Innovation Allocation, Knowledge Composition and Long-Run Growth

Jie Cai and Nan Li*

February 15, 2015

Abstract

Technologies differ in their scopes of applications. The types of knowledge a country possesses have important implications on its growth. This paper develop a multi-sector model of innovation, trade and growth, in which knowledge in one sector is applicable to innovation in another sector in various degrees and a country's composition of knowledge is endogenously determined. We find that lower trade costs and better institutions (that increase production productivity) improve aggregate innovation efficiency through the within-country allocation of R&D towards sectors with higher knowledge applicability. We construct measures quantifying the sectoral knowledge *applicability* using cross-sector patent citations. Based on this index, we present cross-country evidence that broadly supports the model's implications.

Keywords: Intersectoral knowledge linkages; Knowledge composition; R&D; Endogenous growth; Technology space; Trade costs

JEL Classification: O30, O40, F43.

*Cai: Department of Economics, Australian School of Business Building, University of New South Wales, Sydney, NSW 2052, Australia; april.cai@unsw.edu.au. Li: International Monetary Fund, 700 19th Street NW, Washington DC 20431, U.S.A.; nanli1@gmail.com. *Acknowledgement*: We thank Phillip Aghion, Julian Di Giovanni, Ricardo Hausmann, Frank Neffke, Roberto Samaniego, Marc Schiffbauer, Nikola Spatafora, Muhammed Yildirim, Shangjin Wei, as well as seminar participants at the Center for International Development of Harvard University, National University of Singapore, University of British Columbia, University of Melbourne, University of New South Wales, Ohio State University, Society of Economic Dynamics Meeting 2013, AEA Annual Meeting 2012, International Monetary Fund for helpful comments. The views expressed herein are those of the author and should not be attributed to the IMF, its Executive Board, or its management.

1 Introduction

Long-run economic growth is accompanied and fueled by technological advances. New knowledge creation is often built on prior knowledge from various areas. While some knowledge can be readily adapted to make new products in many other sectors, others are limited in their scope of application. When the interconnections between knowledge from different sectors are intrinsically asymmetric, it is not just the amount of knowledge capital a country possesses that matters for growth, but also its *composition of knowledge*. The latter, however, has been largely absent from the growth literature, especially in theoretical models.

This paper incorporates such a network of knowledge linkages across sectors into an endogenous growth model, and develops a tractable framework where a country's composition of knowledge is endogenously determined. The framework is useful to analyze (a) the role of external trade environment and institutional factors (such as rule of law, regulation, etc) in directing the allocation of R&D resources and shaping a country's knowledge composition, and (b) the channels through which the knowledge composition affects growth. Lower trade costs—besides leading to more trade as in conventional models—improve aggregate innovation efficiency through the within-country allocation of R&D funds towards sectors with higher knowledge spillovers. We then present cross-country evidence that broadly supports the model's implications. First, data on cross-sector patent citations, as a proxy for intersectoral knowledge linkages, are used to construct a quantitative measure of *'knowledge applicability'* for each sector. Based on this measure, we show that factors affecting trade costs and institutions that affects production productivity have a distributional effect on a country's knowledge accumulation as predicted by the model. A country's initial knowledge applicability is also found to bear a statistically and economically significant relationship to subsequent growth differences.

Understanding the economic forces driving a country's composition of knowledge and its implications for growth is informative about the efficacy of policy interventions. Indeed, it has been long debated whether growth-promoting industrial policies should target sectors with large positive externalities (Lin 2009, 2010).[1] The empirical evidence so far is, however, mixed. Producing technologically sophisticated goods appears to offer growth benefits in Hausmann, Hwang and Rodrik (2007), and producing goods that have strong synergy with each other and are 'close' to potential new products in the product space improves growth in Hidalgo, Klinger, Barasasi and Hausmann (2007), Hausmann and Klinger (2007) and Kali, Reys, McGee and Shirrell (2012). Lederman and

[1] It is captured by the debate over the comparative advantage defying strategies, referring to government-led industrial policies that direct resources to technologically sophisticated industries without paying attention to their existing comparative advantages. It is based on the observation that economies that are more complex than their level of income would suggest have a tendency to catch up with a spurt of rapid growth.

Maloney (2012) and Wang, Wei and Wong (2010), on the other hand, provide a dissenting view after considering other omitted variables or alternative characterizations of a country's product structure.

The dispute perhaps is an outcome of the following factors. First, it is difficult to establish causality using the commonly adopted regression-based approaches. After all, growth may actually drive structural changes and provides the means to promote sectors with larger externalities. Second, it is difficult to examine general equilibrium effects of changing technology mix using these approaches. Lastly, it is difficult to identify sectors with large externalities in the data. The prevailing approach adopts outcome-based indicators to indirectly infer the interconnections between sectors (and hence, their externalities). For example, two industries are assumed to have synergy if they are frequently exported together by the same country (as in Hidalgo et al. 2007; Hausmann and Klinger 2007; Kali et al. 2012). The network resulting from this approach is undirected (e.g. if i is closely related to j then j must be closely related to i). More importantly, it can be an outcome of confounding external forces. For example, one sector may appear to have synergy with another if they demand similar infrastructure or resources, even though its development does not inherently benefit the other.

We focus upon a particular source of externality in this paper—the applicability of knowledge embodied in a specific sector in the process of creating new knowledge in others. We develop a theory in which the concept of technology interconnections can be made more precise, and identify a novel channel through which trade environment and institutional factors generate cross-sector variations in knowledge accumulation.[2]

We interpret the variations in knowledge applicability as a result of intrinsic characteristics of technologies or the state of exogenous scientific knowledge at a particular point in time. In the model, the exogenous inter-sectoral knowledge linkages govern the productivity of research effort when adapting knowledge in one sector to innovate in another. When firms choose R&D optimally in such a setting, the equilibrium value associated with a new innovation is determined not just by its own future profit, but also by its *application value* as a knowledge supplier to chains of innovation in downstream technologies. Trade costs reduce profit in highly applicable center sectors more than periphery sectors in the knowledge diffusion network because center sectors export more and thus are more sensitive to trade conditions. The loss of profitability directly discourages innovation in these sectors. Since new knowledge is built on previous knowledge from various sectors, the reduction in the amount of knowledge that can be applied lowers the application value of these

[2]Throughout the paper, we use the terms 'technology' and 'sector' interchangeably. In the model, one sector embodies one type of technology. In the empirical analysis, detailed technological categories are aggregated into larger industrial sectors in order to be combined with the export data.

upstream technologies to an even greater extent than it affects downstream technologies, further deterring their R&D investment. Therefore, the model predicts that trade costs disproportionately hinder knowledge accumulation in highly applicable technologies. Since these technologies foster subsequent innovations in many different sectors, underinvestment in these sectors generates large multiplier effects in a path-dependent world, impeding growth at the aggregate.

Similarly, a country with better institutions enjoy higher production productivity and higher profit in all sectors. This raises the application value of upstream technologies more than it raises the value of downstream technologies because of the cumulative effects, inducing greater allocation of R&D resources to these sectors and enhancing growth at the aggregate.

Empirically we construct the test as follows. Technology interconnections are conceptual and difficult to measure. We identify a sector's knowledge applicability from data on cross-sector patent citations provided by U.S. Patent and Trade Office, which contains information related to patents applied by inventors from all over the world. Patent citations, albeit some noises, contain information on which technologies are used and in what intensity in the innovation process of other technologies.[3]; hence, allow us to directly uncover the intrinsic knowledge linkages between sectors. By applying Kleinberg's (1998) iterative algorithm to the cross-sector patent citation matrix we construct a measure called 'applicability' that allows us to evaluate, for each sector, its importance as a knowledge supplier to its immediately application sectors as well as its role as an indirect contributor to chains of downstream sectors.[4] Under the further assumption that such a knowledge linkages across sectors carries over to other countries, we examine whether countries that are geographically further away from the rest of the world (higher trade costs) tend to specialize more on highly applicable sectors, controlling for other factors.

With these measures at the sectoral level, we proceed to describe the applicability of a country's knowledge composition. However, it is not possible, with available data, to directly observe a country's composition of knowledge. What we can observe are only various economic manifestations of the country's progress in knowledge accumulation. For example, it is reasonable to assume that making a product requires specific types of knowledge. Countries can acquire the knowledge to make a product that they did not invent by other kinds of activities, such as learning-by-doing, imitating, or even simply replicating. Therefore, what a country produces captures information regarding what it knows. For this reason, we follow the insight of the previous literature on product

[3] HERE WE SHOULD MENTION THE SHORTCOMINGS OF PATENT CITATION DATA

[4] Our knowledge applicability measures are both conceptually and empirically distinct from the product sophistication measure of Hidalgo and Hausmann (2009). Although most sectors with lower applicability produce simple products (e.g. food and kindred products, primary ferrous products), some of these sectors actually produce complicated products (e.g. transportation equipment, aircraft, guided missiles and space vehicles) but the knowledge in these sectors could be too specific to have pervasive applications.

space by evaluating a country's knowledge composition by its export composition, for which rich comparable data are available for a large set of countries.[5] We then calculate summary measures of the knowledge applicability of a country's export portfolio, which are used as indicators of how productive it is for a given country to apply its existing knowledge to create new products.

We find that a country's initial knowledge applicability is significantly and positively related to subsequent growth differences. This relationship is robust to controlling for a large set of covariates, including initial per capita income, human capital, investment, diversification, openness, institutional quality, etc. This relationship, however, may not reflect an effect of knowledge composition on growth since the pattern of specialization itself could be endogenous. We find that geography—specifically, (population-weighted) average distance to the rest of the world—and population play a significant role in driving the differences in knowledge applicability across countries. Interestingly, geography not only a determines how much a country exports, but also has significance for what a country exports. We then use these variables as instruments to correct for potential reverse causality. The estimated effect of knowledge applicability on growth continues to be significant and of even larger magnitude than the OLS estimates. Moreover, results from panel growth regressions with fixed effects confirm this finding.

Relating to the Literature The paper contributes to several streams of literature. First, previous empirical studies examine whether a country's *overall* R&D investment affects its subsequent growth, and do not find significant relationships (Klenow and Rodriguez-Clare 2005). This paper argues that if inter-sectoral knowledge spillovers are heterogenous and their distribution is highly skewed—as they demonstrated in the data—then even though the average R&D level may not matter, the allocation of innovation effort and knowledge across sectors affects growth. This paper thus contributes to a growing literature emphasizing that a country's product composition plays an important role in its economic performance (e.g. Hausmann et al. 2007; Hidalgo et al. 2007; Koren and Tenreyro 2007; Kali et al. 2009; Nunn and Trefler 2010; Hausmann and Hidalgo 2011). Unlike existing empirical research in the context of innovation and growth—which typically distinguishes sectors by their technology intensity[6]—we focus on the role of explicit knowledge linkages between sectors in innovation, yielding new insights on why some countries are substantially richer than others.

Second, we contribute to an earlier literature in development economics which argues that

[5] This approximation was also adopted in previous papers such as Lall et al. (2005), Hidalgo et al. (2007), Hausman and Hidalgo (2011) and Kali et al. (2012).

[6] The technology intensity of a sector is typically characterized by input measures of innovation—such as research and development as a share of sales and the employment share of scientists and engineers in total—or output measures—such as the number of patents taken out by the sector.

linkages across sectors—the vertical input-output relationships in production, in particular—can be central to economic performance (e.g. Leontief 1936; Hirschman 1958). These insights have recently been incorporated into modern macro models with far-reaching implications (e.g. Ciccone 2002; Jones 2011a, 2011b; Acemoglu et al. 2012; Blonigen 2012). Unlike these studies, we explore the inter-sectoral linkages dictated by the knowledge content of sectors, which is more suitable for understanding the mechanics of technological progress and have not been previously explored in a cross-country study. One exception is Cai and Li (2012), which develops a closed-economy multi-sector model with inter-sectoral knowledge spillovers and pays particular attention to the dynamic decisions of heterogeneous firms in the technology space.[7]

Third, in the broader scheme of things this paper joins the large literature on the growth implications of trade. Recent research explains the gains from trade via reallocations across economic units with heterogenous productivities (i.e. sectors, firms or products) (e.g. Melitz (2002), Arkolakis, et al. (2008) and Arkolakis, et al. (2010)). In this paper we find that once heterogeneous knowledge externalities are taken into account, the reallocation of R&D across sectors affects innovation and growth. Trade costs, therefore, through reallocation effects, have significant growth impact beyond the effects that have been stressed in the previous literature.[8]

The rest of the paper proceeds as follows. Section 3 describes the construction of our measure of knowledge applicability and presents the empirical findings using cross-country sectoral trade data. Section 2 introduces the model, discusses characteristics of the general equilibrium and solves the model. Section 4 concludes and discusses policy implications and potential future research.

2 The Model: R&D Allocation and Growth

This section presents an open-economy model of multi-sector growth to illustrate (a) how trade costs and and institutional factors affect firms' optimal cross-sector allocation of research resources, hence the composition of knowledge in the economy; and (b) how the composition of knowledge matters for growth. Our theoretical framework extends the traditional model of endogenous growth (e.g. Romer 1990; Grossman and Helpman, 1991) to allow for knowledge interconnections between different sectors. It is closely related to Cai and Li (2014), which develops a closed-economy general equilibrium model of heterogeneous firm innovation in multiple sectors. This paper studies an open-economy, and abstracts from heterogeneity across firms to focus on the aggregate implications.

[7] Another exception is the literature of general purpose technologies, such as Jovanovic and Rousseau (2005), Helpman (1998) and Bresnahan and Trajtenberg (1995). However, there are no explicit linkages between different technologies.

[8] Another related literature studies the differential responses of trade components to trade liberalization. For example, Hillberry and Hummels (2002) (2008) show that the trade volume of intermediate inputs at the early stage of the production chain are more sensitive to shipping cost.

The world is made up of home country and the rest of the world (henceforth, RoW) that each produces and consumes varieties of a finite but expandable number of product categories. Trade is induced by the "love for varieties". Home market is relatively small, thus unable to affect foreign innovation specialization, but prices are flexible and firms optimally determine prices of their exports in the foreign market. Both Home and the RoW each has a given supply of a single primary factor, labor, and engage in two activities—production and R&D, and consumers over the world share the same preference. Since the interest of this paper is innovation, we assume that identical labor productivity in production in every sector. Home and the RoW differ in sizes (population), production productivity and trade costs.

In reality, one country may be intrinsically better at producing some products than others—either due to better relative endowment of certain input factors or differences in contract environment (Nunn 2007), financial systems (Beck 2003, Manova, 2008), and labor market frictions (Helpman and Itskhoki, 2010) which have *direct* disproportionate impact on different sectors. The model, however, abstracts from these existing sources of comparative advantage, and instead focuses on endogenous comparative advantages. We will show, in the following sections, that because knowledge upstream sectors provide large knowledge capital to downstream sectors the effects on knowledge downstream sectors induced by changes in economy-wide factors (such as trade costs, labor productivity, population) accumulate to upstream sectors, generating multiplier effects.

In the following sections, we describe the production and innovation decisions in the home country, given wage, productivity, labor supply and innovation activities in the RoW. Variables with an asterisk are the RoW counterparts of home variables.

2.1 Goods Demand and Production

A representative household inelastically supplies labor and orders its preference over consumption streams of a single final good according to $U = \sum_{t=0}^{\infty} \beta^t \log C_t$, where final consumption (C_t) is a Cobb-Douglas combination of sectoral products, indexed by $i = 1, 2, ...K$; here K represents the total number of sectors.

$$\log C_t = \sum_{i=1}^{K} s^i \log Q_t^i, \tag{1}$$

where s^i governs the share of income spent in that sector, and Q^i is a CES aggregate of differentiated products denoted by k,

$$Q_t^i = \left(\int_0^{n^i + n^{i*}} x_t^i(k)^{\frac{\sigma-1}{\sigma}} dk \right)^{\frac{\sigma}{\sigma-1}}. \tag{2}$$

$n^i + n^{i*}$ is the number of varieties available worldwide, which comprises varieties produced by the home country in sector i (n^i), and those produced by the RoW (n^{i*}). The elasticity of substitution between any two varieties from the same sector is governed by $\sigma(> 1)$. The corresponding sectoral price index is $P_t^i = \left(\int_0^{n^i+n^{i*}} p_t^i(k)^{1-\sigma} dk\right)^{\frac{1}{1-\sigma}}$. The demand function for varieties within a sector is thus given by

$$x_t^i(k) = \left(\frac{p_t^i(k)}{P_t^i}\right)^{-\sigma} Q_t^i \tag{3}$$

where $Q_t^i = s^i E_t / P_t^i$ and E_t is the country's final consumption expenditure.

There is a continuum of symmetric *multi-sector* firms with a total mass of M in Home country. Once enter the economy, the representative firm innovates and produces goods in all sectors and engages in monopolistic competition in the product market in each sector. To focus on the heterogeneity of knowledge applicability across sectors, we assume that sectors within a country do not differ in their production productivity. Home (foreign) firms hire one unit of labor to produce ϕ (ϕ^*) units of goods in each sector. The home production function is given by $y_t^i(k) = \phi l_t$.

Prices can differ across countries due to trade costs, represented by $\tau(> 1)$. Let trade costs take the standard "iceberg" form: for one unit of a variety to arrive in the foreign country, τ units must be shipped. Importantly, we note that τ does not vary across sectors; hence, there is no explicit policy bias towards any sector. Given the wage, w, monopolistic competitive prices for the domestic market (p_h^i) and foreign markets (p_f^i) follow the usual fixed-markup pricing rule,

$$p_h^i(k) = p_h^i = \frac{\sigma}{\sigma - 1}\frac{w}{\phi} \quad \text{and} \quad p_f^i(k) = \tau p_h^i. \tag{4}$$

Competition in the final-good sectors ensures marginal-cost pricing. Hence, the home sectoral price index is given by $P^i = [n^i(p_h^i)^{1-\sigma} + n^{i*}(p_h^{i*})^{1-\sigma}]^{1/(1-\sigma)}$, where $p_h^{i*} = \frac{\sigma}{\sigma-1}\frac{w^*}{\phi^*}\tau^*$ is the domestic price of foreign sector-i products. Because preferences across countries are identical, home and foreign country consumers purchase the exact same home and foreign produced varieties, although in different quantities. Therefore, the foreign sectoral price index is $P^{i*} = [n^i(p_f^i)^{1-\sigma} + n^{i*}(p_f^{i*})^{1-\sigma}]^{1/(1-\sigma)}$.

The revenue per variety sold in the domestic market is $r_h^i = s^i E \left(\frac{p_h^i}{P^i}\right)^{1-\sigma}$, and in the foreign market $r_f^i = s^i E^* \left(\frac{p_f^i}{P^{i*}}\right)^{1-\sigma}$, where E (E^*) is home (foreign) total consumption expenditure. Based on this, we can derive the profit in real terms (using wage as numeraire) of the home representative firm in sector i as

$$\pi^i = \frac{(r_h^i + r_f^i)\tilde{n}^i}{\sigma w}, \tag{5}$$

where $\tilde{n}^i = n^i / M$ is the number of variety per firm in sector i. The firm's demand for production workers in sector i is $L_p = (\sigma - 1)\pi^i$.

2.2 R&D Allocations Over Multiple Sectors

Economic growth is driven by firms' innovation associated with the development of new blueprints (new varieties). It is reflected in the CES aggregation (2), which introduces a "love-for-variety" effect (as in Ethier, 1982). This section describes the endogenous evolution of the number of varieties over time.

The representative multi-sector firm is defined by a vector of its differentiated products in all K sectors, $\boldsymbol{z}_t = (z_t^1, z_t^2, ..., z_t^K)$, where z_t^i is the number of varieties produced by this firm in sector i. New technologies or new varieties are introduced through an innovation process, and each new variety is then turned into a product under monopolistic competition in the next period. Since only the firm inventing the variety has the right to manufacture it, $\boldsymbol{z}_t$ also characterizes the distribution of the firm's knowledge capital across sectors. For simplicity, we assume that the firm's knowledge capital accumulates in every sector without depreciation:

$$z_{t+1}^i = z_t^i + \Delta z_t^i, \quad \text{for } \forall i. \tag{6}$$

where the new knowledge capital, Δz_t^i, is created by employing researchers and utilizing existing knowledge capital. What marks this paper from the existing literature is that the firm can adapt its accessible knowledge from *all* sectors and fully internalize knowledge spillovers across sectors in their innovation process.[9] Since knowledge spillovers are heterogeneous across sectors, we decompose the firm's R&D investment in a given target sector according to its knowledge source sector.[10] Let R^{ij} denote a firm's R&D input when applying sector j's knowledge to generate new knowledge in sector i. The productivity of R&D associated with this activity depends on the (exogenous) knowledge linkages—the knowledge linkage from j to i, A^{ij}. Similar to Klette and Kortum (2004), we assume that new knowledge in sector i is created based on a Cobb-Douglas combination of innovation productivity, R&D investment and the existing stock of knowledge capital:

$$\Delta z_t^i = \sum_{j=1}^{K} A^{ij} \left(\bar{z}_t^i R_t^{ij}\right)^{\alpha} \left(z_t^j\right)^{1-\alpha}, \tag{7}$$

[9] This is equivalent to assuming each firm innovates and produces in one sector but the knowledge spillovers *across firms* are complete within a country. In reality, there are all kinds of barriers for this perfect internalization of inter-sectoral knowledge spillovers and countries can differ substantially in their ability to internalize these spillovers. This variation, although interesting, is not the focus of the current paper and is left for future endeavor. A possible extension of the current model is to allow for sectoral entry barriers which might entice countries to also differ in the set of products they produce.

[10] This can be interpreted as firms having to devote a certain amount of time to digesting and adopting knowledge in one sector to apply it to another. Thus, every research activity is source-knowledge-and-target-knowledge-specific.

where α is the share of R&D input in the innovation production. Here, we allow for knowledge externality across firms within the country to some extent: the researchers' R&D efficiency is assumed to be proportional to the average knowledge per firm in the innovating sector, $\bar{z}_t^i$.[11] Note that for simplicity and to keep our focus on cross-sector diffusion, we assume that knowledge is not diffused directly across countries in this model.

Since each variety is sold in the same quantity and priced at the same level, the profit per variety in sector i is given by $\frac{\pi^i}{\tilde{n}^i}$. A firm with a knowledge portfolio of $\boldsymbol{z}_t$ in period t thus receives a flow of total profit $\sum_{i=1}^K \frac{\pi_t^i}{\tilde{n}_t^i} z_t^i$ in the product market. It chooses an R&D investment portfolio $(R_t^{ij})_{i,j\in J}$ to maximize its present value $V(\mathbf{z}_t)$, given the interest rate r_t. The firm needs to hire researchers to conduct R&D, whose wage is the same as that of the production workers and is used as the numeraire throughout the rest of the paper. Formally, given the exogenous knowledge diffusion matrix $A = (A^{ij})_{K\times K}$, the firm solves the following optimal R&D investment problem:

$$\max_{\{R_t^{ij}\}_{i,j\in\{1,2,\ldots,K\}}} V(\boldsymbol{z}_t) = \sum_{j=1}^K \frac{\pi_t^j}{\tilde{n}_t^j} z_t^j - \sum_{i=1}^K \sum_{j=1}^K R_t^{ij} + \frac{V(\boldsymbol{z}_{t+1})}{1+r_t}, \tag{8}$$

subject to the knowledge accumulation equation (6) and the incremental innovation production function (7).

We focus on the balanced growth path (BGP) equilibrium in which growth rates of aggregate variables remain constant over time and trade is balanced. Households' time preference pins down the discount factor $\frac{1}{1+r_t} = \beta \frac{u'(C_{t+1})/P_{t+1}}{u'(C_t)/P_t} \frac{w_{t+1}}{w_t} = \beta$. Define the BGP growth rate of the number of varieties in sector i as $g_t^i \equiv n_{t+1}^i / n_t^i - 1$. Cross-sector knowledge spillovers ensure that all sectors grow at the same constant rate on the BGP: $g_t^i = g$, $\forall i$ (see Appendix A). Thus, the relative size of sectors is constant over time: $n_t^i / n_t^j = n^i / n^j, \forall i, j, t$. The linear form of the Bellman equation and the constant-return-to-scale knowledge production allow us to derive closed-form solutions for the firm's optimal R&D decisions.

Define $\rho \equiv \frac{\beta}{1+g}$. In Appendix A, we show that in the BGP equilibrium, the firm's value is a *linear* aggregate of the value of its knowledge capital in all sectors: $V(z) = \sum_{i=1}^K v^i$, where the market value of the firm's knowledge capital in sector i is given by

$$v^i = (1-\rho)^{-1} \left(\pi^i + \sum_{j=1}^K \omega^{ji} \right), \tag{9}$$

and ω^{ji} captures the *application value* of sector i's knowledge to innovation in sector j. It increases

[11] This assumption keeps the number of researchers constant while the number of varieties increases in the BGP equilibrium.

with the knowledge abundance in sector i relative to j (n^i/n^j), the value of the target sector (v^j) and the knowledge linkages from i to j, A^{ji}:

$$\omega^{ji} = \frac{1-\alpha}{\alpha}\frac{n^i}{n^j}\left(A^{ji}\alpha\rho v^j\right)^{\frac{1}{1-\alpha}}. \tag{10}$$

Substituting (10) into (9) generates

$$v^i = (1-\rho)^{-1}\left(\pi^i + \sum_{j=1}^{K}\frac{1-\alpha}{\alpha}\frac{n^i}{n^j}\left(A^{ji}\alpha\rho v^j\right)^{\frac{1}{1-\alpha}}\right). \tag{11}$$

Importantly, it shows that the market value of knowledge per firm in sector i, v^i, depends on not only the *direct* profit return (i.e. the present value of the future profits in sector i), but also on the *indirect* capital return captured by its contribution to future innovations in all K sectors. Thus, solving for the equilibrium value of knowledge capital, $(v^i)_{1\times K}$, is an iterative process: the knowledge value of any given sector depends upon the knowledge value of all other sectors.

The firm's optimal investment associated with applying sector-j knowledge to i is proportional to its share of knowledge capital in the knowledge-source sector $(\frac{z^j}{n^j})$ and is positively related to the application value of sector j to i (ω^{ij}):

$$R^{ij} = \frac{\alpha}{1-\alpha}\omega^{ij}\frac{z^j}{\tilde{n}^j}. \tag{12}$$

2.3 Aggregate Conditions

In this section, we complete the list of equilibrium requirements by adding conditions that stipulate market clearing in factor and goods markets. The population supplies L units of labor in every period which are allocated as production workers and researchers:

$$L = \sum_{i=1}^{K} L_p^i M + \sum_{i=1}^{K}\sum_{j=1}^{K} R^{ij} M. \tag{13}$$

In addition, firms need to make an initial fixed-cost investment in the form of final goods $F > 0$ (using wage as numeraire) to enter. Free entry conditions imply that firms enter until their future discounted profit (after covering their R&D costs in each period) is the same as the entry cost F:

$$\frac{1}{1-\beta}\left(\sum_{i=1}^{K}\pi^i - \sum_{i=1}^{K}\sum_{j=1}^{K} R^{ij}\right) = F. \tag{14}$$

This equilibrium condition helps to determine the total number of firms M.

We assume financial autarky which implies that trade is balanced in every period in the equilibrium:

$$\sum_{i=1}^{K} r_h^{i*} n^{i*} = \sum_{i=1}^{K} r_f^i n^i. \tag{15}$$

2.4 Implications for Equilibrium R&D Allocation Across Sectors and Growth

In this section, we derive and discuss reduced-form implications of aggregate R&D allocation across sectors and the relationship between knowledge composition and growth in the model.

Proposition 1 *Define the total R&D expenditure in sector i as $R^i \equiv \sum_{j=1}^{K} R^{ij}$. At the aggregate, R&D resources are allocated according to the sectoral knowledge value in the equilibrium. That is*

$$\frac{R^i}{R^j} = \frac{v^i}{v^j}. \tag{16}$$

Proof. See the Appendix.

Recall from (9) and (10), we have

$$v^i = (1-\rho)^{-1} \left[\pi^i + \sum_{j=1}^{K} \frac{1-\alpha}{\alpha} \frac{n^i}{n^j} (A^{ji} \alpha \rho v^j)^{\frac{1}{1-\alpha}} \right]. \tag{17}$$

The market value of sectoral knowledge capital depends on both the future profit in its sector and its application value in other sectors, which hinges on its relative knowledge abundance to the application sector ($\frac{n^i}{n^j}$), and the market value of the application sector (v^j), as long as $A^{ji} > 0$. For illustrative purpose, consider a stark example of two sectors: the center sector (denoted by c) whose knowledge can be applied to the other sector, and the periphery sector (denoted by p) whose knowledge is not that applicable (i.e. $A^{pc} > 0$ and $A^{cp} = 0$). When the transport cost, τ, is high, profit in the center sector is low, discouraging its own innovation activity directly and the resulting insufficient knowledge accumulation (low n^i/n^j) further decreases its application value. In contrast, the periphery sector has no application value, and thus its market value depends only on its own profit. Therefore, as will be shown in Section 2.5, with reasonable parameter values, higher τ disproportionately reduces the market value of knowledge capital in the center sector more than that in the periphery sector, leading to a flattening of the distribution of R&D intensity: $\partial(R^c/R^p)/\partial\tau < 0$.

Now, how does the change of R&D allocation and composition of knowledge affect growth? The source of growth in this economy comes from increasing varieties. Intuitively, when a country invests disproportionately more in highly applicable sectors, the economy benefits more from the knowledge spillovers from these sectors and creates more varieties at the aggregate. We call this the *composition effect* of R&D. It can be seen from the following proposition.

Proposition 2 *On the BGP, the aggregate innovation rate:*

$$g = \left(\beta(1-\alpha) \frac{\sum_i v^i}{\sum_i \sum_j \omega^{ij}} - 1 \right)^{-1}. \tag{18}$$

And the aggregate real output growth rate is $\frac{Y_{t+1}}{Y_t} = (1+g)^{\frac{1}{\sigma-1}}$.

Proof. See the Appendix.

(18) implies that innovation rate and growth rate are increasing functions of $\sum_i \sum_j \omega^{ij} / \sum_i v^i$, the fraction of the total knowledge value in all sectors that is accounted for by their application value in the whole economy. Using the previous illustration, when α is very small (assuming $\alpha \to 0$), it can easily be shown based on (9) and (10), that g strictly increases with n^c/n^p. In this case, when higher trade costs hinder the accumulation of knowledge in the center sector, growth also suffers. That is, $\partial g / \partial \tau < 0$.

It is useful to note that the v^i of a center sector—generally speaking, the sector with large positive values of A^{ji}, given j—is sensitive to the knowledge value of its application sectors (v^j) and its relative knowledge abundance ($\frac{n^i}{n^j}$), while the v^i of a periphery sector is more responsive to changes to its own profit (π^i). We will show in Section 2.5 that increasing transport costs disproportionally reduces both the profit and application value of center sectors, deterring R&D investment and endogenous accumulation of knowledge in center sectors, the effects of which permeate the whole economy, hurting the country's aggregate knowledge accumulation.

2.5 Solving the Model with a Star Network of Knowledge Linkages

In this section, we explore how changes in the trade cost (τ) and population (L) affect the knowledge composition and growth in general equilibrium, given reasonable parameter values. Appendix B offers a complete set of equilibrium conditions that are used to exactly solve the model.

Here, we solve the model economy for a special case of two types of sectors: one center sector and $K-1$ identical periphery sectors. More specifically, consider a star-shaped knowledge diffusion network depicted in Figure 1, in which sector 1 is the sole input supplier to all others, where the other $K-1$ sectors are applicable to sector 1 but not to each other. That is, $A^{ii} = a$, $\forall i$, $A^{1j} = A^{j1} = a$, for $j > 1$ and $A^{ij} = 0$, for $i > 1$, $j > 1$. We set a to 0.1 such that the aggregate growth rates fluctuate within a reasonable range when τ varies. As simple as it seems, this star-shaped network captures well the highly skewed distribution of knowledge linkages across sectors estimated using patent citation data (in Section 3.1). In addition, we consider K=20, and the elasticity of substitution between different varieties in the same sector, $\sigma = 6$, which is broadly consistent with the empirical evidence at 3-digit level.[12] We assume that the home country is small relative to the rest of the world: $L^* = 50L$. Let us normalize the foreign wage, labor productivity, population to 1, and the foreign number of varieties per sector to 50. The subjective discount rate $\beta = 0.98$, and the share of researchers in knowledge production $\alpha = 0.4$ according to Cai and Li (2012).

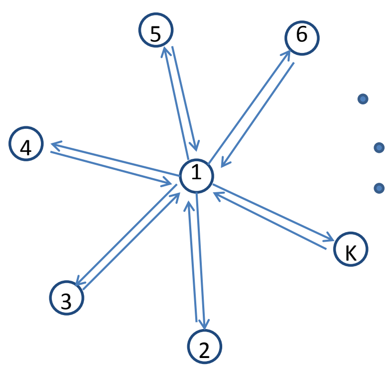
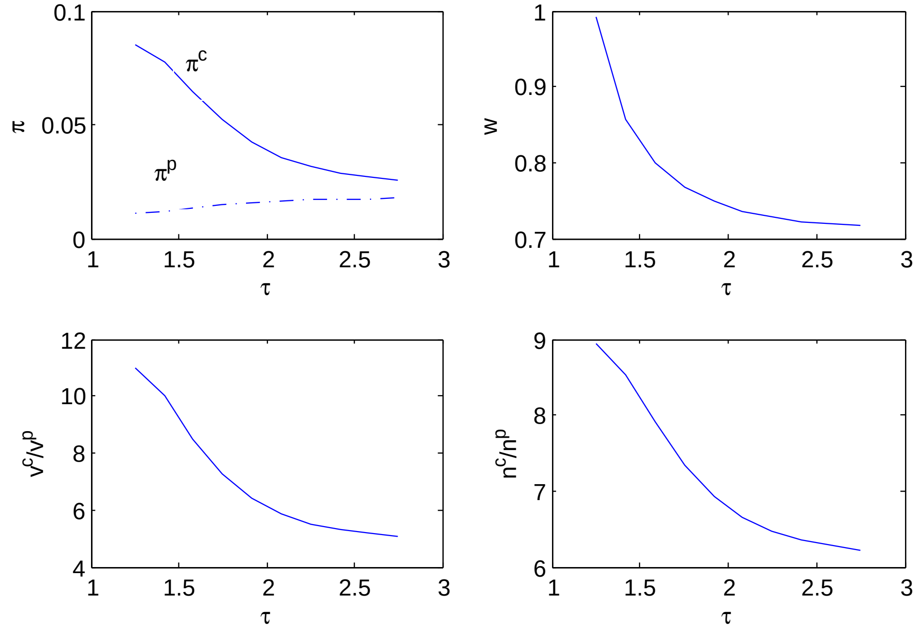


Figure 1: A Star Network of Knowledge Diffusion between K sectors

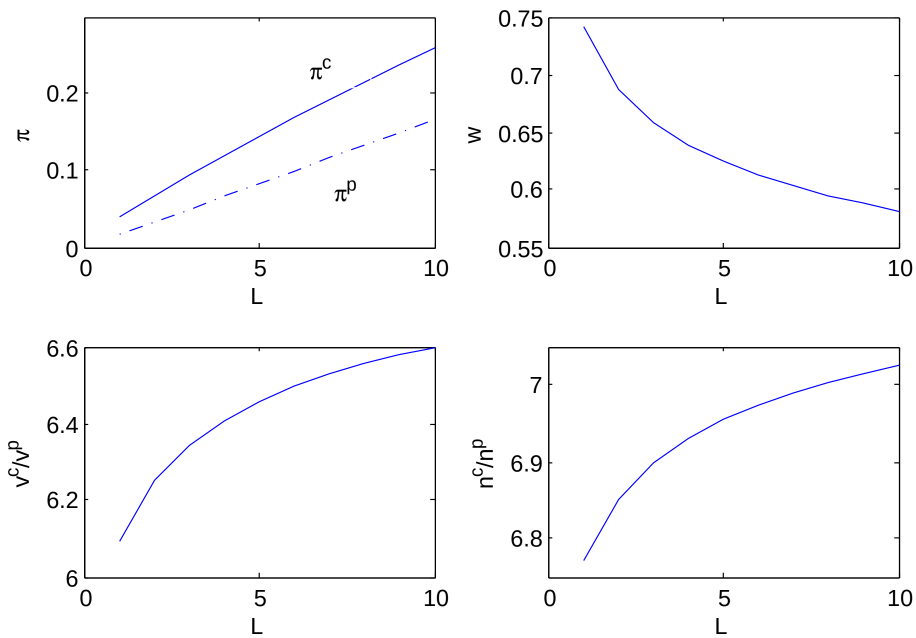
Figure 2 shows the effects of increasing trade cost (τ) and increasing population (L) on sectoral profit (π^c for total profit in the center sector and π^p total profit in periphery sectors), equilibrium wage (w), value of knowledge capital in the center sector relative to that in the periphery sector (v^c/v^p) and the knowledge composition (n^c/n^p) at Home. Figure 3 illustrates the relationship between aggregate growth and the composition of knowledge. In both cases, growth (g) slows down when the relative knowledge accumulated in the center sector as a ratio to that in the periphery sector (n^c/n^p) decreases.

As shown in Figure 2a, in general equilibrium, when the trade cost rises, wages decrease as the demand for researchers and production workers falls. Nevertheless, the profit in the center sector still suffers due to the greater loss in competitiveness associated with higher trade costs in the export market. Profit in periphery sectors, however, slightly increases, because these sectors have small export markets, and hence are less affected by trade costs. Lower wages associated with rising trade cost implies higher profit in these sectors. As firms have relatively less incentive to innovate in the center sector, the total number of varieties developed in the center sector declines more than in

[12] For estimates of elasticity of substitution, see Anderson and Wincoop (2004).



(a) The Effects of Changing Trade Costs, τ.



(b) The Effects of Changing Population, L.

Figure 2: General Equilibrium Effects of Changing Trade Costs and Population

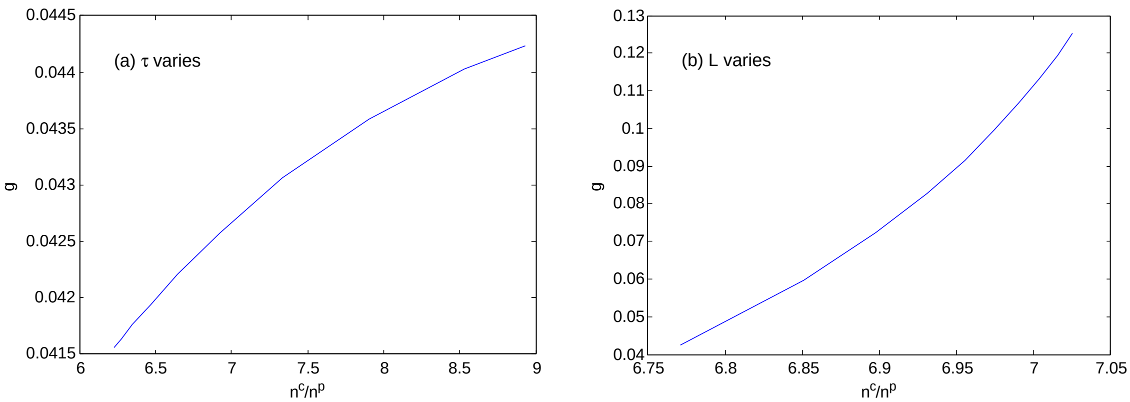


Figure 3: Relative Knowledge Accumulation and Growth

the periphery. The value of knowledge capital in the center sector relative to that of the periphery (v^c/v^p) also drops as a result of (a) decreased profitability and (b) reduced application value as less knowledge is accumulated in this sector (as n^c/n^p falls), further deterring R&D allocation in the center (Proposition 1). Since knowledge in the center is responsible for fostering innovation in many application sectors, lower investment in these sectors hurts innovation and growth in the whole economy, as demonstrated in Figure 3a.

On the other hand, Figure 2b shows that when the home population (L) grows, wages drop as supply of labor improves more than demand. Production profit in both center and periphery rises due to larger domestic demand and lower wages. v^c/v^p rises (and rises more than π^c/π^p), as the center sector has broader applications and its value reflects the *cumulative* effects of improved profitability in the downstream sectors, while the value of periphery knowledge depends on the profitability of a limited number of sectors (as shown in (17)). Consequently, n^c/n^p increases as a higher v^c/v^p attracts more research resources into the center sector. Again, higher spillovers generated by the center sector to the overall economy enhances growth, as in Figure 3b.

In summary, our model implies that, all other things being equal, countries of different transport costs to potential trading partners and different population sizes innovate and produce a different composition of products. The value of knowledge capital in a given sector consists of two components—its own discounted future profit (in the product market) and its value as knowledge input to create new knowledge in all related sectors. Countries with larger population and lower transport costs specialize more in the center sector—as the differential value between center and periphery sectors is larger—and grow faster. Thus, the model accounts for the empirical findings documented earlier in the paper.

3 Empirical Evidence: Determinants of the Knowledge Composition, and Relationship with Growth

This section In our empirical work, we proxy a country's composition of knowledge by its export structure, based on the premise that making a product requires specific types of knowledge, which can be either created by innovating or acquired elsewhere. The composition of exports thus contains evidence of this process of knowledge acquisition and accumulation. In order to rank sectors according to their knowledge applicability, we first construct a sector-level measure that characterizes the importance of different sectors as knowledge suppliers to all the knowledge-downstream sectors (both immediate application sectors and indirectly related knowledge downstream sectors). With this sector-specific index, we then construct country-specific measures of knowledge composition.

3.1 Measures of Knowledge Applicability

The Proxy for Knowledge Linkages Across Sectors Direct observation on the actual adaption of knowledge across sectors is not available as knowledge flows are invisible. The literature, however, has typically found that patent citations seem to represent an indicator of knowledge spillovers, albeit with some degree of noise (Jaffe et al. 2000, Bottazzi and Peri, 2003, Branstetter, 2006, etc.).[13] One of the advantages of patent citation data, as noted in Hall, Jaffe and Trajtenberg (2001), is that "the decision regarding which patents to cite ultimately rests with the patent examiner, who is supposed to be an expert in the area and hence to be able to identify relevant prior art that the applicant misses or conceals." Thus, citations are informative of links between innovations. If a single technology is cited in numerous patents, it is apparently involved in many developmental efforts. We thus use patent citations across sectors to trace the direction and intensity of knowledge flows.

We assume that the technology interconnections are intrinsic characteristics of technologies. In this, we take the view of Nelson and Winter (1977) that "innovations follow 'natural trajectories' that have a technological or scientific rationale rather than being fine tuned to changes in demand and cost conditions." Moreover, we assume that the differences in the applicability of knowledge in one sector to another persist across countries, so that we can use a sector's knowledge applicability as identified in the U.S. patent database as a measure of its applicability in other countries. Note that patents applied in U.S. are not necessarily generated by U.S. inventors. Due to the territorial principle in U.S. patent laws, anyone intending to claim exclusive rights for inventions is required to

[13]For example, not all innovations are patented, especially process innovations (which are often protected in other ways such as copyright, trademarks and secrecy). Levin et al (1987) find that secrecy was more effective for process innovations, We implicitly assume that for any sector, the unpatented and patented knowledge utilizes knowledge (patented or unpatented) from other sectors in the same manner, with the same likelihood and intensity.

file U.S. patents. In fact, about 50 percent of patents applied in U.S. in the early 2000s were from foreign inventors. Given that the U.S. has been the largest technology consumption market in the world over the past few decades, it is reasonable to assume that most important innovations from other countries have been patented in the U.S. Therefore, the knowledge spillover linkages uncovered in the U.S. patent data are reasonably representative of the deep fundamental relationship of technologies. All we really need is that statements of the following sort hold: If knowledge in electronic components sector is potentially useful for develop new products in radio and television receiving equipment in the U.S., similar relationship also holds for inventors in Mexico. Even if the linkages captured by the U.S. patent citation network had not currently been explored in developing countries, they might be in the future. It is precisely this underlying relationship that predicts future product entry and innovation which leads to growth.

Construction of the Knowledge Applicability The method to construct the applicability measure is discussed in detail in Cai and Li (2014) and here we content ourselves by outlining the main idea. We use data from the 2006 edition patent database provided by the U.S. Patent and Trade Office (USPTO).[14] In the dataset, each patent belongs to one to seven out of the 41 2-4 digit Standard Industrial Classification (SIC) categories. We use the probability mapping provided by USPTO to aggregate patents and the associated citations (generated or received) into different SIC categories.[15]

We first start by adding up citations made from (and to) patents that belong to the same sector to generate a *cross-sector* citation matrix $(c^{ij})_{(i,j)\in J\times J}$, where c^{ij} denotes the number of citations to sector i made by j. For each sector i, we calculate the total number of patent applications, $(s^i)_{i\in J}$. We then apply the iterative algorithm developed by Kleinberg (1998) to the citation matrix and construct an index, called *authority weight* (aw), to capture the 'knowledge applicability' of each sector—specifically, the extent to which they enable the creation of knowledge in all sectors. The algorithm simultaneously generates another index, hub weight (hw), which characterizes the extent

[14]The updated NBER patent database is available at: https://sites.google.com/site/patentdataproject/Home. It contains detailed patent and citation information, including the patent application year, grant year, the technological area to which it belongs, the nationality of patent inventors, the patent assignees, the citations made and received by each patent, etc.

[15]Details of the concordance are available at http://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/sic conc. Each patent corresponds to one of the 3-digit United States Patent Classification System (USPCS) technological classes, as well as categories at the 2-4 digit US SIC level. We build our empirical analysis based on the latter since trade data is available only by industry classification. The patents are classified according to either the intrinsic nature of the invention, or the function for which the invention is used or applied. It is inherently difficult to allocate the technological category into economically relevant industries in a finer differentiation, even with detailed firm level information.

to which the sector relies on knowledge from other sectors. Formally,

$$
\begin{aligned}
aw^i &= \lambda^{-1} \sum_{j \in J} W^{ji} hw^j \\
hw^i &= \mu^{-1} \sum_{j \in J} W^{ij} aw^j
\end{aligned} \tag{19}
$$

where λ and μ are the norms of vectors $(aw^i)_{i\in J}$ and $(hw^i)_{i\in J}$, respectively. W^{ji} corresponds to the degree of knowledge contribution from the source sector i to the application sector j. Since different sectors have different propensity to patent (Hall et al., 2006), we normalize cross-sector citations by the number of patents in the citing sector and the cited sector: $W^{ji} = c^{ji}/(s^j s^i)$. Thus W^{ji} reflects the number of citations received per patent in sector i from an average patent in j. We calculate the time-variant aw_t based on rolling window subsamples, pooling citations from the previous 10 years for every period.

Generally speaking, a sector with high aw provides large knowledge spillover to sectors with highly ranked hw; a sector with high hw utilizes large knowledge flow from sectors with highly ranked aw. Cai and Li (2014) discuss that this two-level iterative algorithm is highly efficient at extracting information from a highly linked network environment compared to other quantitative estimates such as Garfield's "impact factor" and Pinski and Narin's "influence weight".

Importantly for our analysis, we find that citation linkages across sectors are highly heterogeneous, implying that the knowledge embodied in a small number of sectors aids a disproportionately large number of subsequent innovations. This observation renders particular importance to the effects of a country's initial knowledge composition on its subsequent growth. The calculated aw based on (19) thus has a highly skewed distribution. In Table 1 we tabulate by SIC code our measures of knowledge applicability for all the 41 sectors in 1995. The sectors are selected due to data availability XX

As one would expect, in general, more complicated sectors have higher applicability, such as "Electronics" and"Professional and scientific instruments", implying that they are more likely to be located at the core of the knowledge spillover network. In contrast, more primary products tend to be in the periphery. There are a few exceptions, for example, "railroad equipment" and "motorcycles, bicycles and parts" have low authority weights. This is not particularly surprising given that the technology incorporated in the innovation of these sectors is likely to be sector-specific. The ranking for most sectors does not change drastically over the period 1976-2006, although the quality of our measure decreases close to the end of the sample as a result of citation lags. The average correlation of the ranking across different decades is about 0.90.

3.2 Proxy for A Country's Knowledge Composition

Industry level data on exports at the 4-digit Standard International Trade Classification (SITC) level comes from the World Trade Dataset (Feenstra et al. 2005). To match with the patent data, we aggregated the detailed export data up to the 41 sectors listed in Table 1 using Zhu's and USPTO's concordance.[16] Because not all export sectors fall into one of the 41 innovating sectors, we exclude countries whose significant share of export cannot be mapped into innovating sectors. This yields a sample of 112 countries for the period 1976-2000[EXPAND].[17]

Data on real GDP per capita, population, investment, the number of workers, and the measure of openness (exports plus imports divided by GDP) are taken from Penn World Table Mark 7.1 (PWT). Human capital stock is measured using Mincerian non-linear returns to education (the average years of schooling for the population aged 25 years old) as reported by Barro and Lee (2010). Physical capital stocks are constructed using the perpetual inventory method, as explained in Caselli (2005). The measures of the rule of law and regulation quality are from World Bank's Worldwide Governance Indicator (2009). Financial development is measured by the amount of credit by banks and other financial intermediaries to the private sector as a share of GDP from Beck et al. (2000). Data on distance to equator are from Hall and Jones (1999) and other geographic data (i.e. size, bilateral distance) are from Frankel and Romer (1999) and Helpman Melitz and Rubinstein (2008).

Measures of Knowledge Applicability of a Country's Exports We are now equipped to describe a country's knowledge applicability associated with its export basket. We define $\log TA_c$, as a weighted average of sectoral knowledge applicability (in log) for each country, using the share of export by the country in the respective sectors, X_c^i/X_c, as weights. That is,

$$\log(TA_c) = \sum_i \log(aw^i)\frac{X_c^i}{X_c}$$

For robustness, we also consider an alternative country-specific measure in our exercise, $Perc33$, defined as the fraction of exports in the most applicable 1/3 of all sectors.

[16]Thanks to Susan Zhu, who provides a converter derived from Feenstra (1997) mapping the 4-digit SITC codes into 4-digit US SIC (1972 basis). Her converter also carefully deals with the roll-up problems which are detailed in Feenstra et al. (1997) and Feenstra (2000).

[17]We have also explored the United Nations Industrial Development Organization (UNIDO)'s industry statistics database which provides industrial production information at the 4-digit ISIC_rev3 level. However, the large number of missing observations in the UNIDO data at the 4-digit ISIC level significantly impedes the accuracy of our empirical analysis. Therefore, we focus on the results from trade flow data.

Table 1: List of 41 Sectors Ranked According to the Authority Weight (aw), 1995

SIC code	Sector Names	aw	U
38 (ex 3825)	Professional and scientific instruments	0.539	1.414
366-367	Electronic components and accessories and communications equip	0.356	1.365
357	Office computing and accounting machines	0.307	1.227
365	Radio and television receiving equipment (ex. communication)	0.277	1.079
369	Miscellaneous electrical machinery, equipment and supplies	0.257	1.115
361, 3825	Electrical transmission and distribution equipment	0.196	1.127
362	Electrical industrial apparatus	0.191	1.144
364	Electrical lighting and wiring equipment	0.173	1.104
376	Guided missiles and space vehicles and parts	0.170	1.060
22	Textile mill products	0.145	1.095
30	Rubber and miscellaneous plastics products	0.130	1.320
333-336, 339(ex 3399), 3463	Primary and secondary non-ferrous metals	0.127	1.080
32	Stone, clay, glass and concrete products	0.110	1.124
356	General industrial machinery and equipment	0.105	1.280
372	Aircraft and parts	0.096	1.103
355	Special industry machinery, ex metal working	0.096	1.225
358	Refrigeration and service industry machinery	0.094	1.083
34 (ex 3462, 3463, 348)	Fabricated metal products	0.094	1.328
289	Miscellaneous chemical products	0.092	1.135
354	Metal working machinery and equipment	0.091	1.135
363	Household appliances	0.088	1.087
371	Motor vehicles and other motor vehicle equipment	0.080	1.170
285	Paints, varnishes, lacquers, enamels, and allied products	0.078	1.097
13, 29	Petroleum and natural gas extraction	0.077	1.108
282	Plastics materials and synthetic resins	0.074	1.137
353	Construction, mining and material handling machinery and equip	0.070	1.191
352	Farm and garden machinery and equipment	0.069	1.144
281	Industrial inorganic chemistry	0.066	1.123
379 (ex 3795)	Miscellaneous transportation equipment	0.066	1.060
359	Miscellaneous machinery, ex electrical	0.062	1.046
284	Soaps, detergents, cleaners, perfumes, cosmetics and toiletries	0.057	1.118
348, 3795	Ordinance ex missiles	0.056	1.126
283	Drugs and medicines	0.048	1.124
20	Food and kindred products	0.043	1.119
331,332, 33,993,462	Primary ferrous products	0.040	1.087
286	Industrial organic chemistry	0.038	1.194
374	Railroad equipment	0.038	1.095
351	Engines and turbines	0.038	1.193
375	Motorcycles, bicycles, and parts	0.034	1.101
287	Agricultural chemicals	0.033	1.196
373	Ship and boat building and repairing	0.029	1.101

Notes: The table shows the calculated sector-specific aw using cross-sector patent citations provided by U.S. Patent and Trade Office (USPTO). The calculation is based on Kleinberg (1998) iterative algorithm specified in (19).

3.3 Determinants of a Country's Knowledge Applicability

Table 2: Determinants of a Country's Knowledge Applicability

	Dependent variable: $\log TA_c$ in 1995				
	(1)	(2)	(3)	(4)	(5)
log GDP per capita	0.05	0.05	0.11	0.10	0.09
	(1.16)	(1.13)	(1.70)	(1.13)	(1.25)
log human capital	0.05	0.10	0.23	0.15	0.18
	(0.28)	(0.44)	(0.87)	(0.49)	(0.70)
log investment-output ratio	0.23	0.16	0.16	0.16	0.14
	(2.71)***	(2.17)**	(1.82)	(1.71)	(1.60)
log area		-0.10	-0.06	-0.06	-0.06
		(-3.67)***	(-1.62)	(-1.72)	(-1.65)
log population		0.15	0.10	0.09	0.10
		(5.05)***	(2.85)***	(2.34)**	(2.96)***
population weighted distance			-0.54	-0.43	-0.52
			(-3.03)***	(-2.44)**	(-3.00)***
distance to the equator			-0.81	-0.77	-0.91
			(-2.36)**	(-2.15)**	(-2.60)**
landlock			0.12	0.16	0.10
			(0.89)	(1.03)	(0.76)
financial development				0.12	
				(0.94)	
rule of law					0.08
					(1.22)
Observations	116	100	91	84	91
R^2	0.16	0.34	0.42	0.41	0.43

Robust t statistics in parentheses. ** $p < 0.05$, *** $p < 0.01$

Table 2 shows that population in a country is positively associated with its knowledge applicability, and the (population-weighted-average) distance to other countries negatively affects its knowledge applicability, even when we control for per capita GDP, human capital, level of physical investment, area size, financial development level and institutional quality (proxies by the rule of law). Both can be interpreted as casual relationships, as population size and geography should not be affected by a country's knowledge composition. It is somewhat interesting that human capital, institutional quality and financial development level do not seem to play significant roles in determining a country's knowledge applicability. More surprisingly, distance to the equator, which typically is an exogenous historical determinant for social infrastructure (Hall and Jones (1999)), is found to be negatively associated with the applicability of a country's technology. One plausible explanation is that the absolute value of latitude captures the average hours of daylight, which matter for the duration and efficacy of communication and the exchange of ideas. Based on these findings, we later use the distance to the rest of the world, population and area size as instruments to correct for reverse causality in the cross-country growth regressions.

Our theoretical model presented in Section 2 explains how geography and the size of the population determine the pattern of knowledge accumulation. The former determines the trade cost, which reduces the payoff of accumulating knowledge in center sectors more than in periphery sectors, and the latter affects home wage and market size, which has differential implications for the profit and knowledge value in different sectors

3.4 The Composition of Knowledge and Growth

We now turn to examine the impact of the knowledge applicability revealed through a country's exports on its subsequent growth. We examine the following empirical specification:

$$(\ln y_{i,t} - \ln y_{i,0})/t = \beta_1 + \beta_2 \log(TA_{i,0}) + \boldsymbol{\delta X}_{i,0} + \varepsilon_i \tag{20}$$

The left-hand-side measures the annual growth rate of per capita GDP(y) for country i from year 0 to t. $\log TA_i$ (constructed in Section 3.1) is the applicability of knowledge associated with country i's export composition. $\boldsymbol{X}_i$ includes standard controls for initial country characteristics suggested by the growth literature (see Hall and Jones (1999), Acemoglu et al. (2001) (2005), Dollar and Kraay (2003), Rodrik et al. (2004)). Specifically, we control for initial GDP per capita, initial human capital, initial investment to GDP ratio, the distance to the equator, the landlocked dummy, the initial openness, and the rule of law indicator. In addition, countries also differ greatly in the levels of export diversification. A more diversified product structure would allow countries to better internalize inter-sectoral knowledge spillovers and impact growth. Thus, we also include standard measures of export concentration (Herfindahl-Hirschman index) in our regression. We are particularly interested in the coefficient β_2 in Equation (20), which measures the impact of $\log(TA_0)$ on growth.

Estimates of Equation (20) are reported in Table 3. Columns (1)-(5) show OLS regression results from a series of cross-country growth regressions. In addition, $\log(TA_i)$ could be endogenous as countries tend to specialize more in sectors with high knowledge spillovers when they are richer. Columns (6)-(9) address this concern and report the results from IV-GMM estimation of the effect of knowledge applicability on growth. Guided by the empirical findings in Section 3.3, we use population, land area and the (population-weighted-average) distance to all the other countries as exogenous instruments in the IV-GMM specification. We argue that country size and population satisfy excludability constraint as existing empirical studies typically report no scale effects in growth (see Jones (1995) and Rose (2006)). The excludability of distance to all the other countries from the second-stage regression, however, might be somewhat problematic, as it may affect the level of trade which in turn impacts growth. However, we find that the impact of the initial knowledge applicability on growth is essentially intact when controlling for differences in trade openness. In fact, despite its (arguable) role of causing income differences,[18] when controlling for $\log TA$ and other covariates, trade openness does not seem to have a significant impact on subsequent growth differences. Moreover, results from Hansen's over-identification test also suggest that the distance to other countries could be reasonably excluded from the growth regression and could affect growth through its impact on a country's export specialization.

We find that the coefficients on $\log(TA_0)$ are always positive and highly significant across all specifications, suggesting that specializing in sectors with large knowledge spillovers brings growth in the future. The size of the estimated effect is large. The estimated coefficients vary from 1.1 to 4.7, implying that a ten percent increase in $\log(TA_0)$, which is approximately what Thailand and Poland achieved between 1975 and 1980, on average enhances a country's subsequent growth by 1/4 percent per year. In addition, all the other initial control variables have the correct signs. Notably, initial investment to GDP ratio, export diversification and openness do not seem to enter in a robustly significant way, and including institutional quality does not greatly affect the significance of $\log TA_0$ either.

Next, we replace the $\log(TA_0)$ variable with an alternative measure of knowledge applicability associated with a country's exports—$Perc33$—and re-estimate all the regressions. The results for each specification are presented in Table 4. Again, the coefficients on $Perc33$ are always positive and statistically even more significant than when the previous measure is used. The magnitudes of the coefficients are also larger, with an average equal to 5.5. This implies that a 10 percent increase in $Perc33$ boosts annual growth by half a percentage point, which is substantial.

Figure 4a presents the partial regression plot for $\log(TA)$ from Column (2) of Table 3 and Figure 4b displays the partial regression plot for $Perc33$ from Column (2) of Table 4. They show that our results are not driven by outliers.

The cross-country regressions demonstrate that countries that initially specialize in exporting goods that embody highly applicable knowledge subsequently grow faster. As in all cross-section specifications, these regressions suffer from omitted variable bias. For example, we implicitly assume

[18] See Frankel and Romer (1999), Feyrer (2009) and Rodriguez and Rodrik (2000).

Table 3: Country-level per capita GDP Growth Regressions using log(TA).

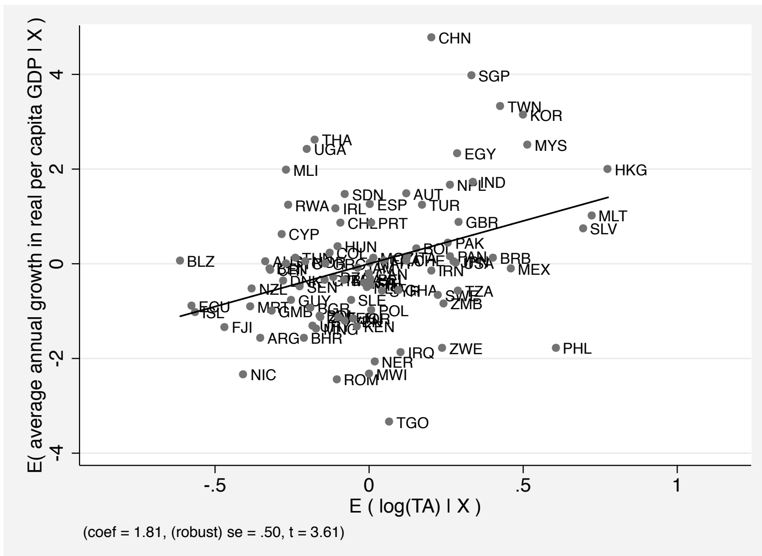
	Dependent variable: growth rate of GDP per capita over 1980-2005								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	IV-GMM	IV-GMM	IV-GMM	IV-GMM
log init TA	1.39	1.81	1.32	1.15	1.11	4.34	3.82	4.74	4.44
	(2.60)**	(3.61)***	(2.31)**	(2.24)**	(2.07)**	(3.99)***	(4.00)***	(3.13)***	(3.23)***
log init GDPpc	-0.51	-0.97	-0.94	-1.15	-0.85	-0.76	-1.17	-1.18	-0.85
	(-1.39)	(-2.55)**	(-2.57)**	(-3.33)***	(-3.67)***	(-2.13)**	(-3.21)***	(-3.01)***	(-2.85)***
log init I/Y	0.00	0.22	0.22	0.12	-0.13	-0.09	0.09	0.01	-0.23
	(0.00)	(0.58)	(0.58)	(0.34)	(-0.43)	(-0.23)	(0.24)	(0.04)	(-0.72)
log init HC	3.09	2.57	2.38	1.39	0.85	2.87	2.41	2.54	-0.36
	(3.04)***	(2.82)***	(2.68)***	(1.61)	(1.17)	(2.85)***	(2.55)**	(2.41)**	(-0.35)
dist to the equator		2.86	2.35	0.98	0.41		3.32	3.85	
		(2.76)***	(2.21)**	(1.01)	(0.47)		(3.42)***	(3.40)***	
landlock		-1.38	-1.24	-1.40	-1.22		-1.31	-1.50	-1.33
		(-2.68)***	(-2.44)**	(-3.01)***	(-2.92)***		(-2.50)**	(-2.50)**	(-2.80)***
diversification			-1.19	-0.81	-0.52			1.44	2.37
			(-1.89)	(-1.23)	(-0.79)			(1.23)	(1.80)
rule of law				0.96	1.03				1.70
				(5.41)***	(6.01)***				(3.30)***
openness					0.00				-0.01
					(0.35)				(-1.65)
Instruments									
log population-weighted distance						X	X	X	X
log area						X	X	X	X
log population						X	X	X	X
Distance to the Equator									X
Observations	96	91	91	91	85	95	91	91	85
R^2	0.20	0.36	0.37	0.49	0.50				
Weak Instrument (KP F-stat)						22.0	26.0	8.6	2.4
Hansen J test (p-value)						0.27	0.70	0.78	0.51
Endogeneity test (p-value)						0.001	0.004	0.005	0.008

Robust t statistics in parentheses. ** $p < 0.05$, *** $p < 0.01$

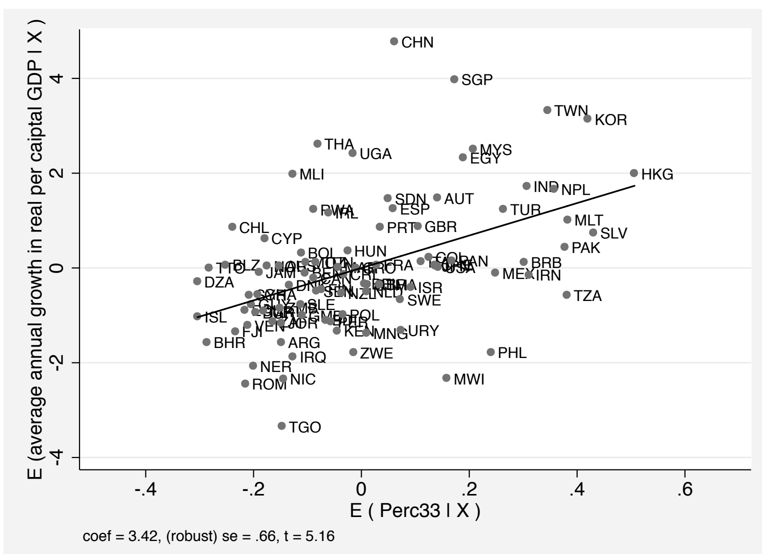
Table 4: Country-level per capita GDP Growth Regressions using $Perc33$.

	Dependent variable: growth rate of GDP per capita over 1980-2005								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	IV-GMM	IV-GMM	IV-GMM	IV-GMM
init Perc33	3.10	3.42	3.14	2.57	2.66	6.66	5.72	7.89	6.97
	(3.06)***	(5.16)***	(3.98)***	(3.39)***	(3.42)***	(4.56)***	(4.16)***	(2.98)***	(3.56)***
log init GDPpc	-0.46	-0.81	-0.81	-1.02	-0.73	-0.54	-0.82	-0.67	-0.47
	(-1.36)	(-2.21)**	(-2.22)**	(-2.95)***	(-3.43)***	(-1.80)	(-2.61)***	(-1.92)	(-1.64)
log init I/Y	-0.10	0.12	0.12	0.06	-0.22	-0.30	-0.04	-0.22	-0.39
	(-0.24)	(0.34)	(0.35)	(0.16)	(-0.78)	(-0.83)	(-0.13)	(-0.61)	(-1.27)
log init HC	3.06	2.52	2.46	1.53	1.03	2.89	2.40	2.61	0.80
	(3.10)***	(2.93)***	(2.93)***	(1.82)	(1.51)	(3.09)***	(2.83)***	(2.67)***	(0.76)
dist to the equator		2.06	1.95	0.73	0.45		1.85	2.01	
		(1.96)	(1.84)	(0.76)	(0.53)		(1.92)	(1.95)	
landlock		-1.31	-1.27	-1.40	-1.18		-1.18	-1.36	-1.30
		(-2.67)***	(-2.61)**	(-3.08)***	(-2.97)***		(-2.51)**	(-2.56)**	(-2.94)***
diversification			-0.42	-0.29	0.04			2.30	2.73
			(-0.65)	(-0.42)	(0.06)			(1.63)	(2.02)**
rule of law				0.88	0.88				1.01
				(4.78)***	(4.77)***				(2.08)**
openness					0.00				-0.01
					(1.02)				(-0.93)
Instruments									
log population-weighted distance						X	X	X	X
log area						X	X	X	X
log population						X	X	X	X
Distance to the Equator									X
Observations	96	91	91	91	85	95	91	91	85
R^2	0.28	0.42	0.42	0.51	0.54				
Weak Instrument (KP F-stat)						23.4	21.9	5.2	3.3
Hansen J test (p-value)						0.84	0.60	0.62	0.80

Robust t statistics in parentheses. ** $p < 0.05$, *** $p < 0.01$



(a) Average annual per capita GDP growth and log(TA).



(b) Average annual per capita GDP growth and $Perc33$.

Figure 4: Partial Regression Plots

that all the differences in productivity growth across countries are captured by the differences in the existing control variables such as $\log(TA)$, human capital and institutional quality. As an extension that relaxes this assumption, we adopt a panel analysis with country fixed effects.

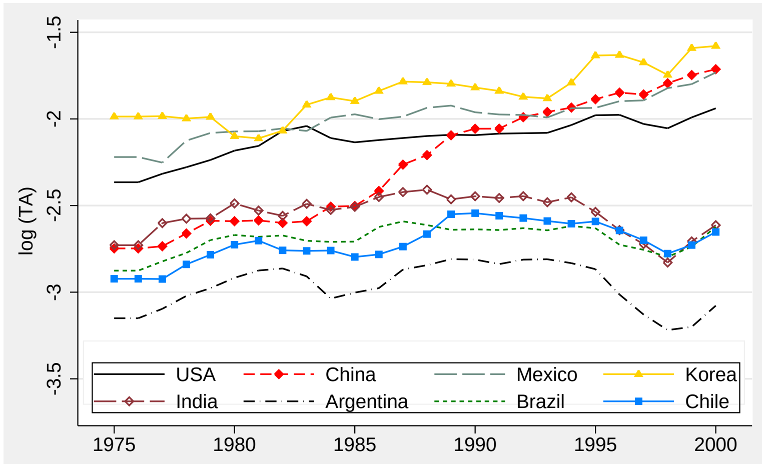


Figure 5: Knowledge Applicability Over Time for Selected Countries

First, we ask how knowledge applicability embodied in a country's exports changes over time in different countries. Figure 5 presents the time trend for $\log(TA)$ for a sample of eight countries—USA, China, South Korea, India, Mexico, Chile, Argentina and Brazil. South Korea has the highest knowledge applicability in its exports, lying above Mexico and the U.S. most of the time. The most striking observation is that China's knowledge applicability has been growing steadily and rapidly, converging with South Korea and exceeding the U.S. over recent decades.[19] Although higher than the three representative Latin American countries, India's $\log TA$ has been lagging behind. This is mainly because our measure does not include India's software and service exports. At the other end, the exports of Argentina, Brazil and Chile have lower knowledge applicability, reflecting the fact that their exports are primarily simple products or natural resources. It is worth noting that, significantly different from the measure of export sophistication developed in Hausmann et al (2007), Chile's $\log(TA)$ rose until late 90s and is higher than those of Argentina and Brazil (during the later part of the sample period), consistent with the growth experience in Latin America in recent decades.

Table 5 shows the results of the panel regressions. Data are grouped into five-year intervals using pooled OLS, OLS with country and period fixed effects. Again, even after controlling for time-invariant country characteristics, the estimated coefficients on log initial TA are significantly positive in all cases and are comparable in magnitude to the cross-country results reported earlier.

[19] As pointed out in Koopman, Wang and Wei (2008), however, a significant share of China's exports is based on processing trade, where sophisticated product parts are imported to produce a sophisticated final product.

Table 5: Panel Growth Regression (1975-2005, 5-year panels)

	(1) OLS	(2) FE	(3) FE	(4) FE	(5) FE
log init TA	1.19	1.37	1.36	1.21	1.40
	(3.78)***	(2.15)**	(2.45)**	(2.12)**	(2.51)**
log init GDP per capita	-0.29	-6.45	-6.42	-6.86	-7.42
	(-0.73)	(-5.49)***	(-4.67)***	(-4.99)***	(-5.24)***
log init human capital	3.11	-0.91	-0.74	-0.82	2.22
	(3.75)***	(-0.37)	(-0.27)	(-0.30)	(0.75)
log init I/Y	0.39	0.88	0.94	0.81	0.95
	(1.04)	(0.98)	(1.28)	(1.15)	(1.39)
log init K/L	-0.15	-0.81	-0.79	-0.91	-1.06
	(-0.40)	(-0.91)	(-0.70)	(-0.73)	(-0.88)
init diversification			-1.73	-1.33	-1.61
			(-1.24)	(-0.95)	(-1.16)
init openness				0.00	0.00
				(0.11)	(0.10)
log init population					-3.50
					(-2.37)**
Period Dummies	Yes	Yes	Yes	Yes	Yes
Observations	594	594	594	552	552
R^2	0.13	0.29	0.30	0.32	0.33

Robust t statistics in parentheses. ** $p < 0.05$, *** $p < 0.01$.

Using population and trading partner's $\log(TA)$ as instruments, we find that the Durbin-Wu-Hausman test fails to reject the null hypothesis that $\log(TA)$ can be treated as exogenous. This implies that an IV approach is not necessary; the results from IV are thus not reported here.[20]

4 Final Remarks

This paper provides a systematic analysis to investigate the relationship between the composition of knowledge and growth. There are two contributions: (1) Using cross-sector patent citation data, we propose an original measure of knowledge applicability for each specific sector and use this measure to describe the applicability of knowledge a country possesses. We then document a statistically and economically significant positive relationship between our measures of knowledge applicability and cross-country growth differences, controlling for various standard covariates. (2) We incorporate heterogenous inter-sectoral knowledge linkages into a formal model of trade and endogenous growth.

[20] In Appendix C, we also demonstrate that the results are robust to using the alternative quantitative measure of sectoral knowledge applicability–"upstreamness".

The model provides a theoretical interpretation of how exogenous factors such as geography and population size can account for differences in countries' composition of knowledge accumulation, which in turn impacts growth through its implication of knowledge spillovers. Traditionally, lower trade costs increase growth by granting firms a larger market and higher incentive to innovate. We describe in this paper that lower trade costs are also associated with 'composition effect', in that it encourages countries to allocate more R&D resources towards highly knowledge-applicable sectors, which provide ample knowledge spillovers and growth opportunities to the rest of the economy.

Our evidence motivates the mechanism highlighted in our model. In this sense, knowledge specialization can be another source of economic prosperity. The natural questions to ask are: How do countries increase the amount of applicable knowledge? What are potential barriers to this process? Can policy changes such as trade liberalization help to improve the knowledge structure of the economy? The preceding theoretical analysis in Section 2.5 is well-suited to answer some of the questions. In particular it can trace the equilibrium outcome of an economy undergoing a change in trade costs resulting either from reductions in real cost levels or from multilateral agreements to reduce tariffs (changes in τ) or non-tariff barriers to trade (changes in exchange rate captured by relative wage w in the model). The main impact of lower trade barriers—besides leading to more exposure to trade as in conventional trade models—is an increase in aggregate innovation productivity generated by a reallocation of R&D resources towards sectors with higher knowledge applicability. Our empirical studies, however, focus on exploring how geography-induced technology specialization affects a country's subsequent growth. Thus, it does not directly examine whether countries with lower policy-induced barriers grow more quickly. More empirical studies in this direction will be helpful in providing a vigorous answer to these questions.

Moreover, it is worth pointing out that to keep the discussion focused on the composition of knowledge rather than the diversification of knowledge, we have assumed that the total number of sectors in which a country innovates and produces is constant and fixed in the model. Intuitively, a country producing in a larger range of sectors can internalize more inter-sectoral knowledge spillers and can thus enjoy more growth opportunities.Our example with a star-shaped knowledge diffusion network implies that a country with a higher degree of diversification would specialize more in highly applicable knowledge, since the model predicts that R&D resources are allocated according to sectoral knowledge value. In practice, the ability of a country to diversify and move into new sectors depends on its existing knowledge structure and other country characteristics. This dynamic entry decision is absent in our model, but can be explored once allowing for sectoral entry barriers. This kind of extension can provide valuable insights, as policy interventions can affect the fixed cost of doing business (i.e. license, regulation fees). This could be a promising venue for future research.

References

[1]

[2] Acemoglu, D., V. M. Carvalho, A. Ozdaglar and A. Tahbaz-Salehi. 2012. "The Network Origins of Aggregate Fluctuations". *Econometrica* 80(5):1977-2016.

[3] Aghion, P., M. Dewatripont, L. Du, A. Harrison and P. Legros. 2012. "Industrial Policy and Competition". NBER Working Paper No. 18048.

[4] Antras, P. D. Chor, T. Fally and R. Hillberry. 2012. "Measuring the Upstreamness of Production and Trade Flows. " *American Economic Review*, 102(3): 412-16.

[5] Barro, R. J., and J.W. Lee. 2010. "International Data on Educational Attainment: Updates And Implications". *Oxford Economic Papers*, 53: 541-63.

[6] Beck, T., Demirgüç-Kunt, A. and R. Levine. 2000. "A New Database on Financial Development and Structure." *World Bank Economic Review*, 597-605.

[7] Blonigen, Bruce. 2013. "Industrial Policy and Downstream Export Performance". NBER working paper No. 18964.

[8] Bresnahan, T. and M. Trajtenberg. 1995. "General Purpose Technologies 'Engines of Growth'?", *Journal of Econometrics*, 65: 83-108.

[9] Cai, J. and N. Li. 2012. "Growth Through Intersectoral Knowledge Linkages". mimeo, Ohio State University.

[10] Ciccone, A. 2002. "Input Chains and Industrialization". *The Review of Economic Studies*, 69(3): 565-587.

[11] Dollar, D. and A. Kraay. 2004. "Trade, Growth and Poverty". *The Economic Journal*, 114(493): 22-49.

[12] Feenstra, R. C., R.E. Lipsey, Deng, H., Ma, A.C. and Hengyong Mo. 2005. "World Trade Flows." 1962-2000, NBER Working Paper 11040.

[13] Frankel, J. A. and D. Romer. 1999. "Does Trade Cause Growth?" *American Economic Review*, 89(3): 379-399.

[14] Feyrer, J. 2009. "Trade and Income – Exploiting Time Series in Geography". mimeo, Dartmouth College.

[15] Grossman, G. and E. Helpman. 1991. "Innovation and Growth in the Global Economy." MIT Press, Cambridge, MA.

[16] Grossman, G. and E. Helpman. 1990. "Comparative Advantage and Long-Run Growth". *American Economic Review*, 80 (4): 796-815.

[17] Hall, R. E., & Jones, C. I. 1999. "Why Do Some Countries Produce So Much More Output Per Worker Than Others?" *Quarterly Journal of Economics*, 114(1): 83–116.

[18] Hall, B, A. Jaffe, and M. Trajtenberg. 2001. "The NBER Patent Citations Data File: lessons, Insights, and Methodological Tools". NBER Working Paper 8498.

[19] Harrison, A. and A. Rodriguez-Clare. 2010. "Trade, Foreign Investment, and Industrial Policy", in *Handbook of Development Economics*, Vol 5, edited by D.Rodrik and M. Rosenzweig.

[20] Hausmann, R., J. Hwang and D. Rodrik. 2007. "What You Export Matters". *Journal of Economic Growth*, 12(1), 1-25.

[21] Hausmann, R. and C. A. Hidalgo. 2011. "The Network Structure of Economic Output". *Journal of Economic Growth*. 16: 309-342.

[22] Hausmann R., and B. Klinger. 2007. "The Structure of the Product Space and the Evolution of Comparative Advantage". CID working paper.

[23] Helpman, E., M. Melitz and Y. Rubinstein. 2008. "Estimating Trade Flows: Trading Partners and Trading Volumes". *Quarterly Journal of Economics*, 123(2): 441-487.

[24] Hidalgo, C. A. and Hausmann, R. 2009. "The Building Blocks of Economic Complexity". *Proceedings of the National Academy of Sciences of the United States of America*, 106(26): 10570-10575

[25] Hidalgo, C.A., B. Klinger, A.L. Barabasi and R. Hausman. 2007. "The Product Space Conditions the Development of Nations". *Science*, 317: 482-487.

[26] Jaffe, A., M. Trajtenberg and M. S. Fogarty. 2000. "Knowledge Spillovers and Patent Citations: Evidence from a Survey of Inventors". *American Economic Review* 90(2), 215-218.

[27] Jones, C. I. 2011a. "Intermediate Goods and Weak Links in the Theory of Economic Development". *American Economic Journal: Macroeconomics*, 3(2): 1-28.

[28] Jones, C. I. 2011b. "Misallocations, Economic Growth, and Input-Output Economics". In *Proceedings of Econometric Society World Congress* (D. Acemoglu, M. Arellano, and E. Dekel, eds.), Cambridge University Press.

[29] Jones, C. I. 1995. "Time Series Tests of Endogenous Growth models". *Quarterly Journal of Economics*, 110:495-525.

[30] Kali, R., J. Reyes, J. McGee and S. Shirrell. 2009. "Growth Networks". *Journal of Development Economics*, 101: 216-227.

[31] King, R. and R. Levine.1993. "Finance and Growth: Schumpeter Might Be Right." *Quarterly Journal of Economics*, 58(3): 717-737.

[32] Klenow P. and A. Rodriguez-Clare. 2005. "Externalities and Growth", *Handbook of Economic Growth*, Vol 1A, P. Aghion and S. Durlauf, eds. 817-861.

[33] Koren M. and S. Tenreyro. 2007. "Volatility and Development". *Quarterly Journal of Economics*, 122(1): 243-287.

[34] Kleinberg, R. 1998. "Authoritative Sources in a Hyperlinked Environment" in Proceedings of ACM-SIAM Symposium on Discrete Algorithms, 668-677.

[35] Klette, T. J. and S. Kortum. 2004. "Innovating Firms and Aggregate Innovation." *Journal of Political Economy*, 112: 986-1018.

[36] La Porta, R., Lopez-de-Silanes, F., Shleifer, A. and R. Vishny. 1998. "Law and Finance." *Journal of Political Economy*, 106: 1113-55.

[37] Melitz, M. 2002. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity". *Econometrica*, 71(6): 1695-1725.

[38] Newman, M. E. J. 2003. "The Structure and Function of Complex Networks". *SIAM Review* 45, 167-256.

[39] Ngai R. and R. Samaniego. 2011. "Accounting for Research and Productivity Growth Across Industries." *Review of Economic Dynamics*, 14(3): 475-495.

[40] Nunn, N. and D. Trefler. 2010. "The Structure of Tariffs and Long-Term Growth." *American Economic Journal: Macroeconomics*, 2(4): 158-94.

[41] Rodriguez, F. and D. Rodrik. 2001. "Trade Policy and Economic Growth: A Sceptic's Guide to the Cross-National Evidence?" *NBER Macroeconomics Annual 2000*. Cambridge, MA: MIT Press, pp. 261-324.

[42] Romer, P. and C. Jones. 2010. "The New Kaldor Facts: Ideas, Institutions, Population and Human Capital". Forthcoming, *American Economic Journal: Macroeconomics*.

[43] Rose, A. K. 2006. "Size Really Doesn't Matter: In Search of a National Scale Effect". *NBER Working Paper* No. 12191.

[44] Sachs, J. and A. Warner. 1995. "Economic Reform and the Process of Global Integra-tion", *Brookings Papers on Economic Activity*, 1: 1-118.

[45] Schmoch, U. F. Laville, P. Patel, R. Frietsch. 2003. "Linking Technology Areas to Industrial Sectors". European Commision, DG Research.

[46] Wang, Z. and S.J. Wei, 2008. "What Accounts For the Rising Sophistication of China's Exports?" NBER working paper No. 13771.

[47] Wang, Z., S. J. Wei and A. Wong, 2010. "Does a Leapfrogging Growth Strategy Raise Growth Rate? Some International Evidence". NBER working paper No. 16390.

A The Firm's Optimal R&D Decision and General Equilibrium Conditions

[For Online Publication]

We solve the firm's R&D decision along the BGP. We adopt the guess-and-verify method to solve the all-sector firm's problem. Guess that the value of a firm is a linear combination of its accessible knowledge capital in all the sectors:

$$V(z_t) = \sum_{j=1}^{K} \left(v_t^j \frac{z_t^j}{n_t^j}. \right)$$

Substituting it back to the Bellman equation (8), we get

$$V(z_t) = \sum_{j=1}^{K} (\pi_t^j \frac{z_t^j}{n_t^j}) - \sum_{i=1}^{K} \sum_{j=1}^{K} \left(R_t^{ij} \right) + \frac{1}{1+r} \sum_{j=1}^{K} (v_{t+1}^j \frac{z_t^j + \sum_{i=1}^{K} \left[A^{ji} \left(\bar{z}_t^j R_{f,t}^{ji} \right)^{\alpha} \left(z_t^i \right)^{1-\alpha} \right]}{n_{t+1}^j}). \tag{21}$$

The first order condition with respect to $R_{f,t}^{ij}$ is:

$$R_t^{ij} = \frac{n_t^j}{n_t^i} \left(A^{ij} \alpha \rho_t^i v_{t+1}^i \right)^{\frac{1}{1-\alpha}} \frac{z_t^j}{n_t^j}. \tag{22}$$

where $\rho_t^j = \frac{1}{1+r} \frac{n_t^j}{n_{t+1}^j}$. Substituting the optimal R&D in (22) back to (21), we get:

$$\begin{aligned} \sum_{j=1}^{K} \left(v_{t+1}^j \frac{z_t^j}{n_t^j} \right) &= \sum_{j=1}^{K} \left(\pi^j \frac{z_t^j}{n_t^j} \right) - \sum_{i=1}^{K} \sum_{j=1}^{K} \frac{n_t^j}{n_t^i} \left(A^{ij} \alpha \rho_t^i v_{t+1}^i \right)^{\frac{1}{1-\alpha}} \left(\frac{z_t^j}{n_t^j} \right) \\ &+ \frac{1}{1+r_t} [\sum_{j=1}^{K} \frac{v_{t+1}^j z_t^j}{n_{t+1}^j} + \sum_{j=1}^{K} \sum_{i=1}^{K} \frac{v_{t+1}^i}{n_{t+1}^i} A^{ij} \left(A^{ij} \alpha \rho_t^i v_{t+1}^i \right)^{\frac{\alpha}{1-\alpha}} \left(z_t^j \right)]. \end{aligned}$$

Comparing the coefficients of z_t^j on both sides, we have

$$\frac{v_t^j}{n_t^j} = \frac{\pi_t^j}{n_t^j} - \sum_{i=1}^{K} \frac{n_t^j}{n_t^i} \left(A^{ij} \alpha \rho_t^i v_{t+1}^i \right)^{\frac{1}{1-\alpha}} \frac{1}{n_t^j} + \frac{1}{1+r_t} \sum_{i=1}^{K} A^{ij} \left(A^{ij} \alpha \rho_t^i v_{t+1}^i \right)^{\frac{\alpha}{1-\alpha}} \frac{v_{t+1}^i}{n_{t+1}^i} + \frac{1}{1+r_t} \frac{v_{t+1}^j}{n_{t+1}^j}.$$

The transversality condition takes the form

$$\lim_{T \to \infty} \prod_{t=0}^{T} (\frac{1}{1+r_t}) \frac{v_T^i}{n_T^i} = 0, \forall i.$$

In a stationary BGP equilibrium, the sectoral knowledge values and the application value of knowledge j to i are all constant, i.e. $v_t^i = v^i, u_t^i = u^i$, (to be proved later). Now we get:

$$v^j = (1 - \rho_t^j)^{-1} [\pi^j + \frac{1-\alpha}{\alpha} \sum_{i=1}^{K} \frac{n_t^j}{n_t^i} \left(A^{ij} \alpha \rho_t^i v^i \right)^{\frac{1}{1-\alpha}}]$$

To simplify the notations, define the value of sector j's knowledge in contributing to innovations in sector i as

$$\omega^{ij} = \frac{1-\alpha}{\alpha} \frac{n_t^j}{n_t^i} \left(A^{ij} \alpha \rho_t^i v^i\right)^{\frac{1}{1-\alpha}}$$

Substituting it back, we have

$$v^j = (1-\rho_t^j)^{-1}(\pi^j + \sum_{i=1}^{K} \omega_t^{ij}),$$

and given that firms are identical with measure one

$$R_t^{ij} = \frac{\alpha}{1-\alpha} \omega_t^{ij} \frac{z_t^j}{n_t^j} = \frac{\alpha}{1-\alpha} \omega_t^{ij}.$$

To prove that $\rho_t^j, v_t^j, u_t^j, \omega_t^{ij}$ are all constants, we first need to show that the innovation rates across sectors are the same on the BGP; therefore, we need to show $\frac{n_t^i}{n_t^j} = \frac{n^i}{n^j}, \forall t$. The evolution of the number of varieties in sector i is:

$$\begin{aligned} n_{t+1}^i &= n_t^i + \triangle z_t^i \qquad (23) \\ &= n_t^i + \sum_{j=1}^{K} (A^{ij})^{\frac{1}{1-\alpha}} \left(\alpha \rho_t^i v^i\right)^{\frac{\alpha}{1-\alpha}} z_t^j \\ &= n_t^i + \sum_{j=1}^{K} \left[(A^{ij})^{\frac{1}{1-\alpha}} \left(\alpha \beta v^i\right)^{\frac{\alpha}{1-\alpha}}\right] (n_t^j). \end{aligned}$$

The innovation rate (the growth rate of varieties) in sector i is $g_t^i = n_{t+1}^i / n_t^i$. Rearranging the terms, we have

$$(g_t^i - 1)(g_t^i)^{\frac{\alpha}{1-\alpha}} = \left(\alpha \beta v^i\right)^{\frac{\alpha}{1-\alpha}} \sum_{j=1}^{K} \left(A^{ij}\right)^{\frac{1}{1-\alpha}} (\frac{n_t^j}{n_t^i}), \qquad (24)$$

The number of goods in every sector grows at the same speed, because inter-sector knowledge spillovers keep all sectors on the same track. More specifically, if one sector i had been growing more slowly than other sectors for a lengthy period, its number of goods would be extremely small relative to other sectors. (24) implies that the cross-sector knowledge spillovers would increase g_t^i tremendously through a large ratio n_t^j / n_t^i until g_t^i is the same as the innovation rates in other sectors. This is vice versa for sectors starting with a faster growth rate. Therefore, in the stationary BGP equilibrium, $g^i = g^j = g$ and the distribution of the sector is stable and rank-preserving. Denote $\frac{n_t^i}{n_t^j} = \frac{n^i}{n^j}, \forall t$.

This result implies that $\rho_t^j = \beta/\gamma \equiv \rho$ and $\omega_t^{ij} \equiv \omega^{ij}$ are both constants, consistent with our original guess. Therefore, we have (9), (10) and (12). Now we can verify our previous guess that the all-sector firm's value is a linear constant-coefficient combination of its knowledge in all sectors.

Re-arranging (18) implies the common innovation rate as

$$g = 1 + \sum_{j=1}^{K} \frac{\omega^{ij}}{(1-\alpha)\rho v^i}. \qquad (25)$$

Based on (9), we can rewrite the equation above as

$$g = 1 + \frac{1-\rho}{(1-\alpha)\rho} \frac{\sum_{i=1}^{K} \sum_{j=1}^{K} \omega^{ij}}{\sum_{i=1}^{K} \pi^i + \sum_{i=1}^{K} \sum_{j=1}^{K} \omega^{ij}}, \tag{26}$$

Substituting out $\rho = \beta/g$ leads to (26) after rearranging the terms, we get (18).

The sectoral research effort is given by: $R^i = \sum_{j=1}^{K} R^{ij}$. Substitute the optimal R&D expenditure (12) and (18) into the equation, we have

$$R^i = \alpha\rho(g-1)v^i.$$

B Solving the Model: Collated GE Conditions

The model specified previously offers closed-form solutions at the BGP equilibrium. This section provides the collated list of equilibrium conditions that are used to compute the model economy in Section 2.5. Given the parameter values $\{\beta, \alpha, \sigma, (s^i)_{1\times K}, (A^{ij})_{K\times K}, L, L^*, \tau, \tau^*, \phi, \phi^*\}$, we solve for $3(K+1)$ number of unknowns: $(v^i)_{K\times 1}$, $(\pi^i)_{K\times 1}, (n^i/n^{i*})_{K\times 1}$, M, g and w/w^* in the general equilibrium. They are determined by the exact same numbers of equations, including K numbers of equations determining the per-firm knowledge value in each sector,

$$v^j = (1-\rho)^{-1} \left[\pi^j + \sum_{i=1}^{K} \frac{1-\alpha}{\alpha} \frac{n^j}{n^i} \left(A^{ij} \alpha\rho v^i \right)^{\frac{1}{1-\alpha}} \right],$$

where $\rho = \beta/g$, and K equations specifying the sectoral aggregate profit, based on (4) and (5):

$$\pi^i = \frac{s^i}{\sigma M} \left[\frac{L}{1 + \frac{n^{i*}}{n^i} \left(\frac{\phi w^*}{\phi^* w} \right)^{1-\sigma} (\tau^*)^{1-\sigma}} + \frac{\frac{w^*}{w} L^*}{1 + \frac{n^{i*}}{n^i} \left(\frac{\phi w^*}{\phi^* w} \right)^{1-\sigma} \tau^{\sigma-1}} \right],$$

K number of equations on aggregate growth rate, based on (10) and (25):

$$g = 1 + \left(\alpha\rho v^i \right)^{\frac{\alpha}{1-\alpha}} \sum_{j=1}^{K} (A^{ij})^{\frac{1}{1-\alpha}} \frac{n^j}{n^i},$$

and three aggregate equilibrium conditions specifying the balance of trade condition:

$$\sum_{i=1}^{K} \frac{\frac{w^*}{w} L^*}{1 + \frac{n^{i*}}{h^i} \left(\frac{\phi}{\phi^*} \frac{w^*}{w} \frac{1}{\tau^*} \right)^{1-\sigma}} = \sum_{i=1}^{K} \frac{L}{1 + \frac{n^i}{h^{i*}} \left(\frac{\phi^*}{\phi} \frac{w}{w^*} \tau \right)^{1-\sigma}},$$

the labor market clearing condition:

$$L = \sum_{i=1}^{K} (\sigma - 1) \pi^i M + \alpha\rho(g-1) \sum_{i=1}^{K} v^i M,$$

and the free entry condition:

$$\frac{1}{1-\beta}[\sum_{i=1}^{K}\pi^{i}-\alpha\rho(g-1)\sum_{i=1}^{K}v^{i}]=F.$$

C Growth Regression Using an Alternative Measure of Knowledge Applicability–Upstreamness

To check robustness, we consider a second measure based on the idea that knowledge production is like goods production in that it draws knowledge input from related sectors to create new knowledge which itself in turn becomes a knowledge input for further knowledge production. The measure is called 'upstreamness' and describes the relative position of a specific type of knowledge in the chain of knowledge production—namely whether the sector tends to be a knowledge supplier or a knowledge user. It was originally designed by Antras, Chor, Fally and Hillberry (2012) to capture the relative production line position of an industry in the Input-Output Table. Adapting from their formula, we define the 'upstreamness' of knowledge embodied in sector i in the knowledge production process, U^i, by $U^i = 1 + \sum_{j\in J} \frac{c^{ij}}{c^i} U^j$, where $\frac{c^{ij}}{c^i}$ is the share of total citations received by i that are made by j. The correlation between (log) authority weight and upstreamness is 0.68.

Table A.1 presents regression results using upstreamness as an alternative measure of the knowledge applicability of different sectors. Both cross-section and panel regressions suggest that the main findings are not altered.

Table A.1: Growth Regressions Using Upstreamness as an Alternative Measure of Knowledge Applicability, 1975-2005

Dependent variable	Cross-national	5-year Panels				
	(1)	(2)	(2)	(3)	(4)	(5)
	OLS	OLS	FE	FE	FE	FE
Init Upstreamness	19.85	9.56	12.52	14.62	15.57	16.09
	(3.131)***	(3.27)***	(2.08)**	(2.43)**	(2.25)**	(2.35)**
log init GDP pc	-1.00	-0.32	-6.53	-6.53	-7.00	-7.52
	(-2.59)***	(-0.79)	(-5.49)***	(-4.70)***	(-5.05)***	(-5.28)***
log init human capital	2.45	3.01	-1.08	-0.78	-0.88	1.84
	(2.77)***	(3.67)***	(-0.42)	(-0.28)	(-0.32)	(0.61)
log init I/Y	0.38	0.47	0.86	0.95	0.84	0.96
	(1.02)	(1.25)	(0.93)	(1.29)	(1.20)	(1.40)
dist to the equator	2.96					
	(2.756)***					
landlock	-1.399					
	(-2.762)***					
log init K/L		-0.12	-0.86	-0.92	-1.08	-1.19
		(-0.34)	(-0.91)	(-0.86)	(-0.94)	(-1.05)
init diversification				-2.23	-1.84	-2.12
				(-1.51)	(-1.24)	(-1.43)
init openness					-0.00	-0.00
					(-0.01)	(-0.02)
log init population						-3.21
						(-2.18)**
Period Dummies	No	Yes	Yes	Yes	Yes	Yes
Observations	91	594	594	594	552	552
R^2	0.33	0.12	0.29	0.30	0.32	0.33

Robust t statistics in parentheses. ** $p < 0.05$, *** $p < 0.01$.