma-1}(\frac{\sigma-1}{\sigma})^{\sigma} {X_s^*}^{\delta_s(\sigma-1)} \frac{\varphi_s}{(1+\tau_{I_s})c_s} [\frac{(1+\tau_{K_s})r_s}{\alpha_s}]^{\alpha_s(1-\sigma)} [\frac{(1+\tau_{L_s})\omega_{L_s}}{\beta_s}]^{\beta_s(1-\sigma)} [\frac{(1+\tau_{H_s})\omega_{H_s}}{\gamma_s}]^{\gamma_s(1-\sigma)} \tag{15}$$

With this assumption of fixed industry-level quantity of input, the firm's reallocated input is derived to be positively related to its productivity, which is shown below.

Now we derive the optimal R&D spillover X_s^*. First, using (13) and (15), we find

$$I_{si}^* = \frac{{B_{si}}^{\sigma-1}}{\sum_i {B_{si}}^{\sigma-1}} I_s \tag{16}$$

In particular, $H_{si}^* = \frac{B_{si}{}^{\sigma-1}}{\sum_i B_{si}{}^{\sigma-1}} H_s$. The relationship between the reallocated firm-level R&D and the aggregate industry R&D stock implies that firm si's productivity and its reallocated R&D input are positively related. This indicates that firms with higher productivity should use more R&D capital to achieve a higher allocation efficiency. Substituting (16) into the formula for X_s in (5), the new R&D spillover X_s^* can be calculated as

$$X_s^* = \frac{\prod_{i=1}^{m_s} B_{si}{}^{\frac{\sigma-1}{m_s}}}{\sum_i B_{si}{}^{\sigma-1}} H_s \tag{17}$$

From the aggregate industry input in (15) we can observe the relationship between distortions and the aggregate inputs:

$$\frac{H_s}{L_s} = \frac{\frac{(1+\tau_{L_s})\omega_{L_s}}{\beta_s}}{\frac{(1+\tau_{H_s})\omega_{H_s}}{\gamma_s}} \tag{18}$$

$$\frac{H_s}{K_s} = \frac{\frac{(1+\tau_{K_s})r_s}{\alpha_s}}{\frac{(1+\tau_{H_s})\omega_{H_s}}{\gamma_s}} \tag{19}$$

We use (18) and (19) to eliminate τ_{L_s} and τ_{K_s} in industry aggregate input (15) when $I_s = H_s$:

$$H_s = \sum_i B_{si}{}^{\sigma-1} \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} X_s^{*\delta_s(\sigma-1)} \left[\frac{(1+\tau_{K_s})r_s}{\alpha_s}\right]^{\alpha_s(1-\sigma)} \left[\frac{(1+\tau_{L_s})\omega_{L_s}}{\beta_s}\right]^{\beta_s(1-\sigma)} \left[\frac{(1+\tau_{H_s})\omega_{H_s}}{\gamma_s}\right]^{\gamma_s(1-\sigma)-1}$$

$$= \sum_i B_{si}{}^{\sigma-1} \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} X_s^{*\delta_s(\sigma-1)} \left[\frac{(1+\tau_{H_s})\omega_{H_s}}{\gamma_s}\right]^{-\sigma} \left(\frac{H_s}{K_s}\right)^{\alpha_s(1-\sigma)} \left(\frac{H_s}{L_s}\right)^{\beta_s(1-\sigma)}$$

One can use this equation to find τ_{H_s} and then find τ_{L_s} and τ_{K_s} from (18) and (19). The industry-level distortions can be expressed as a function of the aggregate industry inputs as:

$$1 + \tau_{I_s} = \frac{\varphi_s}{c_s}\frac{H_s}{I_s}\left(\frac{1}{H_s}\sum_{i=1}^{m_s} B_{si}{}^{\sigma-1}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma} (X_s^*)^{\delta_s(\sigma-1)} \left(\frac{H_s}{K_s}\right)^{\alpha_s(1-\sigma)} \left(\frac{H_s}{L_s}\right)^{\beta_s(1-\sigma)}\right)^{\frac{1}{\sigma}}$$

, where I_s is the industry level aggregate input and there are 3 input factors in I_s: K_s,

L_s and H_s.

The input allocation at the firm-level (13) and the industry-level (15) implies the input ratios for the firm si and the industry s are the same:

$$\frac{H_{si}^*}{K_{si}^*} = \frac{H_s}{K_s} \tag{20}$$

$$\frac{H_{si}^*}{L_{si}^*} = \frac{H_s}{L_s} \tag{21}$$

In order to compute the new output Y_{si}^*, we use (20) and (21) to replace the firm-level input ratios with the industry-level input ratios. The new output with reallocated input and new R&D spillover then can be expressed as:

$$Y_{si}^* = B_{si}(K_{si}^*)^{\alpha_s}(L_{si}^*)^{\beta_s}(H_{si}^*)^{\gamma_s}(X_s^*)^{\delta_s} = B_{si}\left(\frac{K_{si}^*}{H_{si}^*}\right)^{\alpha_s}\left(\frac{L_{si}^*}{H_{si}^*}\right)^{\beta_s} H_{si}^*(X_s^*)^{\delta_s}$$

$$= B_{si}H_{si}^*\left(\frac{K_s}{H_s}\right)^{\alpha_s}\left(\frac{L_s}{H_s}\right)^{\beta_s}(X_s^*)^{\delta_s} = \frac{B_{si}{}^{\sigma}}{\sum_j B_{sj}{}^{\sigma-1}} H_s\left(\frac{K_s}{H_s}\right)^{\alpha_s}\left(\frac{L_s}{H_s}\right)^{\beta_s}(X_s^*)^{\delta_s}$$

$$= \frac{B_{si}{}^{\sigma}}{\sum_j B_{sj}{}^{\sigma-1}} K_s{}^{\alpha_s} L_s{}^{\beta_s} H_s{}^{\gamma_s}(X_s^*)^{\delta_s} = B_{si}{}^{\sigma}\Phi_s \tag{22}$$

, where Y_{si}^* is the new output when the firm si reallocates its inputs with the equalized industry level input distortions and new R&D spillover. Φ_s is the same for all the firms in industry s and it equals to $\frac{K_s{}^{\alpha_s} L_s{}^{\beta_s} H_s{}^{\gamma_s}(X_s^*)^{\delta_s}}{\sum_i B_{si}{}^{\sigma-1}}$. In this expression, the new output depends on its physical productivity B_{si}.

With the new output, the industry-level output gap can be measured as:

$$\frac{Y_s^*}{Y_s} = \left[\frac{\sum_{i=1}^{m_s}(Y_{si}^*)^{\frac{\sigma-1}{\sigma}}}{\sum_{i=1}^{m_s}(Y_{si})^{\frac{\sigma-1}{\sigma}}}\right]^{\frac{\sigma}{\sigma-1}} \tag{23}$$

Using the Cobb-Douglas aggregator, the output gain for the whole economy is

$$\frac{Y^*}{Y} = \prod_{s=1}^{S}\left\{\frac{Y_s^*}{Y_s}\right\}^{\theta_s} \tag{24}$$

2.3.3 The relationship between output gap, the dispersion of productivity and R&D spillover

We can also express the industry-level output gap in terms of the dispersion of firms' revenue productivity and R&D spillover to gauge the relationship between the industry-level output gain and firms' productivity. The industry level physical productivity is defined as

$$TFP_s \equiv \frac{Y_s}{K_s{}^{\alpha_s} L_s{}^{\beta_s} H_s{}^{\gamma_s} X_s{}^{\delta_s}} \tag{25}$$

Since the aggregate industry inputs do not change, we have

$$\frac{Y_s^*}{Y_s} = \frac{TFP_s^*}{TFP_s}\frac{X_s^{*\delta_s}}{X_s{}^{\delta_s}} \tag{26}$$

In logarithm, the output gap is

$$logY_s^* - logY_s = logTFP_s^* - logTFP_s + \delta_s(logX_s^* - logX_s) \tag{27}$$

From central limit theorem, the industry level TFP after reallocation can be approximated as

$$logTFP_s^* = E[logB_{si}] + \frac{\sigma-1}{2} var(logB_{si}) \tag{28}$$

Now we find the other term $logTFP_s$ as it is also required in the output gap. After substituting the initial firm-level inputs in terms of firm-level distortions (14) and the industry aggregate input (15) into the above expression of TFP_s, the industry productivity in logarithm becomes

$$logTFP_s = E[logB_{si}] + \frac{\sigma-1}{2} var(logB_{si}) - \frac{\sigma}{2} var(log\Theta_{si}) - \frac{\alpha_s(1-\alpha_s)}{2} var\big(\log\big(1 + \tau_{K_{si}}\big)\big) - \frac{\beta_s(1-\beta_s)}{2} var\big(\log\big(1 + \tau_{L_{si}}\big)\big) - \frac{\gamma_s(1-\gamma_s)}{2} var\big(\log\big(1 + \tau_{H_{si}}\big)\big) \tag{29}$$

where $\Theta_{si} = \left(1 + \tau_{K_{si}}\right)^{\alpha_s}\left(1 + \tau_{L_{si}}\right)^{\beta_s}\left(1 + \tau_{H_{si}}\right)^{\gamma_s}$

In the presence of the R&D spillover in the production function, the firm-specific TFPR (total factor revenue productivity) is defined as the product of firm-specific output price and productivity $P_{si}B_{si}$ and it measures the revenue productivity of firm si:

$$TFPR_{si} = P_{si}B_{si} = \frac{P_{si}Y_{si}}{X_s^{\delta_s} K_{si}^{\alpha_s} L_{si}^{\beta_s} H_{si}^{\gamma_s}}$$

$$= \frac{1}{X_s^{\delta_s}} \frac{\sigma}{\sigma-1} \left(\frac{r_s\left(1+\tau_{K_{si}}\right)}{\alpha_s}\right)^{\alpha_s} \left(\frac{\omega_{L_s}\left(1+\tau_{L_{si}}\right)}{\beta_s}\right)^{\beta_s} \left(\frac{\omega_{H_s}\left(1+\tau_{H_{si}}\right)}{\gamma_s}\right)^{\gamma_s} \quad (30)$$

And in approximation, it becomes

$$var(logTFPR_{si}) = var(log\Theta_{si}) \quad (31)$$

where $\Theta_{si} = \left(1+\tau_{K_{si}}\right)^{\alpha_s}\left(1+\tau_{L_{si}}\right)^{\beta_s}\left(1+\tau_{H_{si}}\right)^{\gamma_s}$.

Therefore, the industry level productivity in logarithm can be written as

$$logTFP_s = logTFP_s^* - \frac{\sigma-1}{2} var(logTFPR_{si}) - \frac{\alpha_s}{2} var\left(\log\left(1+\tau_{K_{si}}\right)\right)$$
$$-\frac{\beta_s}{2} var\left(\log\left(1+\tau_{L_{si}}\right)\right) - \frac{\gamma_s}{2} var\left(\log\left(1+\tau_{H_{si}}\right)\right) \quad (32)$$

After substituting $logTFP_s$ and $logTFP_s^*$ in to the output gap (26), we can see that the output gain comes not only from eliminating dispersion in distortions of inputs, but also from the R&D spillover term:

$$logY_s^* - logY_s = logTFP_s^* - logTFP_s + \delta_s(logX_s^* - logX_s)$$
$$= \frac{\sigma-1}{2} var(logTFPR_{si}) + \delta_s(logX_s^* - logX_s)$$
$$+\frac{\alpha_s}{2} var\left(\log\left(1+\tau_{K_{si}}\right)\right) + \frac{\beta_s}{2} var\left(\log\left(1+\tau_{L_{si}}\right)\right) + \frac{\gamma_s}{2} var\left(\log\left(1+\tau_{H_{si}}\right)\right) \quad (33)$$

2.3.4 Importance of each input distortion to the output loss

We also measure the contribution to the output gain of eliminating separately each input distortion. We equalize one input distortion at a time and keep the other two input allocations fixed at the same time (Dias et al. 2014).

When the firm-specific physical capital distortions are equalized at the industry level, each firm adjusts physical capital input to maximize its profit, while they fix the other two inputs. The firms would also want to change the use of other inputs when the capital distortions change. However, we still want to ensure that the industry level use of inputs stays the same as originally, but by changing only capital distortions, we cannot ensure that the use of all three inputs will stay the same at the industry level. Therefore, we assume that the firms simply cannot change their other two inputs. The equalized industry-level capital distortion is derived under the assumption that the aggregate capital input in the industry s stays fixed after reallocating capital input across firms. (Detailed derivation and calculations are available in the Appendix 2.A). After obtaining the reallocated capital stock and initial labour and R&D human capital, one can get the new output of eliminating the physical capital distortion. And we apply the same approach to get the output gain from eliminating labour distortion. When eliminating R&D capital distortion, we need to take into account that the R&D spillover also changes as it is a geometric average of optimal firm-level R&D human capital stock.

2.3.5 An alternative approach to improve the allocation outcome

In the presence of externality of the R&D spillover, the input reallocation will not result in the most efficient output when distortions are equalized at the industry level, as it is done in the previous studies (Dias, et al. 2014; Benkovskis, 2015; Chen, 2017; Choi, 2020). In fact, the initial output might be higher than the output from equalizing all the distortions in some industries, which indicates that the reallocated inputs might not achieve the efficient outcome.

It seems that there does not exist an explicit analytical solution for distortions that lead to the first best allocation of inputs. However, we suggest an alternative allocation approach that improves on the outcome with equalized distortions. The input distortions derived from this alternative allocation might provide policy implications for firms with different levels of productivity.

An industry-wide output is

$$Y_s = \left(\sum_{i=1}^{m_s} \left(B_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s} H_{si}^{\gamma_s} \left(\prod_{j=1}^{m_s} H_{sj}^{\frac{1}{m_s}} \right)^{\delta_s} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

$$= \left(\sum_{i=1}^{m_s} \left(B_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s} H_{si}^{\gamma_s} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \left(\prod_{j=1}^{m_s} H_{sj}^{\frac{1}{m_s}} \right)^{\delta_s} \tag{34}$$

After taking the logarithm, it becomes

$$\log Y_s = \frac{\sigma}{\sigma-1} \log \left(\sum_{i=1}^{m_s} \left(B_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s} H_{si}^{\gamma_s} \right)^{\frac{\sigma-1}{\sigma}} \right) + \frac{\delta_s}{m_s} \sum_{j=1}^{m_s} \log H_{sj} \tag{35}$$

If we maximize the first term subject to the resource constraint:

$$\max_{K_{si}, L_{si}, H_{si}} \left(\sum_{i=1}^{m_s} \left(B_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s} H_{si}^{\gamma_s} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

s.t.

$$I_s = \sum_{i=1}^{m_s} I_{si}$$

From the FOCs, the input allocation is:

$$I_{si} = \frac{B_{si}^{\sigma-1}}{\sum_{sj} B_{sj}^{\sigma-1}} I_s$$

which is exactly what we obtain when equalizing distortions across firms. The R&D allocation would be different if we maximize the second term in (35) subject to R&D human capital resource constraint:

$$H_{si} = \frac{1}{m_s} H_s$$

That is, X_s is maximized if all firms in industry s get an equal share of H_s.

Note that $\log Y_s$ is a strictly concave function in $(H_{s1}, \dots, H_{sm_s})$,

$$\log Y_s \left(\lambda_s \widehat{H}_{s1} + (1-\lambda_s) \breve{H}_{s1}, \dots, \lambda_s \widehat{H}_{sm_s} + (1-\lambda_s) \breve{H}_{sm_s} \right)$$

$$> \lambda_s \log Y_s \left(\widehat{H}_{s1}, \dots, \widehat{H}_{sm_s} \right) + (1-\lambda_s) \log Y_s \left(\widehat{H}_{s1}, \dots, \breve{H}_{sm_s} \right)$$

, where $\widehat{H}_{si} = \frac{B_{si}^{\sigma-1}}{\sum_{sj} B_{sj}^{\sigma-1}} H_s$ and $\breve{H}_{si} = \frac{1}{m_s} H_s$.

Therefore, we choose an R&D allocation as a mixed solution of $\widehat{H}_{si}$ and $\breve{H}_{si}$.

$$\widetilde{H}_{si} \equiv \lambda_s \widehat{H}_{si} + (1-\lambda_s)\breve{H}_{si} = \frac{\gamma_s B_{si}^{\sigma-1} + \frac{\delta_s}{m_s}\sum_{sj} B_{sj}^{\sigma-1}}{(\gamma_s+\delta_s)\sum_{sj} B_{sj}^{\sigma-1}} H_s \tag{36}$$

, where $\lambda_s = \frac{\gamma_s}{\gamma_s+\delta_s}$. This alternative allocation of R&D input, which is a weighted average of the allocations when maximizing the output without the spillover term and when maximizing R&D spillover, could improve on the competitive outcome with the equalized distortions. Though, it does not guarantee to improve on the initial outcomes as the initial outcome in some industries could happen to be the first best, which is higher than the outcome resulting from alternative allocations.

2.4 Data

2.4.1. Data sources and sample

Our dataset includes information on Chinese manufacturing firms listed on Shanghai Stock Exchange and Shenzhen Stock Exchange in mainland China. Industries are classified according to the benchmark of CSRC Industry Classification (2012 Edition). All data is collected in CSMAR database (China Stock Market and Accounting Research Database). Our study starts with the year 2015 as the data of firm-specific R&D personnel in CSMAR database is only available from 2015. The sample period is from 2015 to 2018.

Our initial data includes 1586 firms with 6344 observations. We drop 119 observations with missing or non-positive value of the data on sales, fixed assets, employees, R&D employment, R&D expenditure and wage bill. We then exclude observations with values of the fixed assets and employment above the 99th percentile or below 1st percentile to eliminate outliers. The resulting sample includes 1460 firms with 5840 observations.

2.4.2. Definitions of main variables

The main variables in this study are nominal output, physical capital stock, non-R&D

employment and R&D human capital, which are measured by sales, fixed assets, the number of employees hired in non-R&D activities and the number of employees hired in R&D activities respectively. We deflate the sales by Purchasing Price Indices for Industrial Producers and use deflated sales as nominal output. As a measure of R&D human capital, we use the number of employees in R&D activities of the firm. And since we only have employment data for all employees and R&D employees, we measure the number of non-R&D employees by the difference between the number of total employees and R&D employees of the firm.

Table 2.1 Descriptive Statistics

		Total		Low-tech		Medium-tech		High-tech	
		100%		12.5%		46.5%		40.0%	
		5840		724		2708		2328	
Variable		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
$P_{si}Y_{si}$	Nominal output (revenue)	5467.135	13112.705	5110.718	8944.143	6260.89	14739.195	4144.064	8992.252
K_{si}	Capital stock (fixed asset)	1928.857	3638.229	1633.938	2257.46	2471.242	4556.073	1246.113	1989.224
L_{si}	Non-R&D employment	4194.642	7126.443	5439.635	8489.716	3895.169	6131.366	3848.649	6214.597
H_{si}	R&D employment	544.745	1260.149	286.119	348.184	490.031	938.043	661.938	1606.564
α_s	Capital share	0.377	0.152	0.352	0.146	0.433	0.167	0.315	0.089
β_s	Non-R&D labour share	0.484	0.121	0.592	0.145	0.458	0.123	0.479	0.059
γ_s	R&D human capital share	0.139	0.08	0.055	0.018	0.109	0.063	0.206	0.064
r_s	Rental rate of capital	3.076	2.196	3.239	1.203	2.57	0.845	3.305	0.713
ω_{L_s}	Non-R&D labour cost	0.016	0.006	0.018	0.009	0.018	0.005	0.014	0.003
ω_{H_s}	R&D labour cost	0.035	0.016	0.033	0.021	0.032	0.018	0.036	0.008

2.4.3. Descriptive statistics

Table 2.1 presents the descriptive statistics for the total sample of the manufacturing firms listed in Shanghai and Shenzhen stock exchanges as well as three groups according to firms' type (Low-tech industries, Medium-tech industries and High-tech industries). The classification of the three technology types for industries is based on An and Qian (2021) and Jiang and Guan (2008) and High-tech industry (manufacturing industry) Classification (2017 Edition) issued by Chinese National Bureau of Statistics. We use this classification to measure the allocative efficiency loss for groups of different technology type separately, as the R&D resource misallocation and R&D spillover effect might differ in industries of different technology type. There are 1460 firms in the sample and 12.5 of them are classified as low-tech firms, 46.5% as medium-tech firms and 40.0% as high-tech firms. The mean value of sales is 5467.135 million RMB. The standard deviation is 13112.705, indicating that the revenues of sample firms take a broad range of values. On average, the capital stock is 1928.857 million RMB. The standard deviation of 3638.229 also reflects a wide range of values for the capital stock. Firms in the medium-tech group have the highest mean value of 2471.242 million RMB, which is almost twice of that for the firms in the high-tech group that invest the least in capital stock. On average, firms hire 4194.642 non-R&D employees. The standard deviation is 7126.443, indicating a wide range of firms' non-R&D employment. Firms in the low-tech group have the highest mean value of 5439.635 non-R&D employees. Firms in the other two groups have, on average, a similar number of non-R&D employees, which is around 3850. The mean value of R&D employment for the total sample of firms is 544.745. The standard deviation of 1260.149 reflects a broad range of R&D employment. The ranking of mean values of R&D employment for each group is closely related to the technology type. Firms in the high-tech group hire the most R&D employees, with a mean value of 661.938. The mean value of R&D employees of firms in the low-tech group is only around one third of that of firms in the high-tech group, while that of firms in the medium-tech group is 490.031.

From the data, we also calculate the shares of capital stock, non-R&D employment and R&D employment in the output for each industry. The average capital input share is 0.377 for all industries. The difference across firms is indicated by a standard deviation of 0.152 as well as a minimum of 0.032 and a maximum of 0.962. Firms in the medium-tech group have the highest capital share among the three groups, exhibiting a mean value of 0.433, whereas firms in the high-tech group have the lowest capital share of 0.315. The average share of non-R&D employment for the total sample is 0.484 and it also differs a lot across firms. Firms in the low-tech group rely the most on non-R&D labour in the production among all groups as the mean value of 0.592 is the highest, while firms in the medium-tech group have the lowest average share of non-R&D employment. With regard to the share of R&D employment, the average for the entire sample is 0.139. R&D employment share is the highest in the high-tech group and lowest in the low-tech group, exhibiting mean values of 0.206 and 0.055, respectively.

Concerning the input factor prices (Parameter calibration is in Appendix 2.B), the average rental rate of capital for all firms is 3.076 million RMB while that for firms in the medium-tech group is the lowest at 2.57 million RMB and in the high-tech group is the highest at 3.305 million RMB. On average, the labour cost for non-R&D employees is 16000 RMB. The mean value of non-R&D labour cost in the high-tech group is lower than in the other two groups. Firms in the low-tech group and the medium-tech group pay a similar estimated wage rate with an average of 18000 RMB to non-R&D employees. As for R&D labour cost, its mean value for the entire sample is more than double that of the non-R&D labour cost. R&D employees hired in the high-tech industry are paid the highest wage rate with a mean of 36000 RMB and those hired in the low-tech industry and medium-tech industry are paid similar wage rates of 33000 RMB and 32000 RMB, respectively.

The industry composition is shown in Table 2.2 The low-tech industry takes up the smallest part, representing 12.5% of the whole sample. Within the low-tech industry, firms are more evenly distributed when compared with the other two groups. Medium-tech and high-tech groups make up a similar percentage of the whole sample, which is around 43% for each group. These two groups take up most of the sample. Within the medium-tech industry, the number of firms in the industry of Raw Chemical Materials and Chemical Products (C26) is the highest, accounting for around 10% of the total sample. Within the high-tech industry, there are the most firms in the Computer, Communication and Other Electronic Device Manufacturing Industry (C39), taking up 13.63% of all firms in the sample.

Table 2.2 Industry Composition

Industry	Code	Obs	%
Low-tech industries			
Farm and Sideline Products Processing	C13	29	1.99
Food Manufacturing	C14	29	1.99
Wine, Drinks and Refined Tea Manufacturing	C15	26	1.78
Textile Industry	C17	26	1.78
Textiles, Garments and Apparel Industry	C18	27	1.85
Leather, Fur, Feathers, and Related Products and Shoe-making	C19	6	0.41
Timber Processing, Bamboo, Cane, Palm Fiber and Straw Products	C20	5	0.34
Furniture Manufacturing	C21	9	0.62
Paper-making & Paper Products	C22	21	1.44
Printing and Reproduction of Recorded Media	C23	6	0.41
Culture and Education, Arts and Crafts, Sports and Entertainment Products Manufacturing	C24	6	0.41
Medium-tech industries			
Petroleum Processing, Coking and Nuclear Fuel Processing	C25	8	0.55
Raw Chemical Materials and Chemical Products	C26	147	10.07
Chemical Fiber Manufacturing	C28	16	1.10
Rubber and Plastic Product Industry	C29	45	3.08
Non-metallic Mineral Products	C30	52	3.56
Ferrous Metal Smelting and Extruding	C31	14	0.96
Non-ferrous Metals Smelting & Rolling Processing	C32	52	3.56
Metal Products	C33	36	2.47
General Equipment Manufacturing	C34	91	6.23
Special Equipment Manufacturing	C35	142	9.72
Automobile Manufacturing	C36	82	5.62
High-tech industries			
Medicine Manufacturing	C27	153	10.48
Railway, Shipbuilding, Aerospace and Other Transportation Equipment Manufacturing	C37	31	2.12
Electric Machines and Apparatuses Manufacturing	C38	169	11.58
Computer, Communication and Other Electronic Device Manufacturing	C39	199	13.63
Instrument and Meter Manufacturing	C40	23	1.58
Total		1460	100

Note: Low-tech industries and medium-tech industries are classified using the methodology in Jiang and Guan (2021). High-tech industries are classified by High-tech industry (manufacturing industry) Classification (2017 Edition) issued by Chinese National Bureau of Statistics.

2.5 Empirical results

This section presents the results of measurement of resource misallocation and the output gain from a more efficient reallocation for Chinese listed manufacturing firms. The first part discusses the input resource misallocation in the presence of the knowledge spillover for the whole economy as well as that within and between the industries of different technology type: low-tech, medium-tech and high-tech. The second part presents the results of the output gain from input reallocation by eliminating all distortions. TFPR levels are equalized across firms when all distortions are equalized. The third part describes the contribution of eliminating each input distortion at a time for the output gain. The last part presents the results of the output gain from the alternative reallocation approach of adopting a weighted average of the allocations when maximizing the output without the spillover term and when maximizing only R&D spillover term.

2.5.1 Resource misallocation for Chinese manufacturing firms

From the equation (33) in the model section, efficient resource allocation requires the equalized TFPR across firms, accompanied by a change in the magnitude of the R&D spillover. Since the logarithm output gap is expressed in terms of the dispersion in TFPR in equation (33), we present the logarithm scaled TFPR (the firm level TFPR over the industry level TFPR) dispersion statistics for the whole economy as well as for the three groups in Table 2.3.

Table 2.3 The dispersion of TFPR

	Whole economy	Low-tech	Medium-tech	High-tech
2015	0.664	0.574	0.685	0.628
2016	0.624	0.566	0.655	0.576
2017	0.625	0.609	0.643	0.593
2018	0.639	0.592	0.635	0.628

Note: Entries are standard deviation of the logarithm scaled TFPR ($\frac{TFPR_{si}}{TFPR_s^*}$).

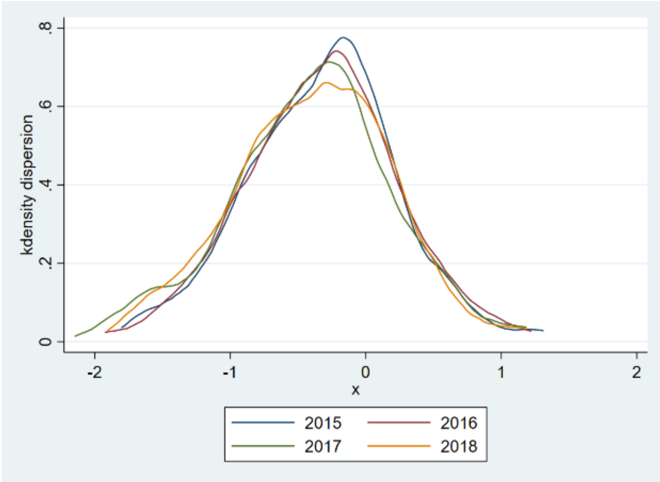
The efficiency gain is higher the larger the dispersion of the scaled TFPR (Dias, et al., 2016). The standard deviation is significantly larger than zero for all years and all groups, suggesting the misallocation exists in all groups. For the three groups, the standard deviation is the lowest in the low-tech group, and highest in the medium-tech group. This indicates that the input misallocation problem is the least serious in the low-tech industries and the most serious in the medium-tech industries. This is consistent with the actual economic situation in China. The level of market competition in the low-tech industries, such as for Food Manufacturing (C14), Textiles, Garments and Apparel Industry (C18) and Leather, Fur, Feathers, and Related Products and Shoe-making (C19), is the highest among the three groups. Therefore, the resource misallocation is the lowest in the low-tech industries. Medium-tech industries, including Raw Chemical Materials and Chemical Products (C26), Ferrous Metal Smelting and Extruding (C31) and Non-ferrous Metals Smelting & Rolling Processing (C32), rely heavily on the natural resources. Due to the monopolization and the control by the government, the market competition is insufficient in these industries, so the misallocation is larger (Wang and Niu, 2019).

Now we look at the TFPR dispersion change over the sample period. For the total economy, the change seems negligeable, decreasing from 0.664 in 2015 to 0.639 in 2018. The decrease in the TFPR dispersion indicates the allocation is more efficient. By looking at the TFPR dispersion change in the three groups, the TFPR dispersion in the low-tech group increases as the standard deviation increases from 0.574 in 2015 to 0.592 in 2018. The TFPR dispersion for high-tech firms stay at the same level in 2018 as in 2016, while it decreases a little in the middle of the sample years. It is noticeable that there is a consistent decrease of the TFPR dispersion in the medium-tech group. Wang and Niu (2019) explain that this is due to the success of supply side reforms in China from 2015, which aims to alleviate the industrial overcapacity. Therefore, we find that the input allocation becomes more efficient for medium-tech firms.

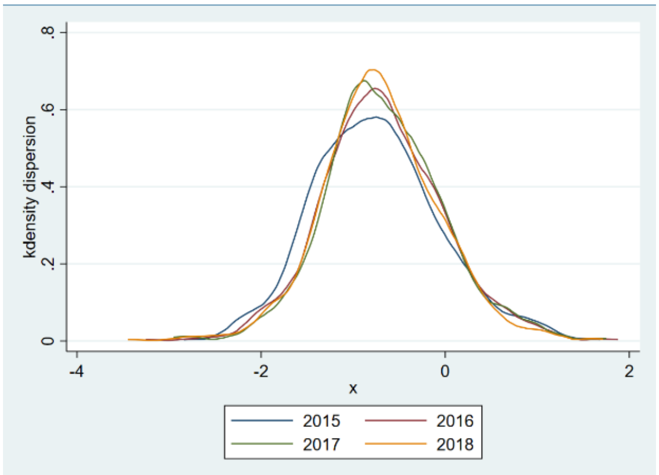
Figure 2.1 presents the distribution of the scaled TFPR for firms in the low-tech group, medium-tech group and high-tech group over the sample period. The density graphs show the change of the dispersion of scaled TFPR in each year, which is consistent with the S.D. change reported in Table 2.3. The tail becomes thicker for low-tech groups over time, while that for medium-tech firms becomes thinner, suggesting a less efficient input allocation and a more efficient allocation over time respectively.

Figure 2.1 Density of TFPR for three groups

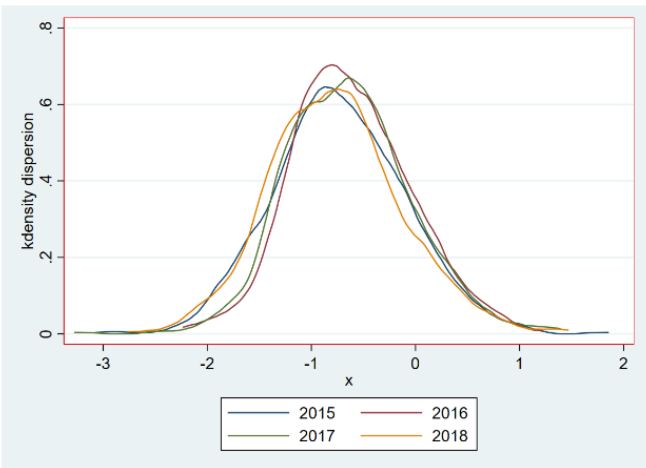
Low-tech group



Medium-tech group



High-tech group



We follow Dias et al. (2016)'s methodology to measure the correlation between the firms' productivity and their distortion. The results are shown in Table 2.4. Dias, et al. (2016) find that if the firms' productivity and their distortions are strongly positively correlated, the output gain would be higher, which means the efficiency loss from the inefficient allocation is larger. And if the physical productivity is not correlated with TFPR, the dispersion of TFPR would not cause a large efficiency loss and, the output gain would be small (Restuccia and Rogerson, 2008; Dias, et al., 2016). The positive correlation coefficient implies that more productive firms face higher distortions. The input for firms with higher productivity is insufficient so they tend to produce less, while firms with lower productivity tend to overproduce as they hire too much of inputs.

Table 2.4 Correlation between productivity and distortions

	Average (2015-2018)	2015	2016	2017	2018
whole economy	0.587	0.57	0.579	0.603	0.602
low-tech	0.632	0.558	0.644	0.697	0.657
medium-tech	0.566	0.538	0.547	0.6	0.589
high-tech	0.67	0.69	0.631	0.668	0.693

Note: Entries are the correlation coefficients between the firms' productivity and input distortions. We follow Dias et al. (2016)'s methodology to measure the correlation, where they use a firm's productivity weight in the industry $\rho_{si} = \frac{B_{si}^{\sigma-1}}{\sum_{i=1}^{m_s} B_{si}^{\sigma-1}}$ to replace a firm's productivity. They use the scaled TFPR ($\frac{TFPR_{si}}{TFPR_s^*}$) to express the firm-level distortion as $TFPR_{si}$ can be expressed in terms of the three input distortions in equation (19).

2.5.2 Reallocation gains

The R&D externality in our model plays an important role in the allocative efficiency gain. In the literature without any externality, the allocative efficiency gain only depends on the dispersion of the scaled TFPR. But in our model, as Eq. (33) suggests, the allocative efficiency gain depends not only on the dispersion of TFPR, but also on the change in R&D spillover after reallocation.

$$logY_s^* - logY_s = logTFP_s^* - logTFP_s + \delta_s(logX_s^* - logX_s)$$
$$= \frac{\sigma-1}{2} var(logTFPR_{si}) + \delta_s(logX_s^* - logX_s)$$

$$+\frac{\alpha_s}{2}var\big(\log\big(1+\tau_{K_{si}}\big)\big)+\frac{\beta_s}{2}var\big(\log\big(1+\tau_{L_{si}}\big)\big)$$
$$+\frac{\gamma_s}{2}var\big(\log\big(1+\tau_{H_{si}}\big)\big) \quad (33)$$

Table 2.5 Output gains from equalizing TFPR within industries

years	whole economy	low-tech	medium-tech	high-tech
2015	48.742	36.224	61.061	35.238
2016	41.092	34.017	47.928	33.849
2017	39.326	44.805	44.562	29.716
2018	36.324	40.323	38.682	31.354

Note: Entries for the output gains are given by $(Y^*/Y-1)*100$ and the output gap Y^*/Y is computed form Eq.(24). All the output gains are presented in percentages (%).

Table 2.5 presents the aggregate output gain from eliminating all the distortions by equalizing TFPR across firms in the same industry, which is computed from Eq. (22) and Eq. (23). We generate the output gain for each sample year from 2015 to 2018 and for the three groups. The output gain for the whole economy decreases over time, suggesting the allocative efficiency has improved after 2015. Wang and Niu (2019) explain the decreased resource misallocation as a result of the industrial adjustment in China in recent years. From our results, the largest (potential) gain occurs in the medium-tech group in the first two years, reaching at 61% in 2015 and 48% in 2016, while it reaches 45% in the low-tech group in 2017 and 40% in 2018. High-tech firms always gain the least from equalizing all distortions during the sample period, with the magnitude of 35% in 2015, 34% in 2016, 30% in 2017 and 31%in 2018. This suggests that high-tech firms are the most efficient in resource allocation between the three groups as the efficiency loss from the distortions in the high-tech industry is the smallest between the three types of firms.

The effect of the R&D externality differs for firms with different technology type. As Table 2.3 suggests, medium-tech firms are the main driver of the resource misallocation as the scaled TFPR for medium-tech firms is the most dispersed for all four years. They should always have the largest output gain when there is no externality. From our results with the R&D externality in Table 2.5, in 2015 and 2016, medium-tech firms have the largest gain and it is consistent with what literature suggests. But in the next two years, their output gain becomes lower than that in the low-tech group, which implies that the allocative gain is affected by R&D externality. For high-tech firms, the TFPR dispersion is lower than for the medium-tech group and higher than for the low-tech group. However, the output gain in the high-tech group from the reallocation is the smallest for all years, indicating that high-tech firms are the most efficient in resource allocation. We attribute this to the R&D spillover effect that high-tech firms benefit from. On the contrary, the scaled TFPR for low-tech firms is the least dispersed in Table 2.3. But the results in Table 2.5 show that the efficiency loss in the low-tech group is not the smallest among all groups in 2017 and 2018, which is not consistent to the literature that does not consider externality. Since R&D input only takes a small proportion in low-tech industries, the R&D spillover does not make a large effect in alleviating resource misallocation.

In order to gauge to what extent the R&D externality affects the allocative efficiency gain, we keep the R&D spillover fixed at the level before the reallocation to represent the situation where there is no R&D externality. In Table 2.6, the efficiency loss increases by around 50 percentage points for all the three groups. Particularly, high-tech firms now have the largest efficiency gain in the last two years, increasing from 30% to 93% in 2017 and from 31% to 119% in 2018. This implies that the efficiency loss could be overestimated when the R&D externality is not considered. Low-tech firms now have the smallest efficiency loss and this result is consistent with this group having the smallest dispersion in Table 2.3. The substantial increase in the output gain emphasizes the importance of R&D externality in alleviating the resource misallocation.

Table 2.6 Output gains from equalizing TFPR within industries (R&D spillover fixed)

years	whole economy	low-tech	medium-tech	high-tech
2015	95.379	42.513	108.656	100.007
2016	80.781	40.514	88.411	87.161
2017	85.635	54.613	89.359	92.921
2018	91.698	51.762	86.064	119.068

Note: Entries for the output gains are given by $(Y^*/Y-1)*100$ and the output gap Y^*/Y is computed form Eq.(24). All the output gains are presented in percentages (%).

2.5.3 Individual contribution of each input misallocation

In order to evaluate the contribution of eliminating each input distortion at a time to the output gain, we use eq. (33) to decompose the overall output gain into four parts: contribution from eliminating capital distortion, non-R&D labour distortion, R&D distortion and the interaction of the three input factors. Table 2.7 and Figure 2.2 present the output gain from eliminating one input distortion at a time while keeping the other two inputs fixed. From the results, the labour distortion contributes the most to the total output loss for the whole economy. The output gain is 23% in 2015, 17% in 2016, 19% in 2017 and 20% in 2018 if the labour distortions across firms are equalized at the industry level. This is consistent with Jin, et al. (2018), suggesting that labour misallocation is more serious than capital misallocation, though their study focuses on the misallocation aross industries and our study concentrates more on the misallocation within industries. However, the trend of the change in the importance of the labour distortion is different for the three technology groups. Its importance has an increasing trend from 17% in 2015 to 19% in 2018 in the low-tech group, while it decreases by around 4 pp in medium-tech group and high-tech group.

The capital distortion is the second most important in resource misallocation for the whole economy. In the low-tech group and the medium-tech group, the contribution of capital distortion to the output gain is significantly lower than labour distortion, while in the high-tech group, capital distortion contributes the most among the three distortions from 2016 to 2018.

Compared to above two distortions, the contribution from eliminating R&D distortion is much smaller as the largest size it has achieved is 1.8% in 2018 in the low-tech group. The maginitude of the R&D misallocation in the low-tech group is relatively the highest, while that in the medium-tech firms is the lowest. In particular, it causes an negative output gain of -0.2% for the whole economy in 2016. The negative output gain comes from the medium-tech group, -1.457% in 2016 and -0.024% in 2018. This indicates that the initial R&D allocation is more efficient for medium-tech firms in 2016 and 2018.

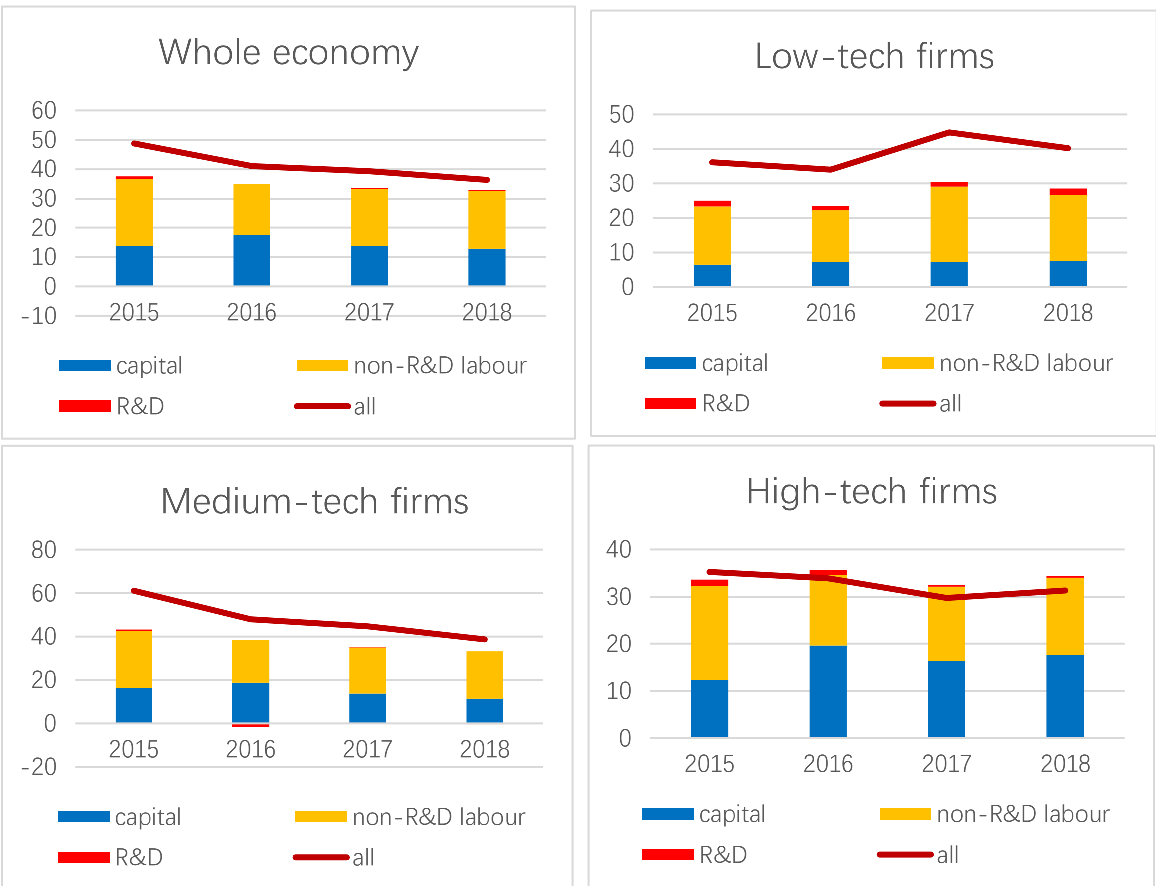
Table 2.7 Contribution of each distortion

	Whole economy				Low-tech firms			
	2015	2016	2017	2018	2015	2016	2017	2018
all	48.742	41.092	39.326	36.324	36.224	34.017	44.805	40.323
capital	13.64	17.539	13.776	12.91	6.529	7.307	7.209	7.529
labour	22.976	17.373	19.418	19.681	16.915	14.887	21.875	19.12
R&D	0.894	-0.216	0.42	0.387	1.618	1.377	1.385	1.813

	Medium-tech firms				High-tech firms			
	2015	2016	2017	2018	2015	2016	2017	2018
all	61.061	47.928	44.562	38.682	35.238	33.849	29.716	31.354
capital	16.369	18.89	13.761	11.265	12.254	19.672	16.383	17.62
labour	26.388	19.676	21.293	22.028	20.036	14.876	15.689	16.38
R&D	0.447	-1.457	0.158	-0.024	1.329	1.091	0.454	0.481

Note: Entries in the first row are the output gains from eliminating all the distortions simutaneously and are presented in Table 2.5. Entries in the second to forth row are the output gains from eliminating the distortion individually while keeping the other two inputs fixed at the initial level.

Figure 2.2 Contribution of each distortion



2.5.4 Alternative approach

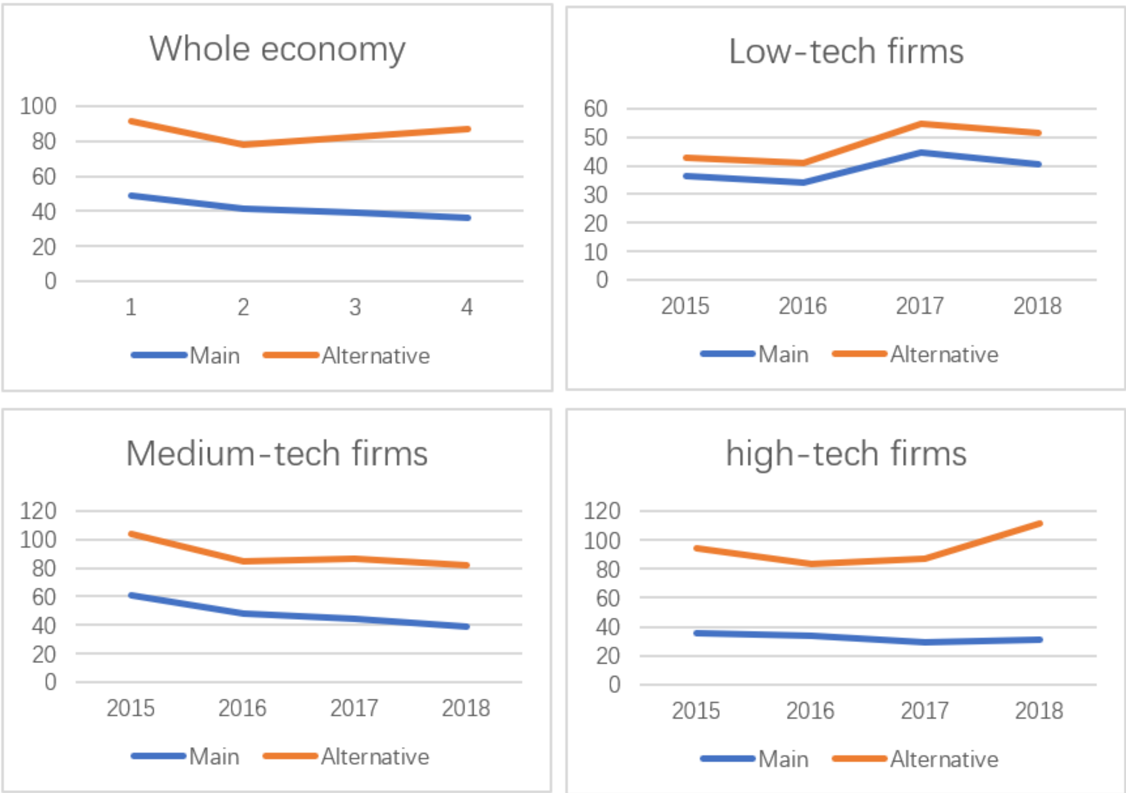
The input reallocation by equalizing the firm level distortions to the industry level does not achieve the most efficient level due to the R&D externality. We now consider the alternative approach that takes R&D spillover into account, by setting the new firm level R&D labour input to be a weighted average of the optimal amount of R&D employees that maximize the output without R&D spillover and the optimal amount of R&D employees that only maximize the R&D spillover. Therefore, when the firms choose their R&D input, it depends not only on the firm's own productivity level, but also on the industry level productivity, which relates to the R&D spillover. In our analysis, we find that this new allocation approach increases the output gain significantly. Table 2.8 and Figure 2.3 present the comparison between the output gain from the alternative allocation approach and from the baseline model. For the whole economy, the output gain from the alternative approach is higher than that from the main approach for all sample years, increasing by 42 pp in 2015, 37 pp in 2016, 43 pp in 2017 and 51 pp in 2018. The changes in the efficiency gain from these two approaches have a similar trend for the three groups with different technology types but the magnitudes differ. The high-tech group can benefit the most from the alternative allocation approach as the output gain increases by 59 pp in 2015, 50 pp in 2016, 57 pp in 2017 and 80 pp in 2018. The output gain in the medium-tech group increases by around 45 pp in each year. The extra gain for low-tech firms is the smallest, only increasing by 7 pp in 2015 and 2016, 10 pp in 2017 and 12 pp in 2018. Although the magnitude of the increase in the output gain differs across groups, all the groups can benefit from it, which stresses the necessity of considering R&D spillover in the R&D input decision. Therefore, there is no need to eliminate all R&D distortions in the industry. Rather, the output gain could be higher when the R&D distortion is partly kept when an appropriate weights for the solutions of maximizing the output and maximizing the R&D spillover are found.

Table 2.8 Output gain from the alternative reallocation approach

	whole economy		low-tech		medium-tech		high-tech	
years	Main	Alternative	Main	Alternative	Main	Alternative	Main	Alternative
2015	48.742	91.012	36.224	42.877	61.061	103.66	35.238	94.008
2016	41.092	77.762	34.017	40.756	47.928	84.737	33.849	83.516
2017	39.326	82.188	44.805	54.545	44.562	86.236	29.716	87.436
2018	36.324	87.002	40.323	51.722	38.682	81.714	31.354	111.384

Note: Both the output gains from equalizing TFPR in Table 2.5 and the output gains from the alternative reallocation approach are presented in Table 2.8. In the alternative reallocation approach, R&D input is a weighted average of the optimal amount of maximizing the output without R&D spillover and maximizing the R&D spillover only.

Figure 2.3 Output gain from alternative allocation approach



2.6 Robustness checks

2.6.1 The weight of R&D spillover in the output

The baseline model assumes that the R&D spillover and the firm's own R&D input have the same weight in the firm's output. That is, the parameter of the R&D spillover δ_s is equal to the parameter of the firm's own R&D input γ_s. The weight of R&D spillover δ_s in the output is the same for all firms in the same industry. In the robustness check, the magnitude of the impact of the R&D spillover is equalized for all the firms in all industries. We firstly compute the firm-level productivity that includes the R&D spillover:

$$A_{si} = \frac{Y_{si}}{{K_{si}}^{\alpha_s}{L_{si}}^{\beta_s}{H_{si}}^{\gamma_s}} \quad (37)$$

Then we regress it on the R&D spillover X_s in logarithm level using OLS:

$$lnA_{si} = c + \delta lnX_s \quad (38)$$

The estimated coefficient for the R&D spillover δ is the new measurement of the weight of R&D spillover δ_s. Table 2.9 shows the coefficient for the weight of the R&D spillover δ_s computed from the above approach and from the baseline model. In 2016 and 2017, both the low-tech group and the medium-tech group have higher δ_s than that in the baseline model, while δ_s in the high-tech group is lower. In 2015 and 2018, δ_s in the medium-tech group is only a half of that in the baseline model and δ_s in the low-tech group nearly does not change. Although δ_s in the high-tech group in the robustness check is always lower, the value in 2015 and 2018 is less than a third of that in the baseline model.

Table 2.9 The weight of R&D spillover in the output δ_s

		Low-tech	Meidum-tech	High-tech
	new	baseline	baseline	baseline
2015	0.041	0.044	0.092	0.189
2016	0.146	0.046	0.091	0.183
2017	0.153	0.056	0.112	0.204
2018	0.07	0.069	0.14	0.238

Note: The weight of R&D spillover in the baseline model is the average across all the industries in the subgroup.

Table 2.10 and Figure 2.4 present the reallocation gain with the δ_s in the robustness check (solid lines) and in the baseline model (dashed lines). By comparing the results, δ_s is closely related to the output gain as the output gain in Table 2.10 is consistent with the change of δ_s in Table 2.9. The increased δ_s causes a more efficient initial input allocation, while a smaller δ_s suggests a larger allocative efficiency loss. The output gain in the low-tech group does not change much in 2015 and 2018, but it decreases by 12pp in 2016 and 17pp in 2017. Medium-tech firms have lower output gains in 2016 and 2017 and higher gains in 2015 and 2018. The reallocation gain in the high-tech group with the new δ_s is always larger than that in the baseline model, especially in 2015 and 2018. It is because the externality of R&D could alleviate resource misallocation to some extent. As suggested by equation (33),

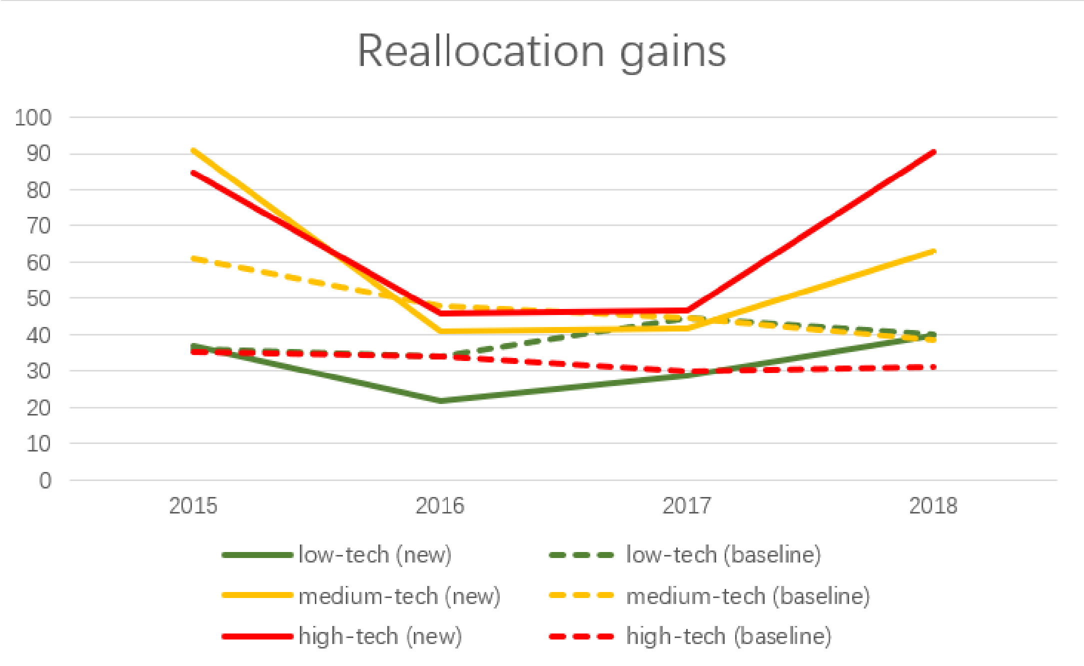
$$\begin{aligned} logY_s^* - logY_s &= logTFP_s^* - logTFP_s + \delta_s(logX_s{}^* - logX_s) \\ &= \frac{\sigma - 1}{2} var(logTFPR_{si}) + \delta_s(logX_s{}^* - logX_s) \\ &+ \frac{\alpha_s}{2} var(log(1+\tau_{K_{si}})) \frac{\beta_s}{2} var(log(1+\tau_{L_{si}})) \frac{\gamma_s}{2} var(log(1+\tau_{H_{si}})) \end{aligned} \quad (33)$$

According to the data, the R&D spillover after reallocation $X_s{}^*$ is smaller than its initial level X_s, so the change in the R&D spillover $(logX_s{}^* - logX_s)$ decreases the output gap $(logY_s^* - logY_s)$. Therefore, the output gap $(logY_s^* - logY_s)$ with a larger weight of R&D spillover δ_s is smaller than that with a smaller weight. The change in the weight of R&D spillover in Table 2.9 is consistent with the output gain change in Table 2.10 and Figure 2.4, showing that the larger the weight of the R&D spillover in the output, the smaller is the allocative efficiency loss and therefore the more efficient is the initial resource allocation.

Table 2.10 Output gains (with newly defined R&D spillover weight δ_s)

	low-tech		medium-tech		high-tech	
	new	baseline	new	baseline	new	baseline
2015	36.96	36.224	90.678	61.061	84.86	35.238
2016	21.92	34.017	41.031	47.928	45.866	33.849
2017	28.653	44.805	41.767	44.562	46.757	29.716
2018	39.807	40.323	63.021	38.682	90.313	31.354

Figure 2.4. Output gains (with newly defined R&D spillover weight δ_s)



2.6.2 R&D stock as a measure of R&D input

The baseline model uses the number of R&D employees to measure the R&D input. But one may argue that it takes time to hire new R&D employees that fit a firm's R&D project and due to the competition of the R&D activities across firms, firms would not arbitrarily hire or fire R&D employees in the same way as non-R&D employees. Therefore, R&D employees might not fully represent a firm's investment in the R&D input. However, R&D stock, which is measured by spending sum on R&D activities, is more flexible when a firm decides to increase or decrease the R&D input.

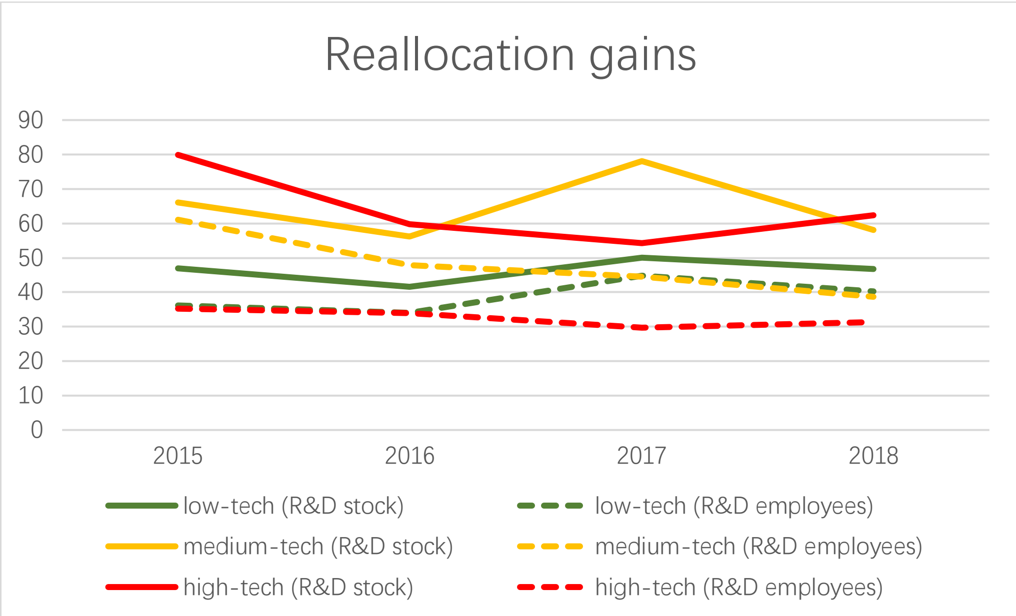
We replace the R&D employees with the R&D stock to see whether the results would change. The calibration of weights in the production function unchanged as we have the assumption that the sum of the weights of three inputs equals to 1. We show how the parameters are calibrated in Appendix 2.B.

The reallocation gain results of using R&D stock as the measure of R&D input are shown in Table 2.11 and Figure 2.5. The output loss estimated with R&D stock is shown with solid lines and that estimated with R&D employees in the baseline model is shown with dashed lines. The largest increase of the output gain happens in the high-tech group, increasing from 35% to 80% in 2015 and from 31% to 62% in 2018. Low-tech firms, on the contrary, have smaller output loss using the R&D stock as input, except that it does not change much in 2015. The reason of differences of the output gain change could be the different magnitudes of the variable of R&D input. In the robustness check, R&D spending takes a larger proportion of the inputs in the production in high-tech firms than the R&D employees. It achieves the largest output increase in this group. But in the low-tech group, it is not as important as in the high-tech group, so whether the R&D stock or the number of R&D employees is chosen does not make much difference.

Table 2.11 Output gains (R&D input is measured by R&D stock)

	low-tech		medium-tech		high-tech	
	R&D stock	baseline (R&D employees)	R&D stock	baseline (R&D employees)	R&D stock	baseline (R&D employees)
2015	46.957	36.224	66.128	61.061	79.892	35.238
2016	41.581	34.017	56.191	47.928	59.816	33.849
2017	50.043	44.805	78.085	44.562	54.265	29.716
2018	46.73	40.323	58.087	38.682	62.362	31.354

Figure 2.5 Output gains (R&D input is measured by R&D stock)



2.7 Conclusion

In this chapter, we quantify the output loss from capital, labour and R&D input misallocation in Chinese manufacturing industries by including R&D input and R&D externality in Hsieh and Klenow (2009) resource misallocation model. We find that in the presence of R&D externality, the output loss from resource misallocation for all manufacturing industries is around 49% in 2015 and decreases to 36% in 2018. This indicates that the initial resource allocation efficiency has improved during the sample period. We also compute the allocative efficiency loss for sub groups of industries with different technology type. The results show that the allocative efficiency loss in medium-tech manufacturing industries（Industries that rely heavily on natural resources such as Chemical Products industry and Ferrous Metal Smelting and Extruding industry）is significantly higher than that in low- and high- tech manufacturing industries. But it improves in the following years. This shows that the reform, which began in 2015, in reducing overcapacity in China, has had significant results. Allocative efficiency losses have been relatively low in the high-tech industry. This is related to large share of R&D investment in high-tech industries that generates large scale of R&D externality. It mitigates the misallocation of R&D resources to some extent.

To explore the impact of the externality of R&D on allocative efficiency, we compare the results generated from the model with and without R&D spillover. The results show that when R&D externalities are not included in the model, the estimated efficiency loss caused by resource misallocation is substantially higher, especially in high-tech industries. The difference of the estimated output losses indicates the significant impact of R&D externality on resource allocative efficiency.

As R&D externalities can have a significant impact on the efficiency of resource allocation, this factor should be taken into account in the search for optimal resource allocation approach. Therefore, we adjust the traditional R&D allocation approach of equalizing R&D distortions across firms. Instead, we adopt a weighted mix of the solution of the traditional approach that maximize firms' output and the solution that maximizes the R&D spillover. The result shows that this new allocation approach generates higher aggregate output, especially for high-tech industries. The empirical result is consistent with our theoretical derivation: In the presence of R&D externality, equalizing all the distortions across firms does not lead to the most efficient allocation. This result gives similar conclusions to Ayerst's (2021) findings, which emphasize the extra contribution of dealing with the gap between private and public returns.

The findings provide some policy suggestions. The misallocation of input resources, while decreasing over time, has not been completely eliminated. The government should cultivate market system and improve marketization degree of input factor resources. Also, subsidies and support for low-productivity firms should be reduced, so that high-productivity firms can get access to more resources. Regarding the R&D or human capital resources, developing the information infrastructure is more encouraged as it facilitates the communication of human capital. The economic performance can be improved by the increased R&D spillover without eliminating all human capital misallocation. The government should create environment for firms to promote cooperation and competition, which enhance the R&D spillover effect and increase the public return.

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Appendix 2.A Contribution of eliminating each input misallocation separately

A1. Eliminating capital misallocation

Assuming that the firms keep their inputs of labour and human capital fixed, they maximize their profits w.r.t. K_{si}:

$$\max_{K_{si}} \left(B_{si}K_{si}^{\alpha_s}L_{si}^{\beta_s}H_{si}^{\gamma_s}X_s^{\delta_s}\right)^{1-\frac{1}{\sigma}} - \left(1+\tau_{K_s}\right)r_s K_{si}$$

The FOC is

$$\alpha_s \frac{\sigma-1}{\sigma}\left(B_{si}L_{si}^{\beta_s}H_{si}^{\gamma_s}X_s^{\delta_s}\right)^{\frac{\sigma-1}{\sigma}} K_{si}^{\alpha_s\frac{\sigma-1}{\sigma}-1} = \left(1+\tau_{K_s}\right)r_s$$

Let $\Psi_{si} \equiv B_{si}L_{si}^{\beta_s}H_{si}^{\gamma_s}X_s^{\delta_s}$. (It is evaluated at the original values.) Thus,

$$K_{si} = \left(\frac{\alpha_s}{\left(1+\tau_{K_s}\right)r_s}\frac{\sigma-1}{\sigma}\right)^{\frac{\sigma}{\sigma-\alpha_s(\sigma-1)}} \Psi_{si}^{\frac{\sigma-1}{\sigma-\alpha_s(\sigma-1)}}$$

$$K_s = \left(\frac{\alpha_s}{\left(1+\tau_{K_s}\right)r_s}\frac{\sigma-1}{\sigma}\right)^{\frac{\sigma}{\sigma-\alpha_s(\sigma-1)}} \sum_i \Psi_{si}^{\frac{\sigma-1}{\sigma-\alpha_s(\sigma-1)}}$$

From the above two equations, the new capital input of firm si is

$$K_{si} = K_s \frac{\Psi_{si}^{\frac{\sigma-1}{\sigma-\alpha_s(\sigma-1)}}}{\sum_i \Psi_{si}^{\frac{\sigma-1}{\sigma-\alpha_s(\sigma-1)}}}$$

We can also calculate the common capital distortion in sector s such that the aggregate capital stock stays fixed.

$$1+\tau_{K_s} = \frac{\alpha_s}{r_s}\frac{\sigma-1}{\sigma}\left(\sum_i \Psi_{si}^{\frac{\sigma-1}{\sigma-\alpha_s(\sigma-1)}}\right)^{\frac{\sigma-\alpha_s(\sigma-1)}{\sigma}} K_s^{\frac{\alpha_s(\sigma-1)-\sigma}{\sigma}}$$

Finally, one can calculate

$$\widetilde{Y_{si}} = \Psi_{si}K_{si}^{\alpha_s}.$$

Then, the output gap is

$$\frac{\widetilde{Y_s}}{Y_s} = \left(\frac{\sum_i \left(\widetilde{Y}_{si}\right)^{\frac{\sigma-1}{\sigma}}}{\sum_i \left(Y_{si}\right)^{\frac{\sigma-1}{\sigma}}}\right)^{\frac{\sigma}{\sigma-1}}$$

A2. Eliminating labour misallocation

Assuming that the firms keep their inputs of physical and human capital fixed, they maximize their profits w.r.t. L_{si}:

$$\max_{L_{si}} \left(B_{si}K_{si}^{\alpha_s}L_{si}^{\beta_s}H_{si}^{\gamma_s}X_s^{\delta_s}\right)^{1-\frac{1}{\sigma}} - \omega_{L_s}\left(1+\tau_{L_{si}}\right)L_{si}$$

The FOC is

$$\beta_s \frac{\sigma-1}{\sigma}\left(B_{si}K_{si}^{\alpha_s}H_{si}^{\gamma_s}X_s^{\delta_s}\right)^{\frac{\sigma-1}{\sigma}} L_{si}^{\beta_s\frac{\sigma-1}{\sigma}-1} = \left(1+\tau_{L_s}\right)\omega_{L_s}$$

Let $\Psi_{si} \equiv B_{si}K_{si}^{\alpha_s}H_{si}^{\gamma_s}X_s^{\delta_s}$. (It is again evaluated at the original values.) Thus,

$$L_{si} = \left(\frac{\beta_s}{\left(1+\tau_{L_s}\right)\omega_{L_s}}\frac{\sigma-1}{\sigma}\right)^{\frac{\sigma}{\sigma-\beta_s(\sigma-1)}} \Psi_{si}^{\frac{\sigma-1}{\sigma-\beta_s(\sigma-1)}}$$

$$L_s = \left(\frac{\beta_s}{\left(1+\tau_{L_s}\right)\omega_{L_s}}\frac{\sigma-1}{\sigma}\right)^{\frac{\sigma}{\sigma-\beta_s(\sigma-1)}} \sum_i \Psi_{si}^{\frac{\sigma-1}{\sigma-\beta_s(\sigma-1)}}$$

From the above two equations, the new labour input of firm si is

$$L_{si} = L_s \frac{\Psi_{si}^{\frac{\sigma-1}{\sigma-\alpha_s(\sigma-1)}}}{\sum_i \Psi_{si}^{\frac{\sigma-1}{\sigma-\alpha_s(\sigma-1)}}}$$

We can also calculate the common labour distortion in sector s such that the aggregate labour stock stays fixed.

$$1+\tau_{L_s} = \frac{\beta_s}{\omega_{L_s}}\frac{\sigma-1}{\sigma}\left(\sum_i \Psi_{si}^{\frac{\sigma-1}{\sigma-\beta_s(\sigma-1)}}\right)^{\frac{\sigma-\beta_s(\sigma-1)}{\sigma}} K_s^{\frac{\beta_s(\sigma-1)-\sigma}{\sigma}}$$

Finally, calculate

$$\widetilde{Y_{si}} = \Psi_{si}L_{si}^{\beta_s}$$

The output gap is again:

$$\frac{\widetilde{Y_s}}{Y_s} = \left(\frac{\sum_i\left(\widetilde{Y}_{si}\right)^{\frac{\sigma-1}{\sigma}}}{\sum_i\left(Y_{si}\right)^{\frac{\sigma-1}{\sigma}}}\right)^{\frac{\sigma}{\sigma-1}}$$

A3. Eliminating R&D distortion

Assuming that the firms keep their inputs of labour and physical capital fixed, they maximize their profits w.r.t. H_{si}:

$$\max_{H_{si}} \left(B_{si}K_{si}^{\alpha_s}L_{si}^{\beta_s}H_{si}^{\gamma_s}X_s^{\delta_s}\right)^{1-\frac{1}{\sigma}} - \omega_{H_s}(1+\tau_{H_{si}})H_{si}$$

The FOC is

$$\gamma_s\frac{\sigma-1}{\sigma}\left(B_{si}L_{si}^{\beta_s}H_{si}^{\gamma_s}X_s^{\delta_s}\right)^{\frac{\sigma-1}{\sigma}}H_{si}^{\gamma_s\frac{\sigma-1}{\sigma}-1} = \left(1+\tau_{H_s}\right)\omega_{H_s}$$

Let now $\Psi_{si} \equiv B_{si}K_{si}^{\alpha_s}L_{si}^{\beta_s}$. (It is evaluated at the original values.) Thus,

$$H_{si} = \left(\frac{\gamma_s}{\left(1+\tau_{H_s}\right)\omega_{H_s}}\frac{\sigma-1}{\sigma}\right)^{\frac{\sigma}{\sigma-\gamma_s(\sigma-1)}}X_s^{\frac{\delta_s(\sigma-1)}{\sigma-\gamma_s(\sigma-1)}}\Psi_{si}^{\frac{\sigma-1}{\sigma-\gamma_s(\sigma-1)}}$$

$$H_s = \left(\frac{\gamma_s}{\left(1+\tau_{H_s}\right)\omega_{H_s}}\frac{\sigma-1}{\sigma}\right)^{\frac{\sigma}{\sigma-\gamma_s(\sigma-1)}}X_s^{\frac{\delta_s(\sigma-1)}{\sigma-\gamma_s(\sigma-1)}}\sum_i\Psi_{si}^{\frac{\sigma-1}{\sigma-\gamma_s(\sigma-1)}}$$

From the last two equations:

$$H_{si} = \frac{\Psi_{si}^{\frac{\sigma-1}{\sigma-\gamma_s(\sigma-1)}}}{\sum_i\Psi_{si}^{\frac{\sigma-1}{\sigma-\gamma_s(\sigma-1)}}}H_s$$

$$X_s = \Pi_i H_{si}^{\frac{1}{m_s}} = \frac{\Pi_i\Psi_{si}^{\frac{1}{m_s}\frac{\sigma-1}{\sigma-\gamma_s(\sigma-1)}}}{\sum_i\Psi_{si}^{\frac{\sigma-1}{\sigma-\gamma_s(\sigma-1)}}}H_s$$

Finally,

$$\widetilde{Y_{si}} = \Psi_{si}X_s^{\delta_s}H_{si}^{\gamma_s}$$

Appendix 2.B Parameter calibration

In the robustness test, we replace R&D employees with R&D stock in the measurement of the R&D input. In Table Appendix 2.B, we show how parameters are calibrated in the benchmark model where the R&D input is measured by R&D employees and robustness check where it is measured by R&D stock. We calibrate weights in production function under the assumption that the sum of the weights of three inputs equals to 1. The capital share α_s in both benchmark model and the robustness test are calibrated by the ratio of the aggregate physical capital stock to the aggregate output, which measures capital's contribution to the output in the industry. In the benchmark model, we use the ratio of aggregate new product sales to the aggregate main business sales ζ_s in the industry to separate the rest shares into the non-R&D labour share β_s and the R&D share γ_s, where we adopt the aggregate new product sales to represent the contribution of R&D to the output. In the robustness test, we calibrate the R&D share γ_s with the ratio of aggregate R&D stock to the aggregate output. The non-R&D labour share β_s is calibrated with the assumption that the sum of weights of three inputs equals to 1.

And for the parameters of the price of the three inputs, we adopt Chen (2017)'s assumption that the sum of all the three input cost equals to the aggregate output, which implies that the cost of each input equals the output of it. The non-R&D labour cost ω_{L_s} in both benchmark and robustness test is calibrated by dividing the aggregate wage for non-R&D employees by the total amount of non-R&D employees. Then we use the ratio of the aggregate new product sales to the aggregate output ζ_s to separate the total wage into the wage for non-R&D employees and the wage for R&D employees in the benchmark. And in the robustness test, since we measure R&D input by R&D stock, we use ζ_s to separate the total cost of physical capital stock and R&D stock into the cost for physical capital stock and the cost for R&D stock. Then the rental rate of capital r_s is calibrated by dividing the revenue or output of physical capital (equals to the cost of physical capital under the assumption) by the total amount physical capital stock. The R&D cost ω_{H_s} (equals to the cost of R&D capital under the assumption) is calibrated by dividing the output from the R&D by the total amount of R&D stock.

Appendix 2.B Parameter calibration

	Benchmark	Robustness
	R&D input (R&D employees)	R&D input (R&D stock)
α_s capital share	$\frac{\sum_{i=1}^{m_s} K_{si}}{\sum_{i=1}^{m_s} P_{si}Y_{si}}$	$\frac{\sum_{i=1}^{m_s} K_{si}}{\sum_{i=1}^{m_s} P_{si}Y_{si}}$
β_s non-R&D labour share	$\frac{(1-\zeta_s) * (\sum_{i=1}^{m_s} P_{si}Y_{si} - \sum_{i=1}^{m_s} K_{si})}{\sum_{i=1}^{m_s} P_{si}Y_{si}}$	$\frac{(\sum_{i=1}^{m_s} P_{si}Y_{si} - \sum_{i=1}^{m_s} K_{si} - \sum_{i=1}^{m_s} R\&D\ stock_{si})}{\sum_{i=1}^{m_s} P_{si}Y_{si}}$
γ_s R&D share	$\frac{\zeta_s * (\sum_{i=1}^{m_s} P_{si}Y_{si} - \sum_{i=1}^{m_s} K_{si})}{\sum_{i=1}^{m_s} P_{si}Y_{si}}$	$\frac{\sum_{i=1}^{m_s} R\&D\ stock_{si}}{\sum_{i=1}^{m_s} P_{si}Y_{si}}$
ω_{L_s} non-R&D labour cost	$\frac{\zeta_s * \sum_{i=1}^{m_s} Wage\ bill_{si}}{\sum_{i=1}^{m_s} L_{si}}$	$\frac{\zeta_s * \sum_{i=1}^{m_s} Wage\ bill_{si}}{\sum_{i=1}^{m_s} L_{si}}$
r_s rental rate of capital	$\frac{\sum_{i=1}^{m_s} P_{si}Y_{si} - \sum_{i=1}^{m_s} Wage\ bill_{si}}{\sum_{i=1}^{m_s} K_{si}}$	$\frac{(1-\zeta_s) * (\sum_{i=1}^{m_s} P_{si}Y_{si} - \zeta_s * \sum_{i=1}^{m_s} Wage\ bill_{si})}{\sum_{i=1}^{m_s} K_{si}}$
ω_{H_s} R&D cost	$\frac{(1-\zeta_s) * \sum_{i=1}^{m_s} Wage\ bill_{si}}{\sum_{i=1}^{m_s} H_{si}}$	$\frac{\zeta_s * [\sum_{i=1}^{m_s} P_{si}Y_{si} - (1-\zeta_s) * \sum_{i=1}^{m_s} Wage\ bill_{si}]}{\sum_{i=1}^{m_s} H_{si}}$

Note: ζ_s is the ratio of total new product sales to the total main business revenue in industry s. This ratio is used to separate the wage paid for R&D and non-R&D employees in the benchmark model and separate the physical capital cost and R&D capital cost in the robustness test.

Chapter 3 Resource misallocation in the presence of R&D spillovers in the UK manufacturing sector

3.1 Introduction

It is well known that UK productivity growth has slowed down after the 2008 financial crisis (Patterson et al., 2016; Goodridge et al., 2018; Crafts and Mills, 2020), and it is known as the "UK productivity puzzle". Poor economic performance attracts people's interest in exploring the determinants of output and productivity. One perspective is to focus on resource misallocation (Restuccia and Rogerson (2008); Hsieh and Klenow (2009); Jones, 2011; Song et al., 2015; Boeing, 2016; Choi, 2020), including the inputs of capital, labour, energy, and R&D resources.

In addition to these regular input resources, R&D spillover also matters for productivity (Arrow, 1962; Nelson, 1959). Ugur et al. (2020) note the two sides of the externality of R&D. While the R&D spillover effect would cause an under-investment problem, it would also lead to a productivity increase. They also find that the impact of R&D spillover is smaller than that of R&D capital itself. In contrast, Audretsch and Belitski (2020) find that knowledge spillovers are more critical than R&D for firm productivity in the UK. Therefore, we would like to explore the contribution of R&D spillover to productivity and output.

Our analysis aims to gauge the resource misallocation in the presence of the externality of R&D spillover. It follows a similar structure to the literature (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Jones, 2011; Song et al., 2015; Boeing, 2016; Choi, 2020). Similar to the literature, we represent the firm-level input price distortion by introducing a concept of "wedge" or "tax", which is measured by the marginal revenue product of each input factor. As the literature suggests, the allocation is inefficient when firms pay different actual input prices. That is when more productive firms have to pay higher prices to hire inputs while the less effective firms pay less. This would cause output loss. The literature suggests that the policymaker should implement policies to ensure all firms face the same input price to achieve an efficient resource allocation and, therefore, a larger output. Therefore, more productive firms would be able to hire more inputs, and less productive firms hire less. During the process, as the more productive firms hire more inputs with a lower price, the marginal product of each input factor would decrease, and vice versa. Until the marginal products of input factors become equivalent for all firms, the input allocation is the most efficient. However, our results are different from the results generated in the literature. In our model, the optimum allocation does not require the marginal products of R&D input to be equivalent among firms. Instead, the output gain is larger when a certain level of dispersion in R&D input distortion is kept. That is, firms with lower productivity should pay a lower price for R&D inputs than suggested in the literature. At the same time, higher productivity firms should have higher R&D input costs than suggested in the literature.

The main difference is that we consider the effect of the externality of R&D, which is an essential characteristic of R&D input. The production function in our model consists of capital, labour, and R&D inputs, as well as R&D spillover. To present the role of the externality of R&D spillover in production, we compare the output gain when the R&D spillover factor changes with the R&D input allocation and when the R&D spillover factor is fixed at the initial value. There are mainly two allocation approaches to eliminate resource misallocation. The first approach follows the insight of the literature, in which there does not exist any externality. The literature suggests that allocation is optimal when all firms face the same input price wedge, in other words, when the input price distortions are equalised across firms. In the second allocation approach, we allocate inputs to maximize the aggregate output in the presence of R&D spillover. Due to the externality of R&D spillover, this approach keeps the dispersion in the R&D input distortions across firms, implying that the allocation policy would allow the actual R&D input price to be different for firms. We also evaluate the individual contribution of each input misallocation to the output loss. Similar to the literature (Hsieh and Klenow, 2009; Chen and Irarrazabal, 2013; Ryzhenkov and Mykola, 2016), we do it by decomposing the productivity in terms of input distortions under the central limit theorem. In the end, we compare the results in 2019 and 2013 to see whether there is deterioration in allocative efficiency.

In the traditional estimation approach, there is no externality. The estimated output loss from resource misallocation is around 76% in 2019. The allocative efficiency differs in groups with different technology types. The medium-high-tech industries suffer the most from misallocation, while the output loss in the medium-low-tech industries is the smallest among all groups. In addition, we also find that the output loss is overestimated when we analyse R&D input misallocation without considering its externality. Once we allow the R&D spillover to change, the output gain is smaller. The estimated output loss is larger when we use the initial value of R&D spillover in reallocation.

We then propose an optimal solution that generates a larger output gain given the externality of R&D spillover. In the industry output decomposition section, we find that capital misallocation contributes the largest to output loss. Labour misallocation also reduces the output, but the magnitude is much smaller than due to capital misallocation. The initial R&D allocation does not harm the output, which makes the estimated output gain smaller in the traditional allocation approach that equalises R&D input distortions. In the optimal allocation, the contribution of eliminating the capital and labour misallocation remains the same. But the reallocation of R&D input could generate a higher output and, therefore, higher allocative efficiency. In the end, we compare the allocative efficiency in 2019 and 2013. The allocation is more efficient in 2013, as the estimated output loss is smaller in all groups, indicating an allocative efficiency deterioration in 2019.

Our analysis contributes to the vast literature on resource misallocation by emphasising the role of the externality. We find a trade-off between productivity and knowledge spillover, which indicates that the allocation approach suggested by the literature is not the most efficient and can be improved whenever there are externalities. We propose an improved resource allocation approach by including the R&D spillover term in the output maximisation problem. This approach improves allocative efficiency, which leads to higher output.

The rest of this chapter is structured as follows. Section 2 presents the theoretical framework to link the output with the input misallocation. It also describes the resource reallocation approaches as well as the output decomposition. Section 3 describes the data used in the analysis, parameter calibration, and industry classification. Section 4 discusses the empirical results and gives policy suggestions. The conclusion is in Section 5.

3.2 Model

3.2.1 Theoretical framework

We extend the model of Hsieh and Klenow (2009) by introducing R&D externality. There is a single final good that is produced by a representative firm in a perfectly competitive market. To produce the final good, this firm combines the outputs of industries $s = 1, \dots, S$ using a Cobb-Douglas production technology:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s}$$

where Y and Y_s are the quantities of the final good and industry s output, respectively. Production exhibits constant returns to scale, $\prod_{s=1}^{S} \theta_s = 1$. In the equilibrium, $\theta_s = \frac{P_s Y_s}{PY}$ holds, where P and P_s are the prices of the final good and industry s output, respectively. The final good serves as a numeraire, and so $P = 1$.

The industry s output is also produced by a representative firm in a perfectly competitive market. It combines the differentiated products of firms si, $i = 1, \dots, m_s$, using a CES production technology:

$$Y_s = \left(\sum_{i=1}^{m_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

, where Y_{si} is the quantity of firm si output. σ is the elasticity of substitution, which is the same for all industries. In the equilibrium,

$$P_{si} = P_s \left(\frac{Y_s}{Y_{si}} \right)^{\frac{1}{\sigma}}$$

holds, where P_{si} is the price of firm si output. We will only consider intra-industry reallocation of resources. Therefore, similar to Dias et al. (2016), we impose a normalization that $P_s Y_s^{1/\sigma} = 1$, and so $P_{si} = Y_{si}^{-1/\sigma}$. We say that firms si, $i = 1, \dots, m_s$ belong to industry s.

Firm si ($s = 1, \dots, S$, $i = 1, \dots, m_s$) produces its output using a Cobb-Douglas production technology:

$$Y_{si} = B_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s} H_{si}^{\gamma_s} X_s^{\delta_s} \tag{2}$$

where B_{si}, K_{si}, and L_{si} are firm si total factor productivity (TFP), capital, and labour, respectively. H_{si} stands for the resources that firm si devotes to R&D. In this study we use the number of researchers conducting R&D activities as R&D input, we will refer to H_{si} as R&D input or R&D researchers. There is ample empirical evidence that R&D often results in spill-overs that affect other firms in the industry (Jaffe, 1986; Keller, 2004; Mahony and Vecchi, 2007; Xiao et al., 2021).

R&D spill-over, which is the same for all firms in industry s, is captured by the variable X_s, and it is a geometric average of $R\&D$ inputs by the firms in industry s:

$$X_s = \prod_{j=1}^{m_s} H_{si}^{\frac{1}{m_s}} \tag{3}$$

Although R&D spill-over depends on H_{si}, we assume that firm si treats X_s as exogenous. α_s, β_s, and γ_s are the industry-specific factor shares that take values between 0 and 1. We assume that the production function exhibits constant returns to scale in the inputs that the firm controls: $\alpha_s + \beta_s + \gamma_s = 1$. The parameter δ_s determines the strength of R&D spill-over on firm si output.

The parameters r_s, w_s, and q_s denote the rental rate of capital, the wage rate of labour, and the price of R&D input, respectively. We allow the input prices to be industry specific. Firm si might employ an input at a level where the marginal revenue product of that input is not equalized to its price. We can think that firm si effectively faces prices of $(1+\tau_{K_{si}})r_s$, $(1+\tau_{L_{si}})w_s$, and $(1+\tau_{H_{si}})q_s$ for capital, labour, and R&D input. We refer to the variables $\tau_{K_{si}}$, $\tau_{L_{si}}$, and $\tau_{H_{si}}$ as distortions.

Since firm si produces a differentiated product, it possesses a market power. This implies that it faces a downward sloping inverse demand function $P_{si} = Y_{si}^{-1/\sigma}$. Firm si chooses inputs to maximize its profit:

$$P_{si}Y_{si} - (1+\tau_{K_{si}})r_s K_{si} - (1+\tau_{L_{si}})w_s L_{si} - (1+\tau_{H_{si}})q_s H_{si}$$

subject to the production function in (2) and the inverse demand function. The first order conditions are

$$\frac{\sigma-1}{\sigma}\frac{\alpha_s Y_{si}^{\frac{\sigma-1}{\sigma}}}{K_{si}} = (1+\tau_{K_{si}})r_s \tag{4}$$

$$\frac{\sigma-1}{\sigma}\frac{\beta_s Y_{si}^{\frac{\sigma-1}{\sigma}}}{L_{si}} = \left(1+\tau_{L_{si}}\right)\omega_s \tag{5}$$

$$\frac{\sigma-1}{\sigma}\frac{\gamma_s Y_{si}^{\frac{\sigma-1}{\sigma}}}{H_{si}} = \left(1+\tau_{H_{si}}\right)q_s \tag{6}$$

If there is a change in distortions due to the government intervention, it will lead to reallocation of resources and, consequently, to a change in output. In fact, it is easier to start by defining the new allocation of resources. Then, we can use (3) to calculate the new R&D spill-overs and (2) to calculate the new outputs. Finally, we use (4)-(6) to recover the new distortions. Note, however, that we will keep the input prices at their original level. Therefore, we only consider the reallocation of resources that keep the aggregate industry demand for inputs at the original level.

3.2.2 The social planner's problem

In this section, we identify a couple of candidates for allocation of inputs. Later we use the data from British manufacturing industries to evaluate the output gains from implementing these allocations.

Let $K_s = \sum_{i=1}^{m_s} K_{si}$, $L_s = \sum_{i=1}^{m_s} L_{si}$, and $H_s = \sum_{i=1}^{m_s} H_{si}$ be the aggregate quantities of inputs in industry s. The social planner maximizes Y_s taking the aggregate quantities of inputs in industry s as given. Substituting (2) and (3) into (1) and taking the logarithm, the planner's problem is

$$\max_{\{K_{si},L_{si},H_{si}\}_{i=1}^{m_s}} \log Y_s = \frac{\sigma}{\sigma-1}\log\left(\sum_{j=1}^{m_s}\left(B_{sj}K_{sj}^{\alpha_s}L_{si}^{\beta_s}H_{sj}^{\gamma_s}\right)^{\frac{\sigma-1}{\sigma}}\right) + \frac{\delta_s}{m_s}\sum_{j=1}^{m_s}\log H_{sj}$$

subject to

$$K_s = \sum_{i=1}^{m_s} K_{si},$$

$$L_s = \sum_{i=1}^{m_s} L_{si}$$

$$H_s = \sum_{i=1}^{m_s} H_{si}$$

We firstly assume that there are no R&D spillover effects: $\delta_s = 0$. The solution to the planner's problem is given by

$$\frac{K_{si}}{K_s} = \frac{L_{si}}{L_s} = \frac{H_{si}}{H_s} = \frac{Y_{si}^{\frac{\sigma-1}{\sigma}}}{\sum_{j=1}^{m_s} Y_{sj}^{\frac{\sigma-1}{\sigma}}} = \frac{B_{si}^{\sigma-1}}{\sum_{j=1}^{m_s} B_{sj}^{\sigma-1}} \tag{7}$$

for all $i = 1, \dots, m_s$. Comparison with (4)-(6) tells that if we want to implement this solution as the equilibrium outcome, the distortions must be equalized across firms: There exist τ_{K_s}, τ_{L_s}, and τ_{H_s} such that $\tau_{K_{si}} = \tau_{K_s}$, $\tau_{L_{si}} = \tau_{L_s}$, and $\tau_{H_{si}} = \tau_{H_s}$ for all $i = 1, \dots, m_s$. This is the standard case that is considered in the literature when there are no externalities (Hsieh and Klenow, 2009; Marques, et al. 2014; Benkovskis, 2015; Chen, 2017; Choi, 2020).

Now we consider the planner's problem in the presence of R&D spill-over. The conditions that describe the optimum are

$$\frac{K_{si}}{K_s} = \frac{L_{si}}{L_s} = \frac{Y_{si}^{\frac{\sigma-1}{\sigma}}}{\sum_{j=1}^{m_s} Y_{sj}^{\frac{\sigma-1}{\sigma}}} \tag{8}$$

and

$$\frac{H_{si}}{H_s} = \frac{\gamma_s Y_{si}^{\frac{\sigma-1}{\sigma}} + \frac{\delta_s}{m_s} \sum_{j=1}^{m_s} Y_{sj}^{\frac{\sigma-1}{\sigma}}}{(\gamma_s + \delta_s) \sum_{j=1}^{m_s} Y_{sj}^{\frac{\sigma-1}{\sigma}}} \tag{9}$$

for all $i = 1, \dots, m_s$. These conditions imply that in the optimum, $\tau_{K_{si}} = \tau_{K_s}$ and $\tau_{L_{si}} = \tau_{L_s}$ still hold for all $i = 1, \dots, m_s$, but $\tau_{H_{si}}$ is increasing in Y_{si}.

To understand (9) better, note that when $\delta_s = 0$, (9) together with (8) reduces to the solution with no R&D spill-over given in (7). But, when $\gamma_s = 0$, (9) reduces to

$$H_{si} = \frac{H_s}{m_s} \tag{10}$$

for all $i = 1, \dots, m_s$. This is the allocation of R&D input that we would obtain if we maximized R&D spill-over X_s or, equivalently, $\sum_{j=1}^{m_s} \log H_{sj}$ subject to $H_s = \sum_{i=1}^{m_s} H_{si}$. That is, R&D spill-over is maximized if R&D input is shared equally by the firms. Therefore, we can interpret the expression in (9) as a weighted average of allocations in two extreme cases when $\delta_s = 0$ and when $\gamma_s = 0$.

It appears that there is no closed form solution to the optimal allocation of inputs in terms of the exogenous model parameters. Therefore, we will consider an allocation of inputs that, while not optimal, is close to optimal.

First, given any allocation of R&D input, H_{si} for $i = 1, \dots, m_s$, let the allocation of capital and labour be

$$\frac{K_{si}}{K_s} = \frac{L_{si}}{L_s} = \frac{\left(B_{si} H_{si}^{\gamma_s}\right)^{\frac{\sigma-1}{1+\gamma_s(\sigma-1)}}}{\sum_{j=1}^{m_s}\left(B_{sj} H_{sj}^{\gamma_s}\right)^{\frac{\sigma-1}{1+\gamma_s(\sigma-1)}}} \tag{11}$$

for all $i = 1, \dots, m_s$. If we substitute (11) into (2), we can verify that

$$\frac{Y_{si}^{\frac{\sigma-1}{\sigma}}}{\sum_{j=1}^{m_s} Y_{sj}^{\frac{\sigma-1}{\sigma}}} = \frac{\left(B_{si} H_{si}^{\gamma_s}\right)^{\frac{\sigma-1}{1+\gamma_s(\sigma-1)}}}{\sum_{j=1}^{m_s}\left(B_{sj} H_{sj}^{\gamma_s}\right)^{\frac{\sigma-1}{1+\gamma_s(\sigma-1)}}} \tag{12}$$

also holds. It then follows from (4)-(5) that the proposed capital and labour allocation in (11) still ensures that $\tau_{K_{si}} = \tau_{K_s}$ and $\tau_{L_{si}} = \tau_{L_s}$ hold for all $i = 1, \dots, m_s$.

It remains to determine the allocation of R&D input. In the next section, we decompose the industry output assuming that productivity and distortions are log-normally distributed. Using that decomposition, we find the output is maximized when

$$var\left(\log\left(1 + \tau_{H_{si}}\right)\right) = \left(\frac{\delta_s(\sigma - 1)}{\gamma_s + \delta_s + \gamma_s \delta_s(\sigma - 1)}\right)^2 var(\log B_{si})$$

$$cov\left(\log B_{si}, \log\left(1 + \tau_{H_{si}}\right)\right) = \frac{\delta_s(\sigma - 1)}{\gamma_s + \delta_s + \gamma_s \delta_s(\sigma - 1)} var(\log B_{si})$$

This will be the case if the allocation of R&D input H_{si} for all $i = 1, \dots, m_s$ is given by

$$\frac{H_{si}}{H_s} = \frac{B_{si}^{\frac{\gamma_s(\sigma-1)}{\gamma_s+\delta_s+\gamma_s\delta_s(\sigma-1)}}}{\sum_{j=1}^{m_s} B_{sj}^{\frac{\gamma_s(\sigma-1)}{\gamma_s+\delta_s+\gamma_s\delta_s(\sigma-1)}}} \tag{13}$$

To see it, we combine (13) with (12) and (6). This gives that $\left(1 + \tau_{H_{si}}\right) \propto B_{si}^{\frac{\delta_s(\sigma-1)}{\gamma_s+\delta_s+\gamma_s\delta_s(\sigma-1)}}$, that is, the above variance and covariance relationships are indeed satisfied.

The allocation in (13) is only approximately optimal. We can improve on it through the iterative process where we substitute (13) into (12), which we then substitute into (9) to get a new allocation of R&D input:

$$\frac{H_{si}}{H_s} = \frac{\gamma_s B_{si}^{\frac{(\gamma_s+\delta_s)(\sigma-1)}{\gamma_s+\delta_s+\gamma_s\delta_s(\sigma-1)}} + \frac{\delta_s}{m_s}\sum_{j=1}^{m_s} B_{sj}^{\frac{(\gamma_s+\delta_s)(\sigma-1)}{\gamma_s+\delta_s+\gamma_s\delta_s(\sigma-1)}}}{(\gamma_s+\delta_s)\sum_{j=1}^{m_s} B_{sj}^{\frac{(\gamma_s+\delta_s)(\sigma-1)}{\gamma_s+\delta_s+\gamma_s\delta_s(\sigma-1)}}} \tag{14}$$

Although we could continue iteratively producing new allocations of R&D input by using (12) and (9), we will view (14) already as a good approximation and use it in the empirical analysis.

3.2.3 Decomposition of Industry Output

In order to gauge how much each type of distortion contributes to the output loss, we now decompose the industry output similarly to how it is done in (Hsieh and Klenow, 2009; Chen and Irarrazabal, 2013; Ryzhenkov, 2016). We assume that B_{si} and $1 + \tau_{I_{si}}$ for $I = K, L, H$ are drawn from a multivariate log-normal distribution. The draws are independent across firms. The variance-covariance matrix of $\log B_{si}$ and $\log(1 + \tau_{I_{si}})$ for $I = K, L, H$ for all i is

$$\sum = \begin{pmatrix} \sigma_{Bs}^2 & \sigma_{BKs} & \sigma_{BLs} & \sigma_{BHs} \\ \sigma_{BKs} & \sigma_{Ks}^2 & 0 & 0 \\ \sigma_{BLs} & 0 & \sigma_{Ls}^2 & 0 \\ \sigma_{BHs} & 0 & 0 & \sigma_{Hs}^2 \end{pmatrix}$$

where σ_{Bs}^2 stands for $var(\log B_{si})$, and σ_{Is}^2 and σ_{BIs} respectively stand for $var(\log(1 + \tau_{I_{si}}))$ and $cov(\log B_{si}, \log(1 + \tau_{I_{si}}))$ for $I = K, L, H$. Thus, distortions can be correlated with the productivity, but for simplicity, we assume that there is no correlation between the distortions.

Let industry s TFP be defined as

$$TFP_s \equiv \frac{Y_s}{K_s^{\alpha_s} L_s^{\beta_s} H_s^{\gamma_s} X_s^{\delta_s}} \tag{15}$$

Then, the industry output can be expressed as $\log Y_s = logTFP_s + \delta_s \log X_s + \log\left(K_s^{\alpha_s} L_s^{\beta_s} H_s^{\gamma_s}\right)$. We show in Appendix 3.A1 that TFP can be approximated as

$$\log TFP_s = E[logB_{si}] + \frac{\sigma-1}{2}\sigma_{Bs}^2 - \frac{(\sigma-1)\alpha_s^2+\alpha_s}{2}\sigma_{Ks}^2 - \frac{(\sigma-1)\beta_s^2+\beta_s}{2}\sigma_{Ls}^2 - \frac{(\sigma-1)\gamma_s^2+\gamma_s}{2}\sigma_{Hs}^2 \tag{16}$$

(16) implies that industry s TFP is maximal when all firms face the same distortions

because then the variances are zero. Similarly, R&D spill-over can be approximated as

$$\log X_s = \log H_s - \frac{(\sigma-1)^2}{2}\sigma_{Bs}^2 - \frac{(\sigma-1)^2\alpha_s^2}{2}\sigma_{Ks}^2 - \frac{(\sigma-1)^2\beta_s^2}{2}\sigma_{Ls}^2 - \frac{(1+(\sigma-1)\gamma_s)^2}{2}\sigma_{Hs}^2 + (\sigma-1)^2\alpha_s\sigma_{BKs} + (\sigma-1)^2\beta_s\sigma_{BLs} + (\sigma-1)(1+(\sigma-1)\gamma_s)\sigma_{BHs} \tag{17}$$

(17) says that the spill-over is decreasing in the variances of distortions but increasing in their covariances with the productivity parameter. Since it is impossible to have zero variance and positive covariance, if the covariance is positive, so is the variance. This, in turn, implies that there is a trade-off between maximizing industry TFP and R&D spill-over.

Given (16) and (17), industry s output is

$$\begin{aligned}\log Y_s = \frac{1}{2}\{&(\sigma-1)\big(1-\delta_s(\sigma-1)\big)\sigma_{Bs}{}^2 - \big((\sigma-1)\alpha_s^2 + \alpha_s + \delta_s(\sigma-1)^2\alpha_s^2\big)\sigma_{Ks}^2 \\ &- \big((\sigma-1)\beta_s^2 + \beta_s + \delta_s(\sigma-1)^2\beta_s^2\big)\sigma_{Ls}^2 \\ &- \big((\sigma-1)\gamma_s^2 + \gamma_s + \delta_s(1+(\sigma-1)^2)\gamma_s^2\big)\sigma_{Hs}^2 + 2\delta_s(\sigma-1)^2\alpha_s\sigma_{BKs} \\ &+ 2\delta_s(\sigma-1)^2\beta_s\sigma_{BLs} + 2\delta_s(\sigma-1)(1+(\sigma-1)\gamma_s)\sigma_{BHs}\} + const\end{aligned} \tag{18}$$

, where $const$ contains all those terms which are independent of distortions.

Maximizing (18) w.r.t. σ_{Is}^2 and σ_{BIs} for $I = K, L, H$ subject to the constraint that Σ_s is a positive semi-definite matrix, we find that $\sigma_{Ks}^2 = \sigma_{Ls}^2 = \sigma_{BKs} = \sigma_{BLs} = 0$,

$$\sigma_{BHs} = \frac{\delta_s(\sigma-1)}{\gamma_s + \delta_s + \gamma_s\delta_s(\sigma-1)}\sigma_{Bs}^2$$

$$\sigma_{Hs}^2 = \left(\frac{\delta_s(\sigma-1)}{\gamma_s + \delta_s + \gamma_s\delta_s(\sigma-1)}\right)^2\sigma_{Bs}^2$$

3.3 Data

3.3.1 Data source

Our dataset consists of firm-level information on the UK manufacturing industries. There are two primary sources of data. One is the Annual Business Survey (ABS) database, the largest annual survey conducted by the Office for National Statistics (ONS). The ABS database is a good choice for UK business data studies, as it contains more respondents and a more comprehensive set of questions than other surveys. This database provides information on indicators of business activity, including revenue, expenditure, costs, inventory, etc. Another data source is the Business Expenditure on Research and Development (BERD). It is also an annual survey administered by the ONS. It mainly provides information on the use of funds, sources, and amounts of funds and firms' employment in R&D. In our research, we use information about companies' R&D spending and R&D employment from BERD. Therefore, we generate our dataset by linking ABS and BERD via the enterprise reference number in both databases.

We choose manufacturing firms that conduct R&D activities as sample firms and 2019 and 2013 as sample years. Firms with non-positive or missing value in turnover, value-added, capital stock, employment and R&D expenditure are excluded. In order to eliminate outliers, we exclude firms whose capital stock is above the 95th percentile or below the 5th percentile. After data cleaning, there are 1760 firms in our database.

3.3.2 Measurement of primary variables and parameter calibration

The main variables in this study are output, capital stock, non-R&D labour, and R&D labour. All variables are at the firm level. The output is measured by value-added. The capital stock is proxied by the total value of all stocks at the end of the year. We choose the number of scientists and researchers to present the R&D input. Non-R&D labour is measured by the difference between the number of all employees and the number of scientists and researchers. All the variables can be found in the ABS and BERD databases. Detailed information on the main variables and the variables used to calibrate parameters are shown in the Appendix 3.B. Similar to Hsieh and Klenow (2009) and Dias et al. (2016), we calibrate the elasticity of substitution $\sigma = 3$. The industry-specific parameters consist of input factor shares and input factor price in the production function. We calibrate the non-R&D labour share β_s as the ratio of industry aggregate wage for non-R&D employees to the industry aggregate revenue and the R&D labour share γ_s as the ratio of industry aggregate wage for R&D employees to the industry aggregate revenue. With the assumption that the three input shares add up to one: $\alpha_s + \beta_s + \gamma_s = 1$, the capital share is calibrated as the ratio of the gap between the industry aggregate revenue and employment cost to the industry aggregate revenue. To summarize, the input shares are expressed as below:

$$\beta_s = \frac{\sum_{i=1}^{m_s}(non - R\&D\ Wage_{si})}{\sum_{i=1}^{m_s} P_{si}Y_{si}}$$

$$\gamma_s = \frac{\sum_{i=1}^{m_s}(R\&D\ Wage_{si})}{\sum_{i=1}^{m_s} P_{si}Y_{si}}$$

Since we only have data on the total wage bill and the wage bill only for the scientists and researchers is not provided in the database, we need to split the total wage bill into two parts: the wage for non-R&D employees and the wage for scientists and researchers. We calibrate the wage for non-R&D employees and R&D employees with the ratio of R&D expenditure to total expenditure:

$$non - R\&D\ Wage_{si} = Wage_{si} * \left(1 - \frac{R\&D\ expenditure_{si}}{R\&D\ expenditure_{si} + Capital\ expenditure_{si}}\right)$$

and

$$R\&D\ Wage_{si} = Wage_{si} * \frac{R\&D\ expenditure_{si}}{R\&D\ expenditure_{si} + Capital\ expenditure_{si}}$$

The price of each input factor is calibrated as the ratio of the industry revenue to the industry aggregate of that factor:

$$r_s = \left(\sum_{i=1}^{m_s} P_{si}Y_{si} - \sum_{i=1}^{m_s} Wage_{si}\right) / \sum_{i=1}^{m_s} K_{si}$$

$$\omega_{L_s} = \sum_{i=1}^{m_s} non - R\&D\ Wage_{si} / \sum_{i=1}^{m_s} L_{si}$$

$$\omega_{H_s} = \sum_{i=1}^{m_s} R\&D\ Wage_{si} / \sum_{i=1}^{m_s} H_{si}$$

To calibrate the weight of R&D spill-over δ_s, we assume that it is the same for all industries. We cannot estimate a separate δ_s for each industry because X_s is the same for all firms in the same industry. Therefore, we need to assume that all industries have the same δ_s, which we then estimate by exploiting the variation in X_s across industries. We first calculate the firm-level productivity that includes R&D spill-over:

$$A_{si} = \frac{P_{si}Y_{si}^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s}L_{si}^{\beta_s}H_{si}^{\gamma_s}}$$

Then we estimate the weight of R&D spill-over δ_s, which is common to all industries, by regressing the logarithm firm-level productivity $logA_{si}$ on the logarithm R&D spill-over $logX_s$:

$$logA_{si} = \delta_s logX_s$$

The results are in Table 3.1. The estimated δ_s is 0.12 under both OLS and GLS estimation methods, and both results are significant at high level of precision (P-value of 0). Hence, we calibrate the weight of R&D spill-over equal to 0.12.

Table 3.1 Estimated weight of R&D spill-over $\boldsymbol{\delta_s}$

Variable	OLS	GLS
δ_s	0.12***	0.12***
	(0.0152)	(0.0219)
P-value	0	0

In Table 3.2, we adopt the industry classification reported by ONS to split the manufacturing industries into four groups: low, medium-low, medium-high and high technology. The R&D intensity is the criterion in the classification. There are 22 manufacturing industries in total. The manufacture of pharmaceutical products and the manufacture of computer, electronic and optical products are classified as high-technology industries. The low technology group comprises ten industries, including food products, beverages, etc. 5 industries are classified as medium-low technology industries, mainly related to metal and non-metallic products. Medium-high tech group consists of 6 industries, and they are mainly related to chemical, machinery, and equipment.

Table 3.2 Industry classification

	Code	**SIC07 2-digit level description**
Low Technology	10	Manufacture of food products
	11	Manufacture of beverages

	13	Manufacture of textiles
	15	Manufacture of leather products
	16	Manufacture of wood products, except furniture
	17	Manufacture of paper products
	18	Printing and reproduction of recorded media
	31	Manufacture of furniture
	32	Other manufacturing
Medium-Low Technology	22	Manufacture of rubber and plastic products
	23	Manufacture of other non-metallic mineral products
	24	Manufacture of basic metals
	25	Manufacture of fabricated metal products
	33	Repair and installation of machinery and equipment
Medium-High Technology	19	Manufacture of coke and petroleum
	20	Manufacture of chemicals
	27	Manufacture of electrical equipment
	28	Manufacture of machinery and equipment
	29	Manufacture of motor vehicles
	30	Manufacture of other transport equipment
High Technology	21	Manufacture of pharmaceutical products
	26	Manufacture of computer, electronic and optical products

Table 3.3 shows the descriptive statistic for the main variables (output, capital, non-R&D labour, and R&D labour) in 2019 and 2013, respectively. The large standard deviation implies that the output across firms is highly dispersed. Notably, firms in the high-tech group hire more employees in R&D activities, with a mean value of 19.59. This is followed by the medium-high group, where R&D employees are half the amount

in the high-tech group. Comparatively, R&D employees in the low-tech and medium-low-tech groups are much lower, only around 5. In terms of other main variables, low-tech industries have larger amounts of value-added, capital stock and non-R&D employees than other counterparts. And the high standard deviation also reveals significant heterogeneity in all groups. In 2013, all the main variables (output, capital stock, non-R&D labour, and R&D labour) have larger magnitudes and higher dispersion than those in 2019.

Table 3.3 also presents the industry-level input shares. The higher mean value of capital share among the three input factors indicates that capital takes the most important role in production in both years, though it varies across industries. In 2019, among four groups with different technology levels, high-tech industries have the largest capital share with a mean value of 0.46, while low-tech industries display a relatively lower value of 0.39. The non-R&D labour share, on the contrary, takes a more important role in low-tech industries. When comparing over time, the mean value of R&D share decreases from 0.25 in 2013 to 0.22 in 2019 in the whole economy. And it is significantly higher in the high-tech group, reaching 0.31 in 2019 and 0.36 in 2013. This is followed by the medium-high-tech group, with a mean value of 0.24 in 2019 and 0.33 in 2013. The medium-low and the low-tech group have a relatively lower R&D share in both years.

We also summarize the rental cost for three input factors in the model. The mean values of all three parameters are higher in 2019. The capital rental rate is the highest in the low-tech group and lowest in the medium-high-tech group in both years. Regarding the wage rate, the wage rate of R&D employees displays significant heterogeneity between groups. In 2019 the R&D wage rate in the high-tech group (249.03 thousand GBP) is only around one-third of that in the low-tech group (749.11 thousand GBP). In 2013, the gap between the two groups is smaller, but the R&D wage in the high-tech group remains the lowest. The wage rate of non-R&D employees is comparatively more even, with the highest value of 29.64 in the medium-low tech group and the smallest value of 22.76 in the high-tech group in 2019. The average value in 2013 is smaller than in 2019 by around 2 thousand GBP.

Table 3.3 Descriptive Statistics and parameter calibration

Year		Whole economy		Low tech		Medium low tech		Medium high tech		High tech	
2019		100%		14%		26%		44%		15%	
	Obs	1759		251		462		778		268	
Variable	Name	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev	Mean	Std. Dev.	Mean	Std. Dev.
$P_{si}Y_{si}$	Output	19245.16	40057.80	34806.52	66708	16570.736	38416.476	16616.33	31724.72	16912.71	25612.52
K_{si}	Capital stock	5752.14	7537.42	7254.25	8951.801	4871.341	7314.301	5987.81	7424.60	5197.55	6503.33
L_{si}	Non-R&D employees	258.3	457.34	551.7304	874.97	229.753	406.906	212.47	287.28	165.74	199.01
H_{si}	R&D employees	9.01	20.41	5.56	6.35	4.26	11.845	9.29	20.84	19.59	32.22
α_s	Capital share	0.43	0.08	0.39	0.09	0.43	0.056	0.43	0.10	0.46	0.05
β_s	Non-R&D labour share	0.35	0.08	0.41	0.06	0.412	0.058	0.33	0.05	0.23	0.02
γ_s	R&D human capital share	0.22	0.09	0.19	0.13	0.157	0.09	0.24	0.06	0.31	0.02
r_s	Rental rate of capital	1.39	0.46	1.76	0.73	1.47	0.295	1.19	0.34	1.47	0.34
ω_s	Non-R&D labour cost	26.41	4.19	25.69	6.40	29.631	2.975	25.99	3.19	22.76	0.53
q_s	R&D labour cost	508.64	248.52	749.11	405.63	646.39	119.888	434.69	139.97	249.03	40.99

Year		Whole economy		Low tech		Medium low tech		Medium high tech		High tech	
2013		100%		20%		20%		42%		13%	
	Obs	1141		277		230		480		154	
Variable	Name	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev	Mean	Std. Dev.	Mean	Std. Dev.
$P_{si}Y_{si}$	Output	26932.88	56966.83	39091.40	95958.20	22329.46	30310.59	21247.65	32433.31	29658.78	49928.59
K_{si}	Capital stock	7291.67	9252.50	7491.46	9561.08	6871.42	8848.28	7639.21	9574.59	6476.70	8209.44
L_{si}	Non-R&D employees	394.29	715.08	613.11	1243.13	372.82	387.74	304.751	385.748	311.86	460.41
H_{si}	R&D employees	12.92	39.73	6.39	10.45	5.98	7.86	14.83	44.40	29.08	69.82
α_s	Capital share	0.41	0.09	0.45	0.13	0.40	0.04	0.37	0.07	0.47	0.02
β_s	Non-R&D labour share	0.35	0.11	0.41	0.08	0.47	0.03	0.31	0.06	0.17	0.003
γ_s	R&D human capital share	0.25	0.11	0.14	0.09	0.14	0.06	0.33	0.05	0.36	0.02
r_s	Rental rate of capital	1.53	0.99	2.30	1.53	1.30	0.15	1.02	0.35	2.08	0.61
ω_s	Non-R&D labour cost	22.15	5.55	23.42	5.41	27.95	2.13	20.63	4.76	15.97	0.57
q_s	R&D labour cost	489.45	141.32	537.84	99.41	557.16	154.31	464.48	82.05	379.16	221.23

Note: The value in value added, capital stock, rental rate of capital, non-R&D labour cost, and R&D labour cost are presented in thousand GBP.

3.4 Empirical results

3.4.1 Output gain

We first calculate the new output and the output gap between the new output and the initial output with different allocation approaches. The results are in Table 3.4 Allocation in column (1) and column (2) solve the maximization problem of the logarithm industry aggregate output. The solutions are provided in (7). Allocation in column (3) and column (4) aims to maximize an approximation of output that is decomposed into variance and covariance of input terms in (18), and the solution is provided by (11), (13) and (14).

The first column presents the output gain when we do not consider the effect of R&D spill-over in allocation ($\delta_s = 0$). This is the general allocation approach adopted in the literature. Under this assumption, we use (7) to allocate inputs, which requires input distortions to be equalised across firms in industry s. After reallocation, the dispersion of the capital, labour, and R&D inputs distortions become zero. Both the variances of distortions and covariances between distortions and productivity become 0. From the results, for the whole economy, the output gain is 76.28%, implying the allocative efficiency is significantly increased. If one looks at groups with different technology types, the medium-high-tech group has the most significant output gain, achieving 103.21%. The output in the medium-low-tech group also increases significantly with an output gain of 43.16%, though this magnitude is smallest among all groups.

The difference between the results in column (1) and column (2) is that, column (1) presents the case when we adopt the allocation approach suggested in the literature with the assumption of no R&D spillover effect (which implies that after reallocation the input distortions are equalised), but count for the fact that the actual R&D spillover will change after reallocation. We use (3) to calculate the new R&D spill-over after the reallocation of R&D input, which is a geometric average of the R&D input in industry s. Column (2) presents the case when we adopt the same allocation approach suggested in the literature as in column (1), but at the same time, assuming that the actual R&D spillover does not change as there is no spillover effect. The output gains in column (2) would be the results generated by the literature, as they do not consider any externality. The results in column (2) are higher than those in column (1) by around 40pp to50 pp.

The most significant change in the output gain is in the medium-high-tech group, increasing by around 63pp. The results in column (1) indicate that if the role of R&D spill-over is ignored, the output loss from misallocation would be overestimated, especially for those industries where R&D input takes a more critical role.

Table 3.4 Output gains from eliminating input misallocation in 2019

	no R&D spillover	fixed R&D spillover	with R&D spillover	with R&D spillover (improved)
	(1)	(2)	(3)	(4)
Whole economy	76.28	128.087	110.483	118.768
Low-tech	75.174	128.606	116.48	121.18
Medium-low-tech	43.158	82.313	67.806	73.759
Medium-high-tech	103.21	165.759	143.577	154.703
High-tech	69.082	114.393	92.756	104.861

Note: Entries for the output gains are given by $(Y^*/Y-1)*100$, where Y^* is the new output after reallocation and Y is the initial output. All the output gains are presented in percentages (%)

Column (3) shows the output gains from the allocation in (11) and (13), where the R&D spill-over effect is now taken into account. The R&D allocation in (13) suggests that the variance of R&D distortion is not reduced to zero as in columns (1) and (2). Instead, it is kept at a certain level, and the covariance between productivity and R&D distortion is positive. In this approach, the capital and labour allocations do not change, and their distortions are equalised across firms. The variances of capital and labour distortion and the covariances between these distortions and productivity are still reduced to zero. The results in column (3) are significantly larger than in column (1), which increased by around 34pp for the whole economy. The results emphasise the role of R&D spill-over in production. In the production function in (2), there are not only three types of inputs, but also an R&D spill-over term. Therefore, the social planner should also consider R&D spill-over in the maximisation problem, as it also influences the output like the other input factors do.

However, the results in column (3) are only approximately optimal, and the allocation can be improved by an iterative process of substituting R&D allocation in (13) into capital and labour allocation in (12) and then into the optimum R&D allocation in (9). The results in column (4) are the output gain from the improved allocation. Compared with column (3), the output gains in column (4) are more prominent in all groups, especially in medium high-tech and high-tech groups. The output gain increased by around 5pp in low- and medium-low-tech groups and increased by more than 10pp in medium-high and high-tech groups, implying that the output gain increased with the industry R&D intensity.

By comparing the results in column (1) and column (4), the output gain from improved R&D allocation in (14) increased by around 42pp for the whole economy. The most considerable improvement is in the medium high-tech group, with an output gain of 154.7%. This is followed for the low-tech and high-tech groups, with the increased output gain of 121.18% and 104.86%, respectively. The increase in the medium-low-tech group is the smallest among all groups, though it still has an output gain of 73.76% after reallocation.

3.4.2 Output decomposition and individual contribution of each input distortion

We measure the individual contribution of each type of input distortion to the output loss. We decompose the output and express it in terms of variances of input distortions and covariances between input distortions and productivity in (18). All the expressions are in logarithms. The empirical results are in Table 3.4. In our model, the industry aggregate output consists of industry productivity, industry R&D spill-over and industry aggregate input. From (16) and (17), the sum of variances and covariances represents the sum of industry productivity $logTFP_s$ and the R&D spill-over term $\delta_s logX_s$. There are some constant terms, such as the average productivity $E[logB_{si}]$ in the expression of industry productivity $logTFP_s$ in (16) and aggregate R&D input $logH_s$ in the expression of industry R&D spill-over $logX_s$ in (17). Due to this, the sum of all variance and covariance is not equivalent to the sum of industry productivity and R&D spill-over term. The discrepancy between the sum of industry productivity and R&D spill-over and the sum of all variance and covariance terms may also come from the decomposition process. We use an approximation in the decomposition. It assumes that the distortions are log-normally distributed and that there are an infinite number of firms, which would cause discrepancies with the actual data we adopt.

3.4.2.1 Initial allocation

The empirical results in Table 3.4 show that input distortions' variances negatively contribute to the output. In contrast, the covariances positively contribute, consistent with our theoretical derivation in (18). The first column presents the output decomposition for the original allocation of inputs. By looking at the variances of input distortions, capital dispersion contributes the most to the output loss. The variance term is -0.406 for the whole economy, -0.425 in the low-tech group, -0.398 in the medium-low-tech group, -0.327 in the medium-high-tech group and -0.609 in the high-tech group. Labour is less dispersed than capital; its variance term is -0.241 in the low-tech group and less than 0.2 in other groups. The high-tech group has the most dispersed R&D input with a variance term of -0.367.

Regarding covariance between input distortions and productivity, it positively affects output as all the relevant terms have a positive magnitude. The positive covariance term would offset the output loss caused by input distortion. When gauging the individual contribution of each type of input distortion, the sum of the magnitude of both variance and covariance would be less than the one from only considering the variance term itself. The covariance terms between R&D distortion and productivity are 0.278, 0.225, 0.347, 0.222 and 0.42 for the whole economy, low-tech, medium-low-tech, medium-high-tech, and high-tech groups, respectively. The magnitudes are larger than the other two types of covariances, implying that the output loss attributed to R&D input distortion is much less than the other two input distortions due to the larger covariance term.

Since the output is composed of both variance input distortion and the covariance between distortion and productivity, we look at the sum of these two components to gauge the individual contribution of each type of distortion. The capital distortion contributes most significantly to the output loss among the three input distortions, with a magnitude of -0.24 for the whole economy. The sum of the variance and covariance terms of capital distortion in the high-tech group is -0.319, the highest across all groups. The contribution of labour distortion is lower than that of capital distortion, only contributing -0.056 to the output of the entire economy. Within four groups with different technology types, the low-tech group suffers more from labour distortion than other groups, given the sum of variance and covariance term of -0.103. Therefore we conclude that the initial capital and labour allocations cause output loss. Regarding R&D distortion, different from capital and labour distortions, the magnitude of covariance between productivity and R&D distortion is larger than the variance of R&D distortion, which leads to a positive sum of these two terms. This indicates that the initial R&D input positively contributes to the output at the initial allocation, though the optimal R&D input contributes more.

Table 3.5 Industry output decomposition in 2019

Whole economy	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry output	21.993	22.558	0.566	22.736	0.743	22.774	0.782
Industry productivity	10.8	11.624	0.824	11.562	0.762	11.574	0.774
Industry R&D spillover	0.178	-0.08	-0.258	0.159	-0.019	0.186	0.008
Capital distortion variance	-0.406	0	0.406	0	0.406	0	0.406
Labour distortion variance	-0.166	0	0.166	0	0.166	0	0.166
R&D distortion variance	-0.224	0	0.224	-0.158	0.066	-0.428	-0.204
Capital distortion covariance	0.166	0	-0.166	0	-0.166	0	-0.166
Labour distortion covariance	0.11	0	-0.11	0	-0.11	0	-0.11
R&D distortion covariance	0.278	0	-0.278	0.316	0.039	0.499	0.222
Aggregate contribution							
capital	-0.24		0.24		0.24		0.24
labour	-0.056		0.056		0.056		0.056
R&D	0.054		-0.054		0.105		0.018

Low tech	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry output	21.835	22.395	0.561	22.607	0.772	22.628	0.794
Industry productivity	10.65	11.477	0.827	11.419	0.769	11.436	0.786
Industry R&D spillover	0.156	-0.11	-0.266	0.16	0.004	0.164	0.008
Capital distortion variance	-0.425	0	0.425	0	0.425	0	0.425
Labour distortion variance	-0.241	0	0.241	0	0.241	0	0.241
R&D distortion variance	-0.13	0	0.13	-0.191	-0.062	-0.301	-0.172
Capital distortion covariance	0.159	0	-0.159	0	-0.159	0	-0.159
Labour distortion covariance	0.138	0	-0.138	0	-0.138	0	-0.138
R&D distortion covariance	0.225	0	-0.225	0.383	0.157	0.471	0.246
Aggregate contribution							
capital	-0.266		0.266		0.266		0.266
labour	-0.103		0.103		0.103		0.103
R&D	0.095		-0.095		0.095		0.074

Medium-low tech	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry output	21.612	21.966	0.354	22.125	0.513	22.16	0.548
Industry productivity	10.782	11.378	0.596	11.328	0.546	11.332	0.55
Industry R&D spillover	0.121	-0.121	-0.242	0.088	-0.033	0.119	-0.002

Capital distortion variance	-0.398	0	0.398	0	0.398	0	0.398
Labour distortion variance	-0.18	0	0.18	0	0.18	0	0.18
R&D distortion variance	-0.286	0	0.286	-0.171	0.115	-0.485	-0.199
Capital distortion covariance	0.166	0	-0.166	0	-0.166	0	-0.166
Labour distortion covariance	0.122	0	-0.122	0	-0.122	0	-0.122
R&D distortion covariance	0.347	0	-0.347	0.342	-0.004	0.555	0.208
Aggregate contribution							
capital	-0.232		0.232		0.232		0.232
labour	-0.058		0.058		0.058		0.058
R&D	0.061		-0.061		0.111		0.009

Medium-high tech	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry output	22.31	23.019	0.709	23.2	0.89	23.245	0.935
Industry productivity	10.961	11.939	0.977	11.866	0.905	11.883	0.922
Industry R&D spillover	0.187	-0.082	-0.268	0.172	-0.014	0.2	0.013
Capital distortion variance	-0.327	0	0.327	0	0.327	0	0.327
Labour distortion variance	-0.122	0	0.122	0	0.122	0	0.122
R&D distortion variance	-0.202	0	0.202	-0.117	0.085	-0.368	-0.166
Capital distortion covariance	0.126	0	-0.126	0	-0.126	0	-0.126
Labour distortion covariance	0.086	0	-0.086	0	-0.086	0	-0.086
R&D distortion covariance	0.222	0	-0.222	0.233	0.011	0.402	0.18
Aggregate contribution							
capital	-0.201		0.201		0.201		0.201
labour	-0.036		0.036		0.036		0.036
R&D	0.02		-0.02		0.096		0.014

High tech	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry output	22.035	22.56	0.525	22.691	0.656	22.752	0.717
Industry productivity	10.661	11.424	0.763	11.369	0.707	11.371	0.709
Industry R&D spillover	0.289	0.052	-0.237	0.238	-0.051	0.297	0.008
Capital distortion variance	-0.609	0	0.609	0	0.609	0	0.609
Labour distortion variance	-0.124	0	0.124	0	0.124	0	0.124
R&D distortion variance	-0.367	0	0.367	-0.19	0.177	-0.747	-0.38
Capital distortion covariance	0.29	0	-0.29	0	-0.29	0	-0.29
Labour distortion covariance	0.104	0	-0.104	0	-0.104	0	-0.104

R&D distortion covariance	0.42	0	-0.42	0.38	-0.04	0.736	0.317
Aggregate contribution							
capital	-0.319		0.319		0.319		0.319
labour	-0.02		0.02		0.02		0.02
R&D	0.053		-0.053		0.137		-0.063

Note: We decompose the industry output and present the variance and covariance terms for all types of inputs in eq. (18). All the values are in logarithm.

Column (1) is the industry output decomposition in the initial allocation.

Column (2) is the industry output decomposition when there is no R&D spillover effect, where we use eq. (7) to allocate inputs. Column (3) describes the change from the initial value. It is the difference between the Column (2) and Column (1).

Column (4) is the industry output decomposition in the presence of R&D spillover, where we use eq. (11) and eq. (13) to allocate inputs. Column (5) describes the change from the initial value. It is the difference between the Column (4) and Column (1).

Column (6) is an improved version based on the results in Column (4), where we use eq. (11) and eq. (14) to allocate inputs. Column (5) describes the change from the initial value. It is the difference between the Column (6) and Column (1).

3.4.2.2 Allocation without the externality of R&D spill-over

In this section we analyse the individual contribution of each type of input misallocation to the output loss. We adopt the solution under the assumption of no externality in (7) and substitute it in (2) to generate the new output. The literature (Hsieh and Klenow, 2009; Marques et al., 2014; Benkovskis, 2015; Chen, 2017; Choi, 2020) suggests that the optimal allocation approach is to equalise input distortions across firms. But when we use (2) to compute the new output, in addition to inputs, we still count for the actual R&D spillover change by measuring the new R&D spillover as the geometric average of the new R&D input as suggested in (3). The optimal solution in (7) suggests that the input use should be proportional to productivity. Column (2) shows the results of output decomposition after equalising all distortions; therefore, the magnitudes of all types of variances and covariances become zero. Column (3) is the change in each component in the decomposition. After all types of input distortions are equalised, the output becomes larger, implying an increase in the allocative efficiency. The output after reallocation increases by 56.6%. The output gain in this approach is different with Table 3.3, because the solution in this approach is for the maximization problem of an approximate industry output in (18). The R&D spill-over effect becomes smaller than it was initially in all groups. The elimination of capital distortion takes up the largest proportion of the increase in the output in all groups. The contribution of eliminating capital dispersion is 24pp in the whole economy. Regarding groups, it is noticeable that the contribution is substantial in the high-tech group, with a magnitude of 31.9pp. In the medium-low-tech group, eliminating capital misallocation contributes 23.2pp to the output gain of 35.4%, which also takes up a substantial share. In the low-tech and medium-high-tech groups, the capital misallocation contributes 26.6pp and 20.1pp to the output loss, respectively. The contribution of labour distortion is much less when compared to capital distortion, with 5.6pp for the whole economy. Output loss caused by labour input dispersion is larger in low- and medium-low-tech groups, as the contribution of eliminating labour input dispersion takes up 18% and 16% of the output increase, respectively. In the other two groups with higher R&D intensity, labour input dispersion only takes up 5% and 4% of the output loss.

As for R&D input dispersion, the allocation approach that equalises R&D distortions across firms does not generate a positive contribution to the increase in output as capital and labour counterparts do. Instead, the changes in the sum of R&D variance and covariance terms become negative for the whole economy and all groups with different technology types in column (3). The R&D allocation with equalised distortion reduces the output gain by 5.4pp in the whole economy, 9.5pp in the low-tech group, 6.1pp in the medium-low-tech group, and 2pp in the medium-high-tech and 5.3pp in the high-tech group. The results indicate that equalising R&D input distortion is not the optimal approach to generate larger output.

3.4.2.3 Allocation in the presence of the externality of R&D spill-over

Next, we take R&D spill-over into consideration. Since there is no externality in capital and labour, the allocation of capital and labour in (11) would still generate zero dispersion in their distortions. The R&D allocation in (12) is the solution of a weighted average in the case where the social planner's objective is to maximise the output where there is no R&D spill-over and the case where the objective is to maximise R&D spill-over. Therefore, the R&D input distortions will not be equalised as suggested in (7). Instead, R&D input dispersion is kept at a certain level, and the variance and covariance would not be zero in this allocation approach. The decomposition results are presented in columns (4) and (5). Compared with the results in column (2) and (3), the contribution of capital and labour distortions do not change. However, now the R&D allocation is the optimal solution in the social planner's problem to maximise the output in the presence of R&D spill-over. The magnitudes of both variance and covariance term in R&D distortion has changed, where the variance terms decrease and covariance terms increase for all groups. In addition, the R&D input reallocation now positively contributes to the output gain, as the sum of the variance and covariance terms has now increased to a positive value in column (5). The magnitudes are 10.5pp for the whole economy, 9.5pp in the low-tech group, 11.1pp in the medium-low-tech group, 9.6pp in the medium-high-tech group, and 13.7pp in the high-tech group, implying that the R&D allocation now generates a positive contribution to the output gain.

3.4.2.4 An improved allocation approach

We also improve the R&D allocation through an iterative process by substituting (13) into (12). The results in column (6) and (7) indicate that the output could be larger under this allocation. The contributions of capital and labour distortion are still the same as those in column (2) and column (4). Since there is no externality in capital and labour, the distortions are equalised, and the dispersions become zero after reallocation. The improved output comes from the R&D allocation, where the output gain is 78.2% in the whole economy. The largest output gain is in the medium-high-tech group, with a 93.5pp increase, followed by the high-tech group, with a 79.4pp increase. Medium-low-tech group has a relatively smaller output gain, though the output gain still increases by 54.8pp. The contribution of R&D reallocation is measured by the sum of variance and covariance terms of R&D input. The magnitude is significantly larger (1.8pp in the whole economy) than in the allocation that equalises all distortions (-5.4 pp in the whole economy). The low-tech group benefits the most from this allocation, as its R&D distortions reduce output gain the most under the original allocation but now the magnitude of its contribution becomes the largest among the four groups (7.4pp). The R&D contribution in column (7) is smaller than that in column (5), but the output gain in column (7) is higher than that in column (5). This is because the values in column (4) are the solution to the approximation problem of industry output maximization in (18). Since they are only close to optimal, there are still spaces to improve the output by continuing the iterative process.

3.4.3 Industry productivity and R&D spill-over

From (16), the industry productivity $logTFP_s$ is negatively correlated to the variances of input distortions. The second row in Table 3.4 presents the value of $logTFP_s$ generated by the initial and the three new allocation approaches. From the empirical results, the industry productivity $logTFP_s$ is the largest in column (2), where all types of input distortions are equalised across firms within industry s, and therefore the variance terms are zero. The highest productivity in column (2) is consistent with (16), which indicates that the industry productivity is maximised when the dispersion in all types of input distortions is eliminated.

However, different from industry productivity, the industry R&D spill-over $logX_s$ in (17) is not only negatively related to the variances of input distortions but also positively related to covariances between productivity and input distortion. The third row shows the industry R&D spill-over in the initial and new allocations. The R&D spill-overs under the improved R&D allocation in column (6) have reached a level quite close to the initial value (almost zero change to the initial value). This implies that in optimum, the R&D contribution is similar to that in the initial allocation, though it is not precise as it also depends on the level of other distortions.

3.4.3.1 Trade-off between industry productivity and R&D spill-over

Since the industry aggregate output consists of the industry productivity, industry R&D spill-over, and industry aggregate inputs, the changes in industry productivity and industry R&D spill-over matter for the output gain. In (16), the industry productivity is maximised when all variances become zero. However, in (17), the covariance terms also increase with the variance. Therefore, it is impossible to have a positive covariance term and keep the variance to zero simultaneously. This implies that in the output maximisation problem, there is a trade-off between maximising the industry productivity and R&D spill-over. In Table 3.4, when we compare the industry TFP and R&D spill-over term across the initial allocation and new allocations, we can see that as the industry TFP becomes larger in all groups, the R&D spill-overs become less than the initial value. Although in the improved allocation in (11) and (14), both terms are slightly larger than the ones in the allocation approach in (11) and (13), the differences are quite minor between these two allocations. This also indicates that the R&D allocation in the last approach is more efficient, as it is improved from the second approach.

3.4.4 Output and decomposition change in 2013

We also do the output decomposition in 2013 in Table 3.5 and compare it with the results in 2019 to see how the input allocation efficiency differed in 2013. The results show that capital distortion still generates the largest contribution to the output loss, though the magnitude was smaller in 2013. In column (3), the output loss caused by capital distortion is 13.3pp for the whole economy. The smaller output loss implies that capital input was allocated more efficiently in 2013. In the low-tech group, the magnitude of capital distortion contribution remains mostly the same, only decreasing by 3.4pp in 2013 compared to the value in 2019. Nevertheless, the capital input allocation in the rest of groups is more efficient in 2013: The output loss due to capital distortion is reduced to 9.4pp in the medium-low-tech group, 5.1pp in the medium-high-tech group, and 12.6pp in the high-tech group. It is noticeable that in 2013 the initial labour allocation does not harm the productivity as well as the output, as the sum of the variance and the covariance terms in column (1) is positive in all groups. Therefore, when all labour distortions are equalised across firms, the contribution is negative and around -4pp in column (3). Similar to labour input, the initial R&D allocation is efficient as column (1) shows a positive value of the sum of the variance term and covariance term. Therefore, when R&D distortions are equalised, it reduces the output gain by 14.3pp in the whole economy, 33.5pp in the low-tech group, 9.1pp in the medium-low-tech group, 5pp in the medium-high-tech group, and 7.6pp in the high-tech group. In total, for all input types, the initial allocation is more efficient in 2013, leading to a smaller output gain in column (3).

Now we look at the improved allocation approach that keeps a certain level of dispersion in R&D distortion. These allocations generate a higher output in all groups. Compared with 2019, the contribution of capital and labour distortions to the output gain is smaller. However, the magnitude of R&D's contribution is more prominent in 2013, with 32.9pp in the whole economy, 33pp in the low-tech group, 18.1pp in the medium-low-tech group, 37pp in the high-tech group, and 40.3pp in the high-tech group. The contribution is particularly significant in high-tech groups, as the output gain generated by the optimal allocation of inputs (108.5% in column (5) and 116.9% in column (7)) exceeds the value in 2019 (65.6% in column (5) and 71.7% in column (7)).

Table 3.6 Industry output decomposition in 2013

Whole economy	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry output	21.892	22.258	0.366	22.736	0.844	22.779	0.888
Industry productivity	10.563	11.411	0.848	11.304	0.741	11.326	0.763
Industry R&D spillover	0.4	-0.081	-0.482	0.504	0.103	0.525	0.125
Capital distortion variance	-0.542	0	0.542	0	0.542	0	0.542
Labour distortion variance	-0.158	0	0.158	0	0.158	0	0.158
R&D distortion variance	-0.402	0	0.402	-0.472	-0.071	-0.753	-0.352
Capital distortion covariance	0.409	0	-0.409	0	-0.409	0	-0.409
Labour distortion covariance	0.198	0	-0.198	0	-0.198	0	-0.198
R&D distortion covariance	0.545	0	-0.545	0.945	0.4	1.169	0.624
Aggregate contribution							
capital	-0.133		0.133		0.133		0.133
labour	0.04		-0.04		-0.04		-0.04
R&D	0.143		-0.143		0.329		0.272

Low tech	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry output	22.451	22.7	0.249	23.413	0.962	23.447	0.996
Industry productivity	10.444	11.418	0.974	11.315	0.871	11.349	0.906
Industry R&D spillover	0.328	-0.397	-0.725	0.418	0.09	0.418	0.09
Capital distortion variance	-0.81	0	0.81	0	0.81	0	0.81
Labour distortion variance	-0.235	0	0.235	0	0.235	0	0.235
R&D distortion variance	-0.182	0	0.182	-0.666	-0.484	-0.859	-0.678
Capital distortion covariance	0.578	0	-0.578	0	-0.578	0	-0.578
Labour distortion covariance	0.268	0	-0.268	0	-0.268	0	-0.268
R&D distortion covariance	0.517	0	-0.517	1.332	0.814	1.499	0.982
Aggregate contribution							
capital	-0.232		0.232	0.034	0.232		0.232
labour	0.033		-0.033		-0.033		-0.033
R&D	0.335		-0.335		0.33		0.304

Medium-low tech	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry output	20.969	21.152	0.183	21.423	0.454	21.445	0.477
Industry productivity	10.213	10.688	0.475	10.605	0.392	10.624	0.412
Industry R&D spillover	0.344	0.052	-0.292	0.405	0.062	0.408	0.065

Capital distortion variance	-0.272	0	0.272	0	0.272	0	0.272
Labour distortion variance	-0.141	0	0.141	0	0.141	0	0.141
R&D distortion variance	-0.235	0	0.235	-0.272	-0.037	-0.383	-0.148
Capital distortion covariance	0.178	0	-0.178	0	-0.178	0	-0.178
Labour distortion covariance	0.162	0	-0.162	0	-0.162	0	-0.162
R&D distortion covariance	0.326	0	-0.326	0.544	0.218	0.635	0.309
Aggregate contribution							
capital	-0.094		0.094	0.138	0.094		0.094
labour	0.021		-0.021		-0.021		-0.021
R&D	0.091		-0.091		0.181		0.161

Meidum-high tech	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry output	21.708	22.205	0.497	22.516	0.808	22.561	0.853
Industry productivity	10.801	11.543	0.743	11.439	0.639	11.451	0.65
Industry R&D spillover	0.411	0.165	-0.246	0.58	0.169	0.614	0.203
Capital distortion variance	-0.337	0	0.337	0	0.337	0	0.337
Labour distortion variance	-0.122	0	0.122	0	0.122	0	0.122
R&D distortion variance	-0.583	0	0.583	-0.365	0.218	-0.688	-0.105
Capital distortion covariance	0.286	0	-0.286	0	-0.286	0	-0.286
Labour distortion covariance	0.173	0	-0.173	0	-0.173	0	-0.173
R&D distortion covariance	0.578	0	-0.578	0.73	0.152	0.984	0.406
Aggregate contribution							
capital	-0.051		0.051		0.051		0.051
labour	0.051		-0.051		-0.051		-0.051
R&D	-0.005		0.005		0.37		0.301

High tech	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry output	22.013	22.571	0.558	23.097	1.085	23.182	1.169
Industry productivity	10.712	11.915	1.203	11.763	1.051	11.783	1.071
Industry R&D spillover	0.613	-0.031	-0.644	0.646	0.034	0.711	0.099
Capital distortion variance	-0.67	0	0.67	0	0.67	0	0.67
Labour distortion variance	-0.078	0	0.078	0	0.078	0	0.078
R&D distortion variance	-0.706	0	0.706	-0.478	0.228	-1.064	-0.358
Capital distortion covariance	0.544	0	-0.544	0	-0.544	0	-0.544
Labour distortion covariance	0.128	0	-0.128	0	-0.128	0	-0.123

R&D distortion covariance	0.782	0	-0.782	0.957	0.175	1.401	0.62
Aggregate contribution							
capital	-0.126		0.126		0.126		0.126
labour	0.05		-0.05		-0.05		-0.045
R&D	0.076		-0.076		0.403		0.262

Note: We decompose the industry output and present the variance and covariance terms for all types of inputs in eq. (18). All the values are in logarithm.

Column (1) is the industry output decomposition in the initial allocation.

Column (2) is the industry output decomposition when there is no R&D spillover effect, where we use eq. (7) to allocate inputs. Column (3) describes the change from the initial value. It is the difference between the Column (2) and Column (1).

Column (4) is the industry output decomposition in the presence of R&D spillover, where we use eq. (11) and eq. (13) to allocate inputs. Column (5) describes the change from the initial value. It is the difference between the Column (4) and Column (1).

Column (6) is an improved version based on the results in Column (4), where we use eq. (11) and eq. (14) to allocate inputs. Column (5) describes the change from the initial value. It is the difference between the Column (6) and Column (1).

From (15), the industry output is influenced by industry productivity, industry R&D spill-overs and the industry aggregate inputs. We compare the decomposition of the initial allocation in 2013 and 2019 in Table 3.7 to see whether the change in output in 2019 is mainly due to changes in industry productivity and R&D spill-overs or to changes in the industry aggregate inputs. Industry output increased by 10pp for the whole economy in 2019. 8.6pp of the output gain are explained by the change in industry aggregate100 inputs. Industry productivity and R&D spill-overs also contributed to the increase in output, but the combined effect was smaller, at a 1.5pp improvement. In the low-tech group, industry output in 2019 is 61.6pp lower than in 2013. While industry productivity and R&D spill-overs have a positive effect on generating greater output, it is offset by the considerable reduction in aggregate inputs. Notably, total industry inputs decreased by 65pp in 2019, which is greater than the change in output. The low- and medium-technology industries benefited from both increases in the industry inputs and the combined effect of productivity and R&D spill-overs. The output increases by 64.3pp in 2019, with the industry aggregate inputs contributing 29.7pp and industry productivity and R&D spill-overs contributing 34.6pp. Industry output growth in the medium-high technology group is similar to that of the medium-low technology group. However, there is a slight difference. In this group, the scale of the increase in industry inputs exceeded the industry output. Meanwhile, the combined effect of industry productivity and R&D spill-overs falls by 6.4pp in 2019. The change in the high-tech group follows a similar trend to that of the medium-high-tech group. It also shows a large increase in the industry aggregate inputs by 39.7pp. However, due to the massive decline of 37.5pp in industry productivity and R&D spill-overs, output changed little, increasing by only 2.2pp.

After comparison, industry output is mainly influenced by the aggregate inputs and the industry output changes in the same direction. The low-tech group had fewer inputs and smaller outputs, while the other groups had larger inputs and, therefore, higher outputs. In terms of the impact of industry productivity and R&D spill-over, it has a slight impact on the industry output. It was observed that this impact in 2019 becomes smaller for industries with lower R&D intensity (low-tech and low-medium technology groups) and larger for industries with higher R&D intensity (medium-high and high-tech industries).

Table 3.7 Comparison of the industry output decomposition in 2013 and 2019

	2013	2019	change
Whole economy	(1)	(2)	(3)
Industry output	**21.892**	**21.993**	**0.101**
Industry aggregate input	**10.929**	**11.015**	**0.086**
Industry productivity	10.563	10.8	0.237
Industry R&D spill-over	0.4	0.178	-0.222
Aggregate effect of industry productivity and R&D spill-over	**10.963**	**10.978**	**0.015**
Low-tech	(1)	(2)	(3)
Industry output	**22.451**	**21.835**	**-0.616**
Industry aggregate input	**11.679**	**11.029**	**-0.65**
Industry productivity	10.444	10.65	0.206
Industry R&D spill-over	0.328	0.156	-0.172
Aggregate effect of industry productivity and R&D spill-over	**10.772**	**10.806**	**0.034**
	0.136	-0.274	
Medium-low-tech	(1)	(2)	(3)
Industry output	**20.969**	**21.612**	**0.643**
Industry aggregate input	**10.412**	**10.709**	**0.297**
Industry productivity	10.213	10.782	0.569
Industry R&D spill-over	0.344	0.121	-0.223
Aggregate effect of industry productivity and R&D spill-over	**10.557**	**10.903**	**0.346**
Medium-high-tech	(1)	(2)	(3)
Industry output	**21.708**	**22.31**	**0.602**
Industry aggregate input	**10.496**	**11.162**	**0.666**
Industry productivity	10.801	10.961	0.16
Industry R&D spill-over	0.411	0.187	-0.224
Aggregate effect of industry productivity and R&D spill-over	**11.212**	**11.148**	**-0.064**
High-tech	(1)	(2)	(3)
Industry output	**22.013**	**22.035**	**0.022**
Industry aggregate input	**10.688**	**11.085**	**0.397**
Industry productivity	10.712	10.661	-0.051
Industry R&D spill-over	0.613	0.289	-0.324
Aggregate effect of industry productivity and R&D spill-over	**11.325**	**10.95**	**-0.375**

3.4.5 Policy suggestions

From the output decomposition in Table 3.3 and Table 3.4, we find that capital distortion plays the most prominent role in contributing to the output loss, with 40.6pp in 2019 and 27.2pp in 2013. The results provide some suggestions. In order to eliminate the resource misallocation caused by the initial capital and labour input allocation, the policymaker should efficiency in capital and labour markets. This requires that firms face the same actual input price, in which capital and labour distortions are equalised across firms. In order to improve the efficiency of capital and labour resource allocation government should take actions to improve the efficiency of capital and labour resource allocation, such as reducing subsidies to less productive firms and implementing tax deductions or subsidies to more productive firms.

However, regarding R&D input, the policy suggestions are different. When we compare the results from two different R&D allocation approaches (one is equalising R&D distortions across firms, and in the other one, a certain level of dispersion in R&D distortion is retained), the latter allocation generates a larger output. This indicates that in the optimum the R&D input is used more evenly. Therefore, the policymaker should be aware of the externality of R&D activities and allow for a certain level of inequality in R&D input price. The results suggest that firms with higher productivity pay a higher price to hire R&D resources, and the less productive firms pay R&D input at a lower price. Therefore, the policymaker could encourage less productive firms with the ambition to conduct R&D activities by subsidising the R&D input price they pay.

3.5 Conclusion

In this chapter, we measure the allocative efficiency of capital, labour and R&D resource in UK manufacturing industries. We also analyse how the externality of R&D spillover would affect the results. We employ a similar methodology to the literature but with R&D spill-over added to compute the output loss caused by input resource misallocation across firms. The results show that the output loss in 2019 is around 76% for the whole economy. Regarding the industries with different technology type, the medium-high-tech group suffer the most from the misallocation, with an output loss exceeding 100%. The medium-low-tech group is more efficient in allocation, and the output loss is 43%. In 2013, the allocation is more efficient in all groups, as the results of output loss are smaller.

We also find that the output loss measured in the literature would be overestimated if the effect of R&D spillover on the output is ignored. By comparing the allocation where R&D spillover changes with the R&D allocation and where the R&D spillover is fixed at the initial level, the output in the latter case is larger by around 50 percentage points.

In order to see the role of knowledge spillover in production, we compute the output gain from the improved allocation approach and compare it with the results from the approach introduced in the literature. In the literature, since there does not exist any externality, the allocation is the most efficient when all firms pay the same actual input price. In other words, the input distortions (wedges) are equalised across firms. But in our model, the externality of R&D spillover influences the input allocation. We allow for a certain degree of R&D distortion which is increasing in the firm's productivity. The results show that our improved allocation is more efficient in generating larger output gain. Regarding groups, the medium-high-tech and high-tech groups benefit the most from the improved approach, where the output gain is the largest in the high-tech group in 2013 and the largest in the medium-high-tech group in 2019. In contrast, the medium-low group benefits the least from this approach in both years. The reason might be that the R&D expenditure ratio is the lowest in the medium-low-tech group, in which the industries are mainly related to metals and mineral products. Therefore, the improvement in R&D input allocation makes less difference than for other groups that rely more on R&D input.

We decompose the industry output to see which input misallocation contributes the most to the output loss. The results show that capital misallocation makes the most prominent part. The capital misallocation problem is the most serious in the high-tech group, with a contribution of 12.6pp and 31.9pp in 2013 and 2019, respectively. Labour misallocation also matters, but the magnitude is much smaller. The low-tech group has the largest labour misallocation contribution. Due to the R&D spillover effect, the initial R&D allocation does not harm the output. However, it can still be improved to generate a larger output gain when R&D input distortion maintains a certain level of dispersion. In addition, we find a trade-off between industry productivity and R&D spillover. This indicates that only maximising productivity is not the best solution. Instead, it should be a weighted average of maximising the industry productivity and R&D spillover.

Based on the results, we also provide some policy suggestions. The policymaker should implement policies such as subsidising or tax reduction to encourage firms with higher productivity to hire more capital and labour. On the contrary, less productive firms should be allocated less capital and labour resources. Feasible policies include strengthening the exit mechanism for firms with low productivity and reducing subsidies to less effective firms.

The findings suggest that the magnitude of output gains and input misallocation differs across groups with different technology. Further study is needed to explore what causes these differences. For example, what is the reason that causes the capital misallocation to be more severe in the high-tech group? Or what makes the labour misallocation to be worse in the low-tech group? Except for that, we observe a discrepancy between the output change and the changes in variance and covariance terms. In future research, one can reduce the discrepancy by extending the current model to study the part in the output gain that has not been explained by output decomposition in the current allocation approach.

3.6 Reference

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Appendix 3.A

Appendix 3.A1. Decomposition of industry TFP

We start by substituting (4)-(6) into the production function (2) to arrive at

$$Y_{si} = \left(\frac{B_{si}\Gamma_s X_s^{\delta_s}}{\Theta_{si}}\right)^{\sigma} \tag{19}$$

Where $\Gamma_s \equiv \frac{\sigma-1}{\sigma}\left(\frac{\alpha_s}{r_s}\right)^{\alpha_s}\left(\frac{\beta_s}{w_s}\right)^{\beta_s}\left(\frac{\gamma_s}{q_s}\right)^{\gamma_s}$ and $\Theta_{si} \equiv \left(1+\tau_{K_{si}}\right)^{\alpha_s}\left(1+\tau_{L_{si}}\right)^{\beta_s}\left(1+\tau_{H_{si}}\right)^{\gamma_s}$.

Given (19), the industry s output in (1) becomes

$$Y_s = \left(\Gamma_s X_s^{\delta_s}\right)^{\sigma}\left(\sum_{i=1}^{m_s}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}\right)^{\frac{\sigma}{\sigma-1}}$$

Also, if we substitute (19) back into (4)-(6) and sum across the firms, input demands by industry s are

$$K_s = \frac{\sigma-1}{\sigma}\left(\Gamma_s X_s^{\delta_s}\right)^{\sigma-1}\frac{\alpha_s}{r_s}\sum_{i=1}^{m_s}\frac{1}{1+\tau_{K_{si}}}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}$$

$$L_s = \frac{\sigma-1}{\sigma}\left(\Gamma_s X_s^{\delta_s}\right)^{\sigma-1}\frac{\beta_s}{w_s}\sum_{i=1}^{m_s}\frac{1}{1+\tau_{L_{si}}}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}$$

$$H_s = \frac{\sigma-1}{\sigma}\left(\Gamma_s X_s^{\delta_s}\right)^{\sigma-1}\frac{\gamma_s}{q_s}\sum_{i=1}^{m_s}\frac{1}{1+\tau_{H_{si}}}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}$$

We can use the above expressions for Y_s, K_s, L_s, and H_s to write industry TFP in (15) as

$$TFP_s = \frac{\left(\sum_{i=1}^{m_s}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}\right)^{\frac{\sigma}{\sigma-1}}}{\left(\sum_{i=1}^{m_s}\frac{1}{1+\tau_{K_{si}}}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}\right)^{\alpha_s}\left(\sum_{i=1}^{m_s}\frac{1}{1+\tau_{L_{si}}}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}\right)^{\beta_s}\left(\sum_{i=1}^{m_s}\frac{1}{1+\tau_{H_{si}}}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}\right)^{\gamma_s}}$$

Similar to (Hsieh and Klenow, 2009; Chen and Irarrazabal, 2013; Ryzhenkov and Mykola, 2016), we now provide an approximation of TFP_s assuming that distortions and firm TFPs are log-normally distributed with the variance-covariance matrix given by Σ_s and the number of firms in the industry tends to infinity. Let $\mu_{\Theta s} \equiv E[\log\Theta_{si}], \sigma^2_{\Theta s} \equiv var(\log\Theta_{si}), and \sigma_{B\Theta s} = cov(\log B_{si}, \log\Theta_{si})$. Then,

$$\log TFP_s = \frac{\sigma}{\sigma-1}\log\int\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}di - \alpha_s\log\int\frac{1}{1+\tau_{K_{si}}}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}di$$
$$-\beta_s\log\int\frac{1}{1+\tau_{L_{si}}}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}di - \gamma_s\log\int\frac{1}{1+\tau_{H_{si}}}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}di$$

, where

$$\log\int\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}di = (\sigma-1)(\mu_{Bs}-\mu_{\Theta s}) + \frac{(\sigma-1)^2}{2}(\sigma_{Bs}^2+\sigma_{\Theta s}^2) - (\sigma-1)^2\sigma_{B\Theta s}$$

and

$$\log\int\frac{1}{1+\tau_{I_{si}}}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}di = (\sigma-1)(\mu_{Bs}-\mu_{\Theta s}) - \mu_{Is} + \frac{(\sigma-1)^2}{2}(\sigma_{Bs}^2+\sigma_{\Theta s}^2)$$
$$+\frac{1}{2}\sigma_{Is}^2 - (\sigma-1)^2\sigma_{B\Theta s} - (\sigma-1)(\sigma_{BIs}-\sigma_{\Theta Is})$$

, for $I = K, L, H$. Observe that

$$\mu_{\Theta s} = \alpha_s\mu_{Ks} + \beta_s\mu_{Ls} + \gamma_s\mu_{Hs}$$
$$\sigma_{\Theta s}^2 = \alpha_s^2\sigma_{Ks}^2 + \beta_s^2\sigma_{Ls}^2 + \gamma_s^2\sigma_{Hs}^2$$
$$\sigma_{\Theta Is} = \phi_{Is}\sigma_{Is}^2$$

where $\phi_{Is} = \alpha_s$, β_s, γ_s for $I = K, L, H$, respectively. Substituting it all in the expression for $\log TFP_s$ and noting that$\alpha_s + \beta_s + \gamma_s = 1$, we obtain the expression in (16).

To write $\log X_s$ in terms of variances and covariances of distortions and firm TFPs, we note that

$$\log H_s = \log\int H_{si}\,di = E[\log H_{si}] + \frac{1}{2}var(\log H_{si})$$
$$= \log X_s + \frac{1}{2}var\left(\log\left(\frac{1}{1+\tau_{H_{si}}}\left(\frac{B_{si}}{\Theta_{si}}\right)^{\sigma-1}\right)\right)$$

Hence,

$$\log X_s = \log H_s - \frac{(\sigma-1)^2}{2}(\sigma_{Bs}^2+\sigma_{\Theta s}^2) - \frac{1}{2}\sigma_{Hs}^2 + (\sigma-1)^2\sigma_{B\Theta s}$$
$$+ (\sigma-1)(\sigma_{BHs}-\sigma_{\Theta Hs})$$

After substituting the expressions for $\sigma_{\Theta s}^2$, $\sigma_{\Theta Hs}$, and $\sigma_{B\Theta s} = \alpha_s\sigma_{BKs} + \beta_s\sigma_{BLs} + \gamma_s\sigma_{BHs}$, we arrive at (17).

Appendix 3.A2. Maximizing industry output

We want to maximize (18) subject to the constraint that Σ_s is a positive semi-definite matrix. A symmetric matrix is positive semi-definite if and only if all of its principal minors are nonnegative:

$$\sigma_{Ks}^2 \geq 0 \tag{20}$$

$$\sigma_{Ls}^2 \geq 0 \tag{21}$$

$$\sigma_{Hs}^2 \geq 0 \tag{22}$$

$$\sigma_{Bs}^2\sigma_{Ks}^2 - \sigma_{BKs}^2 \geq 0 \tag{23}$$

$$\sigma_{Bs}^2\sigma_{Ls}^2 - \sigma_{BLs}^2 \geq 0 \tag{24}$$

$$\sigma_{Bs}^2\sigma_{Hs}^2 - \sigma_{BHs}^2 \geq 0 \tag{25}$$

$$\sigma_{Bs}^2\sigma_{Ks}^2\sigma_{Ls}^2 - \sigma_{BKs}^2\sigma_{Ls}^2 - \sigma_{BLs}^2\sigma_{Ks}^2 \geq 0 \tag{26}$$

$$\sigma_{Bs}^2\sigma_{Ks}^2\sigma_{Hs}^2 - \sigma_{BKs}^2\sigma_{Hs}^2 - \sigma_{BHs}^2\sigma_{Ks}^2 \geq 0 \tag{27}$$

$$\sigma_{Bs}^2\sigma_{Ls}^2\sigma_{Hs}^2 - \sigma_{BLs}^2\sigma_{Hs}^2 - \sigma_{BHs}^2\sigma_{Ls}^2 \geq 0 \tag{28}$$

$$\sigma_{Bs}^2\sigma_{Ks}^2\sigma_{Ls}^2\sigma_{Hs}^2 - \sigma_{BKs}^2\sigma_{Ls}^2\sigma_{Hs}^2 - \sigma_{BLs}^2\sigma_{Ks}^2\sigma_{Hs}^2 - \sigma_{BHs}^2\sigma_{Ks}^2\sigma_{Ls}^2 \geq 0 \tag{29}$$

There are four more constraints

$$\sigma_{Ks}^2\sigma_{Ls}^2 \geq 0$$

$$\sigma_{Ks}^2\sigma_{Hs}^2 \geq 0$$

$$\sigma_{Ls}^2\sigma_{Hs}^2 \geq 0$$

$$\sigma_{Ks}^2\sigma_{Ls}^2\sigma_{Hs}^2 \geq 0$$

, but they are automatically satisfied if the other constraints are satisfied.

We will minimize

$$a_{Ks}\sigma_{Ks}^2 + a_{Ls}\sigma_{Ls}^2 + a_{Hs}\sigma_{Hs}^2 - 2b_{Ks}\sigma_{BKs} - 2b_{Ls}\sigma_{BLs} - 2b_{Hs}\sigma_{BHs}$$

subject to (20)-(29) where

$$a_{Ks} = \alpha_s + (\sigma - 1)\alpha_s^2 + \delta_s(\sigma - 1)^2\alpha_s^2$$

$$a_{Ls} = \beta_s + (\sigma - 1)\beta_s^2 + \delta_s(\sigma - 1)^2\beta_s^2$$

$$a_{Hs} = \gamma_s(1 + (\sigma - 1)\gamma_s) + \delta_s(1 + (\sigma - 1)\gamma_s)^2$$

$$b_{Ks} = \delta_s(\sigma - 1)^2\alpha_s$$

$$b_{Ls} = \delta_s(\sigma - 1)^2\beta_s$$

$$b_{Hs} = \delta_s(\sigma - 1)(1 + (\sigma - 1)\gamma_s)$$

As it turns out, the constraint qualifications are not satisfied in this problem and, therefore, the Kuhn-Tucker conditions are not necessary conditions. We identify the solution in several steps. First, suppose the solution is such that $\sigma_{BKs}^2 > 0$, $\sigma_{BLs}^2 > 0$ and $\sigma_{BHs}^2 > 0$. But then from (23)-(25), $\sigma_{Ks}^2 > 0$, $\sigma_{Ls}^2 > 0$, $\sigma_{Hs}^2 > 0$. Furthermore, the only constraint that binds is (29). To see it, suppose for example that (23) binds. But then from (29), $\sigma_{BLs}^2\sigma_{Ks}^2\sigma_{Hs}^2 + \sigma_{BHs}^2\sigma_{Ks}^2\sigma_{Ls}^2 = 0$, a contradiction. The same applies if we assume that any other constraint from (24) to (28) binds. Hence, we solve the following problem:

$$\min L = a_{Ks}\sigma_{Ks}^2 + a_{Ls}\sigma_{Ls}^2 + a_{Hs}\sigma_{Hs}^2 - 2b_{Ks}\sigma_{BKs} - 2b_{Ls}\sigma_{BLs} - 2b_{Hs}\sigma_{BHs}$$
$$-\lambda(\sigma_{Bs}^2\sigma_{Ks}^2\sigma_{Ls}^2\sigma_{Hs}^2 - \sigma_{BKs}^2\sigma_{Ls}^2\sigma_{Hs}^2 - \sigma_{BLs}^2\sigma_{Ks}^2\sigma_{Hs}^2 - \sigma_{BHs}^2\sigma_{Ks}^2\sigma_{Ls}^2)$$

The Kuhn-Tucker conditions are

$$\frac{\partial L}{\partial \sigma_{Ks}^2} = a_{Ks} - \lambda\sigma_{Ls}^2\sigma_{Hs}^2\left(\sigma_{Bs}^2 - \frac{\sigma_{BLs}^2}{\sigma_{Ls}^2} - \frac{\sigma_{BHs}^2}{\sigma_{Hs}^2}\right) = 0 \tag{30}$$

$$\frac{\partial L}{\partial \sigma_{Ls}^2} = a_{Ls} - \lambda\sigma_{Ks}^2\sigma_{Hs}^2\left(\sigma_{Bs}^2 - \frac{\sigma_{BKs}^2}{\sigma_{Ks}^2} - \frac{\sigma_{BHs}^2}{\sigma_{Hs}^2}\right) = 0 \tag{31}$$

$$\frac{\partial L}{\partial \sigma_{Hs}^2} = a_{Hs} - \lambda\sigma_{Ks}^2\sigma_{Ls}^2\left(\sigma_{Bs}^2 - \frac{\sigma_{BKs}^2}{\sigma_{Ks}^2} - \frac{\sigma_{BLs}^2}{\sigma_{Ls}^2}\right) = 0 \tag{32}$$

$$\frac{\partial L}{\partial \sigma_{BKs}} = -b_{Ks} + \lambda\sigma_{BKs}\sigma_{Ls}^2\sigma_{Hs}^2 = 0 \tag{33}$$

$$\frac{\partial L}{\partial \sigma_{BLs}} = -b_{Ls} + \lambda\sigma_{BLs}\sigma_{Ks}^2\sigma_{Hs}^2 = 0 \tag{34}$$

$$\frac{\partial L}{\partial \sigma_{BHs}} = -b_{Hs} + \lambda\sigma_{BHs}\sigma_{Ks}^2\sigma_{Ls}^2 = 0 \tag{35}$$

$$\frac{\partial L}{\partial \lambda} = \sigma_{Bs}^2 - \frac{\sigma_{BKs}^2}{\sigma_{Ks}^2} - \frac{\sigma_{BLs}^2}{\sigma_{Ls}^2} - \frac{\sigma_{BHs}^2}{\sigma_{Hs}^2} = 0 \tag{36}$$

If one plugs (36) into (30)-(32), one gets that

$$a_{Ks} - \lambda\sigma_{Ls}^2\sigma_{Hs}^2\frac{\sigma_{BKs}^2}{\sigma_{Ks}^2} = 0$$

$$a_{Ls} - \lambda\sigma_{Ks}^2\sigma_{Hs}^2\frac{\sigma_{BLs}^2}{\sigma_{Ls}^2} = 0$$

$$a_{Hs} - \lambda\sigma_{Ks}^2\sigma_{Ls}^2\frac{\sigma_{BHs}^2}{\sigma_{Hs}^2} = 0$$

Substituting (33)-(35) into the above expressions, one gets that

$$\frac{\sigma_{BKs}}{\sigma_{Ks}^2} = \frac{a_{Ks}}{b_{Ks}}$$

$$\frac{\sigma_{BLs}}{\sigma_{Ls}^2} = \frac{a_{Ls}}{b_{Ls}}$$

$$\frac{\sigma_{BHs}}{\sigma_{Hs}^2} = \frac{a_{Hs}}{b_{Hs}}$$

However, from (33)-(35), we also have that

$$\frac{b_{Ks}}{b_{Ls}} = \frac{\sigma_{BKs}\sigma_{Ls}^2}{\sigma_{BLs}\sigma_{Ks}^2}$$

$$\frac{b_{Ks}}{b_{Hs}} = \frac{\sigma_{BKs}\sigma_{Hs}^2}{\sigma_{BHs}\sigma_{Ks}^2}$$

which imply

$$\frac{\sigma_{BKs}}{\sigma_{Ks}^2} = \frac{b_{Ks}}{b_{Ls}}\frac{\sigma_{BLs}}{\sigma_{Ls}^2} = \frac{b_{Ks}}{b_{Hs}}\frac{\sigma_{BHs}}{\sigma_{Hs}^2}$$

$$\frac{a_{Ks}}{b_{Ks}} = \frac{b_{Ks}}{b_{Ls}}\frac{a_{Ls}}{b_{Ls}} = \frac{b_{Ks}}{b_{Hs}}\frac{a_{Hs}}{b_{Hs}}$$

However, these equalities cannot be satisfied simultaneously. It follows that the solution cannot be such that $\sigma_{BKs}^2 > 0$, $\sigma_{BLs}^2 > 0$, and $\sigma_{BHs}^2 > 0$ hold.

Second, suppose the solution is such that $\sigma_{BKs}^2 > 0$ and $\sigma_{BLs}^2 > 0$, while $\sigma_{BHs}^2 = 0$. From (23)-(24), $\sigma_{Ks}^2 > 0$ and $\sigma_{Ls}^2 > 0$ hold. Further, inspection of (20)-(29) tells that $\sigma_{Hs}^2 > 0$ does not help to relax any of the constraints, while the objective is decreasing in σ_{Hs}^2. Therefore, $\sigma_{Hs}^2 = 0$ must hold. Then, (25) and (27)-(29) are all automatically satisfied. Of the remaining constraints, (23)-(24) and (26), only the last will bind. To see it, suppose for example that (23) binds. But then from (26), $\sigma_{BLs}^2\sigma_{Ks}^2 = 0$, a contradiction. The same applies if we assume that (24) binds. Hence, we solve the following problem:

$$\min L = a_{Ks}\sigma_{Ks}^2 + a_{Ls}\sigma_{Ls}^2 - 2b_{Ks}\sigma_{BKs} - 2b_{Ls}\sigma_{BLs}$$
$$-\lambda(\sigma_{Bs}^2\sigma_{Ks}^2\sigma_{Ls}^2 - \sigma_{BKs}^2\sigma_{Ls}^2 - \sigma_{BLs}^2\sigma_{Ks}^2)$$

Using similar steps as before, we find the solution where

$$\frac{\sigma_{BKs}}{\sigma_{Ks}^2} = \frac{b_{Ks}}{b_{Ls}}\frac{\sigma_{BLs}}{\sigma_{Ls}^2}$$

$$\frac{a_{Ks}}{b_{Ks}} = \frac{b_{Ks}}{b_{Ls}}\frac{a_{Ls}}{b_{Ls}}$$

However, this equality again is not satisfied. It follows that the solution cannot be such that $\sigma_{BKs}^2 > 0$, $\sigma_{BLs}^2 > 0$, and $\sigma_{BHs}^2 = 0$ hold. By symmetry, the same is true if only $\sigma_{BKs}^2 = 0$ or $\sigma_{BLs}^2 = 0$ holds.

Third, the remaining case is when only one of the covariances is strictly positive. Thus, suppose that $\sigma_{BKs}^2 > 0$, while $\sigma_{BLs}^2 = 0$ and $\sigma_{BHs}^2 = 0$. From (23), $\sigma_{Ks}^2 > 0$ holds.

Further, inspection of (20)-(29) tells that $\sigma_{BLs}^2 > 0$ or $\sigma_{Hs}^2 > 0$ does not help to relax any of the constraints, while the objective is decreasing in σ_{BLs}^2 and σ_{Hs}^2. Therefore, $\sigma_{BLs}^2 = \sigma_{Hs}^2 = 0$ must hold. Then, (24)-(29) are all automatically satisfied. The only constraint that we need to take into account is (23), which will bind.

If it did not, we could decrease the objective by decreasing σ_{Ks}^2. Hence, we solve the following problem:

$$\min L = a_{Ks}\sigma_{Ks}^2 - 2b_{Ks}\sigma_{BKs} - \lambda(\sigma_{Bs}^2\sigma_{Ks}^2 - \sigma_{BKs}^2)$$

The solution is

$$\sigma_{BKs} = \frac{b_{Ks}}{a_{Ks}}\sigma_{Bs}^2$$

$$\sigma_{Ks}^2 = \left(\frac{b_{Ks}}{a_{Ks}}\right)^2 \sigma_{Bs}^2$$

Evaluating the objective at this solution, gives that

$$-\frac{b_{Ks}^2}{a_{Ks}}\sigma_{Bs}^2$$

Similar analysis would apply if we assumed that either only $\sigma_{BLs}^2 > 0$ or only $\sigma_{BHs}^2 > 0$ holds. To decide which of these covariances is strictly positive, we need to compare $\frac{b_{Ks}^2}{a_{Ks}}$, $\frac{b_{Ls}^2}{a_{Ls}}$, and $\frac{b_{Hs}^2}{a_{Hs}}$, and pick the largest. One can verify that $\frac{b_{Hs}^2}{a_{Hs}}$ takes the largest value if either $0 \leq \delta_s \leq \max\{1, \sigma\}$ or $\sigma \geq 2$ holds, both of which are satisfied by our calibration of the model. We conclude that the output is maximized when $\sigma_{Ks}^2 = \sigma_{Ls}^2 = \sigma_{BKs} = \sigma_{BLs} = 0$,

$$\sigma_{BHs} = \frac{\delta_s(\sigma - 1)}{\gamma_s + \delta_s + \gamma_s\delta_s(\sigma - 1)}\sigma_{Bs}^2$$

$$\sigma_{Hs}^2 = \left(\frac{\delta_s(\sigma - 1)}{\gamma_s + \delta_s + \gamma_s\delta_s(\sigma - 1)}\right)^2 \sigma_{Bs}^2$$

Appendix 3.B

B1. Main variables

$P_{si}Y_{si}$	Value added	WQ613	Approximate Gross Value Added (aGVA) at basic prices (£,000)	
K_{si}	Total stock	WQ599	Total value of all stocks at the end of the year (£,000)	
L_{si}	Non-R&D employees	empment emp_sci	IDBR employment at time of sample selection minus Number of scientists, researchers	$L_{si} = empment_{si} - emp\_sci_{si}$
H_{si}	R&D employees	emp_sci	number of scientist & researchers	

B2. Parameter calibration

α_s	Capital share	WQ613 slries	Approximate Gross Value Added (aGVA) at basic prices (£,000) Salaries and wages	$\alpha_s = \frac{\sum_{i=1}^{m_s}(P_{si}Y_{si} - Wage_{si})}{\sum_{i=1}^{m_s} P_{si}Y_{si}}$
β_s	Non-R&D labour share	WQ613 slries WQ522 intram	Approximate Gross Value Added (aGVA) at basic prices (£,000) Salaries and wages Value of total net capex (excluding NYIP) (£,000) R&D Intramural/in-house expenditure total	$\beta_s = \frac{\sum_{i=1}^{m_s}(non - R\&D\ Wage_{si})}{\sum_{i=1}^{m_s} P_{si}Y_{si}}$
γ_s	R&D human capital share	WQ613 slries WQ522 intram	Approximate Gross Value Added (aGVA) at basic prices (£,000) Salaries and wages Value of total net capex (excluding NYIP) (£,000) R&D Intramural/in-house expenditure total	$\gamma_s = \frac{\sum_{i=1}^{m_s}(R\&D\ Wage_{si})}{\sum_{i=1}^{m_s} P_{si}Y_{si}}$
r_s	Rental rate of capital	WQ613 slries WQ599	Approximate Gross Value Added (aGVA) at basic prices (£,000) Salaries and wages Total value of all stocks at the end of the year (£,000)	$r_s = \left(\sum_{i=1}^{m_s} P_{si}Y_{si} - \sum_{i=1}^{m_s} Wage_{si}\right) / \sum_{i=1}^{m_s} K_{si}$
ω_{L_s}	Non-R&D labour cost	empment emp_sci slries WQ522 intram	IDBR employment at time of sample selection Number of scientists, researchers Salaries and wages Value of total net capex (excluding NYIP) (£,000) R&D Intramural/in-house expenditure total	$\omega_{L_s} = \sum_{i=1}^{m_s} non - R\&D\ Wage_{si} / \sum_{i=1}^{m_s} L_{si}$
ω_{H_s}	R&D labour cost	emp_sci slries WQ522 intram	number of scientist & researchers Salaries and wages Value of total net capex (excluding NYIP) (£,000) R&D Intramural/in-house expenditure total	$\omega_{H_s} = \sum_{i=1}^{m_s} R\&D\ Wage_{si} / \sum_{i=1}^{m_s} H_{si}$

Note: WQ613, WQ522, WQ599, empment are available in the ABS database. emp_sci, slries, intram are available in the BERD database.

Chapter 4 R&D and Productivity: A Study of Chinese Listed Firms

4.1 Introduction

This chapter evaluates the effects of firms' accumulated R&D capital and knowledge spillovers on firm level productivity across the sample of listed Chinese firms encompassing both the manufacturing and non-manufacturing sectors. R&D activities have caught up more attention in recent years in China. As the Chinese economy is growing, the marginal effect of investment in infrastructure is diminishing (Shi et al., 2017). This implies that physical capital accumulation may not be the main driver of economic growth as much as it used to be. Grill et al. (2007) explained this issue as the "middle-income trap". To address this issue, one of the approaches is to switch the development strategy from producing low-end goods to high value-added products (Eichengreen et al. 2011). This requires improvement in the productivity of firms. R&D activities and innovations are seen to play an important role in this regard. Hence, in this chapter we set out to explore the R&D and firm level productivity relationship in China. In doing so, we will also explore the role of several other factors that are viewed to shape the firm level productivity.

We follow the basic framework of R&D and productivity popularized by Griliches (1979). He investigated the impact of R&D capital and/or R&D investment on productivity growth in the United States using large R&D-performing firm data (Griliches, 1980, 1986). A positive role of R&D capital or R&D investment in explaining productivity growth is also found in other countries, e.g., France, Japan, and the UK (Cuneo and Mairesse, 1984; Griliches and Mairesse, 1991; Wakelin, 2001). For the effect of knowledge spillover on productivity, Romer (1986) and Krugman (1979), among others, point out that knowledge spillovers between firms generate higher levels of productivity. Therefore, this paper considers firms' own accumulated R&D capital stock as well as intra- and inter-industry knowledge spillovers on the productivity of Chinese listed firms.

The main contribution of this chapter is that we jointly model the potential effects of intra- and inter-industry knowledge spillovers on firm level productivity. This idea has been long ago emphasized by Schumpeter (1934) who argues that knowledge, to a large extent, is a non-rival public good which exhibits externalities. One's consumption of knowledge does not preclude others from consuming it. Thus, a firm's productivity can be driven by not only its own R&D investment but also other firms' innovations. Although there exists a voluminous literature examining the effect of firm's own R&D on productivity, studies exploring knowledge spillovers across firms are scant. In contrast, macro studies have examined cross-country knowledge spillovers in greater detail (Coe & Helpman, 1995; Coe et al., 2009; Luintel & Khan, 2004; Luintel & Khan, 2017). This chapter fills the void by scrutinizing the effects of knowledge spillovers on productivity at the firm-level using data of Chinese listed firms. We also extend the analyses by examining if firms that do not undertake R&D activities benefit through knowledge spillovers accruing from those that are engaged in R&D activities. In addition, we look at the effects of government subsidy, financing sources, ownership, firm size and board size on the productivity as in the literature not all these issues have been covered by one study/paper.

We also consider the heterogeneity in firms with different types of ownership. Hu (2001) found that R&D productivity differs between SOEs (state-owned enterprises) and POEs (private-owned enterprises), and that SOEs are less efficient in transferring R&D into productivity. But few studies mention the knowledge spillover effect together with firms' ownership.

This study takes forward the extant literature on R&D, knowledge spillover, and firm level productivity involving the Chinese listed firms. We find that R&D investment could significantly increase productivity in manufacturing sector and the estimated spillover parameters suggest intense competition across Chinese firms. However, the magnitude of competition differs across firms with different ownership. Foreign firms appear to have technological cooperation and positive knowledge spillovers while private Chinese firms appear to compete. For other relevant factors, government subsidy has a negative effect on the productivity and the ease of financial constraints promotes both the productivity and the output. Larger firms are more productive in manufacturing sector while in non-manufacturing sector smaller firms are more productive ceteris paribus.

The remainder of the Chapter is organised as follows. Section 2 summarises the theories about the impact of a firm's own R&D investment and knowledge spillover on productivity and output as well as relevant empirical studies. It also discusses other factors that may have an impact on productivity such as government subsidies, financing sources and ownership. Section 3 describes the method to measure R&D knowledge stocks and the models employed to evaluate the effects of R&D capital and knowledge spillovers on productivity and output in the long run and short run. Section 4 describes the sample, data sources and construction of variables. The econometric methodology is discussed in section 5. Section 6 discusses the empirical results. Section 7 concludes the Chapter and comments on policy implications and avenues for future studies.

4.2 Literature Review

4.2.1 R&D, productivity, and output growth

There is already a lot of literature explaining R&D as one of the factors driving productivity and output growth which is not explained by Solow economic growth model (Solow, 1957). Firms' R&D investment increases their productivity, which drives their output growth (Griliches, 1979, 1988; Grossman and Helpman,1991; Coe and Helpman, 1995). Grossman and Helpman (1991) and Aghion and Howitt (1992) build a quality-ladder model where labour is taken as a factor to conduct R&D activities to improve the quality of intermediate goods or to produce intermediate goods. Intermediate good is used to produce final goods. Denicolò and Zanchettin (2014) also find that a firm's R&D investment can influence its output by a different mechanism, where they develop a lab-equipment model and assume final goods rather than labour to be employed in improving the quality of goods in the production function.

Recent literature focuses on how knowledge could affect productivity. Rodrik (2006) made a supplementary point to the traditional opinion of fostering economic growth that labour should move from low-productivity industries such as agriculture to 'modern' industries, by emphasizing the productive diversification. Increasing the range of manufactured goods is an integral part of economic development. In the process of economic development, learning to develop new things, rather than what has already been done, should be more focused on. This requires innovation and R&D activities in expanding the diversification in manufacturing industries. Wang et al. (2017) used a fixed effects panel model to estimate a region-level production function to analyse the relationship between various technology inputs and productivity changes for 29 Chinese regions from 1990 to 2005. They choose value added as the dependent variable. Region-level R&D stock, generated from expenditure on science and technology activities by perpetual inventory method, is adopted as each region's own R&D input. They find that regional R&D expenditure has positive effect on the regional industrial growth. Shen et al. (2019) used a panel data for 30 Chinese provinces from 1978 to 2014 to estimate the effect of R&D capital on regional productivity by OLS and GMM estimates. They concluded that R&D can promote growth in regional TFP by absorbing new technologies embodied in FDI and foreign trade.

Literature also reveals that the magnitude of R&D's effect on productivity and output growth varies across industries with different taxonomies and/or different countries. For example, O'Mahony and Vecchi (2009) estimate the R&D's effect in industries classified by capital-intensive, labour-intensive, high-tech intensive. Griliches (1985) found both federally financed R&D and privately financed R&D have a positive effect on productivity growth in the U.S. manufacturing sector. But the benefit for the privately financed R&D is much higher. Cuneo and Mairesse (1984) reported the elasticity of output to R&D to be higher in France than that in the US. Harhoff (1998) and Griffith et al. (2006) also found a positive effect of R&D on output growth in Germany and the UK, respectively. Sassenou (1988) reported a positive effect of R&D on output growth in Japanese manufacturing sector and the R&D elasticity in scientific sector is higher than what is reported in other sectors. O'Mahony and Vecchi (2009) analysed the impact of R&D on output growth and the spillover effect for different taxonomies of industries: R&D intensive industry and other kinds of industries (e.g., labour-intensive industry, capital-intensive industry, advertising-intensive industry, and others). The results show that the firm's R&D promotes output growth in both manufacturing and non-manufacturing sectors in the US, UK, Japan, France and Germany. Ortega-Argilés (2011) found the overall impact of knowledge stock on a firm's productivity is positive and significant for 532 European R&D firms from 2000 to 2005. The elasticity appears to be the highest in high-tech sector while it is smaller in low-tech sectors, which suggests that companies in the high-tech sector are in a leading position in R&D productivity. Kancs et al. (2016) used firm-level data for OECD countries and found a non-linear relationship between R&D investment and firm productivity growth. The productivity elasticity is higher for firms with higher R&D intensity and firms in high-tech industries have a higher level of productivity gain related to R&D activities. Besides, Ugur et al. (2016) employed a meta-regression analysis to explore the relationship between R&D and productivity. They found that the private and social returns to R&D investment are smaller and more heterogeneous than those in prior literature, though they are still positive.

However, some studies stressed the importance of R&D efficiency. R&D efficiency can be considered as a ratio of innovation outputs over R&D inputs (Hollanders and Celikel-Esser, 2007). They mentioned that the R&D inputs are always education, R&D investment, firm-level R&D activities, etc. The R&D outputs are often measured by patents, revenues earned from new product and so on. In their research, intellectual property is treated as the innovation output. A higher R&D efficiency means firms invest the same amount in R&D but can get more in output. However, the results show that as the R&D investment increase, the R&D efficiency does not change in Chinese high-tech industries (Han et at., 2017). This suggests R&D investment cannot be well transferred to output in the current development stage and the quality of innovation should be improved.

4.2.2 Knowledge spillover

Although Griliches (1979) generated a production function and measured the effect of the knowledge capital on the output, he did not consider the knowledge spillovers. However, Romer (1990) and Grossman & Helpman (1991) emphasized the knowledge spillover effect in generating higher productivity and economic growth in the long run. Schumpeter (1942) illustrated the idea of the knowledge spillover effect. He mentioned that a firm which creates the new technology or invention cannot capitalize all benefit from its innovation. Instead, other firms would also benefit from this innovation. This would attract competitors and then the competition would decrease the profit of the innovation to the inventors. Arrow (1962) and Nelson (1959) show that not only the traditional factors of physical capital and labour but also the knowledge capital plays a role in the production. The distinctive characteristic of knowledge capital is its non-exclusiveness and non-rivalry and technological achievements or information can be considered as public goods. They generate externalities, which means all firms with and without R&D effort can benefit from existing knowledge and information as they are shared by all firms in the same technological environment. Research shows that knowledge has strong externalities, and it generates a much higher return to the society compared to the firm's own benefits. Terleckyj (1980) found that the social return of R&D investment exceeds 100% while the private return of R&D is only 25%, implying that the external effect of R&D is three times larger than its internal effect. Scherer (1982) obtained similar results, indicating that the social return of R&D is three times higher than the private return of R&D. Keller (2004) analysed the international knowledge diffusion and found that countries which do not pay the full cost in R&D can still benefit from the knowledge diffused from other countries. This indicates that knowledge investment has both private and social returns. Sena (2004) found that social return is extremely high and knowledge spillover from other industries is more obvious. She also pointed out that R&D spillover is embodied in intermediate goods which firms purchase and use in their production processes.

Some recent literature brought up issues that may cause biases in the estimation of private and social returns on R&D investment. Manski (1993) discussed a situation when the estimates of social returns on R&D might be upward biased. If all firms spend more in R&D when there is a new research opportunity, social returns on R&D might contain spillover effect as well as the effect of firms' own R&D on productivity and this would cause biased estimates of social return. Bloom et al. (2013) addressed this issue by constructing an instrumental variable for R&D expenditure. They use the changes in firm-specific R&D tax as instrument to estimate the causal impact of knowledge spillovers. They also separated the positive knowledge spillovers and negative private return caused by product-market competition by identifying a firm's market position using its information on distribution of its sales activity across different industries. Ugur et al. (2016) elaborated on R&D and productivity at firm- and industry- level for OECD countries through a meta-regression analysis. Their finding on the private and social returns on R&D contrasts with the prior mainstream of literature, which suggest that social return to R&D is much higher than private return. Instead, their result not only shows that the private and within-industry social return to R&D are smaller and more heterogeneous than that in prior literature, but also reports that private return and intra-industry social return are similar.

There are micro and macro studies on the knowledge spillover effects. In firm-level studies, Jaffe (1986) illustrated that the spillover effect implies a situation that firms with R&D effort would let other firms obtain benefit with fewer R&D activities. Although both kind of firms with and without R&D effort would get extra gains, there are studies which reveal that investing in R&D helps firms better to acquire existing knowledge (Cohen and Levinthal, 1989, Griffith et al., 2004). Mahony and Vecchi (2009) extended this research by measuring productivity in industries with different taxonomies and found a higher TFP in R&D intensive and skill intensive industries. They take this result as evidence of the spillover effect in R&D- and skill- intensive industries. Also, even if a firm is not involved in R&D activities but operates in the same industry with other firms that are involved in R&D, it can also generate extra productivity gains. Some studies focus on international knowledge spillover effect on productivity. For macro studies, Frantzen (2002) and Pueyo et al. (2008) calculated both domestic and foreign intra- and inter- sectoral R&D capital stock to analyse the international and domestic knowledge spillover effect for OECD countries. Liu and Buck (2007) explored the international knowledge spillover effect on innovation in high-tech industries in China. They concluded that export and import can promote innovation for high-tech industries. Also, R&D capital stock in multinational enterprises has a significant effect on domestic innovation only when the absorptive ability is considered. Eberhardt et al. (2013) expanded the Griliches knowledge production framework by conflating economy's own R&D stock and spillover effects for ten OECD economies. The results imply that knowledge spillovers cannot be neglected at least in these OECD economies. Luintel & Khan (2017) gauged the knowledge spillover from emerging countries (EMEs) countries and Organisation for Economic Cooperative Development (OECD) countries to EMEs through several knowledge diffusion channels (e.g., total import, machinery import and geographical proximity). They found that there does not exist positive and significant knowledge diffusion across EMEs while there are intellectual knowledge spillovers from OECD countries through the geographical distance channel and disembodied channels.

There are several channels of knowledge spillover. One of the most important channels is FDI. Griffith et al. (2006) point out that UK firms could reap higher knowledge spillover if they undertake their innovation activities in the US. Spillover induced from FDI not only contributes to the regional economic growth (Kuo & Yang, 2008) but also impacts the productivity and efficiency of regional innovation production. MNEs are willing to impart technology and management experience to enterprises from which they supply or purchase intermediate goods in the industry (Javorcik, 2004; Gorodnichenko et al., 2015). Keller (2009) pointed out that the reason for the significant backward spillover (MNEs buy inputs from domestic firms) is that MNEs' hope to obtain high-quality intermediate goods supply from host country enterprises. These findings imply that foreign-related firms might perform differently than domestic firms in knowledge spillover effect, hence we also consider the ownership factor in this chapter.

4.2.3 Firm Ownership, R&D, and Productivity

Except for foreign-related firms, state-owned and private-owned firms also perform differently as they have different objectives. Tan et al. (2007) suggest that for many SOEs (state-owned enterprises/firms), their objectives are different due to state ownership and are mainly to achieve social policy goals (including guarantying employment rate, doing research and development on prominent technologies). But for other firms with a different type of ownership, the objective is often just profit maximization. This difference could cause a different attitude towards R&D activities. Hu (2001) found that state-owned firms are less efficient in transferring R&D into productivity than private-owned firms in Chinese industry. Boeing et al. (2016) use a two-periods panel data for Chinese listed firms and found that privately-owned enterprises have higher return on R&D than state-owned enterprise. Zhou and Deng (2009) explored the R&D efficiency in high-tech industries for SOEs and foreign-funded enterprises in China and concluded that the R&D efficiency in SOEs is comparatively lower.

However, although literature shows Chinese SOEs have lower R&D efficiency, they want to innovate because a successful innovation can have externalities and generate social welfare. This technological spillover effect would benefit other firms and industries. Due to this reason, state-owned firms tolerate the low success rate of R&D and are willing to spend more on R&D (Howell, 2017). For private-owned firms, since their main objective is to achieve short-term profit maximization, they might not spend much on R&D because the cost is high and the success of R&D is not guaranteed. Arrow (1962) illustrated that private-owned firms tend to invest in a suboptimal level in R&D. Yue and Zhang (2017) found that the main source of R&D investment for state-owned enterprises is government subsidy and that for non-state-owned enterprises is internal funds. Since the literature reports differential effects of firm level R&D on productivity across firms with different types of ownership, we are going to address this issue as well in this chapter.

4.2.4 Other related factors (control variables)

4.2.4.1 Firm size

Firm size affecting R&D and innovation has a long history. The relationship between innovation and firm size is firstly proposed by Schumpeter (1942). He found that different from small-sized firms, monopoly firms are more likely to create innovation. This implies firms with larger size and commanding greater share in their industries tend to engage more in R&D activities. He argued that firms with monopoly power have advantage in capturing the returns to innovation (Schumpeter, 1942). Ace and Audretsch (1987) extended Schumpeter's hypothesis by pointing out that the relative innovative advantage of large and small firms is determined by the extent of the imperfect competition in a market. Rather than finding a relationship between firm size and R&D activities, exploring the circumstances that provide innovative advantage to large firms or small firms is more important. Cohen and Klepper (1996) showed that there is an advantage for large firms to conduct R&D activities due to the fixed costs. Also, larger firms might get access to external financing more easily, which eases the financial constraints on their innovation activities. Cohen et al. (1987) found that firm size has an insignificant effect on research intensity. But they found that firm size is positively related to the probability of conducting R&D activities. Benavente (2006) obtained a similar conclusion in the context of Chile. In the analysis of the relation of firm size to R&D productivity, Kim et al. (2009) found that patents per R&D increase with firm size for semiconductor and pharmaceutical industries, which is consistent with Schumpeter's hypothesis. In addition, technological regime such as laws on intellectual property right also matters for the R&D productivity of firms with different size. Antonio and Zulima (2012) found that larger firms' R&D productivity is higher with limited use of intellectual property rights while small firms' innovation performs better under the regime which uses intellectual property rights as a means of appropriation. Scholars use different indicators to measure firm size. Boeing (2016) adopts the log of the number of employees to measure firm size while Guo et al. (2016) measure firm size by the natural logarithm of the annual sales of the firm each year.

4.2.4.2 Board size and firm management

Literature shows the importance of board size on R&D and productivity. As board size is closely related to a firm's management, some studies note that the board size has a negative effect on a firm's performance. The board size is related to a firm's management and decision making, which would later affect its R&D activities. Jensen (1993) illustrated that a larger board, which includes more directors, would cause a lower efficiency in the communication about the firm's management decision making. It is more difficult to achieve the consensus and the final decision would be more compromised than in those firms with less directors (Sah and Stiglitz, 1991). This hypothesis is supported by Cheng (2008)'s empirical study, which shows that the board size id negatively related to the variability of the firm's performance. He explained this result by noting that a larger board make more moderate decisions and thus the firm's performance is more stable. There are also empirical studies showing that the board size has a negative impact on the firm's performance. Yermack (1996), Eisenberg et al. (1998), Mak and Kusnadi (2005) and Guest (2009) found the negative impact of a larger board size on the firm value or profitability in the case of the US, Finland, Singapore and Malaysia, and the UK, respectively. Another way a larger board influence on the firm's management, can be considered as the outcome of the "agency problem", which would cause the under-investment in R&D. The CEO has more power in decision making and controlling the board when the board size is larger (Jensen, 1993). Then the firm would opt for a lower level of R&D investment. This is because the R&D activities are more uncertain, but the CEO aims to conduct low-risk activities and acquire short-term profits (Jensen and Meckling, 1976). Chen (2012) found that board size has a negative effect on firms' R&D investment in the electronic industry in Taiwan. The author suggests that firms should consider having a smaller board size if they are competing in innovation. Kao and Chen (2020) found high-tech firms which have their CEO in duality or longer tenure tends to invest more in R&D. On the other hands, there are also other researches suggesting that a larger board size has a positive effect on firms' management. Haynes and Hillman (2010) and Goodstein et al. (1994) explained board size should have a beneficial effect on firms whose main business focuses on innovation because a larger board size would make the firm have more experts. This provides the firm with more professional information on their product development, industry prospects and development strategies. Ruigrok et al. (2006) suggested that the quality of strategic decision on innovation and R&D activities can be improved with more experts providing valuable information. Also, Kackling and Johl (2009) made a point that a larger board size often comes with more external financial resources, which might stimulate the firm's R&D activities and productivity. Pfeffer and Salancik (1978) mentioned another benefit with larger board size. That is, more experts can provide more intellectual information and reduce the risk of uncertainty. Given these conflicting arguments and empirical evidence vis-a-vis firm's board size, R&D and productivity, we would like to evaluate this issue across Chinese listed firms.

4.2.4.3 Ownership concentration

Ownership concentration could be another important factor determining a firm's R&D, innovation, and hence the productivity. Due to the information asymmetry between a firm's manager and owners, they always have different opinions on operating strategy and decision on R&D activity investment. The separation of ownership and actual control would cause agency problem, which might harm a firm's development (Ortega-Argiles et al., 2005). Jensen and Meckling (1976) and Berle and Means (1991) indicated that there would be conflict between managers and owners because managers are more willing to take low-risk activities and get short-term profits while owners are more interested in the firm's further development. The different objectives make managers and owners have different attitudes to R&D investment because R&D activities are always considered as high-risk and cannot be treated as other normal business. Literature shows there is a negative impact of low ownership concentration on innovation activities. Holmstrom (1989) explained this by noting the high contracting costs of R&D activities. Such contracting costs in firms with low ownership concentration would cause the reduction in investment in innovative activity. Due to the characteristics of innovation activities, which include high risk and unpredictability, a firm with low ownership concentration would prefer short-term projects with more immediate and certain returns if it has little management ownership. Other literature suggests that concentrated ownership is effective in reducing the high agency and contracting costs in R&D activities. They indicated that a firm with high ownership concentration would be more innovative (Francis and Smith, 1995; Harris and Raviv, 2008). By contrast, Ortega-Argiles et al. (2005) analysed the link between a firm's ownership structure and their innovation activities. Their results show that a high degree of ownership concentration reduces firm's R&D expenditure and harms R&D output. They illustrated that the management team is more likely to be controlled in a firm with the high concentrated ownership, which would limit managers to provide professional advice on innovation activities. They concluded that the lack of specialisation in decision making is not good for R&D projects investment and performance and diffusely held firms are more likely to invest in R&D projects as the managers are more flexible. Due to the contradictory evidence on the effect of ownership concentration on R&D, we would also consider this factor in this chapter.

4.2.4.4 Source of finance

Bank finance plays a role in easing the resource constraints in R&D firms. In the analysis of the relationship between financial constraints and firm productivity, the mainstream literature illustrates that financial constraints do affect firm productivity by influencing the firm's investment decision and R&D activities.

One of the main issues is to explore how far financial constraints inhibit firms' innovations. Once this relationship is determined, the influence on the firm productivity is then determined because the technology is driven by R&D activities. Although the famous M-M theory (Modigliani & Miller, 1958) indicates that firm's investment decisions both in physical capital and innovation activities are not affected by its capital structure and liquidity, it just holds for a perfect capital market scenario. In real world, capital market is imperfect, and more so in emerging countries like China. Financial constraints would influence firms' investment behaviours and innovativeness, and hence firm productivity (Jin, Zhao & Kumbhakar, 2019). Due to the characteristics of innovative activities, such as high risk and information asymmetry, Hall (1993) concluded that the firm with a higher level of debt finance does not favour innovation projects. Literature also suggests the opposite, however. Denis and Sibilkov (2010) found that unconstrainted firms invest less in R&D activities. They explain this as the outcome of agency problem, indicating that agents are more likely to 'waste' money instead of investing in productivity-increasing activities.

Besides, there is a strand of literature which adopts nonparametric DEA approach and shows a positive effect of financial constraints on firm performance efficiency. This approach does not set the specific parametric function. Instead, it uses the concept of production frontier. The efficiency is measured as a ratio of the productivity of a specific firm to the productivity of the firms on the production frontier. The economic activity is defined as efficient when the ratio equals to one and inefficient when the ratio is less than one. Färe, Grosskopf, and Lee (1990) firstly apply this approach to construct a deterministic frontier profit function with and without expenditure constraints. The results show that firms with financial constraint are more efficient. They explain this as unconstrainted firms are more likely to use excessive inputs in the production process, which causes lower efficiency than financially constrained firms. Later researches by Arnade and Gopinath (2000), Blancard et al. (2006), Fletschner et al. (2010) and Smith et al. (2011) also use the DEA approach to analyse the relationship between efficiency or productivity and financial constraints for Russian, French, Peruvian and Indian firms, respectively.

The relationship between financial constraints and firm productivity might be non-monotonic as some researchers show it to be positive while others negative. Following Whited (1992) and Love (2003)'s model structure, Jin et al. (2019) generate an endogenous relationship between financial constraints and productivity through the channel of R&D investment for Chinese manufacturing firms. They find that this relationship appears to be an inverse U-shaped, which implies that there will be threshold (turning point) of financial constraint beyond which constraint hurts productivity. Financial constraint increases productivity before it reaches the threshold. By adjusting an unconstrainted firm's financial constraint to the productivity-maximising level, the firm's productivity can be increased both in long and short runs.

Innovative firms might be resource constrained due to the uncertainty associated with innovation activities, particularly the low probability associated with the success of R&D projects (Carpenter and Petersen 2002), information asymmetries between researchers and investors (Guiso 1998), and limited collateral value of innovations ((Kamien and Schwartz 1978; Honjo et al. 2014). Galende and De la Fuente（2003）examined the factors affecting innovative firms in Spain. They found that firms in a higher level of financial debt generated more incremental innovations rather than radical innovation, where a radical innovation refers to those creating major disruptive change to the market or firms' economic activities and an incremental innovation refers to those enhancing or upgrading an existing product or service continuously (Schumpeter, 1942). This is because radical innovation has high information asymmetries and transaction cost, and such R&D activities have high risk and are intangible. This characteristic of investment in R&D leads to the difficulty of debt financing. This implies that firms with higher level of financial constraints might invest less in R&D activities than unconstrainted firms and thus their firm productivity is lower. But internal financing can overcome this problem. Also, internal financing can effectively prevent their innovation and important technologies leaking in the competitive market.

4.2.4.5 Government subsidy

Arrow (1972) explained the importance of the government subsidies on firms' R&D. Due to the high risk and moral hazard problem in R&D activities, there would be difficulties in financing innovation activities for firms. This would lead to an underinvestment in R&D activities. Government R&D subsidies could correct such sub-optimal investment in R&D and thereby incentivize firm's own R&D investment. In China, firms receive government subsidies through a competitive proposing process. R&D projects that are more relevant to policy goals have higher chance to be selected by the central government. However, in the process of China's reform, provincial governments become more powerful in implementing the innovation policies (Springut et al. 2011). This may cause the implementation results not completely consistent with the plan of the central government (Boeing, 2016). Therefore, we also consider the government subsidies in this chapter.

Government subsidies are related to the firm's ownership type in China. Hu (2001) pointed out that the government's science development policies are in favour of State-owned enterprises (SOEs). However, the results showed that SOEs are less efficient in R&D activities than Privately-owned enterprises (POEs), which suggests that the government should reallocate subsidies between firms with different ownerships. Cheng et al. (2019) found that innovation subsidies are more likely to be allocated to SOEs and politically connected firms. Their results also suggest that subsidised firms do not necessarily have higher productivity, which implies the inefficiency in the innovation subsidy allocation in China. Whether a firm would obtain the subsidies not only relates to its ownership, but also the political connection of its managers. Wu et al. (2012) found privately-owned firms with politically connected managers in the private firms help the firm to gain favourable treatment such as subsidy from the government, while this does not happen in SOEs as the main function of state-owned enterprises is more likely to carry out government policies such as ensuring employment rather than increasing earnings. Haley and Haley (2013) revealed that the Chinese government generally would not apply its industrial strategies directly. Instead, it tends to achieve its macroeconomics policy goals by ensuring that firms are dependent on its financial assistance. This is easier to take place in state-owned enterprises. Cull et al. (2014) explained that SOEs and government have a closer relationship than privately-owned firms. Boeing (2016) also gave similar interpretations. The goal of privately-owned firms is to maximize short-term profit. Although they also need financial assistance, they might reject joining government's R&D programs to keep themselves dependent on government's control. Thus, whether a firm would get subsidies from the government depends on its type of ownership. But Harris and Li (2019) reported a different result, where foreign-owned firms received the highest rate of government assistance while SOEs received the lowest level of assistance between 1998-2007 in China. Due to the contradictory empirical results, we include the factor of the firm's ownership type into our model.

Government subsidies might affect firms' R&D behaviour by reducing the marginal cost of firms' innovation activities. Therefore, firms are more likely to invest more in

R&D projects (David et al. 2000). Xie et al. (2009) concluded that the effect of the subsidy on a firm's own R&D investment is significantly positive. But in their model, R&D effect is picked by a dummy variable. The dummy variable equals to 1 when the firm reports R&D investment and equals to zero when it does not report R&D activities. Therefore, the result in this model is less substantive compared to other models, which capture this effect not by a dummy variable but by the accurate data on firm's R&D expenditure or R&D stock. Hu and Jafferson (2008) found that government subsidies drive firms' R&D spending in China, and Howell (2017) pointed out that subsidized high-tech firms spend more on R&D. Audretsch et al. (2002), Lach (2002), Görg and Strobl (2007), Aerts and Schmidt (2008), Czarnitzki and Lopes Bent (2011) and Huergo and Moreno (2017) also found that subsidized firms invest more in their R&D than firms without subsidies in US, Israel, Ireland, Germany and Spain respectively. Also, Li et al. (2019) found there is a signalling effect of government subsidy for firms. Government subsidy can be considered as a certificate or guarantee for a firm, which reduces information asymmetry and helps them to get external finance more easily. Thus, firms might get more bank loans or other external finance once they are subsidised by the government. Also, the government can better identify firms with good R&D projects or innovation than outside investors. This is because firms are more willing to provide relevant R&D information to the government to get subsidies, not worrying about competition or information leakage to competitors (Bhattacharya and Ritter, 1983 and Ueda, 2004). This indicates that the government subsidy certificate helps firms to ease the financial constraints in R&D activities. Wu (2017) proved that firms are more likely to get more external finance after certificated by the government.

However, there are studies which suggest the opposite. The market imperfections and the externalities of innovation activities would affect the implementation of R&D policy (Montmartin and Massard, 2015), which might cause the failure in stimulating firms' private R&D spending. If the public subsidies are the perfect substitutes for firms' private R&D investment, there would be a crowding-out effect of the government subsidies on firms' private R&D expenditure. Boeing (2016) explained a possible reason for the failure in promoting firms' private R&D spending by the government subsidies. That is, the government cannot be sure the selected R&D projects would not be undertaken without government support. He investigated the effectiveness of government's subsidy to R&D activities in Chinese listed firms. The result shows that the R&D subsidies have a crowding-out effect on firm's own R&D investment in short run but become neutral later. He suggests that if the subsidy results in crowding-out or neutrality instead of a net addition, then the subsidy policy cannot be considered as successful and should be adjusted to achieve higher efficiency. He also mentioned that the effectiveness of R&D subsidy varies with firm's type of industry and type of ownership. The results show that the crowding-out effect generally does not take place across high-tech firms or state-owned firms. Likewise, by using the data of renewable energy firms listed on Chinese stock exchanges, Yu et al. (2016) found the government subsidies have a significant crowding-out effect on firms' R&D investment. David et al. (2000), Wallsten (2000) and Lv and Yu (2011) also found the crowding-out effect of government subsidies on firms' own R&D expenditure. In addition, there are also researches undertaken by Klette and Møen (1999), Brander et al. (2008), Lööf and Hesmati (2005) and Clausen (2009) which find that government R&D program does not help much to increase firms' own R&D investment and their economic performance.

The total amount of the Chinese government subsidy to enterprises increased from 18.39 billion yuan in 2009 to 49.13 billion yuan in 2018. In order to promote R&D by enterprises, the Chinese government developed specific R&D policies to help R&D conducting firms in purchasing equipment, talent accumulation, innovation activities, and enterprise development (Jia et al., 2021). According to the National Statistics Bureau of China, government subsidies to R&D for enterprises have been increasing at an annual growth rate of 30% from 1997 to 2012 (Zhang and Wu, 2014).

In terms of the impact of government subsidies, Huang (2015) shows that TFP of firms after enjoying tax credit could be stimulated. Regarding subsidy, many studies are testing whether subsidies from the government have a direct impact on the firm's TFP or output. Griliches and Regev (1998) found that government subsidies could lead to a higher level of TFP in Israel. And Branstetter and Sakakibara (1998) obtained a similar conclusion for Japan. However, Managi (2010) shows that there exists a negative effect of government subsidy on firm's TFP. Koski and Pajarinen (2015) show that government subsidy for enterprises R&D activities does not have a significant effect on labour productivity in Finland. Howell (2015) found that fewer subsidy drives TFP while more subsidies harm TFP. For empirical evidence in Chinese industry, Harris and Li (2019) test whether receiving government's assistance has an impact on the firm's productivity in China. They claim that government assistance would reduce the cost of capital, which encourages them to improve their product quality and increase capital stock and then their productivity would be increased. The results vary with the level of assistance. But generally receiving government assistance helps to increase firm's productivity growth. They also mentioned that the effect is partly determined by firms' political connections and their type of ownership. Guo et al. (2016) reported that government R&D program stimulates firms R&D output for small and medium size firm in Chinese manufacturing sector. Howell (2017) also found that public subsidies promote innovation in high-tech industries but would decrease firms' TFP for both low-tech and medium-tech industries. He explained this in terms of government's hope that some subsidized firms become successful in innovation, which could have social welfare and spillover effect. However, David et al. (2000) pointed out that there is an endogeneity problem caused by selection. In China's R&D programs, the government are more likely to choose high-tech firms, for which TFP is already higher than that for other firms. This causes an overestimation of the effect of government subsidy.

4.3. Model

4.3.1 Measurement of Total Factor Productivity (TFP)

To analyse the relationship between R&D knowledge stock and firm-level productivity, we firstly adopt a Cobb-Douglas production function:

$$Y_{it} = A_{it}K_{it}^{\beta_k}L_{it}^{\beta_l} \tag{1}$$

Where Y_{it} is output, K_{it} is physical capital stock, and L_{it} is labour input. A_{it} is productivity. After taking logs, the linearized production function becomes:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + e_{it} \tag{2}$$

where y_{it} is sales deflated by producer price index, k_{it} is tangible assets and l_{it} is the number of employees. e_{it} is total factor productivity. All the variables are in logarithm.

Solow (1957) decomposed economic growth into the part explained by factor inputs (capital and labour), and the residual explained by productivity. The literature (Griliches, 1979,1988; Grossman and Helpman, 1991; Coe and Helpman, 1995) models R&D as one of the main factors driving productivity. We measure Total Factor Productivity (TFP) as the residual of the linearized production function (2):

$$e_{it} = TFP_{it} = y_{it} - \beta_0 - \beta_k k_{it} - \beta_l l_{it} \tag{3}$$

Equation (3) gives a measure of the level of TFP. To model the short run R&D-productivity relationship, we follow O'Mahony and Vecchi (2009) and take the first difference of production function (2):

$$\Delta y_{it} = \beta_0 + \beta_k \Delta k_{it} + \beta_l \Delta l_{it} + \Delta e_{it} \tag{4}$$

Where Δy_{it} is output growth and Δe_{it} is the growth rate of productivity. The TFP growth rate is estimated from the first difference equation:

$$\Delta e_{it} = \Delta TFP_{it} = \Delta y_{it} - \beta_0 - \beta_k \Delta k_{it} - \beta_l \Delta l_{it} \tag{5}$$

We do not choose the Ordinary Least Squares (OLS) method to estimate the production functions (2) and (4) due to simultaneity bias. This is because the factor inputs are not exogenous and are correlated with unobservable productivity shock. This can be explained as follows. Producers could get some information about the productivity change in advance and then change their inputs of capital and labour depending on the productivity shock. Thus, capital and labour input are endogenous, which violates the assumption of OLS. Instead, we adopt the method proposed by Levinson and Petrin (2003) as it addresses the simultaneity problem. They use an indicator for intermediate goods inputs as a proxy variable for the productivity shock. They show that in order for the intermediate inputs to be a valid proxy/instrument, two conditions must be met: (i) intermediate inputs are affected only by capital and productivity; and (ii) a monotonicity condition requiring that, for a fixed amount of capital, more intermediate inputs are used by firms with higher productivity. Under these assumptions/conditions intermediate input is a valid instrument to address the simultaneity problem while estimating the production function. We adopt the LP method to generate TFP in the production functions shown in equations (2) and (4).

4.3.2 Construction of knowledge stocks and spillover pools

We convert the real flow of each firm's R&D expenditures to stock measures by perpetual inventory method, which is standard and widely used in the literature. The initial R&D capital stock for the i[th] firm is calculated as:

$$S_{i,0}^{F} = \frac{\overline{\dot{S}_{i,t}^{F}}}{g_i + \delta}$$

where g_i is the average annual growth rate of R&D expenditure in the sample; δ is the depreciation rate of R&D capital stock; $\overline{\dot{S}_{i,t}^{F}}$ is the mean value of the R&D expenditure over the seven years in the sample. The calculated R&D capital stock $S_{i,0}^{F}$ is used as the initial value in R&D expenditure flow. We calibrate the depreciation rate of R&D stock to be 15% as the most researchers do (Hall, 2007).

With the initial R&D capital stock $S_{i,0}^{F}$, we then generate the R&D stock for the next 6 years as:

$$S_{i,t}^{F} = log[(1-\delta)S_{i,t-1}^{F} + \dot{S}_{i,t}^{F}]$$

To measure the spillover effect across firms undertaking R&D, we generate intra- and inter-industry R&D knowledge stocks relevant to each firm in the sample. The intra- and inter-industry is also known as within- and between- industry R&D in the literatures. The relevant intra-industry R&D stock for the i[th] firm is measured as:

$$S_{i,t}^{I-TRA} = \sum_{j=1}^{m} S_{j,t}^{F} S - S_{i,t}^{F} \tag{6}$$

Where 'j' denotes all firms in an industry such that $j = 1, 2, \ldots, i \ldots, m$; and, $S_{i,t}^{F}$ denotes the i[th] firm's own R&D capital stock. Thus, $S_{i,t}^{I-TRA}$ is the sum of R&D stock of all firms in an industry excluding that of the i[th] firm.

The relevant inter-industry R&D for the i[th] firm is measured as:

$$S_{i,t}^{I-TER} = \sum_{k=1}^{n} \sum_{j=1}^{m_k} S_{j,k,t}^{F} - \sum_{j=1}^{m_{k(i)}} S_{j,k(i),t}^{F} \tag{7}$$

Where $S_{j,k,t}^{F}$ denotes the R&D stock of firm j in industry k, while $k(i)$ denotes the industry which firm i belongs to. It is assumed that there are n industries in total and industry k has m_k firms.

4.3.3. Model Specifications

Our general econometric model of the knowledge-productivity relationship is as follows:

$$TFP_{it} = \alpha_0 + \beta_{TFP}TFP_{i,t-1} + \beta_F S_{i,t}^F + \beta_{I-TRA}S_{i,t-1}^{I-TRA} + \beta_{I-TER}S_{i,t-1}^{I-TER} + \beta_{FD}S_{i,t}^F * Ds + \beta_{I-TRAD}S_{i,t-1}^{I-TRA} * Ds + \beta_{I-TERD}S_{i,t-1}^{I-TER} * Ds + \gamma' X_{it} + v_{it} \quad (8)$$

$$Ds = D1, D2, D3, D4$$

Where TFP_{it} is the total factor productivity calculated from equation (3); $S_{i,t}^F$ is the R&D capital stock; $S_{i,t-1}^{I-TRA}$ is the lagged value of intra-industry knowledge stock; $S_{i,t-1}^{I-TER}$ is lagged value of the inter-industry knowledge stock. $S_{i,t}^F$, $S_{i,t-1}^{I-TRA}$ and $S_{i,t-1}^{I-TER}$ are calculated in section 3.2. X_{it} is the vector of other (non-R&D) covariates (determinants) of productivity. They include government subsidy ratio, firm size, loan growth ratio, concentration ratio and board size. D1, …, D4 respectively, are dummy variables for state-owned firms, private firms, foreign firms, and joint venture (private and foreign owned) firms. $S_{i,t}^F * Ds$ is the interaction term between firm's own R&D capital stock and the ownership dummy variable. $S_{i,t-1}^{I-TRA} * Ds$ is the interaction term between lagged intra-industry spillover and the firm's ownership structure. Likewise, $S_{i,t-1}^{I-TER} * Ds$ is the interaction term between the lagged inter-industry spillover and firm's ownership dummy. All variables are in logarithm except for the ratio of credit flow to sales and board size, as both of these are small numbers.

We specify a contemporaneous relationship between the productivity and firm's own R&D stock. The change in lags does not affect the result (Hall and Mairesse,1995; Mairesse and Sassenou, 1991). Besides, one can also use lagged output (Harhoff, 1998). As the knowledge diffusion cross firms and industries takes time (Luintel and Khan, 2017), we choose first order lag of the variables of intra-industry and inter-industry R&D capital stocks. Research shows that it takes one or two years for the knowledge diffusion (Mansfield, 1985; Caballero and Jaffe, 1993), though it is in the international dimension. β_F is the parameter that measures the elasticity of the productivity with respect to the ith firm's own knowledge stock. It is supposed to be positive as firms would not conduct R&D projects that hurt their productivity. β_{I-TRA} is the spillover parameter associated with the intra-industry knowledge spillover pool. A significantly positive β_{I-TRA} implies that firms can benefit from other firms' R&D knowledge stocks within the same industry. This implies there are formal conduits including employee mobility (Franco and Filson, 2000) or informal networks such as information trading (Von Hippel, 1987) or the exchange of innovation information that promote the knowledge diffusion (Luintel and Khan, 2017). Due to lack of data on inter- and intra-firm and/or industry transactions, we use disembodied measures of inter- and intra-industry knowledge pools relevant to each of the firms in the sample. A significantly negative β_{I-TRA} indicates intense competition across firms within the same industry whereby innovation of other firms hurts the productivity of the i^{th} firm. The technology competition inhibits the increase in rival's productivity as there might be "patent blocking" to increase the rivals' R&D cost (Luintel and Khan, 2017). Similarly, an inter-industry knowledge spillover requires the coefficient β_{I-TER} to be significantly positive for positive externality across industries.

The above model measures the effect of a firm's own R&D knowledge stock and knowledge spillovers from intra- and inter- industry R&D knowledge stocks on firm-level productivity. We also examine if firms that are not involved in R&D activities benefit from the inter- and intra-industry knowledge spillovers accruing from firms engaged in R&D. We generate industry-specific total R&D capital stock as intra-industry knowledge pool and match it to the firms in the same industry which are not engaged in R&D activities. (E.g., a pharmaceutical firm not undertaking R&D is matched with the sum of R&D capital stocks of all pharmaceutical firms involved in R&D.) Similarly, we sum R&D from all industries excluding the industry of the ith firm as the inter-industry R&D stock pool for firms not involved in R&D activities.

We also generate dummy variables of types of ownership of a firm to see whether the ownership structure plays any role in determining the effect of a firm's own R&D and knowledge spillovers on productivity. There are four types of ownership: state-owned, private-owned, foreign-owned and private-and-foreign-jointly-owned. Since state-owned firms are controlled by the government and the main objective of this kind of firms is to achieve public policy goals, it can obtain special help from the government (e.g., experts and R&D subsidy) for some R&D projects that private firms are not allowed to take, e.g., in transportation or electricity area. State-owned firms might generate higher productivity. On the contrary, it is also possible for them to be inefficient in R&D activities because most SOEs have a closer relation to the government than private firms so that they can get more subsidies to invest in R&D activities even though they get the same innovation output as that of other types of firms in the end. Yue and Zhang (2017) found that the main source of R&D expenditure for state-owned firms is from government subsidy and that for the non-state-owned firms is from internal finance. This might generate different efficiency in R&D activities for firms with different types of ownership. The knowledge spillover effect can also differ for different types of ownership; hence, we add slope dummy variables of four types of ownership into the model.

Our general specification is equation (8), in which we measure how firm's own R&D knowledge stock and spillover from intra- and inter-industry knowledge pools affect firm-level TFP in the long run. Besides this general model, we also estimate different versions of it to account for R&D as well as ownership structure in the short- and long-run relationships. We examine the short-run knowledge-productivity relationships by replacing all variables except for board size, from levels to first-order differences in the alternative specifications.

In equation (9), we measure the direct effect of R&D stocks on firm's output, instead of productivity:

$$y_{it} = \beta_0 + \beta_y y_{i,t-1} + \beta_k k_{it} + \beta_l l_{it} + \beta_F S_{i,t}^{F} + \beta_{I-TRA} S_{i,t-1}^{I-TRA} + \beta_{I-TER} S_{i,t-1}^{I-TER} + \gamma' X_{it} + \beta_{FD} S_{i,t}^{F} * Ds + \beta_{I-TRAD} S_{i,t-1}^{I-TRA} * Ds + \beta_{I-TERD} S_{i,t-1}^{I-TER} * Ds + v_{it} \quad (9)$$

Where y_{it} denotes output, k_{it} denotes tangible assets and l_{it} denotes the number of employees.

4.4 Data

All data used in this study are collected from CSMAR database (China Stock Market and Accounting Research Database). This database is one of the largest data providers for the Chinese economy and is widely used both in macro and micro (firm-level) research. All data on Chinese Listed Firms Research Series and Chinese Stock Market Series are available in the CSMAR database.

The main data for the analysis include sales, number of employees, tangible assets, intangible assets, R&D expenditure and others control variables. Output is measured as the total sales, which is listed as the real total operating revenue in each firm's income statement. The nominal sales and R&D expenditure are deflated by Purchasing Price Index for Industrial Producers. The perpetual inventory method is adopted to calculate R&D capital stock, with a depreciation rate of 15%. The intermediate input is calculated as the difference between output and value-added, where value-added is measured as the depreciation of fixed assets + payment to employment + taxes + operating profit (Ren and Sun, 2014). The capital stock is measured by tangible assets, which is calculated as: total assets minus intangible assets minus goodwill. These data series are available from the firms' financial statements and income statements provided in CSMAR database. Firm size is measured by the firm's market value. Government subsidy ratio is defined as government subsidy over sales. The data on government subsidies in the database is the sum of all types of subsidies that enterprises received from the government, including tax rebates, financial appropriation, R&D tax incentives, etc. The ownership concentration ratio is total assets over the number of the firm's equity owners. Financial constraint is considered as another factor that might affect firm-level productivity, which is measured by the ratio of credit flow from bank to total sales. All indicators are collected from financial statements and other sectors in the CSMAR database.

We drop sample firms with abnormal data such as zero and/or negative sales, costs, intangible assets, employees. This is because if, for instance, the number of a firm employees is reported to be zero, it only means the employment data is missing, rather than that it does not have any worker. For such firms with missing employment data, they are removed from the sample. The resulting sample of 1897 firms covering 7 years from 2012 to 2018 is divided into four subgroups: 1183 innovating firms and 399 non-innovating firms in manufacturing sector as well as 29 innovating firms and 286 non-innovating firms in non-manufacturing sector.

Table 4.1 presents the descriptive statistics for the four subgroups respectively. The mean value of firm-level productivity for both innovating and non-innovating firms is higher in manufacturing sector. The standard deviation is also a little higher in manufacturing sector. The mean value of output for non-manufacturing firms is significantly higher than that for manufacturing sector. Because the output is measured by the total sales, a possible explanation could be that the financial and insurance industries are included in non-manufacturing sector and their main businesses with large cash flow cause their total sales to be higher than firms in other industries. There is a considerable variation in output in all the four subgroups, ranging from 1 million to around 1,200,000 million Yuan. A similar characteristic can also be observed for tangible assets and ownership concentration ratio, due to the same reason of the larger cash flow in financial and insurance firms in non-manufacturing sector.

Table 4.1 Descriptive statistics

Part A: Manufacturing firms that report R&D expenditure

Descriptive Statistics	Definitions	Obs	Mean	Std. Dev.	Min	Max
TFP	Total factor productivity	8416	3.579	2.709	0.061	34.986
Output	Total operating revenue	8421	6500.472	25209.881	41.87	898631.47
R&D capital stock	Firm's own R&D knowledge stock	8421	2303.202	41606.835	0.465	2044292.3
Intra-industry R&D capital stock	The sum of R&D stocks of all firms (excluding the i^{th} firm) in the same industry	8421	98195.838	176419.84	199.514	2047293.4
Inter-industry R&D capital stock	The sum of R&D stocks of all industries (excluding i^{th} firm's industry)	8421	2670253.3	460132.23	1397786.1	3537283.3
Physical capital	Tangible asset	8421	9422.942	25787.768	217.71	782769.85
Employment	Number of employees	8416	5133.925	10558.552	58	220152
Government subsidy ratio	Government subsidy/Output	8421	0.015	0.034	0	1.249
Firm size	Market value	8415	10424.715	21377.226	149.93	876185.4
Ownership concentration ratio	Total assets/Number of shareholders	8421	0.199	0.296	0.006	6.819
Financial constraint	Bank loan growth/Total operating revenue	7780	0.027	0.413	-13.281	6.338
Board size	Number of directors	8420	8.582	1.644	4	18

Part B: Non-manufacturing firms that report R&D expenditure

Descriptive Statistics	Definitions	Obs	Mean	Std. Dev.	Min	Max
TFP	Total factor productivity	2791	2.275	2.434	0.133	42.155
Output	Total operating revenue	2793	15070.785	69889.784	36.084	1199324.5
R&D capital stock	Firm's own R&D knowledge stock	2793	1759.586	19508.927	0.67	565457.88
Intra-industry R&D capital stock	The sum of R&D stocks of all firms (excluding the i^{th} firm) in the same industry	2793	36473.319	58794.923	0	568314.75
Inter-industry R&D capital stock	The sum of R&D stocks of all industries (excluding i^{th} firm's industry)	2793	663842.1	79816.626	231403.94	799897.88
Physical capital	Tangible asset	2793	23526.317	98112.101	177.833	1861840.3
Employment	Number of employees	2791	8856.413	28868.825	64	302827
Government subsidy ratio	Government subsidy/Output	2793	0.015	0.024	0	0.375
Firm size	Market value	2790	14201.566	25402.221	694.5	349360
Ownership concentration ratio	Total assets/Number of shareholders	2793	0.254	0.443	0.005	7.259
Financial constraint	Bank loan growth/Total operating revenue	2558	0.052	0.458	-6.805	9.238
Board size	Number of directors	2793	8.602	1.791	3	17

Part C: Manufacturing firms that do not report R&D expenditure

Descriptive Statistics	Definitions	Obs	Mean	Std. Dev.	Min	Max
TFP	Total factor productivity	202	74.823	91.575	0.256	821.004
Output	Total operating revenue	203	975.578	1462.439	1.003	14138.028
Intra-industry R&D capital stock	The sum of R&D stocks of all firms (excluding the i^{th} firm) in the same industry	203	32498.425	41363.63	1190.093	229000.52
Inter-industry R&D capital stock	The sum of R&D stocks of all industries (excluding i^{th} firm's industry)	203	2738253.9	427903.7	2099020	3536438.3
Physical capital	Tangible asset	203	2038.861	2286.426	25.361	13563.173
Employment	Number of employees	202	1293.901	1517.989	11	7647
Government subsidy ratio	Government subsidy/Output	203	0.121	0.737	0	9.255
Firm size	Market value	199	3924.761	3196.617	746.46	22849.769
Ownership concentration ratio	Total assets/Number of shareholders	203	0.078	0.114	0.001	0.732
Financial constraint	Bank loan growth/Total operating revenue	203	0.522	8.176	-18.261	110.109
Board size	Number of directors	203	8.034	1.123	4	10

Part D: Non-manufacturing firms that do not report R&D expenditure

Descriptive Statistics	Definitions	Obs	Mean	Std. Dev.	Min	Max
TFP	Total factor productivity	1927	11.644	16.816	0.102	301.371
Output	Total operating revenue	2044	20409.107	78685.922	3.481	928726
Intra-industry R&D capital stock	The sum of R&D stocks of all firms (excluding the i^{th} firm) in the same industry	1834	5324.308	17948.624	3.729	244661.44
Inter-industry R&D capital stock	The sum of R&D stocks of all industries (excluding i^{th} firm's industry)	1834	696750.69	50205.937	461181.13	799897.88
Physical capital	Tangible asset	2044	440128.35	2383322.1	9.986	27699540
Employment	Number of employees	2044	13397.002	81503.776	10	2869967
Government subsidy ratio	Government subsidy/Output	2044	0.013	0.192	0	8.468
Firm size	Market value	2035	30797.941	116966.76	75.867	1671595.7
Ownership concentration ratio	Total assets/Number of shareholders	2042	1.518	5.638	0	67.082
Financial constraint	Bank loan growth/Total operating revenue	2040	0.104	2.114	-19.011	63.656
Board size	Number of directors	2044	9.174	2.398	5	22

Regarding R&D stock-related variables, manufacturing firms invest more in innovation activities as the mean value of firm's own R&D stock is higher. The intra-industry R&D stock in manufacturing sector is three times higher than for the firms in the non-manufacturing sector. This is mainly due to the reason that the amount of manufacturing firms which are engaged in innovation activities is much larger than that of non-manufacturing firms. This also leads to a larger inter-industry R&D capital stock in manufacturing sector as in our model we only allow inter-industry R&D spillover within each sector. For the non-R&D variables, non-manufacturing firms hire more workers as the mean value is higher, while the standard deviation is also higher. And, the subgroup of manufacturing firms not undertaking R&D activities tend to have the highest government subsidy ratio than the other three counterparts, which implies a significant government policy preference to this kind of firms. The growth of the loan ratio from the bank and other financial institutions is higher in non-manufacturing sector, indicating an easier access to loans. This could ease the financial constraint for firms and then promote their productivity. Firm size and board size appear to have similar value in both sectors, though the firm size for firms not undertaking R&D activities is much smaller in manufacturing sector.

In Table 4.2, we report the composition of firms' ownership type (State-owned firms, Private firms, Foreign-owned firms and Private-and-foreign-jointly owned firms) in each subgroup. It is noticeable that, in both manufacturing and non-manufacturing sectors, private firms take up the largest part, followed by SOEs (state-owned enterprises). Firms with foreign-related ownership only account for a small proportion in all kinds of firms. Since the R&D performance might differ with the ownership type (Boeing et al., 2016; Howell, 2017), one of the objectives in this chapter is to gauge whether the relationship between R&D knowledge stock and productivity is related to firms' ownership type.

Table 4.2 Composition of the sample: type of ownership

	firms reporting R&D expenditure	
	manufacturing	non-manufacturing
state-owned	389	144
Privately-owned	731	240
Foreign-owned	39	9
Private and foreign jointly-owned	24	6
Total	1183	399

	firms not reporting R&D expenditure	
	manufacturing	non-manufacturing
state-owned	9	187
private	20	85
foreign	0	14
Private and foreign jointly-owned	0	0
Total	29	286

4.5 Econometric methodology

Since productivity is taken as the unobservable part that cannot be explained by input factors such as capital stock or labour, following the literature, we use residuals from production function to measure productivity. One of the assumptions in OLS estimator is the uncorrelation between the prior information set X and the error term:

$$E(X'\varepsilon) = 0$$

where X is the information set of physical capital and labour inputs. ε is the forecast error in predicting the output at time t. This assumption implies the change in the output is only caused by the productivity shock at time t. Therefore, it is unforecastable. But in reality, producers have prior knowledge about their productivity, which means they could get some information about the productivity shock in advance. This makes their decision on capital and labour inputs related to productivity shock. Firms with higher productivity might invest more in physical capital and labour, which implies an issue of reverse causality while estimating firm level productivity (Baum and Schaffer, 2003;

Levinson and Petrin, 2003). In this production function estimation, capital and labour inputs become endogenous as they are correlated with the error term. Since the OLS estimator requires all explanatory variables to be exogenous, this orthogonality condition is violated and cause the estimated parameters to be biased and inconsistent:

$$E(X'\varepsilon) \neq 0$$

In our model, we estimate

$$TFP_{it} = \beta_0 + \beta_{TFP} TFP_{i,t-1} + \beta_F S_{i,t}^F + \beta_{I-TRA} S_{i,t-1}^{I-TRA} + \beta_{I-TER} S_{i,t-1}^{I-TER} + \beta_{FD} S_{i,t}^F * Ds + \beta_{I-TRAD} S_{i,t-1}^{I-TRA} * Ds + \beta_{I-TERD} S_{i,t-1}^{I-TER} * Ds + \gamma' X_{it} + v_{it} \quad (8)$$

We use both the Ordinary Least Squares (OLS) and the Generalised Method of Moments (GMM) estimators to estimate the knowledge-productivity relations outlined above. Despite the potential issue of simultaneity, we have used OLS for its simplicity and intuition. Nevertheless, Motohashi et al. (2009) and Yang et al. (2010) suggest that there might be reverse causality when estimating the relationship between firm-level TFP and input factors, including R&D stock. Firms with higher productivity might invest more in R&D. To avoid biased estimates of coefficients, we deal with this endogeneity problem using GMM estimation approach.

Here we note that GMM is a more general estimator of which IV is a special case. In the presence of heterogeneity, the general formula for the asymptotic variance of a general GMM estimator still holds (Baum et al., 2003) and GMM estimator is more asymptotically efficient than IV estimator (Dinardo and Johnston, 1997). Although the estimated coefficients of IV estimator are still consistent, the standard errors of the IV estimator become inconsistent, which causes the inference to be invalid. In this case, IV estimator is inefficient and it is a special case of GMM estimator with a suboptimal weighting matrix. And if there is homoscedasticity in the error term, the GMM estimator is equivalent to IV estimator. Therefore, we employ GMM estimator introduced by Hansen (1982) to achieve the estimator efficiency as GMM estimator is robust to the presence of heteroskedasticity. Though the use of it has a price that GMM estimator has poor small sample properties (Baum et al., 2003), this shortcoming can be ignored as we have enough observations.

One is able to generate efficient estimates of the coefficients and efficient standard errors by minimizing the GMM criterion function

$$J = N * g' * W * g$$

, where N is the sample size. g is the orthogonality or moment condition, which implies that all the exogenous or instrument variables are independent with the error term. W is the weighting matrix. In the two-step efficient GMM estimator, the efficient matrix is the inverse of an estimate of the covariance matrix of orthogonality conditions. The efficiency gains of this estimator are from the use of optimal weighting matrix, the overidentifying restrictions of the model, and the relaxation of the i.i.d. assumption.

In our model, we adopt lagged productivity $TFP_{i,t-3}$ and $TFP_{i,t-4}$ as instruments. The instrumental variables must satisfy two conditions: to be correlated to endogenous variables and uncorrelated to the error term. Lagged productivity is correlated to contemporaneous productivity and uncorrelated to the "news" in time t. The latter is the orthogonality condition that instrumental variables must satisfy:

$$E[Z'v] = 0$$

We express the instrumental variables in the form of matrix:

$$X = [1 \quad TFP_{i,t-1}]$$

$$Z = [1 \quad TFP_{i,t-3} \quad TFP_{i,t-4}]$$

There is overidentification when the number of restrictions that the instruments give is larger than the number of endogenous variables. GMM estimator addresses overidentification by weighting each restriction. The weight for restrictions of less efficient estimates is smaller than that for restrictions of more efficient estimates (smaller variance).

Johnston and Dinardo (1997) illustrate the detailed process for GMM estimator. From the orthogonality condition, we can have the efficient estimates of the coefficients that are generated by minimizing the GMM criterion function:

$$\min_{\beta}(\frac{1}{n}Z'(y - X\beta))'W(\frac{1}{n}[Z'(y - X\beta)]))$$

, where W is the optimal weighting matrix. Hansen (1982) suggests that the optimal weighting matrix is the heteroskedasticity-consistent estimate of the matrix $E[Z'v(Z'v)']^{-1} = \Omega^{-1}$. The estimate of the inverse asymptotic variance matrix

$[var(\frac{1}{n})(Z'v)]^{-1}$ can be denoted as $[(\frac{1}{n^2})(\widehat{Z'\Omega Z})]^{-1}$. The consistent estimate is generated in two steps: Firstly, we generate the consistent estimate $\hat{\beta}_{i,t}$ by 2SLS regression, taking $(Z'Z)^{-1}$ as W. Then we calculate the residual using the estimated coefficients:

$$r_{i,t} = y_{i,t} - X\hat{\beta}_{i,t}$$

The estimate of the matrix $[(\frac{1}{n^2})(Z'\Omega Z)]^{-1}$ is

$$W_n = [(\frac{1}{n^2})\sum_i z_{i,t} z_{i,t}' r_{i,t}^2]^{-1}$$

, where $z_{i,t}$ is a column of the matrix Z.

With the estimated optimal weighting matrix W_n, the minimization of the GMM criterion function can be solved by selecting the GMM estimate of the coefficients β:

$$\hat{\beta}_{GMM} = [X'Z(\widehat{Z'\Omega Z})^{-1}Z'X]^{-1}X'Z(\widehat{Z'\Omega Z})^{-1}Z'y$$

Hansen J statistic is reported to test whether the chosen instrumental variables are valid in GMM estimation. The J statistic is consistent in the presence of heteroskedasticity and autocorrelation. The null hypothesis of the test is that the instruments are valid and a rejection of the null implies the chosen instruments are not suitable.

4.6 Results

Results for specifications (8) and (9) are reported in this section. In the literature, researchers model the relationship either between R&D stock and productivity (Griliches and Mairesse, 1991; Wakelin, 2001; Ortega-Argilés, 2011; Kancs et al., 2016) or between R&D stock and output (O'Mahony and Vecchi, 2009; Boeing et al., 2016), while we model both. This will reveal if benefits of R&D are fully reflected in firm's TFP or not.

We report the results of estimation of (2) and (4) in Table 4.3. The results of both (2) and (4) are estimated with the method that Levinson and Petrin (2003) provided.

Table 4.3 The estimation results of production in the long run and short run

long run	Firms that report R&D expenditure		Firms that do not report R&D expenditure	
	Manufacturing	Non-manufacturing	Manufacturing	Non-manufacturing
	(1)	(2)	(3)	(4)
VARIABLES	y_{it}	y_{it}	y_{it}	y_{it}
k_{it}	0.729***	0.772***	0.204	0.776***
	(0.0255)	(0.0546)	(0.277)	(0.196)
l_{it}	0.0688***	0.0808***	0.132	0.0243
	(0.00675)	(0.0150)	(0.107)	(0.0411)
Observations	8,405	2,771	174	198

short run	Firms that report R&D expenditure		Firms that do not report R&D expenditure	
	Manufacturing	Non-manufacturing	Manufacturing	Non-manufacturing
	(1)	(2)	(3)	(4)
VARIABLES	y_{it}	y_{it}	y_{it}	y_{it}
k_{it}	0.614***	0.683***	-0.184	0.894***
	(0.0338)	(0.0613)	(0.379)	(0.208)
l_{it}	0.0479***	0.0875***	0.100	-0.0658
	(0.0133)	(0.0225)	(0.199)	(0.127)
Observations	7,191	2,368	140	157

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

There are two parts in Table 4.3. The upper part is the estimation results of the long-run production function in (2), while the lower part is the ones of the short-run production function. In columns (1) and (2), it can be seen that the estimated coefficients for firms that report R&D expenditure are significant no matter whether it is the long run or short run. However, due to a small sample size, the results are not significant for manufacturing firms with no R&D expenditure in column (3). Therefore, we mainly focus on all non-manufacturing firms as well as manufacturing firms that conduct R&D activities when analyzing the effect of R&D.

4.6.1 Firm's own R&D, knowledge spillover and other factors

Table 4.4 presents the knowledge-productivity relationship (Eq. (8)) and knowledge-output relationship (Eq. (9)) at the firm level for both manufacturing sector and non-manufacturing sector in the long run. The knowledge stocks consist of firm's own knowledge (own R&D) stock, and intra- and inter-industry knowledge pools as the sources of spillovers. As stated above, we present results from two estimators: OLS and GMM estimators but focus of the results from GMM as our preferred estimator.

Table 4.4 Effects of R&D knowledge stock on productivity and output in the long run

	Manufacturing				Non-manufacturing			
	OLS		GMM		OLS		GMM	
long run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}
$y_{i,t-1}$		0.700***		0.708***		0.602***		0.683***
		(0.016)		(0.0235)		(0.0421)		(0.0515)
k_{it}		0.167***		0.178***		0.216***		0.133***
		(0.0149)		(0.0205)		(0.0378)		(0.0454)
l_{it}		0.115***		0.111***		0.145***		0.145***
		(0.0105)		(0.0132)		(0.0245)		(0.0283)
$S_{i,t}^{F}$	0.0439***	0.00806	0.0575**	-0.000471	-0.000204	-0.00888	-0.00491	-0.00739
	(0.012)	(0.00544)	(0.0261)	(0.00915)	(0.0204)	(0.0101)	(0.019)	(0.0132)
$S_{i,t-1}^{I-TRA}$	-0.000839	0.00482	-0.0563***	-0.00916*	-0.0175	0.00761	0.00809	0.0114
	(0.00907)	(0.00352)	(0.0187)	(0.00536)	(0.0114)	(0.00598)	(0.0163)	(0.00915)
$S_{i,t-1}^{I-TER}$	-0.458***	-0.0336	-2.518***	-0.517***	-0.431***	0.099	0.681***	0.224
	(0.0719)	(0.0206)	(0.362)	(0.0833)	(0.167)	(0.0747)	(0.241)	(0.162)
$sub_{i,t}$	-0.119***	-0.0619***	-0.167***	-0.0664***	-0.0836***	-0.0782***	-0.0981***	-0.0709***
	(0.0114)	(0.00466)	(0.0203)	(0.00659)	(0.0175)	(0.01)	(0.0291)	(0.0136)
$rcf_{i,t}$	0.0759	0.123***	0.110*	0.144***	-0.0135	0.0466**	0.00357	0.0658
	(0.0501)	(0.0284)	(0.0562)	(0.0335)	(0.0217)	(0.0206)	(0.0419)	(0.0461)

$size_{i,t}$	-0.0466***	0.0191***	-0.0399	0.0117	-0.0413*	0.0580***	-0.128***	0.0209
	(0.0173)	(0.00675)	(0.0275)	(0.00982)	(0.0224)	(0.017)	(0.0318)	(0.0271)
$concr_{i,t}$	0.0477***	0.0610***	0.0619**	0.0564***	-0.0141	0.0955***	-0.00303	0.117***
	(0.0151)	(0.0062)	(0.0261)	(0.00854)	(0.0403)	(0.0153)	(0.0628)	(0.0215)
$bs_{i,t}$	0.0184**	0.00365	0.0116	-0.000107	-0.0143	-0.0045	-0.000562	-0.00464
	(0.00728)	(0.00278)	(0.0109)	(0.00346)	(0.00986)	(0.00656)	(0.0126)	(0.00751)
$TFP_{i,t-1}$	0.911***		0.895***		0.954***		1.005***	
	(0.00977)		(0.0156)		(0.0324)		(0.0459)	
Constant	6.656***	0.1	37.25***	7.335***	6.131***	-1.849*	-8.392**	-3.069
	(1.131)	(0.336)	(5.343)	(1.241)	(2.375)	(1.113)	(3.284)	(2.242)
Observations	7,100	7,103	3,524	3,532	2,299	2,300	1,155	1,159
sample size	1,203	1,203	1201	1202	392	392	392	392
R-squared	0.8875	0.9612			0.8388	0.9528		
Hansen			2.347	2.354			2.062	5.043
Hansen P-value			0.126	0.125			0.151	0.0247

Note: Standard errors (in brackets) are reported below the coefficient estimates. ***, ** and * denote significance at 1%, 5% and 10%. R-squared is goodness of fit statistics. R-squared in GMM estimator is uninformative so it is not reported for GMM estimator (Wooldridge, 2012). Hansen is the Hansen test of the overidentification. Hansen P-values of the null hypothesis of instruments validity are reported under the Hansen J statistic.

This table reports the results of the regression of firm-level productivity TFP_{it} and firm-level output (proxied by sales) y_{it} on firm's own R&D knowledge stock $S_{i,t}^{F}$, intra-industry R&D knowledge stock $S_{i,t-1}^{I-TRA}$, inter-industry R&D knowledge stock $S_{i,t-1}^{I-TER}$ as well as other firm characteristics in the long run. Firm's own R&D knowledge stock is converted from firm's own R&D expenditure using perpetual inventory method. Reported stock measures are calculated at 15% depreciation rate. Intra-industry R&D knowledge stock $S_{i,t-1}^{I-TRA}$ is the sum of all firms' R&D knowledge stock within the same industry, the calculation is show in equation (6) in the text. Inter-industry R&D knowledge stock $S_{i,t-1}^{I-TER}$ is the sum of all firms' R&D knowledge stock from all industries except its own industry, this is shown in equation (7) in the text. Subsidy ratio $sub_{i,t}$ is the ratio of firm-level government subsidy over total sales. $rcf_{i,t}$ is the ratio of the credit flow (first difference of the bank loan stock) to total sales. Since TFP and firm's output are flow concepts therefore it makes sense to use the flow of bank credit. Firm size $size_{i,t}$ is the market value of the firm. Ownership concentration ratio $concr_{i,t}$ is measured by the firm-level total assets over the number of equity owners. $bs_{i,t}$ is the board size. The output and the three R&D related variables are deflated from nominal value to real value by the industrial producer price index in the contemporaneous year. All variables are in logarithm except for the ratio of credit flow to sales and board size, as both of these are small numbers.

In view of the data dimension, the 3rd and the 4th order lags of TFP are chosen as the instrumental variables in regressions of columns (3) and (7). The output estimates are instrumented accordingly in regressions (4) and (8).

Taking the manufacturing sector first, both OLS and GMM estimates reveal a significantly positive effect of firm's own R&D stock $S_{i,t}^{F}$ on TFP_{it}, with the estimated point elasticity of 0.044 and 0.058, respectively. But there is no evidence showing that the firm's own R&D stock $S_{i,t}^{F}$ has a significant effect on its output y_{it}. This implies that the output effect of firms' R&D is not picked with precision up by our estimates whereas TFP effects are. Instead, the firm's R&D stock indirectly benefits the output by transmitting to increased productivity. However, the intra-industry knowledge spillover $S_{i,t-1}^{I-TRA}$ and inter-industry knowledge spillovers $S_{i,t-1}^{I-TER}$ both appear negative and significant in explaining the firm level TFP under GMM while only inter-industry knowledge spillovers $S_{i,t-1}^{I-TER}$ appear negative and significant under OLS. We interpret these parameters similar to Luintel and Khan (2017), although their research is based on country-level rather than firm-level knowledge spillover. The negative signs of the parameters of $S_{i,t-1}^{I-TRA}$ and $S_{i,t-1}^{I-TER}$ implies competitive pressure and technology rivalry between firms undertaking R&D activities. It does not mean that the 'pure' R&D knowledge spillovers are negative, instead, it may reflect the spiraling cost of innovative activities and technology blocking by other firms which inhibit rivals benefiting from technological externalities. There is no evidence showing that a firm's R&D stock has a direct effect on output even though it contributes to the increase in productivity. This indicates that a firm's R&D activities promote their output indirectly via productivity routes. In contrast, the competitive pressure evidenced from the negative intra- and inter-industry knowledge spillover parameters appear to affect both firm level productivity as well as output.

Although non-manufacturing firms also made some R&D effort, it does not appear to enhance productivity, as the coefficients for a firm's own R&D $S_{i,t}^{F}$ are insignificant under both OLS and GMM estimates.

There is no evidence of significant knowledge spillover between firms in the same industry as the coefficients for $S_{i,t-1}^{I-TRA}$ are insignificant. However, the inter-industry R&D $S_{i,t-1}^{I-TER}$ appears positive and significant in explaining TFP under GMM estimate. The output is not affected by either the firm's own R&D stock or the spillovers originating from the intra- and inter- industry knowledge pools. Overall, results do not show productivity effects accruing from own knowledge stocks as well as from intra-industry knowledge spillover pool but show significant spillover effect from inter-industry knowledge pool for the panel of Chinese non-manufacturing firms involved in R&D activities.

There are other factors included in Eq. (8) and Eq. (9) that might affect productivity. The results show that the sources of firms' finance matters for their productivity and output. Managi (2010) and Howell (2015) suggest that government subsidies have a negative effect on firms' productivity. Similarly, government subsidy ratio $sub_{i,t}$ in our model also shows a significant negative effect on both productivity TFP_{it} and output y_{it} in manufacturing and non-manufacturing sectors. These estimates are robust across specifications and estimators. This indicates that government subsidy does not contribute to firms' innovation activities for most Chinese listed firms, but instead it appears to discourage innovation, which is rather surprising. This might indicate the issue of misallocation of resources and this problem appears more serious in manufacturing sector. At the same time, the parameters of the flow of credit from banks $rcf_{i,t}$ appear significantly positive in productivity TFP_{it} and output y_{it} but only in manufacturing sector. This reveals that the ease of financial constraints can stimulate the productivity and output only for manufacturing firms. Our results have the same implication as that of Whited (1992), Love (2003) and Hottenrott and Peters (2012). The financial constraints lead to a loss in R&D investment, which causes a lower productivity. The insignificance of credit flows $rcf_{i,t}$ in explaining productivity TFP_{it} and output y_{it} of non-manufacturing firms is rather unexpected.

Firm size $size_{i,t}$ is another factor that influences firms' innovation. It is measured by the market value of a firm. The elasticity of productivity with respect to firm size in non-manufacturing sector is negative and significant in both estimate methods. In the manufacturing sector, the firm size is also negatively correlated to the productivity, but only significant in OLS estimate. This result is in consistent with Crespi and Zuniga (2012)'s results, indicating that larger firms are less likely to undertake innovation as they are monopolies and could obtain more output and profits with current business. Smaller firms are more willing to invest in R&D, hoping innovation could increase their productivity. Therefore, ceteris paribus, R&D productivity in small firms is higher in the long run for Chinese listed firms.

Firm's ownership concentration ratio $concr_{i,t}$ is another factor which matters for productivity TFP_{it}. In manufacturing sector, the parameters of $concr_{i,t}$ are positive and significant for both productivity TFP_{it} and output y_{it} under both OLS and GMM, indicating that the concentrated ownership of firms could increase both productivity and output. This result is consistent with the findings of Holmstrom (1989), Francis and Smith (1995), Harris and Raviv (2008), suggesting that a higher concentration could reduce the high agency and contracting costs. Therefore, firms would invest more in R&D activities and this would increase their productivity and output. But this result is different from the alternative opinion that highly concentrated ownership would limit managers to provide professional advice on R&D projects and harms the R&D performance (Hill and Snell, 1988; Burhart et al., 1997; Ortega-Argiles et al., 2005). However, in non-manufacturing sector, a higher $concr_{i,t}$ only contributes to the output y_{it} but not to the firm's productivity TFP_{it}, which is hard to explain. Board size $bs_{i,t}$ does not appear to affect firms' TFP and output in both sectors in the long run as almost all the results are insignificant.

Table 4.5 presents the short-run relationship between R&D knowledge stock and productivity at firm level for manufacturing sector and non-manufacturing sector. In order to estimate the short-run relationship, we modify the model (8) to a first difference specification. Specifically, TFP, output, firm's own R&D knowledge stock, intra- and inter-industry R&D stocks are all changed to first order differences: ΔTFP_{it}, Δy_{it}, $\Delta S_{i,t}^{F}$, $\Delta S_{i,t-1}^{I-TRA}$ and $\Delta S_{i,t-1}^{I-TER}$. In the manufacturing sector, the growth rate of firm's own knowledge stock $\Delta S_{i,t}^{F}$ shows significant positive effect on TFP growth ΔTFP_{it} under both OLS (0.413) and GMM (0.245) estimates. Both $\Delta S_{i,t-1}^{I-TRA}$ and $\Delta S_{i,t-1}^{I-TER}$ exhibit a negative and significant effect on TFP growth ΔTFP_{it} and output growth Δy_{it} under GMM. This implies that the innovation results are not shared among firms and they cannot benefit from rivals' R&D activities in the short run. Innovative competition across firms exists not only in the same industrial environment but also across different industries in manufacturing sector. In non-manufacturing sector, there is no evidence showing that the R&D-related factors could influence TFP growth and output growth under both OLS and GMM estimate.

The effects of other determinants of productivity and output are also presented in Table 4.5. Both OLS and GMM estimates indicate that government subsidy significantly harms firms' productivity and output growth in both manufacturing and non-manufacturing sectors in the short run. The estimate of the effect of government subsidy on TFP is -0.0653 in manufacturing sector and this effect is slightly weaker in non-manufacturing sector (-0.0455). The short-run results are consistent with the long-run results, indicating the issue of resource allocation inefficiency brought up by government subsidy. Since it does not help increasing firms' innovation or output, the government should change the way of encouraging the firm's innovation from directly allocating subsidies to firms to other policies. The GMM estimates of $rcf_{i,t}$ are insignificant for both TFP growth ΔTFP_{it} (Column 3 and Column 7) and output growth Δy_{it} (Column 4 and Column 8) in both sectors. Compared to the significantly positive effect in the long run (Table 4.4), credit flow ratio does not affect productivity and output for both sector in the short run. Therefore, the effect of the ease of financial constraints does not appear significant for both sectors in the short run.

Table 4.5 Effects of R&D knowledge stock on productivity and output in the short run

	manufacturing				non-manufacturing			
	OLS		GMM		OLS		GMM	
short run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}
$\Delta y_{i,t-1}$		0.0234		1.285***		-0.00142		0.313
		(0.0167)		(0.407)		(0.0238)		(0.414)
Δk_{it}		0.374***		0.480***		0.522***		0.455***
		(0.0413)		(0.157)		(0.0618)		(0.145)
Δl_{it}		0.187***		0.173**		0.308***		0.321***
		(0.0327)		(0.0874)		(0.0502)		(0.0716)
$\Delta S_{i,t}^{F}$	0.413***	0.310***	0.245*	-0.466*	0.425***	0.240***	0.182	0.0628
	(0.0576)	(0.0391)	(0.137)	(0.239)	(0.111)	(0.0526)	(0.177)	(0.192)
$\Delta S_{i,t-1}^{I-TRA}$	-0.0222	0.0387	-0.491**	-0.537**	-0.044	-0.0337	-0.164	-0.174
	(0.0757)	(0.0482)	(0.193)	(0.239)	(0.0879)	(0.0473)	(0.26)	(0.317)
$\Delta S_{i,t-1}^{I-TER}$	1.986***	1.711***	-3.008**	-4.068**	2.643***	1.265***	-0.078	-0.163
	(0.266)	(0.198)	(1.328)	(1.601)	(0.678)	(0.231)	(1.483)	(0.733)
$\Delta sub_{i,t}$	-0.0548***	-0.0449***	-0.0653***	-0.0586***	-0.0744***	-0.0488***	-0.0455*	-0.0283**
	(0.00816)	(0.00495)	(0.0123)	(0.0142)	(0.0151)	(0.00853)	(0.0232)	(0.0121)
$rcf_{i,t}$	0.0275	0.0801**	0.0193	0.0151	0.0153	0.0237	0.034	0.0195

	(0.0183)	(0.0394)	(0.0379)	(0.0729)	(0.0235)	(0.0197)	(0.06)	(0.0579)
$\Delta size_{i,t}$	0.0371**	0.0451***	0.0726*	0.0735**	0.159**	0.0784***	0.223	0.0869
	(0.0163)	(0.0118)	(0.0385)	(0.036)	(0.0643)	(0.0217)	(0.181)	(0.0808)
$\Delta concr_{i,t}$	-0.0338**	-0.00156	0.05	0.0973**	-0.057	-0.0639***	-0.25	-0.0279
	(0.0152)	(0.00896)	(0.06)	(0.0472)	(0.0913)	(0.02)	(0.329)	(0.0651)
$bs_{i,t}$	-0.00292	-0.00116	-0.00909**	-0.00786	-0.00920*	-0.00274	-0.0183**	-0.00706
	(0.00234)	(0.00168)	(0.00425)	(0.0054)	(0.00504)	(0.00281)	(0.00929)	(0.0065)
$\Delta TFP_{i,t-1}$	-0.0344		0.804***		-0.0866***		0.556	
	(0.0269)		(0.278)		(0.0257)		(0.443)	
Constant	1.239***	0.156***	0.212	-0.0883	1.301***	0.0756**	0.798*	0.147**
	(0.0476)	(0.0234)	(0.336)	(0.107)	(0.0717)	(0.0301)	(0.416)	(0.057)
Observations	5,839	5,842	2,262	2,269	1,895	1,896	748	752
sample size	1,202	1,202	1133	1136	392	392	375	377
R-squared	0.0913	0.378			0.0728	0.5346		
Hansen			0.211	1.537			0.016	0.128
Hansen P-value			0.6457	0.2151			0.8987	0.7209

Note: Standard errors (in brackets) are reported below the coefficient estimates. ***, ** and * denote significance at 1%, 5% and 10%. R-squared is goodness of fit statistics. R-squared in GMM estimator is uninformative so it is not reported in GMM estimator (Wooldridge, 2012). Hansen is the Hansen test of the overidentification. Hansen P-values of the null of instruments validity are reported under the Hansen J statistic.

Firm size appears to have a significantly positive short-run effect on both productivity (0.0726) and output (0.0735) in manufacturing sector under GMM estimate. And this result is also seen in OLS estimates. In non-manufacturing sector, both OLS and GMM estimates of firm size for TFP and output are positive but they are significant only under OLS. Concentration ratio $\Delta concr_{i,t}$shows the short-run positive effect on output but insignificant on TFP growth for manufacturing firms under GMM. Board size reveals a significantly negative but very small effect on TFP growth in manufacturing sector (-0.00909, Column 3) and in non-manufacturing sector (-0.0183, Column 7) under GMM estimate. This result is consistent with Chen (2012). He provides the empirical evidence of a negative effect of a larger board size on R&D investment, which could decrease the firm's productivity. Jensen (1993) attributes the negative effect of a larger board size on productivity to a larger power of CEO in decision making and controlling the board. Therefore, firms with a larger power of CEO would invest less in high-risk projects such as R&D activities as their target is to avoid high-risk activities and make short-term profits.

4.6.2 Knowledge spillover to firms not reporting R&D

4.6.2.1 Intra-industry knowledge spillover

Table 4.6 presents the results of the regression of the productivity and the output on intra-industry R&D stock and other firm characteristic variables for firms that do not report R&D expenditures. The variable intra-industry R&D $S_{i,t-1}^{I-TRA}$ is measured by in the sum of R&D stock of all firms in the same industry sector. A significantly positive result indicates that firms which do not undertake their own innovation projects could benefit from other firms' R&D activities. However, the estimated coefficients for $S_{i,t-1}^{I-TRA}$ are insignificant, implying there is no significant spillovers with the industry. The insignificance may be due to the small sample as there are only 28 firms with 137 observations. In our samples, most of firms in manufacturing sector report their R&D expenditure and only a small proportion do not have R&D activities. Therefore, we lay emphasis on the sub-group of non-manufacturing sector, of which the sample size is large enough to provide a reliable result. In non-manufacturing sector, both OLS and GMM estimates of coefficients for $S_{i,t-1}^{I-TRA}$ show the negative effect of intra knowledge spillovers. This implies firms not undertaking R&D activities cannot benefit from other firms' innovation results. It suggests that competitive pressure from firms engaged in R&D appears important. Firms are preventing their technological information leaking to their competitors. For other non-R&D factors, estimated coefficients for government subsidy ratio $sub_{i,t}$ are significantly negative. This indicates that the direct subsidies from the government hurt both firm-level TFP and output under OLS and GMM, implying that the government subsidies are misallocated. The ratio of credit flow $rcf_{i,t}$ has a negative effect on the output y_{it} in non-manufacturing sector. This means that the ease of financial constraint does not affect the firm-level productivity but hurt the output of firms which do not undertake innovation activities in the long run.

Table 4.6 Long-run effects of intra-industry knowledge stock on productivity and output for firms not reporting R&D

	manufacturing				non-manufacturing			
	OLS		GMM		OLS		GMM	
long run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}
$y_{i,t-1}$		0.655***		0.625***		0.583***		0.859***
		(0.0929)		(0.16)		(0.0458)		(0.0443)
k_{it}		0.534***		0.574***		0.131***		-0.0035
		(0.183)		(0.194)		(0.0406)		(0.0423)
l_{it}		0.139		0.145		0.180***		0.0519**
		(0.117)		(0.127)		(0.0309)		(0.0221)
$S_{i,t-1}^{I-TRA}$	6.568	0.0484	10.28	-0.0164	-0.130**	0.022	-0.260***	-0.0019
	(5.299)	(0.0672)	(10.23)	(0.0447)	(0.0599)	(0.015)	(0.0911)	(0.0128)
$sub_{i,t}$	-5.440*	-0.109**	-10.54	-0.0669	-0.225***	-0.0803***	-0.308***	-0.0591***
	(3.053)	(0.0491)	(9.007)	(0.0492)	(0.057)	(0.0128)	(0.0836)	(0.0128)
$rcf_{i,t}$	0.288	-0.00901***	-0.0555	0.0475	-0.0431	-0.0274***	-0.0159	-0.0191**
	(0.274)	(0.00225)	(1.555)	(0.0404)	(0.0314)	(0.00792)	(0.0212)	(0.0092)
$size_{i,t}$	6.439	0.0583	6.413	-0.029	-0.0226	0.019	-0.0982	0.00586
	(5.155)	(0.0926)	(14.28)	(0.112)	(0.142)	(0.0296)	(0.191)	(0.0327)
$concr_{i,t}$	0.303	-0.146	6.435	0.0612	0.0307	0.112***	0.021	0.116***

	(5.798)	(0.107)	(10.11)	(0.153)	(0.111)	(0.0294)	(0.142)	(0.0372)
$bs_{i,t}$	7.533	-0.0253	10.15	-0.191*	0.00521	0.00248	-0.0487	0.00154
	(5.793)	(0.0659)	(8.688)	(0.102)	(0.0651)	(0.0101)	(0.0904)	(0.0113)
$TFP_{i,t-1}$	1.071***		0.996***		1.011***		1.037***	
	(0.171)		(0.125)		(0.0226)		(0.0272)	
Constant	-203.8	-4.559***	-258.4	-0.985	-0.134	0.123	1.066	0.538
	(137.8)	(1.411)	(261.4)	(1.275)	(1.81)	(0.347)	(2.058)	(0.34)
Observations	137	137	67	67	1299	1299	658	658
sample size	28	28	26	26	255	255	251	251
R-squared	0.7851	0.9048			0.919	0.9144		
Hansen			1.403	1.899			0.778	4.45
Hansen P-value			0.236	0.168			0.3779	0.0349

Note: Standard errors (in brackets) are reported below the coefficient estimates. ***, ** and * denote significance at 1%, 5% and 10%. R-squared is goodness of fit statistics. R-squared in GMM estimator is uninformative so it is not reported in GMM estimator (Wooldridge, 2012). Hansen is the Hansen test of the overidentification. Hansen P-values of the null of instruments validity are reported under the Hansen J statistic.

Table 4.7 Short-run effects of intra-industry knowledge stock on productivity and output for firms not reporting R&D

short run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	manufacturing				non-manufacturing			
	OLS		GMM		OLS		GMM	
VARIABLES	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}
$\Delta y_{i,t-1}$		0.176***		-0.239		-0.052		-0.478
		(0.054)		(0.37)		(0.0555)		(0.359)
Δk_{it}		0.408		0.639		0.377***		0.722**
		(0.3)		(0.381)		(0.0889)		(0.328)
Δl_{it}		0.00771		0.16		0.294***		0.301*
		(0.129)		(0.313)		(0.0782)		(0.162)
$\Delta S_{i,t-1}^{I-TRA}$	3.12	-0.105	0.473	1.277	-0.33	-0.0315	-0.16	0.343
	(4.133)	(0.998)	(1.778)	(1.173)	(0.219)	(0.0843)	(0.38)	(0.218)
$\Delta sub_{i,t}$	-0.217	-0.0393	-0.0864	-0.0661	-0.122***	-0.0714***	-0.147**	-0.0441**
	(0.267)	(0.0632)	(0.0676)	(0.0459)	(0.0332)	(0.0126)	(0.0672)	(0.0187)
$rcf_{i,t}$	-0.00506	-0.00256	0.595	0.392	-0.0472	0.00116	-0.077	0.019
	(0.00321)	(0.00255)	(0.401)	(0.271)	(0.0411)	(0.0274)	(0.103)	(0.0494)
$\Delta size_{i,t}$	0.351	-0.0359	0.0102	-0.135	-0.0106	0.011	0.103	0.123
	(0.442)	(0.0774)	(0.282)	(0.226)	(0.0692)	(0.0371)	(0.245)	(0.128)
$\Delta concr_{i,t}$	0.0629	-0.00699	-0.16	-0.402	-0.054	-0.0414	-0.318	-0.296**
	(0.263)	(0.126)	(0.424)	(0.307)	(0.0676)	(0.048)	(0.224)	(0.147)

$bs_{i,t}$	0.0187	0.0153	0.109	0.069	-0.0526**	-0.000466	-0.0986**	-0.00844
	(0.0812)	(0.0216)	(0.0875)	(0.0768)	(0.0223)	(0.00541)	(0.0442)	(0.0134)
$\Delta TFP_{i,t-1}$	0.0253		-0.0551		-0.149*		-0.166***	
	(0.043)		(0.154)		(0.0767)		(0.0612)	
Constant	1.012	-0.0399	0.573	-0.414	1.799***	0.0254	2.322***	0.165
	(0.689)	(0.172)	(0.868)	(0.578)	(0.269)	(0.0543)	(0.402)	(0.14)
Observations	100	100	37	37	966	966	368	368
sample size	24	24	20	20	236	236	193	193
R-squared	0.0266	0.0889			0.052	0.21		
Hansen			0.668	0.505			0.415	3.626
Hansen P-value			0.4136	0.4773			0.5193	0.0569

Note: Standard errors (in brackets) are reported below the coefficient estimates. ***, ** and * denote significance at 1%, 5% and 10%. R-squared is goodness of fit statistics. R-squared in GMM estimator is uninformative so it is not reported in GMM estimator (Wooldridge, 2012). Hansen is the Hansen test of the overidentification. Hansen P-values of the null of instruments validity are reported under the Hansen J statistic.

The result of the short-run effect of intra-industry R&D spillover to firms not undertaking R&D activities is shown in Table 4.7. It is evident that the effect of intra-industry R&D stock $\Delta S_{i,t-1}^{I-TRA}$ on productivity is insignificant in both types of firms under both OLS and GMM. Firms' output is also not affected by other firms' R&D stock in the short run. Besides, for non-manufacturing firms, the effect of short-run government subsidies $\Delta sub_{i,t}$ remains negative and significant while the effect of the credit flow $rcf_{i,t}$ on the output becomes insignificant in the short run.

4.6.2.2 Inter-industry knowledge spillover

Table 4.8 shows the results of the relationship between the inter-industry R&D stock $S_{i,t-1}^{I-TER}$ and the productivity TFP_{it} as well as the output y_{it} for firms without R&D activities, where the inter-industry R&D stock $S_{i,t-1}^{I-TER}$ is measured by the sum of firm-level R&D stocks in all industries except for the industry of the firm. We still mainly focus on the results in non-manufacturing sector and ignore those reported in the manufacturing sector as they are insignificant and inaccurate due to a too-small sample size (28 firms). In the non-manufacturing sector, the estimated coefficient of $S_{i,t-1}^{I-TER}$ is significantly negative (-7.988, Column 7). We got a similar conclusion as that for intra-industry R&D $S_{i,t-1}^{I-TRA}$: Firms which do not have R&D activities in non-manufacturing industries cannot benefit from the R&D result conducted by firms from other industries. This conclusion is different from that for firms with R&D expenditure, where they can benefit from the knowledge spillover effect on productivity from other industries (Table 4.4) in the long run. However, in the short run, non-manufacturing firms without R&D investment can benefit from the R&D knowledge spillover originating from other industries to increase both productivity (4.367, Column 7) and output (2.264, Column 8) under GMM in Table 4.9. From the results of the short run specification for both intra- and inter-industry R&D spillover in Table 4.7 and Table 4.9, almost all estimates of regressors are insignificant.

Table 4.8 Long-run effects of inter-industry knowledge stock on productivity and output for firms not reporting R&D

long run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	manufacturing				non-manufacturing			
	OLS		GMM		OLS		GMM	
VARIABLES	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}
$y_{i,t-1}$		0.670***		0.618***		0.586***		0.859***
		(0.0946)		(0.157)		(0.0451)		(0.0426)
k_{it}		0.482**		0.649***		0.135***		-0.00208
		(0.189)		(0.203)		(0.04)		(0.0424)
l_{it}		0.164		0.135		0.172***		0.0515**
		(0.107)		(0.128)		(0.0304)		(0.0221)
$S_{i,t-1}^{I-TER}$	-72.34**	-0.318	-557.9	1.523	0.525	0.678***	-7.988*	-0.362
	(33.7)	(0.465)	(336.9)	(1.929)	(1.217)	(0.15)	(4.279)	(0.378)
$sub_{i,t}$	-4.128	-0.101*	-10.05	-0.0753	-0.219***	-0.0823***	-0.277***	-0.0582***
	(2.631)	(0.054)	(8.05)	(0.0485)	(0.0569)	(0.0129)	(0.0873)	(0.0131)
$rcf_{i,t}$	0.245	-0.00857***	-1.083	0.0505	-0.0432	-0.0281***	-0.0162	-0.0191**
	(0.239)	(0.00239)	(2.19)	(0.0396)	(0.0319)	(0.0075)	(0.0221)	(0.00919)
$size_{i,t}$	0.608	0.0389	40.37	-0.118	0.0253	0.0335	0.0206	0.0075
	(4.942)	(0.0983)	(33.22)	(0.105)	(0.134)	(0.0299)	(0.191)	(0.0311)
$concr_{i,t}$	-1.071	-0.123	8.592	0.0281	0.0401	0.114***	0.0532	0.116***

	(5.429)	(0.113)	(10.97)	(0.139)	(0.111)	(0.0295)	(0.144)	(0.0369)
$bs_{i,t}$	8.271	-0.0227	7.457	-0.203*	0.00887	-0.00423	-0.037	0.0019
	(5.535)	(0.0683)	(7.039)	(0.104)	(0.0653)	(0.0101)	(0.0925)	(0.0114)
$TFP_{i,t-1}$	1.125***		0.894***		1.009***		1.030***	
	(0.205)		(0.157)		(0.0228)		(0.0275)	
Constant	974.0**	0.999	7812	-23.33	-8.554	-8.905***	105.3*	5.356
	(439.5)	(7.762)	(4677)	(27.86)	(15.82)	(2.084)	(57.16)	(5.025)
Observations	137	137	67	67	1299	1299	658	658
sample size	28	28	26	26	255	255	251	251
R-squared	0.7894	0.9072			0.9189	0.9142		
Hansen			1.202	1.787			0.764	4.464
Hansen P-value			0.273	0.1813			0.3822	0.0346

Note: Standard errors (in brackets) are reported below the coefficient estimates. ***, ** and * denote significance at 1%, 5% and 10%. R-squared is goodness of fit statistics. R-squared in GMM estimator is uninformative so it is not reported in GMM estimator (Wooldridge, 2012). Hansen is the Hansen test of the overidentification. Hansen P-values of the null of instruments validity are reported under the Hansen J statistic.

Table 4.9 Short-run effects of inter-industry knowledge stock on productivity and output for firms not reporting R&D

short run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	manufacturing				non-manufacturing			
	OLS		GMM		OLS		GMM	
VARIABLES	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}
$\Delta y_{i,t-1}$		0.141***		-0.268		-0.0508		-0.55
		(0.05)		(0.384)		(0.0554)		(0.372)
Δk_{it}		0.408		0.897**		0.367***		0.712**
		(0.296)		(0.4)		(0.0897)		(0.329)
Δl_{it}		0.00628		-0.00539		0.291***		0.310*
		(0.125)		(0.328)		(0.0773)		(0.164)
$\Delta S_{i,t-1}^{I-TER}$	21.11	6.884	-2.589	8.973	1.249	0.486	4.367*	2.264*
	(20.58)	(4.634)	(12.98)	(5.953)	(0.771)	(0.447)	(2.322)	(1.223)
$\Delta sub_{i,t}$	-0.228	-0.0453	-0.0953	-0.0713	-0.126***	-0.0722***	-0.157**	-0.0484***
	(0.27)	(0.06)	(0.079)	(0.0428)	(0.034)	(0.0126)	(0.0676)	(0.018)
$rcf_{i,t}$	-0.0000371	-0.00139	0.666	0.408	-0.0464	0.00144	-0.0726	0.0255
	(0.0031)	(0.00199)	(0.475)	(0.292)	(0.0416)	(0.0276)	(0.103)	(0.0503)
$\Delta size_{i,t}$	0.91	0.14	0.00885	-0.0503	0.0656	0.0396	0.221	0.16
	(0.976)	(0.179)	(0.267)	(0.237)	(0.0795)	(0.0475)	(0.251)	(0.116)
$\Delta concr_{i,t}$	0.212	0.0362	-0.247	-0.344	-0.0633	-0.04	-0.367	-0.325**

	(0.31)	(0.12)	(0.603)	(0.262)	(0.0665)	(0.0484)	(0.231)	(0.152)
$bs_{i,t}$	0.00436	0.0121	0.103	0.0377	-0.0512**	-0.00038	-0.102**	-0.0112
	(0.0768)	(0.0203)	(0.0844)	(0.0646)	(0.0218)	(0.00537)	(0.0444)	(0.0136)
$\Delta TFP_{i,t-1}$	0.0201		-0.0764		-0.143*		-0.185***	
	(0.0412)		(0.179)		(0.0761)		(0.0712)	
Constant	3.094	0.556	0.52	0.514	1.802***	0.0409	2.416***	0.242*
	(2.267)	(0.395)	(0.828)	(0.612)	(0.273)	(0.0591)	(0.399)	(0.134)
Observations	100	100	37	37	966	966	368	368
sample size	24	24	20	20	236	236	193	193
R-squared	0.0342	0.1238			0.0544	0.2108		
Hansen			0.535	0.289			0.546	3.864
Hansen P-value			0.4644	0.591			0.46	0.0493

Note: Standard errors (in brackets) are reported below the coefficient estimates. ***, ** and * denote significance at 1%, 5% and 10%. R-squared is goodness of fit statistics. R-squared in GMM estimator is uninformative so it is not reported in GMM estimator (Wooldridge, 2012). Hansen is the Hansen test of the overidentification. Hansen P-values of the null of instruments validity are reported under the Hansen J statistic.

4.6.3 Interaction between R&D-related factors and ownership

In the literature review section, we have discussed that firm's ownership could capture extra forces that are influencing the effect of R&D on the firm-level productivity and output. To measure this difference caused by a firm's ownership, we add interaction terms between the ownership dummies and R&D stock-related variables in specifications (8) and (9). There are four types of ownership: state-owned, private-owned, foreign-owned and jointly-owned. In the result Tables, the regression is estimated for both manufacturing and non- manufacturing sectors, respectively. Firms which are reporting/not reporting R&D expenditure, are in separate sub-groups. For the firms which do not have R&D activities, we only measure the effect of knowledge spillover emanating from intra-industry and inter-industry R&D stock pools for them, while for firms reporting their own R&D expenditure, we also take the firm-specific R&D stock as one of productivity determinants. To simplify the exposition, we only report the results of the interaction between R&D-related variables and ownership dummies. The rest of the parameter estimates appear similar (largely robust) to the previous estimates which did not include ownership dummies.

4.6.3.1 State-owned firms

Table 4.10 presents the results of measuring whether state-owned firms have different productivity (TFP) benefits from R&D and whether they could benefit more from knowledge spillover originating from other firms and industries. In both long run and short run, state-owned firms which do not undertake R&D activities can neither enjoy extra knowledge spillover within and between the industries, nor have more intense competition with firms conducting innovation activities because the estimated coefficients of $D_1 * S_{i,t-1}^{I-TRA}$ and $D_1 * S_{i,t-1}^{I-TER}$ (from Column 5 to Column 12) for the firm-level TFP and the output are all insignificant in both sectors.

For firms' own R&D productivity $D_1 * S_{i,t}^{F}$, there is no difference between state-owned firms and other three types of firms in manufacturing sector (Column1) and non-manufacturing sector (Column 3) in the long run. So does their R&D effect on output y_{it} (Column 2 and Column 4). In the short run, state-owned firms can generate more output benefits from R&D but not higher productivity in manufacturing sector. On the contrary, firms in non-manufacturing sector are shown to benefit less from R&D in terms of productivity and generate less output due to this ownership.

State-owned firms are not enjoying extra knowledge spillover than the other three types of firms in the short run. But in the long run, the positive and significant coefficient of $D_1 * S_{i,t-1}^{I-TER}$ is 0.0505, implying that a positive knowledge spillover emanating from other industries would cause a higher TFP for state-owned firms in manufacturing sector. Meanwhile, the negative and significant coefficient for the interaction between intra-industry R&D stock and state-ownership dummy $D_1 * S_{i,t-1}^{I-TRA}$ (-0.0629 in Column 1) indicates that TFP of state-owned firms benefit less from R&D within the industry. Other types of firms are preventing their R&D results being shared to state-owned firms and this raises the innovation bar for state-owned firms in the similar technological environment.

Table 4.10 Effect of the interaction between R&D knowledge stock and state-owned ownership dummy on productivity and output (GMM estimates)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	firms reporting R&D expenditure				firms not reporting R&D expenditure							
long run	manufacturing		non-manufacturing		manufacturing		non-manufacturing		manufacturing		non-manufacturing	
VARIABLES	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}
$D_1 * S_{i,t}^{F}$	-0.0183	-0.00952	0.0282	-0.0147								
	(0.024)	(0.00625)	(0.0573)	(0.0152)								
$D_1 * S_{i,t-1}^{I-TRA}$	-0.0629**	-0.00773	-0.0266	0.0132	-1.028	0.0262	-0.0371	-0.00676				
	(0.0315)	(0.00995)	(0.0233)	(0.0119)	(1.847)	(0.0189)	(0.0587)	(0.005)				
$D_1 * S_{i,t-1}^{I-TER}$	0.0505**	0.00772	-0.0028	-0.0085					0.423	0.0186	-0.0219	-0.00392
	(0.023)	(0.00741)	(0.0248)	(0.00938)					(1.103)	(0.0123)	(0.0325)	(0.00295)
Observations	3,524	3,532	1,155	1,159	67	67	658	658	67	67	658	658
sample size	1201	1202	392	392	26	26	251	251	26	26	251	251
Hansen	2.575	3.609	1.955	2.895	1.303	3.022	0.778	4.56	1.269	3.31	0.765	4.612
Hansen P-value	0.1085	0.0575	0.162	0.0889	0.2537	0.0821	0.3777	0.0327	0.26	0.0688	0.3819	0.0318

short run	firms reporting R&D expenditure				firms not reporting R&D expenditure							
	manufacturing		non-manufacturing		manufacturing		non-manufacturing		manufacturing		non-manufacturing	
VARIABLES	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}
$D_1 * \Delta S_{i,t}^{F}$	0.23	0.503***	-0.662*	-0.285**								
	(0.219)	(0.169)	(0.351)	(0.144)								
$D_1 * \Delta S_{i,t-1}^{I-TRA}$	-0.156	-0.371	0.889	0.413	2.072	1.582	-0.944	-0.689				
	(0.277)	(0.273)	(0.638)	(0.278)	(3.673)	(2.934)	(0.64)	(0.428)				
$D_1 * \Delta S_{i,t-1}^{I-TER}$	0.0613	-0.156	1.342	0.208					1.301	0.91	1.278	3.512
	(0.442)	(0.411)	(1.574)	(0.898)					(4.798)	(2.887)	(5.927)	(2.234)
Observations	2,262	2,269	748	752	37	37	368	368	37	37	368	368
sample size	1133	1136	375	377	20	20	193	193	20	20	193	193
Hansen	0.222	1.431	0.031	0.186	0.521	0.388	0.356	3.98	0.567	0.337	0.531	4.232
Hansen P-value	0.6374	0.2316	0.8613	0.6665	0.4704	0.5332	0.5508	0.046	0.4513	0.5619	0.466	0.0397

Note: Standard errors (in brackets) are reported below the coefficient estimates. ***, ** and * denote significance at 1%, 5% and 10%. R-squared is goodness of fit statistics. R-squared in GMM estimator is uninformative so it is not reported in GMM estimator (Wooldridge, 2012). Hansen is the Hansen test of the overidentification. Hansen P-values of the null hypothesis of instruments validity are reported under the Hansen J statistic.

This Table reports the effect of the R&D stock variables for state-owned firms. The dummy variable for state-owned firms is D_1. We only pick out and present the parts that are relative to dummy variables in the regression of eq.(8) and eq.(9).

Table 4.11 Effect of the interaction between R&D knowledge stock and privately-owned ownership dummy on productivity and output (GMM estimates)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	firms reporting R&D expenditure				firms not reporting R&D expenditure							
long run	manufacturing		non-manufacturing		manufacturing		non-manufacturing		manufacturing		non-manufacturing	
VARIABLES	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}
$D_2 * S_{i,t}^{F}$	-0.00879	0.00794	0.0361	0.0284**								
	(0.0207)	(0.00503)	(0.0265)	(0.0139)								
$D_2 * S_{i,t-1}^{I-TRA}$	0.0326	-0.00134	0.00349	-0.0157	0.772	-0.0258	0.0324	0.0109*				
	(0.0297)	(0.00917)	(0.0214)	(0.0112)	(1.608)	(0.0186)	(0.0706)	(0.00615)				
$D_2 * S_{i,t-1}^{I-TER}$	-0.0186	-0.00035	-0.0128	0.00197					-0.369	-0.0194	0.0171	0.00636*
	(0.0211)	(0.00672)	(0.0207)	(0.0099)					(1.039)	(0.0119)	(0.0394)	(0.00359)
Observations	3,524	3,532	1,155	1,159	67	67	658	658	67	67	658	658
sample size	1201	1202	392	392	26	26	251	251	26	26	251	251
Hansen	2.482	3.731	2.03	3.792	1.297	3.683	0.778	4.6	1.281	4.28	0.764	4.685
Hansen P-value	0.1151	0.0534	0.1542	0.0515	0.2548	0.055	0.3779	0.032	0.2576	0.0386	0.3821	0.0304

	firms reporting R&D expenditure				firms not reporting R&D expenditure							
short run	manufacturing		non-manufacturing		manufacturing		non-manufacturing		manufacturing		non-manufacturing	
VARIABLES	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}
$D_2 * \Delta S_{i,t}^{F}$	-0.219	-0.497***	0.616*	0.217								
	(0.212)	(0.157)	(0.328)	(0.136)								
$D_2 * \Delta S_{i,t-1}^{I-TRA}$	0.00485	0.331	-0.851	-0.379*	-0.606	-0.365	0.922	0.505				
	(0.256)	(0.262)	(0.575)	(0.22)	(3.427)	(2.285)	(0.707)	(0.415)				
$D_2 * \Delta S_{i,t-1}^{I-TER}$	-0.289	0.0528	-1.594	-0.393					1.193	-0.0987	-5.004	-2.813
	(0.38)	(0.38)	(1.577)	(0.912)					(8.527)	(3.546)	(8.194)	(2.274)
Observations	2,262	2,269	748	752	37	37	368	368	37	37	368	368
sample size	1133	1136	375	377	20	20	193	193	20	20	193	193
Hansen	0.235	1.588	0.039	0.148	0.57	0.469	0.351	3.943	0.429	0.286	0.453	4.048
Hansen P-value	0.6281	0.2075	0.844	0.7006	0.4502	0.4933	0.5536	0.0471	0.5125	0.5929	0.5008	0.0442

Note: Standard errors (in brackets) are reported below the coefficient estimates. ***, ** and * denote significance at 1%, 5% and 10%. R-squared is goodness of fit statistics. R-squared in GMM estimator is uninformative so it is not reported in GMM estimator (Wooldridge, 2012). Hansen is the Hansen test of the overidentification. Hansen P-values of the null of instruments validity are reported under the Hansen J statistic.

This Table reports the effect of the R&D stock variables for privately-owned firms. The dummy variable for privately-owned firms is D_2. We only pick out and present the parts that are relative to dummy variables in the regression of eq.(8) and eq.(9).

4.6.3.2 Privately-owned firms

The results for private firms are shown in Table 4.11. We firstly discuss the firms not reporting R&D expenditures. There is no significant extra spillover effect $D_2 * \Delta S_{i,t-1}^{I-TRA}$ and $D_2 * \Delta S_{i,t-1}^{I-TER}$ for them in the short run (Column 5 to Column 12, the bottom half of Table 4.10). In the long run (the upper part of Table 4.10), both intra-industry R&D $D_2 * S_{i,t-1}^{I-TRA}$ and inter-industry R&D $D_2 * S_{i,t-1}^{I-TER}$ generate higher output y_{it} for private-owned firms but it only happens in non-manufacturing sector (Column 8 and Column 12). Results for the extra effect of R&D spillover on the productivity for private firms is not significant (Colum 7 and Column 11).

Now we discuss firms which conduct R&D activities. In the manufacturing sector, private-owned firms do not have different TFP benefits from their own R&D in both long run and short run as the coefficients for the interaction between firm's own R&D stock and the ownership dummy $D_2 * S_{i,t}^{F}$ and $D_2 * \Delta S_{i,t}^{F}$ are insignificant (Column 1). The coefficient of the output is significantly lower than that of other types of firms (-0.497 in Column 2) in the short run and becomes similar to other firms in the long run. This implies that the extra effect for the output from firm's own R&D stock for private-owned manufacturing firms disappear in the long run. In the non-manufacturing sector, increase in the firm-level R&D stock generates higher TFP in the short run （0.616 in Column 3） and higher output in the long run (0.0284 in Column 4). This is consistent with Boeing et al. (2016) to some extent. In their research private firms have higher return on R&D than state-owned firms, while in our model the return for private firms is larger than the other three types of firms.

For knowledge spillover effect, privately-owned firms are more competitive in R&D than other types of firms in the short run within the industry in non-manufacturing sector. They have less output benefits from intra-industry R&D pool than the other three types of firms as the significant and negative coefficient for $S_{i,t-1}^{I-TRA}$ is -0.379 (Column 4). There is no positive knowledge spillover found in the long run and short run for both sectors, no matter it is within-industry or between-industry, implying that privately-owned firms make more effort to prevent R&D information leakage and protect innovation results.

4.6.3.3 Foreign-owned firms

Table 4.12 shows the results for foreign-owned firms. For firms which report R&D expenditure, the extra knowledge spillover effect is significant in manufacturing sector. In the short run, the coefficient of interaction between the foreign ownership dummy and inter-industry R&D $D_3 * \Delta S_{i,t-1}^{I-TER}$ to TFP_{it} is significantly positive at 2.708 (Column 1), indicating that there is a significant extra knowledge spillover for foreign-owned firms between industries contributing to the firm-level productivity. In the long run, the coefficient of interaction between intra-industry R&D stock and the foreign ownership dummy $D_3 * S_{i,t-1}^{I-TRA}$ is significantly positive at 0.036 (Column 2), which means R&D spillovers emanating from other firms in the same industry generates more output for foreign-owned firms than for the other three counterparts. However, there is a significant negative effect of foreign ownership on the output. When firms in other industries increase their R&D stock $D_3 * S_{i,t-1}^{I-TER}$ by 1%, foreign-owned firms would generate a lower output y_{it} by 0.0271% (Column 2) than other types of firms.

Firms in non-manufacturing sector do not have a significant difference with other types of firms in both long run and short run as the coefficients for all R&D related interaction variables are insignificant (Column 3 and Column 4).

There is no evidence showing that foreign-owned firms which do not conduct R&D activities could benefit more from knowledge spillover than other firms with different types of ownership in both sectors (Column 5 to Column 12).

Table 4.12 Effect of the interaction between R&D knowledge stock and foreign-owned ownership dummy on productivity and output (GMM estimates)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	firms reporting R&D expenditure				firms not reporting R&D expenditure							
long run	manufacturing		non-manufacturing		manufacturing		non-manufacturing		manufacturing		non-manufacturing	
VARIABLES	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}
$D_3 * S_{i,t}^{F}$	0.0362	0.00484	-0.103	-0.027								
	(0.0303)	(0.0125)	(0.0656)	(0.0662)								
$D_3 * S_{i,t-1}^{I-TRA}$	0.0555	0.0360*	0.475	0.133	-0.259	0.0122	0.091	-0.0083				
	(0.0449)	(0.0203)	(0.346)	(0.133)	(1.85)	(0.0137)	(0.0776)	(0.014)				
$D_3 * S_{i,t-1}^{I-TER}$	-0.0502	-0.0271*	-0.227	-0.0604					0.293	0.0057	0.0525	-0.0047
	(0.031)	(0.0157)	(0.182)	(0.0684)					(1.587)	(0.0148)	(0.0422)	(0.0075)
Observations	3,524	3,532	1,155	1,159	89	89	875	875	89	89	875	875
sample size	1201	1202	392	392	26	26	251	251	26	26	251	251
Hansen	2.343	2.428	2.057	4.809	0.275	0.015	0.779	4.475	1.207	1.789	0.765	4.49
Hansen P-value	0.1258	0.1192	0.1515	0.0283	0.5999	0.9036	0.3774	0.0344	0.2719	0.1811	0.3816	0.0341

	firms reporting R&D expenditure				firms not reporting R&D expenditure							
short run	manufacturing		non-manufacturing		manufacturing		non-manufacturing		manufacturing		non-manufacturing	
VARIABLES	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}
$D_3 * \Delta S_{i,t}^{F}$	0.474	0.732*	-0.184	-0.00022								
	(0.376)	(0.4)	(0.309)	(0.234)								
$D_3 * \Delta S_{i,t-1}^{I-TRA}$	1.322	0.391	0.64	0.742	8.698	2.297	-0.688	1.317				
	(0.804)	(0.687)	(1.58)	(0.74)	(9.046)	(0.916)	(0.913)	(0.835)				
$D_3 * \Delta S_{i,t-1}^{I-TER}$	2.708*	1.624	-5.381	-5.319					16.631	2.703	1.112	-0.896
	(1.453)	(1.126)	(7.631)	(4.08)					(20.55)	(3.334)	(7.393)	(4.405)
Observations	2,262	2,269	748	752	77	77	776	776	77	77	776	776
sample size	1133	1136	375	377	20	20	193	193	20	20	193	193
Hansen	0.214	1.548	0.036	0.041	0.038	0.339	0.411	3.522	0.012	0.89	0.544	3.86
Hansen P-value	0.6433	0.2134	0.8486	0.8397	0.845	0.5605	0.5213	0.0606	0.9127	0.3454	0.4609	0.0495

Note: Standard errors (in brackets) are reported below the coefficient estimates. ***, ** and * denote significance at 1%, 5% and 10%. R-squared is goodness of fit statistics. R-squared in GMM estimator is uninformative so it is not reported in GMM estimator (Wooldridge, 2012). Hansen is the Hansen test of the overidentification. Hansen P-values of the null of instruments validity are reported under the Hansen J statistic.

This Table reports the effect of the R&D stock variables for foreign-owned firms. The dummy variable for foreign-owned firms is D_3. We only pick out and present the parts that are relative to dummy variables in the regression of eq.(8) and eq.(9).

Table 4.13 Effect of the interaction between R&D knowledge stock and private-and-foreign-jointly owned ownership dummy on productivity and output

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	firms reporting R&D expenditure				firms not reporting R&D expenditure							
long run	manufacturing		non-manufacturing		manufacturing		non-manufacturing		manufacturing		non-manufacturing	
VARIABLES	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}	TFP_{it}	y_{it}
$D_4 * S_{i,t}^{F}$	0.0668*	0.0162*	0.00254	0.00417								
	(0.0346)	(0.00939)	(0.0387)	(0.0252)								
$D_4 * S_{i,t-1}^{I-TRA}$	0.0237	0.000948	0.146**	0.044			0.275*	0.0416				
	(0.0579)	(0.0243)	(0.0647)	(0.0453)			(0.162)	(0.0439)				
$D_4 * S_{i,t-1}^{I-TER}$	-0.0452	-0.00789	-0.0962**	-0.0241							0.16	0.0232
	(0.0398)	(0.0167)	(0.0449)	(0.0319)							(0.111)	(0.0298)
Observations	3,524	3,532	1,155	1,159	67	67	658	658	67	67	658	658
sample size	1201	1202	392	392	26	26	251	251	26	26	251	251
Hansen	2.281	2.26	2.071	5.106	1.403	1.899	0.773	4.189	1.202	1.787	0.758	4.246
Hansen P-value	0.131	0.1328	0.1501	0.0238	0.2361	0.1682	0.3793	0.0407	0.2729	0.1813	0.3838	0.0394

	firms reporting R&D expenditure				firms not reporting R&D expenditure							
short run	manufacturing		non-manufacturing		manufacturing		non-manufacturing		manufacturing		non-manufacturing	
VARIABLES	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}	ΔTFP_{it}	Δy_{it}
$D_4 * \Delta S_{i,t}^{F}$	-0.441	-0.852	0.964	0.509								
	(0.492)	(0.603)	(0.84)	(0.525)								
$D_4 * \Delta S_{i,t-1}^{I-TRA}$	2.160***	1.227	-0.567	-0.522			43.66	11.01				
	(0.809)	(0.828)	(1.868)	(1.409)			(43.67)	(13.56)				
$D_4 * \Delta S_{i,t-1}^{I-TER}$	2.635**	0.659	2.66	3.875							32.79	6.158
	(1.117)	(1.223)	(6.084)	(4.758)							(65.04)	(19.69)
Observations	2,262	2,269	748	752	37	37	368	368	37	37	368	368
sample size	1133	1136	375	377	20	20	193	193	20	20	193	193
Hansen	0.209	1.615	0.023	0.107	0.668	0.505	0.558	3.269	0.535	0.289	0.627	3.822
Hansen P-value	0.6475	0.2037	0.8789	0.7434	0.4136	0.4773	0.4549	0.0706	0.4644	0.591	0.4285	0.0506

Note: Standard errors (in brackets) are reported below the coefficient estimates. ***, ** and * denote significance at 1%, 5% and 10%. R-squared is goodness of fit statistics. R-squared in GMM estimator is uninformative so it is not reported in GMM estimator (Wooldridge, 2012). Hansen is the Hansen test of the overidentification. Hansen P-values of the null of instruments validity are reported under the Hansen J statistic.

This Table reports the effect of the R&D stock variables for private-and-foreign-jointly owned firms. The dummy variable for private-and-foreign-jointly owned firms is D_4. We only pick out and present the parts that are relative to dummy variables in the regression of eq.(8) and eq.(9).

The variables of the interaction between the intra-/ inter-industry R&D stocks and the ownership dummy are dropped in the regression for manufacturing firms not reporting R&D expenditure due to the detected collinearities. Thus, there is no estimated coefficients for the variables of intra-industry R&D*D4 and inter-industry R&D*D4 for manufacturing firms not reporting R&D expenditure.

4.6.3.4 Private-and-foreign-jointly owned firms

Table 4.13 presents the results for firms controlled by both private and foreign owners and we refer them as jointly owned firms. For firms not undertaking R&D activities, since there are collinearities in the regressions in the manufacturing group, we could not do the estimation for them. Therefore, we only report the results for non-manufacturing sector. The jointly owned firms can generate a significantly higher TFP benefits from intra-industry R&D pool than other types of firms in the long run as the coefficient for $D_4 * S_{i,t-1}^{I-TRA}$ is positive and significant (0.275 in Column 7).

Compared with other types of firms, jointly owned firms engaged in R&D activities have significant differences in both productivity and output benefits from firms' own R&D and R&D spillovers. In the manufacturing sector, jointly owned firm's own R&D stock $D_4 * S_{i,t}^{F}$'s effects on productivity TFP_{it} and output y_{it} are significantly larger than those on other types of firms, with a higher effect of 0.0668 (Column 1) for TFP and 0.0162 (Column 2) for output in the long run. Therefore, the firm's own R&D stock benefit its productivity as well as the output in the long run. Our result is consistent with Zhou and Deng (2009), suggesting R&D efficiency in foreign-funded firms is higher. In the short run, jointly owned manufacturing firms have positive and significant extra intra- and inter-industry R&D spillover on the productivity, with the coefficients to be 2.16 and 2.635 (Column 1) respectively. In the non-manufacturing sector, jointly owned firms enjoy an extra positive intra-industry R&D spillover contributing to their TFP, with the significant and positive coefficient of $D_4 * S_{i,t-1}^{I-TRA}$ at 0.146 (Column 3). But the TFP contribution from inter-industry R&D spillover $D_4 * S_{i,t-1}^{I-TER}$ is lower than for the other three types of firms, with the significant and negative coefficient of -0.0962 (Column 3). An extra effect of a positive intra-industry R&D spillover indicates that jointly owned firms are more likely to create knowledge networks within the industry, which contribute to their productivity. However, technological rivalry appears to be more intense for jointly owned firms between the industries.

To sum up, firms which are entirely or partly related to private ownership (privately-owned firms and private-and-foreign-jointly owned firms) are more likely to have extra TFP or output benefits from firm's own R&D. Firms with foreign-related ownership (foreign-owned firms and private-and-foreign-jointly owned firms) can benefit more from other firms' R&D activities within the industry than state-owned and privately-owned firms, while the inter-industry knowledge spillover effect is weaker in firms with foreign ownership. State-owned firms, on the contrary, benefit more from knowledge spillover originating from other industries but face more intense technological rivalries in the same industry than other types of firms.

4.7 Conclusion

In recent years, China has achieved a new stage of development, which implies that economic growth should not be driven simply by accumulating physical capital as this development model may cause resource allocation inefficiency. Instead, economic development focused on a high-quality output may be preferred in this stage. This requires economic growth to be driven by a higher level of productivity, where R&D and innovation come into play.

In this chapter we analyze factors which might affect the firm-level productivity and output. Factors include firm's own R&D expenditure as well as other factors such as the government subsidy ratio, debt ratio, firm size, etc. In addition, we also consider intra- and inter-industry knowledge spillovers. The externality of knowledge implies that R&D activities conducted by other firms or in other industries could also influence a firm's productivity or output. We measure the effect of these relative factors on TFP and output for manufacturing sector and non-manufacturing sector separately. The effects are estimated both in the long run and in the short run. In addition, we examine whether the magnitudes of R&D and knowledge spillovers differ across firms with different types of ownership by generating an interaction variable between the R&D stock and the ownership dummies into the model. The extra effect brought up by the four types of ownership are measured separatelyfor state-owned firms, privately-owned firms, foreign-owned firms and private-and-foreign joint ownership firms.

We found that R&D-related factors play an important role in determining firms' productivity. In the manufacturing sector, a firm's own R&D stock significantly increases its productivity both in long and short runs. In the non-manufacturing sector, the impact of a firm's own R&D stock on both productivity and output is insignificant, which indicates that innovation activities might not be the best way to increase the firm-level productivity and output.

Technological rivalry is observed no matter in the same industrial environment or across different industries in manufacturing sector. Significantly negative coefficients for both intra-industry and inter-industry R&D indicate the fact that manufacturing firms protect their innovation by preventing technological information leaking out to other firms. However, in the non-manufacturing sector, there are significant knowledge spillovers across firms in different industries. This spillover effect also exists for firms not engaged in any R&D activities but only in the short run. The results show that there is innovation competition for Chinese listed manufacturing firms while non-manufacturing firms are more likely to communicate and cooperate rather than compete in R&D activities as the estimated results of the effect of R&D spillover for manufacturing firms are significantly negative and those for non-manufacturing firms are either significantly positive or insignificant.

We have also analyzed the effect of other factors that may affect firm-level productivity and output. We found that there is a negative relationship between the government subsidy and the productivity for both manufacturing and non-manufacturing sectors, which indicates the inefficiency in resource allocation. The government should change the way of directly subsidizing firms as this approach cannot promote firms' productivity. Besides, loans from the banks are another financing channel for firms' R&D activities. The results show that the ease of financial constraints has a positive effect on both TFP and output only in the manufacturing sector. In the manufacturing sector, the productivity of larger firms is higher, but only in the short run. However, in the non-manufacturing sector, smaller firms are more productive. Firms with a higher ownership concentration ratio generate higher TFP in manufacturing sector while the effect of this factor is insignificant in non-manufacturing sector.

In the last part, we consider an interaction between R&D related factors and ownership dummies to figure out whether R&D activities and knowledge spillover effect perform differently with different ownership. State-owned manufacturing firms face a more intense innovation competition than other types of firms within the industry but can enjoy more knowledge spillover emanating from inter-industry R&D stock pool to increase the productivity. Their R&D productivity has the same magnitude as the other types of firms, ceteris paribus. However, in the non-manufacturing sector, state-owned firms are less productive in R&D activities than other firms in the short run but become similar to others later. Privately-owned firms in non-manufacturing sector are more productive in R&D activities to increase TFP in the short run and their own R&D stock contributes to the output in the long run. Also, firms not investing in R&D can enjoy higher intra-industry and inter-industry knowledge spillover than other types of firms to increase the output in the long run. But this only happens in non-manufacturing sector. Foreign-owned manufacturing firms generate higher return from their own R&D stock on the output and receive more inter-industry knowledge spillover to increase TFP in the short run. In the long run, there are extra positive intra-industry knowledge spillover but negative inter-industry R&D knowledge externality. Private-and-foreign-jointly owned firms in the manufacturing sector exhibit a distinctly higher R&D productivity in the long run. Also, the intra- and inter-industry knowledge pools generate extra positive knowledge spillover for them in the short run. Non-manufacturing jointly owned firms can better absorb R&D results than other types firms in the same industry even if they do not invest in R&D themselves.

By comparing the results for firms with four different types of ownership, we conclude that in the manufacturing sector, jointly owned firms are the most productive in R&D activities. State-owned firms can better receive positive inter-industry knowledge spillover than other types of firms. Foreign- and private-and-foreign-jointly owned firms have extra intra-industry knowledge spillover effect. In the non-manufacturing sector, privately-owned firms appear to have the highest R&D elasiticity. Jointly owned firms benefit more from an extra intra-industry R&D spillover than the other three counterparts.

Above results implicitly indicate some policy suggestions. Manufacturing firms should be encouraged to transfer their innovation results into commercialization process, which later increase the output growth. The inefficiency of government subsidy in promoting the productivity requires that the government should find alternative policies to stimulate firms' incentive to innovate rather than directly subsidizing them. State-owned firms need reforms such as evaluating innovation results and make CEO to be more responsible for R&D efficiency in their R&D activities. Jointly owned firms have more advanced technologies and are good at applying the advanced knowledge to the final commercialization process. Also, the magnitude of R&D spillover effect is higher in firms which are partly or entirely owned by foreign investors. Thus, the government should make policies to encourage trade and cooperation between domestic and foreign firms as the productivity of the former can be increased by communication and cooperation.

Now we have a brief discussion about the directions for further research. In further research, since the correlation between industries is different, we could find a way to generate a weight for each industry. Then intra- and inter-industry spillover could be generated by a weighted sum of R&D stock from other firms and industries instead of simply summing all firms' R&D stock with the same weight. Also, since we only use disembodied measures of inter- and intra-industry knowledge pools relevant to each of the firms in the sample, addressing embodies knowledge pools will be an extension of this work. Another development we could consider is that the R&D activities might be more efficient in high-tech industries than in other industries, such as labour-intensive or advertising-intensive industries. Thus, one inspiration for further research is to analyse the knowledge spillover effect for industries categorised by different taxonomies separately.

4.8 Reference

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Chapter 5 Conclusion

This thesis aims to explore the reason for economic slowdown in recent years and possible ways to improve productivity and output. There is vast literature studying this question. We choose two aspects of mainstream literature for further exploration. The first aspect of the mainstream literature attributes poor economic performance to resource misallocation. The other aspect emphasises the positive role of R&D and its spillover effect in generating higher productivity. In the thesis, we combine these two aspects. We extend the resource misallocation model by including the externality of R&D spillover.

The existing literature on resource misallocation does not consider any externality. Resource misallocation is eliminated when the input distortions are equalised across firms. After this, the productivity and output will reach a higher level. However, our solution is different as we developed the resource misallocation model by considering the externality of R&D spillover. The optimal solution suggests that productivity and output can be improved when a certain level of dispersion in R&D input distortion is kept. In contrast, the distortion should still be equalised for other inputs that do not have an externality. This conclusion is generated from the empirical results for Chinese manufacturing firms in chapter 2 and UK manufacturing firms in chapter 3. In addition to R&D input, we find that among the three types of input misallocations, labour misallocation makes the largest contribution to the allocative efficiency loss of Chinese manufacturing firms, while the output loss of UK manufacturing firms is mainly explained by capital misallocation.

Since R&D activities are another source of productivity improvement, in chapter 4, we estimate the firm-level effect of R&D investment and R&D spillover on productivity in Chinese manufacturing and non-manufacturing sectors. We find a significant positive effect of a firm's own R&D investment on productivity in the manufacturing sector, while that is insignificant in the non-manufacturing sector. Regarding the R&D

spillover, a technological rivalry is observed in the manufacturing sector. The negative correlation between a firm's productivity and the R&D efforts of other firms indicates innovation competition among manufacturing firms. In the non-manufacturing sector, there is significant positive inter-industry R&D spillover, suggesting that firms can benefit from the R&D efforts of other industries.

The thesis discusses the effect of R&D and its spillover on productivity, and there are policy implications. The role of R&D activities in stimulating productivity cannot be ignored. The policymaker should ensure that the R&D input resource is efficiently allocated across firms. Due to the externality of R&D spillover, a certain level of R&D input distortion should be kept, which implies that it is not a bad thing that more productive firms pay a higher price in R&D activities while less productive firms receive subsidies on their R&D projects. For other types of resources that do not have externality, no firms should receive subsidies or be taxed, that is, all firms should be treated as the same in the optimum.

From empirical results, we find that a firm's own R&D input positively contributes to its productivity. Therefore, the policymaker should encourage firms in their R&D investment. However, the empirical results show a negative correlation between the subsidy in a firm and its productivity, which implies poor resource allocative efficiency. In China, this is, in general, related to the ownership type of a firm. Therefore, evaluating the project results in firms that receive a subsidy is necessary. In addition, the government should create an environment for communication and cooperation among firms, increasing the R&D spillover and achieving a win-win situation.