Opening the Innovation Frontier: Technological Innovation, the Global Pursuit of Knowledge, and Sophisticated Competition

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Abstract
Innovation in technology intensive industries requires direct engagement in the global economy, which includes significant opportunities for access to knowledge and competition engendered in international trade. In this paper, I examine the relationship between domestic innovation and foreign technological activity as mediated through channels of international trade. I build on an established model of innovation in the global economy combined with a novel measure of relative industry strength. I argue that the strategic capabilities in relatively strong industries will be different from those in relatively weak industries. I test these relationships empirically using panel data from four high-technology industries over the period 1973-2001. The results in this paper point to a significant relationship between innovation and international technology diffusion through both exports and imports, and suggest that these two channels might contribute in opposite directions. Second, the results from this analysis strongly suggest that foreign technological activity may have both positive and negative effects for a technologically advanced nation, such as the US. This paper suggests that relative industry strength can play a significant role in mediating the relationship between foreign R&D and domestic innovation through differential impact of international trade.

Keywords: Innovation, International Trade, Revealed Comparative Advantage, R&D
1. Introduction

Innovation in high-technology industries depends on the ability to utilize diverse ideas and to embody knowledge in new or better products or processes, enabling the firm to sustain competitive advantage in a dynamic environment. The literature suggests that foreign technological activity can impact innovation by both domestic and foreign firms. A growing literature identifies foreign technological change as an important source of domestic productivity growth (Gong and Keller, 2003). Knowledge spillovers implicitly underlie the rationale for knowledge-based sourcing by multinational companies. At the firm and industry level, knowledge spillovers implicitly are a driving force in agglomeration tendencies of multinational companies (Feinberg and Majumdar, 2001; Hejazi and Safarian, 1999; Liu et al., 2000). A large literature on the location decisions of multinational enterprises increasingly identifies knowledge seeking as a primary determinant in location choice as well as acquisition (Chung, 2001; Kuemmerle, 1998; Nachum and Wymbs, 2005; Nachum and Zaheer, 2005). Knowledge spillovers have been shown to drive agglomeration tendencies of multinational companies (Chang and Park, 2005; Shaver and Flyer, 2000).

The economics literature explicitly identifies international trade as a significant channel for international technology diffusion. International trade theory suggests that imports and exports are potential channels for the international transmission of knowledge spillovers through reverse engineering, proof of concept, and contact in the normal course of business (Grossman and Helpman, 1995). Empirical studies suggest that R&D from other nations contributes to domestic innovation (Coe and Helpman 1995; Keller 2001, 2002; Connolly 1998; Bernstein and Mohnen 1998; and Nadiri and Kim 1996). At best, foreign R&D potentially represents an expanded pool of knowledge available to domestic firms.

At the same time, in a world of technological competition and R&D rivalry foreign technological activity might also adversely impact domestic innovation. The economics literature on innovation recognizes potentially harmful effects of one firms’ R&D activities on another firm, e.g., in the context of R&D duopoly (Scherer and Ross, 1990; Spencer and Brander, 1983) and shown empirically (Scherer and Huh, 1992). The literature on technology races confirms this view (Lerner, 1997). Industrial organization theory suggests that R&D impacts rivals through competition, which can have both positive and negative effects (Scherer
and Ross, 1990). Intuitively, international trade widens the competitive pool. Import competition has been shown to introduce greater disruptive effects on a firm’s core business than strictly domestic competition (Bowen and Wiersema, 2005). Thus, the interaction of international trade and foreign R&D might have a negative impact on domestic innovation. This negative impact can occur through outright competition including increased technical sophistication in foreign products, increased foreign absorptive capacity, and the threat of increased capabilities by foreign competitors. Indeed, recent empirical work suggests that international R&D spillovers can be harmful to the US (Luintel and Khan, 2004).

This paper builds on the international economics and management literature and bridges a gap between them by directly addressing the interaction of foreign technological activity and international trade in relation to domestic innovation. In the next section, I discuss the tension between the opportunities presented by greater global stocks of knowledge which can contribute to domestic innovation and the challenges posed from increasingly sophisticated foreign competition. I develop hypotheses that incorporate these tensions in the context of the different capabilities present in relatively strong or relatively weak industries. I posit that the strategic capabilities in a relatively strong industry will be different than those in a relatively weak industry, and that the potential upside and downside of globally available knowledge through channels of international trade will thus be different depending on relative industry strength. I then implement a widely used structural model of innovation in a global setting rooted in international trade theory to test these hypotheses and draw conclusions about the relationship between domestic innovation and the interaction of foreign technological activity with international trade.

I test these relationships empirically using panel data on four high-technology industries in the U.S over the period from 1973-2001: computer equipment, communications equipment, household audio and video equipment, and scientific instruments. The selection of industries and the panel setting allow me to discern the contrasting outcomes in industries which exhibit a range of technological maturity and global competitiveness. The insights from the regression analysis are complemented by mini-case studies of each of these industries.

Taken together, the results of this paper suggest that increasing foreign R&D can be a source of knowledge and a source of sophisticated customers, but by its nature creates
increasingly sophisticated competition. The main empirical results strongly suggest that foreign R&D has the greatest impact in relatively strong industries, and might have a detrimental effect in weaker industries. Moreover, the empirical results point to a positive relationship between foreign R&D and domestic innovation that is increasing as exports increase, particularly in relatively strong industries. Finally, the empirical results provide mixed evidence on the relationship between domestic innovation and increasingly sophisticated import competition. This paper thus suggests that international trade at the industry level shapes the strategic environment of firms through competition and through opportunities for learning or knowledge spillovers.

2. Theory and hypotheses

2.1. Foreign R&D

What is the relationship between increasing foreign investment in technological capability and domestic innovation? The economics literature identifies the centrality of R&D spillovers between nations as a driver of productivity growth (Griliches, 1998b; Grossman and Helpman, 1991a). On one hand, increasing the global stock of knowledge in an industry creates a larger pool of knowledge for all firms, domestic and foreign, to tap into. The public good properties of knowledge, particularly non-rivalry and at least partial excludability, lead to knowledge spillovers (Griliches, 1979; 1992) and (Jaffe, 1996). Absorptive capacity is an important component of R&D spillover. Spillovers are more likely to occur if the “receiver” is advanced enough to find new knowledge, recognize its importance, and otherwise prepared to incorporate this knowledge effectively (Cohen and Levinthal, 1990; Cohen and Levinthal, 1989). Thus, prima facie, we would expect that access to global stocks of knowledge should enhance domestic innovation, conditional on the absorptive capacity of domestic firms.\(^1\) As mentioned above, however, the relationship between increasing investment in knowledge abroad and domestic innovation might be more ambiguous. Increasing investment in knowledge abroad reflects technically sophisticated competitors. As foreign R&D increases, we would expect to see the

\(^1\) Empirical studies suggest that international knowledge spillovers are an important component of domestic innovation, but that the barriers that accompany geographic distance impede knowledge diffusion (Keller, 2001, 2002). For example, domestic patents are cited both sooner and more frequently than foreign patents, and that foreign patents are most useful when domestic and foreign R&D are technologically similar (Henderson et al., 1998).
impact of technically challenging competition on domestic innovation. However, the relationship between competition and innovation is equivocal; sophisticated competition might spur innovation or it might discourage it (Scherer and Ross, 1990).

Furthermore, the literature suggests that relative strength and weakness might condition the motivations and impact of foreign technological activity. For example, relatively strong firms invest in foreign R&D to augment technological capabilities, whereas technology laggards do not benefit under the same conditions (Berry, 2006). Industries which are relatively strong will be more likely to have the absorptive capacity to utilize global sources of knowledge and are more likely to able to respond positively to sophisticated competition. Thus, we might expect that industries which are relatively strong should be more able to innovate in the face of sophisticated competition, while industries which are relatively weak are more likely to be overwhelmed by sophisticated competition, resulting in less innovation.² The discussion above suggests the following hypothesis:

_Hypothesis 1:_ All else equal, we expect foreign R&D to contribute more positively to domestic innovation in industries which are relatively strong.

### 2.2. Exports

International trade theory suggests that foreign knowledge can be accessed through the course of importing and exporting. International trade theory suggests that exporting might enhance domestic innovation through several effects: access to a larger market, allowing greater economies of scale; access to knowledge, through contact with foreign R&D and exposure to ideas and products abroad; and access to a broader base of user-generated innovation through customer or supplier feedback. All else equal, these effects could be expected to increase with increasing knowledge abroad, suggesting that domestic innovation will be positively related to exporting. On the other hand, as foreign markets become more technically advanced, exporters face increasingly sophisticated competition and users who can also benefit from knowledge spillovers.³ Empirical evidence on the relationship between exporting and innovation is mixed

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² I will operationalize the concept of relative industry strength using a revealed comparative advantage index, as described in Section 3.1.

³ The latter will be more likely if the exporting is via a foreign subsidiary – especially if the subsidiary does R&D – than if the export goes through foreign distributors and agents without a local institutional presence.
These arguments suggest the following two hypotheses:

Hypothesis 2a: All else equal, we expect foreign R&D to contribute positively to domestic innovation in relatively strong industries as exports increase. (The coefficient on exports* foreign R&D is expected to be positive.)

Hypothesis 2b: All else equal, we expect foreign R&D to contribute negatively to domestic innovation in relatively weak industries as exports increase. (The coefficient on exports*foreign R&D is expected to be negative.)

2.3. Imports

Knowledge embodied in imported final goods and intermediate inputs facilitates innovation through reverse engineering, proof of concept, knowledge transmission through contact (e.g., with scientists and engineers, suppliers, and customers abroad) and other mechanisms documented in the literature (Caves, 1996; Coe and Helpman, 1995). Import competition also stimulates domestic innovation through its effect on market structure and by forcing an innovation response in domestic rivals (Lawrence 2000). On the other hand, the relationship between imports and productivity might be negative if import competition impedes domestic innovation by eroding monopoly profits or by overwhelming the domestic industry, resulting in productivity decrease and ultimately the contraction or loss of a domestic industry. The evidence in the empirical literature provides support for the idea that import competition can have both effects (Grossman, 1982; Lawrence and Weinstein, 1999; Lawrence 2000; MacDonald, 1994; Scherer and Huh, 1992).

These arguments suggest the following two hypotheses:

Hypothesis 3a: All else equal, we expect foreign R&D to contribute positively to domestic innovation in relatively strong industries as imports increase. (The coefficient on imports* foreign R&D is expected to be positive.)

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4 See discussion in Scherer (1992) and in Scherer (1984). There is an extensive literature on market structure and innovation. For example, see Barzel (1968) and Geroski (1990).
Hypothesis 3b: All else equal, we expect foreign R&D to contribute negatively to domestic innovation in relatively weak industries as imports increase. (The coefficient on imports*foreign R&D is expected to be negative.)

3. Measurement

To test these hypotheses about the relationship between foreign R&D and domestic innovation, I employ a parsimonious structural model which relates domestic innovation to domestic and foreign R&D stocks and international trade. The model draws on the widely-used analytical framework developed by Grossman and Helpman (1991a) which examines TFP performance as a function of both domestic and foreign R&D stock and integrates international trade as a conduit for knowledge transmission. I describe the data and measure of innovation in Section 3.1. Section 3.2 discusses the data used to operationalize foreign technological activity, international trade, and relative industry strength. Section 3.3 presents the specification of the model to be estimated empirically.

3.1. Data

The sample is a balanced panel of four high-technology manufacturing industries observed from 1973-2001 for a total of 116 industry-year observations. The industries are chosen by the criteria described below. I develop a comprehensive data set drawn from several sources. The extended time period covers a period of significant change in underlying fundamental technologies, such as the transition from analog technology to digital technology as well as the introduction and adoption of information technology. The time period also covers significant shifts in relative competitiveness of US high-technology industries. A revealed comparative advantage index is constructed to provide a quantitative measure of industry strength. The analysis is augmented with mini-case studies of each of the four industries which highlight key insights from the econometric analysis.5

The level of analysis chosen in this study, industry level delineated by 3-digit SIC, affords several advantages compared to other possible choices. Foremost, the effects being

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5 See Smith (2006) for details of the case study analysis in the context of the computer equipment industry. The mini-case studies are based on successive issues of the US Industrial Outlook and other government reports and industry histories.
studied in this paper condition the environment in which the individual firms that comprise an industry operate (Porter, 1991). It is a hallmark of the microeconomics of innovation that the state of technological advance and the stock of scientific and technological advance varies significantly among industries, and that firm level innovation is conditional on the larger industry environment (Dosi, 1988).6 While firm-level data might yield insight into intra-industry heterogeneity, it would lessen the ability to distinguish important intersectoral differences. Following others in the literature, it is possible to conceptualize the industry level data to be representative of the average of all firms in that industry (Nachum and Zaheer, 2005). Finally, while the econometric analysis is carried out at the industry level, the mini-case studies provide some insight into firm heterogeneity.

3.1.1. Selection of industries

The four industries included in the sample are: computer equipment (SIC 357),7 household audio and video equipment (SIC 366),8 communications equipment (SIC 365),9 and scientific instruments (SIC 381+382).10 The industries were selected for this study based on

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6 For example, Scherer (1984, chapter 9) identifies differences in technological opportunity among industries as being responsible for nearly half of firm level differences in innovative output.

7 SIC 357 is comprised of: computers (3571), storage devices (3572), terminals (3573), peripherals (3574), calculating machines (3578), and office machinery not elsewhere classified (3579). An important distinction is that this classification does not include software. Computers have comprised the largest share of the industry over the entire period, accounting for 45% in 1972 and nearly 60% by 1996. Peripherals make up the next largest group, accounting for 19% in 1972 and 24% in 1996. Computer storage devices accounted for 9% in 1972 and 12% by 1996. Terminals and calculators have been a small and decreasing portion of the industry over the entire period.

8 SIC 366 consists of: telephone and telegraph apparatus (SIC 3661), radio and television broadcasting and communications equipment (SIC 3663), and communications equipment not elsewhere classified (SIC 3669). SIC 3661 is comprised of wire telephone equipment, including switches, transmission, and terminal equipment. This category also includes modems and facsimile. In SIC 3663, important segments are radio and television broadcast equipment, cable TV equipment, satellites, and cellular telephones. The relative share of telephone and telegraph equipment dropped during this period. The relative share of radio and television broadcasting equipment increased, in part because of the tremendous growth in cellular mobile telephones. Together, these two categories account for over 92% of the industry over the entire period.

9 The industry consists of two segments: SIC 3651, household audio and video equipment; and SIC 3652, phonograph records and prerecorded audio tapes and disks. Household audio and video equipment has accounted for over three-quarters of the industry. The share of records, tapes, and discs has increased slightly over the time period, but accounted for less one-quarter of the industry shipments in 1996.

10 The scientific instruments industry (SIC 381+382) consists of several segments which can be grouped as: search and navigation equipment (SIC 3812); electronic test and measurement instruments (SIC 3825); laboratory instruments and apparatus (SIC 3821, 3826, 3827); and measuring and controlling instruments (SIC 3822, 3823, 3824, 3829). Search and navigation equipment accounted for approximately half of the industry over most of the time period. Measuring and controlling instruments accounted for around a quarter of the industry over the time period. Electronic test and measurement instruments and laboratory instruments and apparatus together accounted
several criteria. Industries were identified as high-technology industries, measured in terms of R&D-intensity relative to all US manufacturing industries (National Science Foundation, 1972-2004). The specific industries provide a range in maturity, the nature of technological innovation, and the relative prominence of domestic and foreign firms. The computer equipment industry has been characterized by rapid technological advance. Communications equipment is also a technology driven industry. In contrast, the household audio and video equipment industry involves more low-margin, mass production. Finally, scientific instruments involves incremental technological advance with input from varied scientific disciplines.

The four industries had markedly different experiences in the global trading arena, as measured through relative export intensities. For example, during the period from 1973 to 2001, the average share in world exports for all U.S. manufacturing industries was 11.5%. However, the average was as low as 2.5% in the household audio and video industry and as high as 24.4% in 24.8% in scientific instruments over that period.

3.1.2. Measure of technological change

In order to best capture a direct indicator of innovation at the industry level, total factor productivity (TFP) is used as the dependent variable in this study. This follows an extensive tradition in the economics literature at the firm, industry, and aggregate level of recognizing the direct connection between technological advance and the observable level of output produced with a given quantity of the relevant inputs (Griliches, 1998b). Technological change, by definition, results in an outward shift of the production possibility frontier. In other words, the ability to produce more output from the same quantity of inputs represents an outward shift of the production possibilities frontier, as measured by TFP.

I calculate 3 digit industry level TFP from the NBER Manufacturing Productivity (MP) database (Bartelsman and Gray, 1996). The underlying longitudinal micro-level data provides measures of output and inputs based on the US Census of Manufactures survey of all US manufacturing establishments and the Annual Survey of Manufactures from annual samples of 55,000-75,000 manufacturing establishments and thus provides large scale, time series data from individual manufacturing establishments at multiple points in time (Bartelsman and Doms,
The data is aggregated to the level of 459 4-digit SIC industry codes for the years 1958-1996 in the MP database. In order to match the level of aggregation of domestic and foreign R&D measures (discussed below) I further aggregate the TFP measures to the three-digit level.\textsuperscript{11} I extend this data through 2001 using original source data from the Annual Survey of Manufactures and the 1992 Benchmark Input-Output tables for the US economy. Price deflators for shipments were derived from published Bureau of Economic Analysis deflators. Annual capital stock and deflators are from the Federal Reserve.\textsuperscript{12} One complication in extending the TFP data beyond 1996 is the switch from the SIC system of industrial classification to the NAICS classification in 1997. Thus, bridge tables provided by the US Census Bureau are used to allocate the NAICS based data for the years 1997-2001 to the SIC system.

The choice of TFP as the dependent variable invites commentary on alternative choices, specifically, the choice not to use patent counts or patent citations to measure innovation in this study. Patent data is frequently used as a measure of innovation output in the management literature (Ahuja and Katila, 2001; Hitt et al., 1991; Sampson, 2005). Patents capture particular aspects of inventions very well, specifically non-triviality and novelty. However, patents do not adequately capture many types of research outcomes that lead to innovation, particularly those that can have the most spillover effects (Jaffe and Trajtenberg, 2002). Levin et al (1987) show that patents are an imperfect measure of spillovers, particularly in industries which rely heavily on other means of protecting intellectual property. Moreover, an invention, as measured by a patent, does not necessarily become an innovation until it is successfully introduced into the market.\textsuperscript{13} On the other hand, the outward shift of the production function implied by technological change captures both appropriable and unappropriable aspects of innovation. For example, in the management literature, productivity measures are commonly used to capture implicit spillover effects, e.g. from R&D (Feinberg and Majumdar, 2001; Hejazi and Safarian, 2000).

\textsuperscript{11} Aggregation to the 3-digit level is accomplished through adding the four-digit totals for real inputs (capital, labor, energy, and non-energy materials) and summing to the three-digit totals. Inputs are first deflated at the four-digit level, using the input specific four-digit price deflator. The resulting real four-digit inputs are then aggregated to the three-digit level. Factor shares are calculated using the three-digit inputs and three-digit output, i.e. aggregated first.

\textsuperscript{12} Capital stock data was provided by Norman Morin at the Federal Reserve.

\textsuperscript{13} Many patents are neither licensed nor produce revenue, and thus have little direct connection to innovation. Moreover, while some industries are very dependent on patent protection, such as biotechnology, others such as computer equipment rely heavily on trade secrets.
1999) and from FDI (Chung, 2001; Liu et al., 2000), and to measure technological change directly (Schilling and Steensma, 2001).

3.2. Measures of independent variables

3.2.1. Foreign R&D

Global stocks of knowledge that contribute to domestic innovation as well as create sophisticated foreign competitors will predominantly result from the cumulative available stock of knowledge in other advanced economies. I use R&D data from the OECD ANBERD database to measure the combined cumulative investment in R&D in the European Union and Japan over the time period 1973-2001 (O.E.C.D., 2006). The variable $\lnfrdst_n$ (1987=1) measures foreign R&D stock, the cumulative investment in R&D in the European Union and Japan.

I modified the ANBERD data to match the industry level data from U.S. sources. I matched the ISIC (Revision 2) code to the U.S. SIC code using a protocol described in Smith (2004). Following convention, I measure the cumulative knowledge available by calculating foreign R&D stock using the perpetual inventory method (Coe and Helpman, 1995; Feinberg and Majumdar, 2001; Griliches, 1979). For the benchmark year, 1973:

$$S_0 = \frac{R_0}{g + \delta}$$

where $S_0$ is benchmark R&D capital stock, $R_0$ is R&D expenditure in the benchmark year, $g$ is the average annual logarithmic growth of R&D expenditures over the period, and $\delta$ is the depreciation rate of R&D capital, using $\delta = 0.11$. R&D stock is perpetuated by:

14 These data include all R&D performed in industry, regardless of source of funding. Thus, government funded R&D is included. However, this should not pose a problem, as it is reasonable to assume that the overall stock of R&D abroad, including government funded, constitutes the available pool of scientific and technological knowledge upon which both domestic and foreign firms will draw.

15 The specific countries in the sample are: United Kingdom, Germany, France, Denmark, Finland, Ireland, Italy, Netherlands, Spain, Sweden, and Japan. These countries are included on the basis of continuous data availability over the period and they represent a substantial portion of R&D activity in the industries included in the panel.

16 Estimates of the rate of depreciation of R&D stock range from 0.05-0.15. See Griliches (1998a). Coe and Helpman (1995), for example, assume $\delta = 0.05$, Keller (2001) assumes $\delta = 0.10$, and Griffith (2004) assumes $\delta = 0.15$. Sensitivity tests in these studies, and in my regressions, do not find that the results are changed significantly with varying values of $\delta$. I present results based on $\delta = 0.11$, based on the value used in a comprehensive U.S. Department of Labor study (U. S. Department of Labor, 1989).
\[ S_t = (1-\delta)S_{t-1} + R_{t-1} \]

### 3.2.2. Imports and exports

Industry level import and export data are calculated from the Feenstra bilateral trade dataset (Feenstra, 1997; Feenstra 1996; Feenstra et al., 2002). I extracted bilateral import and export data between the US and Japan and the US and the included nations in the European Union to match the foreign R&D data. For the years 1972-1988 this data is in the 1972 revision of the SIC code. Thus, data for this period had to be translated from the 1972 SIC code to the 1987 SIC code. The data were translated at the four-digit level using the NBER Manufacturing Productivity concordance and then aggregated to the three-digit level. Data for 1989-2001 were in the 1987 SIC classification, which I then aggregated to the 3-digit SIC level.

In the regressions, imports and exports are normalized by net sales. The variables `impsal_1` and `expsal_1` are introduced with a one-year lag. Econometrically, including the lagged variables reduces our concern about endogeneity between contemporaneous trade and total factor productivity.

### 3.2.3. Industry relative strength

An important feature of this paper is the introduction of industry relative strength as an explanatory variable. The four industries are characterized by constructing a revealed compared advantage index provides a quantitative measure of the relative performance of domestic industries (Balassa, 1979). Following Balassa, revealed comparative advantage is calculated as:

\[
RCA_i = \frac{US\ x_i}{world\ x_i} / \frac{US\ x}{world\ x} * 100
\]  

(2.1)

where US\ x_i = U.S. exports in industry i and world\ x_i = combined exports from the European Union, Japan, and the U.S. in industry i. Likewise, US\ x and world\ x are, respectively, the U.S. and combined European Union, Japan, and U.S. exports in all goods. Revealed comparative advantage can be used as a measure of the distribution of competitiveness among industries. Relative industry strength is introduced into the regressions through the variable `lnrca`, the natural logarithm of revealed comparative advantage.

The industries exhibit a range of revealed comparative advantage. According to this framework, the scientific instruments and computer and office equipment industries exhibit...
strong domestic advantage over this time period. Communications equipment also exhibits domestic advantage, but to a lesser extent. Household audio and video equipment exhibits relative disadvantage over this period. Table 1 lists the four industries in order of domestic revealed comparative advantage. A revealed comparative advantage value above 100 means that the U.S. has a larger share in world exports in this industry than it does in total exports of all goods. Conversely, a revealed comparative advantage below 100 means that the U.S. has a smaller share in world exports in this industry than it does in total exports of all goods.

3.2.4. Control variables

Domestic R&D stock. Domestic investment in R&D has been shown to have a significant positive contribution to TFP. Several decades of empirical work have shown a generally positive relationship between R&D and productivity growth. Estimates of the contribution of R&D to productivity growth are sizeable.\(^{17}\) The variable \(\text{lnrdst}_n\) is the log of domestic R&D stock (1987=1), which measures the cumulative investment in R&D. The domestic R&D stock variable is created using the perpetual inventory method.

U.S. R&D data are assembled from the National Science Foundation \textit{R&D in Industry} series. This annual survey is the most comprehensive source of U.S. R&D data. The data include company and other funding, but not federal funds, for industrial R&D in millions of current dollars. The data are based on a survey of a panel of R&D performing companies that is updated periodically. The data are available at the three-digit SIC level, with some exceptions. Industry net sales data are also taken from the NSF \textit{R&D in Industry} series.

Time. Given the trending nature of TFP and R&D, it is common in the literature on productivity to include year dummies or a time trend.\(^{18}\) I include the variable \textit{time} as an exponential time trend to control for effects due primarily to a common trend over time which would otherwise result in a spurious relationship between the dependent variable and trending independent variables.\(^{19}\)

\(^{17}\) For example, Bureau of Labor Statistics estimates a contribution of domestic R&D to TFP growth of 0.49% for the years 1973-87 for all manufacturing. Griliches (1994) estimates 0.36% for the years 1973-89.

\(^{18}\) See, for example, Griliches (1979; 1998a), Coe and Helpman (1995), and Keller (1999).

\(^{19}\) I also include the full set of individual year dummies instead of the time trend in some specifications, which does not affect the econometric results. Given the sample size, I choose to include the time trend in place of year
3.3. Specification of the model

In order to test these hypotheses about the relationship between domestic innovation, foreign R&D, and international trade, I utilize a structural model which relates domestic innovation to domestic and foreign R&D stocks and international trade.\(^{20}\) This model is based on the theoretical framework developed by Grossman and Helpman (1991a).\(^{21}\) The dependent variable, total factor productivity (TFP) captures innovation through technical change, as discussed above. Innovation occurs through investment in R&D, which results in an increase in either the number or the quality of available intermediate goods for the production of final products. As discussed previously, international trade allows access to the cumulative global stock of knowledge; thus, the cumulative stock of knowledge increases with the cumulative volume of international trade.

The specification which will be estimated can be expressed:

\[
\ln \text{tfp}_{i, t} = \beta_0 + \beta_1 \ln \text{rdst}_{i, t} + \beta_2 \ln \text{frdst}_{i, t} + \beta_3 \ln \text{expsal}_{i, t-1} + \beta_4 \ln \text{impsal}_{i, t-1} + \beta_5 \text{lnrca}_{t} + \beta_6 (\text{lnrca}_{t} \times \ln \text{frdst}_{i, t}) + \beta_7 (\text{lnrca}_{t} \times \ln \text{expsal}_{i, t-1}) + \beta_8 (\text{lnrca}_{t} \times \ln \text{impsal}_{i, t-1}) + \beta_9 \text{time} + \epsilon_{i, t}
\]

for industry, \(i\), and year, \(t\). This specification allows us to separate the effects of domestic R&D, foreign R&D, international trade and, importantly, the interaction between them. Industry relative strength is introduced as \(\ln rca\) and an interactive term between \(\ln rca\) and foreign R&D stock:

\[
\ln \text{tfp}_{i, t} = \beta_0 + \beta_1 \ln \text{rdst}_{i, t} + \beta_2 \ln \text{frdst}_{i, t} + \beta_3 \ln \text{expsal}_{i, t-1} + \beta_4 \ln \text{impsal}_{i, t-1} + \beta_5 (\ln rca_{t}) + \beta_6 (\ln rca_{t} \times \ln \text{frdst}_{i, t}) + \beta_7 (\ln rca_{t} \times \ln \text{expsal}_{i, t-1}) + \beta_8 (\ln rca_{t} \times \ln \text{impsal}_{i, t-1}) + \beta_9 \text{time} + \epsilon_{i, t}
\]

The model above is estimated using panel techniques. I utilize the panel structure to account for unobserved heterogeneity across industries and years. For example, differences might arise due to common factors affecting R&D investment and innovation in a given industry. The long time and relatively narrow cross-sectional nature of the data suggests controlling for unobserved heterogeneity using fixed effects over random (Wooldridge, 2001). Results of a

dummies to preserve degrees of freedom.

\(^{20}\) For a complete presentation of this model and the econometric analysis see Smith (2004).

Hausman test confirm this preference. The Breusch-Pagan test for heteroskedasticity rejects the null hypothesis of homoskedastic standard errors. Heteroskedasticity-robust standard errors are used in estimation of the model.

4. Results and discussion

4.1. Econometric analysis

The results of the econometric analysis are summarized in the next section. Summary statistics and correlation coefficients for each industry are given in Table 2 and Table 3, respectively. Regression results are summarized in Table 4. Column 1 presents the results of estimation of the benchmark model reflecting the theoretical relationships between foreign R&D and domestic innovation outlined above and considered in the previous empirical literature at higher levels of aggregation. In column 2, the benchmark model is expanded to test the hypothesis that industry relative strength plays a conditioning role in the relationship between foreign R&D and domestic innovation. As hypothesized, the empirical results provide support for this nuanced relationship. In columns 3 and 4, the significance of relative industry strength is probed further by splitting the sample into relatively strong and relatively weak groups based on revealed comparative advantage. The empirical results in the split sample further suggest that the relationship between foreign and domestic innovation is conditioned by industry strength.

Several econometric problems might result in biases in these results. One issue arises from the potential correlation between R&D and the error term due to simultaneity between R&D spending and TFP. In this case as TFP increases we might expect investments in R&D to also increase, thus imparting an upward bias on the estimated coefficient on R&D stock. Using R&D stock should alleviate this effect to an extent because as a cumulative investment it is less cotemporaneous with TFP in a given year. Likewise, bias potentially is introduced by endogeneity between the international trade terms and TFP. To some extent, using lagged export to sales and lagged import to sales variables, as is done here, might alleviate some of the reverse causation as the current year productivity should not drive the previous year’s exports or imports.

4.2. Foreign R&D and domestic innovation

In the benchmark model in column (1), I regress TFP on cumulative domestic R&D stock, the ratio of cumulative foreign R&D stock to domestic R&D stock, and on lagged values
of exports and imports relative to sales. Industry dummies and a time trend are included to control for industry fixed effects and trending over time.

We expect that domestic and foreign R&D stocks might be highly correlated given the nature of the industries. This multicollinearity between domestic and foreign R&D stocks makes it difficult to separate the partial effect of domestic and foreign R&D stock variables from each other. In order to determine the separate effects of domestic and foreign R&D stocks, the variable $lnf_{dRD_n}$ is introduced. This variable is the natural logarithm of foreign R&D stock relative to domestic R&D stock.

As expected, cumulative domestic R&D stock is associated with an increase in domestic TFP. The coefficients on cumulative domestic R&D stock and the ratio of cumulative foreign to domestic R&D stocks are individually and jointly significant at the 1% level. With foreign R&D stock introduced as a ratio we can determine the partial effect of both foreign and domestic R&D stocks. We can see algebraically that the partial effect of domestic R&D on TFP will now be equal to the coefficient on domestic R&D stock minus the coefficient on the ratio of foreign to domestic R&D stock. We see from column 1 that a 1% increase in domestic R&D is associated with a net 2.5% increase in TFP.

The empirical results provide support for the hypothesis that foreign R&D contributes to domestic TFP. As we would expect, the magnitude of the coefficient on foreign R&D stock is smaller than that on domestic R&D stock. In the benchmark model in column 1, the coefficient on foreign R&D stock is strongly significant individually and in tests of joint significance with the interactive international trade variables. Taking into account the interactive terms and evaluating at the sample means of lagged exports to sales and lagged imports to sales, the net effect of a 1% increase in foreign R&D stock is associated with a net 0.36% increase in domestic TFP. This effect increases as exports increase and decreases as imports increase, as indicated by the coefficients attracted by the respective interactive terms.

In column 2, the benchmark model is expanded to test the hypothesis that relative industry strength conditions the relationship between foreign R&D and domestic innovation. As

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22The net effect is determined by evaluating at a particular point. In this case, the calculation is at the means of exports to sales and imports to sales.
we see in column 2, the net effect of foreign R&D stock decreases when we control for interaction with how strong the industry is, suggesting that the impact of foreign R&D depends on how strong the industry is. The coefficient on the interactive term between relative strength and foreign R&D stock suggests that the combination of relative strength and the availability of foreign R&D to tap into condition the relationship between foreign R&D and domestic TFP.

When we evaluate at industry means of the lagged export and import variables and the industry mean of \( \ln rca \) we find that a 1% increase in foreign R&D stock is associated with a net 0.06% increase in domestic TFP. Again, the effect is increasing with increasing exports to sales and decreasing with increasing imports to sales.

The strong correlation between \( \ln f_dRD_n \) and \( \ln rca \) interferes with our ability to separately identify the effect of relative industry strength. Splitting the sample into relatively stronger and relatively weaker industries allows us to more carefully probe this relationship. The sample is divided by the median value of RCA. Results from estimation on the split sample are summarized in columns 3 and 4.

When we split the sample according to relative strength, we find additional support for the nuanced relationship between foreign R&D and domestic innovation. The results in columns 3 and 4 suggest that both domestic and foreign R&D have a greater relationship to domestic innovation in relatively strong industries. The magnitude of the coefficient on domestic R&D stock is approximately four times greater in relatively strong industries, with a 1% increase in domestic R&D stock associated with a net 4.2% increase in TFP in relatively strong industries, compared to a net 1.2% increase in TFP in relatively weak industries.

The distinct relationship between foreign R&D and domestic TFP is delineated. The coefficient on \( \ln f_dRD_n \) is positive and significant, individually and jointly with the interactive variables, in relatively strong industries. Evaluating at the sample means for this group, a 1% increase in foreign R&D is associated with a net 0.86% increase in domestic TFP. In relatively weak industries, in column 4, the coefficient on \( \ln f_dRD_n \) attracts a negative sign but is not individually significant, although it is jointly significant with the interactive variables at the 5% level. The negative sign attracted by \( \ln f_dRD_n \) suggests that increasing foreign R&D stock relative to domestic R&D stock, ceteris paribus, might present a greater challenge in relatively weak industries. When we consider the net effect of foreign R&D stock by evaluating at the
sample mean for relatively weak industries, a 1% increase in foreign R&D stock is associated with a net 0.51% increase in domestic TFP.

Taken together, the results in columns 2 through 4 suggest that the combination of relative strength and a larger stock of foreign R&D to tap into condition the relationship between foreign R&D and domestic innovation. In order to fully understand this, we need to consider the effects of exports and imports interacted with foreign R&D stocks.

4.3. Exports and domestic innovation

As hypothesized, the relationship between domestic innovation and exports depends on foreign R&D. The interactive variable between lagged exports to sales and foreign R&D stock attracts a positive coefficient in the benchmark model in column 1 and after we control for industry strength in column 2. In the benchmark model, evaluated at the mean of foreign R&D stock the net effect of exports is after taking into account the interactive term is negative; a 1 percentage point increase in exports to sales is associated with a 0.13% decrease in domestic TFP. When we control for industry strength in column 2, we find that a 1 percentage point increase in exports to sales is associated with a 0.015% increase in domestic TFP.

Support for the hypothesis that domestic innovation is positively related to exports in relatively strong industries as a function of increasing foreign R&D is bolstered by the results of splitting the sample between relatively strong and relatively weak industries. When we split the sample between relatively strong and weak industries, in column 3 and column 4, the coefficient remains on the interactive variable remains positive and significant, but the magnitude is substantially larger in relatively strong industries. From the results in column 3 and column 4, a 1 percentage point increase in exports to sales is associated with a 0.78% increase in domestic TFP in relatively strong industries, compared to a 0.55% decrease in TFP in relatively weak industries. The positive contribution of exports to domestic innovation occurs through increasing foreign R&D stock; if we evaluate at the maximum value of foreign R&D stock, the net effect of exports is positive in both strong and weak industries.23

23 Evaluated at the maximum instead of the mean value of foreign R&D stock, a 1 percentage point increase in exports to sales is associated with a 1.77% increase in domestic TFP in relatively strong industries and a 1.87% increase in TFP in relatively weak industries.
4.4. Imports and domestic innovation

The relationship between domestic innovation and imports is also conditioned by foreign R&D. The empirical results provide some support for the hypothesis that that domestic innovation is positively related to imports in relatively strong industries as a function of increasing foreign R&D. The interactive term between lagged imports to sales and foreign R&D stock is negative in the benchmark specification and after we control for industry strength in column 2. When we evaluate at the mean of foreign R&D stock, a 1 percentage point increase in imports to sales is associated with a 0.01% increase in domestic TFP; after we control for industry strength in column 2, the magnitude of the effect increases to 0.05%.

Splitting the sample into relatively strong and weak industries provides additional insight. When we split the sample into relatively strong and relatively weak industries, the coefficient on the interactive term between lagged imports to sales and foreign R&D stock is no longer statistically significant at the usual levels of significance, neither individually nor jointly with lagged imports. Thus, we cannot reject the hypothesis that the relationship between imports and domestic TFP is statistically different from zero in relatively strong industries. However, in relatively weak industries, we find that the coefficient on the interactive term remains negative, and is weakly significant individually, and jointly significant with lagged imports to sales at the 5% level. Evaluated at the mean value of foreign R&D stock, a 1 percentage point increase in imports to sales is associated with a 0.02% decrease in domestic TFP in relatively weak industries, providing support for our hypothesis that foreign R&D contributes negatively to domestic TFP in relatively weak industries as imports increase.

4.5. Further econometric specifications

In addition to estimating the model on the full panel, I also estimate separate regression equations for relatively strong and relatively weak industries, as determined by the RCA index described above. In order to compare the regression coefficients across relatively strong and weak industries, I introduce a dummy variable for relative strength, str_dum, which is equal to 1 in relatively strong and 0 in relatively weak industries. As in the split sample, the median RCA value of 161 is used to split the sample. Note that some SIC-delineated industries are classified as relatively strong in some years and relatively weak in others. Using RCA in this manner allows us to consider relative strength itself. The dummy variable for relative strength is
interacted with each explanatory variable in the regressions. The t-statistics on the interactive terms indicate whether we can reject the null hypothesis that the coefficients are the same across both groups. This approach has been used to compare regression coefficients between groups of industries and firms distinguished by knowledge-intensity, size, and other relevant characteristics (Acs and Audretsch, 1988; Audretsch and Weigand, 2005; Nachum and Zaheer, 2005). The results of this approach are tabulated in Table 5. Column 1 shows the coefficient on the industry strength interactive term for each variable and column 2 indicates the significance. Coefficients which are statistically significant can be interpreted as having a different relationship in relatively strong and weak industries in the direction and magnitude indicated by the coefficient. Results of the Wald test indicate that we can reject the null hypothesis that the two regressions are the same. There is a significant difference between relatively strong and weak industries for most of the key parameters, further substantiating the hypotheses that industry strength plays an important role in modulating the relationship between foreign R&D and domestic innovation, particularly with respect to the interactive terms. Furthermore, the signs of the differences are consistent with the differences we see between columns 3 and 4 in Table 4.

One econometric issue that arises in using a panel that arises with the relatively long time series and narrow cross section is the potential for serial correlation in the errors. I test the robustness of the results using feasible generalized least squares (FGLS) estimation with heteroskedasticity consistent standard errors and correcting for AR(1) correlation in the error term. Overall, the results are robust to the different assumptions about the error term. Results are displayed in Table 6. Coefficients are smaller in magnitude in the FGLS regression (column 2) compared to the fixed effects OLS regressions (column 1) but the sign on the coefficients and significance do not change on most of the variables.

5. Sophisticated competition, knowledge flows, and relative strength

The empirical results discussed above point to a nuanced relationship between foreign R&D and domestic innovation. Importantly, this research suggests that foreign R&D can be double-faced. The results strongly suggest that foreign R&D influences domestic innovation,
although this relationship is not a straightforward story of simply increasing the available stock of knowledge.

The main empirical results strongly suggest that foreign R&D has the greatest impact in relatively strong industries, and might have a detrimental effect in weaker industries. Moreover, the empirical results point to a positive relationship between foreign R&D and domestic innovation that is increasing as exports increase, particularly in relatively strong industries. Finally, the empirical results provide mixed evidence on the relationship between domestic innovation and increasingly sophisticated import competition. Mini case studies of the four industries contribute additional insights into understanding these results. In particular, the industry studies point to the importance of sophisticated competition, international knowledge flows, and relative strength.

As posited earlier, increasing foreign R&D might increase the stock of available technical knowledge but at the same time it also reflects the increasing technical sophistication of competitors abroad. The case studies provide evidence of these two effects. The ultimate impact depends upon the industry reaction, and whether there is a competitive response or submission. In the computer equipment and scientific instrument industries, the two strongest industries in terms of revealed comparative advantage, increasing foreign R&D presented opportunities for the domestic industry in terms of a larger technically sophisticated market for high-end products (the U.S. industry’s strength). Increasing foreign R&D also contributed to international knowledge flows from the R&D of foreign subsidiaries in computer equipment, particularly IBM, and through feedback from exporting to sophisticated foreign users in scientific instruments. The experience in these industries also suggests that increasingly sophisticated competitors can be a challenge to the domestic industry, even in a relatively strong industry. In a weak industry, such as household audio and video equipment, the detrimental effect of foreign R&D is more pronounced, as increasingly sophisticated competition overwhelms the domestic industry. On the other hand, increasingly sophisticated competition is not necessarily a precursor to domestic demise. In communications equipment, the case study evidence suggests that sophisticated foreign competition can force domestic firms to innovate or

lose ground. As well, the case studies of the computer and scientific instruments industries suggest that the threat of foreign competition provided a spur to domestic innovation.

One intriguing implication of this research is that international knowledge flows can be an important contributor to innovation under certain circumstances. In both the computer equipment and scientific instruments industries, the two industries which were relatively strong compared to the foreign industry, technically sophisticated export markets played a positive role in domestic innovation. In part, these benefits seem to derive from international knowledge flows. Contacts with technically sophisticated users abroad as well as insight from users of technically sophisticated imports at home provide potential channels of international knowledge transmission in the scientific instruments industry. When sophisticated U.S. users buy from domestic and foreign firms, these technical users will tell both industries what they like about the other and thus become a willing and knowledgeable means of information exchange internationally. This paradigm particularly holds true for high end items. In the computer equipment industry, as well, the long history of international connections seems to have facilitated international knowledge flows. In some cases foreign affiliates also facilitate this flow of ideas to the parent and ultimately the domestic industry, as in the case of the Japanese and European affiliates of IBM. On the other hand, barriers to international knowledge flows include differences in standards and regulation, as in the communications equipment industry. International knowledge flows also did not appear to play a large role in the U.S. household audio and video equipment industry.

This paper suggests that exporting to technically sophisticated markets contributes positively to domestic innovation when the domestic industry is a technological leader, as in the scientific instruments and computer equipment industries. Importing from technically sophisticated competitors can also help domestic innovation, as in the case of the communications equipment industry. However, exporting to sophisticated markets can be a challenge to the domestic industry, as for communications equipment, when the market abroad includes technically advanced competitors. As well, technically sophisticated imports can hurt the domestic industry, as in the case of the high-end segment of the computer equipment industry in the U.S.

Finally, these results point to the importance of continued innovation as a factor in global
success, with implications for firm dynamic capabilities through investment in human capital and other intangible assets. Industries at the technological forefront were better able to compete globally than those which were not technological leaders. Both the domestic computer equipment industry and the scientific instruments industry maintained an edge in the high-end, technologically advanced segments of these industries. In both of these industries, international knowledge flows appear to play a role in fostering domestic innovation. These two industries have succeeded globally through innovation at the forefront, benefiting from both their own and competitive R&D. Conversely, industries not at the technological forefront had difficulty meeting the global challenge. The household audio and video equipment industry provides an extreme example of this, whereas the communications equipment industry is in the middle.

Taken together, the results from this study point to several important lessons for a larger class of high-technology industries, such as biotechnology and medical devices. The results strongly suggest that international connections can contribute to domestic innovation, both through international knowledge flows and through the competitive spur provided by technically sophisticated foreign competitors. All things equal, when an industry is technologically advanced, the possibility of learning from trade, directly and indirectly, appears to be greater: the ability to benefit from knowledge, e.g. through feedback and the ability to respond to a challenge are greater closer to the forefront. However, the possibility of complacency also increases. In contrast, being technologically far behind makes it less likely that an industry can respond to challenges adroitly. This research suggests, in the broader context of industry competitive analysis that we might place the industry on the spectrum of relative strength compared to these industries, and then assess other dimensions such as whether the industry is at or near the technological forefront, the importance of knowledge flows, and the nature of foreign competition to help predict the impact of international trade and foreign R&D on innovation in that industry.

6. Conclusions

By building on a structural model of international trade and R&D spillovers that is grounded in international trade theory, this paper bridges the economics and management literatures. Importantly, this paper extends the existing literature on international technology diffusion in several dimensions. First, while the theoretical literature points to a role for exports
and imports in international R&D spillovers, the empirical literature has focused on import-weighted R&D shares. The results in this paper point to a significant relationship between innovation and international technology diffusion through both exports and imports, and suggest that these two channels might contribute in opposite directions. Second, the results from this analysis strongly suggest that foreign technological activity may have both positive and negative effects for a technologically advanced nation, such as the US. This makes sense in a world of R&D rivalry and technology competition. Thus, while the existence of spillover from foreign R&D might be substantial, there are pitfalls as well. Notably, this research suggests that the negative effects of increasing foreign technological capabilities are manifest particularly through import channels. By allowing the possibility of negative impact of foreign R&D, this paper fits more closely with the literature on R&D rivalry and extends the spillover literature.

This research presents many implications for R&D policy and our understanding of international technological diffusion. At the industry level, this paper suggests that relative industry strength can play a significant role in mediating the relationship between foreign R&D and domestic innovation through differential impact of international trade. This research has suggested that trade-related benefits beyond efficiency gains from trade liberalization might be significant in some high-technology industries. One compelling suggestion from this research is that trade can have a positive effect on innovation beyond R&D, either through learning or through fear. Our understanding of this would benefit from further research which tests this more explicitly. The research in this paper provides a starting point for a closer look at the nuanced interaction of the global technological environment and the ability to maintain sustained competitive advantage. Further work might probe this at the firm level and in other industries.

7. Acknowledgements

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errors and omissions remain my own.

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Source: Author calculations from OECD, ITCS (International Trade in Commodity Statistics). Following Balassa (1979), revealed comparative advantage is: $RCA_i = \frac{US_i}{world_i} \div \frac{US \times 100}{world \times}$, where $US_i$ = U.S. exports in industry $i$ and $world_i$ = combined exports from the European Union, Japan, and the U.S. in industry $i$. Likewise, $US \times$ and $world \times$ are, respectively, the U.S. and combined European Union, Japan, and U.S. exports in all goods.
Table 2. Summary statistics

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**Table 3. Correlation coefficients**

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Table 4. Full and split sample regression results

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<td>8.199</td>
<td>8.196</td>
<td>6.476</td>
<td>13.581</td>
</tr>
<tr>
<td></td>
<td>(3.15)**</td>
<td>(3.39)**</td>
<td>(5.76)**</td>
<td>(2.86)**</td>
</tr>
<tr>
<td>ml_nrfd_n</td>
<td>-2.763</td>
<td>-3.647</td>
<td>-0.8510</td>
<td>-2.058</td>
</tr>
<tr>
<td></td>
<td>(-4.61)**</td>
<td>(-6.11)**</td>
<td>(-1.14)</td>
<td>(-1.94)*</td>
</tr>
<tr>
<td>lnrca</td>
<td>------</td>
<td>-0.1240</td>
<td>0.2759</td>
<td>0.1415</td>
</tr>
<tr>
<td></td>
<td>------</td>
<td>(3.94)**</td>
<td>(2.75)**</td>
<td>(4.39)**</td>
</tr>
<tr>
<td>rca_interact</td>
<td>------</td>
<td>0.1493</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td></td>
<td>------</td>
<td>(6.08)**</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>time</td>
<td>-0.2582</td>
<td>-0.0251</td>
<td>-0.0585</td>
<td>-0.0046</td>
</tr>
<tr>
<td></td>
<td>(-6.14)**</td>
<td>(-7.36)**</td>
<td>(-13.18)**</td>
<td>(-1.07)</td>
</tr>
<tr>
<td>_cons</td>
<td>-1.6341</td>
<td>-0.8093</td>
<td>-4.329</td>
<td>-0.3911</td>
</tr>
<tr>
<td></td>
<td>(-3.48)**</td>
<td>(-1.79)</td>
<td>(-6.34)**</td>
<td>(-0.77)**</td>
</tr>
</tbody>
</table>

| no. obs.     | 116  | 116  | 57   | 59   |
| R² (within)  | 0.7417 | 0.7909 | 0.9591 | 0.6884 |

Fixed effects OLS regression estimators with heteroskedasticity-consistent standard errors (t-statistics in parentheses)

* p < 0.10
** p < 0.05
*** p < 0.01

\(^a\) Industry strength based on revealed comparative advantage index.

Note: This table summarizes the results from estimation of the equation

\[
\ln \text{tfp}_{i,t} = \beta_0 + \beta_1 \ln \text{rdst}_{i,t} + \beta_2 \ln \text{frdst}_{i,t} + \beta_3 \text{expsal}_{i,t-1} + \beta_4 \text{impsal}_{i,t-1} + \beta_5 (\ln \text{frdst}_{i,t}) + \beta_6 (\ln \text{rdst}_{i,t}) + \beta_7 \ln \text{rca}_{i,t-1} + \beta_8 (\ln \text{rca}_{i,t}) + \epsilon_{i,t}
\]
### Table 5. Test of difference between relatively strong and weak industries

<table>
<thead>
<tr>
<th>Dependent variable: lnfyp_n</th>
<th>(1) difference</th>
<th>(2) t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnrdst_n</td>
<td>1.6209&lt;sup&gt;a&lt;/sup&gt;</td>
<td>4.59***</td>
</tr>
<tr>
<td>lnf_dRD_n</td>
<td>0.0960&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.91</td>
</tr>
<tr>
<td>expsal_1</td>
<td>8.0266&lt;sup&gt;b&lt;/sup&gt;</td>
<td>1.89&lt;sup&gt;*&lt;/sup&gt;</td>
</tr>
<tr>
<td>impsal_1</td>
<td>0.6579</td>
<td>0.51</td>
</tr>
<tr>
<td>x_linfra_n</td>
<td>-6.8776&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-1.73&lt;sup&gt;*&lt;/sup&gt;</td>
</tr>
<tr>
<td>m_linfra_n</td>
<td>-0.4727</td>
<td>-0.37</td>
</tr>
<tr>
<td>lnrca</td>
<td>-0.2889</td>
<td>-4.82***</td>
</tr>
<tr>
<td>time</td>
<td>-0.0291</td>
<td>-6.23***</td>
</tr>
<tr>
<td>_cons</td>
<td>-0.7576</td>
<td>-1.62</td>
</tr>
</tbody>
</table>

| no. obs.                   | 116             |
| R²                         | 0.9336          |

* p < 0.10.
** p < 0.05
*** p < 0.01

<sup>a</sup> jointly significant at 1% level
<sup>b</sup> jointly significant at 5% level
Table 6. Alternative estimation

<table>
<thead>
<tr>
<th>Dependent variable: lntfp_n</th>
<th>(1) Fixed effects</th>
<th>(2) FGLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnrdst_n</td>
<td>2.753</td>
<td>1.9702</td>
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<tr>
<td></td>
<td>(6.35)***</td>
<td>(4.81)***</td>
</tr>
<tr>
<td>lnf_dRD_n</td>
<td>-0.4414</td>
<td>-0.0817</td>
</tr>
<tr>
<td></td>
<td>(-3.65)***</td>
<td>(-1.19)</td>
</tr>
<tr>
<td>expsal_1</td>
<td>-7.97</td>
<td>-3.3754</td>
</tr>
<tr>
<td></td>
<td>(-3.01)***</td>
<td>(-3.27)***</td>
</tr>
<tr>
<td>impsal_1</td>
<td>3.608</td>
<td>1.0834</td>
</tr>
<tr>
<td></td>
<td>(6.09)***</td>
<td>(1.99)**</td>
</tr>
<tr>
<td>x_lnfrd_n</td>
<td>8.196</td>
<td>3.4651</td>
</tr>
<tr>
<td></td>
<td>(3.39)***</td>
<td>(3.50)***</td>
</tr>
<tr>
<td>m_lnfrd_n</td>
<td>-3.647</td>
<td>-1.1272</td>
</tr>
<tr>
<td></td>
<td>(-6.11)***</td>
<td>(-2.06)**</td>
</tr>
<tr>
<td>lnrca</td>
<td>-0.1240</td>
<td>-0.0403</td>
</tr>
<tr>
<td></td>
<td>(-3.94)***</td>
<td>(-1.57)</td>
</tr>
<tr>
<td>rca_interact</td>
<td>0.1493</td>
<td>0.0440</td>
</tr>
<tr>
<td></td>
<td>(6.08)***</td>
<td>(2.45)***</td>
</tr>
<tr>
<td>time</td>
<td>-0.0251</td>
<td>-0.0163</td>
</tr>
<tr>
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<td>(-7.36)***</td>
<td>(-4.25)***</td>
</tr>
<tr>
<td>_cons</td>
<td>-0.8093</td>
<td>-0.5666</td>
</tr>
<tr>
<td></td>
<td>(-1.79)*</td>
<td>(-1.45)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>no. obs.</th>
<th>R²</th>
<th>Wald χ²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>116</td>
<td>0.7909</td>
<td>67.5</td>
</tr>
</tbody>
</table>

Feasible generalized least squares estimators with heteroskedasticity-consistent standard errors
(t-statistics in parentheses in column 1, z-statistics in parentheses in column 2)

* p < 0.10.
** p < 0.05
*** p < 0.01

Note: This table summarizes the results from estimation of the equation

\[
\ln tfp_{n_{i,j}} = \beta_0 + \beta_1 \ln rdst_{n_{i,j}} + \beta_2 \ln frdstd_{n_{i,j}} + \beta_3 \expsal_{l_{i,j-1}} + \beta_4 \impsal_{l_{i,j-1}} + \beta_5 \expsal_{l_{i,j-1}} \ln frdstd_{n_{i,j}} + \beta_6 \impsal_{l_{i,j-1}} \ln frdstd_{n_{i,j}} + \beta_7 \ln rca_{i,j} + \beta_8 \ln rca_{i,j} \ln frdstd_{n_{i,j}} + \beta_9 time + \epsilon_{i,j}
\]
References


Feinberg, S.E., Majumdar, S.K., 2001. Technology spillovers from foreign direct investment in the Indian pharmaceutical industry. Journal of International Business Studies 32(3): 421-
Keller, W., 2001. The geography and channels of diffusion at the world's technology frontier. NBER working paper w8150


