INTERNATIONAL KNOWLEDGE SPILLOVERS

Phil Manners

Abstract

Knowledge diffusion occurs because of interactions. Borders restrict interactions such as trade, investment and migration and reduce knowledge transmission. This is backed up by a plethora of studies showing the local nature of technology diffusion. In this paper, we examine the bigger picture, considering the extent of knowledge transfer between developed countries that occurs through trade, investment and migration linkages. We find that growth in imports of machinery and equipment as a share of GDP is associated with productivity growth, suggesting that these imports may bring knowledge. But we find no evidence that importing machinery and equipment from high knowledge countries provides any additional productivity benefits than importing machinery and equipment in general. We also find that outward migration to high knowledge countries provides productivity benefits. This introduces a role for migration to directly enable knowledge transfer, as well as its indirect role in strengthening trade and investment linkages.

INTERNATIONAL KNOWLEDGE SPILLOVERS[1]

Throughout the world, innovation and globalisation are the two major sources of economic performance.[2]

The greatest economists of their time have understood that technology and knowledge are important sources of economic growth and economic difference. The re-emergence of growth theory that followed the work of Romer (1990) and Grossman and Helpman (1991) has given renewed prominence to the causes of technological change. International technology diffusion, one aspect of technological change, is particularly important as the convergence (or not) of country income levels may well hinge on the degree of technology diffusion. If technology diffuses quickly and fully then country income levels are likely to converge, while if technology remains available only in the country where it was developed then country income levels may not converge.

It is clear that technology does not diffuse instantly around the world or between firms. Farmers around the world operate with both diverse levels of capital and diverse levels of technology. This is similarly true for textile production, mining, transport and many other industries. But it is also clear that there is some diffusion of knowledge across borders and between firms. History provides numerous examples such as the spread of the water wheel, wind mill and printing press through Europe or the spread of computer technology in more recent decades (Mokyr 1990). This paper is essentially an exploration into why technology may diffuse quickly to one country or region and slowly to another.

The factors that impact on technology diffusion may be broken up into two categories. Firstly, technology will only be adopted by businesses where it is likely to be profitable to do so.[3] Secondly, technology is not always diffused where it is socially profitable.

Evidence that businesses will only adopt technology if they expect to earn more profits is ubiquitous. Farmers in Indonesia do not invest in computer technology to help with their accounts or in new tractor technology to plough their fields. This is because adopting these technologies would not be profitable. Applicability to local conditions, local scale and local factor prices will all affect the profitability of new technology. For instance, where labour is abundant and cheap, adopting

[1] The author acknowledges comments from John Muelbauer, Beata Javorcik and Paul Collier and funding from the Fairfax Oxford Australia Trust and the Clarendon Foundation. This work is preliminary so please do not quote without permission.
[2] OECD 2007.
[3] Profitability considerations also include risk.

technology embedded in expensive imported capital may not be a profitable strategy.

The second attribute of technology diffusion is that technology is not always diffused where it would be socially profitable. This can reflect a large number of factors. Search costs could be restrictively high, technology may be subject to patent restrictions or other government regulations and taxes that reduce its profitability, there may be embargoes on trade such as in the case of Cuba or lack of adoption may reflect behavioural factors.

Search costs are likely to be a particularly important element in international knowledge diffusion. Numerous studies have found that knowledge diffusion is much stronger locally, suggesting that search costs matter (Audretsch and Feldman 1996, Jaffe Trajtenberg and Henderson 1993, Branstetter 2001, Keller 2002). Search costs (or information costs) have also been shown to be an important determinant of other international flows, such as cross-border equity flows and trade (Portes and Rey 2005, Rauch 2002). There are a wide variety of institutions, businesses and corporate structures that aim to minimise the search costs for new technology, including business groups, conferences and consultants.

This paper focuses only on one aspect of the technology diffusion process – the movement of knowledge across borders. There are a number of reasons to expect that technology would diffuse across borders less readily than within a country. Firstly, borders tend to reduce or restrict interactions such as trade, people movement and investment, which could be channels for knowledge transfer (McCallum 1995, Helliwell 1999). Secondly, and related to lower interactions, borders involve discrete changes in institutions, customs, protection of technology, education systems and often languages. This second set of factors may inhibit knowledge by reducing the amount of interaction between countries or by reducing the knowledge that flows from interactions.

This paper assesses international knowledge spillovers using bilateral cross-border interactions such as trade, investment and migration and potentially knowledge enhancing commonalities such as language. We are interested in the question of which interactions carry knowledge and, in future work, when do they carry the most knowledge.

There is a prima facie case from surveys of businesses that trade, investment and people movement are important in technology diffusion (Table 1). Many of these interactions are cross-border, suggesting that they could be a way through which technology moves across borders as well.

More than 40 per cent of firms in a survey across five East Asian countries reported new machinery as the most important source of technological innovation (Table 1, Brahnbhatt and Hu 2007). Much new machinery and equipment is imported, with capital equipment production being highly concentrated in a number of high income economies such as the USA, Japan and Germany (Eaton and Kortum 2001).

Cooperation with clients, parents and suppliers are also cited by firms as channels of technology diffusion (Table 1). In the case that clients, parents and suppliers are foreign firms, this would constitute a channel for movement of knowledge across borders. Firm level analysis has shown that firms achieve productivity benefits from supplying multinationals and achieve higher productivity if they are taken over by multinationals (Javorcik 2004, Aitken and Harrison 1999).

Hiring personnel is mentioned as the most important source of technological innovation by 12.2 per cent of firms surveyed in the five East Asian countries. This could also be a channel for international knowledge spillovers. The education industry is a prime example with many foreign students going to overseas universities and then taking what they have learnt back to their home countries. Return migrants have been noted as a source of entrepreneurship in Egypt and Albania, partially through the skills they have acquired overseas (McCormick and Wahba 2001, Kilic et al 2007).

But people movement could also operate in a more subtle way through establishing networks. Rauch (2002) finds that Chinese ethnic networks increase trade. Such networks could also allow access to foreign knowledge. The rise of India's IT sector partly reflects international knowledge spillovers from the US IT industry through the presence of Indian migrants in Silicon Valley, as well as an environment conducive to the use of that knowledge in India (Saxenian 2002).

International interactions in people movement, investment and trade are likely to be inter-related, and so will the movement of knowledge through each of these channels. Migration networks increase trade and FDI, probably through lowering information costs (Rauch 2002, Javorcik et al 2006). Correlations in these interactions may mean that focusing on one channel alone incorrectly attributes knowledge flow to that channel.

Table 1: Most important source of technological innovation – 2003 (% of firms)

	Average of five East Asian countries
Embodied in new machinery	43.4
Cooperation with clients	12.5
By hiring key personnel	12.2
Developed within the firm locally	11.1
Transferred from parent	7.2
Developed with supplier	5.2
Other	8.4

Notes: Countries are Cambodia, Indonesia, Malaysia, Philippines and Thailand. Source: Brahmbhatt and Hu (2007).

The outcomes of countries that have joined the European Union provides additional evidence of the benefits of integration. Countries that joined the EU appear to have achieved faster productivity growth (McGrattan and Prescott 2007). We hypothesise that part of this effect is due to technology transfer. Within the EU, trade, foreign investment and people movement have all increased. Integration has also created a common set of institutions, which could potentially enhance technology transfer.

The discussion above highlights potential channels for the diffusion of technology and knowledge internationally. These channels are much stronger locally than internationally. For instance, trade is estimated to be between 12 and 20 times more dense within a country than between countries, after accounting for geographic distance and language (Helliwell 1999, McCallum 1995). Migration is estimated to be 100 times more dense (Helliwell 1999). Indeed, previous microeconomic studies suggest that knowledge diffusion is stronger at a local level. Industries cluster not only within countries but within much smaller geographic areas. While this clustering reflects more than just knowledge spillovers, Audretsch and Feldman (1996) find that industries in which knowledge is more important cluster more. Using data on patents and patent citations, Jaffe, Trajtenberg and Henderson (1993) find that citations of patents are more likely to be in the same geographic area (narrowly defined) after allowing for the geographic concentration of technology in the area. Using data on US and Japanese firms, Branstetter (2001) finds strong evidence of intranational knowledge spillovers but not of spillovers between Japanese and US companies. Using industry level data, Keller (2002) estimates that knowledge spillovers halve at a geographic distance of 1200 kilometres.

While knowledge transmission may be weaker internationally, the macroeconomic literature has found evidence that it exists. Coe and Helpman (1995) find that the research and development stock of trading partners impacts on productivity growth in OECD countries. Although Keller (1998) suggests that while there may indeed be international knowledge spillovers, it is unclear that these reflect the pattern of international trade. There is less robust evidence of international spillovers from developed to developing countries arising through imports of machinery and equipment (Coe, Helpman and Hoffmaister 1997). Foreign direct investment has also been tentatively explored, with van Pottelsberghe de la Porterie and Lichtenberg (2001) finding that productivity is boosted by FDI outflows to knowledge rich nations but not FDI inflows from knowledge rich nations.

Schiff et al (2002) extend the analysis of trade-related technology spillovers to South-South relationships by noting that trading with a country that trades with high technology countries provides an indirect channel for the transfer of technology. Using industry level data they find that both North-South trade and South-South trade provides technology spillovers. Schneider (2005) finds that the dynamics of innovation and growth differ between developed and developing countries using aggregate country data, with intellectual property rights potentially bringing greater growth in developed countries. Finally, Engelbrecht (1997) introduces human capital into the Coe and Helpman (1995) framework and finds that it is an important determinant of productivity but has little impact on previous estimates of the impact of foreign knowledge on own productivity.

There are a number of potential weaknesses in the macroeconomic literature quantifying knowledge spillovers. Firstly, while the amount of R&D conducted by foreign countries can be reasonably viewed as exogenous, the same is not true for the amount of trade. The estimates highlighted in the knowledge spillover literature may be biased upwards because a growing country will import more. Secondly, the knowledge spillover literature does not effectively distinguish knowledge intensity of trading partners with size of trading partners. The measure of foreign knowledge used in the literature is typically business R&D stock for each trading country (multiplied by import share). Importing from the US is therefore capturing both the knowledge intensiveness of the US (measured as a high R&D stock per dollar of GDP) and its large size (measured as a high GDP). Thirdly, trade flows, which are the focus in the literature, are positively correlated with other interactions that could bring knowledge, such as migration, investment and language commonalities. If these factors are not controlled for then knowledge transmission from trade could be biased upwards.

This paper, then, seeks to improve on the weaknesses identified above in the macroeconomic literature. It has the added advantage of using an independently compiled dataset that stretches from 1980 to 2005. This allows for the possibility that the results in the previous literature were a function of the particular period and dataset used.

The previous literature has focused on the spillovers of technology gained through research and development by businesses. But clearly knowledge spillovers can be broader than this. Economically productive knowledge also includes the institutional frameworks that a country has put in place, such as regulatory policies, taxation and legal systems and research conducted in universities and the public sector. Such knowledge may also spill over between countries. The adoption of inflation targeting by central banks is a striking example of international institutional spillovers. We make some attempt to consider these issues but our focus remains on business research and development. This reflects our empirical findings.

Knowledge also stretches well beyond simply economically productive knowledge. It can include improvements in sanitation practices or environmental technology that may not increase production but will improve welfare. Knowledge spillovers may also be negative. Perhaps obesity and overwight rates in Mexico, the highest in the OECD, are a spillover from the US. Much more obvious negative spillovers are those related to conflict and the technology of weaponry. While these are interesting questions for further research, they are not investigated in this paper.

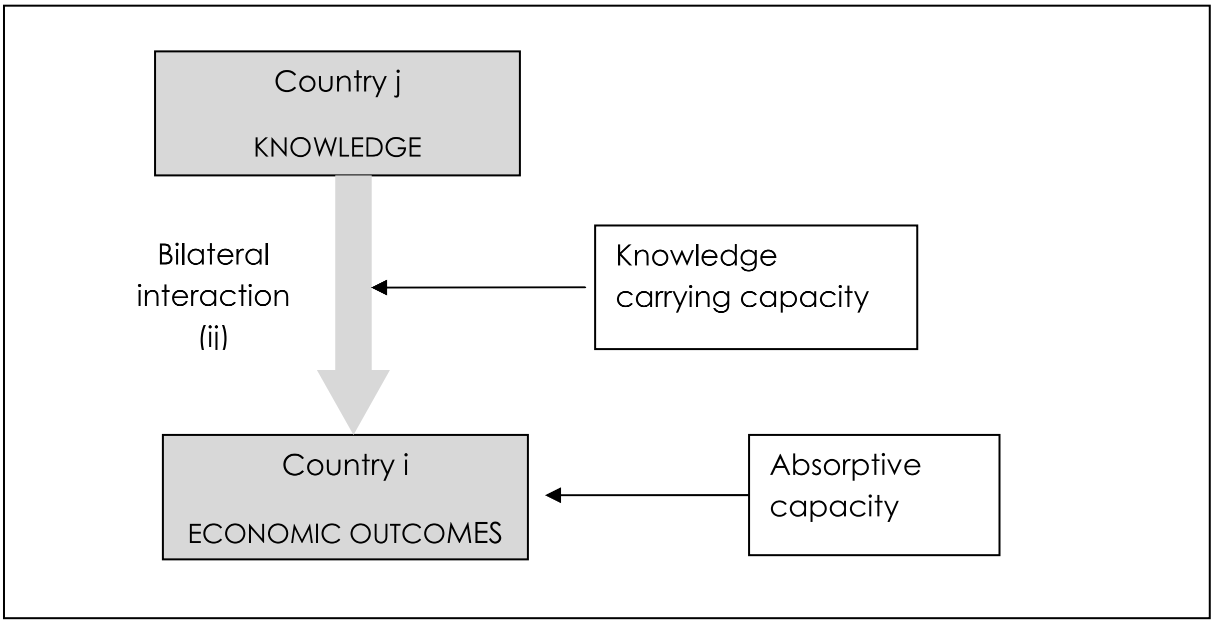
A framework for analysing international knowledge spillovers

If a country is in no way connected to the rest of the world then there is no reason to expect that knowledge can move into it. This paper therefore considers knowledge spillovers as the result of international interactions. Many international interactions are recorded, albeit with varying levels of accuracy. For instance we have data on bilateral merchandise trade flows, disaggregated into product types, data on bilateral foreign direct investment flows and stocks and data on bilateral migration flows and stocks. There are other bilateral interactions that we cannot measure that are likely to move knowledge, such as telecommunications and business trips and conferences.

A bilateral interaction has a host and a source country. The characteristics of these countries are likely to be important in the transfer of knowledge. Most obviously, the level of knowledge that the source country has must be measured in some way. A bilateral interaction also has its own particular characteristics. For instance, exports from the USA to Australia have a quite different composition to exports from the USA to Mexico.

We can combine these elements into a simple diagrammatic framework that highlights the important points to consider (Figure 1). In an ideal world an empirical specification would test how knowledge in country j flows through to outcomes in country i, using the bilateral interactions as a measure of the flow. We would also account for variability in the knowledge carrying capacity of the bilateral interaction (for instance the type of trade or education level of migrants) and the absorptive capacity of country i.

Figure 1: Framework of bilateral interactions



If we were to write such a framework in an equation, we would say that:

$$A_{i,t} = F[AC_{i,t}, KN_{j,t}, \bar{b}_{ij,t}]$$

Where A is the economic outcome in country i, AC is the absorptive capacity of country i, KN is the knowledge in country j and $\bar{b}_{ij,t}$ is the knowledge carrying capacity of a bilateral interaction between the two countries (t is time). We would expect that absorptive capacity, knowledge and the bilateral interaction would all increase the economic outcome. But we would also expect that the cross derivatives would also be positive. That is, a bilateral interaction would have a greater impact on the economic outcome if country j has more knowledge or if country i has a greater absorptive capacity.

In practice we observe bilateral interactions rather than the knowledge carrying capacity of bilateral interactions. In some cases we can make better guesses as to the knowledge carrying capacity of an interaction. For instance, we might think that imports of machinery and equipment have a different knowledge carrying capacity than imports in general.

In this paper we consider three types of international bilateral interactions.

1. Imports (in total and of machinery and equipment)
2. Foreign direct investment
3. Migration

For foreign direct investment we consider inward and outward flows and stocks. For migration we focus on outward flows and outward stocks.

Much of the previous evidence regarding these interactions has been summarised above. Here we discuss further pertinent findings that motivate our use of these interactions.

Investment in equipment has been found to be a causal determinant of productivity with a social rate of return of 30 per cent (Bradford de Long and Summers 1991). Much of this equipment is imported with the aim of accessing foreign knowledge, boosting productivity and increasing profitability. It would therefore be somewhat surprising if imports of machinery and equipment were not positively associated with productivity, even using highly aggregated data. Machinery and equipment imports could also be picking up a more general impact of openness on growth.

Potentially, both inward and outward foreign direct investment could improve technology diffusion. There is a large microeconomic literature discussing inward foreign direct investment and spillovers (Javorcik 2004, Aitken and Harrison 1999). This research suggests that inward foreign direct investment can have positive spillovers on the productivity of firms that are bought out and supplier firms, but may have negative spillovers to competing firms. Despite this distribution of impacts across firms, if foreign direct investment lowers the cost curve in the industry then this should lead to productivity gains for the country, as the products from foreign direct investment are part of the host country's GDP. These effects may be more likely to show up in aggregated data if there are spillovers to other firms.

Outward foreign direct investment may boost home country productivity if the outward investment is used to access foreign knowledge networks. For instance, Kogut and Chang (1991) find that Japanese firms invest in the US in order to share the technological capabilities of the US. In many other cases, outward foreign investment may be to take advantage of lower wages, to jump import tariffs or to serve the host country market. A priori it would appear unlikely that foreign direct investment from developed countries into developing countries is made in order to gain knowledge, but rather to utilise the knowledge advantage that multinationals possess.

Migration may be undertaken for reasons other than gaining or moving knowledge. Migration is often undertaken by individuals to achieve higher wages (or a better standard of living) or to leave a country that is going through conflict or economic downturn. Migration for education purposes may be explicitly aimed at gaining knowledge, potentially for transmission back to the home country.

We may expect that migration could be a channel for knowledge spillovers directly throughlowering search costs and establishing migrant networks. By lowering the costs of trade and investment, it may also lead to indirect knowledge spillovers (Rauch 2002).

Theory and empirical specification

We follow an aggregate production function specification to seek to understand the influence of foreign knowledge on domestic productivity similar to that employed by Coe and Helpman (1995). Specifically,

$$Y_i = A(X_i, R_i, R_i^*).K_i^{\alpha}.L_i^{\beta}$$

Where Y is GDP, K is the capital stock, L is the labour force, i is a subscript for the country and technology A depends on a set of factors X, a country's own R&D stock R (if available) and a country's access to the world R&D stock R^*. Time t subscripts have been dropped for simplicity of reading.

A country's access to the world R&D stock is not actually observed. Following the interaction specification outlined above, we consider that the greater the bilateral interaction between two countries, the greater the impact of country j's knowledge on country i's productivity. The mathematical specification we use that embeds this functional form is:

$$R_i^* = \sum_j \frac{b_{i,j}}{\overline{x}_i}.R^j$$

Here, R^j is the stock of knowledge in country j, $b_{i,j}$ is the bilateral interaction between country i and country j and $\overline{x}_i$ is a normalising variable to account for the size of country i.

We consider a number of bilateral interactions and a number of measures of the stock of knowledge as specified later in the paper.

To estimate an empirical equation we have to place more structure on total factor productivity. We specify it as:

$$A_{it} = A_i.R_{it}^{\beta}.(R_{it}^*)^{\beta^*} e^{\alpha_i t}$$

Where A_i is a country specific constant and $e^{\alpha_i t}$ allows for a country specific time trend. Our focus is on the estimation of β^*.

Estimating an aggregate production function with the inclusion of capital accumulation understates the impact of technology on production growth. This is because higher productivity increases the marginal product of capital and therefore the amount of capital that is accumulated.[4]

In our estimation we also account for other forms of knowledge and other factors that may impact on technology. These include royalty payments and remittances.

By using a linear specification of the variables, where the variables are in logs, we are assuming that the elasticity of productivity with respect to each variable does not depend on the other variables. An alternative specification, similar to that use by Keller 2002, is that:

$$A_{it} = A_t.(R_{it} + \beta^*.R^*_{it})^{\beta}$$

In this case the elasticity of productivity with respect to foreign knowledge is decreasing in home knowledge, as set out below.

$$\frac{dA_{it}}{A_{it}} = \beta.\beta^* \frac{R^*_{it}}{(R_{it} + \beta^*.R^*_{it})} \frac{dR^*_{it}}{R^*_{it}}$$

This type of specification would be estimated with a non-linear estimator such as non-linear least squares. We use both a log linear and a non-linear specification in our empirical work on own knowledge. At this stage we only present results for foreign knowledge based on a log linear specification.

Data

The dependent variable in our specifications is total factor productivity calculated using real purchasing power parity data. We use a period from 1980 to 2005.

We calculate total factor productivity (A) as the residual from a standard Cobb-Douglas Aggregate Production Function:

$$A = \frac{Y}{K^{\alpha}L^{1-\alpha}}$$

We use two measures of α . Our first measure, which generates A, allows for country heterogeneity through allowing α to vary across countries according to their wage shares of income.[5] The second measure, which generates A2, sets α equal to 0.33 for all countries, as done by Hall and Jones (1999) and Coe and Helpman (1995).

In our analysis we focus only on changes in countries across time, so we are concerned that changes within a country are accurate rather than whether comparisons between countries are accurate.

[4] The marginal product of capital is a function of technology. Therefore increased technology increases the capital stock.
[5] Details of our method for doing this are contained in the Data Appendix.

Total factor productivity outcomes have been quite varied. For OECD countries for which we have R&D data, annual productivity growth ranges from -10 per cent (Finland 1991) to +8 per cent (Ireland 1995). Annual productivity growth has averaged 0.8 per cent.

For the sample of OECD countries for which we can calculate R&D stocks, we cannot strongly reject that productivity is non-stationary (Table 2). We therefore use a change specification. We can reject a unit root in productivity growth using the Phillips Perron test but not with the Dickey-Fuller test (Table 3). Because of the low power of unit root tests and our prior that productivity growth will be stationary, we model productivity growth in OECD countries as stationary.

Table 2: Unit root tests for productivity

Variable	A	A	A2	A2
Statistic	46	32	44	32
Probability	0.05	0.49	0.08	0.48
No of Obs.	384	384	384	384
No. Of countries	16	16	16	16
Type of test	Phillips Perron	Dickey Fuller	Phillips Perron	Dickey Fuller

Notes: Null hypothesis is that variable has a unit root. ΔA is the one year change in log productivity, ΔA2 is the one year change in productivity calculated with homogenous wage share. 3 lags are used in the reported specifications. The Fisher test is based on collation of p statistics for unit root tests for each country as set out in Maddala and Wu (1999). It allows for an unbalanced panel.

Table 3: Unit root tests for productivity growth

Variable	ΔA	ΔA	ΔA2	ΔA2
Statistic	30	87	31	87
Probability	0.56	0.00	0.52	0.00
No of Obs.	368	368	368	368
No. Of countries	16	16	16	16
Type of test	Phillips Perron	Dickey Fuller	Phillips Perron	Dickey Fuller

Notes: Null hypothesis is that variable has a unit root. ΔA is the one year change in log productivity, ΔA2 is the one year change in productivity calculated with homogenous wage share. A time trend is included in all specifications.3 lags are used in the reported specifications. The Fisher test is based on collation of p statistics for unit root tests for each country as set out in Maddala and Wu (1999). It allows for an unbalanced panel.

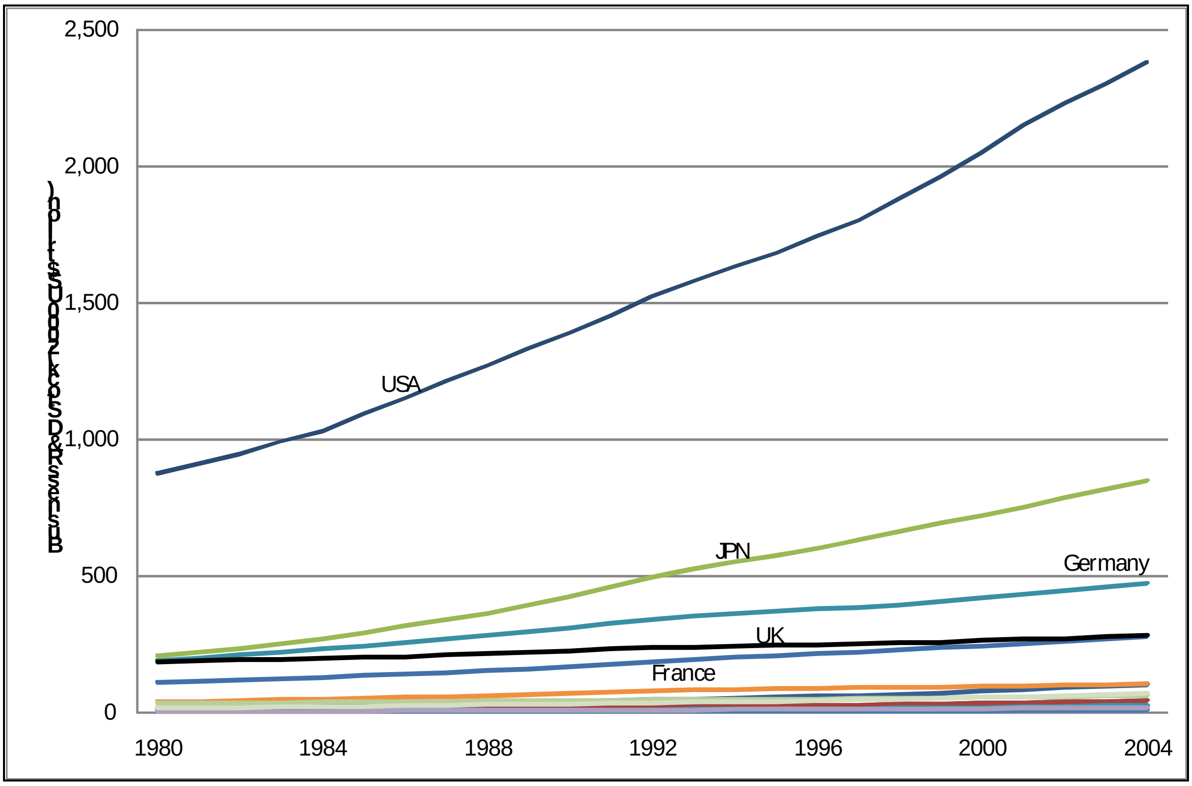
We are concerned with how knowledge impacts on economic production and therefore require a measure of knowledge. Our primary measure of knowledge stock is the cumulative investment in research and development in constant US dollars, with allowance for knowledge depreciation. Using R&D expenditures we construct two measures: one using business research and development expenditures and the second using total research and development expenditures. Business research and development expenditures are typically about half of total research and development expenditures for the countries where data is available for both. Our second measure of knowledge uses the cumulative stock of patents granted by the US and European patent offices.[6]

[6] The stock of patents may differ from the stock of patents in force, as patents last only for a specific period of time.

The striking feature of the cumulative R&D and patent measures is the concentration of `knowledge' in only a few major countries (Figure 2). Most business research and development is conducted in the USA, Japan, Germany, France and the UK (data is only available for OECD countries).[7] Patent data, which captures many more countries, presents an even more striking picture of geographic concentration of knowledge, although patents are measured as those held in Europe and the USA. The fifth ranked economy in terms of business or total R&D stock has an R&D stock per unit of GDP of only about 10 per cent of the highest ranked country. For patents the fifth ranked country has only six per cent of the patents held by the US.

The concentration of research and development activity in a handful of economies is partly due to the size of particular economies. When we deflate R&D stocks by GDP we se a more even picture of investment in new knowledge (Figure 3). Sweden is estimated to have the greatest business R&D stock as a share of GDP in 2004, at just under 30 per cent of GDP. It is closely followed by Japan, the US and Germany.

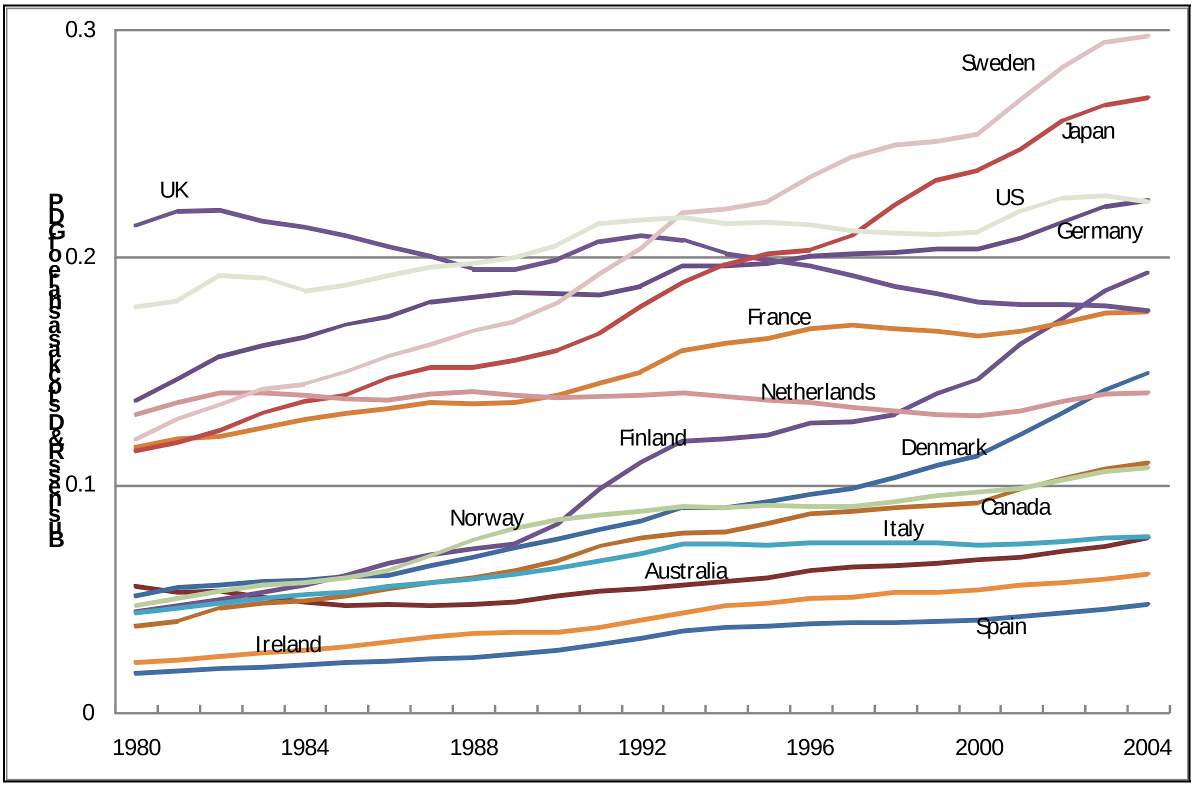
Figure 2: Business R&D stocks



Source: Author's calculations based on OECD R&D expenditure data.

[7] Other countries join this list if we use total R&D data.

Figure 3: Business R&D stocks as a share of GDP



Source: Author’s calculations based on OECD R&D expenditure data.

The previous literature has identified the accessible knowledge of a trading partner through its total R&D stock. In contrast, we focus on a measure of R&D stock deflated by country size.[8] Figures 2 and 3 highlight the difference that this makes. We identify country size as either GDP or population. Deflating by GDP makes sense when we are looking at trade and investment interactions. When we consider migration interactions R&D stock per capita is a better measure of the access to knowledge of each migrant.

The business R&D data collected by the OECD is the most internationally comparable of the data sources that we have. It is collected only for selected OECD countries, as shown in Figure 3. The total R&D measure, constructed using data from the World Bank World Development Indicators is likely to be less comparable but covers more countries. Total R&D will also include significant R&D expenditures on defence that may not be either directly economically productive or allowed to move between countries. We would also expect that total R&D may impact on productivity with a longer lag, as it covers research and development at an earlier stage in the research cycle.

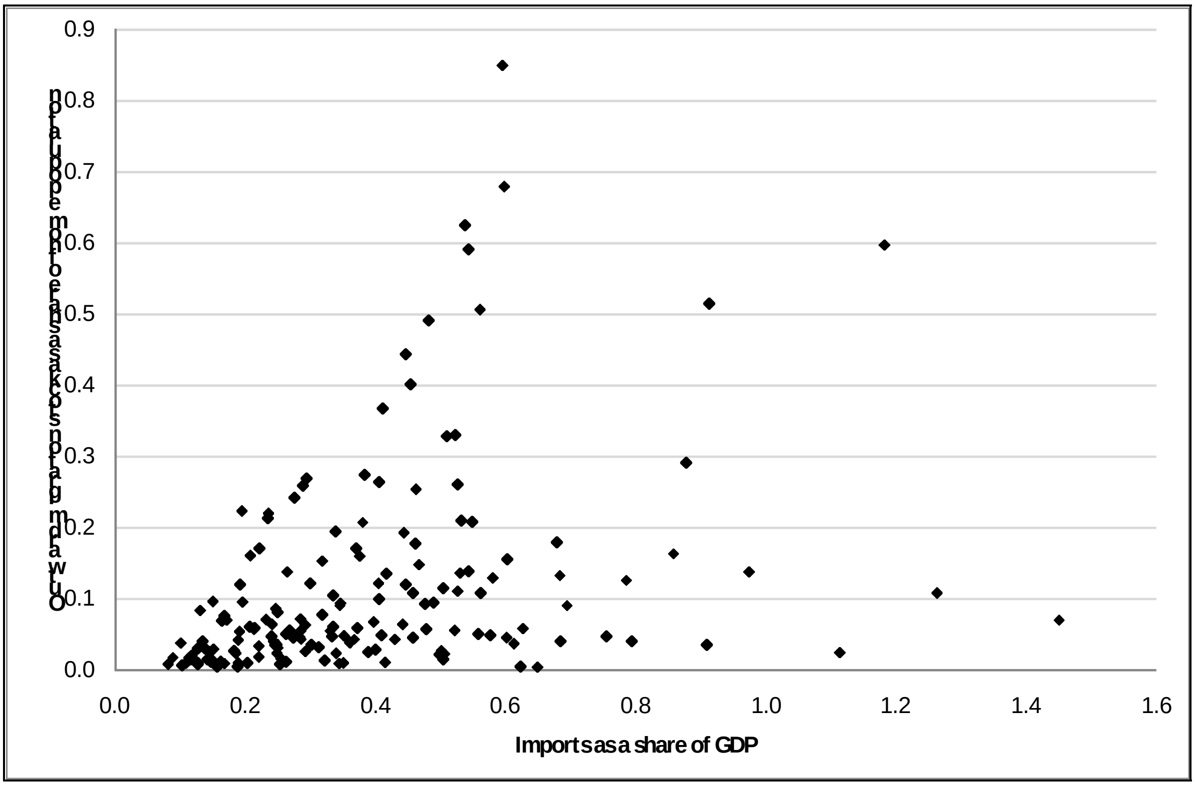
[8] Using a total R&D stock measure would only be appropriate if the economies in knowledge were so extreme that any knowledge could be applied costlessly to all areas of production. In this case each unit of a good imported from a particular country would have benefited from all knowledge in the country, regardless of the size of the country. This seems unreasonable as knowledge is often sector specific and local.

Patent data has the advantage of being available for more countries than R&D data. Patent data also represents outputs from R&D expenditure rather than inputs. However, patent data is from the US patent office and the European patent office. This is likely to bias knowledge measures towards countries in the US and Europe. Further disadvantages of using patent stock data are the substantial increase in the rate of patenting over time and that each patent can represent a very different contribution to knowledge (Hall et al 2001).

In order to understand the knowledge spillover process, we have collected data on bilateral interactions such as trade, foreign direct investment and migration. We use these to construct measures of access to foreign knowledge as discussed above. Before turning to these measures of foreign knowledge, we will consider the nature, magnitude and correlations of these bilateral linkages. For a more detailed discussion of the sources and construction of data see the Data Appendix.

Imports as a share of GDP and migration outward stock as a share of home population are positively correlated in general. For instance for all countries (not just those for which we have R&D data) the correlation is 0.34 for the year 2000 (Figure 4). The positive correlation between outward migration and imports is also evident at the bilateral level, with a correlation of 0.24. This suggests that, if outward migration does transfer knowledge back to the home country, previous estimates of the knowledge transfer through imports may be overstated.

Figure 4: Imports and outward migration stocks, 2000

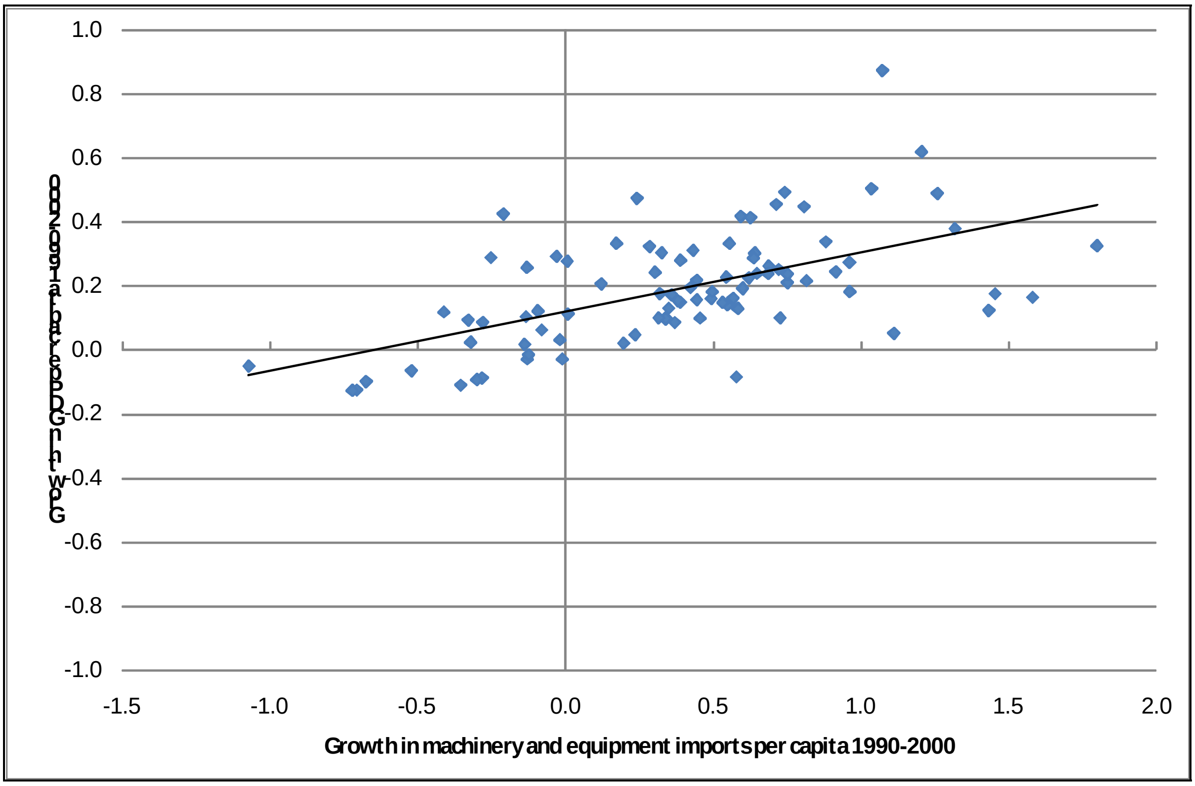


Source: Author's calculations based on DRC (2006), World Bank *World Development Indicators* and IMF *Direction of Trade Statistics*.

We intend to allow for country fixed effects in our empirical specification. We therefore rely on through time estimates of migration, trade and investment. Migration data from 1980 is available from the OECD, covering inflows, instocks and departures of foreigners. We use this to construct bilateral outflow and outstock figures for the partner countries through time. Migration data is less comparable than trade and investment data due to different definitions of foreign, different rules for granting citizenship and different methods of collecting data (OECD 2007b). Data comparability issues are minimised because we consider through time variation.

We also consider imports of machinery and equipment in our empirical specifications. Productivity effects of machinery and equipment imports could capture an inflow of knowledge embedded in machinery, general openness effects or the relationship may not be causal at all. Figure 5 shows that growth in imports of machinery and equipment is correlated with GDP per capita growth, again using all countries i the world rather than the smaller sample for which we have own R&D data.

Figure 5: Growth in imports of machinery and equipment and GDP, 1990-2000



Source: Author's calculations based on UN Comtrade import data and real purchasing power parity GDP from the Penn World Tables.

Descriptive statistics for all our variables are in the Data Appendix.

Empirical results

To estimate the impact of foreign knowledge on domestic productivity we regress the change in productivity against the change in our measures of foreign knowledge. We use a change specification to avoid non-stationarity issues that arise with estimating productivity levels. We allow for country specific productivity growth rates and for time specific productivity shocks. This means that we are focusing on variation through time in a country's change in foreign knowledge and change in productivity.

Our sample of countries is OECD countries for which we have a sufficiently long R&D stock (this includes 16 countries).[9]

Own research and development

For research and development expenditure to be valuable to other countries, it must at least be valuable to its own country. We therefore begin by testing whether there is an empirical relationship between research and development capital stocks and economic performance (Table 3). Using one year differences, our results are weak, suggesting R&D may need a longer period than one year to impact on productivity. If we use two or three year differences then we find that a 10 per cent increase in own business R&D is associated with a 2-3 per cent increase in productivity. We find no significant results for non-business R&D or for patent stocks, suggesting that business R&D is the best measure of knowledge to use. This no doubt reflects that business R&D is late in the research and development life cycle and is directly aimed at profitability. This conclusion is unaffected by using a country-specific wage share to calculate productivity (A) or using a wage share of 0.33 (A2)

Note that our specification includes both time dummies and country fixed effects. This means that we are setting quite a high bar in our estimations. We are using only through time variation for each country. The effect of a country-specific coefficient is to allow each country to not only have its own productivity level, but its own average productivity growth rate.

[9] The countries are Australia, Canada, Germany, Spain, Finland, France, UK, Ireland, Italy, Japan, Netherlands, Norway, Sweden and the USA.

Table 3: Own R&D and productivity

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Dependent variable	ΔA	ΔA	ΔA	ΔA2	ΔA2	ΔA2	ΔA
Years difference	1	2	3	1	2	3	3
Business R&D	0.220	0.298**	0.333**	0.238*	0.315**	0.349**	0.199***
	(0.127)	(0.138)	(0.149)	(0.116)	(0.127)	(0.137)	(0.056)
Non-business R&D	-0.098	-0.192	-0.195	-0.061	-0.149	-0.148	-0.119
	(0.126)	(0.142)	(0.156)	(0.117)	(0.131)	(0.143)	(0.167)
Patent stock	0.045	0.083	0.176	0.075	0.117	0.208	
	(0.138)	(0.160)	(0.163)	(0.141)	(0.161)	(0.162)	
Obs.	330	314	298	330	314	298	330
R2 (adj)	0.329	0.357	0.363	0.335	0.369	0.381	0.393

Notes: All specifications include time dummies and country fixed effects. We include only countries for which we have more than 15 years of R&D stock data. Robust standard errors in parentheses. * is significant at the 10 per cent level, ** at the 5 percent level and *** at the 1 per cent level.

Finally, by running specifications (i) to (vi) in Table 3 above we have not allowed the elasticity of productivity with respect to R&D to be dependent on the types of R&D. We would expect that, if non-business R&D is adding to the stock of knowledge, a given proportional increase in business R&D would have a smaller impact on productivity if business R&D makes up a smaller share of the total knowledge stock. To allow for this possibility we run a non-linear estimation of the change in productivity as follows:

$$\Delta lnA_{t+s,t,i} = \alpha_i + \frac{\beta_1}{K^{RDB}_{t,i} + \beta_2 K^{RDNB}_{t,i}} \cdot (\Delta K^{RDB}_{t+S,t,i} + \beta_2 \Delta K^{RDNB}_{t+S,t,i})$$

This is a three year change version of a productivity function of:

$$A_{i,t} = A_i.(K^{RDB}_{t,i} + \beta_2 . K^{RDNB}_{t,i})^{\beta_1}$$

We find that β_1, which captures the impact of research and development capital on productivity is highly significant but that β_2, which captures the contribution of non-business R&D is not significantly different to zero (specification vii, Table 3).

The results above suggest that countries that have increased their business R&D stock have had higher growth. We also test whether having a high R&D share in GDP increases future growth by estimating:

$$A_{i,t+S} - A_{i,t} = \alpha_i + \beta . \frac{KN_{i,t}}{Y_{i,t}} + D_t$$

Where A is the log of total factor productivity, α_i is a country specific effect, KN is knowledge, Y is GDP and D captures time dummies. S is the number of periods we use to estimate the change in productivity. The results are shown in Table 4, using only business knowledge given the results from Table 3. These results confirm that business R&D intensity is associated with higher future growth. The results are much stronger when we use longer changes, indicating that R&D intensity does not necessarily flow instantly into higher productivity, as we also found in Table 3.

Table 4: Own R&D and productivity

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Dependent variable	ΔA	ΔA	ΔA	ΔA2	ΔA2	ΔA2
Years difference/lag	1	2	3	1	2	3
Business R&D intensity	0.019*	0.046**	0.080**	0.016	0.041*	0.072*
	(0.0090)	(0.021)	(0.034)	(0.0096)	(0.022)	(0.034)
Obs.	362	346	330	362	346	330
R2	0.333	0.355	0.349	0.330	0.351	0.345

Notes: All specifications include time dummies and country fixed effects. We include only countries for which we have more than 15 years of R&D stock data. Robust standard errors in parentheses. * is significant at the 10 per cent level, ** at the 5 percent level and *** at the 1 per cent level.

Foreign research and development

Robustly assessing the impact of own research and development expenditures on growth is complicated by the simultaneity of research and development expenditure and growth. For instance, it is quite plausible that a process of industrialisation increases both research and development expenditure and growth without implying causality. It is similarly plausible that growth leads to demand for research intensive products such as pharmaceutical products, thereby implying causality from growth to R&D. Griliches (1979) discusses these issues in some detail. We have not attempted to deal with these issues above because the focus of our analysis is the transmission of knowledge across borders.

It is a reasonable assumption that foreign research and development is exogenous to home production or production growth, particularly for small countries.[10] We would expect US research and development trajectories to be largely determined by US specific factors. In the case of large countries it is possible that income growth could increase the profitability of foreign R&D by increasing the demand for the products that result from R&D. It is a simple matter to control for this in empirical analysis.

While foreign R&D might be reasonably assumed to be exogenous, access to foreign R&D might not. Our measure of foreign R&D relies on bilateral interactions that proxy for access to foreign R&D that may be endogenous to home production growth. For instance, consider imports of machinery and equipment as a proxy for access to foreign knowledge. Our specification only allows for imports of machinery and equipment to be a driver of production levels, through increasing productivity. But it is plausible, and even likely, that production levels lead to higher incomes, and in turn this leads to higher demand for imports, including imports of machinery and equipment.

[10] In the case of large countries it is possible that income growth could increase the profitability of foreign R&D by increasing the demand for the products that result from R&D.

This is not in itself a problem as access to foreign knowledge relies on the share of machinery and equipment imports in production, rather than the level of machinery and equipment imports. The openness and growth literature has a lot to say about these issues of causality. Frankel and Romer (1999) find that OLS estimates of the effect of openness on growth are not upwardly biased, by using geographic information as instruments. But, as with any instrument, people have questioned its validity. There is no clear cut solution then that emerges from this literature.

In our baseline specifications we adopt a two pronged strategy. Firstly, by using a change specification and country fixed effects we are removing any correlation between trade and production that is driven by fixed factors. Secondly, to ensure that we are not capturing a general openness measure as part of our knowledge measures, we also include separate variables for openness in our regressions that are unrelated to the direction of trade.

Baseline results

Our baseline specification for OECD countries has three sets of variables.

1. Own research and development variables.
2. Openness variables.
3. Foreign knowledge variables.

We use own business R&D stocks as the own knowledge variable as it was found to be the most correlated with own growth above. We adopt a lag of three years again based on the work above. It appeared that three years was a sufficient time period to capture changes in own R&D. If international technology diffusion is not much slower then we will also capture these effects using a three year change. Our errors will be autocorrelated as we are using an overlapping sample. We control for this by using standard errors that are robust to this.

We use openness variables that capture openness to trade and investment. These are the share of machinery and equipment imports in GDP, the share of imports in GDP, FDI outward stock and FDI inward stock (in levels or share of GDP depending on the specification). We do not use a general openness measure for migration outstock in our baseline specification as the change in outward migration is unlikely to be positively correlated with changes in income and we do not know total migration outward stocks to all countries in the world.

Our variables of interest are those that capture foreign knowledge. The construction of these variables has been discussed in detail above and in the Data Appendix. To briefly reiterate, foreign knowledge can rise either because the foreign countries that you interact with make investments in knowledge or because you interact more with these foreign countries. We also include a variable that captures royalty payments – i.e. buying knowledge directly.[11]

Specification (i) in Table 5 replicates the own R&D result from above. Specification (ii) includes openness variables. We can see that changes in machinery and equipment imports are positively and significantly associated with changes in productivity. This could be because machinery and equipment imports allow firms to increase their technological capacity, or it could reflect a changing industrial structure. The other openness variables are either insignificant or only weakly significant.

Specifications (iii) and (iv) add in foreign knowledge variables. (iii) includes all variables while in (iv) we remove less significant variables to provide more degrees of freedom.[12] We see no evidence that trade with high knowledge countries is more important than trade in general. The productivity effects are likely to be the same whether Australia imports $100 more in machinery and equipment from the US (a high knowledge country) or from China (which has zero knowledge in our specification). This is not surprising if the value of a machine captures its productivity effects. We find a negative and significant coefficient on foreign knowledge from investment inward stock, while there is a positive effect of FDI inward stock in general. This is something of a puzzle, as we would expect a priori that greater inward investment from the US would bring potential technological gains relative to inward investment from China or Australia. Or it could be that royalty payments are a better measure of the technology gains from inward FDI than the amount of FDI – although the coefficient on royalty payments is positive it is not statistically different to zero.[13] Note that the countries in this sample are highly developed. For these countries FDI is often cross-border mergers and acquisitions rather than Greenfield. Investment may also be more likely to be used to access foreign markets rather than to utilise technological comparative advantage. The positive coefficient on outward FDI mirrors the findings of van Pottelsberghe de la Potterie et al (2001) for foreign investment flows.

Finally, and of most interest to us, outward migration is found to be positively associated with productivity. This suggests that migration may be an important channel for knowledge spillovers for highly developed countries, beyond the knowledge spillover effects that it has through promoting trade and foreign direct investment.

[11] Royalty payments may also be used by firms in intra-firm transfer pricing schemes as a way of minimising taxes.

[12] We also remove import share as openness should be as well captured through machinery and equipment imports.

[13] For instance Ireland in 2000 had an FDI inward stock of 130 per cent of GDP and its royalty payments were over 8 per cent of GDP, the highest of any country.

Table 5: Foreign R&D and productivity, OECD countries

	(i)	(ii)	(iii)	(iv)
Dependent variable	ΔA	ΔA	ΔA	ΔA
Years used for difference	3	3	3	3
Own business R&D	0.259**	0.165**	0.140***	0.167***
	(0.120)	(0.058)	(0.033)	(0.044)
Openness variables				
Machinery & equip imports as share of GDP		0.189***	0.111*	0.102***
		(0.051)	(0.056)	(0.025)
Imports as a share of GDP		-0.140*	-0.125*	
		(0.070)	(0.064)	
FDI outward stock		0.0189	0.032	0.034
		(0.017)	(0.024)	(0.023)
FDI inward stock		-0.006	-0.011	-0.016
		(0.018)	(0.012)	(0.013)
Foreign knowledge measures				
Royalty payments			0.027	0.022
			(0.016)	(0.015)
Machinery and equip imports			0.047	
			(0.049)	
Imports			0.024	
			(0.064)	
Investment inward stock			-0.014**	-0.017*
			(0.006)	(0.008)
Investment outward stock			0.024***	0.023***
			(0.006)	(0.007)
Migration outward stock			0.047*	0.045**
			(0.026)	(0.020)
N	330	282	239	239
adj. R-sq	0.351	0.493	0.570	0.552

Notes: All specifications include time dummies and country fixed effects. We include only countries for which we have more than 15 years of R&D stock data. The sample changes due to data availability. Robust standard errors in parentheses. * is significant at the 10 per cent level, ** at the 5 percent level and *** at the 1 per cent level.

To test the robustness of the coefficient on migration we undertake a number of checks. Firstly, we remove countries one by one to see whether this effect is purely from one country. This is not the case with the coefficient remaining significant and very close to its level with the full sample. Secondly, we add in the change in remittances to see whether having a large migration outward stock brings not knowledge but finance. We find that this does not change our results – the coefficient on remittances is positive but not significant (Table 6). Third, we use our second measure of productivity. This does not change our results (Table 6).

Table 6: Robustness checks on knowledge through migration

	Base	Including remittances	Using A2
Foreign knowledge through migration			
Coefficient	0.045**	0.043**	0.040*
Standard error	(0.020)	(0.019)	(0.020)

Notes: The specification includes all variables in specification iv of the preceding table. Robust standard errors in parentheses. * is significant at the 10 per cent level, ** at the 5 percent level and *** at the 1 per cent level.

Unreported robustness checks include adding in a measure of foreign knowledge based on language commonalities, distance or neighbour countries. These measures do not change the coefficient on migration although the language and neighbour measures make it less significant. This is not surprising given that migration patterns are much stronger between neighbours such as the US and Canada and countries with the same language. Interestingly, the knowledge measure based on distance is negative once interaction variables are included. This suggests that our interaction framework provides a better measure of knowledge diffusion than a purely spatial model such as used by Keller (2002).

Interpreting the migration coefficient

The estimated coefficient on migration outward stock is about 0.04. This would mean that a 10 per cent increase in the knowledge stocks of all the countries that your citizens have migrated to is associated with a 0.4 per cent increase in productivity. Alternatively, increasing the number of migrants that you have in these countries could increase productivity by a similar amount. This only reflects the knowledge gained directly from migration rather than indirectly through increased trade and investment. In comparison, according to our own R&D estimates, a 10 per cent increase in own knowledge stock leads to productivity growth of 1.5 percent. This suggests that the transfer of knowledge through migration outward stocks is economically important, although much weaker than the domestic effects of knowledge generation.

Discussion and conclusions

Outward migration to high knowledge countries appears to be a channel through which a country may be able to gain access to international knowledge stocks directly and indirectly. Knowledge may flow directly through migration networks. Case study evidence of these effects is easy to find, notably the presence of Indian and Chinese migrants in Silicon Valley allowing these countries to build their own IT industries. Knowledge may also flow indirectly with migration linkages strengthening trade and investment.

We have shown the association between migration outward stocks and productivity growth for OECD economies. These effects may be even more important for developing economies, which is the subject of our current research efforts. For developing countries, home conditions may be particularly important for gaining knowledge from migration. For instance, home education levels and the business environment could influence whether migrant networks can be used as a vehicle for knowledge transfer. Exploring these effects quantitatively is part of our ongoing research.

Growth in machinery and equipment imports as a share of GDP is also associated with productivity growth. This is also likely to capture in part knowledge transfer effects. We find no evidence that the source of machinery and equipment matters – rather it is the value of machinery and equipment imports that is associated with productivity growth.

References

Aitken, B. and A. Harrison (1999), "Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela", *The American Economic Review*, Vol. 89, No. 3., pp. 605-618.

Audretsch, D. and M. Feldman (1996), "R&D Spillovers and the Geography of Innovation and Production", *The American Economic Review*, Vol. 86, No. 3., pp. 630-640.

Barro, R. and J-W. Lee (2000), "International Data on Educational Attainment: Updates and implications", *Centre for International Development at Harvard University Working Papers*, No. 42, April.

Bradford de Long, J. and L. Summers (1991), "Equipment Investment and Economic Growth", *The Quarterly Journal of Economics*, Vol. 106, No. 2., pp. 445-502.

Brahmbhatt, M. and A. Hu (2007), "Ideas and Innovation in East Asia", *World Bank Policy Research Working Papers*, No. 4403, November.

Branstetter, L. (2001), "Are Knowledge Spillovers International or Intranational in Scope? Microeconomic evidence from the U.S. and Japan", *Journal of International Economics*, Vol 53, pp. 53-79.

Coe, D. and E. Helpman (1995), "International R&D Spillovers", *European Economic Review*, Vol. 39, pp. 859-887.

Coe, D., E. Helpman and A. Hoffmaister (1997), "North-South R&D Spillovers", *The Economic Journal*, Vol. 107, No. 440, pp. 134-149.

Eaton, J. and S. Kortum (2001), "Trade in Capital Goods", *European Economic Review*, Vol. 45, pp. 1195-1235.

Engelbrecht, H-J. (1997), "International R &D spillovers, human capital and productivity in OECD economies: An empirical investigation", *European Economic Review*, Vol. 41, pp. 1479-1488

Frankel, J. And D. Romer (1999), "Does Trade Cause Growth?", *The American Economic Review*, Vol. 89, No. 3., pp. 379-399.

Golub, S. (2003), "Measures of Restrictions on Inward Foreign Direct Investment for OECD Countries", *OECD Economics Department Working Papers*, No. 357, June.

Griliches, Z. (1979), "Issues in Assessing the Contribution of Research and Development to Productivity Growth", *The Bell Journal of Economics*, Vol. 10, No. 1., pp. 92-116.

Grossman, G. and E. Helpman (1991), "Quality Ladders in the Theory of Growth", *The Review of Economic Studies*, Vol. 58, No. 1., pp. 43-61.

Hall, B., A. Jaffe and M. Trajtenberg (2001),"The NBER Patent Citations Datafile: Lessons, Insights and Methodological Tools", *NBER Working Papers*, No. 8498, October.

Hall, R. and C. Jones (1999), "Why Do Some Countries Produce So Much More Output Per Worker Than Others?", *The Quarterly Journal of Economics*, Vol. 114, No. 1. pp. 83-116.

Helliwell, J. (1997), "National Borders, Trade and Migration", *NBER Working Papers*, No. 6027, May.

Heston, A., R. Summers and B. Aten (2006), Penn World Table Version 6.2, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, September.

Jaffe, A., M. Trajtenberg and R. Henderson (1993), "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations", *The Quarterly Journal of Economics*, Vol. 108, No. 3., pp. 577-598.

Javorcik, B. (2004), "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers through Backward Linkages", *The American Economic Review*, Vol. 94, No. 3., pp. 605-627.

Javorcik, B., C. Ozden, M. Spatareanu and C. Neagu (2006), "Migrant Networks and Foreign Direct Investment", *World Bank Policy Research Working Papers*, No. 4046, November.

Keller, W. (1998), "Are international R&D spillovers trade-related? Analysing spillovers among randomly matched trade partners", *European Economic Review*, Vol. 42, pp. 1469-1481.

Keller, W. (2002), "Geographic Localization of International Technology Diffusion", *The American Economic Review*, Vol. 92, No. 1., pp. 120-142.

Kilic, T., G. Carletto, B. Davis and A. Zezza (2007), "Investing Back Home: Return Migration and Business Ownership in Albania", *World Bank Policy Research Working Papers*, No. 4366.

Kogut, B. and S. Chang (1991), "Technological Capabilities and Japanese Foreign Direct Investment in the United States", *The Review of Economics and Statistics*, Vol. 73, No. 3., pp. 401-413.

Lederman, D. and L. Saenz (2005), "Innovation and Development around the World: 1960-2000", *World Bank Policy Research Working Papers*, No. 3774, November.

McCallum, J. (1995), "National Borders Matter: Canada-U.S. Regional Trade Patterns", *The American Economic Review*, Vol. 85, No. 3., pp. 615-623.

McCormick, B. and J. Wahba (2001), "Overseas Work Experience, Savings and Entrepreneurship Amongst Return Migrants to LDCs", *Scottish Journal of Political Economy*, Vol. 48, No. 2, pp. 164-178.

Mayda, A. (2007), "International Migration: A panel data analysis of the determinants of bilateral flows", *Centre for Research and Analysis of Migration Discussion Papers*, No. 07/07.

Mokyr, J. (1990), *The Lever of Riches: Technological Creativity and Economic Progress*, Oxford University Press: New York.

OECD (2007), *OECD Science, Technology and Industry Scoreboard 2007: Innovation and performance in the global economy*, OECD: Paris.

OECD (2007b), *International Migration Outlook*, SourceOECD.

Parsons, C., R. Skeldon, T. Walmsley and L.A. Winters (2007), "Quantifying International Migration: A Database of Bilateral Migrant Stocks", *World Bank Policy Research Working Papers*, No. 4165, March.

Portes, R. and H. Rey (2005), "The determinants of cross-border equity transaction flows", *Journal of International Economics*, Vol. 65, pp. 269-296.

van Pottelsberghe de la Porterie, B. and F. Lichtenberg (2001), "Does Foreign Direct Investment Transfer Technology Across Borders?", *The Review of Economics and Statistics*, Vol. 83, No. 3, pp. 490-497.

Rauch, J. (2002), "Ethnic Chinese Networks in International Trade", *The Review of Economics and Statistics*, Vol. 84, No. 1., pp. 116-130.

Romer, P. (1990), "Endogenous Technological Change", *The Journal of Political Economy*, Vol. 98, No. 5, pp. S71-S102.

Saxenian, A. (2002), "Brain Circulation: How High-Skill Immigration Makes Everyone Better Off", *The Brookings Review*, Vol.20 No.1, pp. 28-31.

Schiff, M. Y. Wang and M. Olarreaga (2002), "Trade-Related Technology Diffusion and the Dynamics of North-South and South-South Integration", *World Bank Policy Research Working Papers*, No. 2861, June.

Schneider, P. (2005), "International trade, economic growth and intellectual property rights: A panel data study of developed and developing countries", *Journal of Development Economics*, Vol. 78, pp. 529-547.

Solow, R. (1957), "Technical Change and the Aggregate Production Function", *The Review of Economics and Statistics*, Vol. 39, No. 3., pp. 312-320.

Data Appendix

The following Appendix details data sources and methods of calculation.

Physical capital stock

Physical capital stock is calculated through the perpetual inventory method. We set an initial capital stock equal to 1.6 times GDP in 1950. This assumption is relatively unimportant as our analysis uses data 30 years after the beginning of the capital stock series (for most countries). The initial capital stock figure is derived from the capital stock to GDP ratio at the end of our period (2004) that follows from almost any initial capital stock assumptions.[14]

The capital stock in each year after 1950 is then:

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

We set $\delta = 0.06$ following Hall and Jones (1999). We do not allow the depreciation rate to vary by country or by year.

For countries whose investment series begin later than 1950 we begin their capital stocks at 1.6 times GDP whenever their investment data becomes available.

Investment is from the Penn World Tables (Heston, Summers and Aten 2006). We use the series of the investment share of real GDP multiplied by real purchasing power parity GDP. The Penn World Tables investment share of GDP uses a specific deflator for investment. The capital stock is therefore in purchasing power parity terms.

Labour

Labour is taken as the labour force share times the population. The labour force share and population data are from World Bank World Development Indicators.

GDP

GDP is in purchasing power parity terms from the Penn World Tables (Heston, Summers and Aten 2006).. The series in the real GDP per capita, in 2000 dollars, calculated using chain indices. We multiply it by population from the World Bank to get total real GDP.

Wage share

The wage share is calculated using the average compensation of employees as a share of GDP for the 30 years to 1997. The data series does not continue beyond 1997. This data is from the UN National Accounts, *Household income, current, employee compensation, national currency, current prices (SNA 68, discontinued) [code 21310].* Data is available for 74 countries, for varying time periods.

[14] We are implicitly assuming that the capital stock to GDP ratio stays relatively constant through time by using our end of period figure as a proxy for our start of period figure.

Wage share tends to rise as per capita GDP rises. We therefore interpolate to other countries by assuming a linear relationship between the wage share and log of per capita real GDP in 2000.

Total factor productivity

Total factor productivity (A) is calculated as:

$$A = \frac{Y}{K^{\alpha} L^{1-\alpha}}$$

We use the wage shares, labour and capital figures discussed above. GDP is in purchasing power parity terms from the Penn World Tables.

Research and development capital stock

Business R&D

Business R&D is from the OECD Science, Technology and R&D online database, accessed through Source OECD. Data is in current US$ and is converted into purchasing power parity by assuming that business R&D as a share of current GDP is the same as business R&D as share of real purchasing power parity GDP. We are therefore using the same price index (in purchasing power parity) for GDP as for research and development expenditure.

Total R&D

Total R&D is from the World Bank World Development Indicators. We convert it into purchasing power parity terms by assuming that R&D expenditure as a share of GDP is the same in current prices as in real purchasing power parity prices.

Constructing research capital stocks

Capital stocks are constructed using the perpetual inventory method in a similar fashion as the physical capital stock. Because the data series has a more recent start date (1973 for business R&D), we calculate initial R&D capital by assuming that R&D has grew at the rate achieved in the 10 years since data was available, in the years prior to when data became available.

The R&D capital stock in 1973 is then calculated as:

$$K_0^{RD} = \frac{RD_{1973}}{g + \delta}$$

g is the annual growth from 1973 to 1983 of R&D in real terms. If g is calculated as less than zero then we set it to zero.

We assume that R&D depreciates at a rate of five per cent per year, as in Coe and Helpman (1995).

Patent stocks

Patent stock data is from the World Bank *Innovation and Development Database* (Lederman and Saenz 2005). Patent stocks are accumulated patents from the US

Patent Office and European Patent Office (summed together). The World Bank allocates patents to a country based on the country of residence of the first inventor.

Foreign R&D capital stock

Foreign R&D capital stock is calculated as a weighted average of bilateral relationships and knowledge of foreign countries, as follows.

$$K^{*}_{i,t} = \sum_{j} \frac{x_{i,j,t}}{\bar{x}_{i,t}} . K_{j,t}$$

Where $x_{i,j,t}$ is the bilateral interaction between countries i and j at time t, $\bar{x}_{i,t}$ is a normalising variable, $K_{j,t}$ is the level of knowledge of country j at time t and $K^{*}_{i,t}$ is the foreign knowledge stock of country i at time t.

We try a number of specifications of both the bilateral interactions and the knowledge variable. Our preferred specifications use:

- Migration outward stocks, as a share of population, with foreign knowledge being R&D capital stock per person;
- Imports of machinery and equipment as a share of GDP, with foreign knowledge being R&D capital stock per unit of GDP:
- FDI flows or stocks as a share of GDP, with foreign knowledge being R&D capital stock per unit of GDP.

Trade

Bilateral import data is from the IMF *Direction of Trade Statistics*.

Bilateral imports of machinery and equipment data is from the UN *Comtrade database*. Machinery and equipment is SITC Code 7, Machinery and Transport Equipment.

Migration

Bilateral migration data is from the OECD *Database on International Migration*. Data are from 1980 to 2005. A number of OECD countries report the number of people of each nationality living in their country, who have just migrated to their country or who have just left their country. Using this, we construct data for non-OECD countries on migrant outstocks and migrant outflows. OECD data are likely to miss illegal immigration. Some countries report migrants by nationality and others by country of birth. We use nationality figures by preference but use country of birth if this is not available.

We also use a more comprehensive picture of bilateral migration stocks only available for 2000 from the Development Research Centre on Migration, Globalisation and Poverty (Parsons et al 2007). This is based on census data and covers bilateral migration stocks between 206 countries.

Foreign direct investment

Foreign direct investment data is from OECD, UNCTAD and ASEAN. Data is in US$ current. OECD *International Direct Investment Statistics* from Source OECD, UNCTAD FDI data are from *UNCTAD FDI Country Profiles*. ASEAN data are from *ASEAN Foreign Direct Investment Statistics*.

Where bilateral data is reported only by one country we use this as a mirror value for the other country. Where bilateral data is reported by both we use the data reported by a country in the calculation of its own foreign R&D stocks. Where bilateral data is available from more than one source we use OECD first, UNCTAD second and ASEAN third.

Total FDI figures are from UNCTAD *World Investment Report Annex Tables*. They are in current US$.

FDI figures cover inward flows, inward stocks, outward flows and outward stocks. Flow figures can be negative. We convert figures into purchasing power parity by assuming that the direct investment share of current US$ GDP is the same as the direct investment share or real purchasing power parity GDP.

Language and distance

We take official and ethnic language commonalities and bilateral distance from the CEPII (www.cepii.fr). We use a measure of bilateral distance that captures distance between a number of major cities.

Royalty payments and remittances

Royalty payments and remittances data are in current US$ from the World Bank World Development Indicators. We convert it to a share of GDP using current US$ GDP also from the World Bank World Development Indicators. We then convert it to real purchasing power parity by multiplying it by purchasing power parity GDP.

Country classifications

Country income and region classifications are from the World Bank.

Descriptive statistics

Table A1: Descriptive statistics for variables

Variable	Measure	Obs	Mean	Std. Dev.	Min	Max
Productivity	Level	384	251	132	100	606
	One period change	368	0.01	0.02	-0.10	0.08
	Two period change	352	0.02	0.04	-0.16	0.14
	Three period change	336	0.03	0.05	-0.20	0.22
Productivity2	Level	384	1346	195	952	2011
	One period change	368	0.01	0.02	-0.10	0.08
	Two period change	352	0.02	0.04	-0.15	0.14
	Three period change	336	0.04	0.05	-0.19	0.22
Machinery and equipment imports as a share of GDP	Level	370	0.08	0.05	0.01	0.28
	Three period change	320	0.07	0.18	-0.63	0.66
Imports as a share of GDP	Level	384	0.24	0.12	0.06	0.86
	Three period change	334	0.01	0.13	-0.57	0.33
Business R&D capital stock	Share of GDP	394	0.12	0.07	0.02	0.30
	Three period change	346	0.17	0.07	-0.01	0.38
FDI inward stock as a share of GDP	Level	416	0.21	0.31	-0.11	1.85
	Three period change	346	0.21	0.27	-0.59	1.26
FDI outward stock as a share of GDP	Level	411	0.19	0.19	-0.04	1.06
	Three period change	341	0.27	0.28	-0.51	1.25
Royalties	Three period change	302	0.20	0.27	-0.56	1.07

Notes: Change is change of log of variable rather than proportional change.