University of Groningen

A global value chain perspective on trade, employment, and growth

Ye, Xianjia

Publication date:
2017

Chapter 4

Task Space: the Shift of Comparative Advantage in Globalized Production

4.1 Introduction

For a long time, structural upgrading is understood as a horizontal process in which the employment and export of a country gradually shift across sectors, from agriculture and natural resource extraction to light industries like textile, and subsequently towards more modern manufacturing and the tertiary sectors (see, e.g. the famous Lewis model and Clark-Fisher model on structural change, Lewis 1954 and Clark 1940). However, the rise of offshoring in recent decades has changed the nature of production and international trade. In the past, final goods were mostly made within each country. Nowadays, the advancements in transport and telecommunication technology make it possible for firms to unbundled the tasks in the production process and offshore tasks to different countries to minimize total production cost. The production of final goods is organized in Global Value Chains (GVCs), and the production process becomes increasingly fragmented across national borders. For example, the iPhone is designed in California in the U.S., its chips come from various suppliers located in the U.S., Japan, Korea and other countries, everything is shipped to China for assembly, while other supportive activities like accounting management are handled in countries like Ireland and Luxembourg. When offshoring is possible, a country can join the global value chain of a product if it is strong at a specific task, and it is not necessary to master all knowledge and resources of the whole production process. Therefore offshoring seems to offer underdeveloped countries a shortcut in structural upgrading. Namely, an underdeveloped country first follows its comparative advantage and performs low-skilled tasks in the GVCs of sophisticated products, and then vertically climbs up the value chain through learning-by-doing and technical dissemination to obtain the comparative advantages in high-skilled tasks within the same industry (Lin and Wang 2008, Lin 2012, Taglioni and Winkler 2016).

Has offshoring indeed changed the natural of structural upgrading? And what are the best practices for the policy makers to stimulate the upgrading progress at different stages of development? To provide an answer to these questions, in this paper I try to empirically explore the potential structural upgrading paths when production is globally fragmented and offshoring is pervasive. In particular, I am interested in two types of upgrading, *horizontal* and *vertical*. Horizontal upgrading is the shift of employment *across industries* towards tasks with a higher economic potential, say, re-allocating low-skilled workers from textile to electronics assembly. Vertical upgrading refers to the process that a country vertically climbs up the value chain and upgrade towards higher-skilled tasks *within the same industry*, for example from low-skilled assembly tasks to high-skilled circuit engineering in the electronics industry. Using newly available data on the task content of production and trade from 40 countries over the period from 1995 to 2009, I analyse the relatedness between each pair of tasks as proxied by the correlation in their Revealed Comparative Advantages (RCAs) across countries. And based on these empirical relatedness indices I derive a network representation of production tasks that indicates potential ways for upgrading. I find that the initial export structure of a country is closely related to the potential directions of its future structural change. And I show that horizontal upgrading is relatively easy to achieve, while vertical upgrading is more difficult and gradual although it yields a higher gain in the long run. A different set of policy stimulations might be necessary to achieve vertical upgrading.

To illustrate the potential upgrading paths, I use a similar approach as the so-called "*product space*" framework in Hidalgo *et al.* (2007). The product space is a relatedness network between products that can be used to analyses the development path of a country's export structure. The underlying notion is that the development of an economy is path-dependent, and the difficulty in entering the business of a new product depends on its relatedness with those products that the country is currently strong at. Similar as, say, a sneaker producer finds it easier to add badminton shoes into its product line rather than badminton rackets, at the macro level a new product is more likely to evolve in a country if it has strong ties with the country's current production and export structure. Hidalgo *et al.* (2007) empirically proxy the relatedness of a pair of products by the probability that both products have a revealed comparative advantage in a country, calculated on the basis of gross export data.[1]

However, the relatedness in products (or industries) is an inappropriate perspective under globalized production. In the past when trade was only in final products, most tasks in producing a good were carried out within a country. In that case the exporter of a high-skill intensive good must perform many high-skilled tasks. But when the production process is globally fragmented, the products produced and exported by a country are no longer a good description for the actual production activities that are taking place. Offshoring has created trade in tasks, and the comparative advantage of countries is now realized at task level, as shown in Baldwin (2006) and Grossman and Rossi-Hansberg (2008). Empirical research by Hummels *et al.* (2001), Becker *et al.* (2013) and Timmer *et al.* (2014) has documented a rapid deepening in vertical specialisation and offshoring, and the increasing fragmentation of global value chains in past decades. It is now not

[1] The product space is essentially "revealed relatedness" based on the observational co-existence of the RCAs of products, and it does not require ex-ante defined criteria for relatedness. Similar approaches can be found in Teece *et al.* (1994), Neffke and Henning (2008) and Bryce and Winter (2009). There are other measures that focus on specific and pre-defined aspects of relatedness, for example in Conley and Dupor (2003) and Neffke and Henning (2013). More discussion will follow in section 4.2.

only feasible but also attractive for developing countries to participate in the GVCs of sophisticated and high-skill intensive products by performing low-skilled tasks. For example, Southeast Asia and China have witnessed a strong export growth in electronics since the 1980s. But what they actually did was mainly assembly, which is far away from the "high-tech" stereotype of electronics products they exported. On the other side of the coin, highly developed countries may also perform high-skilled tasks in the value chains of the so-called low-skilled products, like the design and global marketing of clothes, shoes and handbags and the organization of their material supply chain.

Therefore, focusing on the relatedness in products may give a misleading impression on the progress of structural change, and a task-based approach is needed which fits better the new production and trade paradigm with pervasive international production fragmentation. In this paper I following Hidalgo *et al.* (2007) and introduce the concept of *task space*. Task space refers to the network of relatedness between *tasks* instead of products, where a task is defined as a set of activities in an industry carried out by labour with a specific level of educational attainment (low-, medium-, and high-skilled). Furthermore, I will base my measures on the *Value-Added Export* (VAE) of tasks, instead of gross exports that include the value of imported intermediates.

My task-based approach contributes to the current literature in three important aspects. Firstly, it allows for the identification of the vertical alongside the horizontal types of structural change. The product space approach cannot identify the skill levels of tasks behind a product, and current researches on the "climbing up the value chain" hypothesis are mainly from case studies of firms or specific industries (see e.g. Humphrey and Schmitz 2002). There is a lack of systematic research on the feasibility of vertical upgrading within different industries, and this paper aims to bridge this gap. By decomposing the activities of each industry into tasks at various skill levels, my task space approach is capable to evaluate the relative difficulties in both horizontal and vertical upgrading. As I will show later, the difficulties and benefits from these two types of upgrading differ substantially. Therefore, the identification of these two types is relevant.

Secondly, my task space approach uses value-added exports to calculate the RCAs instead of relying on gross exports as in Hidalgo *et al.* VAE based RCAs take into account the complex structure of global production fragmentation, and subsequently give more reliable estimates for task relatedness. The conventional gross-export based RCA exaggerates the comparative advantage of countries located in the down-stream end of the GVC. This is because gross exports of products contain a considerable amount of imported intermediate inputs which cannot be distinguished from the value added by the country itself. As an extreme case, Dedrick *et al.* (2009) show that around 97% of the value in China's exports of iPod and HP laptops originated from outside China. The conventional RCAs are likely to over-estimate China's actual comparative advantages in electronics, and for countries specialized in upstream activities, like the US, it provides an underestimation. This bias is illustrated in Koopman *et al.* (2014) and Los *et al.* (2015) and is also confirmed in this paper. Using VAE resolves this problem since it excludes the value of intermediates and only focuses on the value-adding activities that take place within the country.

Thirdly, Hidalgo *et al.* (2007) focus on structural change in manufacturing sectors.

I extend the scope of research to tasks in service sectors that become an increasingly important part of global trade. I will include directly traded services, as well as indirectly exported services from (non-traded) business supporting sectors that are embedded in the exported goods/services. This is not possible when gross exports are used, but is possible in my approach since the measure of VAE can trace down to the exact (upstream) activities that generated the exported value-added. Therefore this approach allows me to analyze the important role of services in structural change.

The empirical contribution of this paper is to derive the "task space", i.e. a network illustration of potential structural upgrading paths in terms of production tasks. This is based on tasks relatedness. Following Hidalgo *et al.* (2007), the relatedness between two tasks is defined as the probability that both tasks have a value-added based revealed comparative advantage in a country. For this, I first need a measure for VAE of each task, defined as the value-added created by a task that is ultimately absorbed in foreign final demand (Johnson and Noguera 2012). It will be derived from the World Input-Output Database (Timmer *et al.* 2015) which provides detailed cross country-industry supply/use tables and labour compensation per skill level. The WIOD database covers 40 major economies in the world, including both advanced and developing countries. In total I include 28 sectors (ISIC 2-digit level), and I calculate the VAE and subsequently the RCA of a set of 84 unique tasks (each sector has activities at three skill levels[2]). The task space is then an 84×84 matrix; each element represents the bilateral relatedness between a pair of tasks, based on actual task level RCA indices from 40 countries.

The most important finding from my task space is that horizontal and vertical structural upgrading are very different processes. Horizontal upgrading is highly likely to occur in developing countries, while vertical upgrading is much more difficult. . I find that almost all low-skilled tasks in all industries are closely related with each other, meaning that it is relatively easy to re-allocate low-skilled workers horizontally across different industries. It points towards a strategy that in early stages of development, it is feasible and worthwhile for a country to utilize their abundance of low-skilled labour in the low-skilled tasks in the GVCs of sophisticated products (e.g. electronics and automobile) which, as I will show later, have much higher economic potentials than low-skilled tasks in agriculture and light industries (for example, textile and shoes). However, on the other hand, vertical upgrading turns out to be much less common. There is little relatedness between low-skilled and medium/high-skilled tasks. The relatedness remains rather low even for different skilled tasks within the same industry. This is especially the case in sophisticated manufacturing like electronics and automobiles. Some case studies like Humphrey and Schmitz (2002) and Humphrey and Memedovic (2003) illustrate how an enterprise of a regional industry cluster upgrades towards higher value-adding activities along the value chain, but I find the skill upgrading is rather difficult for a country as a whole. This result echoes the findings from Lemoine and Ünal-Kesenci (2004) and Jarreau and Poncet (2012) who show that the gains from assembly trade in China are largely limited within the processing exporter themselves, and their participation in GVCs does not contribute much to technological progress nor growth in the rest of the economy. Hence GVC participation does not guarantee a sustainable growth path in the long-run,

[2]A possible task can be, say, low-skilled activities in textile or high-skilled activities in electronics. Different skilled activities within an industry, for example low- and medium-skilled activities in electronics, are treated as different tasks.

and proper policy stimulations might still be necessary to achieve economy-wide vertical upgrading.

Another interesting finding is that various tasks in utility, logistics and transport sectors are closely related with manufacturing tasks. This highlights the complementarity between tasks in manufacturing and services, and suggests that a pro-trade business service sector can be developed in the early stage of development, which will continue to play a supportive role in the future progress of export upgrading. This important type of complementarity can not be revealed in a product space approach.

To provide further evidence that my task space approach is useful in structural change analysis, I also test whether the relatedness index is relevant for the actual changes in each country's export structure. Using probit regressions, I show that the probability in developing a comparative advantage in a new task is significantly positively related with its proximity with those tasks that in the initial period the country already has a comparative advantage in. This result is robust to alternative specifications, therefore confirms the validity of my task space in analyzing structural change as a dynamic process.

The rest of the paper is organized as follows: in section 4.2 I introduce the concept of relatedness in tasks and compare my relatedness with the current literature. Section 4.3 describes the methodology and the data I use in deriving value-added exports of tasks. Then I explore the task space, i.e. the structure of relatedness in section 4.4, followed by section 4.5 which translates the task relatedness indices into a network graph that illustrates possible ways of structural upgrading. In section 4.6 I explore the dynamics of economic structure in my task space framework. In this section I first plot the actual directions of structural change for countries at different level of development, and find that the paths are largely aligned with the task space network. I further perform econometric analysis and confirm that task relatedness has strong power in predicting the development of new comparative advantages. Section 4.7 concludes and discusses the policy implications from my research.

4.2 Co-occurance in RCA as a Measure for Task Relatedness

I build my task relatedness indices using the method by Hidalgo *et al.* (2007) which traces the relatedness of two products through the correlation in their revealed comparative advantage (RCA). In this paper, I will trace the relatedness in tasks instead of products.

The relatedness between two tasks x and y, denoted as $\phi_{x \to y}$, is defined as the probability that a country i has a comparative advantage in task y, conditional on it having already a comparative advantage in task x:

$$\phi_{x \to y} = \text{Prob}(RCA_{i,y} > 1 | RCA_{i,x} > 1). \tag{4.1}$$

This conditional probability can be empirically calculated by:

$$\phi_{x \to y} = \frac{\text{Number of Countries with } RCA_y > 1 \text{ and } RCA_x > 1}{\text{Number of Countries with } RCA_x > 1}. \tag{4.2}$$

Similar as in Hidalgo *et al.* (2007) and Neffke *et al.* (2008, 2011), I calculate this ϕ statistic for each year in the period of 1995 to 2009 for which the data are available, and take the simple average of $\phi_{x \to y}$ across years to proxy the relatedness between each pair of tasks.

The idea behind this relatedness measure is intuitive. A high $\phi_{x \to y}$ means that a task y is frequently found to be a comparative advantage in the countries that also have a comparative advantage in x, which reveals that the socio-economic environment that nurses task x also fits the requirement for task y. There are several possibilities why two tasks appear to be the comparative advantages of a country at a same time. One may consider, for instance, the force of agglomeration and the regional clustering of certain tasks (Marshall 1920, Ellison *et al.* 2010). Two tasks may have similar requirements on workers, share common technologies and intermediate inputs, have backward/forward linkages within a supply chain, and other sorts of synergy effects such that the development of one task also reinforces the growth of another. It is also possible the existence of a particular task is a prerequisite for another. For example, ICT-related services are unlikely to develop without the construction of a good network infrastructure.

While there are various possible reasons why two tasks emerge together, it should be noticed that in this paper I focus only on how strong are two tasks related. The index $\phi_{x \to y}$ is an empirical similarity measure based on the observed co-existence in RCAs which captures all potential sources of task relatedness, and it remains silent on the exact channels through which two tasks are related. Other research aims at specific pre-defined channels of relatedness between economic activities. Neffke and Henning (2013) use the Swedish official registers on employment to trace the movements of individual employees across different industries, which generates insights into the similarity of labour skill demands by each industry. Conley and Dupor (2003) use the U.S. input-output table and derive two measures of economic distance between industries: one measure investigates the similarity in two industries' input structure, and another focuses on whether two industries have backward/forward input-output linkages.

The derivation of task relatedness requires the data on revealed comparative advantage indices. In this paper I construct the index in a similar way as the conventional RCA proposed by Balassa (1965), but I derive the RCAs using value-added export data on tasks instead of the gross exports of products. The RCA index for a task x in country i is defined as follows:

$$RCA_{i,x} = \frac{VAE_{i,x} / \sum_x VAE_{i,x}}{\sum_i VAE_{i,x} / \sum_{i,x} VAE_{i,x}}, \tag{4.3}$$

The interpretation of the value-added based RCA index is the same as the conventional RCA. The numerator measures the share of task x in country i's exported value-added, while the denominator captures the share of x in the value-added trade of the world. Therefore, a larger-than-unity $RCA_{i,x}$ means that country i exports a higher share of x

relative to the world average, which implies that i has a revealed comparative advantage in task x.

As already discussed in the introduction, the value-added export based RCA is a clearer and more meaningful measure for the comparative advantages and henceforth task relatedness in globalised production. And compared with the relatedness in industries or products, the decomposition of value-added exports into the contributions by tasks at different skill levels provides more information on the actual activities that are taking place in an economy. To give an example, when one overlooks the skill levels and focuses on the export of products, textile and electronics may show up as highly related since textile industry and the final stage in electronics production (i.e. assembly) have actually quite similar requirements for labour, and indeed the largest exports of both electronics and textile show up in South East Asia and China. However, the relatedness between textile and electronics products in this case does not imply that textile is highly related with the "stereotype" high-tech activities in electronics (like the design and manufacturing of silicon microchips)[3]. It remains unknown whether the participation in low-skilled tasks of the electronics industry will induce the development in these higher skilled tasks.

A final comment is needed concerning the asymmetry of task relatedness. Note that in most cases $\phi_{x\to y}$ does not equal $\phi_{y\to x}$. Hidalgo *et al.* (2007) use a symmetric measure constructed from taking the minimum of relatedness from two directions, i.e. $\phi_{x,y} = \phi_{y,x} = \min(\phi_{x\to y}, \phi_{y\to x})$. I use the asymmetric measurement since the difficulty in developing a task x conditional on y is in general not the same as the development of y conditional on x. Two directions of relatedness should be treated separately as argued in Nedelkoska *et al.* (2015) who analyse the relatedness between occupations; it is relatively easy for a person to switch from a tough job to an easier one while the reverse is usually not true. The same argument holds in the process of structural change at country level. For instance, oil refinery and oil-related chemistry are quite likely to evolve in countries that have many oil fields (i.e. a strong oil extraction industry). In a reverse direction, a majority of developed countries have refineries using imported oil, but it is impossible for them to develop a comparative advantage in oil extraction tasks because most of them do not have oil fields anyway. By taking the minimum of $\phi_{x\to y}$ and $\phi_{y\to x}$ as in Hidalgo *et al.*, the "difficult direction" of the transition counts. Therefore, the difficulty of upgrading from oil extraction to processing is largely overestimated. From an analytical point of view, it is more suitable to keep the asymmetric relatedness of both directions, and use the relevant index according to research necessity. Policy makers are usually only interested in the path of upgrading from current activities to new and more preferred ones. In such cases difficulty associated with the "downgrading" path is not of particular interest[4].

[3]Neffke *et al.* (2008) show another example in which the relatedness of industries becomes confusing. They have detected significant relatedness between "other textile" and "other food" industries with medicine manufacturing industry. But their detailed exploration reveals that the factories producing bandages (classified as other textile) usually produce some basic disinfectants that can be combined with their bandages, while the production of spices and herbs are classified as other food but they may also have medical use. This type of nuisance relatedness between industries can be severe when there is a high degree of international production fragmentation, making it more important to splitting the industrial production to tasks at different skill levels and investigate the tasks' relatedness.

[4]Hidalgo *et al.* (2007) are in favour of the symmetric relatedness indicators and in the online appendix

4.3 Deriving the Value-added Export by Tasks

To calculate the relatedness between each pair of tasks, I need to derive first the value-added export (VAE) of tasks. Formally, a task is defined as the set of activities in an industry (or a service sector) that are performed by workers at a certain level of skill (low, medium- and high-skilled), according to the worker's educational attainment. Consider a task x referring to the activities in an industry a using type-f labour. Following Johnson and Noguera (2012) I define VAE of x as the value-added created by type-f labour in a that is ultimately absorbed as final demand in foreign countries.

The derivation of VAEs from a country i follows, briefly speaking, a backward-tracing strategy. The starting point is the final demand of all countries *other than* i itself. Then I use international input-output tables to decompose these foreign final demands into the value-added generated by ultimate factors from different country/industries that are required in the production. The part of value-added generated by tasks in country i is therefore the value-added exports by i that satisfies the definition above. The formal steps of the VAE derivation are illustrated as follows. Assume there are m countries in the world and each country has n industries. The global input-output structure is described by a so-called technical matrix $\boldsymbol{A}$ of the size $mn \times mn$, with the following structure:

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{A}_{11} & \boldsymbol{A}_{12} & \cdots & \boldsymbol{A}_{1m} \\ \boldsymbol{A}_{21} & \boldsymbol{A}_{22} & & \boldsymbol{A}_{2m} \\ \vdots & & \ddots & \vdots \\ \boldsymbol{A}_{m1} & \boldsymbol{A}_{m2} & \cdots & \boldsymbol{A}_{mm} \end{bmatrix}. \tag{4.4}$$

Each block $\boldsymbol{A}_{ij}$ is an $n \times n$ matrix, capturing the traded intermediate inputs from country i that are used by the production in j; a typical element $A_{(i,a),(j,b)}$ stands for the value of intermediate goods produced by country i's industry a that are used in producing \$1 output by industry b in j. The matrix $\boldsymbol{A}_{ii}$ on the diagonal stands for the domestic input-output structure within each country i.

I use $y_{i,a}$ to denote total gross output from country i's industry a. And country j's demand for the final good produced by industry a of country i is denoted by $d^j_{i,a}$. In matrix form, the total production from the world and the final demand of each country

---

they discuss about the potential flaws in using the asymmetric one. When a good z is exported only by one country, the asymmetric relatedness $\phi_{z\to z'}$ will, by construction, equal one for all z' that this country has a comparative advantage. Since one is the upper bound for the relatedness indices, it misleadingly implies a easy structural change from z to all those z'. They claim that this problem is mitigated by taking the minimum of $\phi_{z\to z'}$ and $\phi_{z'\to z}$. However, taking the minimum generates a misleading result from another direction. Namely, $\phi_{z\to z''}$ equals zero for all z'' that this country has a comparative disadvantage, and this zero relatedness "overrides" the non-zero $\phi_{z''\to z}$ in taking the minimum, implying that the product z and all those z'' are completely unrelated. In general, this is a statistical small-sample problem which occurs only when the comparative advantage of a good z is observed in a very limited number of countries. Under such circumstances, the relatedness $\phi_{z\to z'}$, i.e. the probability of having a comparative advantage in z' conditioning on z, cannot be accurately estimated using equation (4.2) due to the lack of observations. Hidalgo *et al.* (2007) use detailed product classifications at the 4-digit level, so it is quite possible that some products are only exported by a single or few countries. This does not occur in this paper since I use a 2-digit industrial classification. According to the data in 2009, a task appears at minimum in 6 countries as a comparative advantage, and more than 90% of the tasks appear as a comparative advantage in 10 or more countries.

are represented in mn-element column vectors $\boldsymbol{y}$ and $\boldsymbol{d}^i$ as follows:

$$\boldsymbol{y} = \begin{bmatrix} y_{1,1} \\ y_{1,2} \\ \vdots \\ y_{1,n} \\ y_{2,1} \\ \vdots \\ y_{2,n} \\ \vdots \\ y_{n,m} \end{bmatrix}, \qquad \boldsymbol{d}^1 = \begin{bmatrix} d^1_{1,1} \\ d^1_{1,2} \\ \vdots \\ d^1_{1,n} \\ d^1_{2,1} \\ \vdots \\ d^1_{2,n} \\ \vdots \\ d^1_{n,m} \end{bmatrix}, \quad \boldsymbol{d}^2 = \begin{bmatrix} d^2_{1,1} \\ d^2_{1,2} \\ \vdots \\ d^2_{1,n} \\ d^2_{2,1} \\ \vdots \\ d^2_{2,n} \\ \vdots \\ d^2_{n,m} \end{bmatrix}, \quad \cdots, \quad \boldsymbol{d}^n = \begin{bmatrix} d^n_{1,1} \\ d^n_{1,2} \\ \vdots \\ d^n_{1,n} \\ d^n_{2,1} \\ \vdots \\ d^n_{2,n} \\ \vdots \\ d^n_{n,m} \end{bmatrix}. \tag{4.5}$$

World final demand is by definition the summation of final demands from all individual countries, i.e. $d^W_{i,a} \equiv \sum_j d^j_{i,a}$ and in matrix notation $\boldsymbol{d}^W \equiv \sum_j \boldsymbol{d}^j$.

Equality holds that $y_{i,a} = d^W_{i,a} + \sum_{j,b} y_{j,b} A_{(i,a),(j,b)}$, i.e. the value of total gross output from country i's sector a equals the total final demand for its products, plus those outputs used as intermediate inputs by all countries and industries. This input-output structure can be written in a compact matrix form as:

$$\boldsymbol{y} = \boldsymbol{d}^W + \boldsymbol{A}\boldsymbol{y}, \tag{4.6}$$

where $\boldsymbol{A}\boldsymbol{y}$ captures the total usage of intermediate inputs. Re-arranging this equation using the Leontief Inverse (Leontief 1949) gives the relationship between total production and total final demand:

$$\boldsymbol{y} = (\boldsymbol{I} - \boldsymbol{A})^{-1} \boldsymbol{d}^W. \tag{4.7}$$

To investigate the value-added export from country i, the total demand $\boldsymbol{d}^W$ can be decomposed into two components: final demand of country i itself, $\boldsymbol{d}^i$, and final demand of all foreign countries $\boldsymbol{d}^{-i} = \sum_{j \neq i} \boldsymbol{d}^j = \boldsymbol{d}^W - \boldsymbol{d}^i$. Correspondingly, the total gross production of the world can also be split into two components:

$$\boldsymbol{y} = (\boldsymbol{I} - \boldsymbol{A})^{-1} \boldsymbol{d}^i + (\boldsymbol{I} - \boldsymbol{A})^{-1} \boldsymbol{d}^{-i} = \boldsymbol{y}^i + \boldsymbol{y}^{-i} \tag{4.8}$$

the part $\boldsymbol{y}^i$ is a vector representing the total gross output in each country/industry required to satisfy final demand of country i, and $\boldsymbol{y}^{-i}$ is the production requirements for satisfying world final demand outside of country i. Each element in the latter term $\boldsymbol{y}^{-i}$ that belongs to the industries of country i, for example $y^{-i}_{i,a}$, captures the gross output of industry a of country i that is required to satisfy the final demand from abroad.

We are interested in the value-added exports by tasks at each skill level f (low-, medium- and high-skilled). I use $\eta_{i,a,f}$ to denote the value added by type-f labour in producing \$1 gross output in sector a of country i. The value-added export by each activity $x \equiv \{a, f\}$ in country i is therefore given by:

$$VAE_{i,x} \equiv VAE_{i,\{a,f\}} = \eta_{i,a,f} y^{-i}_{i,a}. \tag{4.9}$$

Subsequently, the RCA of each task and the task relatedness indices can be calculated by equation (4.3) and then (4.2).

To empirically compute VAE by each task, this paper uses the recently developed World Input Output Database (WIOD, Timmer *et al.* 2015) as the primary data source. The WIOD dataset provides time series multi-regional world input-output tables (WIOTs) from 1995 to 2011. WIOTs tell about the production structure of the world, namely the level of production of each industry and the domestic and imported intermediate input usages for all countries/industries. It also provides information on final consumption of domestic or imported goods/services by each country. The database consists of 40 countries that cover more than 85% of world GDP. It includes many developed countries, but also major emerging economies like Eastern European countries and the "BRIC" (Brazil, Russia, India and China), which are of interests for structural upgrading research. Estimates of the economic structure related with the rest-of-world (RoW) countries are also provided by the WIOTs, such that the production and consumption for the whole world is covered.

WIOTs are constructed from official data sources from multiple agents, including the national supply and use tables provided by national statistical bureaus and UN trade data at disaggregated levels. And the dataset covers trade in services and intangibles based on multiple sources like Eurostat and WTO. The WIOTs are constructed at 2-digit industry level (ISIC Rev.3), and data across countries are harmonized such that industries in different countries are comparable. Note that tasks in several industries are excluded from this analysis, either because the industry has large discrepancies in registration standards across countries, or because the industry serves mainly domestic final use only and associates with neither direct nor indirect exports (the RCA index cannot be calculated for non-exporting tasks). The excluded industries and their ISIC codes are: Hotel and restaurants (H), Other transport and operation of tourist agents (63), Public administration and defense (L), Education (M), Healthcare (N), Personal and community services (O), and Self-employed persons (P)[5]. In total I include 28 out of 35 ISIC industries.

To decompose sectoral value-added output into the contribution by activities at different skill levels, I further use the data on the skill structure of employment in each country/industry (or service), from the Socio-economic Accounts (SEA) in the WIOD project. In particular, I use the shares of factor income earned by low-, medium- and high-skilled labour in each country/industry, according to educational attainment[6]. This supplement dataset is available from 1995 to 2009 and I focus my research on this period. The time-series nature of WIOD also provides a possibility for me to trace the actual dynamics in industrial structure in the 15-year time period for these 40 countries, through which I can systemically investigate the power of relatedness indices in predicting the actual directions of export structure changes.

Compared to gross export data used in the conventional RCA index, VAE properly

[5]The value-added created by tasks in these industries are excluded from the analysis, but the values of intermediates used by them are included. For example, if the Japanese healthcare sector uses the medicines produced in the U.S., these values still count and will appear as the VAE by the U.S. chemistry sector.

[6]The classification of skill level follows the International Standard Classification of Education (ISCED). Low-skilled workers refer to employees with lower-secondary school, or lower level of education. Medium-skilled workers are those who have high school education. High-skilled workers have college or higher level of education.

controls for the position of a task in the global value chain (see also Johnson and Noguera 2012 and Koopman *et al.* 2014). As shown in Koopman *et al.* (2012, 2014), the conventional RCA is sensitive to the position of a country/industry in the production chain. A country located downstream in the GVC has a higher level of gross exports but it is caused by a higher intermediate to gross output ratio. The conventional RCA based on gross exports does not adjust for this, and will exaggerate the comparative advantage of countries downstream. In contrast, when calculating VAEs the higher usage of intermediate inputs translates by construction into a lower ratio of $\eta_{i,a,f}$, and all values related with intermediate inputs are effectively netted out. Furthermore, some sectors (in particular, services) rely largely on indirect export. That is, their output is used by other domestic exporting industries and thus exported indirectly. These indirect exports simply do not show in the gross export data, such that the conventional RCA may systemically understate comparative advantage. Instead, VAE includes both directly exported value-added as well as the value-added that is further used by other domestic exporting industries; the algorithm in calculating VAE identifies where the value-added is created and consumed regardless of the number of intermediate processing stages.

In this paper I focus on tasks performed by labour, and capital share is excluded from calculating RCA. This is because capital value-added and profit cannot be easily decomposed, and in addition multinational companies may book capital income in countries with taxation advantage which differ from the locations where capital truly adds the value (see also footnotes 5 and 9 in chapter 3 for details).

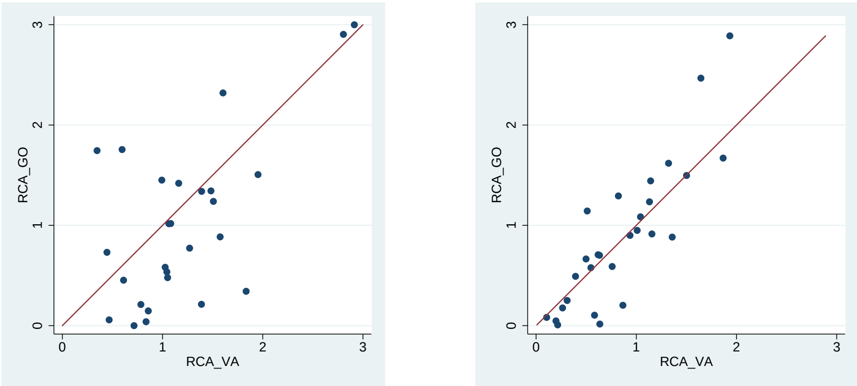
To see the differences between gross export based and VAE based RCAs, I show the value-added RCA at industry level because gross export based RCAs cannot trace the comparative advantages down to the task level. Figures 4.1a and 4.1b show the discrepancy between RCA_{GO} and RCA_{VA} for each industry in China and the US in the year 2009; the differences between these two measures are quite large.

Table 4.1 provides more detailed information about the conventional and new measures of RCA for several industries in China and the US in 2009. The most notable differences in the manufacturing sectors are observed in chemistry and electronics, which provide typical examples for two sorts of distortions as discussed above. For the electronics industry, the gross export based RCA shows that China has a strong comparative advantage with a RCA of 2.3, while U.S. has a comparative disadvantage. In contrast, in the VAE based RCA Chinese electronics industry scores only a moderate 1.6, and the U.S. electronics turns into a comparative advantage. The discrepancy between gross export and VAE based RCAs exceeds 50% (0.88 versus 1.36). The divergence between these two measures is explained by the intermediate input to gross output ratio. The Chinese electronics industry is located in the downstream part of the value chain; it uses a relatively high level of intermediate inputs that comprises 84% of the gross output from the industry. The high intermediate to output ratio inflates gross export statistics and leads to an over-optimistic estimation of RCA. On the other hand, the U.S. electronics industry adds more than 55% value on its own in 2009, and has the lowest intermediate to output ratio among all 40 countries covered by this research.

On the other hand, the chemistry industry shows a very different picture. In China the VAE based RCA index of chemistry is almost twice of the conventional one. It is

Figure 4.1: Comparison of Gross Export and Value-added Export based RCA Index

(a) China (b) USA



Notes: Each dot represents two measures of RCA at 2-digit industry level for the year 2009 (according to ISIC Rev. 3 classification, see appendix table A.1 for details). The horizontal axis plots the value-added RCA of an industry, and the vertical axis plots the conventional RCA based on gross export. The straight line is $y = x$; dots that are further away from the line imply a larger discrepancy between the two RCA measures. Source: WIOD database and author's own calculation.

due to the fact that 87% of output from Chinese chemistry industry is used further as intermediate inputs by other Chinese firms domestically, which is much larger compared to 54% in the U.S. The majority of exported value created by the Chinese chemistry industry therefore goes indirectly through other exported products and it explains the discrepancy between the two RCA measures.[7]

The mismatch between the two RCA measures is also observed in service sectors. For example, the RCA of Chinese finance industry is merely 0.04 according to the conventional measure, while the VAE based one is much higher at 0.84. The disparity follows the same reason as the chemistry industry that most output from Chinese finance industry is used by other domestic industries (79.3%) and the direct export is rather low: according to the WIOD database, in 2009 only less than 0.7% of output in the Chinese finance industry is exported directly, compared with 6% in the U.S.

In fact, some service sectors like land transport, vehicle repairing, and power supply are non-tradable (or very little traded) due to the nature of their production. However, they may play an increasingly important role in supporting other exporting sectors. For example an efficient provision of energy and domestic logistics can be important for the competitiveness of (direct) exporting firms. The conventional RCA cannot be measured for these services since there is no (or very little) direct export from them. As a comparison, the VAE measure is able to identify the indirectly exported value-added which allows me to derive the comparative advantages of these non-tradable business supporting services. While the previous literature about relatedness and structural change (e.g.

[7]More comparisons between gross export and value-added export based RCA can be found in Brakman and van Marrewijk (2015), based on a decomposition of WIOD dataset by Wang Zhi. They also argue that value-added RCA is more suitable in revealing the real economic activities.

Table 4.1: Different Measures of Revealed Comparative Advantages (2009)

I - China

Industry	RCA_{GO}	RCA_{VA}	Ratio	II/GO (%)	DUI (%)	RCA_L	RCA_M	RCA_H
Textile	3.00	2.91	1.03	79.5	56.1	5.05	2.56	0.41
Leather	2.90	2.80	1.04	80.2	47.1	4.48	2.20	0.33
Chemistry	0.54	1.04	0.51	79.4	87.0	1.64	1.04	0.33
Plastic	1.34	1.48	0.91	81.3	81.9	2.78	0.91	0.18
Metal	0.77	1.27	0.61	80.3	89.9	1.94	0.77	0.25
Machinery	1.02	1.06	0.96	77.0	50.3	1.91	0.80	0.27
Electronics	2.32	1.60	1.45	83.9	44.1	3.05	1.37	0.45
Automobile	0.45	0.61	0.74	80.5	51.9	1.28	0.52	0.18
Wholesale	1.42	1.16	1.22	39.9	54.6	0.62	0.79	0.80
Air Transport	1.45	0.99	1.46	75.2	17.5	0.23	0.50	0.94
Post & Communication	1.02	1.08	0.94	40.7	57.9	0.29	0.76	1.25
Finance	0.04	0.84	0.05	31.1	79.3	0.23	1.22	0.42
Business Services	0.73	0.45	1.64	59.3	69.4	1.42	0.42	0.23

II - United States

Industry	RCA_{GO}	RCA_{VA}	Ratio	II/GO (%)	DUI (%)	RCA_L	RCA_M	RCA_H
Textile	0.25	0.31	0.81	56.3	53.7	0.16	0.50	0.72
Leather	0.08	0.11	0.78	51.7	54.5	0.05	0.19	0.30
Chemistry	0.95	1.01	0.94	66.5	53.8	0.09	0.67	1.59
Plastic	0.70	0.63	1.11	67.5	76.3	0.21	0.78	0.70
Metal	0.59	0.76	0.78	66.4	87.5	0.29	1.04	0.82
Machinery	1.08	1.04	1.04	58.0	27.5	0.14	0.75	0.86
Electronics	0.88	1.36	0.65	43.5	32.7	0.22	1.21	2.68
Automobile	1.23	1.13	1.09	72.5	34.5	0.18	0.84	1.36
Wholesale	2.47	1.64	1.50	21.4	42.0	0.55	2.00	1.11
Air Transport	1.67	1.87	0.89	53.9	21.8	0.65	2.38	1.56
Post & Communication	1.62	1.32	1.22	40.4	55.7	0.09	1.68	1.71
Finance	2.89	1.93	1.49	47.0	60.6	0.34	1.61	2.54
Business Services	1.50	1.50	1.00	33.8	75.3	0.45	1.27	1.67

Notes: The column "Ratio" is RCA_{GO}/RCA_{VA}, "II/GO" is the cost share of intermediate inputs in gross output, "DUI" is the share of gross output that are used domestically by other industries as intermediate inputs. When the capital share in the industry is very large (small), it is possible that RCA_L, RCA_M and RCA_H are all smaller (larger) than industrial overall value-added RCA (RCA_{VA}). For example, in the Chinese air transport industry the capital share is higher than 70%, while it is less than 20% in the U.S. In this paper I focus on labour tasks and the values added by capital is excluded from calculating task RCAs. Source: Author's own calculation based on WIOD dataset.

Hidalgo *et al.* 2007 and Neffke and Henning 2013) focuses mostly on the industrial sectors, I am also able to calculate the relatedness of business service tasks with the tasks in the manufacturing sector to investigate the role of services in structural change. Indeed as I will show in the next two sections, tasks in utility and logistics sectors play a quite important role in the upgrading paths.

It is worthwhile to mention that the VAE measure in this paper is different from the domestic value-added share in export (DVS) in Koopman, Wang, and Wei (2012). DVS is defined as the share of domestic value-added that is embedded in one unit of gross output produced by each industry. Thus DVS times the volume of gross exports gives an estimate for the domestic value-added that are embedded in export. The derivation of this measure is easier, as it requires only domestic input-output tables of each country (Los, Timmer, and de Vries, 2016). However, similar as the gross export data, DVS lacks the ability in identifying the exact tasks that generate the value-added in exports. For example, assume that the assembly of electronics products relies on some domestic supporting services. The DVS measure will exclude the value that is embedded in imported intermediates, and account for the value contributed by domestic service. However, in DVS the value that is added upstream will be attributed to the exported products (i.e. electronics) and is not separately identified as the contribution by service tasks.

Another advantage of using VAE is that the industrial value-added export can be further decomposed into the contributions by tasks at different skill levels, and subsequently the RCA indices can be measured at the task level. It is important to identify the comparative advantages for different skilled tasks. Under globalized production, a country may specialise in certain tasks in the production process and it is not required that a country must carry out all production stages. The comparative advantage of an industry as a whole therefore becomes less informative as it does not tell much about the country's exact specialisation, and task level VAE gives more precise information on the actual activities that are taking place.

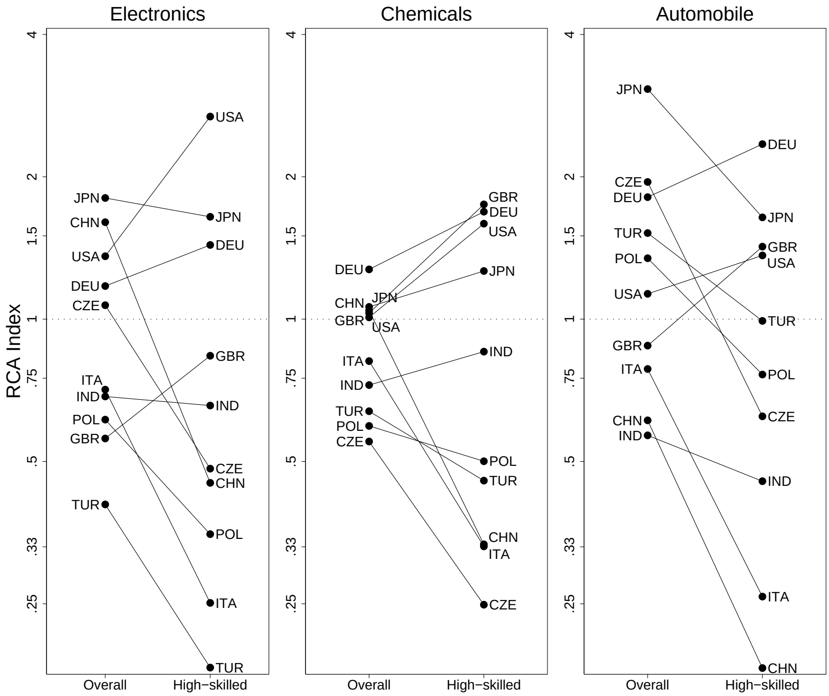
I find that the difference between industry- and task-level RCAs is large and widely existing. In figure 4.2, I plot the RCAs of 10 countries for the the electronics, chemical and automobile industries that are supposed to be the most attractive among all manufacturing industries. The left-hand side of each graph depicts the (VAE based) RCA for each industry as a whole, and the right-hand side depicts the RCA of the high-skilled task in the industry. The industry-level RCAs seem to suggest that developing countries are overtaking the developed world. For example China outperforms Germany and the U.S. in electronics, Germany looks inferior to Czech in automobile, and the U.K. is not performing well in all these three industries. But once we investigate the high-skilled tasks, i.e. the most attractive economic activities in these "favored" industries, the RCAs of developing countries decrease substantially; developed countries like Germany and the U.S. are still playing a dominant role in the world.

The numerical evidence can be also found in the last three columns in table 4.1, where I show the task-level RCAs for the U.S. and China. Looking only at the RCAs of industries (VAE based), the U.S. leads in service sectors but China is not inferior to the U.S. in the sophisticated manufacturing sectors like in electronics and machinery. However, when we investigate task-level RCAs, it becomes clear that China has a strong comparative advantage in the low-skilled tasks of electronics and machinery, which drives up the overall industry-level RCAs. On the other hand the U.S.'s comparative advantages lie mostly in the medium- and high-skilled tasks.

4.4 The Structure of the Relatedness between Tasks

Using the value-added export of tasks, I derive my "task space" which is an 84×84 matrix containing the relatedness between each pair of tasks. The structure of relatedness will

Figure 4.2: The RCAs of Industries and Tasks

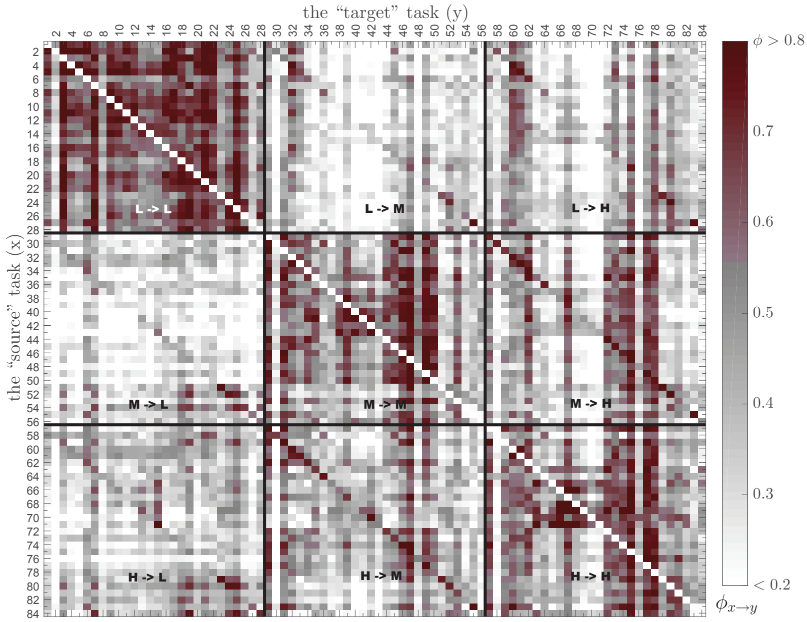


Notes: The plots depict the RCA indices for electronics, chemical and automobile industries. The marks on the left side of each plot, as indicated by "overall", stands for the VAE based RCA indices of each industry. The marks on the right side represent the RCA indices of high-skilled tasks in the same industry. The y-axis is in logarithm scale. Based on author's own calculation using WIOD data of 2009. To avoid congestion in the plots, only 10 countries in the WIOD dataset are shown.

be explored in this section. To have a quick view on the relatedness between tasks, the task space is presented as a heatmap in figure 4.3. I number tasks from 1 to 84, and organize them into three groups according to their skill levels. Tasks numbered 1 to 28, 29 to 56, and 57 to 84 correspond to low-, medium- and high-skilled tasks; detailed correspondence table can be found in the appendix. The heatmap contains 84×84 small squares, the colour of a square on row x column y represents the value of $\phi_{x \to y}$. A darker colour stands for a higher value of the relatedness index; note that in the graph a task associated with a dark-coloured column has strong relatedness with the other tasks, and therefore this task will be relatively easy to enter. To highlight the upgrading in skill, the heatmap is divided by black lines into nine big blocks according to the tasks' skill levels. And to further facilitate the visualization, the colour of a small square is dyed with red if the associated $\phi_{x \to y}$ is above 0.55 which is the criteria for high relatedness as set in Hidalgo *et al.* (2007). In my research about 22% relatedness indices fit this criteria.

It is evident from the heatmap that the three big blocks on the diagonal have a high density of deep coloured squares, indicating that a task is, in general, more closely related with other tasks at the same skill level. This is especially the case among low-skilled tasks as shown by the deepest color in the block $L \to L$ on the north-west corner. The three

Figure 4.3: Heatmap of Bilateral Relatedness Index beteen Tasks



Notes: Based on the task space, i.e. 84×84 matrix of $\phi_{x \to y}$. Darker color is associated with a higher relatedness value. Blocks correspond to $\phi_{x \to y} > 0.55$ are indicated by red.

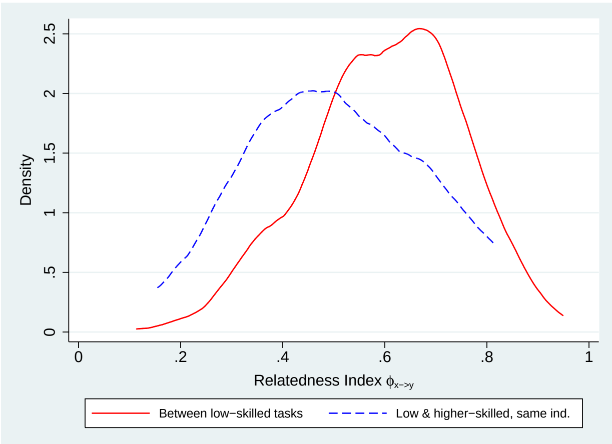
big blocks above the diagonal are the most interesting for developing countries, since the relatedness represented by the squares in these blocks are associated with the likelihood of the structural change towards high-skilled tasks. The upgrading from low-skilled to higher skilled tasks should be difficult according to my task space, as the $L \to M$ and $L \to H$ blocks contain only a few dark cells. The upgrading from medium-skilled to high-skilled tasks is relatively easier, especially in many business services sectors (task codes 72 to 80, see the appendix), however the relatedness between medium- and high-skilled tasks are still low in heavy industries and sophisticated manufacturing sectors (65 to 71).

An important target of the paper is to evaluate the difficulty in horizontal and vertical types of upgrading. The horizontal upgrading, i.e. the shift of low-skilled employment towards other low-skilled activities that are more attractive, will be relatively easy according to the high relatedness between all kinds of low-skilled activities. For example, the relatedness $\phi_{x \to y}$ representing the re-allocation from low-skilled textile task to electronics task is 0.67, and to low-skilled automobile task is 0.63. It means for countries that already have a comparative advantage in low-skilled textile tasks, two-third of them have a comparative advantage in low-skilled tasks in electronics (or automobile) as well, which shows that low-skilled tasks in sophisticated products' value chains have a good fitness with the socio-economic conditions of the less developed world. In other words, my task space predicts that countries at an early stage of development can also participate in the GVCs of sophisticated products (for example electronics or automobile) by performing low-skilled tasks.

What about the difficulty in vertically upgrading for less developed countries, namely the upgrading along the value chain towards higher skilled tasks within an industry? The relatedness structure suggests that vertical upgrading is on average more difficult than the horizontal upgrading, but the difficulty differs a lot across industries.

To investigate within-industry skill upgrading, one should look at the squares on the diagonal lines in the $L \rightarrow M$ and $L \rightarrow H$ blocks, as these squares represent the values of $\phi_{x \rightarrow y}$ such that the task x and y belong to a same industry (i.e. $y - x$ equal to 28 or 56, see also the task code table in the appendix). In the heatmap the diagonal lines are darker than other squares in these two blocks, indicating that the task upgrading towards higher-skilled activities within the same industry is relatively easier than the upgrading towards other higher-skilled activities in other industries. But the heatmap is not particularly suited to compare the vertical upgrading's difficulty with horizontal upgrading. For a clearer comparison, in figure 4.4 I draw the density plots for three sets of relatedness indices that are associated with different types of upgradings. The solid line represents the density of relatedness between two low-skilled tasks (i.e. horizontal shifts), while the dashed line for the relatedness between low-skilled tasks and the medium- and high-skilled counterparts within each industry (i.e. vertical upgrading). As shown in this figure, the relatedness for horizontal upgradings are on average higher than the relatedness for vertical upgrading; in the former case 64% of the relatedness indices are larger than 0.55, while 40% for the latter.

Figure 4.4: Distribution of Relatedness Index for Two Types of Upgrading



Notes: Kernel density distributions of relatedness $\phi_{x \rightarrow y}$. The solid line is the distribution for the relatedness within low-skilled tasks (mean: 0.601, median: 0.610). The dashed line represents within industry vertical upgrading, i.e. the relatedness between low-skilled tasks and the medium- and high-skilled tasks within each industry (mean: 0.503, median: 0.489).

The difficulty in vertical upgrading is also predicted to be quite heterogeneous. Vertical upgrading seems to be relatively easy in the light manufacturing sector (textile, leather and shoes, wood products), the corresponding relatedness between low-skilled tasks and the medium- and high-skilled counterpart is around 0.7 (among the top 10% percentile in all relatedness indices). However, in more "attractive" manufacturing sectors, namely in the GVCs of sophisticated products, vertical upgrading turns out to be much more difficult. The $\phi_{x \to y}$ regarding the upgrading from low- to medium-skilled tasks in machinery, electronics and automobile sectors are only 0.38, 0.33, and 0.32 respectively, which are below the median of all relatedness indices. It suggests that horizontal and vertical upgrading in sophisticated GVCs are different processes. The participation in low-skilled tasks in the GVCs is relatively easy due the strong relatedness with other low-skilled tasks in traditional sectors, but the participation does not seem to guarantee vertical upgrading to happen spontaneously.

An interesting finding is that the task space reveals the complementarity between tasks in manufacturing and several business service sectors. I find that high-skilled tasks in several business service sectors show a high relatedness with their low-skilled counterpart, with a $\phi_{x \to y}$ larger than 0.55. These sectors are electricity, gas and water supply (73), inland transport (78), water transport (79), sale & maintenance of vehicles (75), renting of machinery & equipment and other business services (83), and even air transport (80). Note that all these services are related with utility and logistics that support domestic and international trade. More importantly, the medium- and high-skilled services tasks are also highly related with many other low-skilled tasks in the manufacturing sector, as indicated by the dark colored columns in the $L \to M$ and $L \to H$ blocks. This type of relatedness is likely to be an outcome of complementarity between manufacturing and trade. This pattern is more clearly illustrated in the network analysis in the next section, in which I will also show that the development in higher-skilled trade supporting tasks is empirically observed in the actual upgrading paths of developing countries (for example in China).

4.5 Paths of Structural Change in the Task Space

What are the directions for structural change suggested by the task space? In this section I am going to transform the relatedness indices into a network graph that depicts the possible structural upgrading paths.

4.5.1 The Economic Potential of Tasks

Structural upgrading is a directed process in which a country moves towards more attractive tasks, i.e. the tasks that have higher potentials for economic growth. To evaluate the benefits from a certain upgrading path, it is important to first measure the economic potential (i.e. "desirability") of a task, which has not yet been formally defined.

So far I have assumed that higher-skilled tasks are more attractive than the lower-skilled one within the same industry, which seems to be plausible. But the economic potentials cannot be easily compared for tasks across sectors. This calls for an objective measure of a task's economic potential, since it is crucial when one wants to define "upgrading". In this paper, I follow Hausmann, Hwang and Rodrik (2007) and use a modified PRODY index to measure the economic potentials of tasks. The PRODY index of a task x is defined as follows in this paper:

$$PRODY_x = \frac{\sum_i w_i y_i RCA_{i,x}}{\sum_i w_i RCA_{i,x}}, \tag{4.10}$$

where y_i is the per-capita income of country i, and w_i is an importance weight for each observation and here I use the country's economic size (national GDP)[8].

In table 4.2 I list five tasks that have the highest/lowest PRODY averaged over the period 1995 to 2009. PRODY is a revealed measure of economic potential and can be interpreted as the income level of a representative country that export this task. Thus, a high PRODY means that the task is usually the comparative advantage of developed countries with a high level of income per capita.

Table 4.2: Tasks with the highest and lowest PRODY index

Top 5		Bottom 5	
Task	PRODY	Task	PRODY
High-skilled Electronics	32,064	Low-skilled Agriculture	8,357
Med-skilled Air Transport	31,039	Low-skilled Mining	8,990
High-skilled Publishing	30,784	Low-skilled Leather & Shoes	9,775
High-skilled Business Services	30,661	Low-skilled Textile	10,093
High-skilled Automobile	30,073	Low-skilled Oil Refinery	11,527

Source: Author's own calculation based on WIOD. Averaged PRODY across 1995 to 2009.

PRODY provides an ordering for the attractiveness of tasks in structural change. The magnitude of PRODY is also meaningful, and the benefit from a particular path of structural change can be proxied by the difference between the PRODY indices of two tasks. To give an example, the PRODY indices for low- and medium-skilled tasks are 10,093 and 15,898 in the textile sector, and 17,693 and 25,977 in electronics. So if we do not consider the difficulty in structural change for a moment, starting from the low-skilled tasks in textile, the vertical upgrading is less attractive than the horizontal upgrading towards electronics. If after the integration with the GVCs the country can further achieve the vertical upgrading in the electronics industry as suggested by Lin (2012), a much larger gain is expected for the horizontal upgrading towards electronics.

[8]Income per capita and national GDP are the real (per-capita) output-side GDP, taken from the Penn World Table 8.1 (Feenstra, Inklaar and Timmer 2015). The PRODY index used here is a weighted PRODY which differs from the original one $\frac{\sum_i y_i RCA_{i,x}}{\sum_i RCA_{i,x}}$ as in Hausmann, Hwang and Rodrik (2007). The original PRODY index can be viewed as a weighted average of income per-capita across countries, and the weight for each observation is the comparative advantage of each country. If a task frequently has a high RCA in richer countries, the per-capita incomes of those richer countries get a higher weight and it translates into a higher PRODY index for this task. However, small countries usually have a much higher degree of specialisation and have more extremely high values of RCA indices than larger countries. Effectively small countries are over-represented, making the original PRODY index less meaningful. For example, the top 3 most attractive tasks according to the original PRODY are low-skilled finance, low-skilled business services, and medium-skilled finance. I use economy size (national GDP) as the importance weight w_i for each country, and the weighted PRODY gives a more meaningful ranking of tasks' economic potentials.

4.5.2 Possible Upgrading Paths in a Network Graph

With a proper measure for the economic potentials of tasks, the structural upgrading process of a country can be intuitively described in a so-called "jumping monkey" analogy as discussed in Hidalgo *et al.* (2005). Each task can be viewed as a tree, and its economic potential is represented by the number of fruits that the tree is able to produce. The employment in a task is then in analogy to the monkeys living in a particular tree, and the process of structural upgrading can be viewed as the monkeys jumping towards the trees that provide them with more fruits. But monkeys must take the distance between trees into consideration before making a jump, as a monkey can only jump towards the trees that are close enough to the tree it currently lives in (i.e. two tasks must have sufficiently high relatedness).

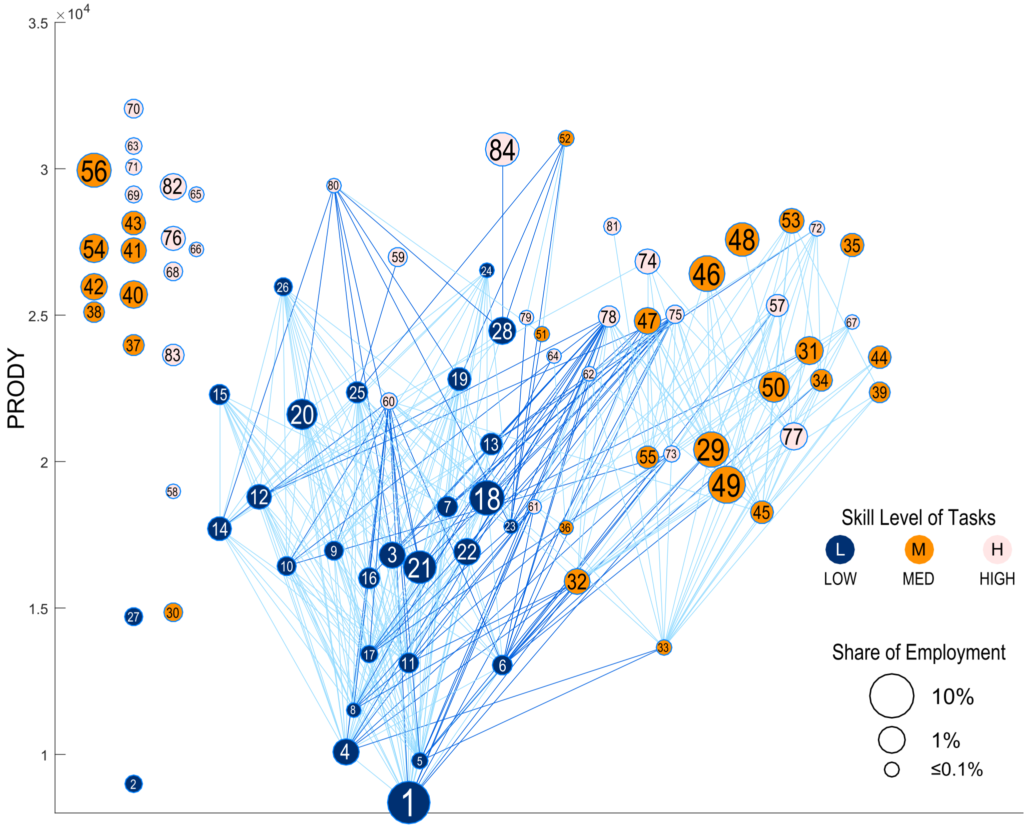
The possible paths for structural change are therefore in analogy to a "map" that plots the possible jumping routes between the trees, and I illustrate it by the means of a network graph as in figure 4.5. A network consists of *nodes* and *edges*. In the network of my task space, nodes represent the tasks at various skill levels. Different skilled tasks are represented by different colors, and their size indicate the average share of employment of tasks in the economy (for the 40 WIOD countries in 1995, unweighted). The edges represent the feasibility of the directions of structural change. The change from one task to another is said to be possible if there is an edge linking these two nodes. In this paper I use the criteria by Hidalgo *et al.* (2007); two nodes are linked by an edge if the associated $\phi_{x \to y}$ is greater than 0.55.

The nodes are vertically positioned in the graph according to their PRODY index, such that in figure 4.5 the nodes from the bottom to the top are in an ascending order according to their economic potentials.[9] To reduce the complexity of the graph and to focus more on the process of structural upgrading, I only draw the edges that are associated with an upgrading direction where the "target" task's PRODY index is at least 20% higher than the "source" (i.e. $\text{PRODY}_y/\text{PRODY}_x \geq 1.2$). I also exclude the relatedness with the tasks in which less than 10 countries have a comparative advantage to increase the reliability of the visualization (see the discussion in footnote 4, in total 3 nodes are affected). Note that there are also many "isolated tasks" that do not have any edge with others; I position these nodes on the left side of the graph.

Figure 4.5 confirms the findings based on the heatmap that horizontal upgrading is much more likely than the vertical one. Nodes of low-skilled tasks are heavily linked with each other, and at the same time low-skilled tasks in different industries show a large heterogeneity in terms of their potentials for economic growth. The low-skilled tasks in sophisticated products (e.g. electronics and automobile) have a PRODY index around \$20,000, which is almost twice of the PRODY of traditional low-skilled activities like in agriculture and textile (around \$10,000). This shows that horizontal upgrading is a feasible option and has an important growth enhancing effect for countries at an early

[9] The horizontal axis of my network graph does not have a particular meaning; the horizontal positions of nodes are chosen to reduce the number of crossings of edges and to make the graph more readable. Note that my network graph is different from the product space network as in Hidalgo *et al.* (2007); they do not visualize the economic potentials of products and both horizontal and vertical positions of nodes are determined by an algorithm to minimize the number of crossings of edges.

Figure 4.5: Network Graph of the Relatedness in the Task Space



stage of development.

On the other hand, there is only a limited number of edges that span from low-skilled tasks towards higher skilled ones (highlighted by a darker colored column in figure 4.5), and mostly towards the medium- and high-skilled tasks in utility and logistics sectors (47, 51, 52, 73, 75, 79, 80, etc). However, the opportunity of vertical upgrading seems to be rather low in most manufacturing sectors; only upgrading towards higher skilled tasks in light industries seems to be promising (in textile and leather products, 32, 33, 60, 61). The medium- and high-skilled tasks in modern manufacturing sectors (37 to 44 and 65 to 72) turn out to have the highest level of PRODY index, therefore the vertical upgrading in these industry is expected to yield a much higher gain for an economy in the future. However there is little relatedness between these tasks with other tasks in the rest of the economy. For example, in electronics industry the relatedness between low- and medium-skilled tasks (14 and 42) is only 0.33, and 0.45 between medium- and high-skilled (42 and 70). When looking at the relatedness index with other tasks, only the high-skilled task in automobile (71) has a relatedness higher than 0.55 with the high-skilled electronics task. However they have very similar levels of PRODY which are among the top of all tasks.

Therefore this route is not very relevant, and is not an option for developing countries that do not have a comparative advantage in high-skilled sophisticated manufacturing.

Similar as in the heatmap, the network graph also shows that medium- and high-skilled tasks in utility and logistics-related business services have a higher probability to evolve even during the early stage of development. There might be two possible reasons behind the relatedness between these services tasks and low-skilled tasks in manufacturing industries. Firstly, utility and logistics sector complement the low-skilled manufacturing tasks by reducing energy and transportation costs. Compared with many medium- and high-skilled manufacturing tasks which are frequently embedded in light-weighted but valuable products, low-skilled manufacturing tasks are usually associated with physical processing and are low in their value-added. The costs spent on energy and logistics constitute therefore a relatively larger share in the effective price. More efficient utility and logistics therefore reduce the effective costs in delivering the low-skilled tasks to the world market, which increase the competitiveness of low-skilled manufacturing firms. And on the other hand, an abundant supply of low-skilled labour means the skills of personnel in logistics and utility sectors can be utilized at a larger scale. This increases the ability and willingness for firms in these services sectors to pay a higher wage and keep high-skilled staff for key positions. This in turn attracts highly educated young people to enter these sectors.

The second reason is the relatively low propensity of offshoring for tasks in utility and trade supporting sectors. In principle the high-skilled tasks in these sectors are remotely transmittable (for instance, the scheduling in logistics), but the nature of these sectors makes the solutions provided outside of the country less competitive. Different from ICT or financial services where remote work from another country will not significantly dampen the quality of output being delivered, many of the high-skilled tasks in utility and logistics require location and relationship specific knowledge that are frequently tacit (for example, knowing the regional traffic or power grid conditions). This might create a natural barrier against foreign competitors, such that the high-skilled tasks have a higher chance to develop even when a country is still at a relatively low level of development.

4.6 The Dynamics of Economic Structure in the Task Space

The task space is static in the sense that the derivation relies on cross sectional data, i.e. it is empirically calculated based on the "snapshot" of countries' comparative advantages in each year. How does my task space fits the dynamics in actual paths of structural change? In this section I will first visualize the changes in comparative advantages in the task space for countries at different levels of development during 1995 to 2009. And in the second subsection I will use regression analysis to formally investigate the role of task space in determining the direction of future structural change.

4.6.1 Actual Structural Upgrading Paths in the Task Space

To see whether the actual directions of export structural change follows the possible paths suggested by the task space, and to investigate the structural dynamics across different type of countries, in figures 4.6(a) to 4.6(c) I depict the changes in task-level RCAs from 1995 to 2009 for three subsets of countries in the WIOD database: Non-European developing countries, Eastern-European countries, and developed countries.[10] In each figure, plots I and II show the comparative advantages of each country group in 1995 and 2009, plot III identifies the new and disappeared comparative advantages, and plot IV identifies the tasks with the largest increase and decrease in the value of their RCA.

Non-European developing countries have on average the lowest level of per-capita income among all countries covered by the WIOD dataset. Their comparative advantages are mainly in low-skilled tasks in both 1995 and 2009. The tasks that have the quickest development are those low-skilled tasks with relatively high economic potentials, most notably in the Machinery, Electronics and Automobile industries (code 13 to 15). New comparative advantages also arise in some non-isolated medium- and high-skilled tasks. However, there is no notable development in the isolated medium- and high-skilled tasks although they have the highest growth potential according to the PRODY index. Low-skilled agricultural tasks remain a comparative advantage in 2009, but the decrease in its RCA value is one of the largest among all tasks. In combination, these patterns suggest that structural change paths of non-European developing countries can be described as horizontal upgrading, i.e. the shift of low-skilled employment from traditional activities towards low-skilled tasks in the value chains of sophisticated products.

Eastern European countries are at a higher level of development. In 1995 they already have many comparative advantages in several non-isolated medium- and high-skilled tasks that are on the upper-right corner of the plot (see Fig.4.6(b)). During 1995 to 2009, a considerable share of comparative advantages in low-skilled tasks has disappeared, and the Eastern European countries were developing their new advantages in medium- and high-skilled tasks, including some of the "isolated" ones. Plot IV also confirms that in Eastern European countries the RCA indices of medium-skilled task in Rubber and Plastic (38) and automobile (43) have the largest increases among all tasks; these tasks are predicted to be hard to enter according to the task space.

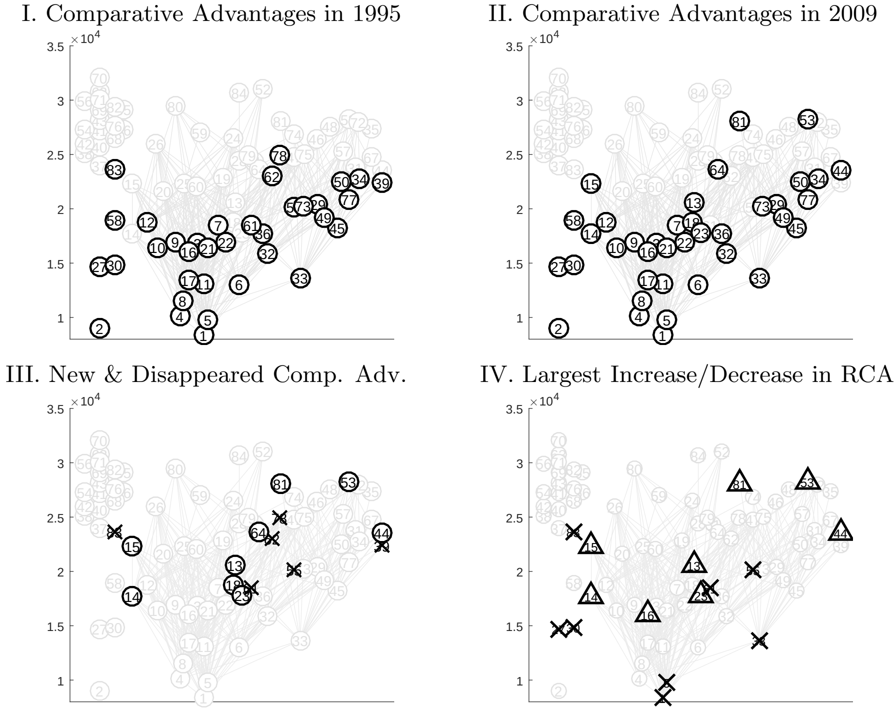
The advanced countries already have a comparative advantage in high- and medium-skilled tasks in 1995, mostly among the favourable but isolated tasks on the upper-left corner (Fig.4.6(c)). During the period examined here, developed countries continued consolidating these comparative advantages. They did not have a comparative advantage in low-skilled tasks from the beginning but the largest decreases in RCA are still observed for these low-skilled ones.

China is a fast emerging economy and a large offshoring destination in recent decades.

[10] Non-European developing countries: Brazil, China, India, Indonesia, Mexico, Russia and Turkey. Eastern European Countries: Bulgaria, Cyprus, Czech Republic, Estonia, Greece, Hungary, Lithuania, Latvia, Malta, Poland, Romania, Slovakia, and Slovenia. Developed countries: other countries in the WIOD database.

Figure 4.6: Dynamics of Comparative Advantages from 1995 to 2009

(a): Non-European Developing Countries

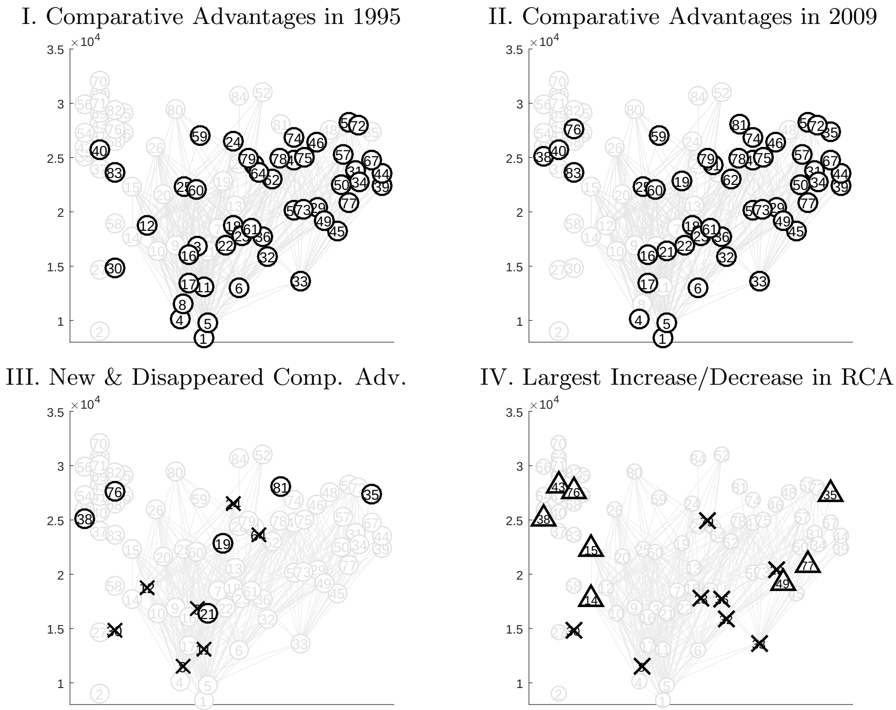


Notes: Figure 4.6(a)-(c) are based on the average RCAs in each country group, weighted by the country sizes in 1995 (or 2009). Figure 4.6d is based on the RCAs in China. In each figure, the rounds and crosses in plot III indicate new and disappeared comparative advantages, respectively. And in Plot IV, triangles and crosses show the tasks with top 10% increases/decreases in their RCA values.

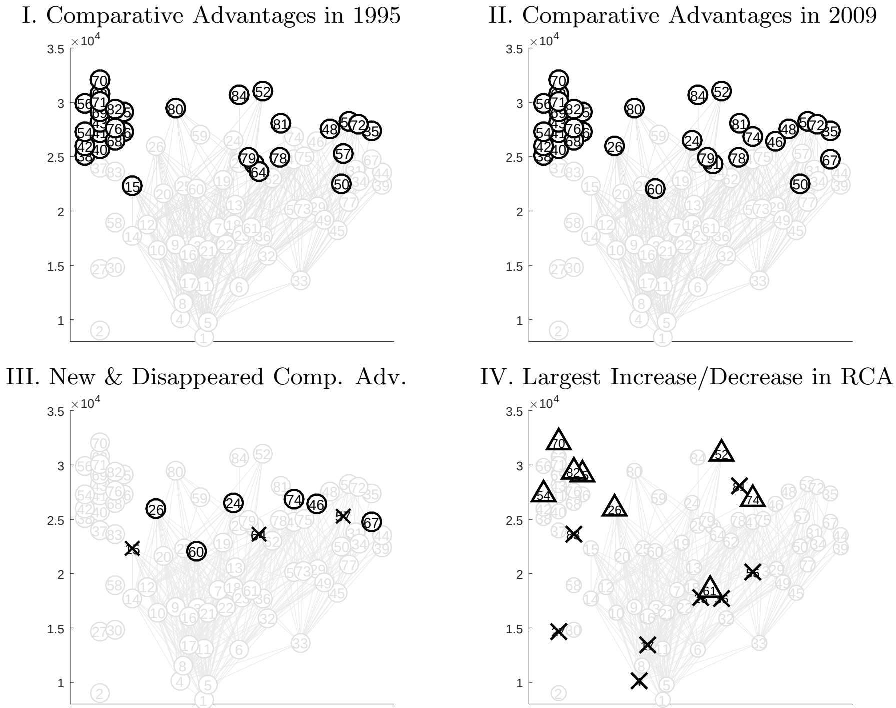
It has quickly integrated in world markets. I illustrate the export structural change of China separately in figure 4.6(d) using the same set of plots as 4.6(a)-(c). Similar as other non-European developing countries, the comparative advantage of China mainly lies in low-skilled tasks. Plot 4.6(d)-III shows that China has gained new comparative advantage in various medium-skilled tasks including several desirable but isolated ones. It seems to suggest that China has overcome the lack of relatedness and has undergone vertical skill upgrading at a quite early stage of development, considering its low income level in 1995 (real income per capita \$3,445 at 2005 constant price according to PWT 8.1, the second lowest among all countries in the WIOD database and comparable to countries like Egypt and Sri Lanka). But when we look at the largest changes in the RCA values, plot IV shows China's upgrading pattern looks much like other developing countries, namely the RCAs rise the most in low-skilled tasks in sophisticated products (13 to 15), and the trade supporting services (23 and 51 on water transport, 73 on utility, and 81 on telecommunication), and the largest decreases in RCA are found in agriculture and traditional manufacturing.

To examine whether China has undergone a rapid vertical upgrading along the value

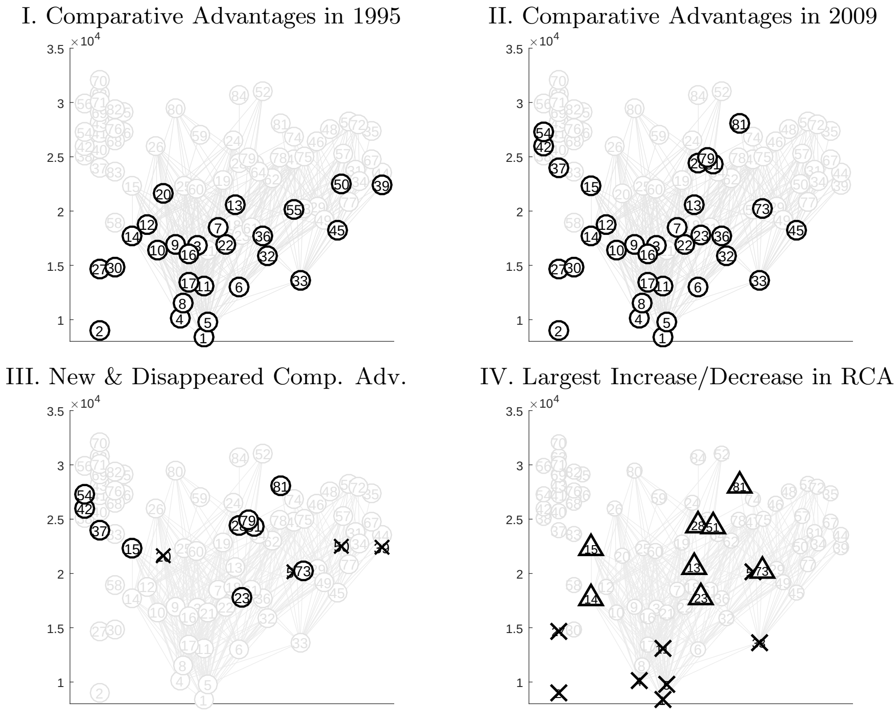
4.6(b): Eastern-European Countries



4.6(c): Developed Countries



4.6(d): China



chain, it is worthwhile to closely investigate changes in the RCA values of each task from 1995 to 2009, as shown in table 4.3. The low-skilled task in electronics has undoubtedly the largest increase in RCA, and the medium-skilled electronics task has also a notable growth in the RCA of more than 0.6 and it turned into a comparative advantage by 2009. For the other two isolated tasks in which China has gained a comparative advantage, i.e. medium-skilled tasks in Chemistry and Finance (37 and 54), their increases in RCA are much more moderate. As a comparison, many tasks in utility and trade supporting sectors not only switched into the status of a comparative advantage, but also have quite large increases in their RCAs. There are also other service tasks that have a large rise in the RCA but in which China has not reach comparative advantage yet, for example the high-skilled tasks in retailing and air transport. When we investigate the skill structure of employment in each Chinese industry,[11] the share of medium- and high-skilled labour in Chinese electronics industry has increased by 6.1 percentage points between 1995 and 2009, which is faster than, but not very different from, other manufacturing sectors. It seems that the new comparative advantage in medium-skilled electronics is an outcome of a rapid expansion of the total size of the Chinese electronics industry rather than within-industry skill upgrading. On the other hand, the largest within-industry skill upgrading is observed in retailing and wholesaling sectors (about 13 percentage points increase in the share of medium- and high-skilled labour in total employment).

[11] The data are provided in the socio-economic account of WIOD. See Table A.2 in the appendix for details.

Table 4.3: Revealed Comparative Advantage of Tasks in China, 1995 and 2009

Sector \ Skillness	1995 L	1995 M	1995 H	2009 L	2009 M	2009 H
Agriculture	6.25	0.65	0.05	4.85	0.88	0.02
Mining	2.66	1.55	0.15	1.63	1.09	0.33
Food Manufacturing	1.35	0.70	0.10	1.69	0.89	0.24
Textile	5.76	2.47	0.20	5.05	2.56	0.41
Leather Products	5.71	2.75	0.19	4.48	2.20	0.30
Furniture	2.71	0.78	0.08	2.99	0.88	0.17
Paper and Publishing	1.50	0.50	0.04	1.70	0.58	0.09
Refinery	1.72	1.54	0.28	1.51	1.48	0.67
Chemistry	1.25	0.77	0.13	1.64	1.04	0.33
Rubber and Plastic	2.34	0.80	0.09	2.78	0.91	0.18
Non-metal Minerals	4.05	1.34	0.13	3.08	0.93	0.16
Metal	1.92	0.79	0.14	1.94	0.77	0.25
Machinary	1.02	0.41	0.08	1.91	0.80	0.27
Electronics	1.67	0.74	0.15	3.05	1.37	0.45
Automobile	0.40	0.18	0.04	1.28	0.52	0.18
Other Manufacturing	1.24	0.37	0.04	1.84	0.54	0.10
Utility	2.51	1.33	0.34	2.57	2.00	1.25
Construction	0.84	0.35	0.06	0.69	0.28	0.10
Sale of Automobile	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Wholesaling	1.04	0.75	0.29	0.62	0.79	0.80
Retailing	0.31	0.35	0.08	0.22	0.37	0.19
Inland Transport	1.73	1.10	0.18	1.25	0.70	0.24
Water Transport	0.95	0.44	0.17	2.58	1.48	1.01
Air Transport	0.26	0.51	0.44	0.23	0.50	0.94
Post and Communication	0.16	0.28	0.29	0.29	0.76	1.25
Finance	0.14	0.98	0.16	0.23	1.22	0.42
Real Estate	4.60	1.80	0.25	3.12	0.99	0.22
Business Services	0.51	0.16	0.04	1.42	0.42	0.23

Source: Author's own calculation based on WIOD dataset. L, M, H stands for the low-, medium- and high-skilled tasks in each industry. Note that China does not have a separated industry classification for "Sale and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel" (ISIC code 50).

4.6.2 Testing the Role of Task Relatedness in the Actual Directions of Structural Change

To provide econometric evidence that countries upgrade through the task space towards highly related tasks, I am going to show that a task's proximity to country's current comparative advantages has significant predictive power on whether the country will develop a new comparative advantage in this task.

The concept of economic activity relatedness has been used in various studies. However, there is still a lack of systemic econometric tests in the literature. Recently Kali *et al.* (2013) calculated the proximity between the set of comparative advantageous products and comparative disadvantageous products in a country, and use this as a measure for the country's proximity to future comparative advantages. They show that a country has a higher probability in experiencing a growth acceleration if its initial economic structure has a closer link with those products that the country correctly does not have a comparative advantage in.

While it is interesting to investigate the economic structure and the probability of a growth acceleration, the data I use cover a period of 15 years which is not long enough for the analysis of long-run economic growth and growth accelerations.[12] Therefore this research has a different focus, namely I am interested in a systematic test on the paths of structural change, to see whether relatedness play a significant role in determining the new comparative advantages in the future. Formally, I am going to test the following hypothesis:

> *The probability that a country gains comparative advantage in a task is positively associated with the proximity of this task with the current export structure of the country.*

I use the following indicator to measure the proximity of a task x to the economic activities in which the country i currently has a comparative advantage:

$$\widetilde{\phi}_{i,x} = \sum_{y \in \mathrm{Adv}_i} s_{i,y} \phi_{y \to x}, \qquad \mathrm{Adv}_i\text{: the set of tasks in country } i \text{ with } \mathrm{RCA}_{i,y} > 1. \quad (4.11)$$

In the equation, $s_{i,y}$ is the share of employment (measured by the number of working hours) by task y in overall employment of country i; all variables are based on the information in the initial period. This measure takes both the strength of relatedness (i.e. $\phi_{y \to x}$) and the relative size of related comparative advantageous tasks ($s_{i,y}$) into consideration. It can be viewed as a support for the development in a new task ("new" means the task is currently a comparative disadvantage of the country) from the economic structure of country i. Namely, a task gets a stronger support if it has higher relatedness to the comparative advantageous tasks that have larger shares of employment in the economy.

This proximity indicator is different from Kali *et al.* (2013) and Hidalgo *et al.* (2007), who separately measure the strength of relatedness and the relative size of the economy related to the new task. Their strength measure is the maximum relatedness of a task with current comparative advantageous tasks, i.e. $\phi_{i,x}^{\max} = \max_{y \in \mathrm{Adv}_i}\{\phi_{y \to x}\}$, which I will include in the robustness check. Another measure they use is constructed as $\omega_{x,i} = \sum_{y \in \mathrm{Adv}_i} \phi_{y \to x} / \sum_y \phi_{y \to x}$ which they refer to as the "density" of relatedness. The target of this variable is to measure the "percentage of neighbouring space around the new task that is already developed in a country" (Hidalgo *et al.* 2005), however it effectively assigns a similar weight to each product code (or task code) and does not take the actual structure of economic activities into consideration.[13]

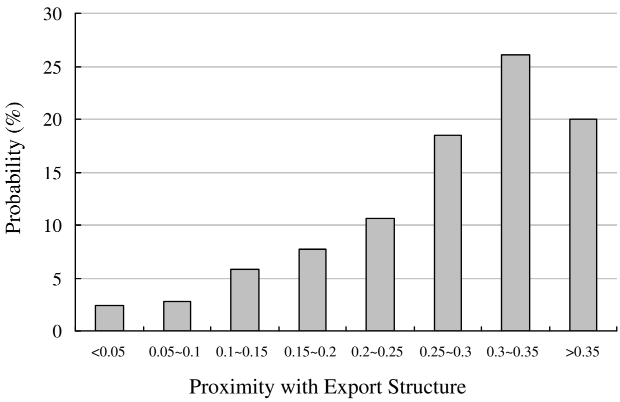
[12] One of the criteria in identifying growth accelerations is that the accelerating period must sustain for at least 8 years (see Hausmann, Pritchett, and Rodrik 2005 and Kali *et al.* 2013). Data coverage for 15 years is therefore too short for this kind of analysis

[13] To see that, consider four products. The relatedness between products 1 & 3 and between 2 & 4 is 0.9; the relatedness between any other pairs is 0.1. Assume country A and B have comparative

The proximity of a task to current comparative advantages of the country (i.e. $\widetilde{\phi}_{i,x}$) is derived based on the pooled task space using RCAs from 1995 to 2009 as described in section 4.2, and the employment structure of the initial period (i.e. 1995). I focus on the tasks that have an $\text{RCA}_{95} < 0.75$ in the initial year. Tasks whose initial RCA is close to one are excluded in the benchmark analysis, since whether the task is a comparative advantage or disadvantage (i.e. whether the RCA is larger or smaller than 1) can be sensitive to the fluctuations in trade and measurement errors in these cases. The growth of RCA from 0.75 to above 1 is large enough to ensure it is not merely due to these fluctuations.[14]

To provide a quick diagnostic on the role of proximity in determine the probability of gaining a new comparative advantage, in figure 4.7 I plot the share of tasks that have gained a comparative advantage for the observations with different levels of $\widetilde{\phi}_{i,x}$. Tasks with the highest level of proximity have almost a 10 times higher probability in becoming a new comparative advantage for the country, compared to those with the lowest level of proximity.

Figure 4.7: Probability of Gaining a Comparative Advantage (95–09)



Notes: Only observations with an initial $\text{RCA}_{95} < 0.75$ are included. The vertical axis is the measured probability in gaining a comparative advantage, calculated as the number of observations that have gained a comparative advantage in the period 1995 to 2009, divided by the total number of observations in a certain range of $\widetilde{\phi}_{i,x}$ as represented on the horizontal axis. The variable $\widetilde{\phi}_{i,x}$ is the task's proximity with the initial export structure of a country, see equation (4.11).

Formally, I test the hypothesis using the following probit regression:

$$\begin{aligned} &\text{Prob}(\text{RCA}_{i,x,09} > 1 | \text{RCA}_{i,x,95} < 0.75) \\ &\quad = \Phi(\text{Const.} + \beta_1 \widetilde{\phi}_{i,x,95} + \beta_2 \mathit{Potential}_{i,x,95} + \beta_3 \text{RCA}_{i,x,95} + \varepsilon_{i,x}), \end{aligned} \tag{4.12}$$

advantage in product 1 and 2. These two products make up, say, 60% and 30% of total employment in A, and 30% and 60% in B. Intuitively, product 3 is more likely to develop in country A (and product 4 in B) since it is related with a larger share of the economy. The density measure as in Hidalgo *et al.* and Kali *et al.* does not use the information of employment structure and will give the relatedness density $\omega_3 = \omega_4 = (0.9 + 0.1)/(0.9 + 0.1 + 0.1) = 10/11$ for both product 3 and 4 in both country A and B.

[14] Hidalgo *et al.* (2007) use a 4-digit industry classification and focus on observations with an initial RCA smaller than 0.5. I classify tasks at the 2-digit level; at such an aggregated level it is more difficult for RCA to grow quickly, therefore a higher threshold of 0.75 is chosen. Focusing on RCAs below 0.5 would result in a smaller sample size and more importantly, much fewer number of tasks have gained a comparative advantage in this subset which dampens the power of probit regressions I use.

where $\Phi(.)$ is the cumulative distribution function of the standard normal distribution. The core parameter in the regression equation is β_1. A positive and significant β_1 implies that the probability in gaining a comparative advantage is positively associated to the proximity of the task to the comparative advantageous tasks, therefore relatedness has predictive power on the actual direction of structural change.

I include two important control variables. Note that structural change is in general an upgrading process, and whether a certain task is attractive for a country not only depends on the economic potential of the task itself, but also on the level of development of the country. So the task's economic potential relative to the country's average level should be controlled for. Following Hausmann, Hwang and Rodrik (2007), the economic potential of a country i can be proxied by the so-called $EXPY$ index, which is a weighted average of PRODY and the weights are the shares of value-added export of each task from i:

$$\text{EXPY}_i = \left(\sum_x VAE_{i,x} \text{PRODY}_x \right) / \sum_x VAE_{i,x}. \tag{4.13}$$

The control variable I use is constructed as $Potential_{i,x,95} = \ln(\text{PRODY}_x / \text{EXPY}_i)$; it is positive (negative) when the PRODY of the task is higher (lower) than the EXPY of the country. I also include the task's initial RCA value as a control variable, because if other things stay the same, it would be easier for a task to obtain the status of comparative advantage (i.e. RCA>1) if it has a higher RCA at the beginning.

The regression results are reported in table 4.4. The "MEF" columns next to a probit regression refer to the marginal effects evaluated at the mean of independent variables. Column 1 is the baseline model corresponding to the regression equation 4.12 above. As expected, the coefficient β_1 is positive and strongly statistically significant, indicating that countries indeed tend to gain comparative advantage in tasks that have higher proximity to current comparative advantageous tasks. The effect is also economically important. The marginal effect for specification (1) shows that when the proximity to current comparative advantages increase by one standard deviation (around 8 percentage points), the probability in gaining a comparative advantage is predicted to increase by 1.7 percentage points. This effect is large in the view that only 7.7% of the tasks have gained a comparative advantage across the whole sample.

In specifications (1a) and (1b), I use $\phi_{i,x}^{\max}$ as an alternative measure for the task's proximity to the current export structure. When only $\phi_{i,x}^{\max}$ is included, the coefficient is positive and significant which confirms the finding in Kali *et al.* (2013), but the R^2 of the regression has decreased compared to (1). And when both proximity measures are included in (1b), only $\widetilde{\phi}_{i,x}$ is significant and the coefficients are very similar as (1), indicating that there is no need to control for the maximum strength of relatedness when $\widetilde{\phi}_{i,x}$ is in place. In column (2) I use the symmetric relatedness (i.e. $\phi_{x,y} = \min(\phi_{x\to y}, \phi_{y\to x})$ as in Hidalgo *et al.* 2007) to construct the proximity measure, and in specification (3) I focus only on developing countries with real GDP per capita lower than \$20,000 in 2000. In both cases I obtain a similar result as the benchmark. Noteworthy, there is no statistical difference in the marginal effects of $\widetilde{\phi}_{i,x}$ in (1) and (3), indicating that the task's proximity to the current export structure has a similar effect on the probability in gaining a comparative advantage for both developing and developed countries.

Table 4.4: Regression Results

I - Main Results

	Baseline		Use $\phi_x^{\max}$	Both	Symmetric Relatedness		Developing Econ	
	(1)	MEF	(1a)	(1b)	(2)	MEF	(3)	MEF
$\widetilde{\phi}_{x,i}$	3.593	0.215		3.948	4.788	0.283	2.767	0.234
	[0.625]	[0.044]		[0.843]	[0.807]	[0.057]	[0.753]	[0.067]
$\phi_{x,i}^{\max}$			1.363	-0.353				
			[0.418]	[0.560]				
Potential_{95}	1.443	0.086	1.625	1.388	1.440	0.085	1.182	0.100
	[0.223]	[0.013]	[0.234]	[0.238]	[0.222]	[0.013]	[0.275]	[0.022]
RCA_{95}	3.300	0.198	3.128	3.342	3.289	0.195	3.205	0.271
	[0.309]	[0.026]	[0.307]	[0.317]	[0.310]	[0.026]	[0.382]	[0.039]
Const.	-3.649		-3.789	-3.506	-3.767		-3.360	
	[0.218]		[0.307]	[0.312]	[0.230]		[0.261]	
R^2	0.260		0.236	0.260	0.262		0.248	
Obs.	1646		1646	1646	1646		843	
# Positive	131	(7.69%)	131	131	131		77	(9.12%)

II - Testing Vertical Upgrading

	M&H Tasks, All Observations				M&H Tasks, Developing Countries			
	(4a)	(4b)	(4c)	(4d)	(5a)	(5b)	(5c)	(5d)
$\widetilde{\phi}_{x,i}$	4.025	4.246	4.102		2.732	3.222	3.135	
	[0.795]	[0.815]	[0.806]		[0.988]	[1.040]	[1.036]	
Potential_{95}	1.499	1.615	1.553	1.380	0.989	1.175	1.155	0.973
	[0.304]	[0.318]	[0.318]	[0.308]	[0.410]	[0.432]	[0.043]	[0.422]
RCA_{95}	3.159	3.242	3.191	3.149	2.902	2.986	2.939	3.001
	[0.347]	[0.353]	[0.351]	[0.343]	[0.433]	[0.437]	[0.434]	[0.432]
RCA_L		-0.069				-0.103		
		[0.052]				[0.068]		
IsRCA_L			-0.076	0.021			-0.232	-0.077
			[0.126]	[0.122]			[0.177]	[0.167]
Const.	-3.680	-3.701	-3.688	-2.968	-3.170	-3.236	-3.217	-2.675
	[0.263]	[0.263]	[0.263]	[0.203]	[0.327]	[0.333]	[0.331]	[0.263]
R^2	0.208	0.210	0.208	0.171	0.173	0.180	0.178	0.154
Obs.	1098				541			
# Positive	107	(9.7%)			61	(11.3%)		

Notes: Standard errors are reported in square brackets. All specifications are probit regressions, the dependent variable is a dummy indicating whether the country has gained a comparative advantage in the task in the year of 2009. I use the observations with initial $\text{RCA}_{95} < 0.75$. Specifications (4) and (5) focus only on medium- and high-skilled tasks, and specifications (3) and (5) uses only the observations from developing countries (real GDP per capita in 2000 smaller than $\$20,000$). MEF is the associated marginal effect evaluated at the mean, using the delta method. "# Positive" indicates the number of observations with a dependent variable equal to one in the probit regression, and the term in bracket indicates the percentage in the total number of observations. The row of R^2 is the pseudo-R^2 of the probit regressions.

In the lower panel of table 4.4, I test the propensity of vertical upgrading. To be more specific, I focus on the subsample of developing a comparative advantage in medium- and high-skilled labour, and to test the hypothesis whether the existence of a comparative advantage in low-skilled tasks of a given industry is positively correlated with the probability that the country gains a comparative advantage in higher skilled tasks within the same industry. Column (4a) replicates the baseline regression for the subsample. Compared to the baseline regression in the column (1) all coefficients do not have statistically significant differences.[15] In (4b) I include the RCA of low-skilled tasks in the same industry as a control variable, and alternatively in (4c) I include a dummy indicating whether the low-skilled task is a comparative advantage of the country in 1995. However, the coefficients on low-skilled tasks' RCAs are insignificant in both specifications, while coefficients on all other variables are almost the same as (4a). It is possible that the effect of vertical relatedness is already controlled by including the "overall" proximity $\widetilde{\phi}_{i,x}$ in the regression. But even when $\widetilde{\phi}_{i,x}$ is excluded, column (4d) shows that the existence of a comparative advantage in the low-skilled task of an industry still has no significant correlation with the probability of gaining comparative advantage in higher-skilled tasks. In column (5a-d) I replicate the probit regressions of (4a-d) but focus on the subsample of developing countries. The coefficients on RCA_L and IsRCA_L are still insignificant; they even have a negative sign.

Therefore, I find no support for the vertical upgrading hypothesis, which has important implication for development strategies. Consider that a developing country aims to gain a comparative advantages in medium- or high-skilled tasks in a particular industry. A common believed strategy is that the country may first participate in the tasks that they currently have a comparative advantage in, i.e. those low-skilled tasks, and then it can further develop the comparative advantages in the higher-skilled tasks through channels like learning by doing and knowledge transfers. However, the outcome in table 4.4-II suggests this strategy may fail; after the country obtains a comparative advantage in the low-skilled task, it does not seem to help the development of higher-skilled ones.

Table 4.5: Regression Results for Alternative Specifications

	All $\mathrm{RCA}_{95} < 1$		RCA Growth> 0.25		Changes in RCA	
	(6)	MEF	(7)	MEF	(8)	(9)
$\widetilde{\phi}_{x,i}$	3.523	0.352	3.102	0.821	0.617	1.498
	[0.514]	[0.056]	[0.451]	[0.119]	[0.085]	[0.202]
$\mathrm{Potential}_{95}$	1.610	0.161	1.336	0.354	0.266	0.842
	[0.180]	[0.017]	[0.131]	[0.032]	[0.017]	[0.041]
RCA_{95}	3.060	0.306	0.996	0.264	0.009	-0.667
	[0.190]	[0.025]	[0.117]	[0.046]	[0.031]	[0.076]
Const.	-3.568		-1.724		0.004	0.148
	[0.171]		[0.109]		[0.017]	[0.042]
R^2	0.307		0.125		0.167	0.261
Obs.	2024		1646		1630	1583
# Positive	271	(13.4%)	368	(22.4%)	-	-

Notes: Standard errors are reported in square brackets. Specification (6) and (7) are probit regressions; MEF is the associated marginal effect evaluated at the mean, using the delta method, and "# Positive" indicates the number of observations with a dependent variable equal one in the probit regression. Column (6) is the replication of (1) but include all observations with $RCA_{95} < 1$. The dependent variable in specification (7) is a dummy indicating whether the RCA of the task has increased by more than 0.25. Specification (8) and (9) are OLS regressions using $\mathrm{RCA}_{09} - \mathrm{RCA}_{95}$ and $\ln(\mathrm{RCA}_{09}) - \ln(\mathrm{RCA}_{95})$ as dependent variables, respectively. The observations in (8) and (9) are trimmed to be within the 0.5 to 99.5 percentile in their dependent variable to control for outliers. Column (6) and (7) report pseudo-R^2; (8) and (9) report adjusted R^2. Note that the number of observation differs in (8) and (9), this is because the dependent variable in (9) is not well defined if a task does not exist in a country in either 1995 or 2009 (i.e. RCA=0).

To check the robustness of my findings that the proximity to the current export structure predicts future comparative advantages, in table 4.5 I perform regressions using

[15] A Wald test has been performed to check whether all coefficients in (1) and (4a) are jointly equal. The Wald statistic is 2.76 with a p-value of 0.598.

several alternative specifications. Column (6) includes all observations that have an initial $RCA_{95} < 1$, and column (7) investigates the probability that the RCA value of a task has grown more than 0.25 between 1995 and 2009. The values of coefficients are not comparable with the baseline specification due to the different sample coverage and regression criteria, but in all cases of $\widetilde{\phi}_{i,x}$ is significant and the marginal effects are large in magnitude.[16] In column (8) and (9) I perform OLS regression on the changes in RCA between 1995 and 2009. The dependent variable in (8) is the difference $RCA_{09} - RCA_{95}$, and in (9) the relative growth of RCA, $\ln(RCA_{09}/RCA_{95})$. There are a few observations with extreme changes in their RCA indices, so I exclude these outliers and only include the observations whose change in RCA is within the 0.5 to 99.5 percentile. Both specifications show that a task's proximity to export structure positively correlates with the growth in its RCA index, which confirms my hypothesis.

Lastly, there are potential validity and endogeneity concerns on the core explanatory variable, i.e. the proximity measure $\widetilde{\phi}_{i,x}$. Note that $\widetilde{\phi}_{i,x}$ is constructed using the relatedness index which is ultimately based on the pooled RCA values from 1995 to 2009. The "pooled" relatedness can be invalid and meaningless for the regression if the structure of task relatedness changed substantially during the time period, and $\widetilde{\phi}_{i,x}$ is not fully exogenous since the dependent variable is determined by changes in RCAs. The validity of the pooled task space is justified since the structure of task space remains quite stable during the 15-year period examined here (see appendix for details). And to exclude the possibility of endogeneity, I derive a new set of bilateral relatedness indices $\phi_{y \to x}^{95-99}$, by pooling only the RCAs from the first five years from 1995 to 1999. Then I construct the explanatory variables $\widetilde{\phi}_{i,x}^{*}$ using the new relatedness index $\phi_{y \to x}^{95-99}$ together with the export structure in 2000. In appendix table A.4 and A.5 I replicate all regressions above but now analyse the development of new comparative advantages from 2000 to 2009, which does not have overlap in time with the construction of the new explantory variables. Since the time period becomes shorter when we only consider 2000 to 2009, the propensity in gaining a comparative advantage is smaller which makes the coefficients less significant and the marginal effects smaller compared to the baseline regressions. But the coefficient for $\widetilde{\phi}_{i,x}^{*}$ is positive in all cases, and in most cases also statistically significant.

4.7 Concluding Remarks and the Implications on Development Strategies

This paper investigates the relatedness between different tasks in a world where offshoring is pervasive and comparative advantage is realised at the task level. Using world input-output tables, I control for trade in intermediate inputs and derive revealed comparative advantages (RCAs) of tasks based on value-added exports (VAE). I follow the methodology as in Hidalgo *et al.* (2007) and derive my task space, i.e. the bilateral relatedness between each pair of tasks defined as the conditional probability that a country has a comparative advantage in both tasks.

[16] For instance, a one standard deviation increase in $\widetilde{\phi}_{i,x}$ is associated with a $0.821 * 8 = 7.16$ percentage points higher probability that the RCA of an underdeveloped task increases at least 0.25.

I find in the analysis that, in general, tasks are more closely related to other tasks at the same skill level, rather than to other tasks in the same industry. This is especially the case for low-skilled tasks as is evident from figure 4.3 and 4.4. The tight relatedness across low-skilled tasks in almost all industries indicates the horizontal upgrading, i.e. shift of low-skilled employment into new tasks with a higher economic potential, is likely to take place. On the other hand, in the manufacturing sectors the relatedness between low- and higher-skilled tasks is rather weak even for tasks within the same industry, with the textile and shoes industries as the only exceptions. Therefore developing countries may face a high difficulty in entering many medium- and high-skilled tasks; vertical upgrading is unlikely to take place especially in the GVCs of sophisticated products like electronics and automobile. Interestingly, in service sectors I find that medium- and high-skilled tasks in utilities, and trade and logistics related services are highly related to not only the low-skilled tasks within these sectors, but also other low-skilled manufacturing tasks. It suggests an important complementarity between manufacturing and trade, and high-skilled tasks in pro-trade services sectors may develop when the country is still at an early stage of development.

I investigate the actual structural change paths of different types of countries over the period from 1995 to 2009. I find that in non-European developing countries, the new comparative advantages emerged mostly in the low-skilled tasks of sophisticated manufacturing sectors, and the structural change pattern of these countries can be described as a process of horizontal upgrading. In China, the most rapidly growing tasks are mainly low-skilled tasks in machinery, electronics, and automobile industries, which is similar to other non-European developing countries. China has also experienced vertical upgrading in some trade supporting services, but not in sophisticated manufacturing. Eastern-European countries seem to outperform other developing countries; they have undergone rapid development in some medium- and high-skilled manufacturing tasks that are predicted to be hard to enter.

I tested my task space against the actual structural change paths for 40 countries from 1995 to 2009 using a set of probit regressions. The econometric analyses confirm that new comparative advantages are more likely to develop in tasks that have strong proximity to the country's current comparative advantage. However, I find no support for vertical upgrading; having a comparative advantage in a low-skilled task is not related to an increase in the probability that higher-skilled tasks in the same industry develop. In other words, this result predicts that the participation in low-skilled tasks in GVCs does not help developing countries to climb up the value chain.

The findings in this paper have important implications for development strategies and it is related to a long-standing debate concerning whether a developing country should follow or defy its current comparative advantages in order to have successful structural change (see, e.g. Lin and Chang 2009). Lin and Monga (2011) argue that a developing country should not aim at too far-out targets in the beginning, but should instead stick to the current comparative advantages in low-skilled labour and try to find the industries where they have a "latent comparative advantage". They also argue that the government should not have strong distortive industrial policies, but instead play a role in information and infrastructure provision. This strategy is partially supported by the outcome from this paper, but my task space also shows several potential challenges from a global value chain perspective.

My result supports the argument that at an an early stage of development a country should not defy its current comparative advantage, which is in the abundance of low-skilled labour. Low-skilled tasks in different industries show a large heterogeneity in terms of their potential for economic growth. Some low-skilled tasks, especially those in sophisticated products' GVCs, have a much higher economic potential than the low-skilled tasks in agriculture and light industries like textile, shoes and food manufacturing. The PRODY of low-skilled tasks is around $20,000 in automobile, machinery, and electronics industries compared with $10,000 in textile and agriculture. Since all kinds of low-skilled tasks are closely related, the horizontal upgrading from traditional industries towards low-skilled tasks in sophisticated global value chains is therefore a strategy which is relatively easy to achieve and should bring substantial gains to the economy.

In the long-run, the country must vertically upgrade in order to achieve further development. Similar to Taglioni and Winkler (2016), I find that participation in GVCs and the upgrading through GVCs are two very different processes; and the latter does not seem to be automatic. My task space network (i.e. figure 4.5) shows that higher-skilled tasks in the GVCs of sophisticated products are very difficult to enter, and the regression analysis further confirms that participation in low-skilled tasks of GVCs does not per se increase the probability of vertical upgrading. A country might instead be trapped in the low-skilled tasks due to the lack of relatedness with higher-skilled tasks in the value chain. This echoes the findings by Jarreau and Poncet (2012) and Lemoine and Ünal-Kesenci (2004) regarding the role of processing trade in China's economic growth. Jarreau and Poncet (2012) show that regions that participate in the production of sophisticated goods indeed grow faster. However, the contribution to economic growth originates only from ordinary firms who perform most production stages domestically. Foreign firms and the domestic firms that only process imported intermediates have neither direct nor indirect effect on growth. Lemoine and Ünal-Kesenci (2004) focus on the electronics industry and they find that imported foreign technology has improved the competitiveness of processing exporters and helped China's export upgrading, but there is little technology diffusion that helps other Chinese firms; the gains from foreign technology are rather limited.

The difficulty in vertical upgrading suggests that a country must be careful in choosing which kind of value chain it is going to enter. Reallocating low-skilled employment towards the GVCs of sophisticated products will generate gains to the economy because their economic potentials are higher than other low-skilled tasks in agriculture and light industries. However, the gain is possibly once-off and there is no guarantee for further vertical upgrading. Before participating in a certain GVC, the policy makers should think whether higher-skilled tasks in that GVC will have high proximity with the economic structure of the country in the near future. This is in analogy with the identification of latent comparative advantage as in Lin and Monga (2011), who suggest that the policy makers should look at a model country which is rapidly growing, has around 100% higher GDP per capita, and had a similar socio-economic structure in the past. And then the latent comparative advantage should be found in a list of tradable products or services which the model country has produced for around 20 years.

However, it is uncertain whether this imitation strategy remains valid under the recent wave of offshoring and production fragmentation. First, the organization of production has drastically changed during past decades due to offshoring and technological change. The way a product is currently produced can be very different from 20 years ago; the production of the same product (or service) may entail completely different tasks which do not necessarily fit the current socio-economic conditions of the country. Second, my task space echoes Baldwin (2013) who states that joining a value chain is a quicker way for industrialisation when offshoring is feasible, but it is questionable whether such "industrialisation" is meaningful. When the division of tasks in a GVC can be finely specialised and unbundled across borders, multinational companies minimize their production costs by re-organizing the production processes such that the offshored tasks are specially designed to fit the conditions in the host country. On the one hand it means that when a host country aims in entering a particular GVC, it may always find some tasks that are specially designed for it, such that the country faces less obstacles in participating. However on the other hand, the name and feature of the products become less meaningful for the host country's future development. The offshored tasks are usually standardized due to the finer task specialisation and contain *less* product-specific core technologies. And tasks that are actually carried out can be similar in very different products, for instance assembling a phone is not that different from assembling a pencil sharper. Tasks in more sophisticated products may end up in even less opportunities for learning which leads to a lower relatedness to the low-skilled tasks in the value chain. Sewing machine operators in a textile firm may gradually gain the experience on how Italians design their cloths, but the assemblers of smart phones will have nearly no chance nor capability to understand how Americans and Japanese make their chips.

As a final remark, this study has two major limitations. First, a task is defined as the activities in an industry that are performed by a particular type of labour. This is an educational attainment based measure which is silent on the type of skill a task requires (math, communication, body strength,etc), and it is possible that higher-skilled labour perform tasks that actually only require a lower level of skill. A better definition of a task could be, for example, the exact occupations of workers. However, data on the occupation structure by industry are currently not available for many countries, so in this paper I stick to the educational attainment measure. Secondly, the WIOD database covers a limited set of developing countries, most of which were relatively successful in development during the past decades. It is therefore uncertain whether the structure of my task space is the same for other developing countries at a lower level of development. The limited coverage of developing countries also forces me to limit the scope of econometric tests in the direction of new comparative advantages, while a more interesting research question would be why some country successfully upgrade and why others not. To test the role of task relatedness in the successfulness of (overall) structural upgrading and long-run economic growth, longer time-series data are needed that should cover a much wider set of developing countries, including both successful and stagnating ones.

Appendix

Table A.1: Industry and Task Code List

ISIC.Rev3 Sector \ Skill Level	Low	Medium	High
AtB: Agriculture, Hunting, Forestry and Fishing	1	29	57
C: Mining and Quarrying	2	30	58
15t16: Food, Beverages and Tobacco	3	31	59
17t18: Textiles and Textile Products	4	32	60
19: Leather, Leather Products and Footwear	5	33	61
20: Wood and Products of Wood and Cork	6	34	62
21t22: Pulp, Paper, Printing and Publishing	7	35	63
23: Coke, Refined Petroleum and Nuclear Fuel	8	36	64
24: Chemicals and Chemical Products	9	37	65
25: Rubber and Plastic	10	38	66
26: Other Non-Metallic Mineral	11	39	67
27t28: Basic Metals and Fabricated Metal	12	40	68
29: Machinery, Not elsewhere classified	13	41	69
30t33: Electrical and Optical Equipment	14	42	70
34t35: Transport Equipment	15	43	71
36t37: Manufacturing, Not elsewhere classified; Recycling	16	44	72
E: Electricity, Gas and Water Supply	17	45	73
F: Construction	18	46	74
50: Sale and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	19	47	75
51: Wholesale Trade, Except of Motor Vehicles and Motorcycles	20	48	76
52: Retail Trade and Repair, Except of Motor Vehicles and Motorcycles	21	49	77
60: Inland Transport	22	50	78
61: Water Transport	23	51	79
62: Air Transport	24	52	80
64: Post and Telecommunication	25	53	81
J: Financial Intermediation	26	54	82
70: Real Estate Activities	27	55	83
71t74: Renting of Machinery & Equipment and Other Business Services	28	56	84

Table A.2: Chinese Employment in Each Task, 1995 and 2009 (billion working hours)

	1995				2009				Chg. in
	L	M	H	%MH	L	M	H	%MH	%MH
Agriculture	488.3	18.16	0.28	3.64	442.8	26.53	0.12	5.68	2.04
Mining	16.04	9.91	0.28	38.85	13.71	11.45	0.94	47.48	8.63
Food Manufacturing	13.28	8.61	0.39	40.39	18.77	14.24	1.40	45.47	5.08
Textile	25.41	9.69	0.20	28.02	34.43	15.38	0.70	31.83	3.81
Leather Products	4.38	1.34	0.02	23.68	10.72	3.82	0.15	27.07	3.39
Furniture	5.11	1.92	0.05	27.82	12.89	5.68	0.30	31.68	3.87
Paper and Publishing	5.77	3.53	0.11	38.66	13.33	9.55	0.62	43.28	4.63
Refinery	0.95	1.02	0.07	53.16	1.12	1.39	0.20	58.81	5.64
Chemistry	8.51	7.73	0.55	49.28	11.39	12.11	1.87	55.09	5.81
Rubber and Plastic	6.70	3.43	0.11	34.60	15.03	9.02	0.64	39.12	4.52
Non-metal Minerals	21.13	8.02	0.21	28.02	16.23	7.21	0.41	31.96	3.93
Metal	13.64	9.16	0.45	41.33	15.24	11.98	1.28	46.54	5.21
Machinary	13.05	9.91	0.60	44.62	16.03	14.25	1.89	50.19	5.57
Electronics	8.67	7.56	0.63	48.57	21.78	22.24	4.02	54.67	6.10
Automobile	5.34	5.20	0.35	50.95	6.86	7.81	1.16	56.68	5.73
Other Manufacturing	13.69	5.12	0.14	27.76	12.26	5.36	0.33	31.72	3.96
Utility	2.24	3.61	0.35	63.91	2.25	6.12	1.58	77.37	13.45
Construction	50.44	28.05	1.25	36.74	75.45	51.45	4.17	42.44	5.69
Sale of Automobile	n.a.	n.a.	n.a.	n.a	n.a.	n.a.	n.a.	n.a.	n.a.
Wholesaling	8.06	13.57	1.41	65.03	6.64	18.84	5.53	78.59	13.56
Retailing	21.80	38.16	2.01	64.82	19.01	56.05	8.35	77.21	12.39
Inland Transport	14.10	14.82	0.49	52.05	20.38	24.28	1.94	56.27	4.21
Water Transport	1.91	1.54	0.13	46.66	2.40	2.20	0.45	52.40	5.74
Air Transport	0.20	0.77	0.19	82.54	0.32	1.36	0.83	87.34	4.80
Post and Communication	1.32	5.88	1.51	84.89	1.57	7.95	4.96	89.15	4.27
Finance	0.13	5.40	0.58	97.84	0.18	7.14	2.33	98.12	0.28
Real Estate	0.88	0.96	0.12	55.34	1.72	1.48	0.31	51.04	-4.29
Business Services	3.10	3.67	0.99	60.05	2.90	2.95	1.86	62.36	2.31
All	754.18	226.74	13.47	24.16	795.39	357.86	48.35	33.81	9.65

Source: Socio-economic Account (SEA) in the WIOD dataset. L, M, H stands for the low-, medium- and high-skilled tasks in each industry. Columns "%MH" are the shares of medium- and high-skill labour in total industrial employment. The last column compares the changes in medium- and high-skilled labour shares between 1995 and 2009.

The Stability of Task Space Across Different Time Periods

The relatedness indices can be derived separately for each year in principle, but in this paper I follow Hidalgo *et al.* (2007) and use a "pooled" relatedness by taking the average of relatedness indices across 1995 to 2009. To justify this choice, I first explore the stability of my task space. I divide the 15 years into three five-year periods, and derive three sets of task spaces based on the data within each period. Table A.3 reports the correlations between task spaces of different years; the upper panel reports Pearson correlation (i.e. the conventional correlation) and the lower panel reports the Spearman's rank-order correlation. The task space is changing but the structure is relatively consistent over time. The correlation between two consecutive five-year periods is higher than 0.9, which is a bit higher than the correlation of product space reported in Hidalgo *et al.* (2007) and Neffke *et al.* (2008). The correlation between a single period's task space and the pooled task space for the whole period is also around 0.9. Given this high stability of the task space, it is therefore safe to assume that the structure of relatedness between tasks stays constant over the whole period, represented by the pooled task space using data for all years.

Table A.3: Stablity of the Task Space across Different Years

Pearson Correlation	95-99	00-04	04-09	95-09
95-99	1			0.7998
00-04	0.9263	1		0.8295
04-09	0.8407	0.9173	1	0.8074

Rank Order Corr.	95-99	00-04	04-09	95-09
95-99	1			0.8801
00-04	0.9190	1		0.9104
04-09	0.8273	0.9099	1	0.8804

Table A.4: Regression Results (Robustness Checks)

I - Main Results

	Baseline		Use $\phi_x^{\max}$	Both	Symmetric Relatedness		Developing Econ	
	(1)	MEF	(1a)	(1b)	(2)	MEF	(3)	MEF
$\widetilde{\phi}^*_{x,i}$	2.350	0.075		2.950	3.153	0.099	1.439	0.067
	[0.783]	[0.028]		[1.006]	[0.932]	[0.034]	[0.939]	[0.045]
$\phi^{\max}_{x,i}$			0.519	-0.621				
			[0.508]	[0.652]				
Potential_{00}	1.083	0.035	1.095	1.014	1.051	0.033	0.757	0.035
	[0.239]	[0.009]	[0.245]	[0.248]	[0.238]	[0.008]	[0.278]	[0.013]
RCA_{00}	3.321	0.106	3.295	3.410	3.336	0.104	3.735	0.173
	[0.417]	[0.019]	[0.423]	[0.429]	[0.418]	[0.019]	[0.521]	[0.034]
Const.	-3.739		-3.630	-3.498	-3.833		-3.602	
	[0.281]		[0.370]	[0.373]	[0.290]		[0.340]	
R^2	0.222		0.208	0.223	0.225		0.242	
Obs.	1584		1584	1584	1584		814	
# Positive	68	(4.3%)	68	68	68		46	(5.7%)

II - Testing Vertical Upgrading

	M&H Tasks, All Observations				M&H Tasks, Developing Countries			
	(4a)	(4b)	(4c)	(4d)	(5a)	(5b)	(5c)	(5d)
$\widetilde{\phi}_{x,i}$	2.486	2.326	2.509		0.958	0.506	1.204	
	[0.985]	[1.009]	[0.989]		[1.236]	[1.324]	[1.273]	
Potential_{00}	1.800	1.673	1.847	1.661	1.409	1.169	1.601	1.465
	[0.400]	[0.430]	[0.428]	[0.419]	[0.556]	[0.597]	[0.610]	[0.594]
RCA_{00}	3.611	3.538	3.639	3.665	4.027	3.930	4.096	4.102
	[0.508]	[0.516]	[0.517]	[0.514]	[0.653]	[0.660]	[0.663]	[0.661]
RCA_L		0.041				0.065		
		[0.052]				[0.061]		
IsRCA_L			-0.049	-0.021			-0.178	-0.128
			[0.163]	[0.162]			[0.224]	[0.218]
Const.	-4.065	-4.035	-4.070	-3.634	-3.830	-3.739	-3.887	3.663
	[0.368]	[0.369]	[0.369]	[0.313]	[0.482]	[0.487]	[0.492]	[0.422]
R^2	0.215	0.216	0.216	0.200	0.229	0.232	0.231	0.227
Obs.	1025				512			
# Positive	53	(5.2%)			35	(6.8%)		

Notes: Replication of the specifications in Table 4.4. The proximity indicator $\widetilde{\phi}^*_{x,i}$ is constructed from the relatedness based on the year 1995 to 1999, and the economic structure in year 2000. The dependent variable is a dummy indicating whether a task with RCA lower than 0.75 in 2000 has gained a comparative advantage in 2009. The dependent variables is a dummy indicating whether a task with RCA lower than 0.75 in 2000 has gained a comparative advantage in 2009.

Table A.5: Regression Results for Alternative Specifications (Robustness Check)

	All $RCA_{00} < 1$		RCA Growth> 0.25		Changes in RCA	
	(6)	MEF	(7)	MEF	(8)	(9)
$\widetilde{\phi}^*_{x,i}$	1.851	0.119	2.370	0.387	0.134	0.217
	[0.584]	[0.039]	[0.521]	[0.085]	[0.065]	[0.181]
Potential_{00}	1.302	0.084	1.415	0.231	0.179	0.557
	[0.189]	[0.013]	[0.160]	[0.022]	[0.012]	[0.034]
RCA_{00}	3.169	0.204	1.308	0.214	-0.053	-0.413
	[0.225]	[0.022]	[0.213]	[0.034]	[0.023]	[0.065]
Const.	-3.598		-2.091		0.051	0.181
	[0.198]		[0.135]		[0.013]	[0.037]
R^2	0.290		0.126		0.122	0.165
Obs.	1990		1584		1570	1529
# Positive	190	(9.6%)	208	(13.2%)	-	-

Notes: Replication of specifications in table 4.5. The proximity indicator $\widetilde{\phi}^*_{x,i}$ is constructed from the relatedness based on the year 1995 to 1999, and the economic structure in year 2000. The dependent variable is similar as in table 4.5 but based on the changes between 2009 and 2000 (instead of 1995).