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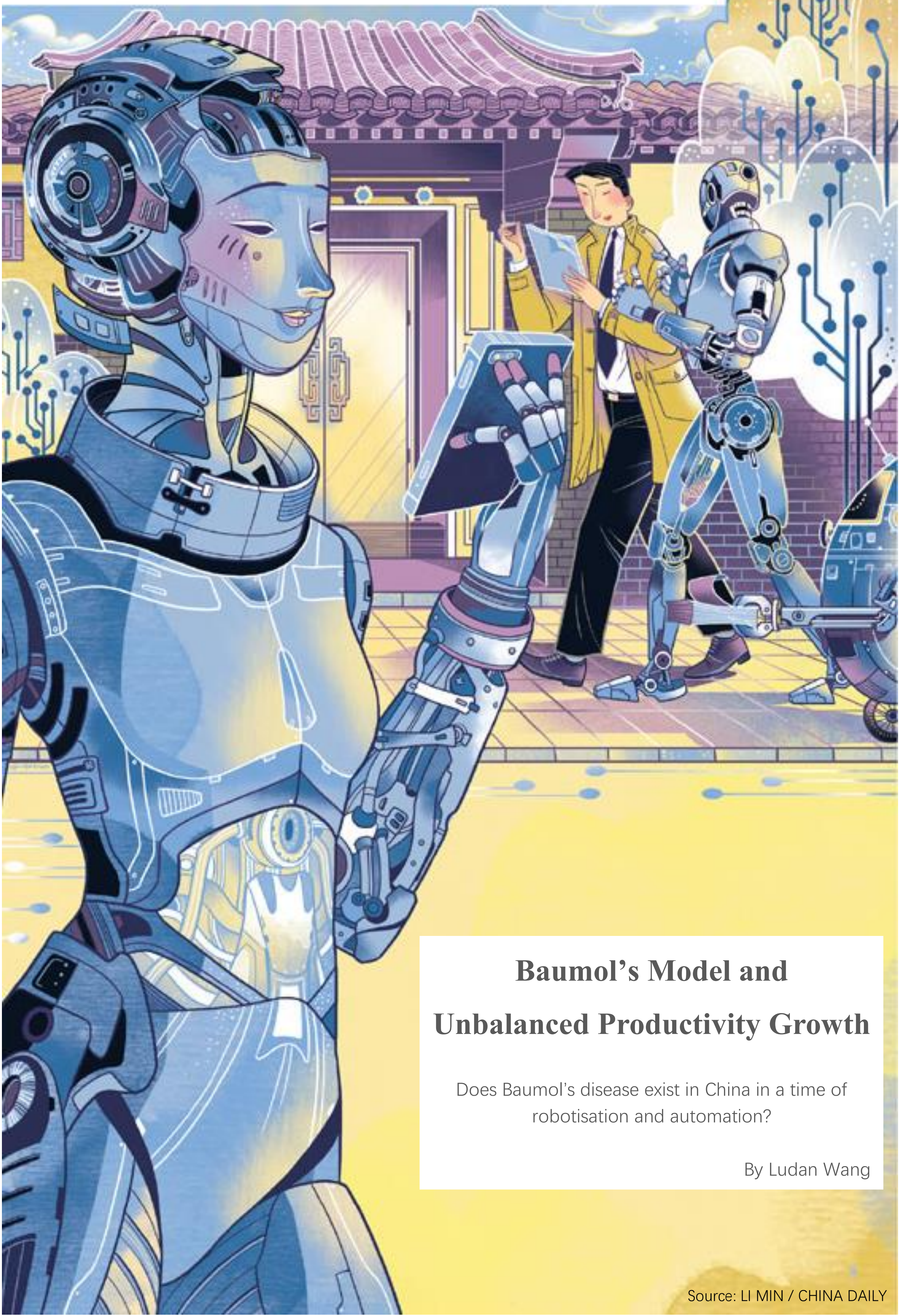

Baumol’s Model and Unbalanced Productivity Growth

Does Baumol’s disease exist in China in a time of robotisation and automation?

By Ludan Wang

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Baumol's Model and Unbalanced Productivity Growth

Does Baumol's disease exist in China in a time of robotisation and automation?

Master thesis submitted to Delft University of Technology

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by

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PREFACE

This thesis becomes a reality with the kind support and help of many individuals. I would like to make use of this opportunity to thank them.

Firstly, I would like to thank my supervisor Dr. Storm who made this work possible. His dedicated support and guidance carried me through all the stages of the thesis project. I enjoyed our discussions very much. I really appreciate his effort and encouragement. Secondly, I would like to thank Prof. van Beers, who chaired my committee and provided valuable feedback on my thesis. His refreshing points of view helped sharpen the discussion sections. Thirdly, I would like to thank my second supervisor - Dr. Mouter, for sending me useful references, and providing critical feedback and insights during the mid-term meeting. I am extremely grateful to have had them as my graduation committee.

Finally, I would like to give special thanks to my friends and parents, whose love and support are with me all the time. I live by the old adage, “Read great books and do great travels”. Sometimes the journey can be unmanageable and tiring. But I always find inspiration in family, friends and mentors. I would express my gratitude to all of them.

I hope you enjoy this thesis!

Warm regards,

Ludan Wang

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Executive Summary

The growing use of labour-saving technologies (including automation, AI and robotics) in manufacturing and other "dynamic" industries is argued to be leading to unbalanced economic growth: while output and productivity rise, and employment stalls or even declines, in the technologically "progressive" sectors (including manufacturing), the technologically 'stagnant' sectors (many services including health care and education) experience low output and productivity growth but relatively high job growth. Consequently, only a few people will receive most of the "dividends" of technological development, and hence the gap between rich and poor increases. From the "demand-side" perspective, the poor will have to reduce consumption, leading to a decrease in aggregate demand. In the long run, it may cause economic stagnation or social unrest. This is why "unbalanced growth" is a major concern for economic policymakers. This thesis examines the effects of the differential growth of productivity across industries on the "unbalanced economic growth". It is crucial for the policy makers to understand whether and how rising productivity polarization contributes to unbalanced growth.

The empirical approach of this thesis is based on Baumol's (1967) model. Baumol considers the manufacturing (or the secondary) industries as the progressive (high-productivity) industries, and the services industries (or the tertiary) industries as the stagnant (low-productivity) industries. He further predicts that the costs and prices in the stagnant industries will grow relative to the progressive industries (a phenomenon known as Baumol's cost disease); and the expansion in the stagnant industries has a negative impact on aggregate productivity growth (Baumol's growth disease). However, there is no consensus in the economic literature that Baumol's disease is universal. For example, Nordhaus (2006) investigates Baumol's disease for the U.S. economy from 1948 to 2001. His study empirically tests six propositions concerning productivity growth, prices, costs and factor rewards and concludes that both Baumol's cost disease and Baumol's growth disease are confirmed for the U.S. economy. Later, this testing framework was used in other papers (e.g., Hartwig, 2010; Oh and Kim, 2015; Hartwig 2019). Hartwig (2010) examines the Swiss economy during 1991-2007 and argues that expenditures do not shift toward the stagnant sectors. In general, the results of Baumol's disease differ empirically by country and period. Besides, the existing literature mostly studied this topic in developed countries.

In this thesis, I look at whether Baumol's disease exists in a rapidly industrializing developing country – China. Since its reform and opening-up in 1978 and the accession to the World Trade Organisation (WTO) in 2001, industrialization has brought about significant changes to China's economic structure. Specifically, a large number of farmers from the rural areas moved to work in the secondary industry and the tertiary industry. The results of the stylized facts analysis on the economic performance during 1987-2010 show that the average annual growth rate of employment in the tertiary industry was 4.22%, while it was 1.61% in the secondary industry (in the context of robotisation and automation). In other words, the tertiary industry creates the most job opportunities to the market. But the average annual growth rate of real wage in the tertiary industry (8.79%) lagged that of the secondary industry (11.64%).

The analytical results imply “unbalanced economic growth” in China. Therefore, the main research objective of this thesis is:

Does Baumol’s disease exist in China in a time of robotisation and automation?

By applying Nordhaus’s (2006) testing framework based on Baumol's model and examining the changes of “Unit Labour Cost” additionally, I empirically test seven sub-questions, concerning the growth rates of “Price index”, “Real output”, “Nominal Output”, “Working Hours”, “Wages” and “Unit Labour Cost” with productivity growth during 1987-2010 for 37 industries.

The results suggest that there is a significant sign of Baumol’s cost disease in China during 1987-2010. As Baumol (1967) predicts, the relative prices in the stagnant sectors are higher than those in the progressive sectors. For instance, the price indexes in education and health increased by 16.3% and 15.3% per year during 1987-2010 respectively, while the average inflation rate was just 4.3% during the same period. In other words, the goods and services supplied by the stagnant sectors keep getting more expensive. However, Baumol (2012) argues that it is not a problem if an economy suffers from “the cost disease”. Despite the increasing costs on education and health care, people pay less for food, clothing, electronics and other goods (produced by the progressive sectors). Again, the stylist facts support his argument. For sectors such as Electric equipment (ELE) and Electronic and telecommunication equipment (ICT), the average annual price increases during 1987-2010 are 3.5% and -2.1%, respectively, which is lower than the inflation rate. Overall, the purchasing power increases with the economy’s constantly growing productivity (Baumol, 2012).

Nevertheless, the rising affordability of the community does not necessarily mean that everyone can equally share the benefits from labour-saving technical progresses. My study reveals that the progressive sectors show a significant decrease in relative employment and unit labour cost, but an increase in relative wages. I further find that the employment growth of the progressive sectors has stagnated. If we assume full employment because in China one must find jobs for survival, then most people have no choice but to accept lower-paying jobs in the stagnant sectors. Thus, unbalanced productivity growth leads to unbalanced economic growth. Moreover, with more and more workers tolerating lower pay in the stagnant sectors, aggregate demand growth in the market will slow down. Eventually, the unbalanced growth may lead to economic stagnation.

The inference is supported by the fact that China has been facing severe income inequality since the reform and opening-up in 1978. According to the World Bank (2020), the country’s income-based Gini coefficient for 2019 is 46.5, which is similar to or slightly lower than some of the most unequal developing countries. Specifically, the eastern coastal area accounts for 84% of the exports, more than half of GDP with just over a third of the population. The polarization of the labour market inhibits the growth of private consumption. Thus, a more balanced growth is needed to prevent stagnation in Chinese economy. Income equality has to be narrowed, so more people are able to afford the goods and services beyond the necessities.

My research leads to the following policy lesson which will be of interest to Chinese and other industrialized countries' macroeconomic policy makers: while the increasing productivity makes the country rich, the economic growth is naturally "unbalanced". Hence, it is necessary to intervene in income distribution through fiscal and monetary policies to make the workers in the stagnant industries benefit from the technological progress (which is concentrated in the progressive sectors). This conclusion not only implies that workers should earn higher wages, but also suggests that the society should create more "good jobs". Laws and regulations are needed to protect vulnerable employment, the poor and the elderly. This approach would improve the community's overall living standards, increase private consumption, thereby preventing the economy from stagnation.

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Chapter 1: Introduction

1.1 Background

In 1930, John Maynard Keynes predicted that the rapid spread of automation technologies would bring “technological unemployment” (Keynes, 1930). As now we live in an era in which technology and innovation seem ubiquitous, and the economic structure and productivity are constantly changing. For instance, Acemoglu and Restrepo (2020) study the effects of industrial robots on US labour markets, and show that one more robot per thousand workers reduces the employment-to-population ratio by 0.2% and wages by 0.42%. Moreover, we currently witness major advances in artificial intelligence (AI), machine learning, and new manufacturing technologies. Generally speaking, the growing use of labour-saving technology has vastly influenced the economy, and the current pandemic is likely to intensify this trend.

But when we look at the situation of different industries in detail, we may get different conclusions. In some industries, such as manufacturing, many jobs have disappeared because of automation, AI and robotics. For instance, Apple devices and iPhone components are mainly produced in Chinese out-source factories, which is supposed to bring thousands of jobs. But now these manufacturers are building unmanned, 'lights-out' factories in China[1] with AI-powered machines to save costs on labour and energy while improving product quality (MailOnline, 2020). However, at the same time, labour-saving technological progress does not seem to have much impact on (most segments of) the service industry. It is easy to understand when you put yourself in the context: you probably don’t want a robot to give you a new haircut. As a result, the difference between technologically ‘progressive’ sectors (manufacturing) and technologically ‘stagnant’ sectors (many services) may cause unbalanced economic growth.

A well-known model that predicts structural change in employment and unbalanced economic growth was proposed by William J. Baumol (1967) in his article ‘Macroeconomics of unbalanced growth’. According to Baumol's model, labour flows from a high productivity-growth sector to a low productivity-growth sector, which eventually leads to a decline in the aggregate productivity growth. In addition, because people in different industries demand the same wage increase, the relative costs and prices of the stagnant industries will increase in response, which is called Baumol's cost disease. In the following decades, Baumol’s study

[1] As one of the main suppliers of Apple and one of the largest employers worldwide, Foxconn has developed and deployed a fully automated “lights-off” manufacturing process in the factories in Shenzhen, China. With an automated optimisation system for machine learning and AI devices, an intelligent self-maintenance system and an intelligent real-time production monitoring system, Foxconn has managed to increase production efficiency by 30%, reduce inventory cycle by 15%, and reduce labour costs compared to semi-automated process. (GSMA, 2020)

provoked a large body of empirical and theoretical research. Many studies conclude that the results of Baumol's disease differ empirically by country and period. Therefore, whether Baumol's disease is a universal phenomenon is unclear.

In this thesis, I look at whether Baumol's disease exists in rapidly industrializing developing countries in a time of robotisation and AI. To achieve this objective, I study the rapidly industrializing country - China. There are three reasons to focus on the Chinese economy. Firstly, manufacturing accounts for a large share of total economy. According to China Labour Statistical Yearbook 2019[2], the value added of the secondary industry accounts for 40.7% of the Gross Domestic Product (GDP) in 2018. Secondly, China is the world's factory. According to data published by the United Nations Statistics Division[3], it accounts for 28% of the global manufacturing output in 2018. Thirdly, although China's success as the "world's factory" has been largely achieved by the demographic dividend[4], the technology upgrading in factories has been stimulating the sales of robots – from a mere 380 units sold in 2000 to 87,000 units sold in 2016, accounting for about 30% of the global robot market (Cheng, 2019). Therefore, China is a relevant research object for studying structural change, robotisation and "technological unemployment".

Finally, I further look at the relationship between the shift of resources to services and economic growth. In Baumol's unbalanced growth model, the dynamic (high-productivity) sector is the manufacturing (or the secondary) industry, and the stagnant sector is generally considered to be the services sector or the tertiary sector. When resources shift towards the relatively stagnant service industries as Baumol's model presents, Oulton (2001) suggests that it may raise rather than lower aggregate productivity growth if the service industries produce intermediate rather than final products. Sasaki (2015) further endogenizes the productivity of the manufacturing and services sectors and shows that aggregate productivity growth does not necessarily decline over time. These studies theoretically explain why the impact of the service sector on economic growth varies from country to country.

1.2 Research Problems

In this thesis, I try to explore when labour flows from agriculture to manufacturing, and finally to the service sectors, what are the consequences for China? Baumol's (1967) unbalanced growth model predicts that the growth of services sectors is likely to increase their costs and prices (relative to costs and prices in manufacturing) and to decelerate overall economic growth over time. Thus, the research problem for this thesis is:

Does Baumol's disease exist in China in a time of robotisation and automation?

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2 See: http://www.stats.gov.cn/.

3 See: https://unstats.un.org/

4 China's economic growth was in part driven by a "demographic dividend"- the benefits of an increase in labour supply (see Wang & Mason, 2007, Cai 2010).

Against the backdrop of earlier empirical analyses, Nordhaus (2006) proposes six hypotheses at the base of Baumol's model that can be tested empirically. Nordhaus's hypotheses have been widely used to analyze the structural change and productivity growth in several countries. By mostly applying Nordhaus's (2006) testing framework, this thesis investigates empirically how much and in what ways the difference in productivity growth rate between industries contributes to the overall economic growth, and whether there are discernible signs of Baumol's disease. In addition, I examine unit labour cost in the progressive and stagnant sectors. Overall, the research contains seven research sub-questions:

1. Does low productivity growth lead to a cost and price disease?

Baumol's model implies that costs grow faster in stagnant industries. Because even though productivity growth is higher in the progressive sector than in the non-progressive—or stagnant sector of the economy, wages grow more or less the same in both sectors. Therefore, we would expect that average costs and also prices rise faster in the stagnant industries.

2. Does low productivity growth lead to stagnating real output?

Because of the rapid rise in relative prices, we would expect that real output in the stagnant industries would grow slowly relative to the overall economy.

3. Do industries with slow productivity growth have increasing nominal output shares?

According to Baumol's model, stagnant industries tend to take a rising share of nominal output when labour flows from the progressive sector to the stagnant sector.

4. Do industries with slow productivity growth have increasing relative employment and hours?

As the progressive sector tends to displace labour, we would expect the progressive industries to experience a negative impact of productivity growth on employment, and contrariwise for stagnant industries.

5. Who captures the gains from innovation?

This sub-question aims to check the uniform wage growth hypothesis: Baumol assumes that wages grow the same across industries. Specifically, wage growth is correlated with productivity growth in the progressive industries, but uncorrelated with it in the stagnant industries.

6. Do industries with slow productivity growth have increasing relative unit labour cost?

In addition to Nordhaus's (2006) testing framework, we also study unit labour cost in the progressive and stagnant sectors. If we assume the demand is fixed, the progressive industries with relatively rapid productivity growth tend to hire less workers, and hence its unit labour cost will decline comparing to that in the stagnant industries.

7. Has the economy suffered from a growth disease?

Baumol's model shows that unbalanced productivity growth will lead to a decrease in the growth rate of overall GDP over time. In other words, if the stagnant industries have rising nominal output shares, then the aggregate growth rate will be reduced as the share of output moves toward the slow productivity-growth industries.

The thesis is organized as follows. Following this introduction, in Chapter 2 an initial overview of the literature is presented, where I explore the knowledge gaps and what I aim to contribute to the existing knowledge. Chapter 3 starts with an introduction of the datasets that I will apply. Next, I will discuss the concept of total factor productivity (TFP) growth, and I present relevant stylized facts in terms of economic performance during 1987-2010 in China and decompose the sources of growth. Chapter 4 provides the results of the regression analysis, in which the variables are the productivity growth rates and the growth rates of 'Price index', 'Real output', 'Nominal Output', 'Working hours', 'Wages' and 'Unit Labour Cost' in 1987-2010 for 37 Chinese industries. Chapter 5 summarises the results and concludes. Chapter 6 gives reflections and recommendations for future research.

Chapter 2: A Review of the Literature

This chapter describes the main findings from the reviewed literature and it is divided in five subsections. Firstly, I start with the origins and the development of Baumol's disease. An overview of the main definitions and assumptions of the model is given. Then I narrow the topic to the empirical studies after Baumol to assess if it can be considered a universal phenomenon. Here, I identify two groups of research papers, one group of studies that finds support for Baumol's prediction and the other group of studies that does not. Next, I argue that the main challenge to empirically investigate Baumol's disease is the lack of unified standards of investigation, especially regarding to the definition of the growth rate and the industrial classification. In the next subsection, an overview of the theoretical development based on Baumol's model is made. The focus is mainly on the relationship between the growing (relative) importance of services in economic growth. Thirdly, I study the transformation of employment structure in China and examine the development of robotization and automation. Finally, I conclude the knowledge gaps and research objective of the thesis in the last subsection.

2.1 The evolution of Baumol's disease

2.1.1 The definition of Baumol's disease

William Baumol (1967) in "Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis" divides the economy into two sectors. In sector one (non-progressive sectors) the productivity of labour is constant, while in sector two (progressive sectors) output per person hour grows cumulatively at a constant compounded rate. Baumol assumes that wages rise commensurately in both sectors. Therefore, when productivity rises cumulatively in progressive sectors, this allows the progressive-sector wage to increase and (as Baumol assumes) the wage in the non-progressive sector will grow at the same rate as the wage in the progressive sector. As productivity is constant in the non-progressive sectors, their costs must rise, which induces an increase in the relative price of the products. Moreover, the aggregate productivity growth declines as the nominal value-added share of the non-progressive sectors in the economy increases. In my discussion of the model, I will draw on the formulation and equations proposed in Baumol (1967).

It needs to be emphasized that there are two assumptions in Baumol's model. Firstly, the demand for technologically stagnant services is hardly price-elastic, which means people are willing to pay even when the price is higher. Secondly, wages rise at the same rate in all industries. Formally, it can be stated as:

$$Y_{1t} = aL_{1t} \tag{1}$$

$$Y_{2t} = bL_{2t}e^{rt} \tag{2}$$

with Y_1 and Y_2 as output at time t, L_1 and L_2 as quantities of labour employed, and a and b as constants, equations (1) and (2) describe the production functions of the two sectors. Labour productivity in sector (1) stays constant, while in sector (2) it grows at the constant rate r.

With W as the wage rate, the nominal wage in both sectors is given by

$$W_t = We^{rt} \tag{3}$$

From equations (1) to (3), we obtain

$$C_1 = \frac{W_t L_{1t}}{Y_{1t}} = \frac{We^{rt}L_{1t}}{aL_{1t}} = \frac{We^{rt}}{a} \tag{4}$$

$$C_2 = \frac{W_t L_{2t}}{Y_{2t}} = \frac{We^{rt}L_{2t}}{bL_{2t}e^{rt}} = \frac{W}{b} \tag{5}$$

That is, cost per unit of output in non-progressive sectors tends toward infinity while it stays constant in the progressive sectors. In addition, as the demand for non-progressive sectors is hardly price-elastic, Baumol (1967) assumes that the relation of real output of the two sectors remains unchanged:

$$(\frac{b}{a})\frac{Y_1}{Y_2} = \frac{L_1}{L_{2t}e^{rt}} = K \tag{6}$$

where K is a constant. With $L(= L_1 + L_2)$ denoting the labour force, we obtain

$$L_1 = L_2Ke^{rt} = (L - L_1)Ke^{rt} \Leftrightarrow L_1 = \frac{LKe^{rt}}{1+Ke^{rt}} \tag{7}$$

From equation (7) we learn that, over the years ($t \to \infty$), L_1 tends towards the labour force L. In other words, labour flows from progressive sectors to non-progressive sectors over time. Meanwhile, under the assumption of constant 'real shares', we could predict that the GDP growth rate drops asymptotically to zero.

To improve his own theory, Baumol (1985) examines the empirical evidence relating to the model and then presents an amended unbalanced growth model by introducing an "asymptotically stagnant sector". Such activities like TV broadcasting and electronic computation contain both a technologically sophisticated component and a relatively irreducible labour-intensive component. The progressivity of such activities is transitory. Therefore, these activities will ultimately show all the characteristics of the stagnant services.

Eventually, the cost disease may affect more activities in the economy than was assumed in Baumol's previous model.

To sum up, Baumol's model shows the impact of differential productivity growth on the health of different sectors. Specifically, non-progressive sectors (technologically stagnant sectors or tertiary activities) experience above average relative unit costs and prices increase (Baumol's cost disease), take a rising share of total economic output, and slow aggregate productivity growth (Baumol's growth disease).

In the above, the definition and development of Baumol's disease have been presented. The classical model provides insights on industrial productivity growth rate and structural change. Many studies attempted to investigate the extent to which economic performance has been affected by Baumol's disease. An overview of the related works is given in the next subsection.

2.1.2 Empirical studies on Baumol's disease

In this subsection, I provide an overview of the empirical studies that assessed if Baumol's disease is a universal phenomenon. My conclusion is that as many studies have examined Baumol's (1967) model of unbalanced growth, there is (as of now) no consensus that Baumol's disease is universal.

Some research supports Baumol's prediction. For instance, based on data for 28 OECD countries from 1990 to 1998, Peneder (2003) shows that although the share of the services sector is positively correlated with income levels, its lagged levels bring a negative impact on GDP per capita and annual growth rates, which is generally consistent with Baumol's hypothesis. Additionally, Hartwig (2011) provides a comprehensive study with EU KLEMS data for an aggregate of EU countries. Applying Nordhaus's (2006) empirical model for the U.S., the thesis points out that the European Union suffers from Baumol's disease. However, there are certain differences. For instance, the relative productivity growth has a stronger impact on industries' relative real value-added growth in the U.S. than in Europe. Hartwig's results deserve further attention.

For the U.S., economy, at the national level, Nordhaus (2006) investigates Baumol's disease by empirically testing six propositions concerning productivity growth, prices, costs and factor rewards. It is worth mentioning that this testing framework is widely used in other papers later (e.g., Hartwig, 2010; Oh and Kim, 2015; Hartwig 2019). It has six implications that can be tested empirically: (1) *The cost and price disease* – the average costs and prices in stagnant industries will grow *relative to* the progressive industries; (2) *Stagnating real output* - real output in stagnant industries will grow slowly *relative to* the overall economy; (3) *Unbalanced growth* – the share in nominal output in stagnant industries will rise; (4) *Impact on employment and hours* –the model predicts a negative correlation between productivity growth and employment growth. Progressive industries tend to displace labour, and thus show lower growth of working hours; (5) *Impact on factor rewards* – Wage growth would be uniform across industries. (6) *Impact on aggregate productivity growth* – finally, unbalanced productivity growth will lead to a decrease in overall growth in productivity. The six 'diseases' identified by Nordhaus provide insights to understand the complex process of structural change in countries.

Nordhaus (2006) proposes a new framework, and then analyses industry data from 1948 to 2001 in the United States. The study reveals that industries with relatively lower productivity growth show a percentage-point for percentage-point higher growth in relative prices. Moreover, as the composition of output has shifted away from sectors with rapid productivity growth to stagnant sectors, the aggregate productivity growth has slowed. In conclusion, both Baumol's cost disease and Baumol's growth disease are confirmed for the U.S. economy during 1948-2001. Additionally, Storm (2017) shows that the U.S. economy is becoming a dual economy: one progressive sector and one stagnant sector. There is no job growth in the 1st sector, but there is job growth in the 2nd. Overall, US productivity growth is declining, which also supports Baumol's prediction.

However, there are also other studies that present contrary results. For example, applying the methodology of Nordhaus (2006) to Swiss data over the period 1991-2007, Hartwig (2010) examines whether Switzerland is affected by Baumol's disease and gets a mixed conclusion: although the employment share of the stagnant part of the economy rises, progressive industries increase their share in GDP. Meanwhile, expenditures do not shift toward the stagnant sectors. Overall, the Swiss economy during 1991-2007 appears to be unaffected by Baumol's disease.

On the other hand, the empirical analyses conducted by Nishi (2016) and Hartwig (2019) examine Japanese economic performance. Nishi (2016) uses the JIP database 2014 compiled by RIETI that covers the period 1970-2011. Hartwig (2019) applies the EU KLEMS dataset for Japan covering the period 1973-2005. Altogether, their results suggest that for the Japanese economy, while the impact of Baumol's growth disease is weak, the impact of Baumol's cost disease is more salient. Similarly, research on South Korea, another developed Asian country, shows that Baumol's cost disease and growth disease are significant but not prominent in Korean industries during 1980-2005 (Oh and Kim, 2015).

In conclusion, the results of Baumol's disease differ empirically by country and period. One possible reason is that the period of some studies may be too short. For instance, Hartwig's (2010) Swiss dataset covers the period 1991-2007 (16 years) and his study rejects Baumol's predictions, while both Nordhaus's (2006) dataset that covers the period 1948– 2001 (43 years) and Storm's (2017) study that covers 1948-2015 (67 years) for the U.S. economy support the predictions. However, overall, there is no evidence that Baumol's disease is a universal phenomenon. But by applying this classical model to a specific country and period, we may get a deep understanding of industrial structural change and the drivers of labour productivity growth. Besides, another important finding is that the existing literature mostly studies this topic in developed countries. There is a knowledge gap for present studies on unbalanced growth in developing countries.

2.1.3 Conceptual Unclarities Concerning Baumol’s disease

After studying varying papers that empirically investigate Baumol’s disease and reach different conclusions, I notice that there are no unified standards or methodology to investigate Baumol’s unbalanced growth. In general, authors explore sectoral labour productivity growth, employment structure, costs and prices to assess if expansion in stagnant sectors has a negative impact on macroeconomic performance. But in detail, economists select different indicators for their empirical analysis, especially regarding to growth rate and industrial classification.

Firstly, there are varying definitions of the “productivity growth rate”. In Baumol (1967)’s model, “output per man hour grows cumulatively at a constant compounded rate” in the progressive sectors, as the definition of growth rate. However, different studies apply different indicators in terms of their hypotheses, including real GDP, aggregate hours of work, real GDP per hour (i.e., labour productivity) and Total Factor Productivity (TFP) growth. The TFP growth rate is essentially an indicator of technological progress, which is considered as “the best available measure of the underlying pace of innovation and technological change” (Gordon, 2015; Storm, 2017).

Secondly, the “industrial sector” has not been uniformly defined. The original Baumol (1967)’s model divides the economy into non-progressive sectors and progressive sectors. There is no clear boundary or criteria to classify industries. Many studies classify the service sector or the tertiary sector as a non-progressive low-productivity sector. Other studies may classify industries into several groups or sectors. For instance, when investigating the Japanese industrial structure, Nishi (2016) refers to the German economy and uses 106 sectors at the lowest classification level, aggregating them into eight main sectors for further research.

Therefore, it is necessary to give clear definitions and descriptions of the productivity growth rate and the industrial classification in my research.

2.2 The relationship between the relative growth of services and aggregate economic growth

Based on the existing literature, I have concluded that Baumol’s disease is not a universal phenomenon. This fact means that the economic growth rate is not necessarily monotonically decreasing as labour flows from progressive sectors to stagnant sectors. As most studies that empirically test Baumol’s model generally classify the service sector or the tertiary sector as the stagnant sector, we further look at the relationship between the shift of resources from manufacturing to services and aggregate economic growth.

Due to the essential role of the service sector for advanced economies, there has been a great research activity about the relationship between the tendency toward services and productivity growth. One such empirical study is presented by Maroto-Sanchez and Cuadrado-Roura (2009), who have examined a sample of 37 OECD countries in the period between 1980 and 2005. The paper shows that the relationship between the growth of services and overall productivity growth is positive and statistically significant. In this subsection, I examine the theoretical development regarding the relationship by presenting related research from two perspectives.

Firstly, the role of services in improving the productivity performance of the economy could be positive. In other words, the economy's overall rate of productivity and real output growth may not be dragged down by a stagnant service sector. Oulton in his paper "Must the growth rate decline? Baumol's unbalanced growth revisited" (2001) suggests that the transfer of labour to the service sector may promote overall productivity growth without causing Baumol's disease. The point is, instead of the stagnant industries producing only final products in Baumol's model, they could produce intermediate inputs and hence stimulate economic growth. However, Oulton (2001)'s model assumes that services are devoted entirely to intermediate inputs into manufacturing, which does not meet reality.

In addition, Pugno (2006) introduces the assumption that household services such as healthcare and education services lead to human capital accumulation, and hence to economic growth. On the other hand, De Vincenti (2007) supports the positive externality that the service sector produces on manufacturing via innovations, the general improvement in human capital available and the learning-by-doing process inside both sectors. Both papers suggest that both productivity of the manufacturing and services sectors keeps endogenously evolving.

Influenced by the studies above, Sasaki (2007, 2012, 2015) investigates the relationship between the employment shift toward services and the economic growth rate. The model integrates two assumptions: (1) The stagnant industries produce both final products and intermediate inputs for manufacturing production; (2) The productivity growth of both manufacturing and services are determined endogenously. The conclusion thus depends on the human capital accumulation function in the model. The relationship is not monotonous. Specifically, if the function exhibits constant returns to scale with respect to the per capita consumption of services, the relationship between the employment share of services and economic growth rate is U-shaped.

Secondly, the productivity of the service industry itself is not necessarily low or stagnant. In other words, what we assume is that "stagnant sector" may not stagnate over time. Let's look back at the US economy. Triplett & Bosworth (2003) find that after 1995, the growth in labour productivity in the United States' service industry was higher than that of the whole economy mainly due to services industry multifactor productivity (MFP) and information technology (IT), indicating that Baumol's disease was not present in the United States. On this topic, Gordon and Sayed (2020) show that most of the 1995-2005 U.S. productivity growth revival was driven by ICT-intensive industries producing market services and computer hardware. However, after 2005, both the U.S. and ten Western European nations (the EU-10) suffered a growth slowdown, indicating that the benefits of the ICT revolution were temporary.

To summarize, while Baumol (1967)'s model shows the result of a constantly decreasing growth rate, these extensions show that the growth rate is not necessarily monotonically decreasing. The point is, the productivity growth of both manufacturing and services could be determined endogenously. Moreover, the productivity of service industries can be improved because of technology.

Thus, we shouldn't simply regard all service activities as stagnant sectors. Especially, there are some services sectors – transportation, logistics, business services etc – that are very closely related to manufacturing. A backward linkage analysis of input-output tables of OECD Structural Analysis (STAN) database shows that one billion US dollars increase in a manufacturing output may increase output of services sector by between 382 and 606 million (Pasadilla and Wirjo, 2015). Hence, one could argue that those service sectors which have strong backward production linkages with dynamic sectors should be considered as part of the dynamic sector. It is an important point that needs to be kept in mind when I classify dynamic vs. stagnant industries in this study – it would make more sense to classify certain services sectors as dynamic sectors.

2.3 Transformation of the employment structure and the Lewis turning point in China

In the book "How Asia Works: Success and Failure in the World's Most Dynamic Region" (Studwell, 2013), Joe Studwell studies how rapid economic transformation is, or is not, achieved in Asia. It argues that there are three interventions that are crucial during this process. The first intervention is to maximize output from agriculture by promoting highly labour-intensive household farming, in order to generate an initial productive surplus of food and agricultural raw materials. Secondly, as workers begin to migrate out of agriculture, governments should invest in manufacturing to create jobs. In addition, successful governments also actively subsidize technological upgrading in manufacturing to build sustainable competitive advantages. Finally, the third key factor to accelerate economic transformation is that governments should keep financial institutions in check, encouraging them to work with small-scale farmers and larger industrial ventures instead of focusing only on their own profits (see also Storm and Naastepad, 2005).

Generally following the developmental strategies above, China's economy has been growing rapidly since the reform and opening-up in 1978 and the accession to WTO in 2001. Meanwhile, industrialization and urbanization have brought about significant change to China's employment structure. In detail, in the more than 40 years since the reforms were initiated in 1978, China's factories have been absorbing a large number of workers from the rural areas into manufacturing employment. Farmers find jobs in factories and thus become workers. According to China Labour Statistical Yearbook, workers who are employed in the secondary industry accounted for only 18.2% of the total employment in 1980, and the share of secondary employment in aggregate employment reached a peak of 30.1% in 2013 (see Figure 1).

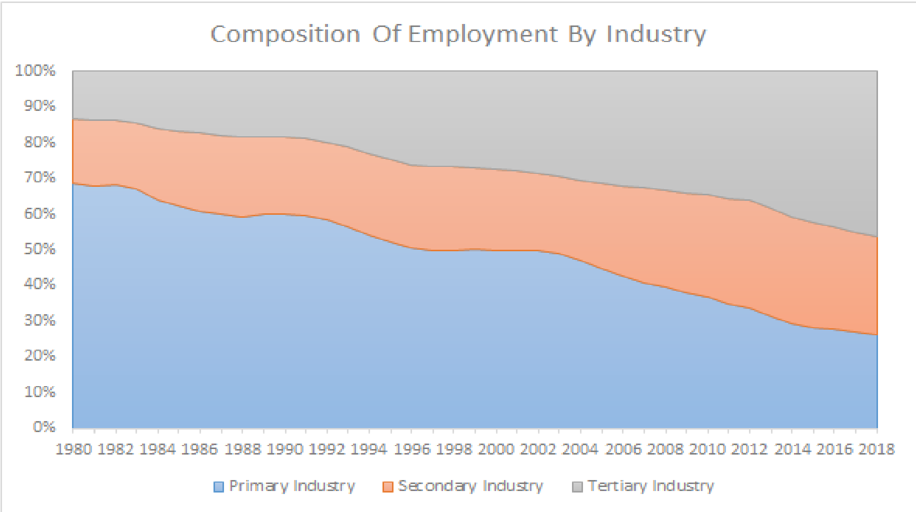

Figure 1: Composition of employment by industry (1980-2018)[5]

China's success as the "world's factory" has been partly achieved by the demographic dividend- the benefits of an increase in labour supply, However, the decline in fertility and the increase in the elderly population have significantly reduced labour input. The annual increase in China's working-age population peaked in 2003 at around 17.7 million, but it then started to decline and turned negative in 2015. The number of persons in employment peaked in 2017 at around 776.4 million, but it then started declining in 2018 (http://www.stats.gov.cn/).

As the manufacturing sector develops to the point where the supply of labour from the agricultural sector becomes limited, real wages begin to rise quickly. This process of economic transformation is known as the Lewis turning point (Lewis, 1954). Examining long-term rural wage data, Zhang (2011) shows that the era of unlimited labour supply has already passed and that the Lewis turning point in rural China arrived in 2003 when real wages both in the peak and slack seasons have begun to rise substantially. In other words, as the labour shortage gives workers more bargaining power, China's manufacturing sector is finding it more and more difficult to maintain a comparative advantage in labour-intensive products.

Consequently, around 2003, the country's manufacturing export-led growth began feeling

5 See: China Labour Statistical Yearbook (http://www.stats.gov.cn/)

the need to gradually reduce its dependence on labour input to keep its competitive advantage. Roughly at the same time, Chinese robotics industry started to grow – as I will discuss below.

2.4 Robotisation and automation in China

As Studwell (2013) suggests in his book, China's government has identified robotization as an important strategy for manufacturing development, along with artificial intelligence and automation, and thus has proposed various programs and subsidies to encourage the use of robots and technology upgrading in factories. For instance, the Ministry of Industry and Information Technology (MIIT) released its "Guidance on the Promotion and Development of the Robot Industry" in 2013, in which it planned to develop 3–5 world-leading robot companies and 8–10 supporting industrial clusters (Cheng, 2019). In addition, in 2015, China issued a 10-year national plan, "Made-in-China 2025", looking forward to moving up the value chain and becoming a world industrialized power (Song, 2015). This initiative sets goals of producing 100,000 industrial robots per year and achieving a density of 150 robots per 10,000 workers by 2020 (State Council, 2015). If I use the estimates for the U.S. provided by the study of Acemoglu and Restrepo (2020), I find that this would reduce the employment-to-population ratio by 3%, which means that about 42 million workers are going to lose their jobs.[6]

Consequently, the sales of robots in China have risen dramatically – from a mere 380 units sold in 2000 to 87,000 units sold in 2016, accounting for about 30% of the global robot market. The top industries for robot adoption are automotive (accounting for 44.5 percent of all manufacturing robots), electronics (24.7 percent), metals (13.9 percent), plastics and chemicals (11.5 percent) (Cheng, 2019).

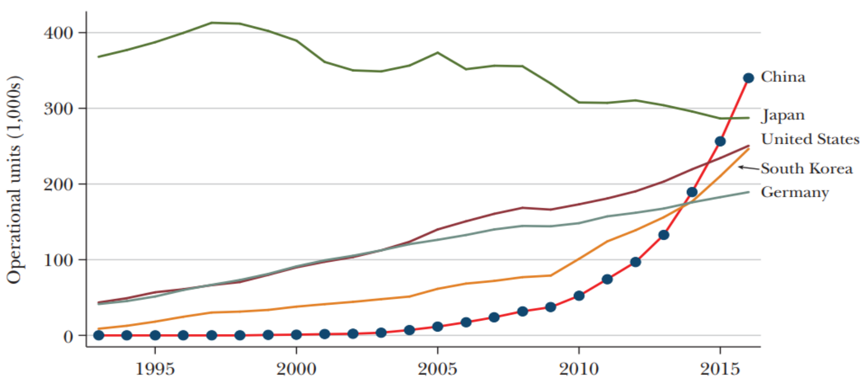

Figure 2: Stock of operational robots in major countries (1993-2016)[7]

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[6] The data used in this calculation are from the Labour Yearbook 2019, and I assume that the Chinese population is 1,400 million. The calculation is a back-of-the-envelope estimation, intended to give an idea of the order of magnitude of the effect.

[7] Source: Data is from International Federation of Robotics (2017).

Because of the increased robotisation and automation, unsurprisingly, many jobs are permanently replaced by robots. A study from McKinsey (2016) shows that manufacturing is one of the sectors that are most susceptible to automation. Because performing physical activities or operating machinery in a predictable environment represents about one-third of the workers' overall time, some 59 percent of all manufacturing activities could be automated based on technical considerations alone. However, many jobs in service sectors, which involves lots of predictable physical activities and the operation of machinery, are also in threat. Again, according to McKinsey's (2016) analysis, 73 percent of the activities workers perform in food service and accommodations have the potential for automation.

Figure 3: An unmanned factory[8]

What happens when robots replace human? People from the rural areas and some industrial workers now have to find jobs in tertiary activities. Data from the China Labour Statistical Yearbook show that the proportion of employees in the tertiary industry was 12.2% in 1978, and reached 46.3% by the end of 2018. Meanwhile, the proportion of workers in the secondary industry gradually declined to 27.6% in the same year (see Figure 1). In conclusion, the shift of labour from manufacturing to service industries has been significant in China.

2.5 Conclusions, knowledge gaps and research objective

The relationship between the economic structure of a country and its overall growth of productivity has been one of the main economic research topics in recent decades. In 1967, William Baumol presented a simple, but insightful, two-sector model, characterized by 'unbalanced' productivity growth between the two sectors: a progressive sector with a positive growth rate of labour productivity and a stagnant sector with zero productivity growth rate. As wages are assumed to grow at the same rate in both sectors and the demand for the stagnant sector is hardly price-elastic, unit costs and prices rise faster in the stagnant sector than in the progressive sector. This phenomenon is known as the 'Baumol's cost disease'.

[8] Source: Documentary *From "The World's Factory" to "The World's Engine"* (2021)

Furthermore, the aggregate productivity growth rate will decline over time as the weight of the stagnant sector steadily increases, which is known as 'Baumol's growth disease'.

Baumol's model provoked a flood of theoretical and empirical studies. As I argued above, there is no consensus that Baumol's growth disease and Baumol's cost disease are universal. In other words, it may differ empirically by country, period and sector. Accordingly, the implications of the sources and consequences may differ by country.

I identify two challenges in researching Baumol's disease. Firstly, there are varying definitions of the "productivity growth rate", of which Total Factor Productivity (TFP) growth and labour productivity growth are the most commonly used. Secondly, the progressive "industrial sector" has not been clearly and/or uniformly defined. In general, most of the studies consider the service sector, or the tertiary sector, as the stagnant sector.

Furthermore, I discuss theoretical developments extended from Baumol's unbalanced growth model. To investigate the relationship between the tendency toward services (stagnant sector) and economic growth, I divide this part into two subsections. Firstly, in some studies, the sectoral productivity growth is not necessarily exogenous as the original model suggested. For example, healthcare and education services could lead to human capital accumulation and therefore to faster productivity growth. On the other hand, services, including business services, could be used for both intermediate inputs into manufacturing (through backward production linkages) and final consumption. Secondly, the hypothetical "stagnant sector" may not stagnate over time, as services industries may experience productivity acceleration with the development of new technology. Consequently, the aggregate productivity growth rate may rise rather than fall when resources shift towards the service sector.

Finally, the main knowledge gap is that while the existing literature mostly studied this topic in developed countries, the employment structure is changing fast in developing countries in a time of robotisation and AI. Taking China as an example, we can see a clear trend of employment structure changes since the reform and opening-up in 1978 and the accession to the World Trade Organisation (WTO) in 2001. Manufacturing (the dynamic sector) firstly absorbs a large number of workers from the rural areas, but then sheds jobs (partly) because of robotisation and automation. So, people have to find employment in tertiary (services) activities (the technologically stagnant sector), which may cause unbalanced economic growth. Therefore, the main research objective of this thesis is:

To study whether Baumol's disease exists in China in a time of robotisation and automation.

Chapter 3: Data Description and Analysis

3.1 Data Identification

Throughout my empirical analysis, I make use of two datasets. The first are the China Labour Statistical Yearbooks. It is an annual statistics publication that is compiled by the National Bureau of Statistical and Ministry of Human Resources and Social Security, Ministry of Agriculture and All-China Federation of Trade Unions. It is the official report which provides information on the composition of population, employment, Gross Domestic Product (GDP), etc. from several perspectives.

However, there are some problems with the official industrial statistics. One is that the general survey mainly divides economies into three sectors of activity:

- The primary industry (Agriculture, Forestry, Farming of Animals and Fishery);
- The secondary industry (Manufacturing, Mining, Construction, Production & Distribution of Electricity, Gas & Water);
- The tertiary industry (All kinds of services to other businesses as well as final consumers).

People can efficiently find economic trends over time through this approach of industrial classification. But the level of disaggregation is not enough in terms of my study. In order to calculate the correlations between productivity growth and price changes, working hours, wages and other factors, a dataset with a more subdivided industry level statistics is needed. Due to this reason, I also apply the China Industrial Productivity (CIP) Database 3.0 (2015).

The China Industrial Productivity (CIP) Database is compiled by the Research Institute of Economy, Trade & Industry, IAA (RIETI), in Japan, and it consists of 1) Input-output tables; 2) Capital input data; 3) Labour input data covering the period 1980-2010 in China.

The development of the CIP database follows the KLEMS principles[9]. One key advantage of the KLEMS database is that it contains data on output, inputs and productivity at the industry-level that can be used to analyze the sources of output and productivity growth in cross-country comparisons or studies of particular industries and different time periods (O'Mahony and Timmer, 2009). It has been proved to be a useful tool for empirical and theoretical research that is widely used in the area of economic growth. The original database was developed for 25 individual EU member states, the US and Japan. Later the analytical KLEMS-type datasets are built up for a broad set of countries around the world, including China.

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[9] KLEMS is used as an acronym for K(C)apital, Labour, Energy, Materials and Services. Corresponding, the gross output of an industry equals the total costs of "KLEMS" and the gross output of an economy equals the sum of the costs of "KLEMS" of all industries. See O'Mahony and Timmer (2009) for an detailed introduction of the EU-KLEMS database.

From the CIP database, the following tables (variables) are utilized:

Table 1: The variables from the CIP database that are utilized in the thesis

1. Input-output tables
a) Gross value of output and b) intermediate input by industry in ml. constant yuan (previous year prices)
Input-output tables 1981-2010 in ml. constant yuan (previous year prices)
Distribution of gross value added in ml. current yuan: a) consumption of fixed capital; b) employee compensation; c) operating surplus; d) net production tax
2. Capital input data[10]
Capital stock in "equipment" by industry of all enterprises in ml 1990 yuan
Capital stock in "non-residential structures" by industry of all enterprises in ml 1990 yuan
3. Labour input data
Numbers employed by industry of all enterprises in 1000s
Hours worked by industry of all enterprises in millions

For the classification of industries, CIP adopts the 2002 version of the Chinese Standard Industrial Classification (CSIC/2002) and reclassifies the economy into 37 industries (Wu and Ito, 2015). (see appendix A) The economy-wide 37 CIP industries can be categorized into the three sectors in line with the official database from China Labour Statistical Yearbooks. To be specific, Table 2 summarizes the correspondence among the classifications.

Table 2: The correspondence among the CIP code and China National Accounts Code

China National Accounts Code	Original no. in CIP	Sector Acronym
I Primary	1	AGR
II Secondary	2-26	CLM, PTM, MEM, NMM, F&B, TBC, TEX, WEA, LEA, W&F, P&P, PET, CHE, R&P, BUI, MET, MEP, MCH, ELE, ICT, INS, TRS, OTH, UTL, CON
III Tertiary	27-37	SAL, HOT, T&S, P&T, FIN, REA, BUS, ADM, EDU, HEA, SER

Besides, the 37 CIP industries can be grouped based on their productivity growth rates. In other words, we can create a dynamic sector and a stagnant sector to help explore the

[10] Wu (2015) provides the features of CIP 3.0 database, where he documents the procedures of constructing industry-level net capital stock and measures capital services in the Chinese economy, including how annual investment flows are constructed for the industrial and nonindustrial sectors and decomposed into non-residential structures and equipment.

unbalanced economic growth empirically.

Regarding the time dimension, although most variables from the CIP database are available from 1981-2010, the dataset for "employee compensation" starts from 1987. Because it is a necessary factor for calculating the growth rate of Total Factor Productivity (TFP), the time period for the analysis, used in this thesis research, is 1987-2010. Fortunately, this adjustment will not impact the conclusions of the study. The reason is that the extent of economic progress and structural change in China's economy was relatively limited and complex in 1980s. Specifically, since the agricultural reform in 1979, the new dual-track price system was developed to smooth the transition from a centrally planned economy to a market economy. Thus, there was only limited liberalization of the market track in the labour market in the 1980s. For example, employers with plan-allocated workers were obliged to retain them at the preexisting wage rates, while the market track applied to new employment, with the market wage rate set by the equilibrium of the residual labour supply and demand. It was in the 1990s that China has officially adopted the paradigm of a "socialist market economy" (Lau, 2000).

In sum, the country's rapid economic development started from the reform and opening-up in 1978, and then moved to the next level following the accession to the WTO in 2001. Because the focus of my research is the unbalanced growth during economic development, 1987-2010 is a relevant period of analysis. In sum, a total of 37 industries across 24 years (1987-2010) are analyzed.

3.2 A Brief Note on Total Factor Productivity

When economists study how the output changes with increases and decreases in the factor input in production, they can decompose the determining factors through production function analysis. However, unlike the factors that can be directly observed in such analysis, there is an output "residual" which is inexplicable using any of the factor changes directly observed. This "growth residual" is what Solow (1957) referred to as total factor productivity (TFP).

To introduce the three approaches to measure TFP growth, I will follow Storm (2017) and start with the neoclassical Cobb-Douglas (constant-returns-to-scale) production function:

$$\chi = \mathrm{A} L^{\phi} K^{1-\phi} \tag{8}$$

Where x is output (or real value added at factor cost); L is working hours; K is the value of the capital stock; Exponent ϕ is typically assumed to correspond to the labour share in GDP.

Defining labour productivity per hour $\lambda = \mathrm{x}/\mathrm{L}$, one obtains:

$$\lambda = A^{\frac{1}{\phi}}\kappa^{\frac{-(1-\phi)}{\phi}} \tag{9}$$

Where $\kappa = x/K$ is capital productivity. Thus, labour productivity growth is:

$$\hat{\lambda} = \frac{1}{\phi}\hat{A} - \frac{1-\phi}{\phi}\hat{\kappa} \tag{10}$$

where $\hat{A}$ stands for TFP growth. It can be defined by the following equation:

$$\hat{A} = \hat{x} - \phi\hat{L} - (1-\phi)\hat{K} \tag{11}$$

In line with Solow's (1957) model, we consider TFP growth as the unexplained "Solow residual". A positive TFP growth reflects the contribution of Hicks-neutral technological progress (innovation) to economic growth, which can increase the output of resources that are already being fully and efficiently utilized. Hence, the first approach to measure TFP growth using real observable data is as follows (Rada & Taylor, 2006):

$$\hat{A} = \phi\hat{\lambda} + (1-\phi)\hat{\kappa} \tag{12}$$

Where $\hat{\lambda} = \hat{x} - \hat{L}$ and $\hat{\kappa} = \hat{x} - \hat{K}$, we obtain:

$$\hat{A} = \hat{\lambda} - (1-\phi)(\hat{K} - \hat{L}) \tag{13}$$

Where $(\hat{K} - \hat{L})$ is also known as capital intensity growth.

In this thesis, I apply Eq. (13) to calculate TFP growth.

The second interpretation of TFP growth is the weighted average growth rate of real wages and real profits (Shaikh, 1974). In line with the National Income and Product Accounts (NIPA) in the U.S., we identify that real GDP at factor cost is the sum of wage income and capital income:

$$\mathrm{x} = \mathrm{wL} + \mathrm{rK} \tag{14}$$

where w is the real wage rate per hour, L is the actual number of hours worked, r is the real profit rate on the capital stock, and K is the value of the capital stock. Under this NIPA condition, instead of "Solow residual", TFP growth can be written in terms of "total-factor-payment growth":

$$\hat{A} = \phi\hat{w} + (1-\phi)\hat{r} \tag{15}$$

Again, we assume ϕ is the observed labour share in income and $(1-\phi)$ is the observed capital share.

While the estimate of TFP growth in Eq. (12) must equal the "dual" estimate in Eq. (15), one can follow the neoclassical model and assume "perfect competition" in product and factor markets, and hence the growth of real wage (profit) must converge to the growth of labour (capital) productivity, or $\widehat{w} = \hat{\lambda}$ and $\hat{r} = \hat{\kappa}$. However, what happened in historical time shows that $\widehat{w} \neq \hat{\lambda}$ and $\hat{r} \neq \hat{\kappa}$ (Storm, 2017). Therefore, from Eq. (12) and Eq. (15), one can only obtain:

$$\phi\left(\widehat{w} - \hat{\lambda}\right) + (1 - \phi)(\hat{r} - \hat{\kappa}) = 0 \tag{16}$$

While the weighted sum of wage share growth $\left(\widehat{w} - \hat{\lambda}\right)$ and profit share growth $(\hat{r} - \hat{\kappa})$ must be zero, this equation presents the zero-sum distributive conflict between workers and profit recipients.

The last approach to calculate TFP growth focuses on capital stock K and capacity utilization u. We assume that ψ is the constant capital-to-potential-output ratio, so the potential output is: $x^* = K/\psi$ and capacity utilization is: $\mathrm{u} = x/x^*$. As actual output $x = uK/\psi$, the growth of real output is the sum of the growth of the capital stock and the growth of capacity utilization:

$$\hat{x} = \hat{u} + \widehat{K} \tag{17}$$

Combining Eq. (11) with Eq. (17), TFP growth becomes:

$$\hat{A} = \hat{u} + \phi(\widehat{K} - \hat{L}) \tag{18}$$

Similar to the second approach, Eq. (18) shows that there is no "Solow residual". Moreover, this approach inspires us to further study the association of aggregate demand, investment and TFP growth rate. For example, Storm (2017) concludes that the demand shortfall due to the polarization of the labour market depressed TFP growth, and eventually caused secular stagnation in the U.S. economy.

3.3 An Overview of Economic Performance

Since opening-up to foreign trade, investment and implementing free-market reforms in 1978, China's economy has been growing significantly. Moreover, the growth was accelerated by the accession to WTO in 2001 as shown in Figure 4. According to the CIP database, the real gross domestic product (real GDP) annual growth rate was 11% during 1987-2010.

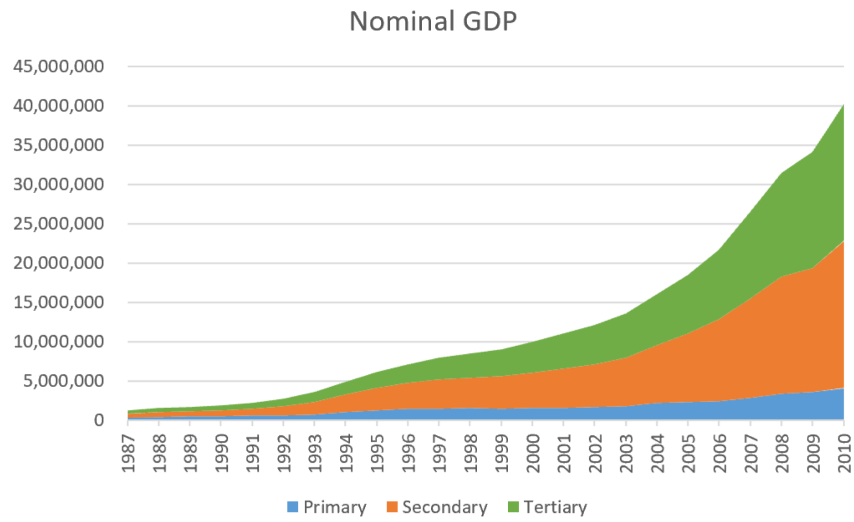


Figure 4: Value added by industry during 1987-2010 (in ml. current yuan)

To futher study the economic performance, I examine the evolution of value added (GDP), price, wage, working hours, employment, labour productivity and unit labour cost in the primary, secondary and tertiary industries (in index numbers with 1987=100) as shown in Figure 5. While value added, wage, working hours and employment are calculated by summing the values of each sector, price index is calculated by weighting it in each industry by the share of real value added. The data described here will be used in the next Chapter to empirically test the hypotheses associated with Baumol's model of unbalanced growth.

Value Added

All industries contribute to the overall value added growth (in panel A of Figure 5) positively during 1987-2010. Although the value added in agriculture remained stagnant over time, there was a relatively stable and significant increase in value added in the other two industries. The secondary industry grew the most rapidly, followed by growth in the tertiary industry. The real GDP annual growth rate reached 11.45% during 1987-2010, of which the average annual growth rates of the primary, secondary and tertiary industries were 2.71%, 14.16% and 8.78% respectively.

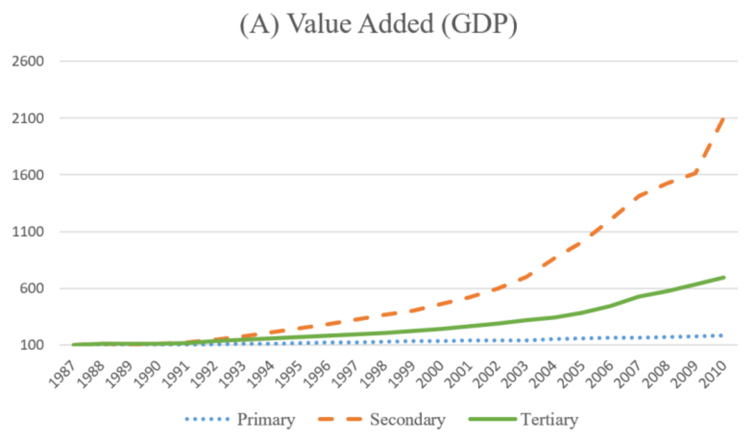


Figure 5: Developments of the key variables in the primary, secondary and tertiary industries in China in 1987-2010 (in index numbers with 1987=100)

Price Index

Generally speaking, the price index (in panel B of Figure 5) was higher in services than in manufacturing during the period of 1987-2010. To be specific, the price index increased at a similar rate in all industries before 1993. But then it experienced a long-term stagnation in the secondary industry, while it kept growing constantly and reached an average annual growth rate of 8.84% in the tertiary industry. During the same period, the growth rate was only 2.38% in the secondary industry. In the primary industry, the growth rate slightly lagged that of the tertiary industry. The gap between them reached a maximum of around 2000, but then it has gradually narrowed over time.

Wage

To calculate the average real wage per employee, I first alculate the annual aggregate GDP deflator: $p = Y/y$, where Y= nominal GDP, and y = real GDP. Dividing the nominal employee compensation by GDP deflator, one obtains the aggregate real wage, and thus obtains the real wage per employee.

The real wage (in panel C of Figure 5) in both the secondary and tertiary industries was growing, but the former grew faster than the latter over time. The growth in the tertiary industry stagnated during 2002-2005, but grew constantly thereafter. It is interesting to note that the wage growth in secondary (manufacturing) was also accelerating after 2005. In the previous chapter I referred tot an empirical study that shows that the Lewis turning point in China has arrived in 2003 (Zhang, 2011), when the supply of labour from the agricultural sector became limited and thus real wages in manufacturing began to rise quickly. Here, we reach a similar conclusion that the Lewis turning point has arrived around 2005.

Working Hours & Employment

The trajectory of workings hours (in panel D of Figure 5) and employment (in panel E of Figure 5) in each sector shows a similar trend. There was constantly increasing employment (and working hours) in the tertiary industry over time. However, before 2002, the employment (and working hours) in the primary and secondary industries stayed relatively stable and similar. Then, the growth rates began to diverge gradually. Since the accession to WTO, a large number of farmers from the rural areas moved to work in factories. As a result, employment in the secondary industry began to clearly increase, while that in the primary industry decreased.

Labour Productivity

There was a long-term steady increase in labour productivity (in panel F of Figure 5) in the secondary industry. However, the primary and tertiary industries lagged far behind. Their labour productivity remained stagnant, and only began to grow slightly around 2002. The average annual growth rate of aggregate labour productivity was 8.78% during 1987-2010 of which 11.26% in the secondary industry, 3.67% and 3.64% in the primary and tertiary industries, respectively. Besides, the growth rate in the secondary industry significantly declined in 2008 due to the global financial crisis, but soon recovered in the next year.

Unit Labour Cost (ULC)

Unit labour cost (G) dynamics concern the complex effects of labour productivity and real wage (per worker) growth dynamics. In our case, ULC (in panel G of Figure 5) in the manufacturing industry stagnated over time, and thus it has gradually widened the gap with the other two industries since 1993. Meanwhile, labour productivity in manufacturing was increasing significantly. The relative decline in ULC of manufacturing thus reflected the fact that labour productivity in manufacturing increased faster than wages. On the other hand, ULC grew at the highest rate (4.97%) in the tertiary industry, although it experienced stagnation during 2000-2007.

Table 3: Average growth rates and sectoral growth rates of selected (1987-2010)

	Total	Secondary	Tertiary

Nominal Value Added	17.55%	16.88%	18.39%
Real Value Added	12.89%	14.16%	8.78%
Price Index	4.12%	2.38%	8.84%
Wage per Worker	10.19%	11.64%	8.79%
Working Hours	3.78%	2.61%	4.96%
Employment	2.92%	1.61%	4.22%

In line with the analysis above, Table 3 shows the annual average growth of value added, price index, wage, working hours, employment for 1987-2010. I dropped agriculture (or primary) industry from the analysis here to focus on the (general) dynamic and stagnant sectors. The reason is that agriculture is not in the scope of Baumol's model. The dynamic sector is the manufacturing (or secondary) industry, and the stagnant sector is considered to be the services (or tertiary) industry.

Baumol (1967) predicts the increasing relative cost and prices of non-progressive sectors. In our case, the average annual growth rate of the price index in the secondary industry (2.38%) lagged that of the tertiary industry (8.84%). Moreover, employment was constantly absorbed by the tertiary industry which increased its nominal output over time, whereas it did not cause an increase in the wages. Thus, our preliminary investigation of the economic performance in 1987-2010 suggests that China has suffered from "unbalanced growth" during its rapid development.

3.4 Decomposition Analysis

In the previous section, I present relevant stylized facts in terms of economic performance during 1987-2010 in China and find signs of "unbalanced growth". Now I make use of three decompositions to examine the sources of economic growth.

3.4.1 Value added, employment and labour productivity

The first one decomposes "economic growth" into two effects - "employment growth" and "productivity growth" – for the economy as a whole and for secondary and tertiary industries.

$$x = L \times \left(\frac{x}{L}\right) = L \times \lambda \tag{7}$$

Where x = real value added; L = number of workers; and $\lambda =$ labour productivity.

Thus, the (compound annual) growth rate is:

$$g(x) = g(L) + g(\lambda) \tag{8}$$

Table 4 shows the decomposition of the real value added in terms of the two effects' contribution and sectoral contribution. It should be noted that, in the previous subsection, labour productivity in industry j = real value added in industry j (constant prices) / hours worked in industry j, while it is calculated using number of workers in the decomposition analysis.

Table 4: Value added growth rate and sectoral contributions (1987-2010)

	Total	Secondary	Tertiary
Labour Productivity	9.97%	12.55%	4.56%
Employment	2.92%	1.61%	4.22%
Value Added	12.89%	14.16%	8.78%

From Table 4 it can be seen that labour productivity growth and value-added growth have been exceptionally high in China during 1987-2010. Among the two effects, the main contribution came from labour productivity growth, while the contribution of employment was rather small (9.97% versus 2.92%). However, the contribution of labour productivity growth and employment growth was almost equal to real value-added growth in the tertiary industry (namely 4.56% versus 4.22%).

One may assume that the rapid growth of economy brings many new jobs to the market. However, Figure 6 tells a different story - the annual growth rate of employment was only 1.61% in the secondary industry during 1987-2010 (In contrast, the annual real GDP growth rate was 14.16% over the same period). I further compare this result with "Number of employment at the year-end" from the China Labour Statistical Yearbooks. The official statistics show that the annual growth rate of employment was 2.7% in the secondary sector during the same period (Table 5), which is considerably higher than the 1.61% per year estimated based on CIP data. Nevertheless, employment growth in the secondary industry is also much below employment growth in the tertiary industry based on data from the China Labour Statistical Yearbooks. I will discuss it later when analyzing the consequences of robotisation and automation in manufacturing.

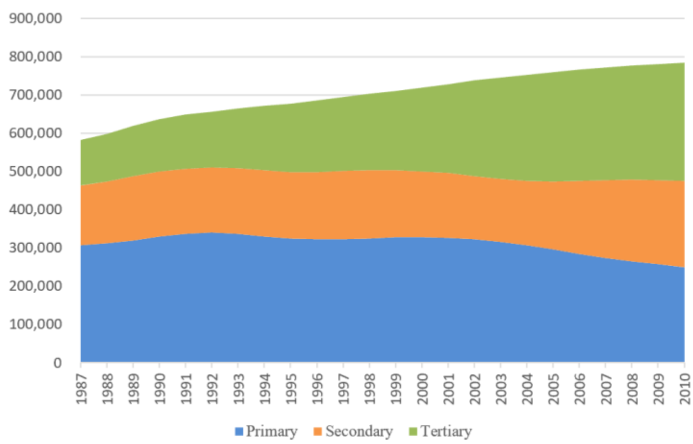


Figure 6: Numbers employed by industry in 1000s (1987-2010)

Table 5: Comparison of employment growth rate from two databases

Employment Growth Rate (1987-2010)		
	CIP 3.0 (2015)	China Labour Statistical Yearbooks
Primary	-0.89%	-0.54%
Secondary	1.61%	2.74%
Tertiary	4.22%	4.58%
Total	1.30%	1.60%

3.4.2 The demographic dividend and its impact on economic growth

The next decomposition investigates how the ratio of labour force to population evolved during 1987-2010 – to see the impact of the demographic dividend on economic growth.

$$x = (\frac{L}{P}) \times (\frac{x}{L}) \times P \tag{9}$$

where $\mathrm{x} =$ real value added; $\mathrm{L} =$ number of workers; and $P =$ population.

Thus, the (annual compound) growth rate is:

$$g(x) = g\left(\frac{L}{P}\right) + g\left(\frac{x}{L}\right) + g(P) \tag{10}$$

This decomposition shows that the growth of total real GDP is the sum of the growth of population ($g(P)$), the growth of real GDP per worker ($g\left(\frac{x}{L}\right)$) and the growth in the share of the working-age population in the total population ($g\left(\frac{L}{P}\right)$).

Table 6: Decomposition of the Real GDP growth between 1987-2010

	$g\left(\frac{L}{P}\right)$	$g\left(\frac{x}{L}\right)$	$g(P)$	$g(x)$
1987-1992	3.26%	1.30%	1.40%	5.96%
1992-1997	0.10%	11.03%	1.08%	12.20%
1997-2002	0.25%	9.69%	0.77%	10.71%
2002-2007	-0.02%	16.07%	0.57%	16.61%
2007-2010	0.31%	12.13%	0.49%	12.93%
1987-2010	0.81%	9.74%	0.89%	11.45%

**Note*: The data of population and labour force is from China Labour Statistical Yearbooks, while the real GDP is from CIP 3.0 (2015) in line with the rest of the analysis.

Table 6 shows that all these three effects positively contributed to the growth of real GDP during the period 1987-2010. Specifically, the contribution of labour productivity growth played the key role all the time, accounting for more than 85% of the real GDP growth over time. Thus, the slowing down of population growth from 1.4% on average per year during 1987-1992 to 0.49% on average per year during 2007-2010, and the slowing down of the growth in the share of labour in the total population from 3.26% on average per year during 1987-1992 to 0.31% on average per year during 2007-2010 did not show a great impact on the overall economic development. In sum, as is shown by Table 6, there is no doubt that China was losing its demographic dividend over time, but it was labour productivity that critically affected economic growth.

3.4.3 Capital intensity, output-capital ratio and labour productivity

Finally, the last decomposition examines the growth of capital intensity, the output-capital ratio and labour productivity:

$$\frac{x}{L} = \left(\frac{K}{L}\right) \times \left(\frac{x}{K}\right) \tag{11}$$

Where $\mathrm{x} =$ real value added; $\mathrm{L} =$ number of workers; and $K =$ labour productivity.

Thus, the (annual compound) growth rate is:

$$g\left(\frac{x}{L}\right) = g\left(\frac{K}{L}\right) + g\left(\frac{x}{K}\right) \tag{12}$$

This decomposition shows that the growth of labour productivity is the sum of the growth of capital intensity and the growth of the output-capital ratio (which is an indicator of the productivity of capital).

Table 7: Decomposition of labour productivity growth rate and sectoral contributions (1987-2010)

	$g\left(\frac{K}{L}\right)$			$g\left(\frac{x}{K}\right)$			$g\left(\frac{x}{L}\right)$		
	Secondary	Tertiary	Total	Secondary	Tertiary	Total	Secondary	Tertiary	Total
1987-1992	9.03%	5.79%	7.66%	-2.27%	-3.55%	-2.71%	6.75%	2.24%	4.95%
1992-1997	14.04%	12.75%	12.68%	1.62%	-10.01%	-1.84%	15.66%	2.74%	10.84%
1997-2002	6.97%	12.20%	7.86%	6.92%	-8.17%	1.40%	13.90%	4.04%	9.26%
2002-2007	11.51%	16.34%	13.93%	2.38%	-6.29%	-0.30%	13.89%	10.06%	13.63%
2007-2010	14.75%	19.83%	17.50%	-3.98%	-9.95%	-5.74%	10.77%	9.88%	11.76%
1987-2010	10.92%	12.73%	11.38%	1.29%	-7.42%	-1.52%	12.21%	5.31%	9.86%

By examining the contributions of $g\left(\frac{K}{L}\right)$ and $g\left(\frac{x}{K}\right)$ to the growth of labour productivity in aggregate growth and in growth of the secondary and tertiary industries in Table 7, we can conclude that the overall growth of labour productivity was closely associated with the growth of capital intensity, which has accelerated since the accession to WTO in 2001.

On the other hand, the output-capital ratio in the secondary industry had grown rapidly during the period 1992-2007 (Table 7), which suggests that the initial stage capital productivity increased strongly – probably due to the arrival of new technologies. Moreover, the fact that the output-capital ratio declines during 2007-2010 in the secondary industry is due to the global financial crisis. While manufacturing output declined, the capital stock remained in place; hence, the ratio output to K declined due to the under-utilisation of production capacity.

Besides, the output-capital ratio in tertiary industry negatively contributed to the aggregate growth rate over time, which means the output produced did not increase as fast as the capital stock in service sectors.

3.4.4 Conclusions

In this subsection I present several stylized facts of China's economic growth process during the period 1987-2010, covering two major events that stimulated the growth of economy-the reform and opening-up in 1978 and the accession to WTO in 2001. Here I conclude this chapter by summarizing the main results.

First, the economy experienced rapid growth during the period 1987-2010. Specifically, the real GDP growth has accelerated since the accession to WTO in 2001. As a result, the average annual GDP growth rate of the secondary and tertiary industries reached 11.45% for 23 years.

Second, the average annual growth rate of price index is lower in the secondary industry (2.38%) than that in the tertiary industry (8.84%), which supports the symptom of Baumol's prediction of cost disease. The relative price of services (to manufacturing) has increased.

Third, although the secondary industry recorded the highest labour productivity growth and the highest wage growth, it did not create as many new jobs as one may have expected. In detail, the average annual growth rate of employment in the tertiary industry reached 4.22%, while it was only 1.61% in the secondary industry during the same period. Decomposition analysis further confirms this conclusion - the contribution of labour productivity growth played the key role all the time, accounting for more than 85% of the real output growth in the secondary and tertiary industries, while the contribution of employment growth to real value-added growth was around 15%.

Fourth, the overall growth of labour productivity was positively associated with the growth of capital intensity. On the contrary, the output-capital ratio in tertiary industry negatively contributed to the aggregate growth rate. Moreover, two major events that affected economic growth can be identified from the analysis: 1) the growth of capital intensity has accelerated since the accession to WTO in 2001; 2) the output-capital ratio declined during 2007-2010 in the secondary industry due to the global financial crisis.

3.5 A Further Investigation into Dynamic Sector and Stagnant Sector

In the previous analysis, I focused on the standard high-level classification and assumed that the secondary industry as the dynamic sector and the tertiary industry as the stagnant sector. However, as I argued in the literature review, there are certain services sectors, such as transportation and logistics, that are very closely related to manufacturing (Pasadilla and Wirjo, 2015). Considering their important role in the dynamic (manufacturing) sector, I classify them as part of the dynamic sector for the empirical analysis.

Therefore, in this subsection, I first create a dynamic sector and a stagnant sector based on their backward production linkages. Next, I investigate in more detail the economic performance in each sector. In the next chapter, I will further compare the consequences of labour productivity dynamics in the dynamic and stagnant sectors in line with Baumol's model.

3.5.1 Sectoral classification: dynamic sector and stagnant sector

This study uses the 37 industries in the China Industrial Productivity (CIP) Database. First, I drop agriculture (primary) industry from the analysis. Then, for the rest 36 industries, I assume that all the 25 sectors in the secondary industry are dynamic. Finally, I examine the 11 sectors in tertiary industry. To calculate the backward production linkages of services and manufacturing, I make use of the input-output table (in ml. current yuan) in 2001[11]. The backward linkage is determined as the column sum of the so-called Leontief inverse; each column sum j gives the increase in gross output in all industries in the economy, caused by an increase in final demand for goods produced by industry j.

Table 8 presents intermediate inputs from each service sector to the manufacturing industry (as a whole) in 2001.

[11] I also analysed the data from other middle years (from 1998 to 2002), and identified the same three industries that should be merged into the dynamic sector – namely, SAL, T&S and SER.

Table 8: Services backward linkage for manufacturing in 2001

Sector Acronym	CIP Sector Description	Intermediate Inputs to the manufacturing Industry in 2001	Share of sectors in total backward linkage
SAL	Wholesale and retail trades	432,527	19.22%
HOT	Hotels and restaurants	201,618	8.96%
T&S	Transport, storage & post services	355,918	15.82%
P&T	Information & computer services	135,914	6.04%
FIN	Financial Intermediations	59,166	2.63%
REA	Real estate services	81,802	3.64%
BUS	Leasing, technical, science & business services	180,979	8.04%
ADM	Government, public administration, and political and social organizations, etc.	183,136	8.14%
EDU	Education	168,303	7.48%
HEA	Healthcare and social security services	182,441	8.11%
SER	Cultural, sports, entertainment services; residential and other services	268,017	11.91%
Total		2,249,822	

The average backward linkage share is 9.09%. Table 8 shows that there are three sectors whose shares are much higher than the average. They are Wholesale and retail trades (SAL, 19.22%), Transport, storage & post services (T&S, 15.82%) and Cultural, sports, entertainment services; residential and other services (SER, 11.91%). Therefore, I classify them as part of the dynamic sector. Table 9 summarises the classification.

Table 9: The correspondence among the CIP sector acronym and sectoral classification (Dynamic & Stagnant)

Sectoral Classification	Sector Acronym in CIP
Dynamic Sector	CLM, PTM, MEM, NMM, F&B, TBC, TEX, WEA, LEA, W&F, P&P, PET, CHE, R&P, BUI, MET, MEP, MCH, ELE, ICT, INS, TRS, OTH, UTL, CON, SAL, T&S, SER
Stagnant Sector	HOT, P&T, FIN, REA, BUS, ADM, EDU, HEA

3.5.2 Revisiting economic performance: dynamic sector vs. stagnant sector

Applying the analysis structure in Chapter 3.3, I empirically compare the economic performance in the dynamic sector and the stagnant sector. Figure 7 shows that both sectors experienced rapid growth during 1987-2010, while the share of the stagnant sector in nominal GDP gradually increased over time.

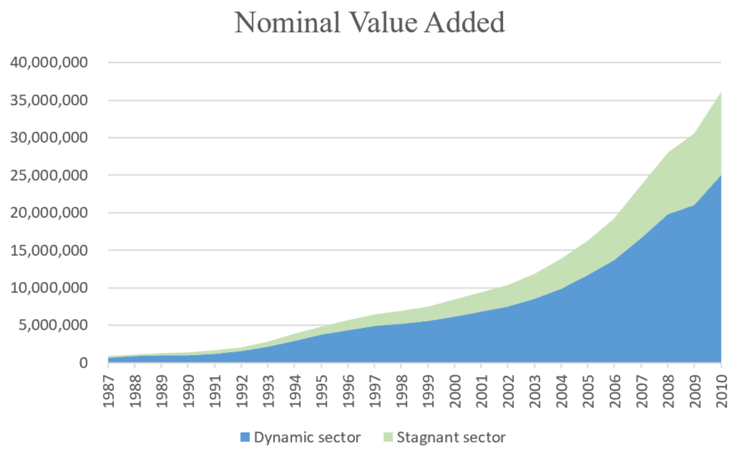
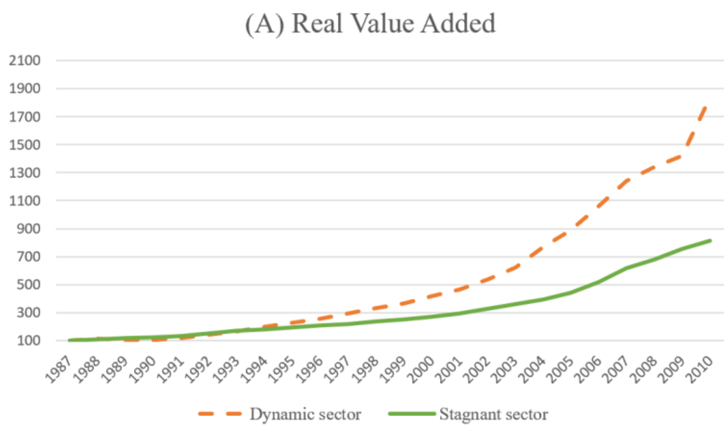


Figure 7: Nominal value added in dynamic sector and stagnant sector during 1987-2010 (in ml. current yuan)

Next, Figure 8 presents the evolution of value added (GDP), price, wage, working hours, employment, labour productivity and unit labour cost in the two sectors (in index numbers with 1987=100). Generally speaking, most trajectories of the key variables in the dynamic and the stagnant sectors are similar to those of the secondary and the tertiary industries, except the wage growth rate. In line with the analysis in Chapter 3.3, I will briefly analyze the results below.



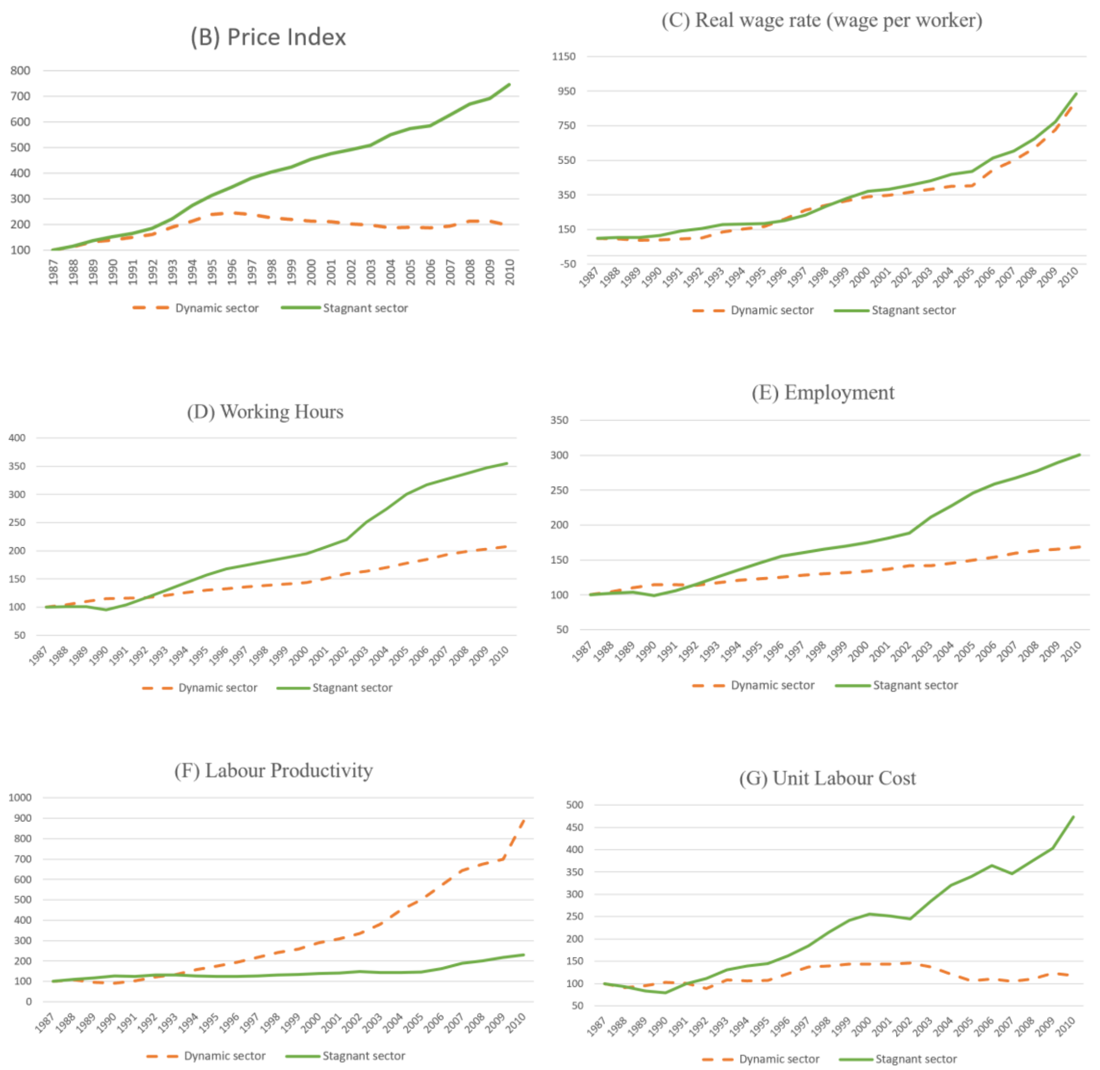


Figure 8: Developments of the key variables in the dynamic sector and the stagnant sector in 1987-2010 (in index numbers with 1987=100)

Value Added

The value added (in panel A of Figure 8) in the dynamic sector grows faster than that in the stagnant sector. The annual growth rate reached 13.49% and 9.54% respectively during the period 1987-2010. In addition, we also identify a significant slowdown of growth in the dynamic sector due to the global financial crisis in 2018, while the stagnant sector was almost unaffected.

Price Index

The price index (in panel B of Figure 8) in the dynamic sector stagnated after around 1995 with an average annual growth rate of 2.98%, while the price index in the stagnant sector was growing steadily over the years, reaching an average annual growth rate of 9.13%.

Wage

Real wage per worker (in panel C of Figure 8) grows at roughly the same rate in the two sectors. This result is different from our previous analysis. However, it is in line with Baumol's

(1976) assumption that the wage growth would be uniform across industries. Besides, one can identify that the Lewis turning point arrived around 2005 (in the dynamic sector).

Working Hours & Employment

The trajectory of workings hours (in panel D of Figure 8) and employment (in panel E of Figure 8) in each sector shows a similar trend. There was constantly increasing employment (and working hours) in the stagnant sector, while employment in the dynamic sector grew slowly. It is interesting to note that employment growth rate in the stagnant sector is higher than that of dynamic sector since the accession to WTO. In other words, in the process of urbanization, the services industry absorbs more labour, most of whom are farmers from the rural areas, than the manufacturing industry.

Labour Productivity

As expected, there was a long-term steady increase in labour productivity (in panel F of Figure 8) in the dynamic sector, while it remained stagnant in the stagnant sector over time. In addition, the global financial crisis in 2018 led to a significant decline in labour productivity in dynamic sector.

Unit Labour Cost (ULC)

Unit labour cost (in pabel G of Figure 8) in the dynamic sector stagnated at a low level with an average annual growth rate of 0.72%. It declined slightly in 2003, which reflected the relative increase in labour productivity in the dynamic sector. In contrast, the growth of ULC in the stagnant sector shows an average annual growth rate of 6.99% during 1987-2019. Thus, it has gradually widened the gap with the dynamic sector since 1991.

Table 10: Average growth rates and sectoral growth rates of selected variables in the dynamic sector and the stagnant sector (1987-2010)

	Total	Dynamic Sector	Stagnant Sector
Nominal Value Added	17.55%	16.87%	19.54%
Real Value Added	12.89%	13.49%	9.54%
Price Index	4.12%	2.98%	9.13%
Wage per Worker	10.19%	10.00%	10.20%
Working Hours	3.78%	3.23%	5.66%
Employment	2.92%	2.29%	4.91%

Table 10 presents the annual average growth of value added, price index, wage, working hours, employment in the two sectors for 1987-2010.

Additionally, Table 10 and Table 11 show the results of decomposition analyses. The first table decomposes the real value-added growth rate into the sum of labour productivity growth rate and employment rate.

Table 11: Value added growth rate and sectoral contributions in the dynamic sector and the stagnant sector (1987-2010)

	Total	Dynamic Sector	Stagnant Sector
Labour Productivity	9.97%	11.20%	4.63%
Employment	2.92%	2.29%	4.91%
Value Added	12.89%	13.49%	9.54%

Overall, the contribution of labour productivity growth accounts for more than 77% of the aggregate real output growth, while the contribution of employment growth is around 23%. Specifically, only about 17% of the real output growth in the dynamic sector is contributed by the growth of employment, while it was more than 50% in the stagnant sector.

Next, I examine the growth of labour productivity in the two sectors. As explained above, the growth of labour productivity can be decomposed into the sum of the growth of capital intensity and the growth of output-capital ratio (which is an indicator of the productivity of capital):

$$g(\frac{x}{L}) = g\left(\frac{K}{L}\right) + g(\frac{x}{K})$$

Table 12: Decomposition of labour productivity growth rate and sectoral contributions in the dynamic sector and the stagnant sector (1987-2010)

	$g\left(\frac{K}{L}\right)$			$g(\frac{x}{K})$			$g(\frac{x}{L})$		
	Dynamic Sector	Stagnant Sector	Total	Dynamic Sector	Stagnant Sector	Total	Dynamic Sector	Stagnan t Sector	Total
1987-1992	7.51%	8.47%	7.66%	-2.87%	-2.40%	-2.71%	4.64%	6.07%	4.95%
1992-1997	12.73%	13.22%	12.68%	0.42%	-11.13%	-1.84%	13.15%	2.09%	10.84%
1997-2002	5.90%	14.38%	7.86%	4.18%	-8.36%	1.40%	10.08%	6.02%	9.26%
2002-2007	12.88%	15.32%	13.93%	2.38%	-8.17%	-0.30%	15.27%	7.15%	13.63%
2007-2010	16.53%	18.69%	17.50%	-3.97%	-11.22%	-5.74%	12.56%	7.46%	11.76%
1987-2010	10.58%	13.57%	11.38%	0.33%	-8.05%	-1.52%	10.91%	5.51%	9.86%

Table 12 shows that the overall growth of labour productivity was closely associated with the growth of capital intensity, which has accelerated since the accession to WTO in 2001. Besides, the output-capital ratio declines during 2007-2010 in both sectors due to the global financial crisis. Similar to the results in Chapter 3.3, the output-capital ratio in stagnant sector negatively contributed to the aggregate growth rate over time.

3.5.3 Conclusions

In this section, I created a dynamic sector and a stagnant sector based on the backward production linkages. Then, in line with the variable analysis in Chapter 3.3, we can also identify an obvious gap of the price index growth between the dynamic sector (2.98%) and the stagnant sector (9.13%). While real value added grew at a lower rate in the stagnant sector, its employment growth rate accelerates above that in the dynamic sector. In addition, the two sectors have a similar wage growth rate over time, which is against the previous analysis results in terms of the secondary and tertiary industries, but meets Baumol's (1967) hypothesis. In sum, the analytical results for the dynamic sector and the stagnant sector imply "unbalanced growth". The differential productivity growth impacts the economic performance of different sectors differently and this has implications for the overall economy.

Chapter 4: Results

In this Chapter, I will statistically test the seven sub-questions of this research, proposed in Chapter 1. To empirically evaluate these hypotheses, this Chapter will analyze (pair-wise) linear regressions between productivity growth ("the independent variable") and a variety of "dependent variables" which include the growth rates of 'Price index', 'Real output', 'Nominal Output', 'Working hours', 'Wages' and 'Unit Labour Cost' during 1987-2010 for all industries. Two different measures of productivity growth are examined: (1) Labour productivity growth, which is the growth in real value added minus the growth in working hours. (2) Total factor productivity (TFP) growth, which is calculated using Eq. (13) in Chapter 3.

To empirically test each of the research questions, I used three different econometric specifications. In the first specification, I did a cross-section analysis by calculating the period-average growth rates of productivity growth and relative variables for each industry; the number of observations is 37 (because my dataset has 37 industries).

Secondly, I constructed five subperiods (during 1987-2010) for estimation. Nordhaus (2006) suggests that the choice of break points should consider the length and quality of data and business cycle position. Because I apply the same database (CIP database 3.0) for the test, the data quality is assumed identical. Thus, based on major events (Table 13) that had huge effects on China's economy (Wu, 2019), turning points during the period I look at, were the years 1992, 1997,2002 and 2008, so the five subperiods are 1987-1992 (5 years), 1992-1997 (5 years), 1997-2002 (5 years), 2002-2008 (6 years), 2008-2010 (2 years). The number of observations for this specification is 5 (sub-periods) x 37 (industries) = 185.

Finally, in the third specification, the third regression analysis is a pooled estimation with annual data. The number of observations is around 888 (24 years x 37 industries). I will compare the econometric results across the three specifications,

Table 13: Major Events that had Huge Effects on China's Economy

Subperiod	Major Economic Events
1987-1992	Urban and industrial reforms propelled by a new dual-track price system.
1992-1997	Deng Xiaoping[12]'s southern tour resumed and reinforced the implementation of "Reforms and Opening-up" program.

[12] Deng was recognized as "Architect of Modern China". He supported a series of far-reaching market-economy reforms including the lifting of price controls and the privatization of state enterprises. The 1992 Southern Tour is widely regarded as a critical point, as it saved the Chinese economic reform which came to a halt after the 1989 Tiananmen Square protests. One of the notable comments from Deng during the tour was "I don't care if the cat is black or white, so long as it catches mice."

1997-2002	Asian financial crisis and its induced long-lasting deflation; further liberalization of private enterprises; deepening banking reforms.
2002-2008	China's accession to the World Trade Organization (WTO) resulted in astounding growth of exports and foreign direct investment.
2008-2010	Global financial crisis and its induced long-lasting deflation; the government's four trillion rescue package to maintain economic growth.

In addition, I pooled the data for 1987-2010 for all industries and did linear regressions with OLS estimates. The estimated linear equations are (in a general form):

$$\mathbf{y} = \boldsymbol{\beta}\mathbf{x} + \boldsymbol{\varepsilon}$$

where x denotes the growth rate of total factor productivity or labour productivity. y represents the dependent variable in each hypothesis, namely the growth rate of 'Price index', 'Real output', 'Nominal Output', 'Working hours', 'Wages' and 'Unit Labour Cost'.

4.1 Results for Price Change

Baumol's (1967) model predicts that the non-progressive sectors (technologically stagnant sectors or tertiary activities) experience above average increases in relative unit costs and (consequently) prices increase. The reason is that the price elasticity for services is relatively low (in absolute terms). In other words, people are willing to pay the higher prices. Meanwhile, the wage level of the services sectors follows closely that of the sectors with higher productivity growth rates (see Eq. 3 in Chapter 2). Consequently, low relative productivity growth leads to high relative price increases.

To calculate the price changes, one can make use of value-added deflators or gross output deflators. Nordhaus (2006) argues that using value added deflators allows us to "identify in a more intuitive way the sources of major technological changes." I will follow this method to calculate the price index.

Table 14 shows the results for three regression analyses.

Table 14: Impact of Productivity Growth on Price Growth (1987–2010)

	Labour Productivity	Total Factor Productivity
Cross-section		
Coefficient	-0.70^{***} (0.09)	-0.63^{***} (0.11)
t-statistics	-7.90	-5.91
Adjusted R^2	0.63	0.49
F-statistic (prob.)	62.46 (0.00)	34.91 (0.00)
Number of obs.	37	37

5 sub-periods		
Coefficient	-0.25^{***} (0.05)	-0.28^{***} (0.06)
t-statistics	-4.93	-4.91
Durbin-Watson	1.73	1.69
Adjusted R^2	0.15	0.16
F-statistic (prob.)	34.67(0.00)	36.68(0.00)
Number of obs.	185	185
Annual data		
Coefficient	-0.07^{***} (0.01)	-0.09^{***} (0.01)
t-statistics	-5.25	-5.93
Durbin-Watson	2.02	2.02
Adjusted R^2	0.03	0.04
F-statistic (prob.)	29.89 (0.00)	37.43 (0.00)
Number of obs.	888	888

Note: * Statistical significance level at 10%; ** Statistical significance level at 5%; *** Statistical significance level at 1%. Standard errors are in parenthesis. Estimates for constant terms not shown.

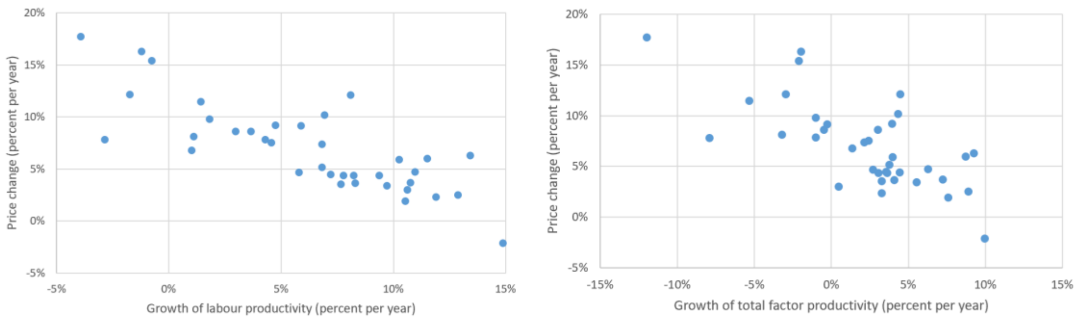


Figure 9: Growth of labour productivity / TFP and price index, 1987-2010

A negative association is clear for the cross-section analysis – the statistics show a coefficient in the range of -0.63 to -0.70. Figure 9 shows two scatter plots of the labour productivity growth / TFP growth with price index changes for 37 industries (R^2 = 0.63 / 0.49, significant at 1%).

To explain the association, let me assume that the progressive sector has an average annual growth rate of 12%, while the stagnant sector has an average annual growth rate of 2%. The coefficient is -0.70. Thus, the relative price of the progressive sector declined by an average annual rate of $(12\% - 2\%) \times 0.7 = 7\%$ during 1987-2010. In fact, there are two sectors whose performance was very close to this estimation. They are Miscellaneous manufacturing industries (OTH), with an average annual growth rate of labour productivity and price growth rate at 12% and 2% respectively, and Cultural, sports, entertainment services; residential and other services (SER), with an average annual growth rate of labour productivity and price growth rate at 2% and 10% respectively. Hence, the relative price of OTH and SER declined by an average of 8% per year.

Moreover, the coefficients for productivity growth are significantly negative (at the 1% level) for the pooled estimations with five sub-periods and with annual data. As shown in Table 14, the former has the coefficient of -0.25 /-0.28, while the latter has the coefficient of -0.07 / -0.09 (close to zero). Again, if I assume that the progressive sector has an average annual growth rate of 12%, and the stagnant sector has an average annual growth rate of 2%, then the relative price of the progressive sector declines by an average annual rate of 2.5% according to the estimation with five sub-periods. Alternatively, it declines by an average annual rate of 0.7% according to the estimation with annual data.

The fact that the association becomes stronger (higher coefficients) as the subperiod's length becomes longer indicates that the increase in productivity gradually reduces the relative prices over a period of time. To be specific, within a short period (say one year), the sectors with higher productivity growth reduce their relative prices only slightly (coefficient = -0.07 / -0.09). But when the length of the economic period is about 5 years, the coefficient drops to -0.25 / -0.28. When the length is as long as 23 years, the coefficient reaches -0.70 / -0.63. Overall, like Nordhaus (2006) states, consumers finally capture most of the gains of technological change.

Adjusted R^2 is lower in the pooled (5-year) data regression and very low in the pooled (annual data) regression. The reason is that there is more heterogeneity in the annual industry-wise data than in the period-average data. This heterogeneity arises because of temporal and structural changes/fluctuations across industries. Besides, the regression model does not include other control variables. As a result of the higher heterogeneity and the absence of control variables, the R-squared is low in the pooled regressions.

In sum, because all the results are statistically significant, the hypothesis that the industries with relatively lower productivity growth show higher growth in relative prices is supported. However, the absolute value of the coefficient increases with the length of the economic period, which implies that productivity growth changes price gradually over time.

4.2 Results for Real Output Change

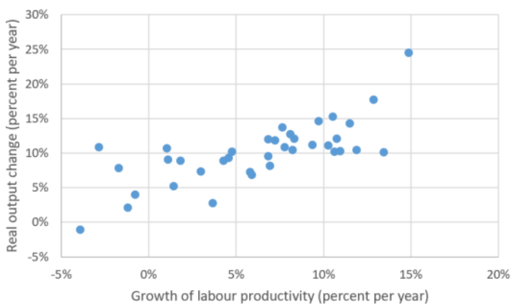
The next hypothesis is that real output in the stagnant industries would grow slowly relative to the overall economy. Baumol (1967, p. 420) states that "We see then that costs in many sectors of the economy will rise relentlessly, and will do so for reasons that are for all practical purposes beyond the control of those involved. The consequence is that the outputs of these sectors may in some cases tend to be driven from the market." In contrast, one may expect that if the output growth is driven primarily by demand shifts rather than supply shifts, then the association between productivity growth and output growth would be relatively weak (Nordhaus, 2006).

Table 15 shows that for the full sample of industries, the coefficient for productivity growth and real output growth is significantly positive (at the 1% level) for the cross-section estimation with the average period growth rates, and the two pooled estimations with five sub-periods and annual data. Additionally, Figure 10 shows two scatter plots of the labour productivity growth / TFP growth with real output growth for 37 industries (R^2 = 0.52 / 0.50, significant at 1%).

Table 15: Impact of Productivity Growth on Gross Real Output Growth (1987–2010)

	Labour Productivity	Total Factor Productivity
Cross-section		
Coefficient	0.67*** (0.11)	0.68*** (0.11)
t-statistics	6.27	6.11
Adjusted R^2	0.52	0.50
F-statistic (prob.)	39.27 (0.00)	37.34 (0.00)
Number of obs.	37	37
5 sub-periods		
Coefficient	0.68*** (0.04)	0.72*** (0.04)
t-statistics	18.50	16.99
Durbin-Watson	1.88	1.81
Adjusted R^2	0.64	0.60
F-statistic (prob.)	324.71 (0.00)	275.13 (0.00)
Number of obs.	185	185
Annual data		
Coefficient	0.96*** (0.01)	0.99*** (0.01)
t-statistics	74.88	82.31
Durbin-Watson	1.98	2.06
Adjusted R^2	0.86	0.88
F-statistic (prob.)	5614.65 (0.00)	6785.00 (0.00)
Number of obs.	888	888

Note: * Statistical significance level at 10%; ** Statistical significance level at 5%; *** Statistical significance level at 1%. Standard errors are in parenthesis. Estimates for constant terms not shown.



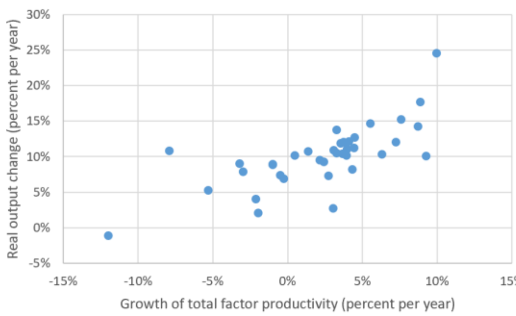


Figure 10: Growth of labour productivity / TFP and real output, 1987-2010

It is worth noting that the coefficients are 0.96 / 0.99 for pooled estimation with annual data.

In other words, the growth rate of real GDP is roughly equal to the growth rate of labour productivity. In the decomposition analysis in Chapter 3, Equation (8) shows that the growth of real GDP is the sum of the growth of labour productivity and the growth of employment. Thus, this result implies that employment growth has been very low (about 4%).

In fact, according to the CIP database, the annual growth rate of employment was only 1.61% in the secondary industry and 4.22% in the tertiary industry during 1987-2010.

On the other hand, the coefficients for the pooled estimations with five sub-periods and the cross-section analysis is about 0.68, and thus employment growth is around 32%. In the previous chapter, through the decomposition of the real value added, we conclude that the contribution of employment was rather small. Specifically, while the annual real GDP growth rate was 12.89% for the secondary and tertiary industries, the contribution of employment was only 2.92%, accounting for about 23% of the real value growth. Generally, the results are in consistent with the stylized facts (reported in Chapter 3).

This implies that differential real output growth in the short term is almost entirely driven by differential productivity growth (such as technological changes, etc.). across industries. Due to the slow growth of employment, its contribution in economic growth only appears in a longer period of time.

Therefore, I conclude that there is clear positive relationship between productivity growth and real output growth over the 1987-2010 period. This hypothesis is strongly confirmed.

4.3 Results for Nominal Output Change

By definition, nominal value added $Y = \mathrm{p} \times \mathrm{y}$, where y is real value added and p is the general price level (in the base year p = 1). If we express it in growth rates, we obtain:

$$\hat{Y} = \hat{p} + \hat{y}$$

Hence, the growth rate of nominal value added = the growth rate of the general price level + the growth rate of real value added. In our case, the coefficients on nominal value added should be equal to the sum of the coefficients on price and real value added.

There are in fact very small deviations as Table 16 shows. For example, if we look at the coefficient for TFP growth of the pooled estimation with four sub-periods, the identity almost exactly holds ($\mathbf{-0.28 + 0.72 \approx 0.43}$).

In terms of the third hypothesis, Baumol predicts that stagnant industries tend to take a rising share of nominal output when labour flows from the progressive sector to the stagnant sector. The reason is that the relative price of the stagnant industries will rise.

However, the result in my case is contrary to the prediction. As shown in Table 16, the coefficients for the pooled estimations with five sub-periods and annual data are all positive and significant at the 1% level. The results of the cross-section analysis are insignificant.

Table 16: Impact of Productivity Growth on Gross Nominal Output Growth (1987–2010)

	Labour Productivity	Total Factor Productivity
Cross-section		
Coefficient	-0.04 (0.10)	0.04 (0.10)
t-statistics	-0.44	0.43
Adjusted R^2	-0.02	-0.02
F-statistic (prob.)	0.19 (0.67)	0.19 (0.67)
Number of obs.	37	37
5 sub-periods		
Coefficient	0.41*** (0.07)	0.43*** (0.07)
t-statistics	6.05	5.85
Durbin-Watson	1.92	2.04
Adjusted R^2	0.16	0.15
F-statistic (prob.)	36.58 (0.00)	34.23 (0.00)
Number of obs.	185	185
Annual data		
Coefficient	1.00*** (0.02)	1.01*** (0.02)
t-statistics	47.43	48.34
Durbin-Watson	2.03	2.06
Adjusted R^2	0.72	0.73
F-statistic (prob.)	2258.36 (0.00)	2345.97 (0.00)
Number of obs.	888	888

Note: * Statistical significance level at 10%; ** Statistical significance level at 5%; *** Statistical significance level at 1%. Standard errors are in parenthesis. Estimates for constant terms not shown.

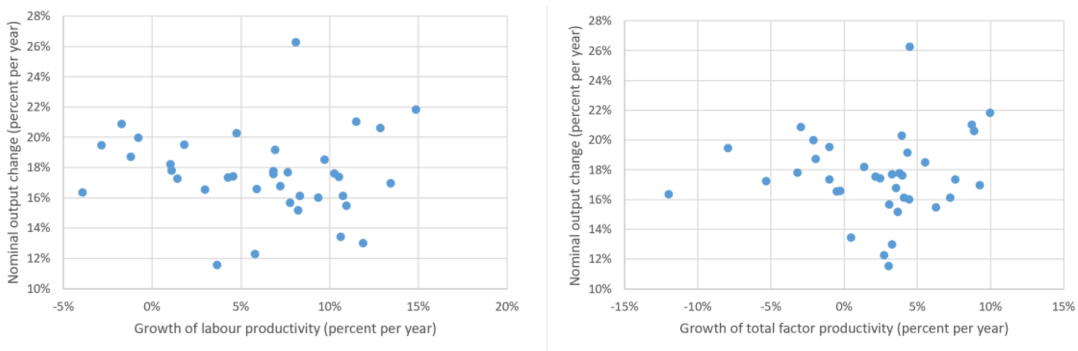


Figure 11: Growth of labour productivity / TFP and nominal output, 1987-2010

It is not surprising to find that the coefficients are close to 1 from the annual data analysis. Because the impact of productivity growth on price change takes time to gradually materialise, the price keeps (almost) unchanged in the short term. As a result, the increase in labour productivity almost entirely contributed to the nominal output. Only over a longer period (say 5 years), the price changes drive the growth rate of nominal output to lower than that of real output by around 40%. The ratio is likely to increase over time.

In conclusion, the progressive industries not only increased their real output shares, but also their shares in nominal output during the period 1987-2010 in China. Besides, although the results show that the positive association of productivity growth with the growth in nominal output declines over time, there was no significant evidence that the stagnant industries gain more weight as Baumol's model suggests. Thus, this hypothesis is rejected.

4.4 Results for Working Hour Changes

The next question is whether stagnant industries are gaining or losing share of labour inputs – either employment or hours. Baumol predicts that when workers are pushed out of employment in progressive sectors, they can only find jobs in stagnant sectors (for survival), which means the increasing employment shares of stagnant sectors over time.

The relationship between productivity growth and working hour changes is presented in Table 17. The coefficients are negative and significant, which means that industries with low productivity growth have experienced increasing working hours. Figure 12 shows two scatter plots of labour productivity growth / TFP growth with working hour changes for 37 industries (R^2 = 0.24 / 0.12, significant at 1% / 5% level).

Table 17: Impact of Productivity Growth on Working Hours Growth (1987–2010)

	Labour Productivity	Total Factor Productivity
Cross-section		
Coefficient	-0.36*** (0.10)	-0.27** (0.11)
t-statistics	-3.53	-2.40
Adjusted R^2	0.24	0.12
F-statistic (prob.)	12.49 (0.00)	5.74 (0.02)
Number of obs.	37	37
5 sub-periods		
Coefficient	-0.36*** (0.04)	-0.32*** (0.04)
t-statistics	-9.67	-7.33
Durbin-Watson	1.87	1.88
Adjusted R^2	0.34	0.22
F-statistic (prob.)	94.35 (0.00)	54.48 (0.00)
Number of obs.	185	185
Annual data		

Coefficient	-0.15*** (0.01)	-0.09*** (0.02)
t-statistics	-10.38	-6.14
Durbin-Watson	2.00	2.00
Adjusted R^2	0.11	0.04
F-statistic (prob.)	107.85	37.81 (0.00)
Number of obs.	888	888

Note: * Statistical significance level at 10%; ** Statistical significance level at 5%; *** Statistical significance level at 1%. Standard errors are in parenthesis. Estimates for constant terms not shown.

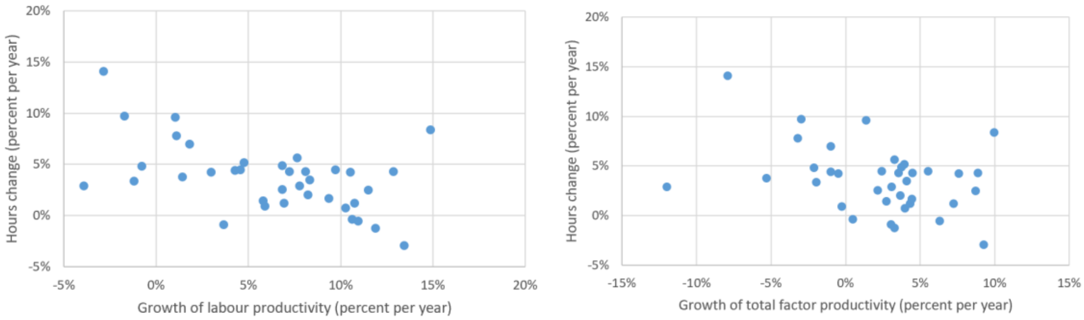


Figure 12: Growth of labour productivity / TFP and working hours, 1987-2010

For the cross-section estimations with the average period growth rates and the pooled estimations with five sub-periods, we find that a 1% higher productivity growth is associated with an around 0.3% lower growth in working hours. However, the absolute value of coefficients (0.15 / 0.09) is relatively small in the analysis of annual data. We can infer that firms are unlikely to fire redundant workers as soon as productivity increases. Normally, they reduce hiring and fire workers gradually over a period of years.

In sum, because the changes of working hours and employment are virtually identical, we conclude that industries with more rapid productivity growth tend to displace labour and show lower growth of employment[13].

4.5 Results for Wages Change

Baumol assumes that there is uniform wage growth across all industries. In the progressive industries, wage growth is assumed to be correlated with productivity growth, but wage growth is assumed to be uncorrelated with productivity growth in the stagnant industries.

Because the CIP database for "employee compensation" starts from 1987, the wage growth

[13] This result is consistent with the findings for the U.S. that I discussed in Chapter 1 - one more robot per thousand workers reduces the employment-to-population ratio by 0.2% and wages by 0.42% on U.S. labour market (Acemoglu and Restrepo, 2020).

rates are estimated from 1988. Thus, the number of observations is around 851 (23 years x 37 industries), the same holds true for the analysis of unit labour cost changes.

As Table 18 shows, the coefficients for productivity growth are significantly positive (at the 1% level) for the pooled estimations. For the cross-section estimation, the coefficient is only significant for the labour productivity growth (at the 5% level), but insignificant for the TFP growth. (see Figure 13). Besides, the coefficients in the annual data analysis (0.30 / 0.23) are smaller than that in the subperiods analysis (0.78 / 0.67), which implies that the impact of productivity growth on wages growth also occurs gradually over time.

Table 18: Impact of Productivity Growth on Wages Growth (1987–2010)

	Labour Productivity	Total Factor Productivity
Cross-section		
Coefficient	0.24^{**} (0.11)	0.14 (0.12)
t-statistics	2.13	1.12
Adjusted R^2	0.09	0.00
F-statistic (prob.)	4.54 (0.04)	1.26 (0.27)
Number of obs.	37	37
5 sub-periods		
Coefficient	0.78^{***} (0.07)	0.67^{***} (0.09)
t-statistics	11.10	7.88
Durbin-Watson	1.67	1.75
Adjusted R^2	0.40	0.25
F-statistic (prob.)	123.19 (0.00)	62.07 (0.00)
Number of obs.	185	185
Annual data		
Coefficient	0.30^{***} (0.03)	0.23^{***} (0.03)
t-statistics	10.02	7.39
Durbin-Watson	1.78	1.78
Adjusted R^2	0.11	0.07
F-statistic (prob.)	108.48 (0.00)	63.03 (0.00)
Number of obs.	851	851

Note: * Statistical significance level at 10%; ** Statistical significance level at 5%; *** Statistical significance level at 1%. Standard errors are in parenthesis. Estimates for constant terms not shown.

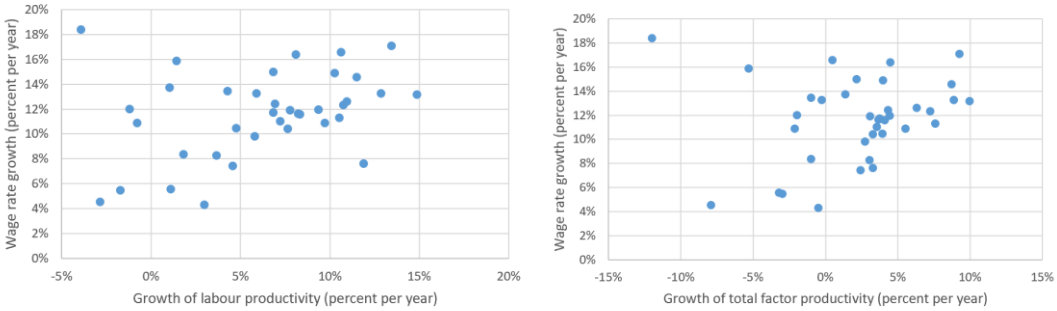


Figure 13: Growth of labour productivity / TFP and real wages, 1987-2010

In conclusion, our result shows that industries with above-average productivity growth also have above-average wage growth. As real wages grow at a higher rate in the progressive sectors relative to that in the stagnant sectors, and the stagnant sectors absorb redundant labour force from the dynamic sectors, the results yield evidence in favor of unbalanced economic growth.

Finally, it is worth mentioning that all the hypotheses in this thesis are concerned with the impact of the labour productivity differences between industries on economic growth. In other words, for all the estimated linear equations: $y = \beta x + \varepsilon$, x denotes the growth rate of total factor productivity or labour productivity and y represents the dependent variable. However, while there is indeed a statistically significant positive relation between productivity growth and real wage growth in our case, it is widely argued that labour productivity growth is determined by real wage growth. Specifically, many empirical studies conclude that real wage growth is a major determinant of productivity growth (Gordon 1987, 2015; Foley and Michl 1999; Marquetti 2004; Basu 2010; Storm and Naastepad 2012, Storm 2017).

The point is, when workers claim higher wages, it provides firms a strong incentive to invest in labour-saving machinery (to stay competitive in the market), and thus labour productivity raises with the technical changes. As I introduced in the previous chapters, the sales of robots in China have risen significantly since the era of unlimited labour supply passed and that the Lewis turning point arrived in around 2003. We can thus infer that while real wages increased due to the limited labour supply, firms invested more in labour-saving techonology – robotisation and automation, which ultimately caused unbalanced economic growth. I will further discuss it in the next chapter.

4.6 Results for Unit Labour Cost Change

In line with Baumol's cost disease, one may expect that unit labour cost in stagnant sectors grows faster than that in progressive sectors. From another perspective, assuming the demand is fixed, progressive sectors with relatively rapid productivity growth tend to hire less workers, and hence its unit labour cost will decline comparing to that in the stagnant sectors.

Table 19 shows that this hypothesis is strongly supported by our data. All the coefficients of productivity growth on unit labour cost are significantly negative (at the 1% level). Additionally, Figure 14 shows two scatter plots of labour productivity growth / TFP growth with unit labour cost changes for 37 industries (R^2 = 0.57 / 0.57, significant at 1% level). The impacts of differential productivity change on unit labour cost stand out clearly.

Table 19: Impact of Productivity Growth on Unit Labour Cost Growth (1987–2010)

	Labour Productivity	Total Factor Productivity
Cross-section		
Coefficient	-0.78*** (0.11)	-0.81*** (0.11)
t-statistics	-6.93	-7.04
Adjusted R^2	0.57	0.57
F-statistic (prob.)	48.07 (0.00)	49.51 (0.00)
Number of obs.	37	37
5 sub-periods		
Coefficient	-0.25*** (0.07)	-0.35*** (0.07)
t-statistics	-3.64	-4.84
Durbin-Watson	1.62	1.67
Adjusted R^2	0.06	0.11
F-statistic (prob.)	13.23 (0.00)	23.38 (0.00)
Number of obs.	185	185
Annual data		
Coefficient	-0.50*** (0.04)	-0.53*** (0.04)
t-statistics	-14.30	-14.82
Durbin-Watson	1.88	1.88
Adjusted R^2	0.20	0.21
F-statistic (prob.)	206.93 (0.00)	222.23 (0.00)
Number of obs.	851	851

Note: * Statistical significance level at 10%; ** Statistical significance level at 5%; *** Statistical significance level at 1%. Standard errors are in parenthesis. Estimates for constant terms not shown.

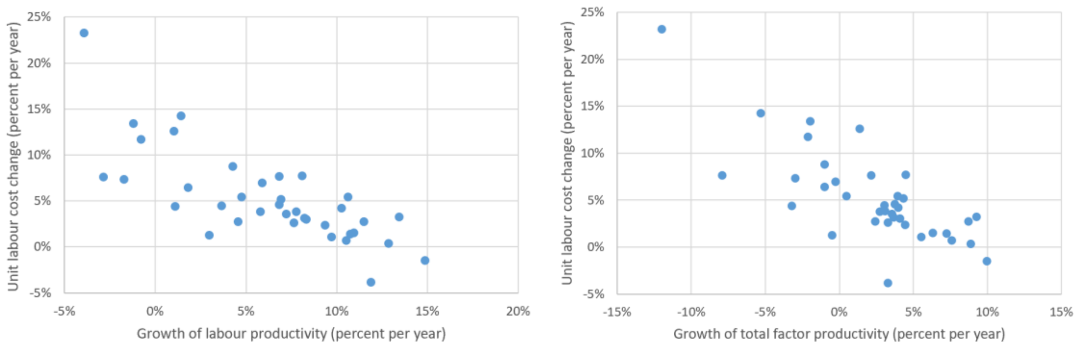


Figure 14: Growth of labour productivity / TFP and unit labour cost, 1987-2010

When I tested the previous hypothesis, I found that the growth of productivity increases wages gradually. On the other hand, productivity growth can more or less instantly reduce production costs. As a result, the absolute value of the coefficients in the annual data analysis (0.50 / 0.53) are greater than that in the subperiods analysis (0.25 / 0.35). Moreover, from the results of the cross-section analysis, it is clear that the firms are able to reduce unit labour cost significantly (by reducing employment, etc.) due to the increased productivity.

Besides, compared to the results for price changes (Table 14), it is clear that productivity growth has a weaker impact on prices than it has on unit labour cost. In other words, when progressive sectors reduce their unit labour cost, it does not necessarily fully reflect on the prices. As a result, firms may be able to increase their profit share under certain circumstances.

In conclusion, the stagnant industries show higher growth in unit labour cost than do the dynamic ones. This evidence supports the prediction of Baumol's model.

4.7 Results for the Growth Disease

The last hypothesis investigates "Baumol's growth disease". Baumol (1967) predicts that as the stagnant industries have rising nominal output shares over time, the aggregate growth rate of overall GDP will be reduced. In line with Nordhaus (2006), to measure the Baumol growth effect, we estimate the growth rate of labour productivity using nominal output shares for a given base year. Define $\hat{a}$ as aggregate productivity growth, we denote the results as the "fixed-shares growth rate" or "FSGR(T)":

$$FSGR(T) = \sum_{i=1}^{n} \hat{a}_{iT}\ S_{iT}$$

By comparing the FSGR(T) for different base years, we examine the impact of changing nominal output shares on the growth of productivity. If the stagnant industries gain weight over time, which is what Baumol's model expects, then the labour productivity growth rate should be higher if earlier years are used as base years.

Table 20 and Figure 15 present the empirical estimates for the fixed-shares growth rate of labour productivity and TFP for six different base years over 1987-2010[14]. It shows that the growth rate of labour productivity was not monotonically decreasing in China. Rather, it was cyclical in a very small range. If we use fixed shares for 1987, the average annual growth rate would be 5.30% in terms of labour productivity growth and 1.34% in terms of TFP growth, whereas if we use the shares for 2010, the average annual growth rate of labour productivity would be 4.94% and TFP growth rate would be 1.30%. Their differences are too small to be economically significant.

[14] Agriculture was dropped from the analysis of Baumol's growth disease. In fact, the contribution of the agriculture sector in nominal GDP was at 13.2% during 1987-2010.

However, this is not a surprising result for us, considering that we have already found out that the progressive industries increased both real output shares and nominal output shares over time. Overall, there was no sign (yet) of "Baumol's growth disease" during the period 1987-2010.

Table 20: Fixed-shares growth rate of labour productivity and TFP for different base years

Base year	Labour Productivity	Total Factor Productivity
1987	5.30%	1.34%
1992	5.32%	1.40%
1997	5.53%	1.63%
2002	5.06%	1.23%
2007	5.00%	1.22%
2010	4.94%	1.30%

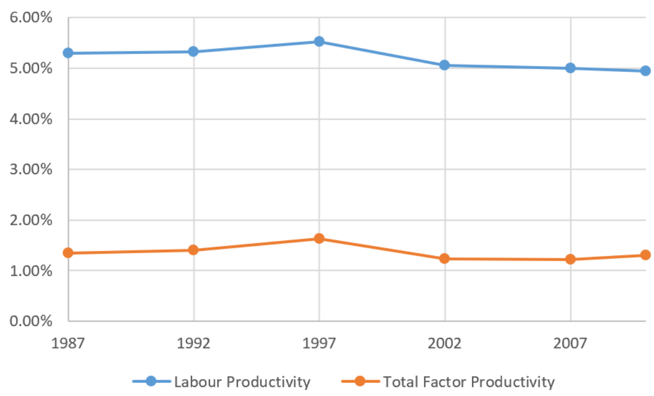


Figure 15: Fixed-shares growth rate of labour productivity and TFP for different base years

4.8 Conclusions

In this chapter I investigated seven hypotheses empirically for the Chinese economy (1987-2010) to assess how much and in what ways differential productivity growth across industries contributes to the overall economic growth, and whether there are discernible signs of Baumol's disease in China's economic development. The major results are as follows.

1. Does low productivity growth lead to a cost and price disease?

Baumol (1967) predicts that low relative productivity growth leads to high relative costs and price increases. Through three sets of regression analysis, the negative association between productivity growth and price growth is clear. However, as the subperiod's length becomes longer, the association also becomes stronger. The coefficient is negative but close to zero in the estimation with annual data, but decline to around -0.25 in the estimation with five sub-periods, finally reaches around -0.70 when analyzing the average growth rates for each industry during 1987-2010 (23 years). Hence, Baumol's cost disease is supported by the historical data, while productivity growth tends to change price gradually over time.

2. Does low productivity growth lead to stagnating real output?
This hypothesis is confirmed. The relationship between productivity growth and real output growth is significantly positive. The contribution of productivity growth accounts for about 68% of the real output growth.

3. Do industries with slow productivity growth have increasing nominal output shares?
This hypothesis is rejected based on my econometric analysis. Industries with higher productivity growth also exhibit increasing nominal output shares. However, this trend had become less pronounced over a longer test period. The reason is that the relative price gradually increases in the stagnant industries, and hence drive the growth rate of nominal output to lower than that of real output.

4. Do industries with slow productivity growth have increasing relative employment and hours?
This hypothesis is supported by the results. Specifically, a 1% higher productivity growth is associated with an around 0.3% lower growth in working hours. I assume that the average number of working hours per employee did not significantly change over time, thus the relationship between productivity growth and working hour changes implies that the progressive industries tend to displace labour and have decreasing relative employment.

5. Is there uniform wage growth across all industries?
No, this hypothesis is strongly rejected. The results indicate that industries with above-average productivity growth also have above-average wage growth. In the estimation with annual data, 1% higher productivity growth is associated with an around 0.3% higher wage growth. Their association implies another possibility that real wage growth is a major determinant of productivity growth.

6. Do industries with slow productivity growth have increasing relative unit labour cost?
This hypothesis is strongly supported. All the coefficients of productivity growth on unit labour cost are significantly negative. This conclusion further confirms that Baumol's cost disease exists. Besides, I find that productivity growth has a stronger impact on unit labour cost than it has on prices, which implies that consumers may not always capture the gains of technological change, firms may rise their profit share instead.

7. Has the economy suffered from a growth disease?
This hypothesis is rejected from my study. Baumol's model predicts that if the stagnant industries have rising nominal output shares, then the aggregate growth rate will be reduced as the share of output moves toward the slow productivity-growth industries. However, the growth rate of labour productivity was not monotonically decreasing in my study. Besides, the progressive industries increased both real output shares and nominal output shares over time. Therefore, there was no sign (yet) of "Baumol's growth disease".

Chapter 5: Discussion

5.1 A Brief Recapitulation of the Empirical Findings

As the average Chinese income level in terms of GDP per capita rose from US$ 634 in 1987 to US$ 4550 in 2010 in constant prices[15], the Chinese economy has been undergoing a structural transformation. In particular, a large number of farmers left the rural areas to find jobs in the cities. Workers who were employed in the secondary industry accounted for only 22.2% of the total employment in 1980, which increased to 28.7% in 2010, and reached a peak of 30.1% in 2013. In addition, the tertiary industry helped to provide new employment opportunities. Its employment share almost doubled - from 17.8% in 1987 to 34.6% in 2010, and has continued to grow over time. The latest report shows that more than 47% of the total employment works in services sectors in 2019.[16]

However, if we look at the output share changes of the services sectors, the nominal output share has increased significantly from 29.6% in 1987 to 43.2% in 2010, while its real output share increased from 28.4% to 40.7%[17] during the same period. In contrast, the nominal output share of the manufacturing sectors has increased from 43.0% in 1987 to 46.7% in 2010. Correspondingly, its real output share has increase from 48.0% to 50.8% according to the CIP database. These facts suggest that the price changes in services sectors are higher than that in manufacturing sectors, which imply the exist of Baumol's disease in China.

By applying Baumol's (1967) unbalanced growth model and Nordhaus's (2006) testing framework, this thesis has studied the differential productivity growth rates between industries, their impact on prices, employment, unit labour costs etc., and finally their contributions to overall economic growth. Baumol's model generally considers the manufacturing (or the secondary) industries as the progressive (high-productivity) industries, and the services industries (or the tertiary) industries are the stagnant (low-productivity) industries. Baumol predicts that the average costs and prices in the stagnant industries will grow relative to the progressive industries (Baumol's cost disease); and the expansion in the stagnant industries has a negative impact on aggregate productivity growth (Baumol's growth disease). In this thesis, I empirically studied the Chinese economy during the period 1987-2010. The main results are summarized as follows:

First, the relative prices and unit labour costs in the stagnant sectors are higher than those in the progressive sectors. To be specific, a 1% lower productivity growth is associated with an around 0.7% higher growth in the price index over the 23-year period. Thus, this is a significant

[15] See: https://data.worldbank.org/

[16] See: http://www.stats.gov.cn/ .

[17] For the real output share of the manufacturing sectors and the services sectors, base year = 2005.

sign of Baumol's cost disease in China during 1987-2010. The change of coefficients with the length of the subperiods indicates that productivity growth tends to affect price gradually over time.

Second, the output share of the progressive sectors has increased in both nominal and real terms. Hence, unlike Baumol's prediction, the aggregate growth rate of overall GDP did not decline with the rising nominal output shares of the stagnant sectors. There was no sign (yet) of "Baumol's growth disease" during the period 1987-2010. But my analysis reveals that the positive association of productivity growth with nominal output growth declines over time (the coefficient is close to zero but insignificant when the period is as long as 23 years). In line with the literature review in Chapter 2, one possible reason that this hypothesis is rejected is that the period of analysis is too short; note here that Nordhaus's (2006) dataset covers the period 1948 – 2001 (43 years) for the U.S. economy and the results support Baumol's prediction. Considering the fact that the nominal GDP share of the tertiary industry continues to grow (Figure 16), and the fact that China's real GDP growth has slowed from 14.2% in 2007 to 6.1% in 2019, if extending the period of analysis, we may find that the association of productivity growth with nominal output growth turns negative, which suggests that the rising nominal output of the stagnant sectors does lead to a decline in economic growth eventually.

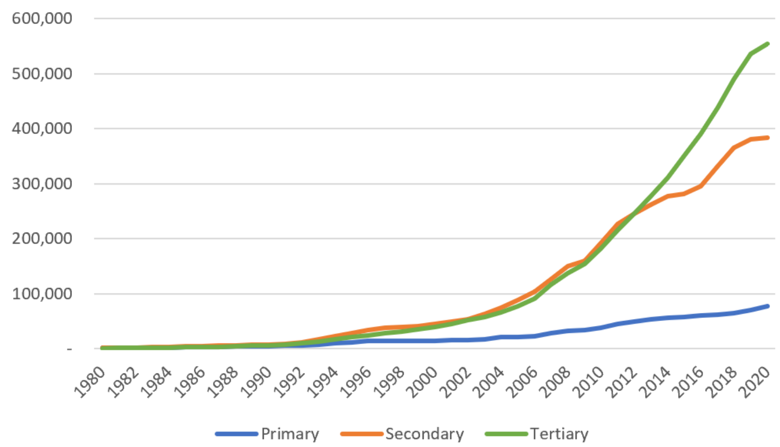


Figure 16: Composition of nominal GDP by industry during 1980-2020 (in 100 million yuan) [18]

Third, the progressive sectors show a decrease in relative employment and working hours, but an increase in relative wages - a 1% higher productivity growth is associated with an around 0.3% lower growth in working hours and a higher growth in wages of 0.24% - 0.78%, respectively. If we assume full employment because workers must find jobs for survival, then labour can only flow from the progressive sectors to the stagnant sectors, tolerating lower pay.

The last point that I want to emphasize is that while productivity growth is instantly reflected in output growth, it only reveals its association with price, wages, working hours and unit labour cost over a longer period of time. For instance, in terms of the association with working

[18] Source: China Labour Statistical Yearbook (http://www.stats.gov.cn/)

hours, the absolute value of the coefficients in the annual data analysis (0.15 / 0.09) are smaller than that in the subperiods analysis (0.36 / 0.32) and that in the cross-section analysis over 23 years (0.36 / 0.27), which implies that employment structure tends to change only gradually with productivity growth.

In addition, one can argue that it is the increase in aggregate demand that was constantly stimulating productivity growth. The evidence is that the growth rate of real output is roughly equal to the growth rate of labour productivity for the pooled estimations with annual data (the coefficients are 0.96 / 0.99). Because real output growth is (by definition) the sum of employment growth and productivity growth (see Eq. 8), while employment has hardly increased in the short term (say one year), the factories must have increased productivity when they receive new orders. A rational option is investing in labour–saving technologies, such as robotization and automation (in response to the wage growth). This finding is not the focus of my study, but it is a plausible explanation.

The above are the main findings from empirical analysis in Chapter 4. Next, to answer the main research question - does Baumol's disease exist in China in a time of robotisation and automation? - I examine the distribution of robot usage in China during the period of analysis and analyze it with labour productivity growth and employment growth in the secondary industry.

5.2 Robot Adoption and Labour Productivity Growth in China

As explained in Chapter 2, robots are mainly used in the manufacturing sectors, such as automotive and electronics. Hence, in line with the stylized facts from Chapter 3, I compare the annual robot sales[19] with the growth of labour productivity and employment in the secondary industry during the period 1987-2010. The results are presented in Table 21 and Figure 17.

Table 21: Annual robot sales in China and the world (1995-2010)

Year	World (1,000 units)	China (1,000 units)	China's share in the world (%)
1995	69.3	0.0	0.0
2000	98.7	0.4	0.4
2005	120.1	4.5	3.7
2010	120.6	15.0	12.4
2011	166.0	22.6	13.6
2012	159.3	23.0	14.4
2013	178.1	36.6	20.5
2014	220.6	57.1	15.9

19 Source: International Federation of Robotics (IFR)

2015	253.7	68.6	27.0
2016	294.3	87.0	29.6

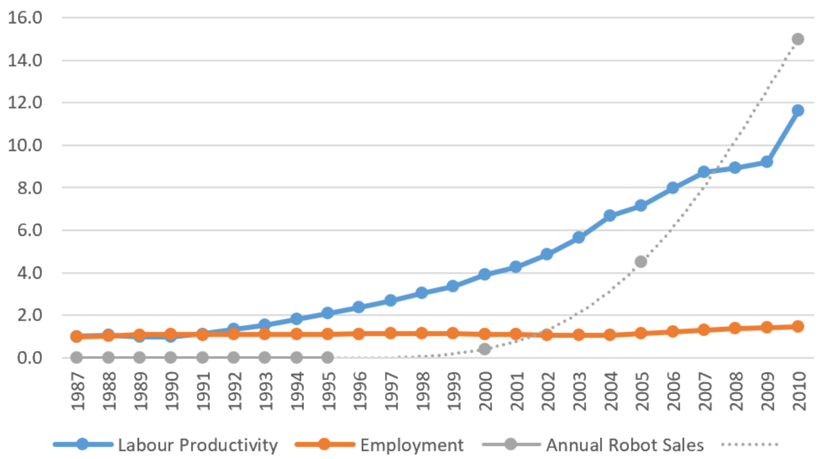


Figure 17: Developments of annual robot sales[20], labour productivity (1987 = 1.0) and employment (1987 = 1.0) in the secondary industry (1987-2010)

In 2000, annual sales of robots in China accounted for only 0.4% of the world total. Then, the share steadily rose to 3.7% in 2005 and 12.4% in 2010, with a growth rate of 12% over 10 years. In contrast, the annual growth rate of employment was only 1.61% in the secondary industry.

Furthermore, let's take 1995 as the turning point for robot adoption in China and divide the time into two subperiods. The average annual growth rate of labour productivity was only 3.25% during the period 1987-1995, but increased to 12.2% during the period 1995-2010 in the secondary industry.

Although productivity growth can be caused by many reasons, the contribution of industrial robots is widely recognized in research. Graetz and Michaels (2018) study robot adoption in seventeen developed countries during 1993-2007. They also use the datasets from the International Federation of Robotics as the main source and find that increased use of robots contributed approximately 0.36% to annual labour productivity growth, accounting for 15% of the aggregate productivity growth. Moreover, we are in the midst of a fourth wave of technological advancement – the so-called "Industry 4.0". Manufacturing productivity is further increased by gathering and analyzing data across machines (robots). The production process is faster, more flexible and more efficient (Rüßmann et al., 2015).

In conclusion, the results suggest that the rise of robots is a main driver of productivity growth, and thus real output growth in China (from a supply-side view). In other words, the success as the "world's factory" has been largely achieved by robotisation and automation. The increasing demand from all over the world has only brought about relatively slow

20 Because the annual sales data has only been available since 1995 and it started from zero, I assume that the annual sales of robots were zero during 1987-1995.

employment growth to the secondary industry.

5.3 Signs of Unbalanced Economic Growth?

The period of analysis from 1987 to 2010 covers three critical events that significantly affected China's economic growth, namely the resumption of the market-oriented "Reforms and Opening-up" program in 1992, the accession to the WTO in 2002, and the Great Global Financial Crisis in 2008. The market reforms have turned the poor and stagnant economy into one of the world's fastest-growing economies. In general, economic growth helps improve people's living standards and reduce poverty. According to the World Bank[21], more than 800 million Chinese people have been lifted out of poverty. However, it does not mean that the economy was growing in balance. As I argued above, the differential growth of productivity across industries has significantly affected the overall economic growth. In this subsection, I summarize the performance of unbalanced economic growth in terms of employment and wages (Table 22).

Table 22: Average growth rates of selected variables – evidence of unbalanced economic growth (1987-2010)

	Total	Secondary	Tertiary
Real Value Added	12.89%	14.16%	8.78%
Labour Productivity	9.97%	12.55%	4.56%
Employment	2.92%	1.61%	4.22%
Wage per Worker	10.19%	11.64%	8.79%
Working Hours	3.78%	2.61%	4.96%

Even though the real GDP annual growth rate reached 11.45% (with agriculture) during 1987-2010 in China, of which the secondary industry contributed the most (14.16%), it is the tertiary industry that creates the most job opportunities to the market. As presented in the previous subsection, manufacturing with rapid productivity growth tend to adopt robots and thus show relatively low growth of employment. The average growth rate of employment in the tertiary industry was 4.22%, while it was 1.61% in the secondary industry. Eventually, the share of the secondary industry in aggregate employment reached 30.1% in 2013, and then it gradually dropped to 27.6% in 2018, while nearly half (47%) of the labour was working in the tertiary industry. In sum, the shift in employment structure is significant.

The empirical analysis has further shown that industries with above-average productivity growth also have above-average wage growth. Specifically, the average annual growth rate of the wage per worker in the tertiary industry (8.79%) lagged that of the secondary industry

21 See: https://www.worldbank.org/.

(11.64%). In other words, while its employment growth has stagnated, the relative real wages growth rates are higher in the secondary industry.

However, the wage growth in the secondary industry did not fully reflect its high productivity growth. Part of the reason must be the fact that workers were facing the threat of being replaced by robots and being pushed out of the factories in a time of robotisation and automation. In addition, as explained in the previous chapter, when workers claim higher wages, it provides firms a strong incentive to invest in labour-saving machinery. Under these circumstances, workers found their wage bargaining power was relatively limited. Hence, the profit share of the secondary industry increased relative to that of the tertiary industry.

Moreover, Table 22 shows that the increase in working hours is greater than the increase in employment. This phenomenon is especially striking in the secondary industry – while the average annual growth rate of employment was 1.61%, the growth rate of working hours reached 2.61%. One explanation is that because the robots in factories usually work 24/7, workers must work longer hours accordingly. But it can also be achieved by hiring more workers (increasing employment). Thus, I conclude that automation and robotisation have reduced the bargaining power of workers. This implies the polarization of the labour market. Workers either accept higher-paying jobs with long working hours, or lower-paying jobs with relatively short working hours.

The American documentary film *American Factory*[22] may provide us an insight on this problem. Chinese manufacturing company Fuyao is one of the largest auto glass producers in the world. It established a factory in an abandoned General Motors plant in Ohio in 2016, hiring two thousand local blue-collar workers. When many workers organized and launched a campaign to form a union, the company promoted anti-union policies and threatened union organizers with termination. Finally, a union vote was held and anti-unionists defeated pro-unionists. Although there were constant concerns and conflicts regarding the unionization, inability to turn a profit, and clashes in cultural norms and customs, new jobs still bring hope and optimism to the workers. However, at the end of the film, most jobs in the factory were simply replaced by robots (Wikipedia, 2021). When it won the Oscar for best documentary in 2020, Barack Obama wrote in a tweet, concluding it as "a complex, moving story about the very human consequences of wrenching economic change."

In conclusion, rapid economic growth does not mean that "good jobs" are easy to find. Assuming workers have to find jobs, and they prefer high-paying jobs with short working hours, unfortunately, it is hard to achieve. However, we can also be optimistic about the situation. When employment grows faster in the tertiary industry, societies are transforming into post-industrial societies (Bell, 1999). I will further discuss it in the next subsection.

[22] American Factory is a 2019 American documentary film directed by Steven Bognar and Julia Reichert. It is distributed by Netflix and is the first film produced by Barack and Michelle Obama's production company, Higher Ground Productions. It won the Oscar for best documentary in 2020.

5.4 Economic Growth in Post-Industrial Society

American sociologist Daniel Bell discussed the concept of "post-industrial society" in the book "*The Coming of Post-Industrial Society*" in 1974. He describes that the following major changes occurred in the post-industrial society: production of goods declined and the production of services increased; the rise of professional and technical employment and the relative decline of workers; theoretical knowledge is the source of invention and innovation. He also emphasizes the importance of human capital and intellectual technology (based on mathematics and linguistics) in the post-industrial society (Bell, 1999).

According to China Labour Statistical Yearbook, the nominal value added of the tertiary industry has surpassed that of the secondary industry since 2013. More than half of the GDP has been contributed by the tertiary industry since 2015, which means that China has structurally transformed toward a post-industrial economy (Figure 18).

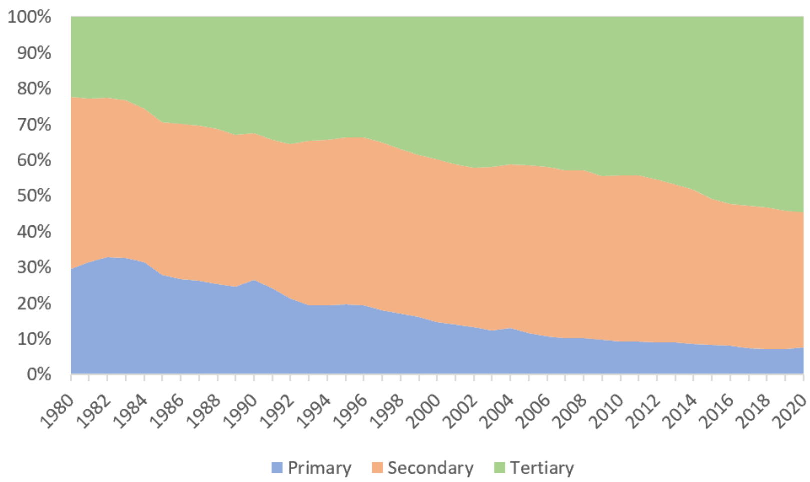


Figure 18: Composition of nominal GDP by industry (1980-2020) [23]

In sum, based on my empirical analysis, I have found that China has structurally transformed into a post-industrial society and it suffers from Baumol's cost disease. What is the solution?

William Baumol (2012) examined his own theory and answered this question. He argues that despite the increasing costs of the goods and services in the stagnant sectors, such as health care and education, these activities will never become unaffordable to society. Overall, incomes and purchasing power rise with the growing productivity. We may spend a large share of our income on education or health care, but it also means that we pay less for food and clothing from the progressive sectors (Baumol, 2012). The point is - we can afford them.

This was indeed what happened in the case of China. The cost of education and health care rose at a rate significantly greater than the economy's rate of inflation (See Table 23 and

[23] Source: China Labour Statistical Yearbook (http://www.stats.gov.cn/)

Figure 19). To be specific, the price indexes in education and health care kept growing over time, with average annual growth rates reaching 16.28% and 15.38% respectively, while the average inflation rate was 4.34% during 1987-2010 in China. Besides, the annual growth rate of real GDP was 11.45% during the same period. Even though education and health care keep getting more expensive, the prices of some industries had rarely changed or even dropped over time, such as Electric equipment (ELE) and Electronic and telecommunication equipment (ICT). Their average annual growth rate of the price index are 3.51% and -2.14%, respectively. Overall, society can afford them.

Table 23: The price changes in education and health care sectors compared to the GDP deflator in China in 1987-2010 (in index numbers with 1987=1.00)

Year	GDP deflator	Price changes in Education	Price changes in Healthcare and social security services
1987	1.00	1.04	1.00
1992	1.66	2.82	2.44
1997	2.73	10.05	9.04
2002	2.49	21.15	14.17
2007	2.54	27.67	20.98
2010	2.66	33.47	26.98
Annual Growth Rate	4.34%	16.28%	15.38%

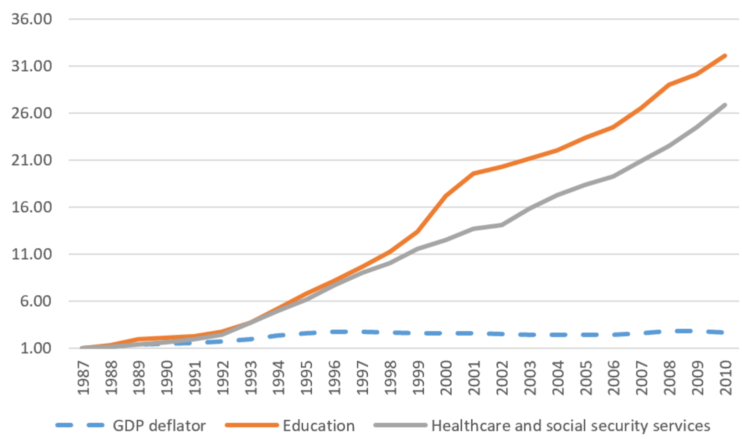


Figure 19: The price changes in education and health care sectors compared to the GDP deflator in China in 1987-2010 (in index numbers with 1987=1.00)

In other words, "Baumol's cost disease" implies the structural changes in production and consumption costs caused by the differential productivity growth across industries. The society, as a whole, benefits from labour-saving technical progresses. However, it doesn't mean that everyone can equally share the benefits of the "productivity-growth dividend" (Storm, 2017). Specifically, our study indicates that real wages grow at a lower rate in the stagnant industries compared to that in the progressive industries. Furthermore, when most people have no choice but to accept lower-paying jobs, it would slowdown aggregate demand growth. Eventually, the unbalanced growth may lead to stagnation. The fact is that China's real GDP growth has slowed significantly, from 14.2% in 2007 to 6.1% in 2019[24] before the pandemic. One can argue that the slowdown is triggered by a series of factors, such as the Great Financial Crisis, the structural changes towards tertiarization (Baumol's growth disease), or deglobalization. But people should also pay attention to income distribution and the unbalanced real wage growth across industries.

Moreover, in terms of employment structure, as a post-industrial economy, the shift of labour shares form the primary and the secondary industries into the tertiary industry is inevitable. In line with Daniel Bell (1999), the demand for professional and technical employment will rise in the labour market, while the demand for skilled workers will decline – they will be replaced by robots over time. Thus, it is crucial to choose the "right" job – the one that robots won't take.

5.5 The Unbalanced Growth during the Pandemic

It is unrealistic to predict future economic growth without discussing the impact of the COVID-19 pandemic. It has inflicted a huge global recession since 2020. As we assume the pandemic is not going to fade soon (Charumilind et al., 2021), there is substantial uncertainty about its impact on people's lives and economic activities.

First, the pandemic requires people to reduce human-to-human contact, which brings uncertainty to the worker's productivity. Hence, it gives firms a solid reason to promote robotisation and automation. Unlike human workers, robots are not susceptible to the virus. For instance, China's leading e-commerce and delivery firms started to apply autonomous deliveries to hospitals and residential compounds on public roads (Sarazen, 2020).

Although robotisation and automation has caused unemployment, it may be not something we should complain about. Leduc and Liu (2020) assess the importance of automation with New Keynesian model and show that automation helps mitigate the adverse impact of uncertainty on productivity and aggregate demand. Without automation, the pandemic could lead to a much deeper recession.

However, the pandemic has exacerbated the unbalanced economic growth. "The pandemic and global recession may cause over 1.4% of the world's population to fall into extreme poverty," said World Bank Group President David Malpass[25]. Even worse, Dang and Nguyen (2021) investigate the impacts of COVID-19 on gender inequality and show that women are 24% more likely to permanently lose their job than men, and they expect their income to fall by 50% more than men do. A possible interpretation of the results is that women have a

[24] See: https://data.worldbank.org/

[25] See: https://www.worldbank.org/

remarkably higher rate of working in services jobs than men. These evidences show that the pandemic has harmed the poor and vulnerable the most.

Overall, the pandemic has long-lasting impact on human behavior and economic activity. One is that automation is coming sooner than we thought (Ramirez, 2020). In line with our study, differential productivity growth brought about by robotisation and automation is likely to reflect on the price, real wages and employment in the next few years. To maintain "balanced economic growth", the policymakers should pay attention to wage growth across the industries and support the poor and vulnerable groups, such as women, the young, and the unskilled.

5.6 Policy Implications to "Re-balance" China's Economy

The major conclusion of this study is that China has been "suffering" from unbalanced economic growth since its rapid industrialization and urbanization. In particular, wages grow at a lower rate in the stagnant sectors than wages in the progressive sectors, while the stagnant sectors have been absorbing most workers over time. Overall, the economic structural changes have led to rising job and income polarization. More and more people have to accept lower-paying jobs, which is slowing down aggregate demand growth and hence economic growth.

To "re-balance" the economy, one may argue that the policy should aim at improving the productivity of the service sectors. But it is not a good idea. There is no doubt that making use of labour-saving technologies in the service sectors can increase the aggregate productivity of the economy. For instance, online distance education allows hundreds of students to attend classes without time or geographic limitations, which improves the productivity of education. But it only turns certain stagnant sectors into progressive sectors. As a result, more people would be looking for jobs in the remaining stagnant sectors, and income polarization is likely to rise further. However, it does not mean that we should slow down or limit technological innovation. As explained previously, increased automation not only helps to increase productivity, but also helps to mitigate the negative impact of (pandemic-induced) uncertainty on the macroeconomy, thereby avoiding potential recessions (Leduc and Liu, 2016; Leduc and Liu, 2020). Hence, the problem is not about labour-saving technologies, but how to make everyone benefit from it.

Based on the fact that labour constantly flows from the progressive sectors to the stagnant sectors due to robotisation and automation, the policymakers should pay more attention to the firms and workers in the stagnant sectors to help them benefit from the overall productivity growth. One effective approach is to increase their income levels. This is particularly important for China for two reasons.

Firstly, the country faces serious income inequality. According to the World Bank (2020), China’s income-based Gini coefficient for 2019 is 46.5, which is similar to or slightly lower than some of the most unequal developing countries, such as Mexico, Brazil, or South Africa. In line with Deng Xiaoping’s notable comment on market-economy reforms: “If all of China is to become rich, some must get rich before others”, the eastern coastal area currently accounts for more than half of GDP, and 84% of the exports with just over a third of the population (World Bank, 2020). To bring the economy closer to “balanced growth”, policies must be re-balanced to foster market integration and reduce inequality.

Secondly, the external environment remains challenging, less supportive, and highly uncertain due to the pandemic and deglobalization. Hence, private consumption is expected to exceed exports and investment as the main driver of economic growth. Shifting China from an export-oriented economy to one centered around domestic household consumption should be supported by a gradual decline in precautionary savings (which are high in China[26]) amid improved consumer confidence. Most importantly, real income inequality has to be narrowed, so that more people's wages can cover consumption beyond the necessities.

However, increasing income levels does not imply that workers should simply earn higher wages for the same jobs. But the society can be more “creative” and “progressive” so there are more “good jobs” on the table. For example, supported by big data and algorithms, there are more than 7 million food deliverymen and more than 3 million couriers in China. But most of them are regarded as “flexible employment”, which implies that the delivery platforms choose to have no direct employment relationship with deliverymen to avoid risks and maximize profits. Evidence shows that current labour law is not sufficient to protect “flexible employment” in the Internet economy (Cheng, 2021). Thereby, authorities need to establish laws and regulations, and expand its social security (welfare) system to take care of these vulnerable groups and the poor.

In addition, the elderly are another group that the government must pay attention to. The demographic transition is one of the main challenges for Chinese society currently. As was argued by Thompson (1929), societies progress from a pre-modern regime of high fertility and high mortality to a post-modern regime of low fertility and low mortality. Notestein (1945) further provided standard theoretical explanation and its types of growth patterns. Caldwell (1976) concluded that fertility will fall to low levels in most societies, even where economic growth has been slow and incomes remain low. Generally speaking, there is an inverse correlation between fertility and industrial development. Additionally, the population control policies in China have further reduced the fertility rate (Scharping, 2013). In line with all this, China’s population is growing older at an unprecedented pace. It is shown that the fertility rate was only 1.7 in 2019, which was significantly lower than the replacement level of 2.1. The proportion of over-65 population is estimated to increase from 12.6% in 2019 to 26.1% in

[26] China’s national saving rates since 2000 have been one of the highest worldwide, surging from below 38% in 2000 to 53% in 2007. The corporate, government, and household sectors have all contributed significantly to the upsurge in national saving. The key caused include the fast economic growth, accession to the WTO accession, rising corporate profits, changes in life cycle earnings, etc. (Kuijs, 2005; Yang, 2012).

2050[27]. My thesis argues that people spend more of the income on healthcare over time. Therefore, to "re-balance" the economy, medical insurance, social welfare and health care system need to be improved so that the ageing population can live a decent life. When elderly feel secure with social welfare, they will be more willing to consume (contributing to domestic demand) rather than save money.

27 See: http://www.stats.gov.cn/.

Chapter 6: Reflections and Recommendations for Future Research

This research provided me the opportunity to explore China's macroeconomic performance since the market-oriented reforms. The research helped me to figure out why most graduates in China find it very challenging to find good jobs every year even though the country is known as the “world’s factory” (Chen, 2021). In addition, I learned about the potential macro-economic impact of technological progress by increasing productivity of certain industries. Differential productivity growth leads to the transformation of employment structure and the structural changes in production and consumption costs. Most importantly, the structural changes are naturally “unbalanced”. Therefore, it is necessary to intervene in income distribution through fiscal and monetary policies, making sure that the workers from the stagnant industries also benefit from technological progress. Moreover, re-balancing the economy will increase private consumption, thereby preventing the economy from stagnation.

There are two points that I would like to reflect on regarding the empirical test in the thesis. The study investigates a series of hypotheses concerning the effects of productivity change on economic growth. I mainly use the CIP database compiled by RIETI throughout the empirical analysis, which is an appropriate database. However, there are two limitations that must be noted. The data for employee compensation (wages paid to workers) are not available for all years[28], so “interpolations” are necessary to estimate real wage growth. Besides, no population data are available in the CIP database. I found these in the China Labour Statistical Yearbooks when I examined how the ratio of labour force to population evolved over time. Except for these data, the CIP database consists of various types of annual data required for my research.

Besides, to empirically test the hypotheses, I pooled the data for 1987-2010 for all industries and did linear regressions with OLS estimates. Prais-Winsten estimation has been applied to solve autocorrelation problems. Alternatively, one could do panel data econometrics, namely fixed effects and random effects regressions, for the analysis, which allows to control for industry-specific variables and the variables that change over time. However, the overall findings are unlikely to significantly change with the analysis techniques. In the cross-section analysis, I estimate the period-average growth rates of the variables and do linear regressions for the 37 industries. The results are not significantly different the pooled estimations (except that the results of the cross-section analysis for nominal output growth are insignificant).

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[28] The data for employee compensation is available for 1987, 1990, 1992, 1995, 1997, 2000, 2002, 2005, 2007 and 2010.

6.1 Recommendations for Future Research

Finally, I would like to provide four recommendations for future research. First, one can select certain regions (provinces / cities) in China for further analysis. In my thesis, I take the whole country as a study case. However, there are significant regional differences regarding economic growth. By 2019, the annual per-capita GDP of China exceeded US$10,000, of which Beijing and Shanghai exceeded US$22,000, Jiangsu Province was nearly US$18,000, while the poor provinces such as Gansu was only around US$6,000[29]. Future research can focus on one region, or study the regional differences in terms of economic development stages.

Second, the CIP 3.0 (2015) database that I applied in the analysis follows the KLEMS principles. Thus, it is possible to analyze differential productivity growth and its contribution to the overall economic growth across counties. Other countries that have KLEMS-type datasets are 28 individual EU member states, the US, Japan, Canada, Russia, Korea, India and Argentina[30]. Alternatively, one can argue that one reason why the results of “Baumol’s growth disease” differ empirically is that the period of some studies may be too short, and thus examine the correlation between the period’s length and the signs of “growth disease”.

Thirdly, throughout the research, the lack of data from 2011 creates the biggest limitation. The CIP 3.0 (2015) database covers the period 1980-2010. I tried to merge it with the official database from China Labour Statistical Yearbooks, which have the annual data for the period 2011-2019. However, the industrial classification is completely different in the two datasets. The CIP 3.0 (2015) database classifies the economy into 37 industries, while the other one classifies it into only 20 industries. Besides, the variables different, too. Thus, one can analyze the same sets of research questions in China in 2010s when the dataset is available. The ICT-related new economies and “supply-side reform” in the past few years may bring new insights in terms of productivity growth and its contribution to the overall economy.

6.2 The Social Contribution & Policy Advice

In this thesis, I analysed the economic impact of labour-saving technologies. In short, technological progress is not only a resource to improve productivity and profitability for firms, but also a trigger to change the employment structure of a society. In line with what I have learnt in the Management of Technology programme, changes in the macro environment, in turn, have a major impact on demand, and hence on business. Especially in the context of Industry 4.0, the growing polarization of productivity between industries leads to significant impacts on future social and business environments. Because of these societal impacts, the study of the economic effects of labour-saving technologies is of vital

[29] See: http://www.stats.gov.cn/

[30] See: http://www.worldklems.net/data.htm

importance to economic policy-makers as well as business executives of firms operating in the progressive and stagnant sectors of the economy.

Finally, one may argue that China is not a “typical” economy to study Baumol’s disease in developing countries. Indeed, the country is unique in terms of political environment, population size and natural resources. Moreover, China has benefited significantly from globalization for more than two decades since its transition to a market economy in 1978 and the accession to the World Trade Organisation (WTO) in 2001. For example, as the world’s most important manufacturing hub for the technology industry, it has been the largest exporter of electronic products since 2004 (OECD, 2006), even though most Chinese cannot afford them at that moment. In addition to the export-driven technological upgrade and foreign direct investment, the government pursued a strategy of “technology in exchange for the market”, which encouraged foreign technology transfer by promising market access to foreign firms (Wang, 2006). On the other hand, the active participation of foreign firms in the domestic market produced competitive pressures on inexperienced Chinese companies that helped to spur technical innovation (Zhou, 2008). As a result, China has systematically moved ahead in creating a self-supporting industrial and innovation ecosystem (Chaudhuri, 2012).

It is clear that the context of economic growth is different for each country. The thesis did not analyze the growth patterns of developing as well as developed countries in detail. Yet other studies suggest that some developing countries which have very different economic structures from China are facing the similar problems. For instance, South Africa’s economic growth has remained low for decades, and shows signs of secular stagnation (Fedderke and Mengisteab, 2017). Its sectoral structure is closer to that of developed countries, with more than 60% of GDP is contributed by the service sectors (the stagnant sectors). Fedderke (2018) shows that the high TFP growth sectors have the lowest rate of labour force growth and highest real output growth. While the relative prices of the progressive sectors fall, their shares in nominal output decline as well. Overall, unbalanced growth can be attributed to sectorally differentiated TFP growth in South Africa.

Though China’s dynamic economy is clearly unique, it still makes sense to analyse its economic performance to study Baumol's disease and unbalanced economic growth in hopes of enlightening the governments in China and other developing countries to critically examine their growth strategies. Firstly, in line with Schumpeter’s theory (Ziemnowicz, 1942), technological innovation and market power are crucial for economic growth. But this thesis has shown based on the case of China (1987-2010) that technological progress, concentrated in progressive sectors (such as manufacturing), can lead to unbalanced growth, the problem of Baumol’s cost disease and (in the long run) to economic stagnation. Unbalanced growth and the cost disease do not need to pose societal problems if the development process is adequately managed. Hence, it is necessary to intervene through fiscal and monetary policies to make all citizens benefit from the technological progress. It would not only improve the community’s overall living standards, but also prevent the economy from stagnation by increasing private consumption.

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Appendices

Appendix A: Industry Definition

The list of industries for each group is provided in Table 24.

Table 24: Industry definition

CIP Code	EU-KLEMS	China National Accounts Code	CSIC/2011	CIP Sector Description	Sector Acronym
1	AtB	I	01t05 (A)	Agriculture, forestry, animal husbandry & fishery	AGR
2	10	II.1	06 (B)	Coal mining	CLM
3	11	II.1	07 (B)	Oil & gas excavation	PTM
4	13	II.1	08t09 (B)	Metal mining	MEM
5	14	II.1	10t11 (B)	Non-metallic minerals mining	NMM
6	15	II.1	12t14 (C)	Food and kindred products	F&B
7	16	II.1	15 ©	Tobacco products	TBC
8	17	II.1	16 (C)	Textile mill products	TEX
9	18	II.1	17 (C)	Apparel and other textile products	WEA
10	19	II.1	18 (C)	Leather and leather products	LEA
11	20	II.1	19t20 (C)	Saw mill products, furniture, fixtures	W&F
12	21t22	II.1	21t22 (C)	Paper products, printing & publishing	P&P
13	23	II.1	24 (C)	Petroleum and coal products	PET
14	24	II.1	25t27 (C)	Chemicals and allied products	CHE
15	25	II.1	28t29 (C)	Rubber and plastics products	R&P
16	26	II.1	30 (C)	Stone, clay, and glass products	BUI
17	27t28	II.1	31t32 (C)	Primary & fabricated metal industries	MET
18	27t28	II.1	33 (C)	Metal products (excluding rolling products)	MEP
19	29	II.1	34t35 (C)	Industrial machinery and equipment	MCH
20	31	II.1	37 (C)	Electric equipment	ELE
21	32	II.1	38 (C)	Electronic and telecommunication equipment	ICT
22	30t33	II.1	39 (C)	Instruments and office equipment	INS
23	34t35	II.1	36 (C)	Motor vehicles & other transportation equipment	TRS

24	36t37	II.1	23,40t41 (C)	Miscellaneous manufacturing industries	OTH
25	E	II.1	42t44 (D)	Power, steam, gas and tap water supply	UTL
26	F	II.2	45t48 (E)	Construction	CON
27	G	III.2	61t62 (H)	Wholesale and retail trades	SAL
28	H	III.3	63t64 (I)	Hotels and restaurants	HOT
29	I	III.1	49t57 (F)	Transport, storage & post services	T&S
30	71t74	III.6	58t60 (G)	Information & computer services	P&T
31	J	III.4	65t68 (J)	Financial Intermediations	FIN
32	K	III.5	69 (K)	Real estate services	REA
33	71t74	III.6	70t75 (L,M)	Leasing, technical, science & business services	BUS
34	L	III.6	76t78 (N), 90t95 (S,T)	Government, public administration, and political and social organizations, etc.	ADM
35	M	III.6	81 (P)	Education	EDU
36	N	III.6	82t84 (Q)	Healthcare and social security services	HEA
37	O&P	III.6	79t80 (O), 85t89 ®	Cultural, sports, entertainment services; residential and other services	SER

Appendix B: Robustness Check

For the regression analysis in terms of pooled estimations with annual data, I include industry dummies in the regression to check whether the associations are "robust". The results are shown below.

Table 25: Impact of Productivity Growth on Price Growth (1987–2010): pooled estimations with annual data including industry-wise dummies

	Labour Productivity	Total Factor Productivity
Annual data (including industry-wise dummies)		
Coefficient	-0.07*** (0.01)	-0.08*** (0.01)
t-statistics	-4.49	-5.39
Durbin-Watson	1.95	1.95
Adjusted R^2	0.07	0.08
F-statistic (prob.)	2.77 (0.00)	3.08 (0.00)
Number of obs.	888	888
Annual data (excluding industry-wise dummies)		
Coefficient	-0.07*** (0.01)	-0.09*** (0.01)
t-statistics	-5.25	-5.93
Durbin-Watson	2.02	2.02
Adjusted R^2	0.03	0.04
F-statistic (prob.)	29.89 (0.00)	37.43 (0.00)
Number of obs.	888	888

Note: * Statistical significance level at 10%; ** Statistical significance level at 5%; *** Statistical significance level at 1%. Standard errors are in parenthesis. Estimates for constant terms not shown.

Table 26: Impact of Productivity Growth on Real Output (1987–2010): pooled estimations with annual data including industry-wise dummies

	Labour Productivity	Total Factor Productivity
Annual data (including industry-wise dummies)		
Coefficient	0.96*** (0.01)	0.99*** (0.01)
t-statistics	72.60	80.13
Durbin-Watson	1.94	2.00
Adjusted R^2	0.86	0.88
F-statistic (prob.)	149.00 (0.00)	181.06 (0.00)
Number of obs.	888	888
Annual data (excluding industry-wise dummies)		
Coefficient	0.96*** (0.01)	0.99*** (0.01)
t-statistics	74.88	82.31
Durbin-Watson	1.98	2.06
Adjusted R^2	0.86	0.88
F-statistic (prob.)	5614.65 (0.00)	6785.00 (0.00)
Number of obs.	888	888

Note: * Statistical significance level at 10%; ** Statistical significance level at 5%; *** Statistical significance level at 1%. Standard errors are in parenthesis. Estimates for constant terms not shown.

Table 27: Impact of Productivity Growth on Nominal Output (1987–2010): pooled estimations with annual data including industry-wise dummies

	Labour Productivity	Total Factor Productivity
Annual data (including industry-wise dummies)		
Coefficient	1.01*** (0.02)	1.02*** (0.02)
t-statistics	46.46	47.10
Durbin-Watson	1.98	2.01
Adjusted R^2	0.71	0.71
F-statistic (prob.)	59.55 (0.00)	61.08 (0.00)
Number of obs.	888	888
Annual data (excluding industry-wise dummies)		
Coefficient	1.00*** (0.02)	1.01*** (0.02)
t-statistics	47.43	48.34
Durbin-Watson	2.03	2.06
Adjusted R^2	0.72	0.73
F-statistic (prob.)	2258.36 (0.00)	2345.97 (0.00)
Number of obs.	888	888

Note: * Statistical significance level at 10%; ** Statistical significance level at 5%; *** Statistical significance level at 1%. Standard errors are in parenthesis. Estimates for constant terms not shown.

Table 28: Impact of Productivity Growth on Working Hours (1987–2010): pooled estimations with annual data including industry-wise dummies

	Labour Productivity	Total Factor Productivity
Annual data (including industry-wise dummies)		
Coefficient	-0.15*** (0.02)	-0.09*** (0.02)
t-statistics	-10.19	-5.95
Durbin-Watson	1.96	1.97
Adjusted R^2	0.14	0.08
F-statistic (prob.)	5.05 (0.00)	2.99 (0.00)
Number of obs.	888	888
Annual data (excluding industry-wise dummies)		
Coefficient	-0.15*** (0.01)	-0.09*** (0.02)
t-statistics	-10.38	-6.14
Durbin-Watson	2.00	2.00
Adjusted R^2	0.11	0.04
F-statistic (prob.)	107.85	37.81 (0.00)
Number of obs.	888	888

Note: * Statistical significance level at 10%; ** Statistical significance level at 5%; *** Statistical significance level at 1%. Standard errors are in parenthesis. Estimates for constant terms not shown.

Table 29: Impact of Productivity Growth on Wages (1987–2010): pooled estimations with annual data including industry-wise dummies

	Labour Productivity	Total Factor Productivity
Annual data (including industry-wise dummies)		
Coefficient	0.31*** (0.03)	0.24*** (0.03)
t-statistics	10.02	7.51
Durbin-Watson	1.78	1.77
Adjusted R^2	0.10	0.05
F-statistic (prob.)	3.59 (0.00)	2.36 (0.00)
Number of obs.	851	851
Annual data (excluding industry-wise dummies)		
Coefficient	0.30*** (0.03)	0.23*** (0.03)
t-statistics	10.02	7.39
Durbin-Watson	1.78	1.78
Adjusted R^2	0.11	0.07
F-statistic (prob.)	108.48 (0.00)	63.03 (0.00)
Number of obs.	851	851

Note: * Statistical significance level at 10%; ** Statistical significance level at 5%; *** Statistical significance level at 1%. Standard errors are in parenthesis. Estimates for constant terms not shown.

Table 30: Impact of Productivity Growth on Unit Labour Cost (1987–2010): pooled estimations with annual data including industry-wise dummies

	Labour Productivity	Total Factor Productivity
Annual data (including industry-wise dummies)		
Coefficient	-0.48*** (0.04)	-0.50*** (0.04)
t-statistics	-13.21	-13.68
Durbin-Watson	1.87	1.87
Adjusted R^2	0.21	0.19
F-statistic (prob.)	5.93 (0.00)	6.25 (0.00)
Number of obs.	851	851
Annual data (excluding industry-wise dummies)		
Coefficient	-0.50*** (0.04)	-0.53*** (0.04)
t-statistics	-14.30	-14.82
Durbin-Watson	1.88	1.88
Adjusted R^2	0.20	0.21
F-statistic (prob.)	206.93 (0.00)	222.23 (0.00)
Number of obs.	851	851

Note: * Statistical significance level at 10%; ** Statistical significance level at 5%; *** Statistical significance level at 1%. Standard errors are in parenthesis. Estimates for constant terms not shown.

As Table 25-30 shows, the regression results of pooled estimations with annual data including industry-wise dummies are close to the ones excluding industry-wise dummies. Thus, the robustness check supports the conclusions.