THREE ESSAYS ON THE STRUCTURAL CHANGES IN MODERN ECONOMY

A Dissertation
submitted to the Faculty of the
Graduate School of Arts and Sciences
of Georgetown University
in partial fulfillment of the requirements for the
degree of
Doctor of Philosophy
in Economics

By

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Washington, DC
April 5, 2011

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ABSTRACT

The intent of this study is to explore the causes of macro-level structural changes and the implications of these changes for the macroeconomic fundamentals.

The cause of the recent sectoral composition change in the US is examined from the perspective of intangible capital accumulation. In the first theoretical model of the study, as the importance of intangible capital increases in the production functions – but at different rates across sectors – labor is shifted from direct goods production to creating sector-specific intangible capital. At the mean time, the real output and employment shares of the high intangible sector increase. The implications of the model are consistent with a series of structural-change-related stylized facts in the US economy. Empirically, it is shown that an industry's future growth in output and employment is strongly correlated with its intangible capital intensity. And the industries in which firms' intangible investments have a higher impact on firms' production tend to grow more.

The study then looks at the recent structural change in the production volatility patterns of the US, namely, a divergence in macro and micro level production volatilities. It is shown that as firms' organization capital becomes increasingly important in the production process, the impact of firm-specific risk factor rises, while that of general risk factor declines. The former raises firm-level volatility; the latter reduces aggregate volatility. Consistent with this theory, it is found that firm-level volatility increases with organizational investment, but general factors' impact on firm performance and a firm's production correlation with other firms decrease with organizational investment.

The study also investigates structural change patterns in different countries. With data from 28 industries across 15 countries, it is shown that at least for the overall capital, the shares of capital intensive industries are significantly bigger with higher initial capital endowment and faster capital accumulation. More importantly, there is a significantly positive relationship between a country's aggregate output growth and the degree of structural coherence in all types of capital.

I am tremendously grateful to my advisor Jinhui Bai for his guidance and encouragement. I would also like to thank my dissertation committee members Behzad Diba and Luca Flabbi for insightful comments and discussions. My appreciation also goes to Sami Alpanda, Nadia Doytch, Mark Huggett, Ann Harrison, Jiandong Ju, Geng Li, Yifu Lin, Josh Rusenko, Antonio Spilimbergo, Leo Sveikauskas, and Yong Wang.

Many thanks,
Xingyuan Che

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Introduction

We are living in a world where the characteristics of economic life are increasingly departing from anything else humanities have experienced before in the recorded history. Technology breakthroughs are happening not in every other hundreds of years, but in every other few years. Capital is accumulating in almost every part of the world at an unprecedented speed. Increased population mobility and new communication systems are making the spread of information and knowledge ever faster and cheaper. It is as if time itself has sped up. One result of all these shifts is that the fundamental changes in macroeconomic structure—from changes in the industrial composition of the economy to changes in the volatility patterns of production– are happening much more frequently in the modern economy than in any previous ages.

These structural changes in macroeconomy provide interesting and important new research topics for economists, and also pose new challenges to existing economic theory and empirical practices. The following chapters explore some of the questions related to these structural changes and their implications for macroeconomic fundamentals such as economic growth and business cycle volatility.

Chapter 2 studies the sectoral composition of the US economy, which has changed dramatically in the past several decades. During the same period, knowledge and information assets are becoming increasingly important in the value creation process of a modern economy. This chaper aims to explain the recent sectoral structural change from the perspective of differences in intangible capital accumulation across sectors. In the two-sector model of the chapter, as the importance of intangible capital increases in the production functions – but at different rates across sectors – labor is shifted from direct goods production to creating sector-specific intangible capital. At the mean time, the real output and employment shares of the high intangible sector increase.

The implications of the model are consistent with the following stylized facts in US economy: (1) the high intangible sector has expanded in both output and employment; (2) intangible capital investment increases in both sectors; (3) the economy's employment composition is shifting towards occupations engaging in intangible investment activities; (4) both sectors' labor productivity growth has declined over time, especially for the high intangible sector.

I further test the relationship between intangible capital and structural change at more disaggregate levels. The industry-level results suggest that an industry's future growth in output and employment is strongly correlated with its intangible capital intensity. The firm-level results show that the industries in which firms' intangible investments have a higher impact on firm production tend to grow more. Both results are consistent with the theory.

The industry level data also indicates that the expanding service industries are primarily intangible capital intensive. Thus the theory developed in this chapter also helps to explain the rise of the service sector in recent decades.

Chapter 3 looks at the structural change in macro and micro level production volatilities in the US.[1] The aggregate output volatility of US economy has declined significantly since the early 1980s, while publicly-traded firms' sales and employment have become more volatile during the same period. The latter fact contradicts many explanations of the "Great Moderation" that imply a direct transfer between macro and firm-level volatilities. In this chapter, I argue that firms' organization capital investment is a key factor causing the macro and micro level volatility divergence. Firm-specific intangible capital accumulation is an important source of idiosyncratic risks, but it also makes a firm less susceptible to general market risks. When organization capital becomes increasingly important in the production process, the impact of firm-specific risk factor rises, while that of general risk factor declines. The former raises firm-level volatility; the latter reduces aggregate volatility, mainly through weakening the positive co-movements among firms. In this sense, the decline in macro volatility during the past two decades is rather a story of the "Great Dissolution".

My empirical analysis found that, consistent with the above hypotheses, firm-level volatility increases with organizational investment, but general factors' impact on firm performance and a firm's correlation with others decrease with organizational investment. Simulations of the general

[1] It should be mentioned that although the focus of Chapter 2 and 3 are in US economy, similar structural change patterns have been observed in the literature for most developed economies.

equilibrium model featuring organization capital investment are capable of replicating the volatility trends at both aggregate and firm level for the past two decades.

In Chapter 4, I empirically study the structural change in industrial composition across countries. The goal here is not only to explain why structural changes happen, but also to investigate its effect on economic growth. Specifically, this chapter studies the industrial composition change induced by factor endowment changes, and explores the linkage between structural coherence and economic growth. Here structural coherence is defined as the degree that a country's industrial structure optimally reflects its factor endowment fundamentals.

Using data from 28 industries across 15 countries, I found that at least for the overall capital, the shares of capital intensive industries were significantly bigger with higher initial capital endowment and faster capital accumulation. More importantly, the results show a significantly positive relationship between a country's aggregate output growth and the degree of structural coherence in all types of capital. Quantitatively, the structural coherence with respect to the overall capital explains about 25% of the growth differential among sample countries. The results of the chapter are mostly robust to alternative measure of capital intensity, to controls for other industry characteristics such as human capital and degree of value-added, and to controls for other determinants of structural change on both demand side and supply side.

Chapter 1

Sectoral Structural Change in a Knowledge Economy

1.1 Introduction

It is a well-known fact that less than half of the economic growth today can be explained by the "tangible" inputs, namely, physical capital and labor. Traditionally, macroeconomists attribute other factors involved in economic value creation to a "residual" term in the production function, which largely remains outside the scope of macroeconomic research. More recently, researchers have started recognizing that besides plants, equipment, land and labor, there are other systemic production inputs that are equally, if not more important in a modern knowledge economy, such as intangible capital. This paper studies the role of intangible capital in the recent sectoral structural change in the US.

The relative importance of various sectors in US economy has been going through dramatic change over time. For example, in the past five decades, the growth of most service-producing industries have largely outpaced that of goods-producing industries. What factors caused the structural change is an intriguing question. Different answers to the question have different implications for long-term economic growth and employment performance.

This paper develops a supply-side explanation of structural change based on sectoral differences in intangible capital accumulation. The basic idea is that the share of intangible capital in the production function differs across sectors. When the productivity of intangible investment increases with exogenous technology progress, more intangible capitals can be produced, given the amount of resources committed. Because intangible capital has a larger contribution to the production process in some sectors than in others, the intangible-capital intensive sector's output increases disproportionately with the productivity increase in intangible investment. At the same time, to take advantage of the increased investment productivity, firms shift labor from direct goods production to intangible capital creation, and this shift is to a larger scale in the intangible capital intensive sector. Take the total employment of a sector as the sum total of the sector's direct production labor and its intangible investment labor. The employment share of intangible-capital intensive sector would increase due to the disproportional expansion of its intangible investment labor.

The term intangible capital refers to knowledge and information based assets, including knowledge acquired through R&D and other creative activities, knowledge embedded in computer software and databases, firm-specific human and structural resources like management experience and brand names.

Modern firms engage in a wide range of knowledge-building activities, such as designing new products, processes and business models, training employees, marketing brands, developing computerized assets, communicating within and without the organization and acquiring information about markets and competitors. These activities mostly do not create any physical assets. However, they create knowledge-based resources indispensable in generating new values for customers and financial returns for the firm. The nature of these business activities is not very different from investment in physical capital – both generate productive resources for the future. In this sense, they should be viewed as capital investment when we analyze the firm's production process.

The advancement in information and communication technology has greatly enhanced the productivity of intangible capital investment in the past several decades. The most obvious change the IT revolution brought about is the proliferation of software and computerized information systems as new forms of intangible assets. But more importantly, it increases the effectiveness of many other knowledge investment endeavors. For example, progress in communication technology and new media increased the reach of firms' marketing efforts. The emergence of internet made many new business models possible, especially in the service sector. Computer networks make finding and sharing of information within and between business entities easier and faster. The use of computer software facilitated innovative work that produces knowledge assets. For instance, an architect who spent days crafting a blue print with pencil and paper can now create the same design in a few hours on a computer. Moreover, the proliferation of information provides powerful tools for managers and directors of enterprises. It promotes such organizational investment as flexible firm structure and decentralized decision-making processes.[1] The result of increased investment productivity is a surge of intangible capital investment in the economy over the recent decades. The empirical evidence of this trend will be reviewed in the next section.

The present paper is motivated by a set of new stylized facts about the linkage between the rise of intangible capital and sectoral structural change during the same period. In the past several decades, the high-intangible-capital industries have grown faster than their low intangible peers. In Figure 1.1, US SIC two-digit industries are divided into two sectors according to industry intangible capital investment intensity.[2] Figure 1.1 plots the real output and employment size of the high intangible capital sector as a proportion of the total private industries. Notice that in a span of five decades, the intangible capital intensive sector has experienced much more rapid growth in both real output and employment than the other sector.

Not only has the high-intangible capital sector expanded, intangible capital investment itself has also increased over time. Figure 1.2 shows intangible capital investment trends for the high and low intangible sector respectively. A sector's intangible investment intensity is calculated as the median investment intensity across industries within the sector. It is easy to see that both growing and declining sectors' intangible capital investments are increasing over time. However, the growing sector's intangible investment increases faster than that of the declining sector.

[1] See Brynjolfsson & Saunders (2009) for a detailed discussion about the relationship between information technology and organizational capital investment.

[2] The methodology of sector classification will be discussed in the calibration Section 4.1.

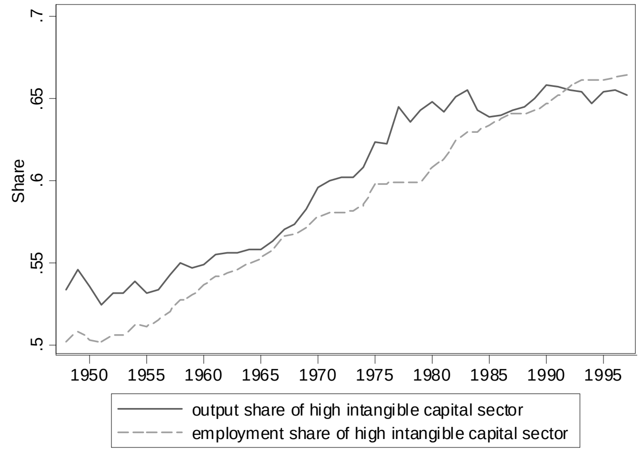

Figure 1.1: Shares of the intangible capital intensive sector

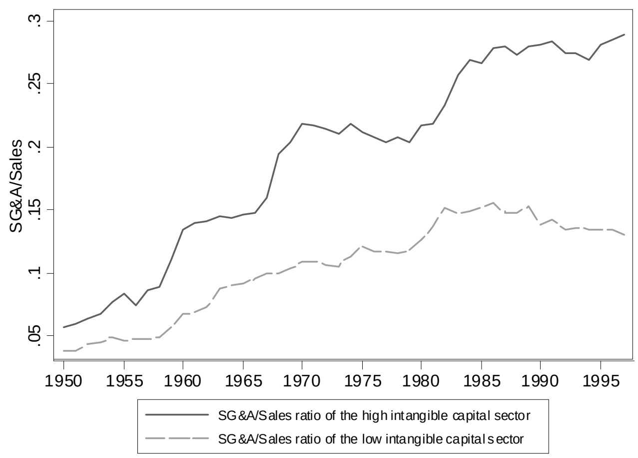

Figure 1.2: Intangible capital investment trends

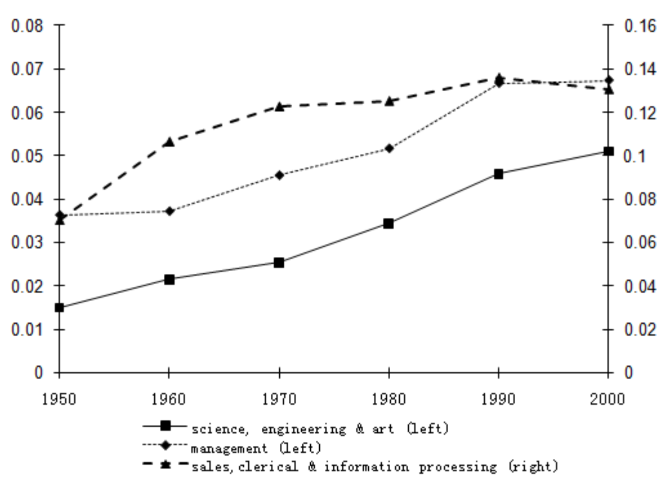

Figure 1.3: Rise of employment engaging in intangible capital investment

In conjunction with the structural change in sectoral composition, the employment composition of the economy has also been shifting – from direct goods production to intangible capital investment activities. In Figure 1.3, I selected several groups of occupations in which work activities typically involve intangible capital production, and calculated their shares in total employment.[3] These occupations are divided into three categories: 1) jobs that mainly involve creativity and innovation, such as engineers, architects, scientists, artists, and entertainers; 2) jobs that deal in organization construction and maintenance, such as managers, administrators, HR specialists, and business consultants; 3) jobs that fulfill marketing and communication functions, such as advertising personnel, customer service representatives, and IT operators. Figure 1.3 indicates that the share of workers engaging in intangible investment as a proportion of the total working population have been increasing overtime.[4]

The fourth stylized fact is concerning the productivity growth of the two sectors. Table 1.1 shows the annual average labor productivity growth[5] of the high and low intangible sectors in two sub-periods of the industry data sample and for the whole sample period from 1950 to 1997.[6] Two things are worth noticing. First, the labor productivity growth has declined in both sectors overtime. Second, the decline is more significant in the growing, high intangible sector. Thus for the whole sample period, the high intangible sector has on average lower productivity growth than the other sector, though its productivity growth is higher in the first sub-period.[7]

[3] Data source: Steven Ruggles, Matthew Sobek, Trent Alexander, Catherine A. Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, & Chad Ronnander. Integrated Public Use Microdata Series: Version 4.0. Minneapolis, MN: Minnesota Population Center [producer and distributor], 2009.

[4] One thing to keep in mind is that this is a very rough measure of the intangible-investment workforce, in the sense that (1) the occupation groups are selected subjectively according to common observations; they are by no means exclusive; (2) for many occupations, included in the list or not, working hours may be split between direct production and intangible investment activities. Therefore, Figure 2 should be taken as suggestive evidence, instead of a precise measure of intangible investment labor.

[5] Here the sectoral labor productivity is calculated as a sector's total real value-added devided by total labor hours.

[6] The BEA stopped producing industry output and employment data by SIC industry classification in 1997 and shifted to NAICS classification. To ensure consistency, I use SIC industry data for the most part of the paper. Therefore the sample period ends at 1997.

[7] This fact is related to the famous "cost disease" hypothesis by William Baumol (Baumol, 1967). The hypothesis was originally focused on the expansion of service industries. It assumes that service industries are intrinsically less likely to experience productivity improvement than goods-producing industries. A direct implication is that as the less productive industries grow bigger, it will eventually bring down the growth of the whole economy. This paper will show later that most of the expanding service industries are high intangible industries. Thus the result in Table 1 seems to be consistent with Baumol's hypothesis. However, as will be discussed in the calibration section, the conventional way to calculate labor productivity does not take into account the fact that part of the labor force is not directly engaged in the production of goods and services, but instead producing intangible investment goods which are not counted in the final outputs. And this is especially true for the high intangible sector.

Annual Labor Productivity Growth (%)			
	1951-1973	1974-1997	1951-1997
High Intangible Sector	2.92	-0.94	0.95
Low Intangible Sector	2.16	0.72	1.43

Table 1.1: Labor productivity growth of the two sectors

The model of the paper replicates most of the stylized facts presented above. In terms of sectoral composition, the calibrated model generates significant increase in the high intangible sector's output and employment shares, the magnitudes comparable to the data. The model also produces rising intangible investments in both sectors, and increasing share of intangible investment labor in the total employment. Finally, both sectors' labor productivity growths decline overtime in the model simulation, and the decline is greater in the high intangible sector.

The empirical part of the paper tests the relationship between intangible capital accumulation and structural change with industry and firm data. The industry-level regressions show that intangible capital intensity has a strong positive correlation with future industry growth in output and employment. The result is robust to the inclusion of other industry characteristics that might impact industry growth. At the firm level, I also find that an industry tend to expand more when intangible investment has a higher impact on the growth of firms in the industry, i.e., when intangible capital is more important in the industry's production function. These findings are consistent with the theory of the chapter.

The rest of the chapter is organized as follows. Section 1.2 gives a review of related literature. Section 1.3 presents a two-sector model featuring intangible capital accumulation, and discusses how the model can generate sectoral structural change. Section 1.4 calibrates the model and presents simulation results. Section 1.5 undertakes empirical analyses to test the implication of the model. Section 1.6 applies the chapter's theory to explain the rise of service sector in recent decades. Section 1.7 concludes.

1.2 Related Literature

Although the neoclassical view of economic growth places little emphasis on sectoral composition change, some early literature from distinguished authors pointed out that structural change is in fact an integral part of growth. Baumol (1967) divided the economy into "progressive" and "non-progressive" sectors according to their rate of productivity growth. He proposed that over time, resources would shift to the sector with lower productivity and that sector would eventually determine the growth rate of the whole economy. Kuznets (1973) suggested two causes of sectoral composition change: shifting income elasticity of demand for different sectors and uneven rates of technological progress.

Recent literature are more or less expositions of the above rationales. For example, Echevarria (1997), Laitner (2000) and Kongsamut, Rebelo & Xie (2001) motivate structural change by assuming non-homothetic preferences in the utility function. Acemoglu & Guerrieri (2008) provides a two-sector model with different physical capital intensities in the sectoral production functions. They show that with aggregate capital deepening in the economy, the real output share of the sector that relies more on capital increases, but at the same time, resources are shifted towards the sector with low capital intensity because of low elasticity of substitution between different sectoral goods. A similar assumption is adopted by Ngai & Pissarides (2007). In their model, structural change is interpreted as labor shifting to sectors with low technological progress, whose shares of employment and nominal output increase over time.

However, as pointed out by Buera & Kaboski (2007), the rise of many advanced service industries since the mid-20th century is an expansion of not only nominal output shares, but also real output shares of those industries. The story of low elasticity of substitution between sectoral goods runs counter to the latter observation. Moreover, theories that assume non-homothetic preferences of consumers neglect the fact that many rising industries, such as business and financial services, are in fact not final goods providers, and their rise can hardly be explained as a result of differences in income elasticity.

In contrast, the present research made simple and standard assumptions about households' utility function and do not rely on demand elasticity to generate the structural change results. The present research identified the cross-sectoral difference in intangible capital intensity as an important source of structural change. The shift in employment shares of sectors is motivated by the change in work tasks from direct goods production to intangible capital production, unlike in most of the existing supply-side literature, which mainly relies on low elasticity of substitution between sectors to generate realistic structural change in employment.

A crucial difference between the industrial-age economy and the modern knowledge economy is that cutting-edge production know-how is no longer embodied in plants, properties and equipment, but are increasingly intangible, carried with workers and organizations. Moreover, the advancement of IT technology drastically reduced the cost of information processing, facilitated applied innovations and transformed the characteristics of business communication. The emergence of IT, as a general purpose technology, both requires and enables new investments in such intangible assets as organizational structure and management processes.

There is abundant evidence suggesting that the business sector's intangible capital investments have been on the rise over the past six decades. Companies' market value as a percentage of GDP has been increasing since the 1980s', while tangible assets relative to GDP declined during the same period. Some researchers argue that an important source for the increase in firms' market capitalization is the accelerated accumulation of intangible assets (e.g., Hall, 2001). Nakumura (2001) inferred the amount of business intangible investment in US economy, using data on industrial expenditures, labor inputs and corporate operating margins. He concluded that by 2000, private firms invested at least \$1 trillion annually in intangible assets, and 1/3 of US corporate assets are in intangibles. Corrado, Hulten & Sichiel (2005, 2006) directly estimated and aggregated different components of business intangible capitals. They concluded that by the end of the 20th century, intangible capital investment had exceeded private firms' physical capital investment, amounting to about 13% of business outputs. Atkeson & Kehoe (2005) emulated plant-life dynamics based on organization capital accumulation. They estimated that the payments to intangible capital owners are on average 110% of those to physical capital owners. According to the above estimations, it is a reasonable conjecture that given the large increase of intangible investment in the economy, it can have impact, and large impact, on the characteristics of production and employment in different sectors.

There is a diverse and quickly expanding literature that relates intangible capital investment to various macroeconomic phenomena.[8] The present research, to my best knowledge, is the first one to analyze the relationship between intangible capital accumulation and the sectoral structural change in modern economy.

1.3 Theory

1.3.1 Model

The model economy is inhabited by a representative household with the preference[9]

$$\sum_{t=0}^{\infty} \beta^t \ln (C_t)$$

The economy has two sectors, which produce their respective sectoral goods $Y_1$and Y_2. A final good is produced competitively by combining the two sectoral goods:

$$Y_t = Y_{1t}^{\gamma_1} Y_{2t}^{\gamma_2} \tag{1.1}$$

where $\gamma_1 + \gamma_2 = 1$.[10]

I assume that there is only one firm in each sector, and the sectoral goods production function

[8] Prescott & Visscher (1980) modeled the information accumulation and transfer process within a firm (a type of organization capital investment), and used it to explain stylized characteristics of firm growth rates and size distributions. Hall (2001) argued that US firms' intangible asset accumulation helps explain the persistent high valuation of common stocks compared to companies' book values. Atkeson & Kehoe (2005) linked the amount of organization capital a plant accumulated with the size of plant-specific rents. They simulated plant distribution dynamics driven by organization capital accumulation, and showed that the result fit the real data well. Jovanovic & Rousseau (2001) hypothesized that the quality of organization capital differs across generations of firms, which explained the "cohort effects" in firms' stock market performance. Brynjolfsson, Hitt & Yang (2002) found that investment in intangible assets complements investment in IT technology, and the combined investment has a significantly larger impact on firms' output and market valuation than isolated investments. McGrattan & Prescott (2007) introduced business intangible investment in a standard growth model and demonstrated that it helped explain US productivity and investment boom in the 1990s. Danthine & Jin (2007) modeled different stochastic processes in intangible capital accumulation and argued that it contributed to high volatility in equity returns.

[9] Here the utility function is in log form and welfare is only derived from consumption. These specific assumptions serve to simplify the non-essential part of the model. A more complicated utility function won't change the major results of the model.

[10] Equation 1.1 implies that the elasticity of substitution between the two sectoral goods is equal to 1. This means that the ratio between the nominal values of the two sectoral goods is always constant – any relative quantity changes are exactly off-set by corresponding changes in prices. The purpose of this assumption is to differentiate the employment structural change mechanism described in the present paper from the mechanism used in some other supply-side structural change papers that rely on non-unity elasticity of substitution between sectors to create labor composition change (e.g., Acemoglu & Guerrieri (2008); Ngai & Pissarides (2007)).

is Cobb-Douglas:

$$Y_{i,t} = K_{i,t}^{a_{i,t}} O_{i,t}^{b_{i,t}} L_{y_i,t}^{1-a_{i,t}-b_{i,t}}, \qquad i = 1, 2$$

where K_i, O_i, L_{y_i} are respectively physical capital, intangible capital and labor engaged in producing sectoral goods Y_i. An important feature of the model is that the factor shares in the production functions, a_{it} and b_{it}, can exogenously change over time, due to changes in technology and production methods.

Physical capital and labor are freely mobile across sectors. The physical capital is assumed to accumulate according to the log-linear form

$$K_{t+1} = K_t^{1-\delta} I_t^{\delta} \tag{1.2}$$

where $(1 - \delta)$ captures the impact of current capital stock on the amount of capital available next period. The log-linear assumption of physical capital formation, combined with log consumer utility, allows us to obtain a closed form solution to the static equilibrium of the model.

Intangible capital is sector-specific and not directly transferrable between the two sectors. It accumulates according to

$$O_{i,t+1} = (1 - \varphi) O_{i,t} + X_{i,t}, \qquad i = 1, 2 \tag{1.3}$$

where $X_{i,t}$ is the intangible investment good in sector i. The production of X_i requires intangible capital and labor inputs:

$$X_{i,t} = B_{i,t} O_{i,t}^{1-d} L_{o_i,t}^{d}$$

L_{o_i} is the part of labor engaged in producing intangible capital. Note that unlike physical capital and labor, the intangible capital O_i is not split between sectoral goods production and intangible investment. The intuition is that the same knowledge, brand name and experiences can be used both to create consumable values and to develop new knowledge, brands and experiences. $B_{i,t}$ denotes the productivity level of sector i's intangible capital investment at period t, which is exogenously given and grows at an annual rate g_{B_i}: $B_{i,t} = B_{i,t-1}(1 + g_{B_i})$.

The final output Y can be used either for consumption or for physical capital investment: $C_t +$

$I_t \leq Y_t$. In other words, the physical capital investment good is of the same unit as consumption. Let q_i denote the price for IC investment goods X_i, and let $\widetilde{Y}$ denote the extended aggregate output: $\widetilde{Y}_t = Y_t + q_{1t}X_{1t} + q_{2t}X_{2t}$. Then the economy's resource constraint can be expressed as

$$C_t + I_t + q_{1t}X_{1t} + q_{2t}X_{2t} \leq \widetilde{Y}_t \tag{1.4}$$

Labor supply in the economy is inelastic and equal to the population size at time t, $\overline{L}_t$. Capital and labor market clearing requires that

$$\begin{aligned} &K_{1,t} + K_{2,t} \leq K_t \\ &L_{y_1,t} + L_{y_2,t} + L_{o_1,t} + L_{o_2,t} \leq \overline{L}_t \end{aligned} \tag{1.5}$$

1.3.2 Competitive Equilibrium

The competitive equilibrium of the model has the following features. First, consumers save by purchasing physical and intangible capitals; they then rent capital services to firms in the next period and sell the un-depreciated capitals. Second, the sectoral goods are used to form consumption and physical capital investment, while intangible capital investment goods are produced separately, with $1/q_i$ representing the relative marginal cost of X_i in terms of consumption and physical investment. Third, the household chooses consumption and physical capital investment, and also the level of intangible investment by choosing the labor inputs going into producing intangible investment goods.

The state of the economy at the beginning of time t is described by $\xi_t = (a_{1t}, a_{2t}, b_{1t}, b_{2t}, B_{1t}, B_{2t}, O_{1t}, O_{2t}, K_t, \overline{L}_t)$. Assume that the equilibrium wage and rental rates are expressed as functions of ξ_t: $w_t = W(\xi_t)$; $r_t^k = R^k(\xi_t)$; $r_t^{o_1} = R^{o_1}(\xi_t)$; $r_t^{o_2} = R^{o_2}(\xi_t)$. Capital stocks evolve according to functions $K_{t+1} = K(\xi_t)$, $O_{1,t+1} = O_1(\xi_t)$, $O_{2,t+1} = O_2(\xi_t)$. The optimization problems of the household and firms are the following.

The household's optimization problem is

$$\max_{\{C_t, I_t, X_{1t}, X_{2t}\}_{t=0}^{\infty}} E \sum_{t=0}^{\infty} \beta^t \ln(C_t) \tag{P1}$$

subject to the constraints

$$C_t + I_t + q_{1t}X_{1t} + q_{2t}X_{2t} \leq w_t L_t + r_t^k K_t + r_t^{o_1} O_{1t} + r_t^{o_2} O_{2t};$$

$$O_{i,t+1} = (1-\varphi)O_{i,t} + X_{i,t}, \qquad i = 1, 2$$

$$K_{t+1} = K_t^{1-\delta} I_t^{\delta}$$

Let $\pi_{1,it} = q_{it}X_{it} - w_t L_{o_i,t}$; and $\pi_{2,it} = p_{it}Y_{it} - w_t L_{y_i,t} - r_t^k K_{it} - r_t^{o_i} O_{it}$. The firms' problem is two-fold, to optimize the intangible investment production and to maximize the current period profit:

$$\max_{\widetilde{L}_{y_i,t}, \widetilde{L}_{o_i,t}, \widetilde{K}_{it}, \widetilde{O}_{it}} \pi_{1,it} + \pi_{2,it} = q_{it}X_{it} + p_{it}Y_{it} - w_t \left(\widetilde{L}_{o_i,t} + \widetilde{L}_{y_i,t}\right) - r_t^k \widetilde{K}_{it} - r_t^{o_i} \widetilde{O}_{it}; \qquad i = 1, 2 \quad \text{(P2)}$$

Because of the constant return to scale and competitive market assumption, the firms make zero profits each period in the equilibrium.

A competitive equilibrium is a set of decision rules $C = C(\xi)$, $I = I(\xi)$, $X_1 = X_1(\xi)$, $X_2 = X_2(\xi)$, $L_{y_1} = L_{y_1}(\xi)$, $L_{y_2} = L_{y_2}(\xi)$, $L_{o_1} = L_{o_1}(\xi)$, $L_{o_2} = L_{o_2}(\xi)$, $K_1 = K_1(\xi)$, $K_2 = K_2(\xi)$, a set of prices $w = W(\xi)$, $r^k = R^k(\xi)$, $r^{o_1} = R^{o_1}(\xi)$, $r^{o_2} = R^{o_2}(\xi)$, and aggregate laws of motion for capital stocks $K_{t+1} = K(\xi_t)$, $O_{1,t+1} = O_1(\xi_t)$, $O_{2,t+1} = O_2(\xi_t)$, such that

1. Household solves problem (P1), taking as given ξ, and pricing functions $W(\cdot)$, $R^k(\cdot)$, $R^{o_1}(\cdot)$, $R^{o_2}(\cdot)$. The solution to the household's problem satisfies $C = C(\xi)$, $I = I(\xi)$, $X_1 = X_1(\xi)$, and $X_2 = X_2(\xi)$.

2. Firms solve problem (P2), given ξ and functions $W(\cdot)$, $R^k(\cdot)$, $R^{o_1}(\cdot)$, $R^{o_2}(\cdot)$. The solution to the firm's problem satisfies $\widetilde{L}_{yi} = L_{y_i}(\xi)$, $\widetilde{L}_{o_1} = L_{o_1}(\xi)$, $\widetilde{O}_i = O_i$, and $\widetilde{K}_i = K_i(\xi)$; $i = 1, 2$.

3. The aggregate resource constraint 1.4 holds in every period. Labor and capital markets clear:

$$K_{1t} + K_{2t} \leq K_t$$

$$L_{y_1,t} + L_{y_2,t} + L_{o_1,t} + L_{o_2,t} \leq \overline{L}_t$$

Normalize the price of the final good to 1. Then the equilibrium prices of the two sectoral goods can be denoted as

$$p_{1t} = \gamma_1 \frac{Y_t}{Y_{1t}}, \qquad p_{2t} = \gamma_2 \frac{Y_t}{Y_{2t}} \tag{1.6}$$

From the solution to firms' maximization problem, the wage rate should be equal to the marginal productivity of labor, which can be expressed relative to the final good price as

$$w_t = (1 - a_i - b_i)\,\gamma_i \frac{Y_t}{L_{y_i,t}}$$

Therefore the ratio of direct production labor between the two sectors is constant and can be written as

$$\frac{L_{y_1,t}}{L_{y_2,t}} = \frac{\gamma_1(1 - a_1 - b_1)}{\gamma_2(1 - a_2 - b_2)} \tag{1.7}$$

Similarly, equalizing the marginal productivity of physical capital between the two sectors, we have

$$\frac{K_{1,t}}{K_{2,t}} = \frac{\gamma_1 a_1}{\gamma_2 a_2} \tag{1.8}$$

Since in the equilibrium the marginal productivity of labor between sectoral goods production and IC investment is equal, we can derive the prices for IC investment goods, $q_{i,t}$, as

$$q_{it} = \frac{(1 - a_i - b_i)\,\gamma_i Y_t L_{o_i,t}}{dX_{i,t} L_{y_i,t}}; \qquad i = 1, 2 \tag{1.9}$$

As I assume that the markets are complete in this economy, the model can also be solved as a social planner's problem. The Lagrangian for the social planner's problem is

$$\begin{aligned}
\mathcal{L} \;=\; & \sum_{t=0}^{\infty} \beta^t \{\ln(C_t) + \lambda_t[Y_{1t}^{\gamma_1} Y_{2t}^{\gamma_2} - C_t - \frac{K_{t+1}^{1/\delta}}{K_t^{(1-\delta)/\delta}}] + \sum_{i=1,2} \mu_{it}[K_{i,t}^{a_i} O_{i,t}^{b_i} L_{y_i,t}^{1-a_i-b_i} - Y_{i,t}] \\
& + \sum_{i=1,2} \eta_{it}[(1-\varphi)\,O_{i,t} + B_{i,t} O_{i,t}^{1-d} L_{o_i,t}^{d} - O_{i,t+1}] + \theta_t(L_t - L_{y_1,t} - L_{y_2,t} - L_{o_1,t} - L_{o_2,t}) \\
& + \phi_t(K_t - K_{1,t} - K_{2,t})
\end{aligned}$$

From the first order conditions of the planner's problem,[11] it can be shown that the household

[11] Specified in the appendix.

always consumes a fixed proportion S_c of the final goods produced each period:

$$S_c = 1 - \frac{\beta\delta(\gamma_1 a_1 + \gamma_2 a_2)}{1-\beta(1-\delta)}$$

1.3.3 Comparative Statics

In this section I show that structural change in static equilibrium can be produced either (1) by altering the intangible investment-specific productivity growth, g_{B_i}, or (2) by changing the sectoral production structures, i.e., changing a_i and b_i in the sectoral goods production functions.

First, note that the Euler equation for intangible capital accumulation in each sector can be written as

$$\frac{(1-a_{it}-b_{it})L_{o_i,t}^{1-d}}{dB_{it}O_{i,t}^{1-d}L_{y_i,t}} = \frac{\beta(1-\varphi)(1-a_{i,t+1}-b_{i,t+1})L_{o_i,t+1}^{1-d}}{dB_{i,t+1}O_{i,t+1}^{1-d}L_{y_i,t+1}} + \frac{\beta(1-d)(1-a_{i,t+1}-b_{i,t+1})L_{o_i,t+1}}{dO_{i,t+1}L_{y_i,t+1}} + \frac{\beta b_{i,t+1}}{O_{i,t+1}} \tag{1.10}$$

In the steady state, $O_i = \frac{B_i L_{o_i}^d}{(g_{B_i}+\varphi)^{1/d}}$. Equation 1.10 can thus be written as

$$\frac{(1-a_i-b_i)}{d\left(g_{B_i}+\varphi\right)L_{y_i}} = \frac{\beta(1-\varphi)\left(1-a_i-b_i\right)}{d(1+g_{B_i})\left(g_{B_i}+\varphi\right)L_{y_i}} + \frac{\beta(1-d)\left(1-a_i-b_i\right)}{d(1+g_{B_i})L_{y_i}} + \frac{\beta b_i}{(1+g_{B_i})L_{o_i}}$$

from which we can calculate the labor allocation within sector i:

$$\frac{L_{o_i}}{L_{y_i}} = \frac{\beta b_i d\left(g_{B_i}+\varphi\right)}{\left(1-a_i-b_i\right)\left[(1+g_{B_i})(1-\beta)+\beta d(g_{B_i}+\varphi)\right]} \tag{1.11}$$

Then it is easy to determine the factors that can affect the within-sector labor allocation:

Proposition 1 *In the static equilibrium,*

$$\frac{\partial\left(L_{o_i}/L_{y_i}\right)}{\partial b_i} > 0, \frac{\partial\left(L_{o_i}/L_{y_i}\right)}{\partial g_{B_i}} > 0, and \frac{\partial^2\left(L_{o_i}/L_{y_i}\right)}{\partial g_{B_i}\partial b_i} > 0.$$

In other words, increases in b_i and g_{B_i} can both lead to a shift in labor allocation from direct goods production to intangible capital investment. And the effects of the two parameters can reinforce each other.

Proof. Taking derivative of Equation 1.11 with respect to b_i and g_{B_i}. ■

Sector i's intangible investment cost at time t is $q_{it}X_{it}$. The steady state intangible investment intensity is also a function of b_i and g_{B_i}:

Proposition 2 *The steady-state intangible investment cost to output ratio in sector i can be written as*

$$\frac{q_i X_i}{p_i Y_i} = \frac{\beta b_i \left(g_{B_i} + \varphi\right)}{(1 + g_{B_i})(1 - \beta) + \beta d(g_{B_i} + \varphi)}, \tag{1.12}$$

which is an increasing function of b_i *and* g_{B_i}.

Proof. *Equation 1.12 can be derived from combining Equation 1.9, 1.6, and Equation 1.11. Then simply take derivative of Equation 1.12 with respect to* b_i *and* g_{B_i}. ■

According to Proposition 1 and 2, the considerable increase in intangible investment/output ratios since the 1950s, and the shift of employment towards knowledge work suggest that either the importance of intangible capital has increased in the production functions (increasing b_i), or the intangible investments have become more efficient(increasing g_{B_i}), or both, if we assume that d and φ are relatively constant over time. Section 1.4 will explore these possibilities through calibration and simulation.

Notice that the employment of sector i is the sum of direct production labor and intangible investment labor:

$$L_i = L_{y_i} + L_{o_i}.$$

The following proposition describes how the economy's sectoral composition of employment changes with the importance of intangible capital in the production functions and with the productivity of intangible investment:

Proposition 3 *In the steady state,*

$$\frac{\partial (L_1/L_2)}{\partial g_{B_1}} > 0, \; \frac{\partial (L_1/L_2)}{\partial g_{B_2}} < 0; \tag{1.13}$$

When $g_{B_1} = g_{B_2} = g_B$,

$$\frac{\partial (L_1/L_2)}{\partial g_B} > 0, \; \textit{if} \; \frac{b_1}{b_2} > \frac{1 - a_1}{1 - a_2}. \tag{1.14}$$

and

$$\frac{\partial(L_1/L_2)}{\partial b_1} > 0, \text{ if } \frac{\partial a_1}{\partial b_1} < \frac{-(1-\beta)(1+g_B)}{(1-\beta)(1+g_B)+\beta d(g_B+\varphi)}; \tag{1.15}$$

Proof. The proof for Proposition 3 is included in the appendix. ■

Equation 1.15 says that sector 1's employment share will increase as intangible capital becomes more important in sector 1's production function, provided that intangible capital is at least to some extent physical capital substituting. Equation 1.13 and 1.14 state that sector 1's employment share will increase when sector 1's efficiency of intangible investment improves faster relative to the other sector. And when intangible investment productivity grows at the same rate for the whole economy, sector 1's employment share is likely to increase with the intangible productivity growth if sector 1 is more capital intensive in either type or both types of capital than the other sector.

The propositions in this section give directions for generating structural changes in the model economy. Before we calibrate the changes in parameters and simulate the model, it is helpful to look at the long-run feature of the economy when the production structure is constant, as will be described in the next section.

1.3.4 Balanced Growth (when production structures do not change)

To examine the long-run growth path of the economy, let's assume for now that the factor shares in the production functions are constant. The economy in the long run can thus be characterized as a balanced growth path, where consumption, physical capital and final output grow at a constant rate, while the output shares of the two sectors can keep shifting.

First, the intangible investment productivities B_i grow at the exogenous rates g_{B_i}. From the resource constraint (1.4) and physical capital accumulation rule (1.2) it is easy to see that Y, C, I, K have to grow at the same rate. Let's denote the rate as g_y. On the other hand, from intangible capital accumulation equation (1.3) it follows that O_i grows at rate g_{o_i}, which satisfies

$$(1+g_{o_i}) = (1+g_{B_i})^d$$

The final goods production function (1.1) implies that

$$(1+g_y) = (1+g_y)^{a_1\gamma_1+a_2\gamma_2}(1+g_{o_1})^{b_1\gamma_1}(1+g_{o_2})^{b_2\gamma_2}$$

Therefore, on the balanced growth path the growth rate of the final output is determined by the intangible investment productivity growth of both sectors:

$$1+g_y = (1+g_{B_1})^{\frac{db_1\gamma_1}{1-a_1\gamma_1-a_2\gamma_2}}(1+g_{B_2})^{\frac{db_2\gamma_2}{1-a_1\gamma_1-a_2\gamma_2}}$$

Let the ratio between the two sectoral outputs be $\phi_t = \frac{Y_{1t}}{Y_{2t}}$. If the two sectors share the same intangible investment productivity growth rate: $g_{B_1} = g_{B_2} = g_B$, then the growth rate of ϕ, g_ϕ, can be expressed as

$$1+g_\phi = \frac{\phi_{t+1}}{\phi_t} = (1+g_B)^{\frac{db_1(1-a_2)-db_2(1-a_1)}{1-a_1\gamma_1-a_2\gamma_2}} \tag{1.16}$$

Therefore, the long-run output composition of the economy is determined by g_B and different factors' shares in the two sectors' production functions:

Proposition 4 *Let $g_B > 0$. Sector 1's real output share $\frac{\phi_t}{1+\phi_t}$ approaches 1 asymptotically: $lim_{t\to\infty}\frac{\phi_t}{1+\phi_t} = 1$, if $\frac{b_1}{b_2} > \frac{1-a_1}{1-a_2}$.*

Proof. *$\frac{b_1}{b_2} > \frac{1-a_1}{1-a_2}$ implies that g_ϕ is positive. The rest of result is straightforward.* ■

In other words, the sector that is more intensive in either type of capital, or in both, is going to be the expanding sector in terms of its real output share, provided that g_B is positive. However, the amount of labor allocated to each production activity always remains constant on the balanced growth path. Therefore, there will be no employment composition change in this economy without changes in production parameters. The goal of the next section is thus to investigate whether the model can generate more realistic structural change through calibrated production structure changes.

1.4 Calibration and Simulation

In this section I assign parameter values to the model, simulate the model, and compare the results to the empirical data in sectoral composition change, trend of intangible investments, occupational composition change and trend in sectoral labor productivity growth. The section proceeds in the following steps: (1) describing in details the method of sector categorization in the data; (2) discussing the calibration strategy and parameter choices; (3) presenting baseline simulation results; (4) presenting sensitivity check results.

1.4.1 Sector Categorization

First, the two sectors, as presented in figure 1.1, are constructed as follows. The industry output and employment data is from BEA and intangible investment data from COMPUSTAT North America. I divide SIC two-digit industries into two sectors, that of high and low intangible-capital intensities. Following the recent empirical accounting literature,[12] I use firms' "sales, general & administrative expenditure" (SG&A) as an approximation of firms' intangible capital investment. Intangible capital intensity is measured by SG&A expenditure to sales ratio for a firm, and by the within-industry median SG&A/sales ratio, for an industry. Industries are then ranked and assigned into two sectors according to the their average intangible-capital intensity from 1950 to 1997.[13] The publicly-traded firms contribute to, on average, over 50% of total business sector output.

Table 1.2a-b list the sector categorization for SIC two-digit industries and their intangible capital intensities. One thing to notice is that service industries concentrate more in the high intangible capital sector. The theory of this chapter can thus help to explain the expansion of service industries over goods-producing industries in recent decades. Section 1.6 will discuss service sector's rise in more details.

[12] See Section 1.5.2.

[13] Note that since firms' financial data are taken from COMPUSTAT, it only includes publicly-traded companies and may bias towards large firms. If large firms tend to invest more in intangible assets than their smaller peers, it can inflate the measure of intangible capital intensity. However, since this bias exist in both sectors, and it is mainly the relative scale of intangible intensity between sectors that affect the simulation results, for the purpose of our simulation exercise, the impact of this bias should be negligible.

Industry	Sector	intangible capital intensity
Coal mining	Low	0.063
Primary metal	Low	0.080
Textile mill products	Low	0.101
Petroleum refining	Low	0.102
Water transportation	Low	0.104
Nonmetallic minerals	Low	0.105
Motor freight transportation and warehousing	Low	0.105
Construction	Low	0.110
Paper and allied products	Low	0.114
Transportation equipment	Low	0.115
Railroad transportation	Low	0.121
Metal Mining	Low	0.123
Stone, clay, glass and concrete products	Low	0.128
Transportation services	Low	0.135
Electric, gas and sanitary services	Low	0.139
Lumber and wood products	Low	0.140
Insurance carriers	Low	0.141
Agriculture	Low	0.146
Wholesale trade	Low	0.147
Air transportation	Low	0.149
Fabricated metal	Low	0.159
Rubber and plastics	Low	0.161
Oil and gas extraction	Low	0.167
Amusement and recreation services	Low	0.169
Hotels and lodging places	Low	0.172
Holding and other investment offices	Low	0.175

Table 1.2a: Sector categorization by intangible capital intensity (1950-1997): low intangible sector

Industry	Sector	intangible capital intensity
Automotive repair and services	High	0.176
Furniture and fixtures	High	0.179
Apparel and fabrics	High	0.186
Food products	High	0.192
Electronics	High	0.203
Health services	High	0.206
Motion pictures	High	0.207
Leather and leather products	High	0.209
Machinery and computer equipment	High	0.214
Retail trade	High	0.224
Miscellaneous manufacturing	High	0.226
Communications	High	0.230
Real estate	High	0.234
Engineering, accounting, research & management	High	0.238
Tobacco products	High	0.239
Personal services	High	0.241
Non-depository institutions	High	0.246
Local and suburban transit	High	0.250
Depository institutions	High	0.253
Security and commodity brokers	High	0.261
Measuring, analyzing and controlling instruments	High	0.275
Printing, publishing and allied industries	High	0.281
Chemicals and allied products	High	0.284
Business Services	High	0.284
Insurance agents, brokers and service	High	0.306
Miscellaneous repairs	High	0.315
Educational services	High	0.417

Table 1.2b: Sector categorization by intangible capital intensity: high intangible sector

1.4.2 Calibration Strategy and Parameters

According to Proposition 3, sector i's employment share increases when b_i is higher, i.e., when intangible capital becomes more important in the sectoral production function. As the model simulation will show, sector i's output level will also shift with changes in b_i. Thus by tracking the changes in b_i for the two sectors over time, we can produce sectoral composition changes in the model.[14]

To calibrate b_i, intangible capital's share in the sectoral production functions, recall from Equa-

[14] Proposition 3 also states that the employment composition of the economy would change with the productivity growth rate of intangible investment, g_B. Thus I also experimented calibration with changing g_B. However, the simulation results show that the magnitude of structural change generated through that approach is too small to match the real data. Thus it seems that the impact of changing intangible investment efficiency on sectoral composition is a minor one. The results are not reported here and are available upon request.

tion 1.12 that in the steady state,

$$b_i = \frac{q_i X_i}{p_i Y_i} \frac{(1 + g_{B_i})(1 - \beta) + \beta d(g + \varphi)}{\beta (g_{B_i} + \varphi)} \tag{1.17}$$

where $\frac{q_i X_i}{p_i Y_i}$ is the intangible investment to output ratio of sector i; the rest of the RHS variables are predetermined parameters. With Equation 1.17, we can infer the values and changes of b_1 and b_2 for each year from the time series of $\frac{q_i X_i}{p_i Y_i}$, using the sectors' SG&A/Sales ratios as the intangible investment to output ratios. Note that since Equation 1.17 describes a steady state relationship, the time-series of b_i calculated in this way are only approximation of the "true" values. Fortunately, since the changes in $\frac{q_i X_i}{p_i Y_i}$ are incremental each year, the calibrated b_is turn out reasonably close to the real values – as the simulation result will show, the gaps between the real intangible investment to output ratios and the simulated series are quite small.

Table 1.3 presents the summary statistics of the calibrated b_i.

	Mean	Std . Dev.	Min	Max
$b_{1,t}$	0.189	0.074	0.057	0.285
$b_{2,t}$	0.103	0.037	0.038	0.153

Table 1.3: Summary Statistics for calibrated b

The values of physical capital's shares in the sectoral production functions, a_1 and a_2, are set to evolve according to the following rule:

$$a_{i,t} = a_{i,t_0} - \tau_i (b_{i,t} - b_{i,t_0}); \qquad t_0 \leq t \leq T$$

where τ_1 and τ_2 are set at 1 and 0.5 respectively in the baseline simulation. The initial year t_0 corresponds to Year 1950 in real data, when COMPUSTAT data was first available. The initial values of a_1 and a_2, and the two sectors' shares in the final goods production function, γ_1 and γ_2, are chosen so that the output and employment shares of the two sectors are of similar scales to those in the data. This leads to $\gamma_1 = 0.65$, $\gamma_2 = 0.35$, $a_{1,t_0} = 0.6 - b_{1,t_0}$, and $a_{2,t_0} = 0.45 - b_{2,t_0}$.

The labor supply is fixed at unity throughout the simulaiton. The growth rate of intangible investment productivity g_B is set at zero, to diffrentiate the impact of production structure change on sectoral composition from the impact of intangible investment productivity change. The rest of the parameters that need to be decided are the following: $\{\beta, d, \delta, \varphi\}$. Physical capital's depreciation rate is set at the standard value $\delta = 0.08$. The depreciation rate of intangible capital is harder to estimate and may differ across categories of intangibles. Following related literature,[15] I choose $\varphi = 0.5$. d, labor's share in the intangible capital investment function, is set at 0.9 for both sectors in the baseline simulation. The following table provides a summary of the chosen parameter values:

β	γ_1	γ_2	δ	φ	d	$\overline{L}$	g_B	τ_1	τ_2
0.96	0.65	0.35	0.08	0.5	0.9	1	0	1	0.5

1.4.3 Simulation of the Model

The following assumptions are made in computing the model: (1) the economy is at an original steady state before period t_0, with factor shares in the production functions constant and equal to those at t_0; (2) the economy is at a new steady state after period T, with factor shares constant and equal to those at time T; (3) at t_0, the agents have complete information about the current values and future changes of factor shares in the production functions. The time paths of all variables are solved by computing the numerical solution to the system of first order conditions from t_0 to T. t_0 and T are set to be the beginning and ending year of the data sample: 1950 and 1997 respectively.

[15] For example, Corrado et al (2006) uses the following depreciation schedules: 33% for computerized information, 20% for R&D, 60% for brand equity, 40% for firms' structural resources.

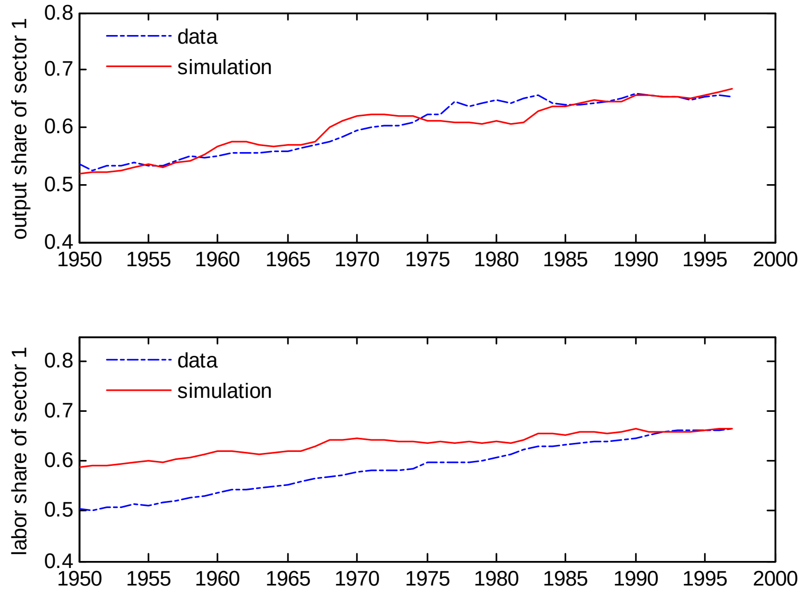

Figure 1.4: Sectoral composition change

Figure 1.4 reports the simulation results for the output and employment shares of sector 1, which is assumed to be the intangible capital intensive sector, in the 48 year time span. For comparison, the empirical data is plotted in the same graphs. Again, the shares of sector 1 in both output and employment have increased significantly during the period. In the model, sector 1's output share increased 28%, from 0.52 to 0.67, compared to 22% in the data, from 0.54 to 0.65. On the employment side, the share of sector 1 rose 13%, from 0.59 in the beginning period to 0.67 in the ending period, compared to 32% in the data, from 0.5 to 0.66.

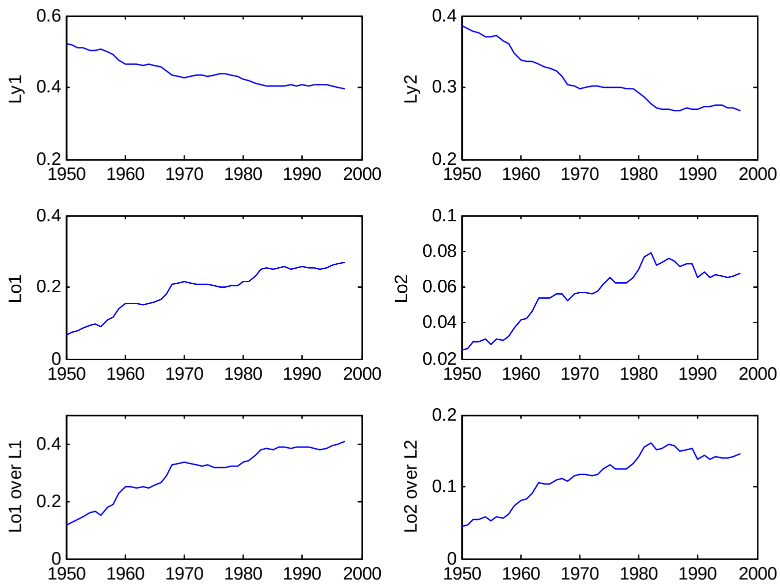

Figure 1.5: Within-sector labor allocation

Since the ratio of workers engaged in direct goods production between the two sectors – L_{y_1}/L_{y_2} – is constant, the increase in sector 1's share of employment is primarily driven by the fact that more labor is allocated to intangible investment activities. Figure 1.5 presents the trend of labor allocation between direct goods production and intangible capital investment in the two sectors. Over time in both sectors labor is shifted from producing sectoral goods to producing intangible capital. But this shift is of a larger magnitude in sector 1, where intangible capital is always more important in the production function. Sector 1's employment share increases as a result.

This mechanism of structural change through shifting work activities is one innovation of the chapter compared to earlier structural change literature. It is also consistent with the stylized fact of changing occupational composition of the economy towards intangible investment related work, as described in the introduction section. Table 1.4 reports the share of total labor allocated to intangible investment in the model, calculated as $(L_{o_1} + L_{o_2})/\overline{L}$, for year 1950, 1970 and 1997. As a comparison, the total employment shares of the three intangible investment related occupation groups in the US, as presented in Figure 1.2[16], are also listed Again, the shares of these professions give a suggestive estimate for the trend of intangible investment labor's share in the total labor

[16] Again, the three occupational groups are: science, engineering and artistical professionals, management professionals, and sales, clerical and information processing professionals. The number for Year 1997 is extrapolated from the data in 1990 and 2000.

force. The message of Table 1.4 is that as in the data, the model produces increasing share of intangible investment labor. But the magnitude of increase is higher than the data.

	Labor engaged in intangible investment activities as a proportion of total employment (%)		
	1950	1970	1997
Data	12.18	19.37	24.90
Model	9.25	27.29	33.64

Table 1.4: Shares of intangible investment labor

Next I look at the labor productivity growth in the two sectors. The first row of Table 1.5 lists the average annual growth rate of labor productivity for the two sectors – calculated as sectoral real output divided by total hours worked – in the data from 1951 to 1997. As mentioned in Section 1, the key characteristics of the data are the following. First, for the earlier sub-period (1951-1973), the high-intangible sector has a higher labor productivity growth than the low-intangible sector, while the opposite is true for the second sub-period (1974-1997). On average, the productivity growth of the high intangible sector is lower than the other sector. Second, both sectors' productivity growth is lower in the second sub-period than in the first, and this drop is more significant in the high intangible sector than in the low intangible sector.

These facts are mostly captured in the model. The second row of Table 1.5 reports the simulated productivity growth of the two sectors. Matching the productivity measure in the data, here labor productivity in sector i is calculated as sectoral output over total employment in the sector, $Y_i / (L_{y_i} + L_{o_i})$. As in the data, the high intangible sector has higher productivity growth than the other sector in the first sub-period. Both sectors' productivity growth declined in the second sub-period. And the decline is greater in the high intangible sector than in the low intangible sector. But in contrast to the data, due to the fact that the decrease of high intangible sector's productivity growth is less dramatic in the model, when the entire sample period is counted, the high intangible sector's productivity growth is still higher than the other sector.

Another thing to note is that in the present model's framework, the ratio $Y_i / (L_{y_i} + L_{o_i})$, which is the counterpart of "labor productivity" in the data, is in fact not the "true" labor productivity in sectoral goods production. Because the sectoral employment includes L_{o_i}, which is not used in producing Y_i. And the true labor productivity in producing sectoral goods should be Y_i/L_{y_i}. The third row of Table 1.5 calculated the growth rate of the labor productivity calculated this way. For both sectors, the true labor productivity growth is higher than those calculated in the standard way. However, due to the limited information we can get from the currently available employment data, it is not yet possible to seperate L_{o_i} from L_{y_i} and calculate the true labor productivity in the real economy.

	Annual labor productivity growth (%)					
	High intangible sector			Low intangible sector		
	1951-1973	1974-1997	1951-1997	1951-1973	1974-1997	1951-1997
Data: $Y_i / (L_{yi} + L_{oi})$	2.92	-0.94	0.95	2.16	0.72	1.43
Model: $Y_i / (L_{yi} + L_{oi})$	2.47	1.67	2.06	1.65	1.26	1.45
Model: Y_i / L_{yi}	3.63	2.21	2.91	2.14	1.47	1.80

Table 1.5: Labor productivity growth of the two sectors

Figure 1.6 reports the simulated intangible investment to output ratios in the two sectors, and compared them to the SG&A/Sales ratios in the data. Not surprisingly, the simulated intangible investment intensity rises in both sectors. And the gaps between the simulated series and the real data are fairly small: 0.0013 per period for sector 1 and 0.0006 per period for sector 2.

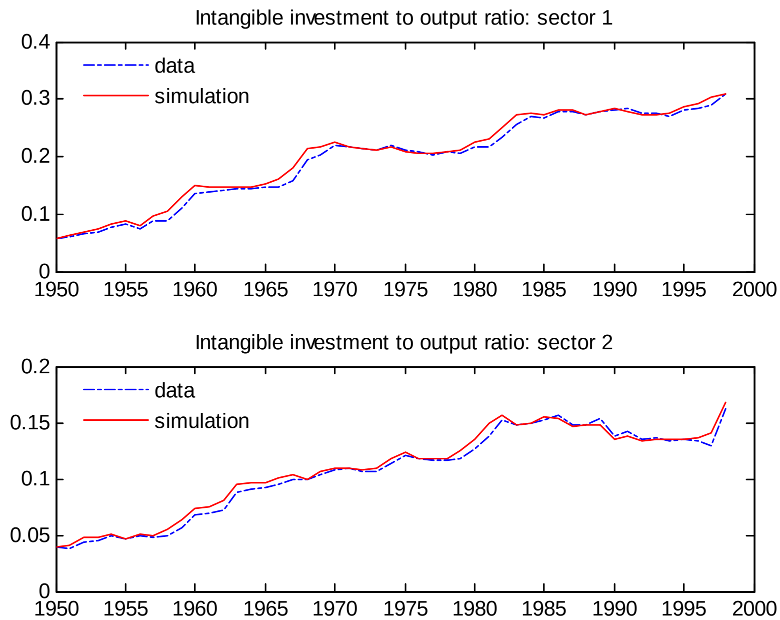

Figure 1.6: Intangible investment to output ratios

Overall, the calibration results show that the model is capable of reproducing the following stylized facts in the data: (1) increasing real output and employment shares of the high intangible sector; (2) shifts in employment composition towards intangible investment activities; (3) increasing intangible capital investment intensities in both sectors; (4) decreasing labor productivity growth in both sectors, and a larger decrease in the high intangible sector. In terms of the magnitude of sectoral composition change, the simulated output share increase of the high intangible sector is slightly higher than that in the data, and the magnitude of employment share increase is about 50% of the data.

1.4.4 Sensitivity Analysis

Certain parameters in the baseline calibration were chosen fairly subjectively due to lack of information in the real data regarding their values. In this section I conduct sensitivity analyses to check how variations in these parameters might influence the simulation results. The parameters I focus on are: (1) the depreciation rate of intangible capital, φ, (2) the share of labor in intangible investment goods production function, d, and (3) the extend to which intangible capital substitutes for physical capital when its shares in the sectoral production functions increase, τ_i.

Table 1.6 reports the percentage growth of sector 1's real output and employment shares with alternative choices of parameters φ, d, and τ_2. Table 1.7 and 1.8 list the corresponding results of the changes in total intangible investment labor share and the two sectors' annual labor productivity growths respectively.

Let's look at the information in these tables parameter by parameter. Column 3 and 4 of Table 1.6 and Table 1.7 report structural change results when $\varphi = 0.25$ and when $\varphi = 0.75$. The results indicates that when the depreciation rate of intangible capital is higher, the intangible intensive sector expands less in terms of both output and employment. Meanwhile the share of L_o in total employment is slightly lower when the depreciation rate is higher. The intuition of the results is the following: when the intangible capital depreciates slower, the future payoff of current period investment is higher. This encourages more intangible investment. Therefore, L_{o_i} is higher in both sectors, and more so in sector 1, where intangibles are more important. And the larger increase in L_{o_1} drives up the employment share of sector 1 much like before, but to a greater extent. Slower depreciation also increases the stocks of O_i, and raises the relative output of sector 1 higher as intangible capital has a higher share in sector 1's production function.

	Data	Baseline	φ = 0.25	φ = 0.75	d = 0.7	d = 0.4	τ_2 = 1	τ_2 = 0.3
Sector 1's output share change (%)	21.80	28.08	32.51	25.68	24.05	17.58	22.74	30.18
Sector 1's employment share change (%)	31.81	12.78	12.94	12.64	10.69	7.38	10.06	13.91

Table 1.6: Sector 1's share changes with alternative parameters

Column 5 and 6 of Table 1.6 and Table 1.7 report structural change results when $d = 0.7$ and when $d = 0.4$. When current period labor input is more important in intangible investment goods production (higher d), sector 1's output and employment shares both increase more, and the share of L_o in the total labor force is also higher. The result can be understood as follows. When the production of intangible investment goods is less dependent on current stock of O_i, and more dependent on current labor input level, the stock of O_i can increase faster corresponding to the increases in b_i. The potential to make more swift adjustment in investment is to the advantage of sector 1, as O_1 has a higher share in the sectoral production function. It also encourages labor to be shifted to L_{o_i} in both sectors.

	Labor engaged in intangible investment activities as a proportion of total employment (%)							
	Data	Baseline	$\varphi = 0.25$	$\varphi = 0.75$	d = 0.7	d = 0.4	$\tau_2 = 1$	$\tau_2 = 0.3$
1950	12.18	9.25	9.25	9.25	7.34	4.33	9.25	9.25
1997	24.90	33.64	34.50	33.06	28.44	19.05	32.85	33.97

Table 1.7: Share of labor engaged in intangible investment activities: alternative parameter values

Column 6 and 7 of Table 1.6 and 1.7 report results when $\tau_2 = 1$ and when $\tau_2 = 0.3$.[17] From the results we can see that the lower τ_2 is relative to τ_1, the larger is the expansion of sector 1. And the intangible investment labor's share in total labor force is also larger. The reason is that if intangible capital's share increases in sector 2's production function without eroding much the share of L_{y_2} (i.e., τ_2 is high), then the level of L_{y_2} will not decline much while the level of L_{o_2} increases, given the level of τ_1. Therefore on the whole, sector 2's labor share will be higher compared to the case when intangible capital substitutes for labor in sector 2's production function (low τ_2). On the other hand, when τ_2 is lower, more labor will be allocated to L_o, since L_{y_2} becomes less important in the production function as b_2 increases.

Overall, Table 1.6 and Table 1.7 shows that although parameter changes do bring about variations in the degree of structural change, the basic characteristics of the original simulation remain the same. Specifically, output and employment shares of sector 1 both rise over time, and the share of intangible investment labor increases. Generally, the change in output composition is more sensitive to parameter values than the employment composition. But no matter how the parameters change, compared to data, the model produces a higher increase in sector 1's output share, and a lower increase in its employment share

[17] The simulation results not reported here show that it is fundamentally the difference between τ_1 and τ_2 that impacts the magnitude of sectoral composition change. So for the sake of simplicity, I keep τ_1 unchanged (equal to 1).

	Annual labor productivity growth (%)					
	High intangible sector			Low intangible sector		
	1951-1973	1974-1997	1951-1997	1951-1973	1974-1997	1951-1997
Data	2.92	-0.94	0.95	2.16	0.72	1.43
Baseline	2.47	1.67	2.06	1.65	1.26	1.45
$\varphi = 0.25$	3.25	2.13	2.68	2.07	1.58	1.82
$\varphi = 0.75$	2.08	1.46	1.76	1.44	1.11	1.27
d = 0.7	2.13	1.56	1.84	1.48	1.15	1.31
d = 0.4	1.73	1.42	1.57	1.31	1.04	1.17
$\tau_2 = 1$	2.60	1.72	2.15	2.01	1.30	1.65
$\tau_2 = 0.3$	2.42	1.66	2.03	1.51	1.25	1.37

Table 1.8: Productivity growth with alternative parameters

Table 1.8 reports the changes in labor productivity growth for both sectors with alternative parameter values. The message in Table 1.8 is, again, that the simulation results are fairly stable with respect to parameter changes. The 3rd and 4th rows of Table 1.8 report productivity growth results with variations in φ. When intangible capital depreciates slower, both sectors' labor productivity growths are higher. The 5th and 6th rows display productivity growth results with changes in d. When intangible investment relies more on current period input, thus more adjustable, both sectors have higher productivity growth. Finally, the 7th and 8th rows show that when τ_i is higher, that is, when intangible capital substitutes for physical capital instead of labor in the sectoral production function, both sectors' productivity growths are higher. In general, the characteristics of the baseline simulation remain present when parameter values change. Specifically, the productivity growth in the second sub-period is lower than in the first sub-period for both sectors, and sector 1's productivity growth declines more than that of sector 2.

1.5 Empirical Analysis

1.5.1 Overview

A central message from the theoretical section of the chapter is that there is a close linkage between intangible capital intensity and sectoral output/employment growth in US economy for the past half century. Figure 1.1 already demonstrated this trend in data at a broad, two-sector level. In this section, using industry and firm data, I check whether the implication of the model also holds at more disaggregate levels. The purpose is twofold: first is to examine the universality of the model's prediction; and second is to provide a more micro level foundation for the secotral composition change depicted in Figure 1.1.

The section consists of two empirical exercises. The first one looks at industry-level data, and asks whether there is a positive linkage between industries' intangible capital intensity and their output and employment growth. Thus the exercise can partly be seen as a disaggregate counterpart of Figure 1.1. An important difference is that here I control for other industry characterisitcs that can potentially affect the structural change process, so as to differentiate the intangible capital effect on growth from other factors.

The second exercise examines the relationship between intangible capital intensity and growth at firm level, and asks whether firms' intangible investment intensity affects firm growth, and whether such an effect translates into growth differentials across industries. Together, these two exercises provide comprehensive tests of the chapter's thesis and offer a more detailed view about the relationship between the rise of intangible capital and the structural change of sectoral/industrial composition in the economy.

1.5.2 Data

The current accounting rules only allow companies to directly recognize a small part of the actual intangible capital as "assets" on their balance sheets. Most of the investments in intangible capital are expensed in firms' Sales, General & Administrative expenditure (SG&A), which includes R&D cost, marketing expenses, management fees, software expenditures, etc. Therefore, recent empirical accounting literature have used SG&A expenditure as approximation for firms' intangible investment (e.g., Lev & Radhakrishnan (2005), Banker, Huang & Natarajan (2006), Eisfeldt & Papanikolaou (2009)). The present research follows this practice. However, since SG&A is not a precise measure of firms' intangible investment, the related regression estimates should be seen as suggestive to the signs and magnitudes of the "true" coefficients. Four data sources are used in the empirical regressions: (1) COMPUSTAT North America, which contains publicly-traded firms' financial statement information, including SG&A expenditure, number of employees, annual sales, total assets, physical capital investment, etc.; (2) BEA annual industry accounts data with information of industries' value-added, price, and employment by SIC two-digit classification; (3) BLS data of capital income and IT investment by industry; and (4) Education level of industry labor force from Current Population Survey. I select data with consistent industry classification from 1950 to 1997 at industry level, and from 1950 to 2007 at firm level. The summary statistics for the key variables at both levels are presented in Table 1.9.

	Mean	Std	Min	Max
	Firm level variables			
Sales ($mn)	1235.036	7073.271	0.009	375376
Employee (thousand)	8.500	32.890	0.001	2100
SG&A expenditure ($mn)	222.047	1196.523	0.002	70297
Physical capital investment ($mn)	85.020	603.041	0.001	40595.290
R&D expenditure ($mn)	53.643	341.054	0.000	12183
Total assets ($mn)	1722.129	24764.370	0.002	3771200
SG&A/sales	0.321	0.529	0.000	9.936
Physical capital investment/sales	0.098	0.309	0.000	9.838
Annual sales growth rate	0.098	0.367	-6.177	7.215
Annual employee growth rate	0.031	0.347	-6.321	7.255
	Industry level variables			
Annual real output share growth	-0.001	0.151	-2.387	2.158
Annual employment share growth	-0.006	0.052	-0.917	0.462
Real output share	0.018	0.026	0.0003	0.158
Employment share	0.018	0.028	0.0002	0.203
Industry SG&A/sales	0.181	0.096	0.000	0.694
Share of college-educated workers	0.345	0.187	0.014	0.878
IT investment/output	0.001	0.003	0.000	0.040
Capital income's share in value-added	0.397	0.193	0.004	0.963

Table 1.9: Summary statistics

1.5.3 Industry Level Estimation

Estimation Model

Applying the prediction of the theoretical model at the industry level, I test the following hypothesis: an industry's real output and employment growths are higher when it is more intangible capital intensive. The calibration section has shown that intangible capital's share in the production function is increasing with the intangible investment to output ratio. Thus our hypothesis can be tested by regressing industry output/employment share growth on industry's intangible investment to output level.

Specifically, I estimate the following equation:

$$\Delta \ln y_{j,t} = a_0 + a_1 INTAN_{j,t-s} + a_2 K_{j,t-s} + a_3 EDU_{j,t-s} + a_4 IT_{j,t-s} + a_5 \ln y_{j,t-s} + a_6 \Delta \ln y_{j,t-1} + \upsilon_{j,t} \tag{1.18}$$

where $\Delta \ln y_{j,t}$ can be either industry j's real output share growth or employment share growth from $t-s$ to t. $\ln y_{j,t-s}$ is the output share or employment share of industry j at $t-s$. $INTAN_j$ is industry j's intangible investment to output ratio, approximated by the median level SG&A expenditure/sales ratio of the industry. As before, $INTAN_{j,t}$ is increasing with intangible capital's share in industry j's production function at time t.

Various other industry characteristics may contribute to the growth differentials across industries. Therefore, I include other industry variables in Equation 1.18 as controls. These variables are chosen according to related literature on structural change and productivity growth, as outlined in the literature review section. They include: K_j, physical capital intensity of industry j, measured by capital income's share in industry value added; EDU_j, human capital intensity of industry j, calculated as the number of workers who received at least some college education as percentage of the total industry workforce; IT_j: the intensity of information technology investment in industry j, calculated as the ratio of industry IT investment to industry value-added.

As some of the above industry characteristics are not stationary over time[18], and we are mostly interested in the impact of the cross-industry differences in these explanatory variables, the standard scores of the above variables are used as regressors in the actual estimations.[19] Besides, given the fact that structural change is a slow process and changes in industry characteristics might not immediately translate into changes in industry growth, I set the baseline time lag s as 5 years. As a robustness check, I also estimated the model with $s = 3$ and $s = 10$.

The error term of Equation 1.18, $\upsilon_{j,t}$, contains an industry fixed effect and an observation specific error. Due to the fact that there is partial overlap between the dependent variables of adjacent time periods, a lagged dependent variable is included on the right hand side. This introduces correlation between the regressor and the error term. Therefore, I use the dynamic GMM estimator developed

[18] For example, industries' intangible capital, human capital and IT intensities have all been on the rise over the sample period.

[19] The standard score of variable z for industry i, $z_{it} = \frac{z_{it} - \overline{z}_t}{\sigma_{z_t}}$, where $\overline{z}_t$ is the mean of z at time t, and σ_{z_t} is the standard deviation of z.

by Arellano & Bond (1991) in regressing the model. The estimator also eliminates endogeneity that may be caused by any correlation between the unobserved industry-specific factor and other right hand side variables.

Industry Level Regression Results

Table 1.10 presents the results of industry level regressions.[20] Let's first look at the performance of the control variables for industry characteristics. The result for human capital intensity mostly confirms the prediction of Buera & Kaboski (2007): human capital has positive and significant impacts on industry's output and employment growth across all time windows. Similarly, the IT intensity variable is positively and significantly correlated with industry output share growth, which lends support to the argument advocating ICT as a general purpose technology and an important source of productivity growth. However, IT's impact on employment share growth is mixed, as the coefficient is positive and significant when $s = 3$, but turns negative and significant when $s = 5$ or 10. This result seems to indicate that ICT is likely be labor substituting in the medium and long run. For physical capital intensity, the coefficient is positive and significant in the output share growth regression except when $s = 3$, while the correlation between physical capital intensity and employment share growth is mostly negative. These results confirm the observation of Acemoglu & Guerrieri (2008), who found that since the 1950s, physical capital intensive industries' output shares have increased in the US and their employment shares decreased.

Now turn to the results for intangible capital. In the output share growth regression, the coefficients for lagged intangible capital intensity are all positive and significant except when $s = 10$, which is positive but not significant. In the employment share growth regressions, the coefficients for intangible capital intensity are all positive and significant. Quantitatively, the coefficients decrease as the time lag gets longer. And consistent with the simulation result, on average intangible capital intensity seems to have a larger impact on output share growth than on employment share growth.

Notice that all the diagnostics of the regression results are satisfactory. Specifically, the absence of 1st order serial correlation is rejected and the absence of 2nd order serial correlation is not rejected. Also the Hansen test for overidentification restrictions is not rejected. These results

[20] ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

indicate that the regression specification used here is an appropriate one.

Overall, the industry-level regression results suggest a strong positive correlation between intangible capital intensity and future industry growth. The impact of intangible capital on growth does not seem to be driven by other industry characteristics.

	Output share growth			Employment share growth		
	3 year window	5 year window	10 year window	3 year window	5 year window	10 year window
Intangible capital intensity	0.152***	0.028***	0.001	0.062***	0.013***	0.003***
	(0.019)	(0.003)	(0.002)	(0.009)	(0.002)	(0.000)
Human capital intensity	0.242***	0.034***	0.015***	0.126***	0.042***	0.001*
	(0.017)	(0.007)	(0.003)	(0.010)	(0.006)	(0.000)
IT intensity	0.280***	0.046***	0.033***	0.033***	-0.011**	-0.003***
	(0.013)	(0.004)	(0.003)	(0.008)	(0.005)	(0.000)
Physical capital intensity	-0.025**	0.010***	0.004**	-0.010	-0.001	-0.001***
	(0.011)	(0.002)	(0.002)	(0.008)	(0.002)	(0.000)
Output / employment size	-0.826***	-0.172***	-0.079***	-0.409***	-0.090***	-0.015***
	(0.013)	(0.005)	(0.002)	(0.025)	(0.003)	(0.001)
N	1543	1439	1179	1543	1439	1179
AR 1 test (p-value)	-2.89	-3.03	-2.89	-2.47	-2.86	-3.04
	(0.004)	(0.002)	(0.004)	(0.013)	(0.004)	(0.002)
AR 2 test (p-value)	-0.88	-1.63	-0.07	0.1	-1.59	-0.34
	(0.381)	(0.102)	(0.944)	(0.924)	(0.113)	(0.734)
Hansen J test (p-value)	33.96	33.08	23.37	31.09	36.04	46.26
	(0.241)	(0.194)	(0.381)	(0.361)	(0.114)	(0.379)

Table 1.10: Intangible capital intensity and industry growth

1.5.4 Firm Level Estimation

Estimation Model

The purpose of this section is to examine whether intangible capital investment also has an impact on the output and employment growth at firm level; and if so, whether the degree of such impact is related to differences in industry growth, which then leads to the aggregate-level structural change.

In a real economy, each sector or industry normally consists of multiple firms. And even for firms in the same industry, capital investment levels vary due to factors such as cross-firm differences in productivity and demand prospect. Assume that firms in the same industry share basically the same production structure in terms of different inputs' importances in the production function. Then it can be proved in the model that the same unit of intangible investment would have a more positive impact on firm growth for firms in the industries where intangible capital is more important in the production function.[21] At the same time, according to our theory these industries are also expected be the expanding industries. Therefore we can test the linkage between intangible capital intensity and industrial structure change from a more disaggregate perspective. Specifically, the hypothesis to test is the following: firms' intangible investment has a positive impact on firms' output and employment growth; and the industries in which firms' intangible investment has a higher impact are the expanding industries.

To test this hypothesis, I estimate the following equation:

$$\begin{aligned} g_{ij,t} &= \beta_0 + \beta_1 \left(\frac{SG\&A}{Sales}\right)_{ij,t-1} + \beta_2 \left(\frac{SG\&A}{Sales}\right)_{ij,t-1} \times grow_j + \beta_3 \left(\frac{I_k}{Sales}\right)_{ij,t-1} \\ &\quad + \beta_4 \left(\frac{I_k}{Sales}\right)_{ij,t-1} \times grow_j + \beta_5 grow_j + \beta_6 \text{control}_{ij,t-1} + u_{ij,t} \end{aligned} \tag{1.19}$$

where the dependent variable $g_{ij,t}$ is either the sales growth rate or the employment growth rate of firm i in industry j from $t-1$ to t; $\frac{SG\&A}{Sales}$ is firm's SG&A expenditure scaled by firm sales, which measures a firm's intangible investment level; $grow_j$ is the output share growth of industry j from 1950 to 1997.[22] To make sure that the coefficient for SG&A is not a substitute for the impact of other investments, and also to compare the effect of intangible capital on growth with that of physical capital investment, I include $\frac{I_k}{Sales}$, firm's physical capital investment scaled by sales, and its interaction with $grow_j$ as regressors. Since it is likely that firm growth is influenced by firm age and size, I include these factors as control variables. The former is approximated by the number of years a firm is listed on the stock market[23], and the latter by firms' sales and total assets at $t-1$. Other factors such as business cycle fluctuation and industry-specific factors can

[21] This proposition can be formally proved with the baseline model extended to allow for multiple firms in each sector. Since it is not essential to the paper's thesis, the extended model and proof are not included here and are available from the author upon request.

[22] I also estimated the model setting $grow_j$ as industry's employment share growth. The results are qualitatively similar.

[23] In the data, newly listed firms' SG&A are often much higher than the average level. This may be due to one-time expenditures related to changing firm status, which is not related to intangible investment. Thus in the estimation I only include firms that are listed for ≥ 5 year.

also affect firm growth. Thus the error term of Equation 1.19 contains firm and time fixed effects: $u_{ij,t} = \mu_{ij} + \varepsilon_t + v_{ij,t}$, where $v_{ij,t}$ is assumed to be i.i.d. across firms with mean 0 and variance σ_v^2.

From Equation 1.19, the impact of intangible investment on firm growth is

$$\frac{\partial g_{ij,t}}{\partial(SG\&A/Sales)_{ij,t-1}} = \beta_1 + \beta_2 grow_j$$

Again, if intangible capital plays any role in industry j's production process, firms' intangible investments are expected to have a positive impact on firm growth; and the degree of this impact is determined by the importance of intangible capital in industry j's production function. If industry j's long-run growth is positively affected by its intangible capital intensity, then β_2, the coefficient for the interaction term between intangible investment and industry output share growth, should be positive.

Firm Level Regression Results

Table 1.11 reports the regression results of Equation 1.19. The 1st column under each dependent variable heading reports the baseline results when intangible investment is taken as exogenous. The assumption of exogenous investment may be challenged if, for example, better growth opportunity of a firm leads to both higher current period investment and higher future growth. However, notice that the potential simultaneity will most likely only decrease the chance of finding a positive β_2.[24] Nevertheless, I estimated Equation 1.19 treating $\left(\frac{SG\&A}{Sales}\right)_{ij,t-1}$ as endogenous and using five-period lagged SG&A to Sales ratio as instrument. The result is reported in the 2nd column under each dependent variable heading. Finally, the 3rd and 6th column of Table 1.11 report results with physical capital investment level and its interaction with industry growth added as regressors.

[24] The reason is the following. A favorable exogenous shock to the future period will lead to increasing investment in the current period, if the firm foresees the shock, and higher future growth as well. In that case, the estimated coefficient for the intangible investment variable will be inflated. However, the shock will only downward bias the coefficient for the interaction term between intangible investment and industry growth, assuming the distribution of shocks is the same across industries. This is because that for the same level of shock, the firms in the growing, high intangible capital industries will choose to raise SG&A investment more than the firms in the low intangible industries, as intangible capital is a more important input for the former. Other things equal, that will lower the association between SG&A and growth for firms in the growing high intangible industries compared to firms in low intangible industries, thus works against our goal of finding a positive β_2.

	Sales Growth			Employment Growth		
	Baseline	IV	physical investment	Baseline	IV	physical investment
SG&A/Sales	0.033***	-0.019	0.033***	-0.058***	0.004	-0.059***
	(0.005)	(0.013)	(0.005)	(0.005)	(0.014)	(0.005)
(SG&A/Sales) × grow	0.036***	0.034**	0.038***	0.013**	0.047***	0.016**
	(0.005)	(0.014)	(0.005)	(0.006)	(0.014)	(0.006)
I_K/Sales			0.005***			0.000
			(0.001)			(0.001)
(I_K/Sales) × grow			-0.003**			-0.002
			(0.001)			(0.002)
age	-0.081***	-0.001***	-0.085***	-0.063***	-0.002***	-0.062***
	(0.008)	(0.000)	(0.009)	(0.010)	(0.000)	(0.011)
log(total asset)	0.262***	0.129***	0.260***	0.042***	0.035***	0.043***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
log(total revenue)	-0.385***	-0.133***	-0.382***	-0.143***	-0.034***	-0.144***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
r2	0.193	0.072	0.194	0.050	0.022	0.049
N	126470	106020	122763	115678	98580	113259

Table 1.11: Intangible investment, firm growth, and industry growth

Across all specifications, the interaction term between SG&A and industry growth is positive and significant at either 1% or 5% level. Treating intangible investment as endogenous does not significantly change the magnitude of the coefficient for the interaction term in the sales growth regression, and increases the value of the coefficient in the employment growth regression. Therefore, the results generally confirm the hypothesis that output growth is higher for industries in which intangible capital has a larger impact on firm growth. One way to perceive the magnitude of the cross-industry difference in intangible capital's significance is the following. The industry at the 20th percentile of output growth is "Primary Metal", while the industry at the 80th percentile is "Non-bank Credit Institutions". According to the estimates of β_1 and β_2 in the 3rd specification of the sales growth regression, the level and variation of intangible investment explains only 0.9 percent of the firm growth and cross-firm growth differentials in the Primary Metal industry, while intangible capital accounts for 10% of the level and variation of firm growth in the Credit

Institution industry.

Contrasting the results for intangible capital, the coefficient for the interaction term between physical capital investment and industry growth is negative and significant in the sales growth regression, and negative but insignificant in the employment growth regression. These results indicate that physical capital seems to have a decreasing impact on firm growth in the expanding industries.

Robustness Check

In this section, I conduct several robustness checks to test how sensitive the results of the baseline regression of Equation 1.19 are to additional restrictions. First, I check if the impact of intangible investment on firm growth is driven by the investment related to R&D. There is a long literature on the productivity-enhancing effect of research and development activities, which is probably the most widely recognized type of intangible capital investment. Since the knowledge assets accumulated through investment in R&D is part of a firm's intangible capital, it raises the concern of whether it is only the R&D-related part of SG&A expenditure that has an impact on firm growth. This question is ultimately about the robustness of the concept of intangible capital itself. Therefore to differentiate R&D's impact from that of other intangible investments, I augment Equation 1.19 with firms' R&D expenses over sales, and its interaction with industry output share growth.

Besides using IV, a second way to correct the endogeneity caused by unobserved exogenous factors is to explicitly include in the estimation equation variables that would capture these factors. Although a firm's growth potential is not directly observable, financial market data can often reveal valuable information about it. Specifically, assuming that different firms are faced with different growth opportunities and the information regarding future growth is reflected in the firm's current stock price, I add in Equation 1.19 a firm's average price to book ratio in year $t-1$ as a measure for the unobserved influences on the firm's future growth. The results with additional controls are presented in Table 1.12. Column 1 and 3 report regression results when R&D controls are added. The variable "R&D/Sales" and its interaction with industry share growth are positive and significant in the firm sales growth regression, which indicates that R&D does creates productive assets and R&D capital is more important in the expanding industries. However, neither of the two variables are significant in the employment growth regression. The lack of influence of R&D

on the employment composition is probably due to the fact that the R&D workforce is highly specialized and small in quantity. On the other hand, the signs and magnitudes of SG&A variables do not significantly change after adding R&D controls. Therefore, the baseline results do not seem to be driven by the R&D part of intangible capitals. The 2nd and 4th Columns of Table 1.12 present results with firm's price-to-book ratio added as control variable. The P/B ratio is positive and significant in both sales growth and employment growth regressions, suggesting that financial market data does incorporate information about firms' future growth prospect. In the sales growth regression, the intangible investment variable and its interaction with industry growth remain positive and significant, though the coefficients are now lower than in the baseline estimation. For the employment growth regression, the intangible investment interaction term maintains its positive sign and significant level, and its coefficient is even higher than before. Overall, the message of Table 1.12 is one of the relative robustness of the relationship between intangible capital intensity and industry growth to additional restrictions.

	Sales growth		Employment growth	
	Adding R&D	Adding P/B ratio	Adding R&D	Adding P/B Ratio
SG&A/Sales	0.032***	0.018***	-0.087***	-0.085***
	(0.007)	(0.006)	(0.008)	(0.007)
(SG&A/Sales) × grow	0.049***	0.029***	0.050***	0.026***
	(0.009)	(0.007)	(0.010)	(0.008)
I_K/Sales	0.017***	0.001	0.001	-0.001
	(0.004)	(0.001)	(0.004)	(0.001)
(I_K/Sales) × grow	-0.029***	0.002	-0.004	0.000
	(0.005)	(0.001)	(0.005)	(0.002)
R&D/Sales	0.026***		-0.009	
	(0.005)		(0.006)	
(R&D/Sales) × grow	0.042***		0.010	
	(0.007)		(0.009)	
price to book ratio		0.062***		0.055***
		(0.002)		(0.002)
age	-0.109***	-0.154***	-0.028	-0.119***
	(0.031)	(0.016)	(0.034)	(0.019)
log(total asset)	0.203***	0.273***	0.024***	0.055***
	(0.004)	(0.004)	(0.005)	(0.004)
log(total sales)	-0.329***	-0.393***	-0.127***	-0.160***
	(0.005)	(0.003)	(0.005)	(0.004)
r2	0.182	0.204	0.047	0.062
N	60413	90868	57541	86461

Table 1.12: Intangible investment, firm growth and industry growth: additional controls

Besides adding additional controls, I also look at whether the baseline results are sensitive to the choice of time period. Table 1.13 reports the estimation results of Equation 1.19 when I break the sample data into two sub-periods: 1950 to 1978 and 1979 to 1997. The interaction term between intangible investment level and industry growth is positive and significant only for the second sub-period. For the earlier sub-period, the interaction term is positive but insignificant in the sales growth regression, and negative in the employment growth regression. These results seem to indicate that the structural change driven by intangible capital accumulation is still a fairly contemporary phenomenon, and the impact of intangible capital on industry growth has increased over time.

All in all, the empirical results with firm data are generally consistent with the prediction of the model regarding the relationship between intangible capital intensity and industry growth. The results are robust to most of the additional sensitivity checks.

	1950 - 1978		1979 - 2007	
	Sales growth	Employment growth	Sales growth	Employment growth
SG&A/Sales	-0.028	0.012	-0.001	-0.078***
	(0.021)	(0.028)	(0.006)	(0.006)
(SG&A/Sales) × grow	0.012	-0.183***	0.043***	0.020***
	(0.024)	(0.037)	(0.006)	(0.007)
I_K/Sales	0.097***	-0.011	0.003***	-0.001
	(0.009)	(0.012)	(0.001)	(0.001)
(I_K/Sales) × grow	-0.007	-0.014	-0.002	-0.001
	(0.010)	(0.013)	(0.001)	(0.002)
age	0.006	0.025	-0.118***	-0.091***
	(0.016)	(0.018)	(0.011)	(0.013)
log(total asset)	0.145***	-0.023***	0.294***	0.041***
	(0.006)	(0.007)	(0.004)	(0.004)
log(total sales)	-0.309***	-0.105***	-0.458***	-0.177***
	(0.006)	(0.007)	(0.004)	(0.004)
r2	0.185	0.076	0.224	0.053
N	38137	33886	84626	79373

Table 1.13: Intangible investment, firm growth and industry growth: different time periods

1.6 An Application: Intangible Capital and the Rise of Service Sector

The aggregate economy can be divided into goods-producing and service-producing sectors, if we classify industries according to the nature of their outputs. It is a well-known fact that in the recent decades, the service sector has expanded relative to the goods-producing sector in both real output and employment. Figure 1.7 documents this fact.

As an application of the chapter's theory, the rise of the service sector can be explained by examining the intangible capital intensities of service industries. First of all, if we examine industry data in more details, it is easy to see that contrary to the popular perception, not all service industries are expanding. Table 1.14a and 1.14b list respectively the service industries whose real value added shares in total economy have increased and decreased over the period of 1977 – 2007, based on consistent NAICS classification.

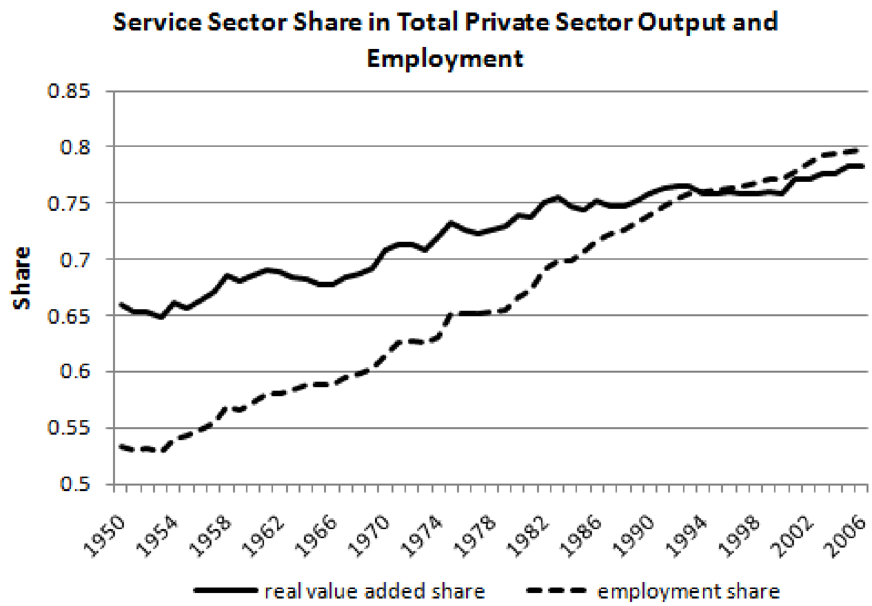

Figure 1.7: Service Sector Share of Real Output and Employment

Further examining the growing service industries, we can see that the growing part of the service sector consists of primarily intangible capital intensive industries. Here as before, I divide industries into high and low intangible capital groups according to whether the industry's SG&A to sales ratio is higher than the cross-industry median. Table 1.14a and 1.14b also report the intangible capital intensity of each service industry and the industry group they belong to. Figure 1.7 plots the real value added share growth rates of all service industries from 1977 to 2007 against their intangible capital intensities over the same period.

High Intangible & Growing Service Industries			
Industry	Intangible Capital Intensity	Real Value Added Share	
		1977	2007
Wholesale trade	0.170	0.047	0.067
Retail trade	0.250	0.060	0.090
Warehousing and storage	0.190	0.002	0.003
Publishing industries (includes software)	0.492	0.009	0.014
Motion picture and sound recording industries	0.208	0.003	0.004
Broadcasting and telecommunications	0.245	0.017	0.040
Information and data processing services	0.222	0.002	0.009
Securities, commodity contracts, & investments	0.378	0.001	0.028
Professional, scientific, and technical services	0.230	0.028	0.058
Computer systems design and related services	0.352	0.003	0.017
Administrative and support services	0.200	0.015	0.029
Ambulatory health care services	0.217	0.041	0.041
	Total share:	0.227	0.398

Low Intangible & Growing Service Industries			
Industry	Intangible Capital Intensity	Real Value Added Share	
		1977	2007
Air transportation	0.099	0.003	0.009
Truck transportation	0.048	0.010	0.010
Rental and leasing services and	0.153	0.008	0.011
Social assistance	0.110	0.003	0.008
Performing arts, sports, museums, etc	0.117	0.003	0.005
Amusements, gambling, and recreation	0.156	0.005	0.006
Food services and drinking places	0.098	0.019	0.020
	Total share:	0.051	0.067

Table 1.14a: IC Intensity of Growing Service Industries (1977-2007)

High Intangible & Declining Service Industries			
Industry	Intangible Capital Intensity	Real Value Added Share	
		1977	2007
Federal Reserve banks, credit intermediation, etc	0.218	0.051	0.040
Legal services	0.260	0.020	0.013
Waste management and remediation services	0.171	0.003	0.003
Educational services	0.363	0.011	0.009
Other services, except government	0.257	0.038	0.023
	Total share:	0.123	0.087

Low Intangible & Declining Service Industries			
Industry	Intangible Capital Intensity	Real Value Added Share	
		1977	2007
Utilities	0.066	0.027	0.020
Rail transportation	0.061	0.004	0.003
Water transportation	0.086	0.001	0.001
Transit and ground passenger transportation	0.110	0.004	0.002
Pipeline transportation	0.047	0.002	0.001
Other transportation and support activities	0.114	0.007	0.007
Insurance carriers and related activities	0.126	0.034	0.025
Funds, trusts, and other financial vehicles	0.012	0.003	0.001
Real estate	0.021	0.136	0.125
Hospitals and nursing and residential care facilities	0.089	0.038	0.026
Accommodation	0.152	0.014	0.009
	Total share:	0.268	0.219

Table 1.14b: IC Intensity of Declining Service Industries (1977-2007)

Table 1.14a-b show that the growing part of the service sector is dominated by intangible capital intensive industries. In 2007, the high-intangible-capital industries, e.g., retail, publishing, investment and computer design services, constitute about 86% of the total real value-added share of the growing service sector. In contrast, the declining part of the service sector mostly consists of industries that are less intangible capital intensive, such as utilities and water/ rail/ pipeline transportations. These low intangible capital industries constitute 72% of the declining service sector's total value-added share in 2007. Figure 1.8 further confirms this trend. When service industry real value-added share is regressed upon industry intangible capital intensity, the regression coefficient is positive and highly significant.

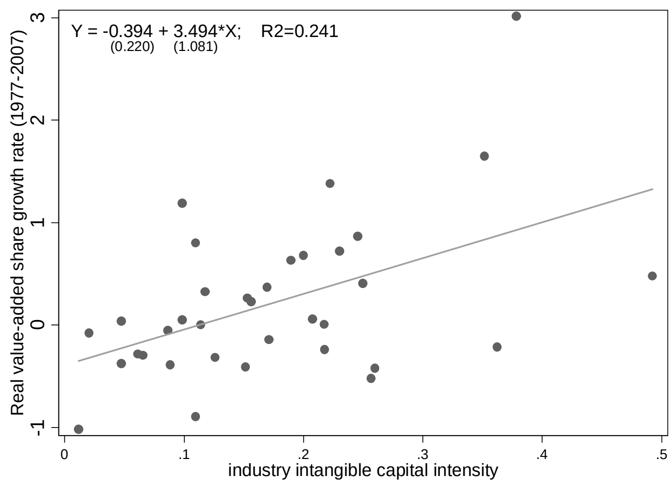

Figure 1.8: Service Inudustries' Growth and Intangible Capital Intensity

1.7 Conclusion

This chapter explores the relationship between sectoral structural change in US economy during the recent decades and rise of intangible capital accumulation. I argue that as the economy relies more and more on knowledge and information assets in creating values, the differences in intangible capital accumulation across sectors will lead to structural change in terms of output and employment compositions of the economy. In the two-sector model of the chapter, the importance of intangible capital in the production function differs across sectors and increases at different rates overtime. There are two kinds of work tasks in this economy: directly producing sectoral goods and producing intangible capital investment goods. When intangible capital's shares in the sectoral production functions increase, both sectors invest more in intangible capital, and the output and employment of the high intangible sector grow faster than those of the other sector.

The implications of the model are generally consistent with the stylized facts about structural change and intangible capital accumulation in the US since the 1950s. The calibrated model is able to replicate the following empirical facts: (1) increasing output and employment shares of the high intangible capital sector since the 1950s'; (2) increasing intangible investments in both sectors; (3) increasing employment share of occupations engaging in intangible investment work; (4) decreasing labor productivity growth for both sectors over the sample period, especially for the high intangible capital sector.

In addition, the model suggests that the conventional calculation of labor productivity– output over total labor input– may underestimate the real productivity in sectoral goods and services production, due to the fact that part of the sectoral labor force is allocated to intangible investment instead of direct production. This underestimation is more severe for the growing, high intangible sector.

Empirically, I test the relationship between intangible capital accumulation and structural change with industry and firm data. The industry-level estimation results show that future industry growths in real output and employment are significantly and positively correlated with industries' intangible capital intensities. The estimation is robust to other industry characteristics that might influence industry growth, such as human capital intensity, physical capital intensity and IT investment intensity. The firm-level result shows that the expanding industries are those where firms' intangible investment has a higher impact on firm growth. The result from a more disaggregate level confirms the thesis of the chapter, that intangible capital is a driving force of industry/sector growth in a modern knowledge economy.

Finally, data shows that the growing part of the service sector is dominated by the high intangible industries. Thus the theory developed in the chapter can also help to explain the rise of service sector in the recent decades.

1.A Appendix

1.A.1 Solving the Planner's Problem

The Lagrangian for the social planner's problem is

$$\begin{aligned}
\mathcal{L} &= \sum_{t=0}^{\infty} \beta^t \{\ln(C_t) + \lambda_t [Y_{1t}^{\gamma_1} Y_{2t}^{\gamma_2} - C_t - \frac{K_{t+1}^{1/\delta}}{K_t^{(1-\delta)/\delta}}] + \sum_{i=1,2} \mu_{it} [K_{i,t}^{a_i} O_{i,t}^{b_i} L_{y_i,t}^{1-a_i-b_i} - Y_{i,t}] \\
&\quad + \sum_{i=1,2} \eta_{it} [(1-\varphi)\, O_{i,t} + B_{i,t} O_{i,t}^{1-d} L_{o_i,t}^{d} - O_{i,t+1}] + \phi_t (K_t - K_{1,t} - K_{2,t}) \\
&\quad + \theta_t (L_t - L_{y_1,t} - L_{y_2,t} - L_{o_1,t} - L_{o_2,t})
\end{aligned}$$

The first order conditions are:

$$C_t: \quad \lambda_t = 1/C_t \tag{1.20}$$

$$Y_{it}: \quad \mu_{it} = \lambda_t \gamma_i \frac{Y_t}{Y_{it}} \tag{1.21}$$

$$K_{it}: \quad \phi_t = \mu_{it} a_i \frac{Y_{it}}{K_{it}} \tag{1.22}$$

$$L_{y_i,t}: \quad \theta_t = \mu_{it} \left(1 - a_i - b_i\right) \frac{Y_{it}}{L_{y_i,t}} \tag{1.23}$$

$$L_{o_i,t}: \quad \theta_t = \eta_{it} d B_{it} O_{it}^{1-d} L_{o_i,t}^{d-1} \tag{1.24}$$

$$K_{t+1}: \ \frac{\lambda_t}{\delta} \frac{K_t^{1-1/\delta}}{K_{t+1}^{1-1/\delta}} = \beta \left[\lambda_{t+1} \frac{1-\delta}{\delta} \frac{K_{t+2}^{1/\delta}}{K_{t+1}^{1/\delta}} + \phi_{t+1}\right] \tag{1.25}$$

$$O_{i,t+1}: \ \eta_{it} = \beta \left[\mu_{i,t+1} b_i \frac{Y_{i,t+1}}{O_{i,t+1}} + \eta_{i,t+1} \left((1-\varphi) + (1-d)\, B_{i,t+1} O_{i,t+1}^{-d} L_{o_i,t+1}^{d}\right)\right] \tag{1.26}$$

Let $S_c = C_t/Y_t$. Combining Equation 1.20, 1.25, 1.22, and 1.21, we have

$$(1 - S_c) = \beta\,(1-\delta)\,(1 - S_c) + \beta\delta\,(\gamma_1 a_1 + \gamma_2 a_2)$$

Therefore,

$$S_c = 1 - \frac{\beta\delta(\gamma_1 a_1 + \gamma_2 a_2)}{1 - \beta(1-\delta)}.$$

From Equation 1.23, 1.24, and 1.21, we get

$$\eta_{it} = \lambda_t \frac{Y_t}{L_{y_i,t}} \frac{\gamma_i \left(1 - a_i - b_i\right)}{d B_{it} O_{it}^{1-d} L_{o_i,t}^{d-1}} \tag{1.27}$$

Plug (1.27) into Equation 1.26 and rearrange:

$$\frac{(1 - a_{it} - b_{it}) L_{o_i,t}^{1-d}}{d B_{it} O_{i,t}^{1-d} L_{y_i,t}} = \frac{\beta(1-\varphi)(1 - a_{i,t+1} - b_{i,t+1}) L_{o_i,t+1}^{1-d}}{d B_{i,t+1} O_{i,t+1}^{1-d} L_{y_i,t+1}} + \frac{\beta(1-d)(1 - a_{i,t+1} - b_{i,t+1}) L_{o_i,t+1}}{d O_{i,t+1} L_{y_i,t+1}} + \frac{\beta b_{i,t+1}}{O_{i,t+1}}$$

1.A.2 Proof of Proposition 3

From Equation 1.11 and Equation 1.7, the ratio between the two sectors' total employments can be written as

$$\frac{L_1}{L_2} = \frac{\gamma_1}{\gamma_2} \frac{\frac{\beta b_1 d\left(g_{B_1}+\varphi\right)}{(1-\beta)\left(1+g_{B_1}\right)+\beta d\left(g_{B_1}+\varphi\right)} + (1-a_1-b_1)}{\frac{\beta b_2 d\left(g_{B2}+\varphi\right)}{(1-\beta)\left(1+g_{B_2}\right)+\beta d\left(g_{B_2}+\varphi\right)} + (1-a_2-b_2)} \tag{1.28}$$

It is easy to see that $\frac{L_1}{L_2}$ is an increasing function of g_{B_1}, and a decreasing function of g_{B_2}. Suppose $g_{B_1} = g_{B_2} = g_B$. Then Equation 1.28 can be rewritten as

$$\frac{L_1}{L_2} = \frac{\gamma_1}{\gamma_2} \frac{\beta b_1 d\left(g_B+\varphi\right) + (1-a_1-b_1)\left[(1-\beta)\left(1+g_B\right)+\beta d\left(g_B+\varphi\right)\right]}{\beta b_2 d\left(g_B+\varphi\right) + (1-a_2-b_2)\left[(1-\beta)\left(1+g_B\right)+\beta d\left(g_B+\varphi\right)\right]} \tag{1.29}$$

Taking derivative of Equation 1.29 with respect to g_B, we get

$$\frac{\partial\left(L_1/L_2\right)}{\partial g_B} = \frac{\gamma_1}{\gamma_2} \frac{\left[(1-a_2)\, b_1 - (1-a_1)\, b_2\right]\beta d\left(1-\beta\right)\left(1-\varphi\right)}{\left[\beta b_2 d\left(g_B+\varphi\right) + (1-a_2-b_2)\left((1-\beta)\left(1+g_B\right)+\beta d\left(g_B+\varphi\right)\right)\right]^2}$$

Thus $\frac{\partial(L_1/L_2)}{\partial g_B} > 0 \Leftrightarrow \frac{b_1}{b_2} > \frac{1-a_1}{1-a_2}$.

Similarly, take derivative of Equation 1.29 with respect to b_1 :

$$\frac{\partial\left(L_1/L_2\right)}{\partial b_1} = \frac{\gamma_1}{\gamma_2} \frac{\left(-\frac{\partial a_1}{\partial b_1}\right)\left[(1-\beta)\left(1+g_B\right)+\beta d\left(g_B+\varphi\right)\right] - (1-\beta)\left(1+g_B\right)}{\beta b_2 d\left(g_B+\varphi\right) + (1-a_2-b_2)\left[(1-\beta)\left(1+g_B\right)+\beta d\left(g_B+\varphi\right)\right]}$$

Therefore, $\frac{\partial(L_1/L_2)}{\partial b_1} > 0 \Leftrightarrow \frac{\partial a_1}{\partial b_1} < \frac{(1-\beta)(1+g_B)}{(1-\beta)(1+g_B)+\beta d(g_B+\varphi)}$.

Chapter 2

The Great Dissolution: Organization Capital and Diverging Volatility Puzzle

2.1 Introduction

The aggregate volatility of economic activities in major developed economies has drastically declined over the past two decades. The phenomenon, dubbed as the "Great Moderation", is well-documented (McConnell & Perez-Quiros (2000), Blanchard & Simon (2001), Stock & Watson (2002)), and has drawn considerable attention from macroeconomists and policy makers. Previous studies offer various explanations to the decline in aggregate fluctuation. The most straightforward answer is probably the "good luck" theory; i.e., smaller volatility is caused by smaller exogenous shocks (Stock & Watson, 2002). Other common suspects include improved monetary policy (Clarida et al., 2000), financial innovation and globalization, (Dynan et al., 2006), and better supply-chain management and inventory control (Kahn et al., 2002).

However, recent empirical studies indicate, contrary to the aggregate trend, sales and employment at the firm level has become more volatile. Comin & Mulani (2006), Comin & Philippon (2005) showed that the volatilities of sales and employment growth for publicly-traded US firms have been increasing in the past 50 years, and the pattern is fairly robust when sample composition change and other exogenous factors are taken into account.[1] Similar upward trend hold for turnover rate of industry leaders and firms' credit default risk. Related studies in finance literature (Pastor & Versonesi (2002), Wei & Zhang (2006), Campbell et al (2001)) have demonstrated strong upward trend in firm stock returns. Outside of US, Thesmar & Thoenig (2004) reported rising sales volatility for French firms. Buch, Dopke & Stahn (2008) showed increasing idiosyncratic firm volatility in Germany.

Figure 2.1 displayed both aggregate and firm level sales volatilities over the past 5 decades, represented by the rolling standard deviation of growth rate in 9-year windows.[2] In most business cycle models with only aggregate uncertainties, there is basically no differentiation between macro and micro level volatility. Why this is not what we see in real data is an interesting question. As an extreme example, consider the case when all firms in the economy are identical. Then macro and firm-level volatilities would be exactly the same. Even when this unrealistic assumption is abandoned, the reason why the two volatilities are heading opposite directions is still not obvious. To study this volatility divergence is the major focus of the chapter. The phenomenon poses challenges to many existing explanations of declining aggregate volatility which assume, directly or implicitly, that the economic environment has become more "tranquil" since the great moderation.

Besides its intellectual appeal, the volatility divergence question is also an important one. From a welfare evaluation point of view, it is relevant to ask what the macro volatility decline actually means to individual agents. Does it imply decreased economic uncertainty for households and firms, as people often intuitively assume, or something else?[3] A study of the question can shed lights on such issues as the evolution of risk factors affecting individual firms, how different firms respond differently to macro-level shocks, and the relevance and limitation of aggregate data in representing business cycle dynamics. All these questions are of central concern to industrial/macro

[1] Davis et al. (2006) showed that rising firm volatility is only present in publicly-traded firms, and hypothesized that it might be due to more risky young firms going public in recent years. But Comin (2008) demonstrated that the upward trend in firm volatility is robust after controlling for age and cohort effects. Thus the phenomenon is not a simple matter of sample selection.

[2] The formula to calculate the rolling standard deviation of variable$i$'s growth rate is: $\sigma_{i,t} = \sqrt{\sum_{\tau=t-4}^{t+4} (g_{i,t} - \overline{g_t})^2}$, where$\overline{g_t}$is the average growth rate between t-4 and t+4. Firm-level volatility at time t is the average standard deviation across all firms:$1/n \sum_{i=1}^{n} \sigma_{i,t}$.

[3] There is another intruguing phenomenon intimately related to the one investigated here: several studies, using household-level data, show that consumption and income volatilities of individual households have actually gone up in the Great Moderation period. See, for example, Dynan et al. (2006), Davis & kahn (2008).

economists and policy makers. Moreover, any trend shifts in business cycle patterns are most likely related to certain fundamental changes in the economic system. Hence, an investigation into the origin of volatility divergence can also serve to deepen our understanding about ongoing structural transformations in the economy.

Though there can be various causes at work behind the volatility divergence, this chapter captures one specific cause—the rise of organization capital (OC) in the business sector. The main hypothesis is the following. As a production factor, organization capital, or firm-specific intangible capital, has become increasingly important over the past decades. Investment in OC involves subjective decision making, trial-and-errors, and unexpected successes and failures for a firm. In other words, it induces firm-specific risks that do not equally affect other firms. But at the same time, accumulation of organization capital protect the firm from general, market-wide risks. As a result of increasing investment in organization capital, firm-level volatility rises, while aggregate volatility declines, mainly due to lowered positive co-movement among firms. In this sense, the observed volatility decrease at the aggregate level should rather be called the "Great Dissolution".

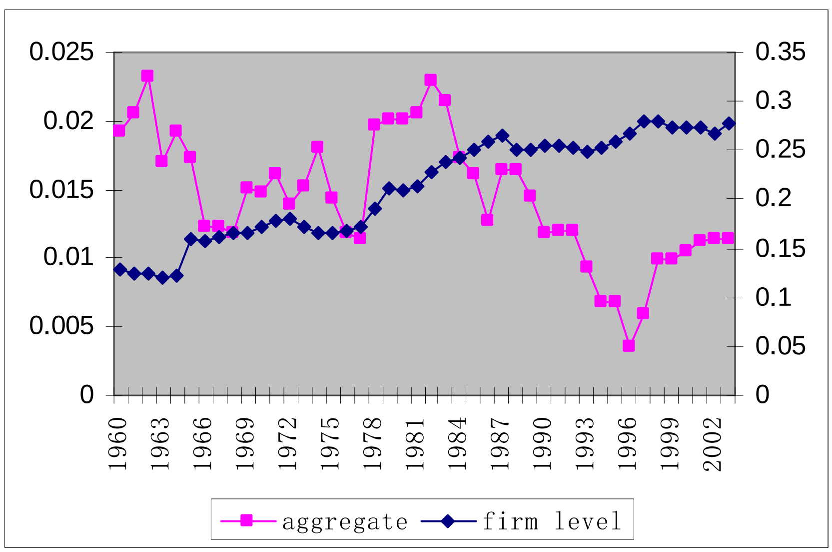

Figure 2.1: Diverging macro and firm level sales volatilities

The chapter is organized in the following way. Section 2.2 decomposes the aggregate and firm level volatilities, explains in detail the hypotheses that link the rise of OC and the trends of output volatilities, and reviews related literature. Section 2.3 specifies the empirical strategies to test the hypotheses and presents the results. Section 2.4 establishes the stochastic general equilibrium model involving OC investment. Section 2.5 simulates the model and compares the model characteristics with empirical data. Section 2.6 discusses the sensitivity of simulations. Section 2.7 adds adjustment cost to the basic model to improve the model's performance in imitating aggregate investment properties. Section 2.8 concludes.

2.2 Volatility Trends and the Role of Organization Capital

2.2.1 Decomposing Volatilities

To see how macro and micro level fluctuations can be trending differently from each other, it's helpful to break volatilities down into different components. Suppose there are n firms in the economy. Write firm i's growth rate $g_{i,t}$as a linear function of two kinds of shocks: macroeconomic shock m_t and firm-specific shock $f_{i,t}$, with σ_m^2 and σ_f^2being respective variance of shocks:

$$g_{i,t} = s_{i,t}^m m_t + s_{i,t}^f f_{i,t}; \quad i = 1, 2, ...n.$$

Therefore, the variance of firm i's growth rate is

$$\left(s_{i,t}^m\right)^2 \sigma_m^2 + \left(s_{i,t}^f\right)^2 \sigma_f^2,$$

and the average firm volatility takes the following form:

$$\text{Weighted Average Firm Volatility} = \textstyle\sum_{i=1}^n w_i \left(s_{i,t}^m\right)^2 \sigma_m^2 + \sum_{i=1}^n w_i \left(s_{i,t}^f\right)^2 \sigma_f^2, \tag{2.1}$$

where$\sum_{i=1}^n w_i = 1$.

The aggregate growth rate of the economy g_t is the weighted average of all firms: $g_t = \sum_{i=1}^n w_{i,t} g_{i,t}$. Thus the aggregate volatility can be written as

$$\begin{aligned} \text{Aggregate Volatility} &= \sum_{i=1}^n (w_i)^2 \left(s_{i,t}^m\right)^2 \sigma_m^2 + \sum_{i=1}^n (w_i)^2 \left(s_{i,t}^f\right)^2 \sigma_f^2 \\ &\quad + \sum_{i=1}^n \sum_{j \neq i} w_i w_j s_{i,t}^m s_{j,t}^m \sigma_m^2. \end{aligned} \tag{2.2}$$

Throughout the chapter, I assume that the structure of exogenous shocks do not change; i.e., σ_m^2 and σ_f^2 remain constant. It's easy to see that the only way to allow the values of (1) and (2) to shift in different directions is to change the relative importance of the two shocks, $s_{i,t}^m$ and $s_{i,t}^f$. More specifically, if the impact of macro shock $s_{i,t}^m$ decreases, while that of firm-specific, idiosyncratic shock $s_{i,t}^f$ increases, it is possible to have firm-level volatility rising and aggregate volatility declining at the same time, while the variances of shocks remain unchanged. In this scenario, the decline in aggregate volatility would be mainly due to a decrease in the covariance term, which is normally much bigger than the two variance terms, given a large number of firms. In other words, the aggregate volatility decreases as a result of reduced positive co-movements among firms.

Therefore, to understand the volatility divergence, it is crucial to find out what factor(s) are affecting the change in relative impact of different shocks. My main hypothesis is: increasing investment in organization capital, or firm-specific intangible capital, is the source of elevated impact of firm-specific risks, which leads to an increase firm-level volatility; at the same time, organization capital decreases the influence of general risk factor, which results in reduced correlation among firms and decreasing aggregate volatility.

Organization Capital in the Modern Economy

Prescott & Visscher (1980) defines organization capital as firm-specific information and knowledge. Jovanovic & Rousseau (2001) uses the phrase "whatever makes a group of people and assets more productive together than apart." Lev (2001) describes it as "the knowledge used to combine human skills and physical capital into systems for producing and delivering want-satisfying products". Though worded differently, there are a couple common elements in these definitions. First, organization capitals are firm-specific resources. Two, they are mostly intangible assets. Thus, I use organization capital and firm-specific intangible capital interchangeably in this chapter. Examples of organization capital abound, such as a firm's brand equity, customer network, R&D resources, management expertise, business processes and other intangible production resources that live beyond one period.

Faced with ever increasing speed of technological change and intensified market competition, a modern firm can no longer rely on the physical assets it possesses for a unique competitive advantage. Indeed, a major difference between industrial-age production and the so-called knowledge economy is that the state-of-art intangible know-hows is no longer embodied in mega-size machines, but carried by workers and organizations. Firms have to distinguish themselves from the peers by developing optimal allocation of decision rights, organization-specific human capital, efficient incentive mechanism, capacity to cope with disruptive technological changes, and extensive customer/supplier network. These "soft" assets have become crucial differentiating factors for modern businesses.[4]

Furthermore, the advancement of IT technology drastically changed the cost of information processing and communication, which often requires complementary investment in organizational structure and management processes. Bresnahan, Brynjolfsson & Hitt (2002) found that greater level of IT investment is associated with increasing organizational redesign. They also found that on average, every \$1 of corporate investment in IT is correlated with \$10 increase in firm's market value, suggesting complementary organizational investment of about \$9, far exceeding the investment in technology itself. At the same time, thanks to the IT revolution and other technological innovations that boost efficiency in direct production processes, more working hours are allocated to building intangible capitals– creating new ideas, products, establishing new categories, managing different resources,etc., so as to "give the world something it didn't know it was missing".

Organization capital is highly firm-specific. The value of a brand, for example, may depend on patent rights to the underlining technology, and expenditures on advertising and other reputational investments. The value of these assets largely depends on the functioning of the organization behind them, thus making them very difficult to trade on an outside market. Changes in firm's organization capital are by no means riskless. It involves innovation, trial-and-error, and very likely, unexpected success and failure. Same amount of investment expenditure may bring about very different results. Studies have found different effects for various companies' advertising expenses in a same industry (Schmalensee, 1972). Empirical researches also suggest high failure rates of business process redesign (e.g., Sauer & Yetton, 1997), and IT related organizational change projects (Kemerer & Sosa, 1991), just like new investment in other technological innovations which involve a high level of uncertainty. Therefore, when the production process requires more organization capital, individual firms' volatilities are likely to rise.

[4] There is abundant literature in management and business economics on the importance of different intangible asset classes. See, for example, Karl Erik (1997), Blair (2001), Teece, Pisano & Shuen (1997).

At the same time, organization capital investment can change the risk profile that a firm is faced with. On one hand, the risk incurred in OC investment is largely firm-specific, or idiosyncratic, in nature. This is because, first, the high cost incurred in copying other firms organizational practice may prevent a quick spread of any new OC innovation across firms; second, even when firms can imitate a winner's practice, the complexity due to complementarity among different investments can make the outcome highly contingent (For example, Kmart may try to emulate Wal-mart; Compaq tries to learn from Dell; but these investments are not likely to achieve the same result as the originator's.). On the other hand, accumulation of organization capital can make a firm less susceptible to general market shocks. Traditionally, companies in the same industry competed with each other on price and quality, which makes firms' performances highly homogeneous, and largely dependent on general market conditions. But today, when reasonable quality and price have become only the entry tickets to the marketplace, unique and inimitable assets, resources, skills, and investments are becoming the primary sources of a firm's competitive advantage.[5] Firms of high OC thus tend to be less prone to market fluctuations, and the demand of their products less affected by common risk factors.

There is abundant evidence suggesting that the business sector's intangible capital investments have been on the rise over the past few decades. Companies' market value as a percentage of GDP has been increasing since the 1980s', while tangible assets relative to GDP declining during the same period. Many researchers argue that an important source for the increase in firms' market capitalization is accelerated accumulation of intangible assets (e.g., Hall, 2001). Nakumura (2001) inferred the amount of business intangible investment in US economy, using data on industrial expenditures, labor inputs and corporate operating margins. He concluded that by 2000, private firms invest at least \$1 trillion annually in intangible assets, and 1/3 of US corporate assets are in intangibles. Corrado, Hulten and Sichiel (2005, 2006) directly estimated and aggregated different components of business intangible capitals. They showed that business sector intangible capital accumulation has been growing fast in the past half century, especially since the 1980s. By the end of the 20th century, intangible capital investment had exceeded private firms' physical capital investment, amount to about 13% of business outputs. Atkeson & Kehoe (2005) emulated plant-

[5]Researches in business strategies have emphasized the importance of various kinds of organization capital in shaping a firm's market competence. See, for example, Barney (1986), Lippman& Pumelt (1982), Montgomery & Wernerfelt (1988).

life dynamics based on organization capital accumulation. They estimated that the payments to intangible capital owners are on average 110% of those to physical capital owners. Therefore, it is a reasonable conjecture that given the large amount of intangible investment in the business sector, if such investment has any impact on firms' risk characteristics, the impact should be considerable.

2.2.2 Other Related Literature

Just like any insightful theoretical concepts, the idea of organization capital or business intangible capital provide unique perspectives into different economic issues. In fact, the literature related to intangible capital is rapidly expanding. Prescott & Visscher modeled the information accumulation and transfer process within a firm (a type of organization capital investment), and used it to explain stylized characteristics of firm growth rates and size distributions. Hall (2001) argued that US firms' intangible asset accumulation helps explain the persistent high valuation of common stocks compared to companies' book values. Atkeson & Kehoe (2005) linked the amount of organization capital a plant accumulated with the size of plant-specific rents. They simulated plant distribution dynamics driven by organization capital accumulation, and showed that the result fit the real data well. Jovanovic & Rousseau (2001) hypothesized that the quality of organization capital differs across generations of firms, which explained the "cohort effects" in firms' stock market performance. Brynjolfsson, Hitt & Yang (2002) found that investment in organization capital complements investment in IT technology, and the combined investment has a significantly larger impact on firms' output and market valuation than isolated investments. McGrattan & Prescott (2007) introduced business intangible investment in a standard growth model and demonstrated that it helped explain US productivity and investment boom in the 1990s. Danthine & Jin (2007) modeled different stochastic processes in intangible capital accumulation and argued that it contributed to high volatility in equity returns.

Although the literature related to business intangible capital is fairly diverse, this study, to my best knowledge, is the first to investigate the relationship between intangible capital accumulation and changes in the volatility characteristics of the economy. Some authors have approached the volatility divergence puzzle from other perspectives. Comin & Mulani (2006) constructed a quality-ladder model where aggregate and firm-level volatilities are driven by "general" and "applied" innovations respectively. They argued that when industry leaders' positions are less stable, resources will be shifted from general to applied technological progress, which increases firm volatility and suppresses aggregate fluctuation. An elegant model as it is, attributing decreases in macro volatility to less frequent general technology shocks is probably not the most convincing. Philippon (2003) contended that intensified market competition causes firm volatility to increase, but at the same time, it leads firms to adjust prices faster, which in turn reduces the impact of aggregate demand shocks. The explanation didn't accommodate the fact that co-movements among firms decrease during the Great Moderation, and it is in fact an important element contributing to the aggregate volatility decline (Comin & Philippon, 2005). Thesmar & Thoenig (2004) linked volatility divergence to financial market innovations. In their paper, financial development, while stabilizing at the macro level, increases firms' willingness to take on more risks by improving risk sharing among firms. Firm-level volatility can rise due to the latter factor. While the theory is intuitively appealing, a financial-market centered explanation is not very likely the most crucial mechanism behind the phenomenon. In sum, the current literature on volatility divergence leaves large room for better theories and further empirical investigations. This study presented a theory from the perspective of structural change in the production process, and made initiatory attempts to empirically test the theory.

2.3 Empirical Tests

2.3.1 Hypotheses

The volatility decomposition in section 2.2 demonstrates the mechanism, from an accounting standpoint, that can generate volatility divergence at macro and firm level. To reiterate, when the impact of firm-specific shocks increases and that of general shocks decreases, firm-level volatility can rise while aggregate volatility is declining due to reduced positive co-movements among firms. I argued in the previous section that the accumulation of organization capital is a fundamental reason that causes the "power shift" in different risk factors.

The goal of the empirical exercises is essentially to examine how organizational investment relates to the impacts of different risk factors. I broke the task down to three hypotheses and designed regressions to test them separately.

- **Hypothesis1: firm volatility increases with the level of organizational investment.**

If the conjecture is true that investment in organization capital involves large firm-specific risk, we shall observe s_i^f increases with organizational investment. In other words, more volatile firms should be associated with higher OC investment intensities.

- **Hypothesis 2: the more a firm invests in organization capital, the less its performance is affected by general risk factor.**

Firms with high OC possess unique competitive advantage, and thus are less susceptible to fluctuations in general market conditions. If this is true, OC investment should help lower s_i^m. And we shall observe a negative correlation between market influence on a firm and its OC investment level.

- **Hypothesis 3: organization capital investment decreases the co-movement among firms.**

In decomposing aggregate volatility, I showed that the bulk of decline in aggregate fluctuation is caused by reduced covariance term. If organizational investment does make firms more heterogeneous and thus reduces aggregate volatility, we should observe that a firm's correlation with other firms decreases with more investment in organization capital. This test thus complements the second hypothesis.

2.3.2 Data Description

To test the above conjectures, we first need a measure of firm-level organizational investment. Estimating the amount of organization capital at firm level is by no means a straight forward task. Historically, intangible capital generated within an organization is not counted as assets on the balance sheet for various reasons. One of the reasons is that for any data to be reported in the financial statement, the information represented must be objective and reliable. But unlike physical assets, intangible asset reporting is more likely to be faced with such problems as uncertain investment returns, asymmetric information, lack of market price, and subjective probability calculation. Therefore, most organization capital investments are traditionally categorized as operating expenditures. The effect of expensing organizational investment is fairly obvious if we compare the cost composition of intangible-intensive companies in emerging industries with that of more traditional manufacturing companies. Table 2.1 compares the cost structures of three well-known companies.

	Sales	COGS	As % of Sales	R & D	As % of Sales	SG&A	As % of Sales
Pfizer (2001)	32259	5034	15.6	4847	15.0	11299	35.0
Microsoft (2002)	28365	5191	18.3	4307	15.2	6957	24.5
Boeing (2001)	58198	48778	83.8	1936	3.3	2389	4.1

Table 2.1: Cost Structure of Three Companies

For intangible-intensive firms like Pfizer and Microsoft, the cost directly related to goods /services production (cost of goods sold) is relatively small, compared to sales, general & administrative cost (SG&A), which includes various intangible investment items, such as costs of marketing, advertising, research & development, and software, as well as management fees and incentive packages.

In the following regressions, I use SG&A expenditure as an approximation for firm-specific intangible investment. Similar treatment has appeared in various accounting studies (see, for example, Lev and Radhakrishnan, 2005), though the emphases of those researches are very different than this study. Imperfect as it is, SG&A expenditure is arguably the best approximate for OC investment by far, considering data availability and accuracy.

Figure 2.2 calculated COGS and SG&A as % of sales for publicly-traded, nonfinancial US firms. It is clear that especially since the 1980s, the share of COGS in the total cost has gone down dramatically, while SG&A expenditure has been steadily increasing. The trend of SG&A is generally in line with other estimates of business intangible investments (e.g., Corrado et al., 2006).

The database I used is COMPUSTAT North America, which covers the financial statement and stock price information for publicly-traded firms since the 1950s. The firms included in the sample are US-based nonfinancial firms that have at least 10 years of continuous sales and expenditure records, which add up to 218,324 firm-year observations from 1950 to 2007. Table 2.2 lists summary statistics for the sample firms.

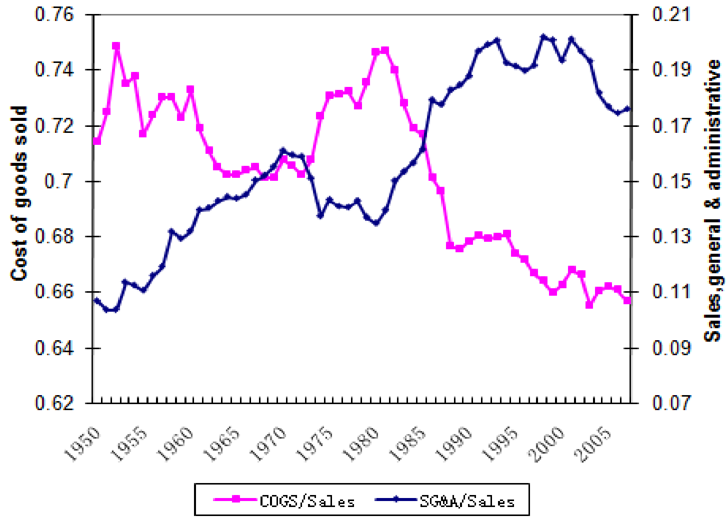

Figure 2.2: Changing cost structure of firms

	Mean	**Std**
Sales ($mn)	1058.49	6418.70
SG&A ($mn)	190.77	1092.61
COGS ($mn)	717.15	4756.65
Employees (thousands)	7.75	31.12
Gross Fixed Asset	728.62	5323.92
SG&A/Sales	0.25	0.18
COGS/Sales	0.65	0.22
Fixed Assets/Sales	0.73	1.56

Table 2.2: Summary Statistics of Sample Firms

2.3.3 Regression Strategies

To test hypothesis 1, I regressed a firm's sales volatility, captured by rolling standard deviation of sales growth, on "SG&A/Sales", the intensity of organization capital investment. To compare the impact of OC investment on volatility with that of other production inputs, I also included "fixed assets/sales" and "employment/sales" as explanatory variables, which capture physical capital and labor intensities of the firm. The estimation equation is as follows:

$$\begin{aligned}\ln\left(\sigma_{g_{i,t}}\right) &= \beta_0+\beta_1\ln\left(sga_{i,t}/sales_{i,t}\right)+\beta_2\ln\left(fixed\ assets_{i,t}/sales_{i,t}\right)\\&\quad+\beta_3\ln\left(employees_{i,t}/sales_{i,t}\right)+e_{i,t}\end{aligned}$$

where $\sigma_{g_{i,t}}=\sqrt{\sum_{\tau=t-4}^{t+4}\left(g_{i,t}-1/9\sum_{\tau=t-4}^{t+4}g_{i,\tau}\right)^2/9}$. If hypothesis 1 is true, we should expect the sign of β_1 to be positive.

The second hypothesis states that OC investment reduces the impact of market risks on a firm's performance. The test consists of two steps. First, I carried out rolling regressions of a firm's sales growth on industry and total sample sales growth in 9 year windows:

$$\ln\left(g_{i,\tau}\right)=\gamma_0+\gamma_1\ln\left(g_{industry,\tau}\right)+\gamma_2\ln\left(g_{market,\tau}\right)+\varepsilon_{i,\tau},\qquad t-4<\tau<t+4.$$

The R^2 of the regression indicates how much a firm's sales performance can be explained by general risk factors, and thus provides a measure of market impact on a firm's production. Next, I regressed the R^2 of the first regression on firms' organization capital, physical capital and labor intensities:

$$\begin{aligned}\ln\left(R2_{i,t}\right) &= \alpha_0+\alpha_1\ln\left(sga_{i,t}/sales_{i,t}\right)+\alpha_2\ln\left(fixed\ assets_{i,t}/sales_{i,t}\right)\\&\quad+\alpha_3\ln\left(employees_{i,t}/sales_{i,t}\right)+\upsilon_{i,t}\end{aligned}$$

If hypothesis 2 holds, the coefficient for $\ln\left(sga_{i,t}/sales_{i,t}\right)$ should be negative.

Thirdly, I tested whether the correlation between a firm's sales growth and the rest of the sample firms is negatively affected by its OC investment intensity. I ran the following regression:

$$\begin{aligned}\ln\left(\rho_{i,t}\right) &= \mu_0+\mu_1\ln\left(sga_{i,t}/sales_{i,t}\right)+\mu_2\ln\left(fixed\ assets_{i,t}/sales_{i,t}\right)\\&\quad+\mu_3\ln\left(employees_{i,t}/sales_{i,t}\right)+\eta_{i,t}\end{aligned}$$

Where $\rho_{i,t}$ is the correlation between firm i's sales growth and that of all other firms in the sample from t-4 to t+4. The necessary condition for hypothesis 3 to be true would be a negative coefficient for the variable $\ln\left(sga_{i,t}/sales_{i,t}\right)$.

2.3.4 Results

Table 2.3 lists the results of regressing firms' rolling standard deviation of sales on the intensities of organization capital, physical capital and labor, for the years from 1955 to 2003. The time point of standard deviation is placed in the middle of the 9-year rolling window.[6] I carried out the estimation using different regression methods. Specifically, the regression are: (1) pooled OLS; (2) least-square regression controlling for industries;[7] (3) least-square regression controlling for years; (4) firm fixed effect panel regression; (5) between-effect panel regression.

	Std of firm growth $(\ln(std))$				
	(1)	(2)	(3)	(4)	(5)
$\ln(sga_{i,t}/sales_{i,t})$	0.15***	0.18***	0.11***	0.08***	0.28***
	(0.002)	(0.003)	(0.003)	(0.005)	(0.009)
$\ln(fixed\ assets_{i,t}/sales_{i,t})$	0.05***	-0.02***	0.05***	-0.01**	0.06***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.007)
$\ln(employees_{i,t}/sales_{i,t})$	-0.13***	-0.10***	-0.04***	-0.03***	-0.14***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.008)
observations	84698	84589	84698	84698	84698

Table 2.3: Impact of SG&A on Firm Volatility

The results show that the coefficients for SG&A investments are all positive and significant across different regressions, suggesting a positive correlation between organizational investment and firm volatility. In contrast, the signs of coefficients for the other two inputs are either inconsistent across different specifications (for physical capital) or negative (for labor). The result thus confirms Hypothesis 1.

Next, I regressed firm growth rate on market and industry growth rate, used the R^2 of the regression as a measure of general shocks' impact on firm performance, and then regress the R^2on firm's production inputs. Table 2.4 listed the results across different regression methods.

[6] The result doesn't differ much if the time point is put at the beginning of the 9-year window.
[7] The sample firms cover 61 SIC two-digit industries.

	R^2 of regressing firm growth on system growth $\ln\left(R^2\right)$				
	(1)	(2)	(3)	(4)	(5)
$\ln\left(sga/sales\right)$	-0.13***	-0.10***	-0.08***	-0.08***	-0.07***
	(0.004)	(0.005)	(0.005)	(0.01)	(0.01)
$\ln\left(fixed\ assets/sales\right)$	0.06***	0.03***	0.07***	-0.04**	0.03***
	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)
$\ln\left(employees/sales\right)$	0.03***	0.05***	-0.07***	0.06***	0.01
	(0.004)	(0.004)	(0.005)	(0.006)	(0.009)
observations	91980	91785	91980	91980	91980

Table 2.4: Relationship between SG&A and general risk factor's impact

The coefficients for SG&A investments are all negative and significant. In other words, the more a firm invests in organization capital, the less it is susceptible to general risk factor's influence, which confirms Hypothesis 2. The same characteristic is not present for the other two inputs.

Table 2.5 presented results for the third regression. Here the focus is how SG&A may affect a firm's co-movement with other firms. I first calculated the correlation between a firm's sales growth and that for the rest of the sample in 9 year rolling windows, then regressed this correlation on the firm's production inputs. As the result shows, the more a firm invests in organizational assets, the less a firm is correlated with the rest of the sample, which is in support of hypothesis 3.

	Correlation between firm growth and market growth (ρ)				
	(1)	(2)	(3)	(4)	(5)
$\ln\left(sga/sales\right)$	-0.06***	-0.06***	-0.04***	-0.04***	-0.05***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
$\ln\left(fixed\ assets/sales\right)$	0.03***	0.02***	0.04***	-0.02**	0.02***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
$\ln\left(employees/sales\right)$	0.02***	0.03***	-0.04***	0.03***	0.009***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
observations	81369	81369	81369	81369	81369

Table 2.5: Impact of SG&A on Correlation with Other Firms

In sum, the empirical tests generally support the hypothesis that organization capital investment increases the impact of firm-specific risks, and decreases that of global risks. As a result of increasing organizational investment, firm-level volatility rises while co-movements among firms decline.

However, the result doesn't mean that organizational investment has the same impact across different time periods. In fact, when I conducted the fixed effect regression by decades, the results show that the impact of organizational investment on firm volatility is only significant for more recent decades. Table 2.6 presents the result of regressing firm volatility on production input intensities by decade. The coefficients for SG&A are only positive and significant starting from the 1980s. So how to explain this result? First, as will be modeled in the next section, production structure in the modern economy is constantly evolving, and intangible capital was recognized as an important production input only recently. Before the 80s, its impact might not have been large enough to influence firms' risk characteristics on a large scale. Second, SG&A expenditure is an imperfect measure of firms' intangible investment, especially in the earlier years when the amount of such investment was relatively small. In those cases, SG&A might be too noisy an indicator for OC investment.

Interestingly, the lack of significance for organizational investment in early periods corresponds to the simulation result I will present later in the chapter—the general equilibrium model featuring firm-specific intangible investment can imitate macro and firm level volatilities fairly well for the 1980s and beyond; but the model didn't do as well in generating realistic macro volatility for the earlier decades.

	standard deviation of firm growth ($\ln(\sigma)$)		
time	$\ln(sga/sales)$	$\ln(fixed\ assets/sales)$	$\ln(employees/sales)$
1960-1969	0.0002	-0.0578***	0.0896***
1970-1979	-0.0057	-0.0083	0.0673***
1980-1989	0.0772***	-0.0166*	-0.0010
1990-1999	0.1083***	-0.0487***	-0.0335***
$\geqq$ 2000	0.0732***	-0.0832***	0.0537***

Table 2.6: Firm fixed effect regression by decade

2.4 A General Equilibrium Model of Organization Capital Accumulation

2.4.1 Model

The economy contains a infinitely-living, representative household and n firms. The household offers labor and capital to firms and receives wage income and profits. She derives utility from consumption and leisure. The household's optimization problem is as follows:

$$\max_{\{C_t,[I^k_{i,t},I^o_{i,t}]^n_{i=1}\}^\infty_{t=0}} E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln(C_t) + \theta \frac{(1-L_t)^{1-\mu}}{1-\mu} \right]$$
$$s.t. \quad C_t + \sum_{i=1}^{n} I^k_{i,t} + \sum_{i=1}^{n} I^o_{i,t} \leq w_t L_t + \sum_{i=1}^{n} \pi_{i,t}$$

where w_t is wage rate and $\pi_{i,t}$ firm i's profit at time t. Firms produce identical goods, using labor (L), physical capital (K) and organization capital (O) as inputs. The production function takes a Cobb-Douglas form:

$$Y_{i,t} = K^{\alpha_t}_{i,t} O^{\gamma_t}_{i,t} (A_t L_{i,t})^{1-\alpha_t-\gamma_t}$$

where A_t is a global productivity shock common to all firms. It evolves according to an AR(1) process:

$$\ln(A_{t+1}) = \rho_a \ln(A_t) + \varepsilon_{t+1}, \quad \varepsilon_{t+1} \tilde{} N(0, \sigma^2_\varepsilon).$$

The shares of different inputs in the production function are subject to change through time. The changes in the relative importance of inputs are purely exogenous, not anticipated by agents.

The accumulation of physical capital is governed by the standard process:

$$K_{i,t+1} = (1-\delta)K_{i,t} + I^k_{i,t}$$

where δ is the depreciation rate for physical capital, and $I^k_{i,t}$ the investment in K at time t.

An important feature of the model is the dynamic process of organization capital accumulation:

$$O_{i,t+1} = (1-\varphi)O_{i,t} + B_{i,t} I^o_{i,t}$$

Here φ and $I^o_{i,t}$ are depreciation rate and investment in organization capital respectively. And $B_{i,t}$ is a firm-specific productivity shock capturing the investment effectiveness in organization capital. In other words, firm i's OC stock at time t+1 depends on un-depreciated OC from time t, investment in OC made in period t and investment specific productivity shock that is known at the beginning of t. $B_{i,t}$ is given by the AR(1) process:

$$\ln(B_{i,t+1}) = \rho_b \ln(B_{i,t}) + \eta_{i,t+1}, \quad \eta_{i,t+1} \tilde{} N(0, \sigma^2_\eta), i.i.d. \quad i = 1, 2, ...n.$$

The intuition is, again, that when a firm invests in organization capital, it is faced with its own path of success and failure, though at the same time, all firms are affected by general productivity shocks.

Given wage rate and its physical and organization capital stocks at time t, a firm makes its hiring decision to maximize the single period profit:

$$\max_{L_{i,t}} \ \pi_{i,t} = K^{\alpha_t}_{i,t} O^{\gamma_t}_{i,t} (A_t L_{i,t})^{1-\alpha_t-\gamma_t} - w_t L_{i,t}$$

Output $Y_{i,t}$ can be used for consumption or investments in both physical and organization capital, which leads to the following aggregate resource constraint:

$$C_t + \sum_{i=1}^{n} I^k_{i,t} + \sum_{i=1}^{n} I^o_{i,t} = \sum_{i=1}^{n} K^{\alpha_t}_{i,t} O^{\gamma_t}_{i,t} (A_t L_{i,t})^{1-\alpha_t-\gamma_t}$$

2.4.2 Equilibrium and Solution

An equilibrium of the economy is given by a time path of labor prices $\{w_t\}^\infty_{t=0}$, and decision rules $\{C_t, (L_{i,t})^n_{i=1}, \left(I^k_{i,t}\right)^n_{i=1}, \left(I^o_{i,t}\right)^n_{i=1}\}^\infty_{t=0}$, such that given the wages, the household's consumption and investment choices maximize her life time utility; firms' hiring decisions maximize their profits; labor and goods markets clear.

Since the market is essentially complete in the economy, the competitive equilibrium allocation is identical to the solution of the following social planner's problem:

$$\max_{\{C_t,[I_{i,t}^k,I_{i,t}^o]_{i=1}^n,[L_{i,t}]_{i=1}^n\}_{t=0}^\infty} E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln(C_t) + \theta \frac{(1-L_t)^{1-\mu}}{1-\mu} \right]$$

$$s.t. \quad C_t + \sum_{i=1}^n I_{i,t}^k + \sum_{i=1}^n I_{i,t}^o = \sum_{i=1}^n K_{i,t}^{\alpha_t} O_{i,t}^{\gamma_t} (A_t L_{i,t})^{1-\alpha_t-\gamma_t}$$

$$\begin{aligned}
K_{i,t+1} &= (1-\delta)K_{i,t} + I_{i,t}^k \\
O_{i,t+1} &= (1-\varphi)O_{i,t} + B_{i,t} I_{i,t}^o \\
\ln(A_{t+1}) &= \rho_a \ln(A_t) + \varepsilon_{t+1}, \quad \varepsilon_{t+1} \tilde{} N(0,\sigma_\varepsilon^2) \\
\ln(B_{i,t+1}) &= \rho_b \ln(B_{i,t}) + \eta_{i,t+1}, \quad \eta_{i,t+1} \tilde{} N(0,\sigma_\eta^2) \\
\sum_{i=1}^n L_{i,t} &= L_t
\end{aligned}$$

To solve the model, I derived the first order conditions from the social planner's problem, log-linearized the first order conditions around the steady states, and numerically computed the policy functions.

The Lagrangian of social planner's problem is:

$$\begin{aligned}
\mathcal{L} = & \max_{\{C_t,[K_{i,t+1},O_{i,t+1}]_{i=1}^n,[L_{i,t}]_{i=1}^n\}_{t=0}^\infty} E_0 \{ \sum_{t=0}^{\infty} \beta^t [\ln(C_t) + \theta \frac{(1-L_t)^{1-\mu}}{1-\mu} \\
& + \lambda_t [\sum_{i=1}^n K_{i,t}^{\alpha_t} O_{i,t}^{\gamma_t} (A_t L_{i,t})^{1-\alpha_t-\gamma_t} + \sum_{i=1}^n (1-\delta) K_{i,t} + \sum_{i=1}^n (1-\varphi) O_{i,t} \\
& - C_t - \sum_{i=1}^n K_{i,t+1} - \sum_{i=1}^n \frac{O_{i,t+1}}{B_{i,t}}] + \varsigma_t (L_t - \sum_{i=1}^n L_{i,t})]\}
\end{aligned}$$

The appendix explains in more details the procedure used to solve the model.

2.5 Calibration

2.5.1 Strategy

To see how well the model can replicate the volatility divergence in data, I calibrated the model economy, assuming that the relative importance of different inputs in the production process has undergone significant changes in the past 50 years.

Recall that the production function in the model takes the form $Y_{i,t} = K_{i,t}^{\alpha_t} O_{i,t}^{\gamma_t} (A_t L_{i,t})^{1-\alpha_t-\gamma_t}$. Structural shifts in the relative importance of production inputs can be represented by changing coefficients for K, O and L in the production function. Such changes in factors' shares result in different steady state variable values and ratios, which, with reasonable parameter choices, should approximate the data trend in US economy.

The steady state equations for the model economy are as follows:

$$\begin{aligned}
\theta(1-\sum_{j=1}^{n} L_j)^{-\mu} &= \frac{1}{C}(1-\alpha-\gamma)AK_i^{\alpha}O_i^{\gamma}L_i^{-\alpha-\gamma} \\
\frac{1}{\beta} &= \alpha AK_i^{\alpha-1}O_i^{\gamma}L_i^{1-\alpha-\gamma} + (1-\delta) \\
\frac{1}{\beta} &= \gamma AK_i^{\alpha}O_i^{\gamma-1}L_i^{1-\alpha-\gamma} + (1-\varphi); \quad i = 1, 2, ...n \\
& C + \delta\sum_{j=1}^{n} K_j + \varphi\sum_{j=1}^{n} O_j = \sum_{j=1}^{n} AK_j^{\alpha}O_j^{\gamma}L_j^{1-\alpha-\gamma}
\end{aligned}$$

where K_i, O_i, L_i, C are steady state values for $K_{i,t}, O_{i,t}, L_{i,t}, C_t$, and A=1. The 3n+1 equations determine the 3n+1 steady state variables $\{K_1, ...K_n,\ O_1, ...O_n,\ L_1, ...L_n, C\}$, with 8 exogenously given parameters $\{\beta, \delta,\ \varphi, \alpha, \gamma, \mu, \theta, n\}$.

I use the standard quarterly discount factor 0.99, which implies an annual discount rate β=0.96. The annual depreciation rate for physical capital is set at 0.048, as in Cooley & Prescott (1995). There is very few information available about the depreciation rate of organization capital. Here I assume an annual depreciation rate of 0.5, which is a mix of the depreciation rates for different classes of business intangibles appeared in the literature.[8] I set μ equal 4, and calculated the value of θ to keep the fraction of total hours worked equal to 0.31. For the autocorrelation coefficients of the two shocks, I assume they are both equal to 0.9. I adopt the standard assumption for the volatility of aggregate technology shocks—the standard deviation of global shocks is set at 0.007. No estimation is available for the standard deviation of idiosyncratic shocks that hit individual firms. In the baseline calibration, I assume it is equal to that of the general shocks.

For physical capital's share in the production function, I assume the usual value α=0.4. To

[8] For example, Corrado et al (2006) advocates the following depreciation schedules: 33% for computerized information, 20% for R&D, 60% for brand equity, 40% for firms' structural resources.

obtain the share of organization capital, notice that from the steady state equations, we can write the relative share of the two capitals as

$$\frac{\alpha}{\gamma} = \frac{1/\beta - (1-\delta)\, K}{1/\beta - (1-\varphi)\, O}.$$

The ratio of the two capital stocks in the steady state is $\frac{K}{O} = \frac{\varphi}{\delta}\frac{I^k}{I^o}$. Substitute it into the above equation, and we obtain the share of organization capital in the production function:

$$\gamma = \frac{1/\beta - (1-\varphi)\,\delta}{1/\beta - (1-\delta)\,\varphi}\left(\frac{I^k}{I^o}\right)\alpha.$$

Corrado et al. (2006) provided time-series estimates for the amount of business intangible investments in the economy by decade. Using their estimation, combined with the total amount of private physical investment from BEA, we can get the decade-average organization capital/physical capital investment ratios (Table 2.7). I take the ratios as mid-decade steady-state I^o/I^ks, which can then be used to obtain a time series of γ. To make the jumps between steady states relatively smooth, I assumed that the shares in production function—therefore steady state variable values—change every half decade, and interpolated a series of steady state I^o/I^k ratios from the numbers given in Table 2.7. Parameter θ is adapted accordingly to preserve the steady state labor supply characteristics. Table 2.8 listed the steady-state I^o/I^k and the calibrated γs. Table 2.9 listed other major parameter values discussed above, which are kept fixed throughout the calibration.

	1950-1959	1960-1969	1970-1979	1980-1989	1990-1999	2000-2003
Business Tangible Investment, I^k	19.4	41.9	103.4	349.3	749.8	1,226.20
Business Intangible Investment, I^o	35.6	67.3	171.4	421.1	676.5	893.4
Ratio: I^o/I^k	0.55	0.62	0.60	0.83	1.11	1.37

Table 2.7: Business Sector Investments and Ratios

($bn, annual average)[9]

[9] Source: Corrado et al. (2006) and BEA.

Time	I^o/I^k	γ	θ
1955-1959	0.545	0.126	0.518
1960-1964	0.584	0.135	0.514
1965-1969	0.623	0.145	0.510
1970-1974	0.613	0.142	0.511
1975-1979	0.603	0.140	0.512
1980-1984	0.716	0.166	0.502
1985-1989	0.829	0.192	0.490
1990-1994	0.969	0.225	0.474
1995-1999	1.108	0.257	0.457
2000-2004	1.24	0.288	0.439
≥ 2005	1.373	0.318	0.419

Table 2.8: Calibrated values of γ

β	δ	φ	μ	α	σ_ε	σ_η	ρ_a	ρ_b	n
0.96	0.048	0.5	4	0.4	0.007	0.007	0.9	0.9	50

Table 2.9: Baseline Parameter Values

2.5.2 Calibration Results

I simulated the model 100 times, each simulation being sixty years from 1950-2010. I then logarithmed and first differenced the simulated output series, and calculated 9-year rolling standard deviations for both aggregate and firm-level output growths. Table 2.10 presents the average rolling standard deviations by decade, using the baseline parameters listed above. For comparison, the corresponding values in empirical data are also listed. To give a more straightforward representation of the model's volatility trends, Figure 2.3 plots the simulated time series for both macro and micro level rolling standard deviations by year.

	Average aggregate volatility (%std)		Average firm-level volatility (%std)	
Time	Model	Data	Model	Data
1955-1959	1.2729	2.4550	7.1262	14.1237
1960-1969	1.3473	1.6802	8.6236	14.2859
1970-1979	1.2937	1.5563	9.0610	17.7532
1980-1989	1.8821	1.7858	11.5345	24.0382
1990-1999	1.6425	0.8828	17.8298	26.1928
2000-2003	1.2316	1.1129	25.1664	27.2878

Table 2.10: Simulation result: average rolling standard deviation of outputs

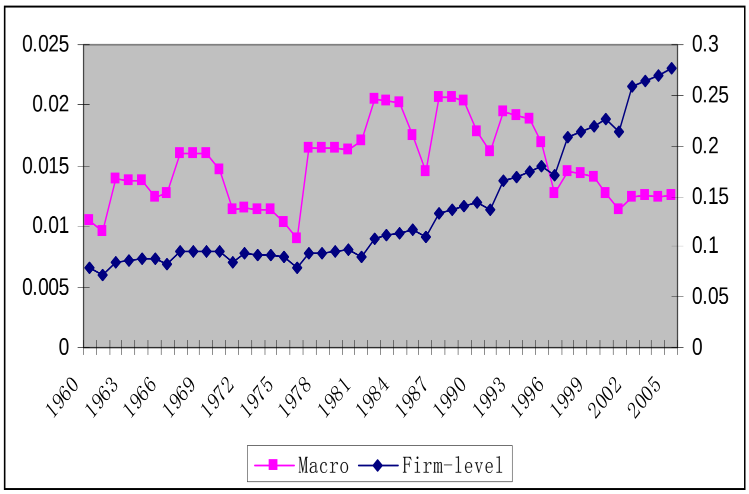

Figure 2.3: Simulated aggregate and firm-level volatilities

How well does the model economy replicate the stylized facts in data? The first thing to notice in Figure 2.3 is that the model does produce a divergence in aggregate and firm-level volatility for the past two decades or so. At the macro level, the model generates decreasing aggregate volatility since the early 1980s, which period was recognized by many researchers as the beginning of significant decline in macroeconomic fluctuations. For the period from 1990 to 1999, the volatility decrease in the model economy is not as sharp as in data, but in general, the model imitates the drop in macro volatility reasonably well. At the firm level, the model is able to generate a trend of consistently increasing volatility, though the magnitude is smaller than in empirical data. The level of firm volatility that the model can produce has a lot to do with the choice of standard deviation for idiosyncratic shocks, which we basically have no reliable information on. I will discuss this relationship in the sensitivity analysis section later.

For the period before 1980s, the simulation did not do very well. The model produces much lower macro volatilities for the 50s and 60s than is seen in data. At the firm level, the simulated volatility is also lower than data, though the model does produce a mildly rising volatility trend for this period, which is consistent with the data.

To sum up, the model successfully captures the divergence in macro and firm-level volatility since the 1980s, in both qualitative and quantitative sense. But the model is not able to generate high macro volatility for earlier periods.

Turning to business cycle properties of other key variables, Table 2.11 reports the average standard deviation, correlation with output and 1st order auto-corelation coefficient for consumption, aggregate investments and hours worked. For consumption and hours, the results are broadly in line with stylized business cycle facts, except that the autocorrelation coefficients for both variables are higher than in real data. The part that deviates most from reality is the volatility of investment. The model produces large swings for investments in both K and O. Especially, the volatility of I^k is much higher than in the data. In addition, I^k and I^o are negatively correlated with output, which is obviously counterfactual. There are two reasons why the model doesn't generate realistic investment volatility at the aggregate level. First, in the calibration, I changed γ multiple times and also the corresponding steady states. The "jumps" between steady states are mostly accomplished by relatively abrupt changes in investments. In periods of transition between steady states, the output level would temporarily decrease because of unexpected change in the production function, while at the same time, investment is going up because of higher intangible capitals' share. This feature of the model largely contributes to the negative correlations between output and investments, and the large swings in investment. In fact, when I carried out the same simulation, but without any increase in γ, the correlation between Y and I^k increases to 0.41 and that between Y and I^o to 0.82, while standard deviations of investments decrease significantly. Second, unlike the standard business cycle model where there are only aggregate productivity shocks, the model generates n+1 i.i.d. shocks every period, n of which are investment specific shocks to individual firms. This induces larger volatility at the firm level, and increases aggregate investment volatility as well. Both volatilities decrease with the choice of n. For example, when I ran the simulation with n=2, the standard deviations of I^k and I^o decreased to 12.5 and 13.46 respectively, while correlations between Y and investments increased remarkably; but at the same time, the divergence between firm-level and aggregate output volatilities disappeared. In section 2.7, I will present an alternative version of the model with additional restrictions on investments, which makes aggregate investment less volatile, yet at the cost of reduced firm-level volatilities.

Variables	%std (std across simulations)	Correlation with output	1st order autocorrelation
Output	1.72 (0.086)	1.00	0.95
Consumption	1.36 (0.023)	0.52	0.86
I^k	321.54 (59.603)	-0.25	0.59
I^o	15.58 (0.547)	-0.45	0.95
Hours	1.40 (0.078)	0.90	0.96

Table 2.11: Business cycle properties of the simulated economy

2.6 Sensitivity Analysis

In the baseline calibration, the share of organization capital in the production function is inferred from parameter values and empirical estimations of I^k/I^o investment ratios. Therefore, the values of γ, steady states and policy functions are highly dependent upon assumptions about relevant parameters. In this section, I adopted alternative assumptions for physical capital's share α, organization capital's depreciation rate φ, standard deviation of idiosyncratic shocks σ_η,and simulated the model for the respective scenarios.

	Aggregate Volatility			Firm-level Volatility		
	$\alpha = 0.2$	$\alpha = 0.3$	$\alpha = 0.45$	$\alpha = 0.2$	$\alpha = 0.3$	$\alpha = 0.45$
1955-1959	1.2492	1.3462	0.6622	5.3576	4.3895	9.2729
1960-1969	1.5482	1.0771	0.7171	6.0324	4.9731	10.8682
1970-1979	1.7968	1.2575	1.1698	6.5189	5.2664	11.8300
1980-1989	3.4898	2.4938	1.7972	8.4908	6.7111	15.3040
1990-1999	3.3714	2.4516	1.7557	11.8223	9.5216	25.5043
2000-2003	2.6557	1.7738	1.7319	14.7713	11.9644	36.7032

Table 2.12: Sensitivity analysis—alternative values of α

Table 2.12 reports the average rolling standard deviations by decade at both macro and firm level for alternative choices of α (the steady states and time series of γ are adjusted accordingly). The starting value 0.2 is from Atkeson & Kehoe (2005)'s estimation of physical capital's share in the output of US manufacturing sector. The result shows that no matter what the choice of α is, the model generates decreasing macro volatility since the 1980s and consistently rising firm-level volatility.

	Aggregate Volatility			Firm-level Volatility		
	$\varphi = 0.25$	$\varphi = 0.45$	$\varphi = 0.65$	$\varphi = 0.25$	$\varphi = 0.45$	$\varphi = 0.65$
1955-1959	1.0615	1.1741	1.1167	8.6189	7.3765	6.8377
1960-1969	0.6945	1.2292	1.0010	10.5576	8.7617	7.8534
1970-1979	1.2277	1.3117	1.1490	11.3991	9.3464	8.3238
1980-1989	1.3810	1.7435	2.3050	14.6057	12.0093	10.9464
1990-1999	1.4611	1.5259	1.7846	22.6387	18.2716	16.6941
2000-2003	2.6658	1.2015	1.1644	31.5412	25.9397	22.1945

Table 2.13: Sensitivity analysis—alternative values of φ

Table 2.13 presents the volatility statistics across different assumptions for the depreciation rate of organization capital. At the firm level, regardless of O's depreciation rate, firm volatilities all increase through time. But at the macro level, the result is fairly sensitive to the choice of

φ. Higher depreciation rates generate a more salient pattern of volatility decline in the past two decades, while a small φ (0.25) fails to produce any decrease in macro volatility.

	Aggregate Volatility			Firm-level Volatility		
	σ_η= 0.006	σ_η= 0.008	σ_η= 0.009	σ_η= 0.006	σ_η= 0.008	σ_η= 0.009
1955-1959	1.2535	1.2241	1.0903	6.2247	8.0162	9.0585
1960-1969	1.3798	1.4909	1.2911	7.5398	9.8231	11.2579
1970-1979	1.2399	1.4224	1.5003	7.9424	10.4785	11.9206
1980-1989	2.0367	1.8185	1.8987	10.0408	13.2423	14.6813
1990-1999	1.8128	1.5576	1.2919	15.9221	19.5503	22.6511
2000-2003	1.5543	1.2940	1.9666	21.1994	28.0999	31.8900

Table 2.14: Sensitivity analysis—alternative values of σ_η

Finally, Table 2.14 lists the volatility results with changes in the standard deviation of idiosyncratic shocks. Quite intuitively, a smaller σ_η produces less volatile firms— firm-level standard deviations increase with σ_η. But at the macro level, the effect of change in σ_η is less obvious, especially for earlier years, when γ is small and the aggregate impact of organization-specific shocks very limited.

Overall, the sensitivity analyses indicate that the volatility divergence generated by changes in organization capital's share in the production function is fairly robust to alternative parameter choices. A fall in macro volatility since the 1980s and continuously rising firm volatility are present across most of the alternative scenarios. But quantitatively, how well the model actually matches data is sensitive to some parameter choices.

2.7 Model with Capital Adjustment Cost

As shown in section 2.5, a shortcoming of the model is that the business cycle properties of aggregate investments are not very realistic. In this section, I introduce adjustment costs in the capital accumulation process to improve the model characteristics of aggregate investments.

The basic setup is the same as in section 2.4, except the capital accumulation rule, which is changed to the following:

$$\begin{aligned} K_{i,t+1} - p_k \ln\left(K_{i,t+1} - (1-\delta) K_{i,t}\right) &= (1-\delta_k)K_{i,t} + I_{i,t}^k \\ O_{i,t+1} - p_o \ln\left(O_{i,t+1} - (1-\varphi) O_{i,t}\right) &= (1-\delta_o)O_{i,t} + B_{i,t} I_{i,t}^o \end{aligned}$$

where p_k and p_o are two small positive numbers.

Since the adjustment cost function $-p_x \ln\left(X_{i,t+1} - (1-\delta) X_{i,t}\right)$ converges to $-\infty$ when $[X_{i,t+1} - (1-\delta) X_{i,t}] \rightarrow_{+} 0$, the term creates a large cost when the new investments in K and O for any firm approach zero, and thus assures that in the solution to the optimization problem, every firm receives positive investments of both capitals in any given period. On the other hand, when a firm's optimal investments are well above zero, the existence of adjustment cost terms will not significantly change the result compared to the original model, as long as p_k and p_o are kept very small.

The Lagrangian for the social planner's problem now takes the following form

$$\begin{aligned} \mathcal{L} = & \max_{\{C_t,[K_{i,t+1},O_{i,t+1}]_{i=1}^n,[L_{i,t}]_{i=1}^n\}_{t=0}^\infty} E_0\{\sum_{t=0}^{\infty} \beta^t [\ln(C_t) + \theta \frac{(1-L_t)^{1-\mu}}{1-\mu} \\ & + \lambda_t [\sum_{i=1}^n K_{i,t}^{\alpha_t} O_{i,t}^{\gamma_t} (A_t L_{i,t})^{1-\alpha_t-\gamma_t} + \sum_{i=1}^n (1-\delta) K_{i,t} + \sum_{i=1}^n (1-\varphi) O_{i,t} \\ & + \sum_{i=1}^n p_k \ln\left(K_{i,t+1} - (1-\delta) K_{i,t}\right) + \sum_{i=1}^n p_o \ln\left(O_{i,t+1} - (1-\varphi) O_{i,t}\right) \\ & - C_t - \sum_{i=1}^n K_{i,t+1} - \sum_{i=1}^n \frac{O_{i,t+1}}{B_{i,t}}] + \varsigma_t (L_t - \sum_{i=1}^n L_{i,t})]\} \end{aligned}$$

It is clear that if p_x=0, we go back to the original solution. In the following simulation exercise, I set $p_k = p_o = 0.000002$. Other parameters are the same as in section 2.5. Table 2.15 presents the cyclical behaviors of the model economy after adding adjustment cost. Compared with the baseline model, one improvement is that, though still higher than empirical observation, the volatility of aggregate investment in K is much lower than in the original model. Besides, the correlation between I^k and Y is now positive, though lower than the data.

Variables	%std (std across simulations)	Correlation with output	1st order autocorrelation
Output	1.64 (0.040)	1.00	0.95
Consumption	1.33 (0.021)	0.49	0.91
I^k	52.82 (20.194)	0.28	0.96
I^o	13.28 (0.289)	-0.46	0.87
Hours	1.32 (0.032)	0.89	0.96

Table 2.15: Business cycle properties of model economy with adjustment cost

The improvements in investment characteristics are not without cost. Table 2.16 and figure 2.4 report the output volatility trends of the model with adjustment costs. Although the aggregate volatility is at the same range as before, the firm level volatility turns out to be much lower, due to the fact that the additional restriction on firm's investment curbed the degree of variations among firms. But qualitatively, the model is still able to generate the divergence in macro and firm-level volatility from the 1980s onward.

	Average aggregate volatility (%std)		Average firm-level volatility (%std)	
Time	Model	Data	Model	Data
1955-1959	1.3541	2.4550	4.0141	14.1237
1960-1969	1.2829	1.6802	4.7188	14.2859
1970-1979	1.1977	1.5563	5.0884	17.7532
1980-1989	1.7510	1.7858	6.2470	24.0382
1990-1999	1.6664	0.8828	9.1524	26.1928
2000-2003	1.0871	1.1129	12.0947	27.2878

Table 2.16: Average rolling standard deviations of outputs

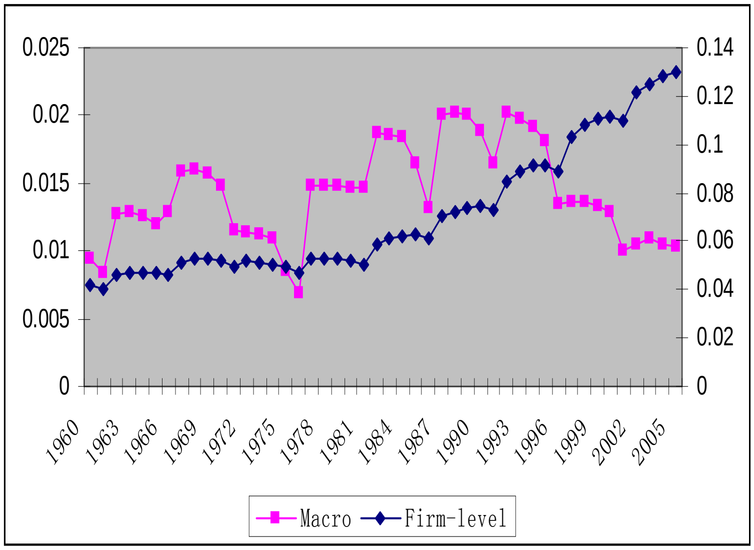

Figure 2.4: Volatility trends of model economy with adjustment costs

2.8 Conclusion

The aggregate output volatility of US economy has declined significantly since the early 1980s, but at the same time, firm performance has become more volatile. The latter fact contradicts many explanations of the "Great Moderation" that imply a direct transfer between macro and firm-level volatilities. This chapter provides a theory to reconcile the two phenomena from the perspective of structural change in production activities.

I argued that organization capital investment is a key factor causing the volatility divergence. During roughly the same period as the great moderation, business sector's organization capital, or firm-specific intangible capital, has been increasing rapidly. Such organizational investment is an important source of idiosyncratic risks, while at the same time it makes a firm less susceptible to general market risks. When firms in the economy invest more in organization capital, the impact of firm-specific risk factor becomes larger and that of general risk factor smaller. The former causes firm-level volatility to increase; the latter, through lowering the positive comovements among firms, reduces aggregate volatility. In this sense, the decline in macro volatility during the past two decades should rather be called the "Great Dissolution".

Using firms' SG&A expenditure as an approximation for organization capital investment, I looked at how a firm's sales volatility, the impact of general risks, and a firm's performance correlation with other firms are affected by its organization capital intensity, compared to the influence of other production inputs. The results show that firms' volatility increases with more investment in organization capital. Meanwhile, organizational investment decreases general shocks' impact and a firm's comovement with others. The result generally supports my hypotheses about the relationship between organizational investment and firms' risk characteristics.

I constructed a general equilibrium model featuring organization capital investment. In the model, a firm is subject to two shocks, a global technology shock that affects all firms alike, and an idiosyncratic productivity shock that is specific to a firm's organization capital accumulation process. With reasonable parameter choices, the model is able to generate volatility divergence during the past two decades and quantitatively match the sales volatility data at both macro and firm level. The simulation result before the 1980s was much less satisfactory, suggesting that organization capital playing a significant role in the production process is a relatively recent phenomenon.

To sum up, the chapter shows that organization capital investment provides a constructive perspective in solving the diverging volatility puzzle. The empirical evidence presented in the chapter is still preliminary. To extend the current investigation, further empirical analysis at different levels of aggregation, e.g., at sector and industry level, can be very helpful.

2.A Appendix: Solution Method

In this section, I explain the solution method of the model.

The first order conditions of the planner's problem are[10]:

$$\begin{aligned}
\frac{1}{C_t} &= \lambda_t \\
\theta(1-\sum_{j=1}^{n} L_{j,t})^{-\mu} &= \lambda_t(1-\alpha-\gamma)K_{i,t}^{\alpha}O_{i,t}^{\gamma}A_t{}^{1-\alpha-\gamma}L_{i,t}^{-\alpha-\gamma} \\
\lambda_t &= \beta E\{\lambda_{t+1}[\alpha K_{i,t}^{\alpha-1}O_{i,t}^{\gamma}(A_t L_{i,t})^{1-\alpha-\gamma}+(1-\delta)]\} \\
\frac{\lambda_t}{B_{i,t}} &= \beta E\{\lambda_{t+1}[\gamma K_{i,t}^{\alpha-1}O_{i,t}^{\gamma-1}(A_t L_{i,t})^{1-\alpha-\gamma}+\frac{(1-\varphi)}{B_{i,t+1}}]\}. \\
i &= 1,2,...n
\end{aligned}$$

The steady state equations are:

$$\begin{aligned}
\theta(1-\sum_{j=1}^{n} L_j)^{-\mu} = \frac{1}{C}(1-\alpha-\gamma)K_i^{\alpha}O_i^{\gamma}L_i^{-\alpha-\gamma} \\
\frac{1}{\beta} = \alpha K_i^{\alpha-1}O_i^{\gamma}L_i^{1-\alpha-\gamma}+(1-\delta) \\
\frac{1}{\beta} = \gamma K_i^{\alpha}O_i^{\gamma-1}L_i^{1-\alpha-\gamma}+(1-\varphi) \\
C+\delta\sum_{j=1}^{n} K_j)+\varphi\sum_{j=1}^{n} O_j = \sum_{j=1}^{n} K_j^{\alpha}O_j^{\gamma}L_j^{1-\alpha-\gamma} \\
A=1; B=1.
\end{aligned}$$

[10] By taking first order conditions, an interior solution is already assumed. Why can we rule out corner solution? In other words, is it possible that in some periods, certain firms get zero investment because they are hit by low shocks? The answer is no. The reason is as follows. Assume all firms start with the same amount of capitals K and O, but firm A has higher organizational investment-specific shock for the next period. Suppose the social planner chooses to concentrate all the new O investment in firm A and starve other firms, obviously all the new K investment has to be made in firm A, too, otherwise too much O makes the marginal productivity of O in firm A go down so much that it can hardly be optimal. Now think of what happens to other firms. They get zero new investment, but are still in business with the left-over K and O from last period. But K and O have very different depreciation rates. Specifically, in the model, I assume depreciation for K around 5% per year, but for O about 50%. So in the next period, the marginal productivity of O in other firms would be much higher than in firm A, if they don't receive any new O investment. The situation can be improved if social planner had chosen to invest some O in these low-shock firms, which means that the investment schedule I assumed in the beginning cannot be optimal. The key thing here is a much higher depreciation rate for O than for K. And this assumption is by no means unrealistic.

Let

$$
\begin{aligned}
R^k_{i,t} &= \alpha K^{\alpha-1}_{i,t} O^{\gamma}_{i,t} (A_t L_{i,t})^{1-\alpha-\gamma} + (1-\delta) \\
R^o_{i,t} &= \gamma K^{\alpha-1}_{i,t} O^{\gamma-1}_{i,t} (A_t L_{i,t})^{1-\alpha-\gamma} + \frac{(1-\varphi)}{B_{i,t}}
\end{aligned}
$$

And let lower case letters denote log-deviations of variables from the steady state. Log-linearizing the first order conditions and constraints around the steady state:

$$
\begin{aligned}
r^k_{i,t+1} &= \frac{\alpha K^{\alpha-1} O^{\gamma} L^{1-\alpha-\gamma}}{R^k}[(\alpha-1)k_{i,t+1} + \gamma o_{i,t+1} + (1-\alpha-\gamma) l_{i,t+1} \\
&\quad +(1-a-\gamma)a_{t+1}] \\
r^o_{i,t+1} &= \frac{\gamma K^{\alpha} O^{\gamma-1} L^{1-\alpha-\gamma}}{R^o}[\alpha k_{i,t+1} + (\gamma-1) o_{i,t+1} + (1-\alpha-\gamma) l_{i,t+1} \\
&\quad +(1-a-\gamma)a_{t+1}] - (1-\varphi) b_{i,t+1}
\end{aligned}
$$

$$
\begin{aligned}
-c_t &= \nu_t \\
\mu \frac{L}{1-nL} l_{i,t} &= \nu_t + \alpha k_{i,t} + \gamma o_{i,t} + (-\alpha-\gamma) l_{i,t} + (1-a-\gamma) a_t \\
\nu_t &= E_t(\nu_{t+1} + r^k_{i,t+1}) \\
\nu_t - b_{i,t} &= E_t(\nu_{t+1} + r^o_{i,t+1})
\end{aligned}
$$

$$
\begin{aligned}
& Cc_t + K\sum_{j=1}^{n} k_{j,t+1} + O\sum_{j=1}^{n} o_{j,t+1} \\
= \; & [\alpha K^{\alpha-1} O^{\gamma} L^{1-\alpha-\gamma} + (1-\delta)K] \sum_{j=1}^{n} k_{j,t} + [\gamma K^{\alpha} O^{\gamma-1} L^{1-\alpha-\gamma} \\
& +(1-\varphi)O] \sum_{j=1}^{n} o_{j,t} + nK^{\alpha} O^{\gamma} L^{1-\alpha-\gamma}(1-\alpha-\gamma) a_t \\
& +K^{\alpha} O^{\gamma} L^{1-\alpha-\gamma}(1-\alpha-\gamma) \sum_{j=1}^{n} l_{j,t} + \varphi O \sum_{j=1}^{n} b_{j,t}
\end{aligned}
$$

Exogenous shock processes take the form:

$$a_{t+1} = \rho_a a_t + \varepsilon_{t+1}, \quad \varepsilon_{t+1} \tilde{}\, iid\ N(0, \sigma_\varepsilon^2)$$

$$b_{i,t+1} = \rho_b b_{i,t} + \eta_{i,t+1},\ i = 1, 2, ...n, \quad \eta_{i,t+1} \tilde{}\, iid\ N(0, \sigma_\eta^2)$$

I then solved for the equilibrium law of motion using Schur factorization method proposed by King & Watson (2002).

Chapter 3

Factor Endowment, Structural Coherence, and Economic Growth

3.1 Introduction

Although neoclassical growth models generally feature balanced growth path, in reality the industrial composition of economies experience continuous shifts, accompanied by massive reallocation of labor and production resources across sectors. Investigations on the causes of structural change have been mostly theoretical. A recent example is Acemoglu & Guerrieri (2008), who modeled structural change as a result of capital accumulation. In their two-sector model, as capital becomes more abundant output increases in the capital-intensive sector, while the direction of employment composition change depends on the elasticity of substitution between sectors.[1] Ju, Lin & Wang (2008), focusing more on developing countries, arrived at similar conclusions: as capital accumulates, a country's industrial structure "upgrades" towards more capital-intensive industries. Moreover, they argue that when the industrial structure is not coherent with the capital endowment level, it can lead to suboptimal economic growth performance.[2]

[1] There are other explanations of structural change, to be sure. On the supply side, for example, Ngai & Pissarides (2007) models industrial composition change as a result of uneven rates of TFP growth across sectors. The demand side literature explains structural change as a combined result of nonhomothetic consumer preference and income growth (Echevarria (1997), Laitner (2000), Buera & Kaboski (2007)). Thus in the empirical regressions, I will control for these other factors that potentially affect structural change process.

[2] In an earlier work, Hollis Chenery (1979) made a similar point. He argues that countries that are short on capital, in considering their development policy, should choose industries and production techniques that have low capital to output ratio.

Ju, Lin & Wang's prediction about the linkage between structural coherence and economic growth can also be derived from Acemoglu & Guerrieri (2008)'s framework, though not explicitly discussed in their paper. The intuition is straightforward: in Acemoglu & Guerrieri's paper, output composition change towards capital-intensive industries is the natural result of the agents' optimal decision as capital accumulates. Hence, any arrangement that obstructs the structural change process towards alignment with factor endowments is not an optimal choice and therefore has a negative impact on long-run growth. Although it is beyond the scope of the current study to identify specific causes of structural incoherence, the incoherence between industrial structure and factor endowment can be caused by such factors as over-restrictive labor market regulation, lack of competition in certain industries, and technology barriers, as identified in related literature.[3]

The major goal of this chapter is to empirically examine the relationship between capital endowment and industrial structure, and to estimate structural coherence' impact on growth. Here is an overview of the main empirical results. For the overall capital, the data shows that the capital-intensive industries' output and employment sizes are larger when capital endowment is higher, and growth in capital endowment also leads industrial structure to shift towards capital-intensive industries. Similar results apply, to various degrees, to detailed types of physical capital.[4] In terms of the relationship between structural coherence and growth, the results show that a country's aggregate growth performance is significantly and positively associated with the coherence level between industrial structure and capital endowment. In the country-level regression, structural coherence related to the overall capital explains about 25% of the variation in country GDP growth. The industry-level regression indicates an effect of similar magnitude. Moreover, the industry-level results are mostly robust to changing the measurement of capital intensity and to controls for other industry characteristics and structural change determinants.

The chapter is related to a large empirical international trade literature that aims to test Heckscher-Ohlin theorem and Rybczynski theorem.[5] Recent examples of this literature are Har-

[3] The linkage between structural change and aggregate economic performance have been discussed in some recent macroeconomic literature, such as, Nickell, Redding & Swaffield (2004), Rogerson (2007), van Ark, O'Mahony & Timmer (2008), and Baily (2001).

[4] My focus in this paper is mostly fixed physical capital. The mechanism examined here can apply to intangible capital, too. Che (2009) argues that the increasing importance of intangible capital in the production process is a cause of sectoral structural change in advanced economies. However, the test on intangible capital is difficult to execute in a cross-country setting due to data limitations.

[5] These theorems state, respectively, that differences in countries' exports are determined by differences in their factor endowments, and that a rise in the endowment of a factor will lead to more than proportional output increase

rigan (1997), Reeve (2002), Romalis (2004) and Schott (2003). Some of these papers found that endowment and change of endowment in physical capital and/or human capital has a significant impact on trade patterns or industrial structure.[6] There are obvious differences in terms of the underlining theory between the present study and most of that literature. Sectoral structural change induced by factor endowment change is a process independent of whether the country is an open economy or not. Thus the present study covers all industries in an economy, regardless of whether the products are considered tradable or not. In terms of methodology, most of the endowment-related trade studies assume identical capital intensities of industries across countries, or at least the same capital intensity ranking in different countries. Thus the literature often uses industry characteristics in one country as proxies for all other countries. Though a reasonable assumption when countries are relatively similar, this assumption is not necessarily true as I will show in Section 3.[7] In this study I allow the capital intensity ranking of industries to change across countries and over time.

The study is also related to empirical investigations of allocative efficiency across industries and firms (e.g., Bartelsman, Haltiwanger & Scarpetta (2008), Arnold, Nicoletti & Scarpetta (2008)). This strand of literature mainly focuses on efficiency in resource allocation according to firm/industry's productivity level, instead of resource allocation according to consistency with factor endowments. To my best knowledge, the present study is the first one to examine the impact of industrial structure-factor endowment coherence on economic growth.

The chapter is organized as follows. Section 3.2 provides a simple theoretical framework to explain the relationship between capital endowment, structural coherence and growth. Section 3.3 discusses the data and defines measures of variables. Section 3.4 and 3.5 present the empirical models, at country and industry level respectively, and discuss the estimation results. I add more restrictions to the industry-level estimation and conduct robustness checks in Section 3.6. Section 3.7 concludes.

in sectors that use the factor intensively, given constant goods prices.

[6]Fitzgerald & Hallak (2002) gives an excellent review of recent empirical literature in trade that is related to factor endowments.

[7]Lewis (2006) shows that production techniques within the same industry vary even within US across different regions according to the production factor mix of the region. Scott (2003) finds that capital abundant countries tend to use more capital-intensive techniques in all industries.

3.2 An Illustrative Model

To examine the relationship between structural coherence and growth, consider a simple two-sector model adapted from Acemoglu & Guerrieri (2008). In the model economy, a single final good is produced by combining two sectoral goods, the elasticity of substitution between the two sectors equal to $\varepsilon \in [0, \infty)$:

$$Y_t = \left[\gamma_1 Y_{1,t}^{(\varepsilon-1)/\varepsilon} + \gamma_2 Y_{2,t}^{(\varepsilon-1)/\varepsilon}\right]^{\varepsilon/(\varepsilon-1)}$$

where $\gamma_1 + \gamma_2 = 1$. There is one firm in each sector. Both sectors' production functions are Cobb-Douglas with capital and labor as production inputs:

$$Y_{i,t} = A_t K_{i,t}^{a_i} L_{i,t}^{1-a_i} \tag{3.1}$$

For simplicity, I assume that the two sectors share the same productivity level, A_t, while Sector 1 is more capital-intensive than Sector 2, i.e., $a_1 - a_2 > 0$.

Let the price of the final good $P_t = 1$, then the prices for the two sectoral goods can be expressed as

$$P_{1,t} = \gamma_1 \left(\frac{Y_t}{Y_{1,t}}\right)^{-1/\varepsilon}, \text{ and } P_{2,t} = \gamma_2 \left(\frac{Y_t}{Y_{2,t}}\right)^{-1/\varepsilon}$$

Thus the direction of change in the ratio of nominal output between the two sectors, $\frac{P_{1,t}Y_{1,t}}{P_{2,t}Y_{2,t}}$, corresponding to a change in the real output ratio $Y_{1,t}/Y_{2,t}$, will depend on the value of ε. When ε>1, the nominal output ratio moves in the same direction as the real output ratio, and the opposite is true for ε<1.

Assume that labor is freely mobile between the two sectors in any given period. Labor market clearing implies

$$L_{1,t} + L_{2,t} = \overline{L}_t \tag{3.2}$$

where $\overline{L}_t$ is the labor supply at time t, which is exogenously given.

Capital is also mobile across sectors. However, changes in the allocation of capital resource are costly. It manifests as a positive adjustment cost $G\left(\frac{K_{1,t}}{K_{2,t}} - s_t\right)$ whenever the ratio between the two sectors' capital differs from a predetermined value , which may be equal to, say, some historical ratio between K_1 and K_2. Capital market clearing requires

$$K_{1,t} + K_{2,t} + G\left(\frac{K_{1,t}}{K_{2,t}} - s_t\right) = K_t \tag{3.3}$$

where K_t is the aggregate capital stock at time t. $G(0) = 0$, $G' > 0$,and $G" \geq 0$. Specifically, I assume that $G(\cdot)$ takes a quadratic form:

$$G(K_{1,t}, K_{2,t}) = \phi\left(\frac{K_{1,t}}{K_{2,t}} - s_t\right)^2 \tag{3.4}$$

where $\phi \geq 0$. The existence of adjustment cost introduces friction into the cross-sector movement of resources, thus can potentially alter the extent of sectoral structural change compared to the case of frictionless economy.

Assume that the markets are complete and competitive. The equilibrium of the economy can be solved as a social planner's problem that maximize the utility of the representative household, $\sum_{t=0}^{\infty} U(C_t)$, subject to the aggregate resource constraint for the economy: $C_t + K_{t+1} = Y_t + (1-\delta) K_t$.

Given capital stock K_t in each period, the intra-temporal component of the planner's problem is to solve

$$\max_{L_{1,t}, L_{2,t}, K_{1,t}, K_{2,t}} Y_t = \left[\gamma_1 Y_{1,t}^{(\varepsilon-1)/\varepsilon} + \gamma_2 Y_{2,t}^{(\varepsilon-1)/\varepsilon}\right]^{\varepsilon/(\varepsilon-1)} \tag{3.5}$$

subject to (3.1), (3.2), (3.3), (3.4).

Solving (3.5) requires the marginal products of capital and labor in the two sectors being equal, which implies:

$$\gamma_1 a_1 \left(\frac{Y_t}{Y_{1,t}}\right)^{1/\varepsilon} \frac{Y_{1,t}}{K_{1,t}} / \left[1 + \frac{2\phi}{K_{2,t}}\left(\frac{K_{1,t}}{K_{2,t}} - s_t\right)\right] = \gamma_2 a_2 \left(\frac{Y_t}{Y_{2,t}}\right)^{1/\varepsilon} \frac{Y_{2,t}}{K_{2,t}} / \left[1 + \frac{2\phi K_{1,t}}{K_{2,t}^2}\left(\frac{K_{1,t}}{K_{2,t}} - s_t\right)\right] \tag{3.6}$$

$$\gamma_1 (1-a_1) \left(\frac{Y_t}{Y_{1,t}}\right)^{1/\varepsilon} \frac{Y_{1,t}}{L_{1,t}} = \gamma_2 (1-a_2) \left(\frac{Y_t}{Y_{2,t}}\right)^{1/\varepsilon} \frac{Y_{2,t}}{L_{2,t}} \tag{3.7}$$

Denote the share of capital and labor allocated to the capital intensive sector (Sector 1) as

$$\lambda_t = \frac{K_{1,t}}{K_{1,t} + K_{2,t}}, \quad \xi_t = \frac{L_{1,t}}{L_{1,t} + L_{2,t}}$$

Then (3.6) and (3.7) imply that

$$\lambda_t + \frac{2\phi \frac{\lambda_t}{1-\lambda_t}\left(\frac{\lambda_t}{1-\lambda_t} - s_t\right)}{K_t - \phi\left(\frac{\lambda_t}{1-\lambda_t} - s_t\right)^2} = \left[1 + \frac{\gamma_2 a_2}{\gamma_1 a_1}\left(\frac{Y_{2,t}}{Y_{1,t}}\right)^{1-1/\varepsilon}\right]^{-1} \tag{3.8}$$

$$\begin{aligned} \xi_t &= \left[1 + \frac{\gamma_2(1-a_2)}{\gamma_1(1-a_1)}\left(\frac{Y_{2,t}}{Y_{1,t}}\right)^{1-1/\varepsilon}\right]^{-1} \\ &= \left[1 + \frac{a_1(1-a_2)}{a_2(1-a_1)} \frac{(1-\lambda_t)K_t - 2\phi\frac{\lambda_t}{1-\lambda_t}\left(\frac{\lambda_t}{1-\lambda_t} - s_t\right)}{\lambda_t K_t - \phi\left(\frac{\lambda_t}{1-\lambda_t} - s_t\right)^2 + 2\phi\frac{\lambda_t}{1-\lambda_t}\left(\frac{\lambda_t}{1-\lambda_t} - s_t\right)}\right]^{-1} \end{aligned} \tag{3.9}$$

Notice that $Y_{1,t}/Y_{2,t}$ is equal to

$$\lambda_t^{a_1}(1-\lambda_t)^{-a_2}\xi_t^{1-a_1}(1-\xi_t)^{a_2-1}K_t^{a_1-a_2}\overline{L}_t^{a_2-a_1} \tag{3.10}$$

Therefore, given the resource allocation λ_t and ξ_t unchanged, an increase in K_t will disproportionately raise the real output of Sector 1 over Sector 2, and the opposite is true when labor endowment increases. Plugging (3.10) into (3.8) and taking derivative of both sides of (3.8) with respect to K_t, we arrive at the following proposition describing the relationship between changes in cross-sector resource allocation and changes in aggregate capital stock in any given period.

Proposition 5 *In the static equilibrium,*

$$\frac{\partial \ln \lambda_t}{\partial \ln K_t} = \frac{(1-\varepsilon)(a_1 - a_2)(1-\lambda_t)}{(1-\varepsilon)(a_1-a_2)(\lambda_t - \xi_t) - a - \Phi_t} > 0 \Leftrightarrow \varepsilon > 1 \tag{3.11}$$

where Φ_t, when $s_t = K_{1,t}/K_{2,t}$, can be expressed as

$$\Phi_t = \frac{2\phi}{1-\lambda_t}\left(1 + \frac{\lambda_t^2}{1-\lambda_t^2}\right)\left[1 - (1-\varepsilon)(a_1 - a_1\xi_t + a_2\xi_t)\right] \tag{3.12}$$

The proposition says that when the elasticity of substitution between sectors is greater than one (which is the relevant scenario in our empirical investigation as Section 3.4 and 3.5 will show), increasing aggregate capital stock will lead to capital being shifted to the capital intensive sector (Sector 1). From (3.9), we know that ξ_t is increasing in λ_t. Thus Sector 1's labor share will also increase with capital stock, when $\varepsilon > 1$. However, the degree of this shift is subdued by the presence of structural adjustment cost, as Φ_t is a positive function of ϕ and it is easy to see from (3.11) and (3.12) that

$$\frac{\partial \left|\partial \ln \lambda_t / \partial \ln K_t\right|}{\partial \phi} < 0 \tag{3.13}$$

What follows from (3.13), combined with (3.10), is that the sectoral structural change in terms of real output when capital stock increases is suppressed by the presence of structural adjustment cost:

$$\frac{\partial^2 \ln \left(Y_{1,t}/Y_{2,t}\right)}{\partial \phi \partial \ln K_t} < 0, \text{ when } \varepsilon > 1.$$

The effect on the output of the final good is also straightforward. When $\phi = 0$, the resource allocation prescribed by the solution to (3.5) achieves the maximized value of given the amount of capital endowment. In other words,

$$\frac{\partial Y_t}{\partial K_t}|_{\phi=0} = \max_{\lambda_t} \frac{\partial Y_t}{\partial K_t}.$$

Therefore, with positive structural adjustment costs, the increase in corresponding to an increase in capital stock is lower compared to the case of zero adjustment cost.

The main conclusion to draw from the theoretical discussion is two folds. First, increasing capital endowment is likely to be accompanied by structural change towards the capital intensive sectors and industries in terms of real output. The change of industrial composition in terms of employment and nominal output depends on the elasticity of substitution between industries. If the elasticity is above unity, then nominal output shares and employment shares of capital-intensive industries will also rise as capital endowment increases. Second, if for any structural reasons the cross-sector reallocation of resources is hindered, then the industrial structure may become insensitive to the changes in factor endowment. And this lack of responsiveness in industrial structure can lead to suboptimal economic performance at the aggregate level. The subsequent part of the chapter will empirically examine both predictions.

3.3 Data and Variables

The data used in this chapter is from the EU KLEMS database sponsored by the European Commission. The database provides industry output, employment, price, capital stock and investment data from 1970 to 2005 for both EU countries and several non-EU countries.[8] Table 3.1 lists the industries covered, the cross-country median growth rates of their real output shares, employment shares and nominal output shares over the 35-year period, and the cross-country medians of industry's overall capital intensity.[9] Industries are sorted by their median real output share growth. It is worth noting that although the industrial composition change is different for each country, in general the real output composition is shifting towards service industries and a few more sophisticated manufacturing industries. This is consistent with the stylized facts about structural transformation documented in the existing literature about US and other advanced economies. Employment composition has a similar trend to real output composition, yet shows an even stronger shift towards service industries. The median growth rate for nominal output shares has the same sign as employment shares but for seven industries.

Consistent with common perceptions, some industries that are traditionally perceived as labor intensive, such as textile and food industries, have relatively low median capital intensity. Somewhat counter-intuitive, though, certain stereotypical "capital-intensive" manufacturing industries, such as machinery and basic metals, do not have particularly high median capital intensity according to Table 3.1; in contrast, service industries such as social and personal services, health, retail, finance and education show up as relatively capital intensive. The reason is that although these service industries are not intensive in machinery capital, they are generally more intensive in ICT capital and structure capital, thus boosting their overall capital intensity scores. The opposite is true for some basic manufacturing industries that rely heavily on machinery, but are not particularly intensive in the other two categories of capital. On the whole, there is a positive correlation between industry's median real output share growth and median overall capital intensity, with a correlation coefficient equal to 0.25 at 1% significance level.

[8] The paper covers 15 countries: Australia, Austria, Denmark, Finland, Germany, Italy, Japan, Korea, Netherland, UK, USA, Czech, Portugal, Slovenia, and Sweden. Data for the last 4 countries is only available starting the mid 1990s.

[9] Capital intensity is calculated as industry real capital stock over real output.

Industry	Median share growth rate from 1970 to 2005			Median capital intensity (Overall capital stock/output)
	Real output share	Employment share	Nominal output share	
Textiles, Textile , Leather And Footwear	-1.323	-1.891	-1.673	0.512
Mining And Quarrying	-0.758	-0.781	-0.555	1.696
Coke, Refined Petroleum And Nuclear Fuel	-0.620	-0.853	-0.064	0.510
Food , Beverages And Tobacco	-0.431	-0.603	-0.584	0.436
Construction	-0.422	-0.301	-0.205	0.232
Wood And Of Wood And Cork	-0.325	-0.494	-0.385	0.508
Hotels And Restaurants	-0.299	0.519	0.017	0.708
Other Non-Metallic Mineral	-0.285	-0.671	-0.434	0.734
Manufacturing Nec; Recycling	-0.193	-0.399	-0.253	0.477
Pulp, Paper, Paper , Printing And Publishing	-0.175	-0.491	-0.231	0.538
Education	-0.119	0.283	0.189	1.493
Basic Metals And Fabricated Metal	-0.114	-0.552	-0.316	0.600
Retail Trade	0.008	0.155	-0.016	0.824
Sale And Repair Of Motor Vehicles And Motorcycles	0.037	0.088	0.026	0.616
Other Community, Social And Personal Services	0.043	0.414	0.399	1.209
Wholesale Trade And Commission Trade	0.106	0.005	0.001	0.550
Real Estate Activities	0.145	0.697	0.532	0.566
Transport And Storage	0.147	-0.017	0.099	1.868
Health And Social Work	0.152	0.633	0.514	0.921
Machinery, Nec	0.176	-0.299	-0.044	0.442
Chemicals And Chemical Products	0.197	-0.559	-0.081	0.754
Electricity, Gas And Water Supply	0.279	-0.383	0.194	3.424
Rubber And Plastics	0.301	-0.113	0.112	0.581
Transport Equipment	0.335	-0.264	0.064	0.510
Financial Intermediation	0.501	0.222	0.502	0.708
Electrical And Optical Equipment	0.715	-0.331	0.054	0.496
Renting Of M&Eq And Other Business Activities	0.826	1.218	0.979	0.555
Post And Telecommunications	1.199	-0.174	0.605	2.231

Table 3.1:Cross-country median industry size growth and capital intensity

Figure 3.1 and Table 3.2 present the trend of aggregate labor income shares by country. In 13 out of the 15 countries covered, labor's share has declined over the sample period. This result is consistent with the fact that the industrial structure of the sample countries is moving towards more capital intensive industries.[10]

[10] The decline of labor income share in these countries has been documented in previous literature. See, for example, Blanchard (1997), Bentolila & Saint-Paul (2003), de Serres, Scarpetta & de la Maisonneuve (2002), and Arpaia, Perez & Pichelmann (2009).

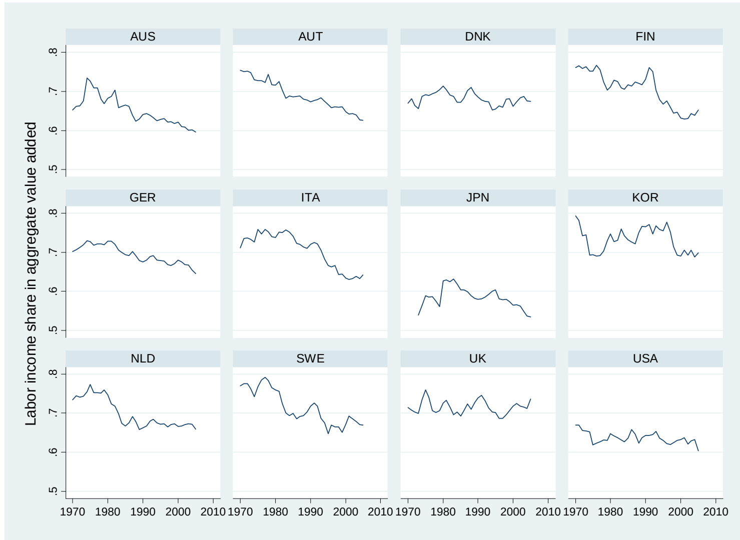

Figure 3.1: Evolution of labor income share by country

	Aggregate labor income share			
country	1975	1995	2005	% change: 1975 - 2005
AUS	0.727	0.629	0.596	-18.019
AUT	0.728	0.666	0.627	-13.874
CZE	n.a.	0.567	0.596	5.115
DNK	0.692	0.656	0.675	-2.457
FIN	0.752	0.668	0.653	-13.165
GER	0.727	0.679	0.646	-11.142
ITA	0.759	0.666	0.643	-15.283
JPN	0.589	0.604	0.535	-9.338
KOR	0.694	0.755	0.698	0.720
NLD	0.773	0.672	0.658	-14.877
PRT	0.681	0.653	0.656	-3.671
SVN	n.a.	0.838	0.719	-14.200
SWE	0.768	0.647	0.670	-12.760
UK	0.759	0.702	0.736	-3.030
USA	0.619	0.630	0.603	-2.585

Table 3.2: Evolution of labor income share over time

I calculate the overall capital endowment of a country as the log of total real fixed capital stock over total labor. The overall capital stock consists of different types of capital, whose roles are arguably unique in the production process and can be seen as different production factors. Examining the relationship between structural change and those detailed types of capital endowment will allow us see if the theory's predictions can universally apply to different production factors. Therefore, in addition to the overall capital, I examine three detailed categories of capital: ICT, machinery and non-residential structure. However, endowment for these detailed types of capital are more complicated to measure. Although the absolute stocks for all three types of capital have been increasing over time in all countries, their relative importance in the total capital stock has changed considerably. Figure 3.2 reports the share changes of each type of capital in total capital stock by country. Notice that ICT capital's importance has risen in all countries while the share of structure capital has almost universally declined. If we consider different types of capital as different production factors, the endowment measure should take into account both the absolute quantity change in capital-x stock against labor and its relative change against other types of capital as well. Therefore, I calculate capital-x endowment as the log of capital-x stock over total labor multiplied by the share of capital-x (K^x) in the overall capital stock(K) of country j:

$$K^x\_ENDW_{j,t} = \ln\left[\left(K^x_{j,t}/L_{j,t}\right) \times \left(K^x_{j,t}/K_{j,t}\right)\right]$$

According to this definition, the change in capital-x endowment can be expressed as

$$\Delta K^x\_ENDW = \frac{\Delta\widetilde{K^x}}{\widetilde{K^x}} + \left(\frac{\Delta\widetilde{K^x}}{\widetilde{K^x}} - \frac{\Delta\widetilde{K}}{\widetilde{K}}\right)$$

where $\widetilde{K}$ denotes the K / L ratio. In other words, the change in capital-x endowment consists two parts: the percentage change in the value of $\widetilde{K^x}$ and the difference between the percentage changes of $\widetilde{K^x}$ and of the overall capital-labor ratio $\widetilde{K}$.

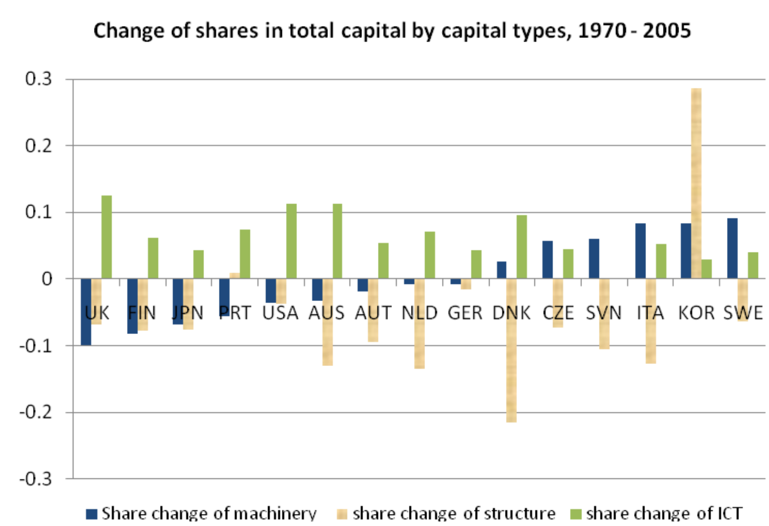

Figure 3.2

Industry's capital stock to real output ratio is used as the main measure of capital intensity.[11] For robustness check, I also use capital's income share in industry value-added as an alternative measure. Human capital intensity is used as control variable in some of the regressions, which is measured by high-skill workers' compensation as a percentage of industry's total compensation. Figure 3.3 plots industry output share-weighted average capital intensities at country level for different types of capital. For all types of capital the average intensities differ across countries. Moreover, at least in some countries, capital intensities are not stationary. This is especially true for ICT capital, the usage of which has experienced surges in all sample countries especially since the 1990s. Even within the same industry, there are often big differences in capital intensity across countries. This difference turns out to be significantly related to the countries' capital endowments. Table 3.3 presents results of regressing capital intensity on country capital endowment industry by industry for three detailed types of capital.[12] The regression coefficients are positive and highly significant for the majority of industries. There can be different factors causing the positive correlation. Since the industry classification used here is fairly broad, within the same industry different countries may be specializing in very different sub-industries according to a country's endowment fundamentals. And even when different countries are producing a similar product or service, the techniques they use can differ so as to take advantage of the more abundant factor in the country. The finding is consistent with Blum (2010), who found that a production factor is more intensively used in all industries of a country when the factor becomes more abundant.

[11] Some studies also used capital stock over value added ratio as a measure of capital intensity; see for example, Nunn (2007) and Ciccone & Papaioannou (2009). The two measures are highly correlated.

[12] The estimation equation is $Capital\ Intensity_{i,j,t} = b_{0,i} + b_{1,i} Capital\ Endowment_{j,t} + e_{i,j,t}$. The equation is estimated for every industry i, and b_1 is the coefficient of capital endowment.

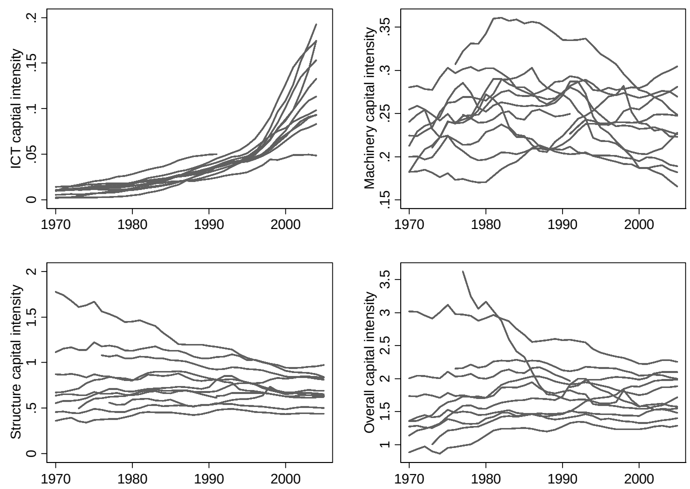

Figure 3.3: Capital intensity by country and types of capital

Since cross-country differences or time trends in capital intensity is not a focus of this chapter, and because correlation between capital endowment and industry capital intensity can potentially cause multicolinearity in the regressions, I use the standard score of capital intensities instead of the raw capital-output ratio in the actual estimations. The standard score is calculated by normalizing an industry's capital-x intensity in country j of time t with the mean and standard deviation of capital-x intensity of all industries in country j at time t. The capital intensity score thus has the same distribution within each country and time period, and measures the within-country variations of capital intensity across industries at a point in time.

	ICT capital			Machinery capital			Structure capital		
Industry code	b_1	T value	R square	b_1	T value	R square	b_1	T value	R square
15t16	0.027	24.361	0.620	0.016	9.847	0.210	0.001	6.409	0.101
17t19	0.033	33.991	0.763	0.021	9.634	0.203	0.004	17.080	0.445
20	0.017	6.205	0.096	0.018	5.429	0.075	0.006	14.877	0.378
21t22	0.070	22.206	0.575	0.021	9.006	0.182	0.002	13.503	0.334
23	0.017	5.129	0.068	0.005	0.916	0.002	0.000	0.211	0.000
24	0.033	17.204	0.448	0.001	0.209	0.000	0.002	7.998	0.149
25	0.024	23.064	0.596	0.001	0.218	0.000	0.002	12.078	0.286
26	0.045	22.162	0.575	-0.017	-3.981	0.042	0.002	9.761	0.207
27t28	0.025	28.900	0.696	0.010	3.042	0.025	0.002	8.938	0.180
29	0.049	40.625	0.819	0.032	11.387	0.263	0.002	14.636	0.370
30t33	0.044	21.307	0.555	-0.004	-1.172	0.004	0.000	2.398	0.016
34t35	0.028	23.500	0.603	0.024	4.946	0.063	0.000	0.614	0.001
36t37	0.040	35.584	0.778	0.012	5.748	0.083	0.003	9.307	0.192
50	0.059	27.044	0.668	-0.002	-0.885	0.002	-0.003	-6.507	0.104
51	0.075	31.695	0.734	0.000	0.091	0.000	0.002	5.110	0.067
52	0.076	29.221	0.701	0.010	2.957	0.023	-0.002	-2.739	0.020
60t63	0.080	11.642	0.271	0.000	-0.009	0.000	-0.006	-2.720	0.020
64	0.148	3.893	0.040	-0.003	-0.266	0.000	0.002	1.077	0.003
70	0.029	23.924	0.615	0.002	2.621	0.019	0.044	9.967	0.214
71t74	0.161	20.177	0.528	-0.002	-0.230	0.000	0.059	13.568	0.336
AtB	0.012	9.334	0.195	0.024	2.443	0.016	0.025	14.602	0.369
C	0.058	21.069	0.553	0.003	0.140	0.000	-0.004	-1.881	0.010
E	0.075	15.108	0.385	0.066	4.868	0.061	0.005	1.395	0.005
F	0.018	26.338	0.657	0.004	3.098	0.026	0.001	3.801	0.038
H	0.032	17.229	0.451	0.016	7.737	0.141	0.002	4.612	0.055
J	0.142	29.145	0.700	0.000	0.194	0.000	0.009	11.245	0.258
L	0.105	22.973	0.592	0.029	10.084	0.218	0.027	8.884	0.178
M	0.088	19.100	0.501	0.004	1.633	0.007	-0.002	-1.501	0.006
N	0.054	25.485	0.641	0.000	-0.091	0.000	-0.003	-3.456	0.032
O	0.092	18.291	0.479	0.023	8.084	0.152	-0.007	-4.541	0.054

Table 3.3: Regression of capital intensity on country capital endowment by industry

Table 3.4 lists summary statistics of main variables and their correlations. A number of correlations are noteworthy. First, richer countries generally have higher capital endowments. The correlation between per worker GDP and the four catogories of capital are 0.83, 0.42, 0.66 and 0.68 respectively, all significant at 1% level. It raises the question of whether the capital endowment variables are simply stand-in factors for country's development stage. Second, industries that are intensive in overall capital, ICT and structure capital also tend to be human capital intensive. One explanation for the positive correlations may be that the "sophisticated" industries tend to be intensive in multiple types of capital. I will revisit these questions later in the robustness check section.

	# of observations	Mean	Std. Dev.	Min	Max
Country variables					
Overall Capital endowment ($mn)	427	5.001	0.460	3.426	5.989
ICT capital endowment	427	-2.869	2.035	-8.921	1.165
Structure capital endowment	427	3.320	0.673	1.131	4.504
Machinery capital endowment	427	1.159	0.472	-0.488	2.441
Annual growth rate of GDP per worker	416	0.020	0.022	-0.058	0.103
Log GDP per worker ($mn)	427	4.481	0.385	3.353	5.303
Industry variables					
Real output share	11033	0.033	0.023	0.000	0.234
Employment share	11033	0.033	0.028	0.000	0.183
Nominal output share	11033	0.033	0.022	0.000	0.137

* Overall capital endowment of a country is calculated as the log of real overall capital stock over total employment ratio. Endowments of the detailed types of capital are measured as the log of capital-x stock over total employment ratio times the log of capital-x's share in the overall capital stock.

Table 3.4a: Summary statistics

	Capital	GDP	ICT	Structure	Machinery
Overall Capital endowment	1.00				
Log GDP per worker	0.83	1.00			
ICT endowment	0.24	0.42	1.00		
Structure endowment	0.67	0.66	0.11	1.00	
Machinery endowment	0.37	0.68	0.36	0.52	1.00

Table 3.4b: Correlation between country variables

	Overall capital	ICT	Structure	Machinery	Human capital	Value-added
Overall capital intensity	1.00					
ICT intensity	0.43	1.00				
Structure intensity	0.81	0.34	1.00			
Machinery intensity	0.19	0.16	0.08	1.00		
Human capital intensity	0.29	0.21	0.20	-0.40	1.00	
Degree of value-added	0.44	0.33	0.49	-0.39	0.45	1.00

Table 3.4c: Correlation between industry variables

3.4 Country Level Analysis

3.4.1 Capital Endowment and Industrial Structure

Before empirically defining and analyzing structural coherence, let's first look at the general patterns in data about the relationship between capital endowment and capital intensity of the industrial structure. One conclusion from Section 3.2 is that there should be a positive correlation between the two when industry size is calculated as the real output share, since capital-intensive industries grow bigger—in terms of real output– when capital endowment increases.

When industry shares are calculated in terms of employment or nominal output, the relationship between capital endowment level and capital intensity of the industrial structure depends on ε, the elasticity of substitution between sectors, as the magnitude of ε determines the magnitude of changes in the relative price corresponding to real output changes. However, in reality several factors can complicate the prediction. First, a real economy has more than two industries and the elasticities of substitution across different industries can be different. Second, as pointed out by Oulton (2001), many industries produce intermediate goods that do not target end consumers, thus making the prediction by elasticity-of-substitution-criteria hard to apply. Third, the countries in the sample are mostly open economies. Hence the domestic demand may have little impact on goods prices, especially for tradable industries in small countries. Although these factors complicate the prediction for the relationship between capital endowment and employment/nominal output share distribution of industries, they do not interfere with the prediction that an industry's employment share and nominal output share should move in the same direction when endowment changes.

Table 3.5a and 3.5b report, for each type of capital, the correlations between capital endowment and capital intensity of industrial structure in terms of real output, employment and nominal output. The capital intensity of industrial structure is measured in two ways: (1) as $COR(Y_{ij,t}, K^x_{ij,t})$, the Spearman rank correlation between an industry's capital-x intensity score, K^x_{ij} , and industry size Y_{ij} , which is in turn measured by real output share, employment share, and nominal output share of the industry in the total economy of country j; (2) as $\sum_{i=1}^{n} K^x_{ij,t} \cdot Y_{ij,t}$, the industry-size-weighted average capital intensity score across all n industries of the economy. From now on, I will refer to the two measures as "correlation measure" and "weighted average measure" of the capital intensity of industrial structure.[13] Keep in mind that since K^x_{ij} is the standard score of capital-x intensity, it captures the capital intensity of industry i relative to other industries within the same country and time period, independent of the average capital intensity of the country. The latter is itself a positive function of the country's capital endowment, as shown in section 3 and in Blum

[13] The two measures have their respective pros and cons. For example, the weighted average measure captures more variations in capital intensity of industries than the correlation measure, but is sensitive to capital intensity changes in individual industries that can be considered as outliners. Therefore, empirical results using both measures are reported in this paper.

(2010).

The results from Table 3.5a-b show that for the overall capital, the capital intensity of industrial structure, no matter whether it is calculated using real output, employment, or nominal output shares, is positively correlated with capital endowment level in the overall capital. All the correlation coefficients are significant at 1% level. In terms of magnitude, the correlation coefficient is highest for real output structure, and lowest for the employment structure. These patterns in the data are present using both correlation measure (Table 3.5a) and weighted average measure (Table 3.5b) for the capital intensity of industrial structure. The capital intensities of industrial real output structure, employment structure and nominal output structure are also positively and significantly correlated with one another. Overall, these results are consistent with the assumption that the elasticity of substitution between industries is generally greater than 1.

	Overall Capital				ICT Capital				Machinery Capital				Structure Capital			
	Int.: real output	Int.: employment	Int.: nominal output	endowment	Int.: real output	Int.: employment	Int.: nominal output	endowment	Int.: real output	Int.: employment	Int.: nominal output	endowment	Int.: real output	Int.: employment	Int.: nominal output	endowment
K^x intensity of real output structure	1.00				1.00				1.00				1.00			
K^x intensity of employment structure	0.54	1.00			0.88	1.00			0.57	1.00			0.68	1.00		
K^x intensity of nominal output structure	0.97	0.59	1.00		0.97	0.88	1.00		0.72	0.60	1.00		0.97	0.71	1.00	
Lagged K^x endowment	0.47	0.27	0.35	1.00	0.45	0.28	0.44	1.00	-0.21	-0.24	-0.30	1.00	0.32	0.07	0.27	1.00

Table 3.5a: Correlation between capital intensity of industrial structure and capital endowment (correlation measure)

	Overall Capital				ICT Capital				Machinery Capital				Structure Capital			
	Int.: real output	Int.: employment	Int.: nominal output	endowment	Int.: real output	Int.: employment	Int.: nominal output	endowment	Int.: real output	Int.: employment	Int.: nominal output	endowment	Int.: real output	Int.: employment	Int.: nominal output	endowment
K^x intensity of real output structure	1.00				1.00				1.00				1.00			
K^x intensity of employment structure	0.45	1.00			0.84	1.00			0.34	1.00			0.60	1.00		
K^x intensity of nominal output structure	0.95	0.54	1.00		0.94	0.81	1.00		0.67	0.52	1.00		0.94	0.71	1.00	
Lagged K^x endowment	0.36	0.12	0.31	1.00	0.55	0.44	0.52	1.00	-0.13	-0.33	-0.30	1.00	0.36	0.12	0.34	1.00

Table 3.5b: Correlation between capital intensity of industrial structure and capital endowment (weighted average measure)

The results for the detailed types of capital are somewhat similar to those for the overall capital. For both ICT and structure capital, capital intensities of industrial structure are positively correlated with capital endowment levels. The correlation coefficients are significant at 1% level except for the correlation between the non-residential structure capital intensity calculated using industry employment shares and the structure capital endowment, which is positive but not significant. In contrast, the correlations between capital intensity of industrial structure and capital endowment are negative for machinery capital, no matter which industry size measure is used.

Despite these exceptions, in general the results from Table 3.5a-b suggest that the industrial structure tends to be more capital intensive when capital is more abundant. This is, however, a very general description of the data. The countries that have similar levels of capital abundance not necessarily share the same industrial structure in terms of capital intensity. What happens if the capital intensity level of a country's industrial structure is not "coherent" with the level of the country's capital endowment? Does the level of this coherence matter for a country's growth performance? One way to answer these questions is to construct a country-level measure for the degree of coherence between industrial structure and capital endowment, and relate it to economic growth. The next section will implement this approach.

3.4.2 Structural Coherence and Growth

I use the term structural coherence to refer to the degree that a country's industrial structure aligns with the country's factor endowment fundamentals. The endowment-based structural change theory predicts that the industrial structure will change towards more capital-intensive industries when the endowment of capital increases, given no distortions to the market system and to individual incentives. However, as Section 3.2 argues, when adjustment cost associated with structural change is high, the magnitude of structural change will be reduced and the aggregate growth performance negatively impacted. Empirically, previous studies have shown that the characteristics of structural change have aggregate effects on countries' labor market performance (Rogerson, 2007) and on aggregate productivity (van Ark, O'Mahony & Timmer, 2008; Duarte & Restuccia, 2010). But little empirical evidence exists on what kind of industrial structure facilitates growth. In this section I first propose a measure for structural coherence at the country level, and then show that the measure can explain some of the cross-country variation in growth.

Measuring Structural Incoherence at the Country Level

I measure structural coherence by its opposite—structural incoherence, that is, the degree that a country's industrial structure deviates from the "optimal" corresponding to the country's capital endowment level. The structural incoherence (SI) index in terms of type-x capital is measured as the absolute gap between the standardized capital-x intensity score of a country's overall industrial structure and the country's capital endowment level, also standardized. In other words, the SI index can be expressed as

$$SI^x_{j,t} = |k^x\_inten_{j,t} - k^x\_endw_{j,t-1}| \tag{3.14}$$

Here lower-cased letters are used to represent the standard score of the actual variable. This measure formulates upon the idea that the capital intensity of the optimal industrial structure should be a strictly increasing function of a country's capital endowment level. Thus in the case of perfect structural coherence, the SI index should be equal to zero; i.e., the level of the industrial structure's capital intensity should be the same as the level of capital endowment, in their respective distributions. Again, to take into account the time lags needed for the industrial structure to adjust to changes in capital endowment, the capital intensity and endowment scores used are those at the ending and beginning years of a 5-year window. Table 3.6 gives summary statistics of the SI index for the overall capital and three detailed categories of capital. In Version 1 of the SI index, the capital intensity of a country's industrial structure is measured as the rank correlation between industries' real output shares and industries' capital intensities, while in Version 2, it is measured as the industry-real-output-share-weighted average of industry capital intensities. Table 3.6 shows that the two versions of SI are of similar range.

	Mean	Std. Dev.	Min	Max
SI (version 1):				
Overall capital	0.877	0.541	0.008	3.004
ICT	0.748	0.613	0.007	2.907
Machinery	1.225	0.865	0.015	4.178
Structure	1.004	0.644	0.002	2.908
SI (version 2):				
Overall capital	0.839	0.730	0.001	3.261
ICT	0.674	0.606	0.014	2.525
Machinery	1.186	0.765	0.007	3.869
Structure	1.013	0.599	0.014	3.425

Table 3.6 Summary statistics of structural incoherence (SI) scores

It is illuminating to compare the structural incoherence scores across countries and over time. Figure 3.4 presents the time trends of the SI score (Version 1) in terms of the overall capital for 11 sample countries that have relatively long time-series data. A few things are worth noting. Among all countries, Japan has experienced the largest increase in structural incoherence over time, its SI scores close to zero in the 1970s and above 3 in 2005. The SI score has also increased since the 1980s in countries such as Italy and Denmark, though to a less degree. In contrast, countries like US and Germany seem to have consistently lower-than-average SI scores. For US, the score has decreased from the beginning of the sample, and was especially low during the 1990s, a period of extraordinary economic growth for the country. Germany's SI score periodically increased right after the re-unification but decreased again in the late 1990s.

To see which of the two components of the SI score is driving the changes over time, Figure 3.5 plotted the time trends for the capital intensity of industrial structure (correlation measure) and capital endowment (k_endw_j) separately for each country. The cause for the dynamics in SI score is now clearer. For all sample countries, the capital endowment has increased overtime to various degrees. However, the trend of industrial structure is far less universal. For some countries such as US, Germany, and UK, the capital intensity of industrial structure has risen along with the movement of capital endowment, which results in steady or even decreasing structural incoherence level overtime. For the countries whose SI scores have been increasing, e.g. Japan, Italy, and Denmark, the rise in structural incoherence level is mainly caused by their "sticky" industrial structure, i.e., the lack of upward movement in the overall capital intensity of the industries, despite consistent capital accumulation. Also notice that compared to the US, all the continental European countries except Germany appear to have less responsive industrial structure to the changes in capital endowment. This is consistent with previous studies comparing the characteristics of structural change between US and EU countries. For example, van Ark, O'Mahony & Timmer (2008) show that the slower structural transformation in European countries contributes to the lower labor productivity growth in Europe compared to the United States.

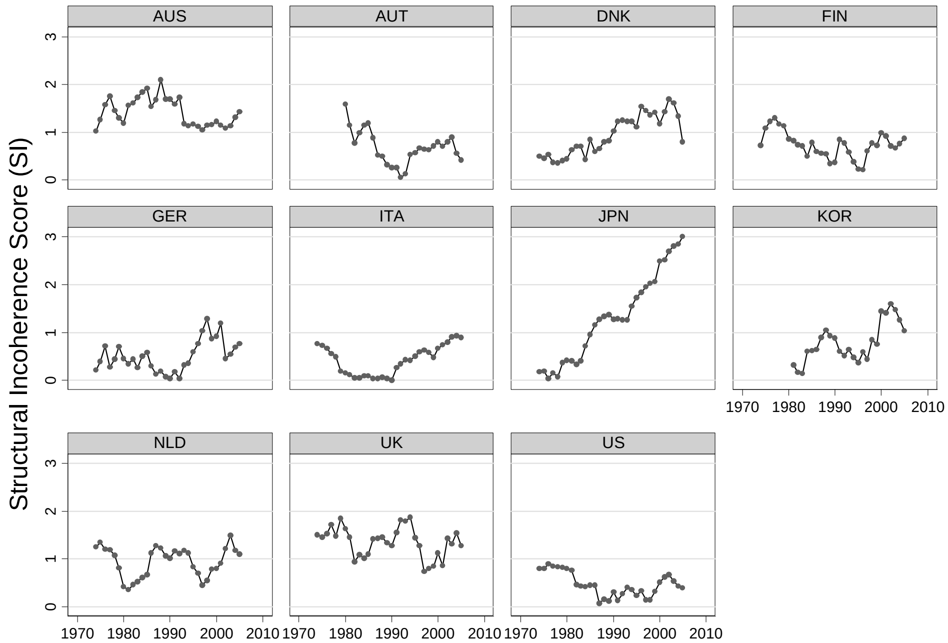

Figure 3.4: Evolution of structural incoherence score by country

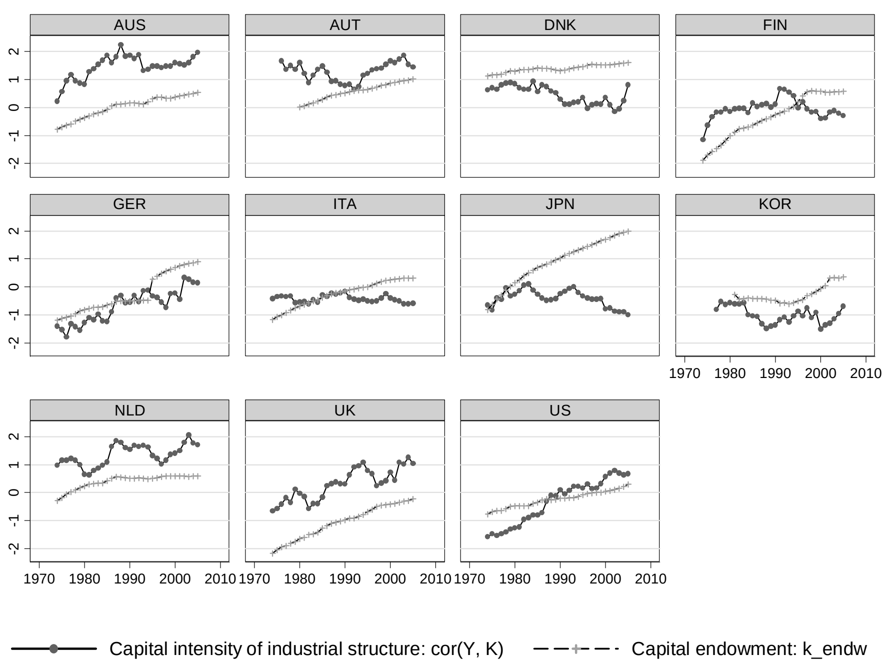

Figure 3.5: Decomposing the structural incoherence score

Structural Coherence Effect on Growth

The country-level estimation equation for the relationship between structural coherence and growth is

$$GROW_{j,t-k,t} = b_1 + b_2 \left(\frac{1}{k} \sum_{\tau=0}^{k-1} SI^{x}_{j,t-\tau} \right) + Z'_{j,t} b_3 + u_{j,t} \tag{3.15}$$

where is $GROW_{j,t-k,t}$ the real GDP growth rate of country j from Year $t-k$ to t. $\frac{1}{k}\sum_{\tau=0}^{k-1} SI^{x}_{j,t-\tau}$ is the country's average structural incoherence score in capital-x from Year $t-k+1$ to t. Thus Equation (3.15) relates aggregate growth rate to the structural incoherence level over the same period, and a set of control variables Z_j. Here Z_j includes countries' initial GDP at $t-k$, countries' average physical capital investment intensity, and countries' average human capital intensity as represented by the shares of high skilled and medium skilled workers in total labor compensation. The error term includes country fixed effect and an observation-specific error.

Table 3.7a and 3.7b report the results of estimating Equation (3.15), using the two versions of the SI index respectively. The standard errors are adjusted for heteroskedasticity at the country level. Column 1 of the two tables display results for the overall capital with the annual GDP growth as the dependent variable, i.e. k equals 1. The coefficient b_2 is negative in both versions of regressions, and has a t-statistic of 4.75 and 2.63 respectively. According to the average estimate between the two versions, decreasing structural incoherence score from the 95 percentile (1.76) to the 5 percentile (0.11) of the distribution is associated with 0.8 percentage point increase in the annual GDP growth rate, which is about 24% of the growth rate differential between the 5 percentile and 95 percentile country-years.

Column 3 and column 5 of Table 3.7a-b report regression results for the overall capital over 5-year (k=4) and 10-year (k=9) non-overlapping time spans respectively. In both cases, b_2 is negative and significant. In Version 1, the t-statistic of b_2 is equal to 2.15 for the 5-year estimation and 3.42 for the 10-year estimation. In Version 2, the t-statistic is 2.25 and 2.61 for the 5-year and 10-year estimations. To check that the results are not driven by outliers, Figure 3.6a-c display partial regression plots for the SI variable in Version 1. The three graphs correspond to estimates in Column 1, 3, and 5 of Table 3.7 respectively. It is clear from the plots that the results are not driven by any particular observations.

Column 2, 4, and 6 of Tabel 3.7a and 3.7b report results for the three detailed types of capital placed in the same regression. For machinery capital, the SI index is negative and significant for all time windows when the capital intensity of industrial structure is calculated using the weighted-average measure (v2), but is only significant in the annual regression in when the capital intensity of industrial structure is calculated with the correlation measure (v1). For sructure capital, the SI index is mostly negative and significant in both versions of regressions. However, the SI of ICT capital is never significant in any of the regressions.

Regressing GDP growth on contemporaneous SI index raises the possibility of endogeneity. For example, a negative productivity shock can bring down output growth rate, and at the same time mess up the effectiveness of resource allocation in the economy. To take into account such concerns, Equation (3.15) is also estimated using 2-stage Least Square, with the SI indices of lagged two periods as instruments for the current period SI. The results are shown in Table 3.8a-b for the two versions of capital intensity of industrial structure. The results indicate that for the overall capital, the magnitudes of the SI index are comparable to, if not larger than those in the baseline regressions. For the detailed types of capital, the SI coefficients for machinery capital are of the similar magnitudes and significance levels to the baseline results; but for structure capital, the SI index now becomes mostly insignificant.

In sum, the estimates of Equation (3.15) show that a country's GDP growth is negatively impacted by the degree of incoherence between its industrial structure and its overall capital endowment level. For detailed types of capital, the relationship also exists but is not as clear. However, estimations at the country level do not exploit all the information contained in the data. The next section will adopt a different approach, to examine the relationship between structural coherence and growth based on an industry-level regression setup.

	Dependent variable: real GDP growth rate					
	k=1		k=4		k=9	
	(1)	(2)	(3)	(4)	(5)	(6)
Structural incoherence index						
Overall capital	-0.010***		-0.042**		-0.149**	
	(0.00)		(0.02)		(0.06)	
ICT		0.004		0.010		0.065
		(0.00)		(0.02)		(0.05)
Machinery (MCH)		-0.004**		-0.017		0.013
		(0.00)		(0.02)		(0.02)
Structure (STR)		-0.005		-0.033*		-0.133**
		(0.00)		(0.02)		(0.05)
Control variables						
High skill	0.001**	0.001**	-0.000	0.006***	-0.015**	0.009*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Medium skill	0.001***	0.001**	0.000	0.005**	0.012**	0.011**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
log(Inv / GDP)	0.019	0.013	0.047	0.023	0.302	0.103
	(0.02)	(0.02)	(0.06)	(0.07)	(0.20)	(0.29)
log(GDP)	-0.025**	-0.033***	-0.222**	-0.178***	-0.275	-0.197
	(0.01)	(0.01)	(0.09)	(0.06)	(0.16)	(0.11)
N	350	350	74	74	29	29
r2	0.076	0.074	0.545	0.283	0.741	0.697

* In constructing SI scores, capital intensity of industrial structure is calculated as the Spearman rank correlation between industry output share and industry capital intensity. Country fixed effect estimator is used in all regressions. Heteroskedasticity-robust standard errors are in the parentheses. Column 1-2 report annual estimates. Column 3-4 and Column 5-6 report estimates for non-overlapping 5- year and 10-year windows respectively. ***: p<0.01; **: p<0.05; *: p<0.1

Table 3.7a: Structural coherence and growth: country level regressions (v1)

	Dependent variable: real GDP growth rate					
	k=1		k=4		k=9	
	(1)	(2)	(3)	(4)	(5)	(6)
Structural incoherence index						
Overall capital	-0.011***		-0.067**		-0.245***	
	(0.00)		(0.03)		(0.05)	
ICT		-0.000		-0.003		0.020
		(0.00)		(0.02)		(0.07)
Machinery (MCH)		-0.010**		-0.061***		-0.110**
		(0.00)		(0.02)		(0.05)
Structure (STR)		-0.005*		-0.022*		-0.053
		(0.00)		(0.01)		(0.04)
Control variables						
High skill	0.001*	0.002***	0.005	0.009***	-0.000	0.012***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Medium skill	0.001**	0.001**	0.002*	0.005**	0.011***	0.012**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
log(Inv / GDP)	0.014	0.031	0.041	0.114	0.256	0.351
	(0.02)	(0.02)	(0.08)	(0.09)	(0.22)	(0.26)
log(GDP)	-0.024**	-0.040***	-0.139	-0.221***	-0.012	-0.319***
	(0.01)	(0.01)	(0.08)	(0.05)	(0.11)	(0.08)
N	346	346	72	72	28	28
r2	0.069	0.097	0.292	0.416	0.731	0.703

* In constructing SI scores, capital intensity of industrial structure is calculated as the industry-output-share-weighted industry capital intensity. Country fixed effect estimator is used in all regressions. Heteroskedasticity-robust standard errors are in the parentheses. Column 1-2 report annual estimates. Column 3-4 and Column 5-6 report estimates for non-overlapping 5- year and 10-year windows respectively. ***: p<0.01; **: p<0.05; *: p<0.1

Table 3.7b Structural coherence and growth: country level regressions (v2)

	Dependent variable: real GDP growth rate					
	k=1		k=4		k=9	
	(1)	(2)	(3)	(4)	(5)	(6)
Structural incoherence index						
Overall capital	-0.010***		-0.047**		-0.176***	
	(0.00)		(0.02)		(0.04)	
ICT		0.001		0.007		-0.082
		(0.00)		(0.02)		(0.12)
Machinery (MCH)		-0.006**		-0.036**		0.007
		(0.00)		(0.01)		(0.03)
Structure (STR)		-0.005		-0.011		-0.162*
		(0.00)		(0.02)		(0.09)
Control variables						
High skill	0.001**	0.001***	-0.001	-0.002	-0.017***	0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Medium skill	0.001**	0.001**	0.001	-0.000	0.013***	0.015**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
log(Inv / GDP)	0.016	0.013	0.037	-0.002	0.334	0.100
	(0.02)	(0.02)	(0.08)	(0.08)	(0.23)	(0.34)
log(GDP)	-0.033***	-0.042***	-0.217***	-0.280***	-0.245**	-0.213*
	(0.01)	(0.01)	(0.05)	(0.05)	(0.11)	(0.13)
N	326	326	69	69	28	28
r2	0.101	0.106	0.555	0.553	0.735	0.541
Hansen J test (p value)	0.383	0.260	0.510	0.210	0.285	0.660

* The SI scores of lagged two periods are used as instruments for the contemporaneous SI scores. ***: p<0.01; **: p<0.05; *: p<0.1

Table 3.8a Structural coherence and growth: country level regressions (v1), IV method

	Dependent variable: real GDP growth rate					
	k=1		k=4		k=9	
	(1)	(2)	(3)	(4)	(5)	(6)
Structural incoherence index						
Overall capital	-0.016***		-0.061**		-0.348***	
	(0.00)		(0.03)		(0.05)	
ICT		-0.000		0.013		0.023
		(0.00)		(0.02)		(0.07)
Machinery (MCH)		-0.013***		-0.056***		-0.127***
		(0.00)		(0.02)		(0.04)
Structure (STR)		-0.004		-0.007		-0.045
		(0.00)		(0.02)		(0.04)
Control variables						
High skill	0.001**	0.002***	0.007*	0.010***	-0.004	0.013***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Medium skill	0.001	0.001**	0.002	0.004	0.013***	0.013**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
log(Inv / GDP)	0.011	0.032**	0.040	0.138	0.288	0.437
	(0.02)	(0.02)	(0.10)	(0.12)	(0.27)	(0.27)
log(GDP)	-0.032***	-0.051***	-0.185***	-0.247***	0.104	-0.326***
	(0.01)	(0.01)	(0.07)	(0.05)	(0.07)	(0.07)
N	320	320	66	66	27	27
r2	0.109	0.136	0.347	0.451	0.671	0.700
Hansen J test (p value)	0.844	0.312	0.586	0.841	0.861	0.213

* The SI scores of lagged two periods are used as instruments for the contemporaneous SI scores. ***: p<0.01; **: p<0.05; *: p<0.1

Table 3.8b: Structural coherence and growth: country level regressions (v2), IV method

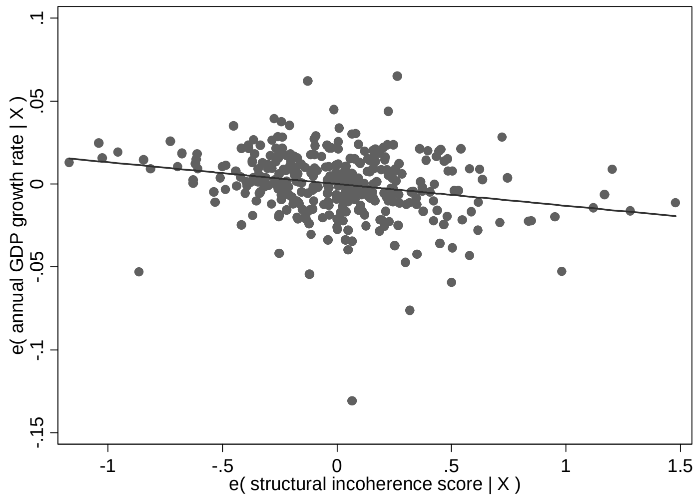

Figure 3.6a: GDP growth and structural incoherence (annual)

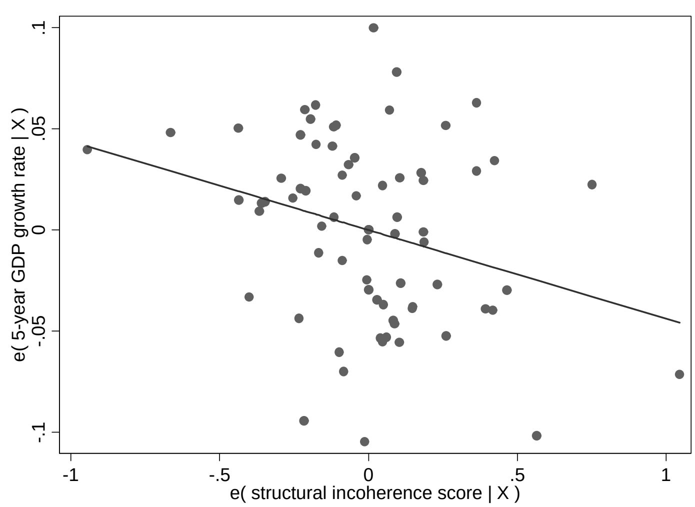

Figure 3.6b: GDP growth and structural incoherence (5-year window)

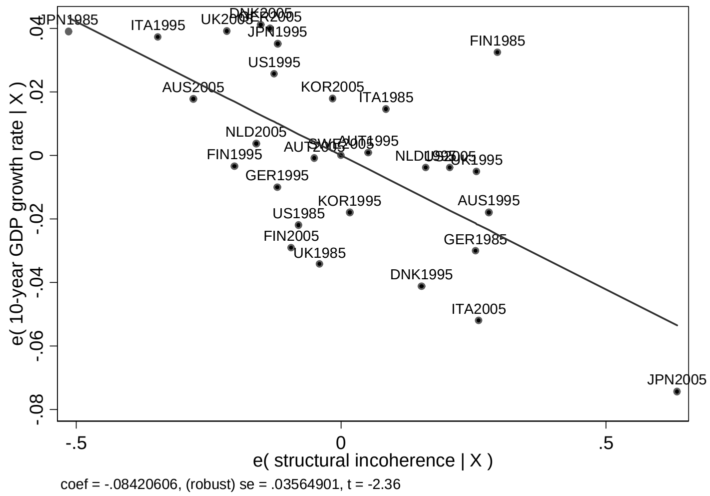

Figure 3.6c: GDP growth and structural incoherence (10-year window)

3.5 Industry Level Analysis

3.5.1 Capital Endowment and Industrial Structure

In this section, I examine the relationship between capital endowment and industrial structure using individual industries' data. Again, to allow for the slow adjustment in the industrial structure, I set the time unit to be 5 years. The basic estimation equation is as follows

$$\ln Y_{ij,t} = a_1 + a_2 K^x_{ij,t-1} + a_3 \left(K^x_{ij,t-1} \times K^x\_ENDW_{j,t-1}\right) + a_5 K^x\_ENDW_{j,t-1} + Z'_{ij,t} a_7 + a_8 \ln Y_{ij,t-1} + e_{ij,t} \tag{3.16}$$

where the dependent variable is the log of real output share, employment share, or nominal output share of industry i in country j in the last year of a 5-year window; $K^x_{ij,t-1}$ is the standardized capital-x intensity of industry i in country j at the beginning year of the 5-year window; $K^x\_ENDW_{j,t-1}$ is the capital-x endowment in country j in the same year.

Equation (3.16) does not account for the possibility that contemporaneous growth in capital endowment can also impact industrial structure. To allow for the endowment growth effect, I augment Equation (3.16) by adding country-level capital endowment growth over the 5-year period and its interaction with initial-year industry capital intensity:

$$\begin{aligned}\ln Y_{ij,t} &= a_1 + a_2 K^x_{ij,t-1} + a_3\left(K^x_{ij,t-1} \times K^x\_ENDW_{j,t-1}\right) + a_4(K^x_{ij,t-1} \\ &\quad \times \Delta K^x\_ENDW_{j,t}) + a_5 K^x\_ENDW_{j,t-1} + a_6 \Delta K^x\_ENDW_{j,t} + Z'_{ij,t}a_7 + a_8 \ln Y_{ij,t-1} + e_{ij,t}\end{aligned} \tag{3.17}$$

where $\Delta K^x\_ENDW_{j,t}$ is the 5-year growth rate of capital-x endowment in country j. In both equations, $Z'_{ij,t}$ is a vector of control variables, which includes country j's log per worker aggregate output at the beginning year and the 5-year growth rate of industry TFP index. To control for the initial difference in the dependent variable, $\ln Y_{ij,t-1}$ is also included on the right hand side. The error term consists of a country-industry fixed effect and an observation specific error: $e_{ij,t} = u_{ij} + \varepsilon_{ij,t}$.

According to Equations (3.16) and (3.17), the capital-x endowment effect and endowment growth effect on the dependent variable $\ln Y_{ij}$ are respectively

$$\frac{\partial \ln Y_{ij,t}}{\partial K\_ENDW_{j,t-1}} = a_3 K^x_{ij,t-1} + a_5, \tag{3.18}$$

and
$$\frac{\partial \ln Y_{ij,t}}{\partial \Delta K\_ENDW_{j,t}} = a_4 K^x_{ij,t-1} + a_6$$

Both terms are linear functions of $K^x_{ij,t-1}$, the capital-x intensity score of industry i. When capital-x endowment is higher, ideally the industries that use capital-x intensively (industries with high K^x_{ij}) should expand in terms of real output. Therefore, when Y_{ij} is the real output share of industry, a_3 and a_4 are expected to be positive. The intercepts a_5 and a_6 help determine the magnitudes of the capital endowment effects on $\ln Y_{ij}$. When Y_{ij} is the employment share or nominal output share, a_3 and a_4 would be positive if the elasticity of substitution between different industrial goods is greater than 1, vice versa.

Again, by standardizing capital intensities, I make sure that the intercepts of the endowment effect, a_5 and a_6 are invariant with respect to the level of capital endowment,[14] and that the endowment effect on industrial structure measured here is separate from any structural change

[14]Suppose that instead of a standard score, the raw capital intensity $\widetilde{k}_{ij}$, which is a function of capital endowment in country j, is used in the estimation. The endowment effect on Y_{ij} is thus: $\partial \ln Y_{ij}/\partial K\_ENDW_j = (a_2+a_3)\,\partial\widetilde{k}_{ij}/\partial K\_ENDW_j + a_3 + a_3\widetilde{k}_{ij}$. The intercept term $(a_2+a_3)\,\partial\widetilde{k}_{ij}/\partial K\_ENDW_j + a_3$ is not constant unless $\partial\widetilde{k}_{ij}/\partial K\_ENDW_j$ is invariant with respect to K_ENDW.

effect caused by endowment-change-induced technology shift.

The error term in Equations (3.16) and (3.17) involves country-industry fixed effects that may co-vary with the dependent variables. The inclusion of lagged dependent variables on the RHS creates correlation between the regressors and the error term, which renders OLS estimation inconsistent. Therefore, I use Arellano – Bond (1991) difference GMM method to estimate the model. One thing to keep in mind is that the structural change patterns are different across countries and time periods. Ideally Equations (3.16) and (3.17) can be estimated for each country and time period separately. This is not achievable due to data limitations and identification problems. By estimating the model in a cross section-time series setting, we get coefficients describing general patterns in the whole data set, which might be quite different than what is going on in a specific country and time. In fact, the assumption that the coefficients for the interaction terms vary across country and time is the basis to test the relationship between structural coherence and growth, which will be specified in Section 3.5.

	Dependent variable: log (Real output share)			log(Employment share)			log(Nominal output share)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	Fixed effect	GMM	GMM	Fixed effect	GMM	GMM	Fixed effect	GMM	GMM
K × K_ENDW	0.135**	0.033*	0.041*	0.132**	0.058**	0.005	0.127*	0.145***	0.190***
	(0.063)	(0.02)	(0.02)	(0.062)	(0.03)	(0.01)	(0.071)	(0.05)	(0.06)
K × ΔK_ENDW			0.043			0.071**			0.531***
			(0.04)			(0.03)			(0.13)
K_ENDW	0.014	0.003	0.006	-0.124	0.053**	-0.004	-0.035	0.042	0.040
	(0.111)	(0.02)	(0.02)	(0.121)	(0.02)	(0.01)	(0.121)	(0.05)	(0.06)
Δ K_ENDW			-0.006			-0.009			0.153*
			(0.03)			(0.03)			(0.08)
TFP growth	0.007***	0.001	0.001	-0.009***	-0.001***	-0.000	-0.001	0.000	0.001
	(0.002)	(0.00)	(0.00)	(0.002)	(0.00)	(0.00)	(0.002)	(0.00)	(0.00)
N	8959	8527	8527	8959	8527	8527	8959	8527	8527
R2	0.22			0.20			0.06		
A-B 2 test (p value)		0.692	0.688		0.357	0.108		0.241	0.731
Hansen J test (p value)		0.122	0.421		0.889	0.646		0.247	0.165

* The fixed-effect estimates are reported in the 1st column under each dependent variable heading. The Arellano-Bond difference GMM estimates are reported in Column 2-3 under each dependent variable heading. Heteroskedasticity-robust standard errors are in the parentheses. K is the overall capital intensity. K_ENDW is overall capital endowment. ΔK_ENDW is the 5-year growth rate of overall capital endowment. Lagged dependent variables and country's real aggregate output per worker are also included as control variables. ***: p value<0.01; **: p value<0.05; *: p value<0.1.

Table 3.8: Overall capital and structural change: baseline estimation

Table 3.8 reports the regression results of Equations (3.16) and (3.17) for the overall capital. Heteroskedasticity-robust standard errors are reported in the parentheses. The main variables of interest are the interaction term between industry capital intensity (K) and initial capital endowment (K_ENDW) and the interaction between capital intensity and endowment growth (ΔK_ENDW). The 2nd column under each explanatory variable heading reports the results of Equation (3.16), and the 3rd column of Equation (3.17), both using Arellano – Bond estimator. For comparison, I also estimated Equation (3.16) using fixed effect estimator, which is reported in the 1st column under each dependent variable heading.

For all the three industry size regressions, the coefficients of capital endowment interaction are positive and significant, except in the 3rd employment share regression. The coefficients of the endowment growth interaction are also positive and mostly significant. The result thus suggests that the sizes of capital-intensive industries' real output, nominal output and employment all grow with higher capital endowment and capital accumulation. These results are also consistent with the assumption of the elasticity of substitution across different industries being higher than one. Comparing the two estimation methods, the estimated a_3 is lower using the GMM estimator in the real output and employment shares regressions, while higher in the nominal output regression. The coefficient for industry TFP growth is positive and significant in the real output share regression, indicating that industrial structure generally shifts towards industries with higher TFP, consistent with the prediction of Ngai & Pissarides (2007).

Table 3.8 also reports the results of Arellano – Bond 2nd order serial correlation test and Hansen J test of overidentification for the GMM estimates. All test scores are satisfactory, indicating that the model specification is basically sound.[15]

Table 3.9 reports estimates of Equation (3.16) and (3.17) when K^xs are the intensities in detailed types of capital. Compared to the results for the overall capital, the relationships between detailed types of capital endowment and structural change are more ambiguous. In all three industry size regressions, the two interaction terms for ICT capital are positive and significant, while the magnitude of the coefficients is generally greater in the nominal and real output share regressions than in the employment share regression. For structure capital, the interaction terms are also mostly

[15] The Hansen J test is weakened by too many instruments, which can lead to improbably good p values of 1 or close to 1. Thus in estimating the model, I either limit the instruments used to up to two lags of the instrumented variable, or collapse longer lags of instruments into smaller set; the 2nd method makes the instrument count linear in the total time periods (Roodman, 2008).

positive, but are only significant in the employment share regression when the GMM estimator is used. For machinery capital, however, the interaction terms are mainly negative, while the significance levels of the coefficients vary.

All in all, echoing the results at the country level, when detailed categories of capital are treated as separate production factors, the results only partially confirm the theoretical prediction about the relationship between factor endowment and industry size. Thus the next section will examine whether these deviations from the theoretical optimal industrial structure have any effect on economic growth, based on the industry-level regression setup.

	Dependent variable:								
	log (Real output share)			log(Employment share)			log(Nominal output share)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	Fixed effect	GMM	GMM	Fixed effect	GMM	GMM	Fixed effect	GMM	GMM
ICT × ICT_ENDW	0.044***	0.031***	0.023***	0.044***	0.005**	0.009**	0.044***	0.044***	0.042***
	(0.006)	(0.01)	(0.00)	(0.006)	(0.00)	(0.00)	(0.006)	(0.01)	(0.01)
STR × STR_ ENDW	0.057	0.002	-0.007	0.057	0.021*	0.039***	0.057	0.045	0.059
	(0.036)	(0.03)	(0.02)	(0.036)	(0.01)	(0.01)	(0.036)	(0.05)	(0.04)
MCH × MCH_ ENDW	0.016	-0.036	-0.024	0.016	-0.028***	-0.055***	0.016	-0.087***	-0.129***
	(0.024)	(0.03)	(0.02)	(0.024)	(0.01)	(0.02)	(0.024)	(0.03)	(0.03)
ICT ×Δ ICT_ENDW			0.029**			0.019**			0.046*
			(0.01)			(0.01)			(0.03)
STR ×Δ STR_ENDW			0.013			0.065**			0.083
			(0.04)			(0.03)			(0.08)
MCH ×Δ MCH_ENDW			-0.068			-0.082***			-0.162**
			(0.04)			(0.03)			(0.07)
TFP growth	0.005***	0.002	-0.001	0.005***	-0.000	-0.002	0.005***	-0.004**	-0.004**
	(0.001)	(0.00)	(0.00)	(0.001)	(0.00)	(0.00)	(0.001)	(0.00)	(0.00)
N	8934	8502	8502	8934	8502	8502	8934	8502	8502
R2	0.40			0.40			0.40		
A-B 2 test (p value)		0.292	0.895		0.125	0.158		0.822	0.512
Hansen J test (p value)		0.244	0.277		0.186	0.253		0.326	0.837

* The fixed-effect estimates are reported in the 1st column under each dependent variable heading. The Arellano-Bond difference GMM estimates are reported in Column 2-3 under each dependent variable heading. Heteroskedasticity-robust standard errors are in the parentheses. ICT, STR and MCH are capital intensities in information technology, structure and machinery capital. K^x _ENDW is capital-x endowment. ΔK^x _ENDW is the 5-year growth rate of capital-x endowment. Lagged dependent variables and country's real aggregate output per worker are also included as control variables. ***: p value<0.01; **: p value<0.05; *: p value<0.1.

Table 3.9: Detailed types of capital and structural change: baseline estimation

3.5.2 Structural Coherence and Economic Growth

Recall that in Equation (3.16), a_3 is the coefficient for the interaction term between industry capital-x intensity and country's capital-x endowment: $K^x_{ij,t-1} \times K^x\_ENDW_{j,t-1}$, which is expected to be positive when the dependent variable is the real output share and the industrial structure is optimally chosen. Ideally, Equation (3.16) can be estimated by each country and time period. The value $a_{3_{j,t}}$ would give a measure of the coherence level between country j's industrial structure and its capital-x endowment level at time t. Suppose that a_3^* is the value of $a_{3_{j,t}}$ when the industrial structure optimally reflects the endowment level. Since frictions and adjustment costs are almost inevitable that obstruct optimal resource allocation and the evolution of industrial structure, this theoretical optimal a_3^* is not very likely to be reached in a real economy. When the sizes of industries are prevented from evolving with capital accumulation, $a_{3_{j,t}}$ will be less than a_3^*. Moreover, the smaller $a_{3_{j,t}}$ is, the less adaptive the industrial structure is to endowment change. In the extreme case when industrial structure change is to the opposite direction of capital endowment change, $a_{3_{j,t}}$ would be negative. The aggregate growth rate of country j, $GROW_j$, can be modeled as a function of a_{3_j}. I assume that this relationship is linear and can be expressed as

$$GROW_j = f_1 + f_2 a_{3_j} \tag{3.19}$$

A high a_{3_j} suggests that the industrial structure is more coherent with endowment level. If the coherence level between industrial structure and capital endowment have a positive impact on a country's growth performance, then f_2 is expected to be positive.

There are obviously important caveats to this functional form. First, it assumes that frictions in the real economy make it costly to adjust resource allocation across industries, as specified in the theoretical model, which generally make industrial structure "sticky", i.e., prevent industrial structure from evolving to reflect endowment change, thus lead to a_{3_j} being lower than a_3^* . But the opposite is also possible. Centralized economic policies by countries such as the former Soviet Union push for rapid industrialization and force the capital-intensive industries to expand too quickly despite the country's low capital endowment, which led to poor growth performance. In that case, a_{3_j} can be higher than the optimal value a_3^*. This extreme case is not captured by assuming a simple linear relationship between growth and a_{3_j}. However, most countries covered in the sample are fairly developed, free market economies. No historical records indicate that forced industrialization has been part of the economic policies in these countries over the sample period.

Thus I assume it is reasonably safe to neglect the case of overly high a_{3_j} in this sample.[16]

Second, the relationship between economic growth and structural coherence specified in Equation (3.19) does not necessarily hold for every single period. Economies experience business cycle fluctuations regularly for non-structural reasons. Besides, the goal of the optimizing agents is not high growth for any single period, but life-time welfare maximization. Despite these qualifications, f_2 should be positive if the observations are over an extended period of time, since Equation (3.19) means to capture the long-run relationship between growth and structural coherence.

Due to limited variation in "K_ENDW" and the small number of observations per country in each period, $a_{3_{j,t}}$ can hardly be identified by estimating Equation (3.16) by country and time. But the identification of f_2 is still achievable. Writing Equation (3.19) as a function of $a_{3_{j,t}}$ and plugging it back to Equation (3.16) with the real output share as the dependent variable, we arrive at the following specification:

$$\begin{aligned} \ln Y_{ij,t} \quad = \quad & d_1 + d_2 K^x_{ij,t-1} \times K^x\_ENDW_{j,t-1} \times GROW_{j,t} + d_3 \left(K^x_{ij,t-1} \times K^x\_ENDW_{j,t-1} \right) \\ & + d_4 K^x\_ENDW_{j,t-1} \times GROW_{j,t} + d_5 K^x_{ij,t-1} \times GROW_{j,t} + d_6 K^x_{ij,t-1} + d_7 K^x\_ENDW_{j,t-1} \\ & + d_8 GROW_{j,t} + Z'_{ij,t} d_9 + d_{10} \ln Y_{ij,t-1} + \zeta_{ij,t} \end{aligned} \tag{3.20}$$

where $\ln Y_{ij,t}$ is the real output share of industry i in country j, $GROW_{j,t}$ is country j's GDP growth rate over the 5-year window. The terms $K^x\_ENDW_{j,t-1} \times GROW_{j,t}$, $K^x_{ij,t-1} \times GROW_{j,t}$, and $GROW_{j,t}$ are added to the regression equation to maintain the statistical balance of the model.

The coefficient a_3 in Equation (3.16) is the counterpart of "$d_2 GROW_{j,t} + d_3$" in Equation (3.20). According to our hypothesis, the coefficient d_2, which is equal to $1/f_2$, is expected to be positive.

The estimation results of Equation (3.20) are reported in Table 3.10 for the overall capital and the three detailed types of capital. The 1st column under each capital type heading estimated Equation (3.20) using OLS with country fixed effects, the 2nd column under each heading reports results using dynamic GMM estimator. The three-way interaction terms "$K^x_{ij,t-1} \times K^x\_ENDW_{j,t-1} \times GROW_{j,t}$" are positive and significant at 1% level for all categories of capital except for the non-residential structure capital when the fixed-effect estimator is used. Therefore, the results gener-

[16] As a robustness check, I also ran the same regressions leaving out data from Czech Republic and Slovenia, two former satellite countries of the Soviet Union. The results did not change very much. Due to space limit, those results are not reported in the paper.

ally confirm the hypothesis of a positive relationship between structural coherence and economic growth. The 2nd order serial correlation test and overidentification test results are mostly satisfactory, except for structure capital. The Hansen's J test score of the structure capital regression is exceptionally high, indicating that the score may be weakened by instrument proliferation.

To get a sense of the magnitude of structural coherence's influence on growth, let's look at the results for the overall capital as an example. Notice that d_2= 0.242 (the 2nd column) implies the value of f_2 around 4.13. Suppose that we take the estimate for a_3, the coefficient for the interaction term "$K \times K\_ENDW$" in Equation (3.16) (the 2nd column of Table 3.8) to be the optimal value a_3^* when industrial structure is fully in line with overall capital endowment. This is most likely an under-estimate of the "true" a_3^* due to various frictions in the real economies. The estimates of Equation (3.16) and (3.20) combined indicate a difference in 5-year aggregate output growth rate of 0.136 between the case of highest structural coherence and the case when structural change happens randomly, in which scenario $a_3$is equal to zero. Calculated this way, the growth differential related to structural coherence is about 25% of the gap between the growth rate of the 5 percentile and the 95 percentile countries in the data. Although calculated using different approaches, the country-level and industry-level estimates give surprisingly consistent assessments about the magnitude of structural coherence's impact on growth. The consistency provides additional confirmation to the estimation results.

	Dependent variable: log(real output share)							
	Overall capital		ICT		Structure		Machinery	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
	Fixed effect	GMM	Fixed effect	GMM	Fixed effect	GMM	Fixed effect	GMM
K ×K_ENDW × GROW	0.231***	0.242***						
	(0.078)	(0.09)						
ICT × ICT_ENDW × GROW			0.118**	0.023**				
			(0.060)	(0.01)				
STR × STR_ENDW × GROW					0.094	0.060**		
					(0.121)	(0.03)		
MCH×MCH_ENDW×GROW							0.385**	0.333***
							(0.190)	(0.13)
K × K_ENDW	0.070***	-0.035						
	(0.020)	(0.03)						
ICT × ICT_ENDW			0.042***	0.005***				
			(0.008)	(0.00)				
STR × STR_ENDW					0.079*	0.017		
					(0.043)	(0.01)		
MCH × MCH_ENDW							-0.009	-0.038
							(0.035)	(0.03)
N	8959	8527	8934	8502	8964	8532	8964	8532
r2	0.25		0.34		0.30		0.20	
A-B 2 test (p value)		0.740		0.729		0.728		0.378
Hansen J test (p value)		0.296		0.288		0.997		0.328

* The dependent variable is the log real output share of industry. Column 1-2 reports estimates for K^x = overall capital; columan 3-8 report results for K^x = ICT, structural and machinery capital respectively. K, ICT, STR and MCH are capital intensities in overall, information technology, structure and machinery capital. K^x _ENDW is capital-x endowment. GROW is the 5-year average aggregate real output growth rate of a country. Fixed-effect estimates are reported in the odd-numbered columns, and Arellano-Bond difference GMM estimates in even-numbered columns. Heteroskedasticity-robust standard errors are in the parentheses. Lagged dependent variable, country's real aggregate output per worker, and industry 5-year TFP growth are included as control variables. ***: p value<0.01; **: p value<0.05; *: p value<0.1.

Table 3.10: Structural coherence and economic growth: baseline estimates

3.6 Robustness

3.6.1 Using income share to measure factor intensity

In the baseline regressions I used the ratio of industry capital-x stock to real output as the measure of industry capital-x intensity. To see how sensitive the main results are to the choice of measurement, here I use capital income share in industry value added as an alternative measure of capital intensity. In Table 3.11 and 3.12, the variables in lowercase letters – k, ict, str, mch – stand for factor intensity scores in overall, ICT, structure and machinery capital, calculated as standardized capital income shares in industry value added.

Table 3.11 reports the regression results of Equation (3.17) with the alternative measure. Compared to the results in Table 3.8 for the overall capital, the coefficients for the initial endowment interaction becomes insignificant in all regressions, while the significance level for the endowment growth interaction term mostly increase except in the employment share regression. Among detailed types of capital, the two interaction terms for the structure capital become more significant in the nominal output size regression. Most of the other coefficients remain the same sign and significance level. The specification test results are all satisfactory except for the 2nd order serial correlation test in the nominal output size regression involving the overall capital.

For the structural coherence and growth regression (Equation (3.20)), as shown in Table 3.12, the three-way interaction terms are positive and significant for all types of capital except for non-residential structure. Compared to the baseline regression, the magnitude of the implied value of f_2 is now smaller for the overall capital and ICT capital, and larger for the machinery capital. All in all, changing the measure of capital intensity does not seem to significantly change the regression results.

	Dependent variable:					
	Log (real output share)		Log (employment share)		Log (nominal output share)	
	(1)	(2)	(1)	(2)	(1)	(2)
k × K_ENDW	0.055		-0.029		0.028	
	(0.08)		(0.04)		(0.05)	
k ×Δ K_ENDW	0.391**		-0.040		0.296*	
	(0.16)		(0.11)		(0.17)	
ict × ICT_ENDW		0.013***		0.017***		0.026***
		(0.00)		(0.01)		(0.01)
str × STR_ ENDW		0.006		0.034**		0.032**
		(0.01)		(0.01)		(0.01)
mch × MCH_ ENDW		-0.019		-0.108***		-0.243***
		(0.01)		(0.03)		(0.05)
ict ×Δ ICT_ENDW		0.028***		-0.020		0.094***
		(0.01)		(0.02)		(0.02)
str ×Δ STR_ENDW		0.017		0.137		0.060
		(0.03)		(0.09)		(0.07)
mch ×Δ MCH_ENDW		-0.002		-0.077		-0.289***
		(0.03)		(0.06)		(0.10)
TFP growth	0.004***	0.001	0.000	-0.008***	0.001**	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	8019	7321	8019	7321	8019	7321
A-B 2 test (p value)	0.541	0.925	0.156	0.921	0.002	0.175
Hansen J test (p value)	0.762	0.182	0.122	0.152	0.229	0.898

* The Arellano-Bond difference GMM estimator is used in all regressions. Heteroskedasticity-robust standard errors are in the parentheses. k, ict, str and mch are capital intensities in overall, information technology, structure and machinery capital, which are measured as capital-x income share in industry value-added. K^x _ENDW is capital-x endowment. ΔK^x _ENDW is the 5-year growth rate of capital-x endowment. Lagged dependent variables and country's real aggregate output per worker are also included as control variables. ***: p value<0.01; **: p value<0.05; *: p value<0.1.

Table 3.11: Capital endowments and structural change: alternative measure of capital intensity

	Dependent variable: log(real output share)			
	Overall capital	ICT	Structure	Machinery
k ×K_ENDW × GROW	0.610*			
	(0.34)			
ict × ICT_ENDW × GROW		0.037**		
		(0.02)		
str × STR_ENDW × GROW			-0.011	
			(0.04)	
mch × MCH_ENDW × GROW				0.191**
				(0.09)
k × K_ENDW	-0.008			
	(0.06)			
ict × ICT_ENDW		0.014***		
		(0.00)		
str × STR_ENDW			0.005	
			(0.01)	
mch × MCH_ENDW				-0.024
				(0.03)
N	8961	8297	7350	8210
A-B 2 test (p value)	0.926	0.773	0.783	0.846
Hansen J test (p value)	0.882	0.144	0.464	0.546

* The dependent variable is the log real output share of industry. Column 1 reports estimates for K^x = overall capital; columan 2-4 report results for K^x = ICT, structural and machinery capital respectively. Capital-x intensity is measured by capital-x's income as a share in industry value added. k, ict, str and mch are capital intensities in overall, information technology, structure and machinery capital. K^x _ENDW is capital-x endowment. GROW is the 5-year average aggregate real output growth rate of a country. The Arellano-Bond difference GMM estimator is used in all regressions. Heteroskedasticity-robust standard errors are in the parentheses. Lagged dependent variable, country's real aggregate output per worker, and industry 5-year TFP growth are also included as control variables. ***: p value<0.01; **: p value<0.05; *: p value<0.1.

Table 3.12: Structural coherence and economic growth: alternative measure of capital intensity

3.6.2 Further Robustness Checks

The results presented so far have not considered a range of other factors affecting the structural change process besides capital endowment and TFP growth. This section aims to address several of these factors. First, it is important to make sure that capital intensities are not stand-in variables for other industry characteristics that would impact industry growth when interacting with capital endowment. One such characteristic is human capital intensity. Ciccone & Papaioannou (2009) found that human capital intensive industries grow faster as human capital accumulates.[17] Table 3.3c has shown that industry human capital intensity has significant positive correlation with overall, ICT and structure capital intensities. Meanwhile, more developed countries may have high endowments in both human capital and various types of physical capital. Therefore, I augmented Equation (3.17) with human capital intensity and the interactions between human capital intensity and different types of physical capital endowment.

It is also possible that capital endowments proxy for other influential variables such as economic

[17] I also estimated Equation (17) for human capital endowment. The result is similar to Ciccone & Papaioannou (2009). Due to space limit, the results are not reported here.

development level. The demand-side literature on structural change motivates shifts in industrial composition by assuming non-homothetic consumer preferences: as a country becomes richer, consumer preference shifts to services and other more "sophisticated" goods (e.g., Echevarris (1997), Laitner (2000), Buera & Kaboski (2009)). If this is true, then since capital-intensive industries generally involve relatively complicated technology and production process, it is possible that those industries grow more in high-income countries due to demand side reasons, and capital endowment level can simply be a substitute for the effect of national income. Similarly, it is possible that rich countries have an advantage in high value-added industries. If those industries happen to be capital intensive, then our previous results can be generated for completely different reasons. To account for these possibilities, I add to Equation (3.17) additional controls including the interactions between industry capital intensities and countries' aggregate output per worker of the same period, and also the interaction between industries' degree of value-added (value-added to industry gross output ratio) and countries' aggregate output per worker.

Table 3.13 reports the regression results of Equation (3.17) for the overall capital, augmented with the above controls. The 1st column under each dependent variable heading is the result when human capital intensity (HUM) and its interaction with overall capital endowment ($HUM \times K\_ENDW$) are added to the model. The coefficients for the human capital interaction terms are all positive and significant in the industry size growth regressions. Adding human capital controls increases the significance level of the initial capital endowment interaction "$K \times K\_ENDW$" in the employment share regression, and of the capital endowment growth interaction "$K \times \Delta K\_ENDW$" in the real output share regression. However, the initial endowment interaction now becomes insignificant in the real output share regression.

The 2nd column under each explanatory heading reports results with controls of countries' GDP per worker (Y) and industries' degree of value-added ($HighVA$). While none of the coefficients for the interaction term "$K \times Y$" is significant, the coefficients for the interaction term "$HighVA \times Y$" are positive in all three industry size regressions, and significant in two of them. These results indicate that high value-added industries are indeed larger in higher-income countries. The main interaction terms "$K \times K\_ENDW$" and "$K \times \Delta K\_ENDW$" remain the same signs and significance levels as before, except that the initial endowment interaction "$K \times K\_ENDW$" is now insignificant in the real output share regression and is more significant in the employment share regression. The results in the nominal output share regressions should be treated with caution, as the serial correlation test results are not satisfactory, which makes the use of lagged dependent variable as instruments questionable.

	Dependent variable:					
	Log (real output share)		Log (employment share)		Log (nominal output share)	
	(1)	(2)	(1)	(2)	(1)	(2)
K × K_ENDW	0.025	0.062	0.040**	0.039*	0.072*	0.081*
	(0.03)	(0.05)	(0.02)	(0.02)	(0.04)	(0.05)
K ×Δ K_ENDW	0.117**	0.111	0.095**	0.133**	0.206***	0.242***
	(0.06)	(0.09)	(0.04)	(0.05)	(0.07)	(0.09)
HUM × K_ENDW	0.070***		0.035***		0.184***	
	(0.02)		(0.01)		(0.03)	
K × Y		-0.003		0.007		-0.075
		(0.03)		(0.01)		(0.07)
HighVA × Y		1.103***		0.095		0.797***
		(0.19)		(0.09)		(0.25)
N	8419	8527	8419	8527	8419	8527
A-B 2 test (p value)	0.745	0.961	0.102	0.115	0.005	0.032
Hansen J test (p value)	0.154	0.366	0.224	0.206	0.235	0.141

* The Arellano-Bond difference GMM estimator is used in all regressions. Heteroskedasticity-robust standard errors are in the parentheses. K and HUM are capital intensities in overall fixed capital and human capital. HighVA is the ratio of industry value-added over gross output. K_ENDW is overall capital endowment. ΔK_ENDW is the 5-year growth rate of overall capital endowment. Y is country's aggregate real output per worker. Lagged dependent variables, country's real aggregate output per worker, and industry TFP growth index are also included as control variables. ***: p value<0.01; **: p value<0.05; *: p value<0.1.

Table 3.13: Overall capital endowment and structural change: additional controls

Table 3.14 reports estimates of Equation (3.17) for the detailed capitals with additional controls. The interaction terms involving human capital intensity are not significant except for the interaction between human capital intensity and ICT endowment in the employment share regression. The interactions between capital intensity and country GDP level are only significant for machinery capital intensity in the employment and nominal output share regressions. The interaction between industries' degree of value added and country GDP is positive in all regressions, but not significant. Compared to the baseline estimates, the main interaction terms lost significance to some extent, especially for structure capital. But the signs of the coefficients remain the same, except for machinery capital, whose interactions changed signs when country GDP related controls are added.

	Dependent variable:					
	Log (real output share)		Log (employment share)		Log (nominal output share)	
	(1)	(2)	(1)	(2)	(1)	(2)
ICT × ICT_ENDW	0.011*	0.009*	0.006	0.009	0.036***	0.030**
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
STR × STR_ ENDW	-0.014	-0.021	0.020	-0.002	0.014	0.026
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.07)
MCH × MCH_ ENDW	-0.064*	0.005	-0.046	0.112*	-0.068	0.052
	(0.04)	(0.04)	(0.06)	(0.07)	(0.06)	(0.11)
ICT ×Δ ICT_ENDW	0.044***	0.046***	0.024**	0.013	0.055**	0.041
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)
STR ×Δ STR_ENDW	-0.008	-0.097	0.088	-0.005	-0.035	0.016
	(0.11)	(0.11)	(0.15)	(0.14)	(0.21)	(0.26)
MCH ×Δ MCH_ENDW	-0.203*	0.005	-0.045	0.361*	-0.111	0.161
	(0.12)	(0.15)	(0.20)	(0.21)	(0.28)	(0.31)
HUM × ICT_ENDW	-0.000		0.010***		0.017	
	(0.00)		(0.00)		(0.01)	
HUM × STR_ ENDW	-0.020		-0.001		0.070	
	(0.03)		(0.03)		(0.08)	
HUM × MCH_ ENDW	0.004		-0.043		-0.084	
	(0.03)		(0.04)		(0.09)	
ICT × Y		-0.015		-0.075		0.083
		(0.07)		(0.08)		(0.22)
STR × Y		-0.042		0.002		-0.039
		(0.03)		(0.03)		(0.08)
MCH × Y		-0.008		-0.090**		-0.143*
		(0.03)		(0.04)		(0.08)
HighVA × Y		0.239		0.216		0.764
		(0.26)		(0.34)		(0.77)
N	8394	8502	8394	8502	8394	8502
A-B 2 test (p value)	0.810	0.815	0.209	0.616	0.874	0.115
Hansen J test (p value)	0.285	0.491	0.116	0.321	0.257	0.327

* The Arellano-Bond difference GMM estimator is used in all regressions. Heteroskedasticity-robust standard errors are in the parentheses. ICT, STR, MCH, and HUM are capital intensities in ICT, structure, machinery, and human capital. HighVA is the ratio of industry value-added over gross output. K^x_ENDW is the endowment in type-x capital. ΔK^x_ENDW is the 5-year growth rate of type-x capital endowment. Y is country's aggregate real output per worker. Lagged dependent variables, country's real aggregate output per worker, and industry TFP growth index are also included as control variables. ***: p value<0.01; **: p value<0.05; *: p value<0.1.

Table 3.14: Detailed capital endowments and structural change: additional controls

Now let's turn to the estimates of the structural coherence regression. I augment Equation (3.20) with interaction terms involving human capital intensity, countries' GDP per worker, industries' degree of value added and TFP growth. First, I add to Equation (3.20) three-way interaction terms involving human capital intensity, different types of capital endowment, and countries' GDP growth.

As shown in Table 3.15a, the three-way interactions "$HUM \times ICT\_ENDW \times GROW$" and "$HUM \times STR\_ENDW \times GROW$" are both negative, while the terms "$HUM \times MCH\_ENDW \times GROW$" and "$HUM \times K\_ENDW \times GROW$" are positive but not significant. On the other hand, the coefficients for the main interaction terms remain positive and significant. The results confirm that the structural coherence' effect on aggregate growth is not driven by human capital related factors.

	Dependent variable: log(real output share)			
	Overall capital	ICT	Structure	Machinery
K ×K_ENDW × GROW	0.092*** (0.03)			
ICT × ICT_ENDW × GROW		0.077** (0.04)		
STR × STR_ENDW × GROW			0.171** (0.09)	
MCH × MCH_ENDW × GROW				0.341** (0.14)
HUM × K_ENDW × GROW	0.012 (0.05)			
HUM × ICT_ENDW × GROW		-0.286*** (0.11)		
HUM × STR_ENDW × GROW			-0.065 (0.05)	
HUM × MCH_ENDW × GROW				0.105 (0.13)
N	8419	8394	8424	8424
A-B 2 test (p value)	0.774	0.790	0.665	0.419
Hansen J test (p value)	0.596	0.460	0.494	0.813

* The dependent variable is the log real output share of industry. Column 1 reports estimates for K^x = overall capital; column 2-4 report results for K^x = ICT, structural and machinery capital respectively. K, ICT, STR, MCH, and HUM are capital intensities in overall, information technology, structure, machinery, and human capital. K^x _ENDW is capital-x endowment. GROW is the 5-year average aggregate real output growth rate of countries. The Arellano-Bond difference GMM estimator is used in all regressions. Heteroskedasticity-robust standard errors are in the parentheses. Lagged dependent variable, country's real aggregate output per worker, and industry 5-year TFP growth are also included as control variables. ***: p value<0.01; **: p value<0.05; *: p value<0.1.

Table 3.15a: Structural coherence and growth: additional controls

Three additional factors that might influence the structural coherence effect are considered: country's development level, industry's degree of value-added, and efficiency in resource allocation according to industry productivity. The third factor is drawn from the literature on allocative efficiency (Bartelsman, Haltiwanger & Scarpetta (2008), Arnold, Nicoletti & Scarpetta (2008)), which suggests that growth is related to whether resources are efficiently distributed to firms and industries with higher productivity. According to this hypothesis, a higher correlation between industry TFP growth and output share, that is, higher allocative efficiency, should also be beneficial to aggregate growth.

Table 3.15b presents estimates of Equation (3.20) with added controls involving countries' total output per worker (Y), industries degree of value added ($HighVA$) and industry TFP growth (TFP_GROW). The coefficients of the three-way interactions between different categories of capital intensity, countries' total output level and aggregate growth rate ($K^x \times Y \times GROW$) are all negative except for machinery capital, which is positive and significant. The interaction "$HighVA \times Y \times GROW$" is positive in the overall capital and structure capital regressions, but is only significant in the latter. The TFP interaction term "$TFP\_GROW \times GROW$" has mostly positive coefficients, indicating that efficient resource allocation in accordance with industry productivity does seem to have a positive impact on aggregate growth, though the variable is only significant in the overall capital regression.

	Dependent variable: log(real output share)			
	Overall capital	ICT	Structure	Machinery
K ×K_ENDW × GROW	0.159*			
	(0.09)			
ICT × ICT_ENDW × GROW		0.029*		
		(0.02)		
STR × STR_ENDW × GROW			0.432***	
			(0.16)	
MCH × MCH_ENDW × GROW				0.119
				(0.12)
K × Y × GROW	-0.011			
	(0.04)			
ICT × Y × GROW		-0.002		
		(0.06)		
STR × Y × GROW			-0.589	
			(0.39)	
MCH × Y × GROW				0.393***
				(0.15)
HighVA × Y × GROW	0.144	-0.016	0.166*	-0.072
	(0.09)	(0.04)	(0.09)	(0.16)
TFP_GROW × GROW	0.010*	-0.001	0.002	0.003
	(0.01)	(0.00)	(0.01)	(0.01)
N	8527	9445	8532	8532
A-B 2 test (p value)	0.753	0.737	0.759	0.769
Hansen J test (p value)	0.257	0.567	0.299	0.849

* The dependent variable is the log real output share of industry. Column 1 reports estimates for K^x = overall capital; column 2-4 report results for K^x = ICT, structural and machinery capital respectively. K, ICT, STR, MCH are capital intensities in overall, information technology, structure, and machinery capital. K^x _ENDW is capital-x endowment. GROW is the 5-year average aggregate real output growth rate of countries. Y is country *j*'s real aggregate output per worker at the beginning year of a period. HighVA is industry value-added over gross output ratio. TFP_GROW is the 5-year growth rate of industry TFP index. The Arellano-Bond difference GMM estimator is used in all regressions. Heteroskedasticity-robust standard errors are in the parentheses. Lagged dependent variable, country's real aggregate output per worker, and industry 5-year TFP growth are also included as control variables. ***: p value<0.01; **: p value<0.05; *: p value<0.1.

Table 3.15b: Structural coherence and growth: additional controls

The main interaction term "$K^x \times K^x\_ENDW \times GROW$" remains positive and significant for the overall capital, ICT capital or structure capital, as in the baseline regressions. However, the interaction for machinery capital is now insignificant. This loss of significance can be due to the fact that national income level is perhaps a better measure of machinery capital endowment than "MCH_ENDW", as the machinery capital stock does not take into account the quality and technology embodied in the capital, while these factors tend to be positively correlated with a country's development level. The fact that the newly-added control "$MCH \times Y \times GROW$" is positive and highly significant is consistent with this argument.

In sum, compared to the baseline results, except for the machinery capital, the main interaction terms between capital intensity, endowment and aggregate growth remain positive and significant after adding additional controls. The effect of structural coherence on growth does not seem to be driven by other omitted factors.

3.7 Conclusion

This chapter examines the pattern of industrial structure change induced by factor endowment changes, and explores the linkage between structural coherence and economic growth. Here structural coherence refers to the degree that a country's industrial structure aligns with its factor endowment fundamentals.

The endowment-based structural change theory predicts that when industries differ in terms of their capital intensities, an increase in capital endowment should raise the output of the capital intensive industries relatively more, which causes the industrial composition to change along with capital accumulation. An extension of this proposition is that since structural change towards industries that intensively use a production factor is the optimal result of resource allocation as the endowment of the factor increases, any arrangement that obstructs the structural change towards alignment with the endowment fundamentals can be a detriment to economic growth.

Using data of 28 industries from 15 countries, I first examine whether higher capital endowment is associated with larger sizes of capital intensive industries for the overall capital and three detailed categories of capital. For the overall capital, the sizes of capital intensive industries are significantly larger with higher initial period capital endowment and with faster capital accumulation. Similar results also apply to ICT capital and partially apply to machinery and structure capital. After confirming the impact of capital endowments on industrial structure, I check whether a higher level of structural coherence is related to better economic growth performance. The result shows that a country's aggregate output growth is higher when the industrial structure is more coherent with the country's endowment level in all types of capital. Quantitatively, the country-level estimation shows that the difference in structural coherence level explains about 30% of the growth differential between the 25 percentile and 75 percentile country-years. The industry-level estimates indicate a coherence effect of similar magnitude.

The results of the chapter are mostly robust to changing measurement of capital intensity, to controls for other industry characteristics such as human capital intensity and degree of value-added, and to controls for other determinants of structural change on both demand side and supply side.

Bibliography

[1] Acemoglu, D. and Guerrieri, V.: Capital deepening and non-balanced economic growth. Journal of Political Economy, vol. 116, no.3, 467-498 (2008)

[2] Arellano, M. and Bond, S.R.: Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58, 277-297 (1991)

[3] Arnold, J., Nicoletti,G. and Scarpetta, S.: Regulation, allocative efficiency and productivity in OECD countries: industry and firm-level evidence. OECD Working Paper (2008)

[4] Arpaia, A., Pérez, E. and Pichelmann, K.: Understanding labor income share dynamics in Europe. European Commission Working Paper (2009)

[5] Atkeson, A., Kehoe, P.: Modeling and measuring organization capital. Journal of Political Economy, vol. 113, no. 5, 1026-1053 (2005)

[6] Atkeson, A., Kehoe, P.: Modeling the transition to a new economy: lessons from two technological revolutions. Research Department Staff Report 296, Federal Reserve Bank of Minneapolis (2006)

[7] Baily, M.: Macroeconomic implications of the new economy. In: Economic Policy for the Information Economy. Federal Reserve Bank of Kansas City (2001)

[8] Bartelsman, E., Haltiwanger, J. and Scarpetta, S.: Cross country differences in productivity: the role of allocative efficiency. Working paper (2008)

[9] Bashein, B.J., Markus, M.L., and Riley, P. "business reengineering: preconditions for BPR success, and how to prevent failure." Information systems management, 11(2), 7-13 (1994)

[10] Baumol, W.J.: Macroeconomics of unbalanced growth: the anatomy of urban crisis. The American Economic Review 57, 415-426 (1967)

[11] Bentolila, S. and Saint-Paul, G.: Explaining movements in the labor share. The B.E. Journal of Macroeconomics, Vol. 3 (1) (2003)

[12] Blair, M. M. ed.: Unseen wealth : report of the Brookings Task Force on intangibles. Washington, DC: Brookings Institution Press (2001)

[13] Blanchard, O., Simon, J.: The long and large decline in US output volatility. Brookings Papers on Economic Activity 1, 135-164 (2001)

[14] Blanchard, O.: The medium run. Brookings Papers on Economic Activity, 2, 89-158 (1997)

[15] Brynjolfsson, E.: Information assets, technology, and organization. Management Science, vol. 40, No. 12, 1645-1662 (1994)

[16] Brynjolfsson, E., Hitt, E.L., Yang, S.: Intangible assets: computers and organizational capital. Brookings Papers on Economic Activity, 1, 137-198 (2002)

[17] Buch, C., Döpke, J., Stahn, K.: Great moderation at the firm level? Unconditional versus conditional output volatility. Deutsche Bundesbank Discussion Paper Series 1 (2008)

[18] Blum, B.: Endowments, Output, and the Bias of Directed Innovation. Review of Economic Studies (forthcoming)

[19] Buera, F. J. and Kaboski, J. P.: The rise of the service economy. NBER Working Paper (2009)

[20] Campell, J., lettau, M., Malkiel, B., Xu, Y.: Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. Journal of Finance, vol. LVI, No.1 (2001)

[21] Chenery, H. B.: Structural change and Development Policy. Oxford University Press (1979)

[22] Chun, H., Kim, J., Morck, R., Yeung, B.: Creative destruction and firm-specific performance heterogeneity. NBER Working Paper No. 13011 (2007)

[23] Ciccone, A. and Papaioannou, E.: Human capital, the structure of production, and growth. Review of Economics and Statistics, 91(1), 66-82 (2009)

[24] Clarida, R., Gali, J., Gertler, M.: Monetary policy rules and macroeconomic stability: evidence and some theory. Quarterly Journal of Economics, 115, 147-180 (2000)

[25] Comin, D., Mulani, S.: A theory of growth and volatility at the aggregate and firm level. NBER Working Paper No. 11503 (2006)

[26] Comin, D., Philippon, T.: The rise in firm-level volatility: causes and consequences. NBER Working Paper No. 11388 (2005)

[27] Comin, D., Mulani, S.: Diverging trends in aggregate and firm volatility. The Review of Economics and Statistics, 88(2), 374-383 (2006)

[28] Cooley, T.F. and Prescott, E.C.: Economic growth and business cycle. In: Cooley, T.F. (ed): Frontiers of Business Cycle Research. Princeton: Princeton University Press (1995)

[29] Corrado, C., Hulten, C., Sichel, D.: Measuring capital and technology: an expanded framework. In Measuring Capital in the New Economy, C. Corrado, J. Haltiwanger, D. Sichel, eds., Studies in Income and Wealth, vol. 65. Chicago: The University of Chicago Press (2005)

[30] Corrado, C., Hulten, C.R., Sichel, D.E.: Intangible capital and economic growth. Finance and Economics discussion series 2006-24, the Federal Reserve Board (2006)

[31] de Serres, A., Scarpetta, S. and de la Maisonneuve, C.: Sectoral shifts in Europe and the united states: how they affect aggregate labour shares and the properties of wage equations. OECD Working Paper (2002)

[32] Danthine, J.P. and Jin, X.: Intangible Capital, corporate valuation and asset pricing. Economic Theory 32, 157-177 (2007)

[33] Davis, S.J, Kahn, J.A.: Interpreting the great moderation: changes in the volatility of economic activity at the macro and micro levels. NBER Working Paper No. 14048 (2008)

[34] Davis, S.J., Haltiwanger, J., Jarmin, R., Miranda, J.: Volatility and dispersion in business growth rates: publicly traded versus privately held firms. NBER Working Paper No. 12354 (2006)

[35] Duarte, M. and Restuccia, D.: The role of the structural transformation in aggregate productivity. Quarterly Journal of Economics, v 125(1), 129–173 (2010)

[36] Dynan, K., Elmendorf, D. W., Sichel, D. E.: Can financial innovation help explain the reduced volatility of economic activity. Journal of Monetary Economics 53, 123-150 (2006)

[37] Dynan, K., Elmendorf, D. W., Sichel, D. E.: The evolution of household income volatility. The Brookings institution (2008)

[38] Echevarria, C.: Changes in sectoral composition associated with economic growth. International Economics Review 38: 431-452

[39] Eisfeldt, A. and Papanikolaou, D.: Organization Capital and the Cross-Section of Expected Returns. Working paper (2009)

[40] Fitzgerald, D. and Hallak, J.C.: Specialization, factor accumulation and development. Journal of International Economics, 64, 277-302 (2004)

[41] Greenwood, J., Hercowitz, Z., Krusell, P.: Long-run implications of investment-specific technological change. The American Economic Review, vol. 87, no. 3, 342-362 (1997)

[42] Hall, R.E.: Struggling to understand the stock market. The American Economic Review Papers and Proceedings 91, 1-11 (2001a)

[43] Hall, R.E.: The stock market and capital accumulation. American Economic Review 91, 1185-1202 (2001b)

[44] Harrigan, J.: Technology, factor supplies and international specialization: testing the neoclassical model. American Economic Review, 87(4), 475-494 (1997)

[45] Jones, C.I.: Growth, Capital shares, and a new perspective on production functions, Working Paper (2003)

[46] Jovanovic, B., Rousseau, P.L.: Vintage organization capital. NBER Working Paper No. 8166 (2001)

[47] Ju, J., Lin, J.Y. and Wang, Y.: Endowment structures, industrial dynamics, and economic growth. World Bank Working Paper (2009)

[48] Kahn, J.A., McConnell, M., Perez-Quiros, G.: On the causes of the increased stability of the US economy. Federal Reserve Bank of New York , Economic Policy Review, 8, 183-202 (2002)

[49] Kemerer, C. F., Sosa, G. L.: Systems development risks in strategic information systems. Information and Software Technology, Vol. 33, 3 (1991)

[50] Kongsamut, P., Rebelo, S. and Xie, D.: Beyond balanced growth. Review of Economic Studies 68, 869-882

[51] Kuznets, S.: Modern economic growth: findings and reflections. The American Economic Review 63: 247-258 (1973)

[52] Laitner, J.: Structural change and economic growth. Review of Economic Studies 67, 545-561 (2000)

[53] Lewis, E.: Immigration, skill mix, and the choice of technique. Federal Reserve Bank of Philadelphia Working Paper (2006)

[54] Lev, B.: Intangibles: Management, Measurement, and Reporting. Washington, DC: Brookings Institution (2001)

[55] McConnell, M., Perez-Quiros, G.: Output flucturations in the United States: what has changed since the early 1980s? American Economic Review 90, 1464-1476 (2000)

[56] McGrattan, E.R., Prescott, E.C.: Unmeasured investment and the puzzling US boom in the 1990s. Research department staff report 369, Federal Reserve Bank of Minneapolis (2007)

[57] Nakamura, L.: What is the US gross investment in intangibles? (at least) one trillion dollars a year! Federal Reserve Bank of Philadelphia Working Paper, No. 01-15 (2001)

[58] Ngai, L.R. and Pissarides, C. A.: Structural change in a multi-sector model of growth. The American Economic Review 97, 429-443 (2007)

[59] Oulton, N.: Must the growth rate decline? Baumol's unbalanced growth revisited. Oxford Economic Papers 53, 605-627 (2001)

[60] Pastor, L., Veronesi, P.: Stock valuation and learning about profitability. Journal of Finance, Vol. LVIII, No.5 (2002)

[61] Prescott, E.C., Visscher, M.: Organization capital. Journal of Political Economy, vol. 88, no. 3, 446-461 (1980)

[62] Rogerson, R.: Structural transformation and the deterioration of European labor market outcomes. NBER Working Paper No.12889 (2007)

[63] Romalis, J.: Factor proportions and the structure of commodity trade. American Economic Review, 94(1), 67-97 (2004)

[64] Roodman, D.: A Note on the Theme of Too Many Instruments. CGD Working Paper 125 (2007)

[65] Rossi-Hansberg, E. and Wright, L.J.: Establishment size dynamics in the aggregate economy. American Economics Review, vol. 97, no. 5, 1639-1666. (2007)

[66] Sauer, C., Yetton, P. W.: Steps to the future: fresh thinking on the management of IT-based organizational transformation. San Francisco, CA: Jossey-Bass (1997)

[67] Schmalensee, R.: The economics of advertising. Amsterdam: North-Holland Pub. Co. (1972)

[68] Schott, P.: One size fits all? Theory, evidence and implications of cones of diversification. American Economic Review 93(3), 686-708 (2003)

[69] Stock, J.H., Watson, M.W.: Has the business cycle changed and why? NBER Macroeconomics Annual. Cambridge, MA: MIT Press, 159-218 (2002)

[70] Sveiby, K. E.: The new organizational wealth: managing & measuring knowledge-based assets. San Francisco, CA: Berrett-Koehler Publishers (1997)

[71] Teece, D. J., Pisano, G., Shuen, A.: Dynamic capabilities and strategic management. Strategic Management Journal, 18:7, 509-533 (1997)

[72] Thesmar, D., Thoenig, M.: Financial market development and the rise in firm level uncertainty. CEPR Discussion Paper No. 4761 (2004)

[73] van Ark, B., O'Mahony, M. and Timmer, M.P.: The productivity gap between europe and the united states: trends and causes. Journal of Economic Perspectives, Volume 22(1), 25-44 (2008)

[74] Wei, S., Zhang, C.: Why did individual stocks become more volatile? Journal of Business, Vol. 79, No. 1 (2006)