Heterogeneous Technology Diffusion and Ricardian Trade Patterns

William R. Kerr*
Harvard Business School

December 2012
(Under Revision)

Abstract

This study tests the importance of Ricardian technology differences for international trade. The developed panel includes both emerging and advanced economies, and particular attention is devoted to the variation exploited in empirical tests. The elasticity of export growth on the intensive margin to the exporter's output development is 0.3 in preferred specifications. The elasticity for trade entry is 0.02. To provide greater empirical traction, specifications exploit uneven technology diffusion from the US through ethnic scientific networks to model Ricardian advantages. The intensive margin elasticity of exports to stronger US scientific integration is 0.15; the extensive margin elasticity is 0.01.

JEL Classification: F11, F14, F15, F22, J44, J61, L14, O31, O33, O57.

Key Words: Trade, Exports, Comparative Advantage, Technological Transfer, Patents, Innovation, Research and Development, Immigration, Networks.

---

*Comments are appreciated and can be sent to wkerr@hbs.edu. This paper is a substantial revision of Chapter 2 of my Ph.D. dissertation (Kerr 2005). I am grateful to Daron Acemoglu, Pol Antras, David Autor, Nick Bloom, Ricardo Caballero, Arnaud Costinot, Julian Di Giovanni, Fritz Foley, Richard Freeman, Ashley Lester, Matt Mitchell, Peter Morrow, Ramana Nanda, Tim Simcoe, Antonio Spilimbergo, Scott Stern, and John Van Reneen for advice on this project and to seminar participants at AEAs, Clemson University, ERSA, Georgetown University, Harvard University, International Monetary Fund, London School of Economics, MIT Economics, MIT Sloan, NBER, Queens University, University of Helsinki, and University of Toronto Rotman for helpful comments. This research is supported by the National Science Foundation, MIT George Schultz Fund, HBS Research, and the Innovation Policy and Economy Group.

1 Introduction

Trade among countries due to technology differences is a core principle in international economics. Countries with heterogeneous technologies focus on producing goods in which they have comparative advantages; subsequent exchanges afford higher standards of living than are possible in isolation. This Ricardian finding is the first lesson in most undergraduate courses on trade, and it undergirds many modelling frameworks on which recent theoretical advances build (e.g., Dornbusch et al. 1977, Eaton and Kortum 2002, Costinot et al. 2012). In response to Stanislaw Ulam's challenge to name a true and nontrivial theory in social sciences, Paul Samuelson chose this principle of comparative advantage due to technology differences.

While empirical tests date back to David Ricardo (1817), quantifying technology differences across countries and industries is extremely difficult. Even when observable proxies for latent technology differences are developed (e.g., labor productivity, industrial specialization), cross-sectional analyses risk confounding heterogeneous technologies with other country-industry determinants of trade. Panel data models can further remove time-invariant characteristics (e.g., distances, colonial histories) and afford explicit controls of time-varying determinants (e.g., factor accumulation, economic development, trading blocs). Quantifying the dynamics of uneven technology advancement across countries is an even more challenging task, however, and whether identified relationships represent causal linkages remains a concern. These limitations are particularly acute for developing and emerging economies. This is unfortunate as non-OECD economies have experienced some of the more dramatic changes in technology sets and manufacturing trade over the last thirty years, providing a useful laboratory for quantifying Ricardian effects.

This study contributes in two ways to the empirical trade literature on Ricardian advantages. The central contribution is a panel analysis of bilateral trade and technology in a setting that includes many emerging economies (e.g., China, India, Korea), a large group of focused manufacturing industries, and an extended time frame. This platform is feasible when modelling Ricardian advantages through industry-level scientific integration with the US. This integration is measured from US patent records as described below. This technique allows stronger tests of the Ricardian model than hereto possible by circumventing the data constraints of productivity and output metrics at the industry-level for emerging economies.

As a second contribution, this study draws attention to the variation being exploited in empirical trade tests. Bilateral manufacturing exports are organized by exporter-importer-industry-year from the 1975-2000 World Trade Flows (WTF) database. Previous tests of the Ricardian model identify elasticities using variations in trade and technology across industries within each country—akin to including longitudinal fixed effects for industry-year and exporter-importer-year developments in the data structure. While these controls account for overall trade and technology levels by country, permanent differences in the levels of these variables across industries within a country are used for identification. This paper is the first to quantify Ricardian elasticities when further modelling cross-sectional fixed effects for exporter-importer-industry observations. This panel approach only exploits variation within industry-level bilateral trading routes, providing a substantially stronger empirical test of the theory.

Before analyzing the US patent data, an initial empirical analysis considers traditional data sources for comparability to earlier work. Latent comparative advantages are proxied by labor productivity and output metrics (i.e., industrial specialization) developed from United Nations data. Panel specifications find positive associations between industrial specialization and exports on both the intensive and extensive margins of trade. Ricardian elasticity estimates range from 0.2 to 0.4 for the intensive margin in the preferred framework. In other words, a 10% output growth by country-industry is associated with a 2% to 4% increase in manufacturing exports. These elasticities are smaller than the 0.6 to 0.9 elasticities obtained when not employing cross-section fixed effects, which is more reflective of previous tests. A 10% output growth is associated with a 0.2% greater likelihood of exporting in the preferred framework.

While comparable to earlier studies, the limitations of the output and productivity data inhibit further progress. To provide greater traction, the remainder of the paper models Ricardian advantages through differences across countries in their access to the US technology frontier. Recent research emphasizes the importance of immigrant scientists and entrepreneurs living in frontier economies for the diffusion of technologies to their home countries (e.g., Saxenian 2002, 2006, Kerr 2008, Papageorgiou and Spilimbergo 2008). These frontier expatriates facilitate the transfer of both codified and tacit details of new innovations, and Kerr (2008) finds foreign countries realize manufacturing gains from the stronger scientific integration, especially with respect to computer-oriented technologies.[1]

As invention is disproportionately concentrated in the US, these ethnic networks significantly influence technology opportunity sets in the short-run for following economies. This study uses heterogeneous technology diffusion from the US to quantify better the importance of technology

[1] Channels for this technology transfer include communications among scientists and engineers (e.g., Saxenian 2002, Kerr 2008, Agrawal et al. 2011), trade flows (e.g., Rauch 2001, Rauch and Trindade 2002), and foreign direct investment (e.g., Kugler and Rapoport 2007, Foley and Kerr 2012). Recent research is further quantifying the role of international labor mobility in these exchanges (e.g., Saxenian 2006, Kapur and McHale 2005, Nanda and Khanna 2010, and Obukhova 2008, 2009). Kerr (2008) provides additional references on the role of ethnic networks in transmitting new technologies. Kerr and Lincoln (2010) provide additional references on characteristics and populations of US immigrant scientists and engineers.

Other sources of heterogeneous technology frontiers are geographic distances to major R&D nations (e.g., Keller 2002b), the innovative efforts of trading partners (e.g., Grossman and Helpman 1991, Coe and Helpman 1995, Coe et al. 1997), or international patenting decisions (e.g., Eaton and Kortum 1999). Keller (2004) reviews the technology transfer literature.

differences across countries in explaining trade patterns. Trade between the US and the foreign country is excluded throughout this study due to network effects operating alongside technology transfers. Attention is instead placed on how differential technology transfer from the US influences the exports from the foreign country to other nations.

The strength of technology flows from the US are measured through US ethnic inventor populations evident in patent records. The ethnicities of inventors are identified through their names (e.g., inventors with the surnames Ming or Wang are more likely of Chinese ethnicity than Hispanic ethnicity). These US ethnic research communities are joined with the detailed WTF export data. For example, US Chinese computer research is paired with China's trade in the computer industry. This data platform affords several empirical advantages: a more uniform measurement of technology capabilities, more detailed industries, and a greater number of years. The approach also reduces the scope for reverse causality as discussed below.

Reduced-form specifications regress bilateral exports on exporters' scientific integration for US technologies as measured in the ethnic patenting dataset. In the panel framework, a 10% increase in access to the US technology frontier correlates with a 1.5% expansion in export volumes and a 0.1% greater likelihood of exporting in a given industry. The remainder of the paper tests these Ricardian advantages in a variety of ways. The importance of the exporter's technology is robust to simultaneously controlling for the importer's technology set. Elasticity estimates for the importer's technology regressor are smaller and not consistently different from zero. Further tests find a consistent lag structure of treatment effects and confirm that measured results are not due to a Rybczynski effect operating within manufacturing following omitted factor accumulations (e.g., Heckscher-Ohlin-Vanek models). Heterogeneity in treatment effects across ethnicities, industries, and distances are also quantified. Effects are strongest among Chinese economies, high-tech industries, and industries that trade intermediate goods.

This study concludes that comparative advantage is an important determinant of trade; moreover, Ricardian differences are relevant for explaining changes in trade patterns over time. These panel exercises are closest in spirit to the industrial specialization work of Harrigan (1997b) and the structural Ricardian model of Costinot et al. (2012). Other tests of the Ricardian model are MacDougall (1951, 1952), Stern (1962), Golub and Hsieh (2000), Morrow (2010), Costinot and Donaldson (2012), Caliendo and Parro (2012), Bombardini et al. (2012), Burstein and Vogel (2012), and Levchenko and Zhang (2012). The comparative advantages of this work are in its substantial attention to non-OECD economies and in its stricter panel assessment using heterogeneous technology diffusion. In addition to contributing to the trade literature, the described phenomena are also important for evaluating the gains and loss for emerging economies from high-skilled emigration of science and engineering talent to frontier economies like the US.[2]

[2] Davis and Weinstein (2002) consider immigration to the US, technology, and Ricardian-based trade. Their

2 Theory and Estimating Framework

This section develops the basic estimating equation from the multi-country Ricardian model of Eaton and Kortum (2002). This framework and Costinot et al. (2012) are unique in relating trade to technology differences across several countries. A simple application builds into this theory ethnic networks and heterogeneous technology diffusion. The boundaries of the framework and the statistical properties of the estimating equation are discussed.[3]

2.1 Theoretical Framework

The world consists of N countries producing and consuming a continuum of goods $j \in [0,1]$. Consumers maximize utility in each period by purchasing these goods in quantities $Q(j)$ according to a constant elasticity of substitution (CES) objective function,

$$U = \left(\int_0^1 Q(j)^{(\sigma-1)/\sigma} dj\right)^{\sigma/(\sigma-1)}, \tag{1}$$

subject to prices determined below. $\sigma > 0$ is the elasticity of substitution across goods for the consumers. Consumers earn wage w and consume their full wages in each period. Accordingly, time subscripts are omitted until the estimating equation is introduced.

Countries are free to produce or trade all goods. Inputs can move among industries within a country but not across countries. Industries are characterized by identical Cobb Douglas production functions employing labor with elasticity α and the continuum of produced goods, also aggregated with (1), with elasticity $1-\alpha$. Factor mobility and identical production functions yield constant input production costs across goods within each country, $c_i(j) = c_i \; \forall j$.

Technology differences exist across countries, so that country i's efficiency in producing good j is $z_i(j)$. With constant returns to scale in production, the unit cost of producing good j in country i is $c_i/z_i(j)$. While countries are free to trade, geographic distance results in "iceberg" transportation costs so that delivering one unit from country i to country n costs $d_{ni} > 1$ units in i. Thus, the delivery to country n of good j made in country i costs

$$p_{ni}(j) = \left(\frac{c_i}{z_i(j)}\right) d_{ni}. \tag{2}$$

An increase in country i's efficiency for good j lowers the price it must charge. Perfect competition allows consumers to buy from producers in the country offering the lowest price inclusive

concern, however, is with the calculation of welfare consequences for US natives as a consequence of immigration due to shifts in trade patterns.

[3] Dornbusch et al. (1977), Wilson (1980), Baxter (1992), Alvarez and Lucas (2007), and Costinot (2009) provide further theoretical underpinnings for comparative advantage.

of shipment costs. Thus, the price that consumers in country n pay for good j is

$$p_n(j) = \min[p_{ni}(j); i = 1, ..., N]. \tag{3}$$

The technology determining the efficiency $z_i(j)$ is modelled as the realization of a random variable Z_i drawn from a country-specific probability distribution $F_i(z) = \Pr[Z_i < z]$. Draws are independent for each industry j within a country. A core innovation of Eaton and Kortum's model is to use the Fréchet functional distribution to model technologies,

$$F_i(z) = e^{-T_i \cdot z^{-\theta}}, \tag{4}$$

where $T_i > 0$ and $\theta > 1$. The country-specific parameter T_i determines the location of the distribution, while the common parameter θ determines the variation within each country's distribution. By the law of large numbers, a larger T_i raises the average efficiency of industries for country i, and therefore its absolute advantage for trade. A larger θ, on the other hand, implies a tighter distribution for industries within every country and thereby limits the scope for comparative advantage across nations.

The Fréchet distribution (4) allows prices from equations (2) and (3) to be determined. The probability that country i is the lowest-cost producer of an arbitrary good for country n is $\pi_{ni} = T_i(c_i d_{ni})^{-\theta} \big/ \sum_{k=1}^{N} T_k(c_k d_{nk})^{-\theta}$.[4] With a continuum of goods, π_{ni} is also the fraction of goods country n purchases from country i. Country n's average expenditure per good does not vary by source country, so that the fraction of country n's expenditure on goods from country i is also

$$\frac{X_{ni}}{X_n} = \frac{T_i(c_i d_{ni})^{-\theta}}{\sum_{k=1}^{N} T_k(c_k d_{nk})^{-\theta}}, \tag{5}$$

where X_n is total expenditure in country n. Holding input prices constant, technology growth in country i increases its exports to country n through entry into industries in which it was previously uncompetitive. Looking across import destinations for an industry in which it already exports, country i also becomes the lowest-cost producer for more distant countries it could not previously serve due to the markup of transportation costs. Condition (5) also shows how trading costs d lead to deviations in the law of one price. This condition can be rearranged as

$$\ln(X_{ni}) = \ln(T_i) - \theta \ln(c_i d_{ni}) + \ln(X_n) - \ln\left(\sum_{k=1}^{N} T_k(c_k d_{nk})^{-\theta}\right). \tag{6}$$

[4] The distribution of prices country i presents to country n is $G_{ni}(p) = \Pr[P_{ni} \le p] = 1 - F_i(c_i d_{ni}/p) = 1 - \exp(-T_i(c_i d_{ni})^{-\theta} p^{\theta})$. Country n buys from the lowest cost producer of each good, so that its realized price distribution is $G_n(p) = \Pr[P_n \le p] = 1 - \prod_{i=1}^{N}[1 - G_{ni}(p)] = 1 - \exp(-p^{\theta} \sum_{i=1}^{N} T_i(c_i d_{ni})^{-\theta})$. The probability is $\pi_{ni} = \Pr[P_{ni}(j) \le \min\{P_{ns}(j); s \ne i\}] = \int_0^{\infty} \prod_{s \ne i}[1 - G_{ns}(p)] dG_{ni}(p)$. See Eaton and Kortum (2002) for the full derivation of the price index.

2.2 Estimating Equation

This study evaluates an approximation of this Ricardian theory through worldwide trade in manufacturing goods. Before proceeding, it is important to identify the broadest boundaries of this model. In contrast to the Ricardian framework, Heckscher-Ohlin-Vanek (HOV) models describe trade as resulting from factor differences across countries (e.g., labor, capital, natural resources). Technology is the only channel promoting export growth in the above framework due to identical factor endowments and no intertemporal factor accumulation. Differences in preferences or non-homothetic utility functions not captured in the objective function (1) can also promote trade. Hunter and Markusen (1988) and Hunter (1991) find these stimulants account for up to 20% of world trade. The specified production function also abstracts from trade due to increasing returns to scale (e.g., Helpman and Krugman 1985, Antweiler and Trefler 2002).

Rather than attempting to jointly model these other determinants of trade (e.g., Davis and Weinstein 2001, Morrow 2010), this study isolates the role of technology differences through empirical specifications that use a battery of fixed effects (FE) to control for confounding factors. The core estimating equations for bilateral exports and technology take the form,

$$\ln(X_{nijt}) = \beta_T \ln(T_{ijt}) + \phi_{nij} + \eta_{nit} + \psi_{jt} + \epsilon_{nijt}. \quad (7)$$

As before, n indexes importers, i indexes exporters, and j indexes goods or industries. Time periods are further indexed by t. Each of the terms in specification (7) is next discussed, especially where differences to condition (6) are introduced to provide empirical traction.

First, the dependent variable is bilateral manufacturing exports by exporter-importer-industry-year. The lack of trade for a large number of bilateral routes at the industry level creates econometric challenges with a log specification. These zero-valued exports are predicted by the model as an exporter is rarely if ever the lowest cost producer for all countries in an industry. Zero-valued cell could also be due to unmodeled factors like explicit trade restrictions. This study approaches this problem by separately testing the intensive and extensive margins of trade. In tests of the intensive margin of trade expansion, the dependent variable is the log value of bilateral exports, $\ln(X_{nijt})$. In tests of extensive margin of trade expansion—that is, commencing exports to new import destinations—the dependent variable in specification (7) is a dichotomous indicator variable for whether measurable exports exist. Differences in the sample construction for these two tests are discussed when describing the trade dataset.[5]

The regressor of interest is T_{ijt}, a measure of the technology state in exporter i and industry j. This specific modelling of technologies at the country-industry level is an important departure

[5] The intensive margin of exports captures both quantities effects and price effects (e.g., Acemoglu and Ventura 2002, Hummels and Klenow 2005).

from Ricardian trade models like Eaton and Kortum (2002). The general equilibrium solution described above requires that the industry-level technology parameters for a country be of the Fréchet functional distribution. This distribution and its extreme value properties characterize the probability of exporting at the bilateral-industry level, but determining trade flows (5) requires further aggregating over a continuum of industries. The empirical specification (7) models the latent industry-level relationship embodied in the probabilities. The associated comparative statics are further discussed after introducing the FEs.

The included panel FEs are very important for interpreting the β_T parameter. First, most estimations include a vector of cross-sectional FEs ϕ_{nij} for each bilateral trading route at the exporter-importer-industry level. These FEs control for time-invariant determinants of trade like pairwise spatial distances and colonial ties. These FEs also remove long-term differences in technology levels across country-industry pairs. Attention is instead placed on technological growth by country-industry and associated export development.

Two longitudinal controls are considered. The preferred specifications include a vector of exporter-importer-year FEs η_{nit}, although weaker variants are also examined. The exporter-importer-year FEs perform several functions. First, these FEs remove aggregate trade growth by exporter-importer pairs common across industries. These uniform expansions could descend from factors specific to one country of the pair (e.g., economic growth and business cycles, factor accumulations, terms of trade) or be specific to the bilateral trading pair (e.g., trade agreements). This framework is thus a powerful check against omitted variables biases, helping to isolate the Ricardian impetus for trade from relative factor scarcities and other determinants of trade. National changes in factor endowments may still influence industries differentially due the Rybczynski effect, which is explicitly tested for below.

The exporter-importer-year FEs also control for aggregate technology development in the exporter. Thus, the β_T parameter is only identified through differential technology growth in one industry of the exporter leading to differential export growth. In other words, China's technology expansion for computer manufacturing must exceed its technology expansion for chemicals manufacturing if export growth is stronger in computers than chemicals.

Many empirical studies in the trade literature include gravity covariates in estimations. Similar to planetary pull, countries tend to trade more with nations that are economically larger and geographically closer. Exporter-importer-industry FEs control for static spatial proximity and for longitudinal variation in the aggregate size of the exporter's and importer's economy, regardless of whether they are interacted or not (e.g., Frankel 1997). The FEs thus account for the importer's economic size, the $\ln(X_n)$ term in condition (6). Exporter-importer-year FEs also account for general equilibrium wage increases c_i in the exporter following technology growth. Moreover, these FEs further account for interactions between these exporter production costs and bilateral distances, the $-\theta \ln(c_i d_{ni})$ term in condition (6). This latter general equilibrium effect is predicted in both Eaton and Kortum (2002) and Costinot et al. (2012).

A vector of industry-year FEs ψ_{jt} removes aggregate trading volumes, prices, and technology levels on an annual, industry-by-industry basis. All estimations include industry-year FEs due to both theoretical and methodology issues discussed below. These controls, along with the exporter-importer-industry FEs η_{nit}, isolate changes in relative technology advantages both across industries within the exporter and relative to the rest of the world. To a first approximation, these industry-year FEs also capture the world technology aggregate, the $-\ln\left(\sum_{k=1}^{N} T_k (c_k d_{nk})^{-\theta}\right)$ term in condition (6).[6]

With the FEs introduced, the approximation of the Ricardian model built into specification (7) can be better explained. Inputs costs c_i are the same for each industry within a country and thus captured by the exporter-importer-year FEs. The exporter-importer-year FEs also capture the aggregate technology state T_i in the exporter. The empirical specifications identify off of differences in technology levels across industries and over time for a country, T_{ijt}. These technological differences are only probabilistic at the bilateral level in the theory, but they are explicitly measured for the empirical application.

More subtly, three differences between multi-country Ricardian frameworks and the classic two-country model of Dornbusch et al. (1977) are worth emphasizing. These differences influence how the comparative static of increasing a single country-industry technology parameter T_{ijt}, *ceteris paribus*, is viewed. First, the multi-country theoretical framework allows for increases in T_{ijt} to reduce exports on some bilateral routes for the exporter-industry. This effect is due to general equilibrium pressures on input costs and extreme value distributions. The treatment effect β_T is measured across all export destinations and thus captures the general Ricardian pattern embedded in the model. This effect, however, is a net effect that may include reduction of exports on some routes.

Second, the use of longitudinal variation at the industry level for identification also does not follow directly from the multi-country theory (e.g., Costinot et al. 2012). In the Dornbusch et al. (1977) model, one can contemplate the comparative static of increasing a specific country-industry technology parameter and how it affects the chain of comparative advantage. The general equilibrium solutions in multi-country models require, however, that the industry distribution for a country conform to the modelled distribution. The traditional comparative static is thus outside of the multi-country model's scope but is modelled in specification (7).

[6] The worldwide technology aggregate is perfectly modelled by industry-year FEs for the cases of frictionless trade or constant trading costs ($d_{nk} = d \ \forall n, k$). If the number of countries is large, the error from modelling the world price and technology aggregate with industry-year effects is small even without constant trading costs, $\lim_{N\to\infty} [\partial \ln(\sum_{k=1}^{N} T_k (c_k d_{nk})^{-\theta}) / \partial \ln(T_i)] = 0$.

Finally, the empirical specifications below contrast the importer's and exporter's technology states for a given industry. This test is somewhat ad hoc as multi-country Ricardian trade models do not yield clear predictions for the role of the importer's technology state. Nevertheless, the contrast is of interest from an empirical perspective as it provides reassurance in the measured role for the exporter's technology. This contrast is also important given the substantial trade in intermediate goods, which are outside of the Ricardian model but perhaps correlated with simultaneous importer and exporter technology development.[7]

2.3 Heterogeneous Technology Diffusion and Ricardian Trade

While the Ricardian framework assigns a causal relationship of export growth to technology development, in practice the empirical estimation of specification (7) can be confounded by reverse causality or omitted variables operating by country-industry-year. Reverse causality may arise if engagement in exporting leads to greater technology adoption, perhaps through learning-by-doing or for compliance with importer's standards and regulations. An example of a country-industry-year omitted factor is a change in government policies to promote a specific industry, perhaps leading to large technology investments and the adoption of policies that favor the chosen industry's exports relative to other manufacturing industries. This would lead to an upward bias in the estimated β_T parameter.[8]

Heterogeneous technology transfer from the US provides an empirical foothold against these complications. Consider a leader-follower model where the technology state in exporter i and industry j is

$$T_{ijt} = T_{jt}^{US} \cdot \Upsilon_{nij} \cdot \Upsilon_{nit} \cdot (H_{ijt})^{\tilde{\beta}_H}. \tag{8}$$

T_{jt}^{US} is the exogenously determined US technology frontier for each industry and year. Two general shifters govern the extent to which foreign nations access this frontier. First, Υ_{nij} models time-invariant differences in the access to or importance of US technologies to country i and industry j, potentially arising due to geographic separation (e.g., Keller 2002), heterogeneous production techniques (e.g., Davis and Weinstein 2001, Acemoglu and Zilibotti 2001), or similar factors. The shifter Υ_{nit} models longitudinal changes in the utilization of US technologies

[7] In the two-country Ricardian framework of Dornbusch et al. (1977), one would expect a negative elasticity for export growth from improvements in the importer's technology set for a given industry j. This prediction is conditional on controlling for the exporter's technology set and assumes the importer's technology expansion is only in industry j. The gain in the relative strength of the importer's technology for industry j reduces the likelihood that the exporter has a comparative advantage in the industry. The simple ordering of industries in the two-country model, however, does not extend to multi-country Ricardian models. Costinot et al. (2012) provide state-of-the-art theoretical results on industry ordering, and these too do not have clear predictions regarding the importer's technology state.

[8] More specifically, the innovation in industrial policy support must be non-proportional across manufacturing industries. Long-term policies to support certain industries more than others are accounted for by cross-sectional FEs. Increased or decreased support in these long-run positions uniform across industries is also jointly accounted for by panel FEs.

common to all industries within country i, for example due to declines in communication and transportation costs, greater general scientific or business integration, and so on. Moreover, both of these shifters can be specific to a potential exporter-importer pair.

Finally, H_{ijt} is the human capital of country i with respect to US innovations in industry j and year t. This can also be thought of as scientific integration across countries through high-skill ethnic networks. Within this framework (8), H_{ijt} affects country i's exports in industry j only through technology transfer and can thus proxy for country i's technology in the Ricardian specification (7). Substituting (8) into (7) yields the reduced-form contribution of these communities for exports from their home countries,

$$\ln(X_{nijt}) = \beta_H \ln(H_{ijt}) + \phi_{nij} + \eta_{nit} + \psi_{jt} + \epsilon_{nijt}, \tag{9}$$

with $\beta_H = \beta_T \cdot \tilde{\beta}_H$. Due to the log form of specification (7), T_{jt}^{US} is separated from H_{ijt} and absorbed into the industry-year FE. Likewise, the exporter-importer-industry and exporter-importer-year FEs absorb the Υ_{nij} and Υ_{nit} shifters, respectively. More generally, technology differences across countries and industries orthogonal to the US ethnic human-capital stock H_{ijt} are absorbed into the error term ϵ_{nijt} without biasing the β_H coefficient.

The empirical tests below first estimate the β_T parameter. The β_T parameter quantifies the elasticity of export expansion with technology development in the exporter. Positive β_T coefficients provide evidence for the Ricardian model. T_{ijt} is unobserved, so proxies are developed through output and productivity measures from United Nations data. Most of the empirical exercises will then measure the reduced-form relationship β_H by modelling H_{ijt} as the number of scientists and engineers of country i's ethnicity working in the US. These measures are developed from the ethnic patenting data.

There are advantages and liabilities of the latter reduced-form approach. The primary liability is that the β_H parameter is intrinsically less interesting than the Ricardian parameter β_T relating latent productivity to exports. The reduced-form elasticity combines both a transmission elasticity ($\tilde{\beta}_H$) and the Ricardian elasticity. On the other hand, the more powerful ethnic patenting data afford many tests of the Ricardian model that are not otherwise possible. In addition, the ethnic patenting approach aids with the reverse causality concerns. The scope for reverse causality is much larger when using observed output or productivity to model technology advantages for trade. These latter variables also contain greater measurement error. These reduced-form advantages will increase the relative precision of the parameter estimates.[9]

[9]This framework suggests that one could use H_{ijt} as an instrument for T_{ijt} to recover the β_T parameter. This study does not take this step for two reasons. First, the output and productivity data are not sufficiently available at the detailed industry-level where specification (9) is best estimated. At the higher level of industry aggregation, it is very hard to separate industry-level technology transfers from country-year FEs (e.g., Kerr 2008). This would result in a weak instruments problem. Second, the exclusion restriction would not be completely satisfied. For example, foreign countries may adopt industrial policies to encourage the exports of industries where technology transfers are possible from the US. This would bias the instrumented relationship between technology and trade.

3 Data Preparation

This section describes the ethnic patenting data, trade data, and output and productivity data employed in this study.

3.1 US Ethnic Human-Capital Stocks

Ethnic human capital with respect to US technologies H_{ijt} are quantified through individual records of all patents granted by the United States Patent and Trademark Office (USPTO) from January 1975 to May 2008. Each patent record provides information about the invention (e.g., technology classification, citations of patents on which the current invention builds) and inventors submitting the application (e.g., name, city). Hall et al. (2001) provide extensive details on this dataset. USPTO patents must list at least one inventor, and multiple inventors are allowed. Approximately 7.8m inventors are associated with 4.5m granted patents during this period.

To estimate ethnicities, two commercial databases of ethnic first names and surnames are mapped into the inventor records. Kerr (2007) documents the name-matching algorithms, lists frequent ethnic names, and provides extensive descriptive statistics. The match rate is 98% for US domestic inventors, and the process affords the distinction of nine ethnicities: Chinese, English, European, Hispanic, Indian, Japanese, Korean, Russian, and Vietnamese. Kerr (2007) also discusses quality assurance exercises performed. For example, the ethnic-name database can be applied to foreign patents registered with the USPTO. The ethnic-name database assigns ethnicities to 98% of foreign records. Moreover, estimated inventor compositions are quite reasonable—for example, approximately 90% of inventors filing from Chinese countries and regions are classified as ethnically Chinese.

Table 1 describes the 1975-2004 US sample; these statistics are just for inventors who are living in the US at the time of their patent application. The trends demonstrate a growing ethnic contribution to US technological development, especially among Chinese and Indian scientists. Ethnic inventors are more concentrated in high-tech industries like computers and pharmaceuticals and in gateway cities relatively closer to their home countries (e.g., Chinese in San Francisco, European in New York, and Hispanic in Miami). The final three rows of Table 1 demonstrate a close correspondence of the estimated mean ethnic composition during the period to the country-of-birth composition of the US SE workforce in the 1990 Census. Figure 1 illustrates the evolving ethnic contribution to US technology development as a percentage of patents granted by the USPTO, while Figure 2 provides a more detailed glimpse of non-English ethnic contributions by broad technology groups.

The sample is organized longitudinally into three-year intervals. Short intervals are selected over an annual framework primarily due to computational constraints with the large number of FEs employed. These intervals consider 1975-1977, ..., 1984-1987, ..., 1999-2001. The ethnic human-capital level H_{ijt} to the US frontier is measured as the mean level of US patenting by ethnicity and industry within the three-year interval. Only inventors residing within the US at the time of their patent application are included, and multiple inventors are discounted so that each patent receives the same weight when measuring inventor populations. The empirical exercises further discuss the lag structure of treatment effects; these exercises will also employ the final period of 2002-2004 for forward regressors.

It was earlier noted that theoretical and methodology rationales exist for always conditioning on industry-year FEs ψ_{jt}. The theoretical rationale is that the US technology frontier is taken as exogenous in model (8). The identification of β_H parameter should thus be independent of the pace of US technology expansion in different industries. A methodology rationale stems from the US patent process. US patent grants have increased dramatically since the early 1980s. While several factors lie behind this increase, it is clear that USPTO grant rates grew faster than the underlying growth of US scientific personnel and innovation can explain. Moreover, differences in grant rates exist across industries. Industry-year FEs ψ_{jt} account for these secular changes in the underlying patenting productivity, effectively contrasting ethnic shares of US patents granted.[10]

More generally, it is worth explicitly noting that specification (9) does *not* estimate the direct impact of US patenting by ethnicities on home-country exports. Isolating the specific channel of patents from other knowledge flows between countries is not feasible with industry-level outcomes. Moreover, much of the gain from diaspora networks comes in the transmission of tacit knowledge about how to implement frontier technologies or business practices, regardless of whether invented by the immigrant or not. The developed ethnic human capital with respect to US technologies H_{ijt} should thus be viewed more generally as a measure of scientific integration with the US by ethnicity-industry. Ethnic patenting data allow a much more detailed metric than otherwise possible. A positive β_H coefficient requires that higher relative growth of Chinese-US computer integration compared to Indian-US integration correlate with higher relative export growth (to non-US countries) for China's computer industry compared to India's computer industry.

These ethnic human-capital stocks for US innovations are developed at the four-digit level of the International Standard Industrial Classification system (ISIC4). This framework distinguishes 81 manufacturing industries at a level of detail straddling the two-digit and three-digit

[10] For example, Griliches (1990), Kortum and Lerner (2000), Kim and Marschke (2004), Hall (2005), Branstetter and Ogura (2005), Jaffe and Lerner (2005), and Lemley and Sampat (2007).

levels of the US Standard Industrial Classification system. Mapping procedures, which include dropping the miscellaneous category within manufacturing, reduce the number of manufacturing industries to 68 for estimation. The appendix lists ISIC4 industries.[11]

3.2 Export Volumes

Bilateral exports X_{nijt} are taken from the 1975-2000 World Trade Flows Database (WTF) developed by Feenstra et al. (2005). This rich data source documents product-level values of bilateral trade for most countries from 1975-2000. These product flows are aggregated into ISIC4 industries developed in the US patent dataset, and exporting countries are grouped into the eight non-English ethnicities that are identifiable with the ethnic-name database. Five ethnicities map to a single country, while the Chinese, European, and Hispanic ethnicities have larger blocs. Table 2 lists the countries studied and their characteristics.

The primary sample includes all export-import-industry combinations where the exporter and importer have identifiable, non-English ethnicities. In other words, the sample is the cross of Table 2 with itself. Exports to countries of English ethnicity (e.g., UK, Australia) or to countries of ethnicities not supported by the ethnic-name database (e.g., Africa, the Middle East) are excluded. These sample restrictions afford a consistent sample size when jointly testing technology transfer from the US to exporters and importers. Due to major political shifts, Russia and Vietnam are also excluded from the primary sample. Altering these sample restrictions to allow exports to countries for which we do not measure the patenting link does not influence the results developed with the core, balanced panel.

Two features of the WTF dataset further shape the sample design. First, a break exists in data collection procedures at 1984. While only weakly influencing total bilateral trading volumes at the manufacturing sector level, shifts in industry-level trading across the break are evident when aggregating to the ISIC4 level. Core estimations thus focus on the 1984-2000 period, with the longer sample reported as a robustness check. Second, the minimum threshold of trade that can be consistently measured across countries and industries is US \$100k. While Feenstra et al. (2005) are able to incorporate smaller trading levels for some countries, these values are ignored to maintain a consistent threshold across observations.

The empirical approach is to study separately the extensive and intensive margins of export expansion. Mean export volumes are taken across exporter-importer-industry observations and

[11] The USPTO issues patents by technology categories rather than by industries. Following Johnson (1999), Silverman (1999), and Kerr (2008), concordances are developed between USPTO classifications and ISIC4 industries in which new inventions are manufactured or used. The main estimations focus on industry-of-use, affording a composite view of the technological opportunity developed for an industry. Studies of advanced economies find accounting for these inter-industry R&D flows important (e.g., Scherer 1984, Keller 2002a). Estimations with manufacturing industries support the using-industry specifications.

three-year intervals constructed above. The 1999-2001 interval uses the mean export levels for 1999-2000. For the extensive margin, entry is defined as exports greater than US $100k. The primary entry sample for 1984-2000 includes 736,848 observations from the unique cross of 43 exporters and importers, 68 industries, and six time periods. This panel extends to 1.1m observations when considering 1975 onwards. On the other hand, the sample for intensive margin estimations is restricted to exporter-importer-industry observations that maintain more than US $100k in exports in all years. A few bilateral series with abnormal changes in export volumes are also dropped (specifically, a 10x growth or 90% decline across three years). The sample size for these estimations is 152,874 over 1984-2000.

The first column of Table 2 presents non-US manufacturing export volumes for each nation averaged over 1984-2000. The 43 economies account for over half of global manufacturing exports, with countries of English ethnicity accounting for most of the residual. The largest exporters are European nations (especially Germany), Japan, and China, while the smallest exporters are found in Latin America. The second column provides compound annual growth rates in manufacturing exports across the 1984-2000 period. The average growth rate is 8%, with Vietnam (29%) and Mainland China (20%) experiencing the most rapid expansions. The third column documents the share of each country's non-US exports that are included in the primary sample. The mean sample share is 76%, with the lowest shares in Singapore (54%) and Belize (51%).

3.3 Output and Productivity Data

Output and productivity measures are taken from the Industrial Statistics Database of the United Nations Industrial Development Organization (UNIDO). The UNIDO collects industry-level manufacturing statistics for *The International Yearbook of Industrial Statistics* and specialized publications on topics like development and competition. Researchers at the UNIDO supplement the data resources of the OECD with national records for non-OECD members, creating a unique global resource. The UNIDO's stated objective is the compilation of internationally comparable and internally consistent series (e.g., variable definitions, accounting units, collection procedures).

UNIDO data are unfortunately not uniformly available. Table 2 notes the countries included and aggregates annual industry-level data to describe country-level manufacturing output levels. While direct comparisons across countries are limited with an unbalanced panel, production differences between industrialized countries and developing nations are clearly evident. Production levels are under-reported relative to exports due to missing industries within UNIDO data. The panel used to estimate the β_T parameter in specification (7) is dictated by the UNIDO data as the

WTF and ethnic patenting data are uniformly available. A small number of country-industry observations with under ten employees or very problematic data are excluded.

Several changes to estimation framework are also made when using this data. First, the data are organized into three five-year blocks, running 1985-1989, 1990-1994, and 1994-1999. Mean levels of exports and UNIDO measures are taken for each time period across available years. Second, the industry dimension is shifted from the four-digit level to the three-digit level of the ISIC system. These shifts are necessary due to UNIDO data constraints. Kerr (2008) provides further details on the UNIDO dataset development, and additional descriptive statistics are provided in the appendix.

4 Empirical Results

This combined dataset is a unique laboratory for evaluating Ricardian technology differences in international trade. This section commences estimating specification (7) using the UNIDO data, providing a bridge to earlier work on Ricardian advantages. Reduced-form specifications (9) then take advantage of the richness of the combined ethnic patenting and trade dataset.

4.1 UNIDO Specifications

Most Ricardian models suggest using labor productivity to measure comparative advantage. This is fortunate in that manufacturing output and employment data are among the most available metrics for the broad grouping of countries under study. Labor is typically the only factor of production in Ricardian models, so a natural extension might be total factor productivity that also allows for capital accumulation as well. Unfortunately, capital data at the country-industry level for this sample is too sparse to be of benefit in a panel study.

Using output or industrial specialization as an observable measure of technology differences is also supported by the Ricardian model. Relative to labor productivity, output also has advantages in the context of developing and emerging economies. Production techniques are endogenous to local environments. Sector reallocation from agriculture to manufacturing can follow from manufacturing technology growth in countries with underutilized labor resources. If an abundant pool of labor is available at a constant outside wage, firms have incentives to expand employment and keep growth in labor productivity minimal compared to output expansion. On the other hand, economies with fully-utilized labor resources must increase labor productivity with output. Output can thus provide a cleaner metric of shifting industrial specialization. The analysis will thus consider both output and labor productivity metrics as proxies for unobserved technology states.

Tables 3A and 3B describe the basic Ricardian relationship evident in least squares estimations. The first table considers the intensive margin of trade, restricting the panel to observations with greater than $100k of bilateral exports in all periods, while Table 3B considers the extensive margin. Panels A and B model labor productivity and output, respectively, as the observable measure of underlying comparative advantage. Industry-year FEs effectively deflate the labor productivity and output measures.

Columns 1-3 of both tables estimate specification (7) without exporter-importer-industry FEs. These estimates identify the β_T parameter through variation within bilateral trading routes and variation across industries of an exporter. This framework parallels most Ricardian empirical studies. A 10% growth in output is correlated with a 6% expansion in exports. The overall elasticity of 0.6 on the intensive margin when modelling labor productivity is somewhat lower than the unit elasticity or greater typically found. Columns 2 and 3 show that this difference descends from the more inclusive sample. The elasticity is 1.2 when looking at just European nations and Japan, more in line with studies employing OECD data, while the elasticity employing the remainder of the sample is 0.6. The total sample effect is not a weighted average of these two elasticities as both groups determine the industry-year FEs ψ_{jt}.

The between elasticity for the intensive margin is 0.9 when using output levels. Output can be viewed in this context as industrial specialization given the implicit country FEs in the exporter-importer-year FEs. The differences between the two sample disaggregations are smaller with this metric. The first three columns of Table 3B find similar patterns for the extensive margin using linear probability models, with an overall entry elasticity of 0.03-0.08 when using between variation.[12]

The last six columns assess the Ricardian elasticity using just variation within the industry-level bilateral panels. This test is new to the empirical trade literature but a very important verification of the model. Columns 4-6 of both tables employ levels specifications that incorporate cross-sectional effects for exporter-importer-industry, and the last three columns report first-differenced specifications. Serial correlation properties of error terms do not dictate a clear choice between the two techniques. A first-differenced form would be slightly preferred on efficiency grounds for intensive margin estimations, while a levels technique is more efficient for quantifying the extensive margin.

The β_T elasticity when using within variation is consistently around 0.3 and 0.01 for intensive and extensive margin estimations, respectively. These estimates are about a third of the magnitude of the between estimates in the first three columns. After removing the longitudinal

[12] This test links exporting in a specific industry with technology for that industry. This approach differs from examinations of the extensive margins of trade that count the number of independent varieties exported (e.g., Feenstra 1994, Hummels and Klenow 2005).

FEs, partial R^2 values for the between estimates are 21% and 4% on the intensive and extensive margin, respectively. These explanatory shares decline to about 1% for the within estimations of the intensive margin, and less than 0.1% for the extensive margin.

The difference between these two explanatory powers is the persistence in levels of output and trade across industries within an exporter. The central advantage of restricting the variation exploited to within panels is to reduced the scope for omitted variable biases, and it is likely that the between estimates are upwardly biased due to omitted factors. However, UNIDO output and productivity metrics are measured with substantial error, and first differencing also exacerbates associated downward biases in coefficient estimates. Relative contributions of these two factors cannot be assessed through least squares.

4.2 Core Reduced-Form Specifications

With this backdrop, Table 4 turns to evaluating the reduced-form specification (9) using the ethnic patenting data. Columns 1-3 model the intensive margin of trade expansion, while Columns 4-6 consider the extensive margin. All estimations include exporter-importer-industry and industry-year FEs. Within each triplet, the second column further incorporates exporter-year and importer-year FEs. The last column of each triplet presents the preferred specification that models exporter-importer-year FEs. These are all variations on the within estimators, and the between estimator is no longer considered. Standard errors are clustered by ethnicity-industry.

Panel A models the exporter's technology level measured through US ethnic human capital. The 0.3 elasticity in the upper-left corner finds a 3% increase in the value of bilateral exports with a 10% increase in the exporter's human capital for US technologies. This estimate, however, may be biased upward by omitted factors discussed earlier. When including the stricter longitudinal controls in Columns 2 and 3, the measured elasticity declines 50% to around 0.15. The 0.15 elasticity remains statistically significant and economically important in magnitude. Growth in relative scientific integration with the US technology frontier for a country-industry clearly correlates with increased relative manufacturing exports.

Linear probability models for the extensive margin of trade entry find a similar pattern in Columns 4-6. Column 4 estimates that an exporter is 0.4% more likely to commence exporting in an industry following a 10% increase in the exporter's human capital for US technologies. This effect weakens to around 0.1% with stronger longitudinal controls. Growth in relative scientific integration correlates with a higher likelihood of exporting.

4.3 Importer Technology States and Sector Reallocation

Panel B of Table 4 extends the core model to provide two additional tests. First, the importer's scientific integration with the US is modelled. As noted in Section 2, contrasting the importer's and exporter's technology states is somewhat ad hoc as Ricardian trade models do not yield clear predictions for the role of the importer's technology state in a multi-country setting. Nevertheless, the contrast is of interest from an empirical perspective as it provides reassurance in the measured role for the exporter's technology. This contrast is also important given the substantial trade in intermediate goods, which are outside of the basic Ricardian model but perhaps correlated with simultaneous importer and exporter technology development.

The second innovation in Panel B is to interact both the importer's and exporter's technology states with their respective 1980 agricultural shares. Agricultural shares are listed in Table 2 and are taken from the United Nations Statistical Division and Sun et al. (2003). The sample mean is 27%, ranging from a low of 1% in Hong Kong to a high of 74% in Mainland China. The main effect for the 1980 agricultural share is absorbed into the panel FEs, and regressors are demeaned prior to interaction to restore main effects.

The agricultural interaction tests whether sector reallocation to manufacturing increases the realized export expansion resulting from technology transfer. Ricardian trade theories typically assume both constant country sizes and that the labor resources of each country are fully employed in manufacturing. Several countries in this sample, however, have large populations of underutilized labor in agriculture, and the transition of these workers to manufacturing is important for characterizing their economic development (e.g., Harris and Todaro 1970). Kerr (2008) finds that technology transfer from the US to emerging economies produces a larger growth in manufacturing output compared to industrialized economies due to employment growth from sector reallocation complementing labor productivity gains. In Section 2's model, this transition process is equivalent to an increase in effective country size. If wage equality with the agricultural sector is maintained, general equilibrium increases in the input production costs for manufacturing c_i are also depressed. Both effects further promote growth in export volumes.[13]

The results are as expected. The elasticity of exports to the importer's technology level exceeds the exporter's elasticity in Columns 1 and 4 of Table 4. This counter-intuitive finding simply descends from technology and economic growth in the importer leading to greater demand for exports from all countries. Once controlling for secular trends in the importer and exporter, the importer's technology state is small and not consistently different from zero in Columns 2-3

[13]Section 2's framework can be extended to include a second sector like agriculture. In this setting, the country-level technology parameter T_i influences the comparative advantage for manufacturing versus the second sector. The associated sector reallocation effects are absent in the base model. Production technologies and wage determination in the non-manufacturing sector will influence the path of production costs for manufacturing following a technology shock.

and 5-6. Statistical tests reject at 90% confidence levels that importer and exporter technology growth have the same impetus for export promotion.

Agricultural interactions also find evidence for sector reallocation effects. Countries with larger initial employment shares in agriculture have larger expansions in exports following growth in manufacturing comparative advantages. This expansion occurs on both extensive and intensive margins. On the other hand, importer interactions are not consistent across the two margins of adjustment. Evidence exists for declining trade volumes on existing export routes, but also for a higher likelihood of new exports.

Partial R^2 values document the share of exports that these reduced-form expressions explain after FEs are removed. For Column 1's unconditional estimations of the intensive margin, the Partial R^2 values are 0.5% in Panel A and 3.4% in Panel B. For Column 3's conditional estimations, the explanatory power is 0.1%-0.2%. Explanatory power in extensive margin estimations is 0.1%-0.4% for unconditional estimations and less than 0.1% for conditional estimations. This explanatory power for intensive margin estimations is reasonably strong given that medium-frequency, within-panel variation is being exploited.

The treatment effects emphasized by these panel estimates center on dynamic growth in East Asian and Indian scientific contributions in the US and associated export development at home. A variety of checks have been performed on the sample composition. The appendix extends these results to the complete 1975-2000 sample. Intensive margin estimations are very similar, while extensive margin estimations lose statistical significance. The latter are discounted due to the difficulty in aligning country-industry trading volumes across the WTF data collection break. Comparable results are also found when all non-US importers are included in the sample. Sector reallocation effects and extensive margin growth are weaker when employing a first-differenced specification, but results discussed in this section carry through. An earlier version of this paper also finds similar results employing the 1980-1997 WTF database developed by Statistics Canada and Feenstra (2000).

4.4 Lag Structure of Treatment Effects

Table 5 provides two robustness checks on the measured treatment effects. Panel A considers the timing of treatment effects by including forward and lagged values of the ethnic technology regressor. The inclusion of forward values is motivated as placebo test. Greater confidence can be placed in the proposed direction of the findings if current exports are not predicting future ethnic innovation in the US. These extensions are also measured over three-year intervals, and the sample size does not change for the primary 1984-2000 WTF estimations as the ethnic patenting data encompass 1975-2005.

Without conditioning on longitudinal FEs, Column 1 finds fairly uniform treatment effects for forward and lagged values of the regressor. Columns 2 and 3, however, present a clearer picture of intensive margin adjustments after conditioning out secular trends with the exporter-year and importer-year FEs. A forward value for intensive adjustment is no longer present, the sharpest export gains occur contemporaneous to technology growth, and gradual declines in treatment effects ensue over the following six years. This pattern of intensive margin effects provides confidence in the baseline empirical specification that technology diffusion is determining export behavior.

Effects on the extensive margin, however, are less clear. While initially favoring lagged treatment effects in Column 4, the forward treatment effect is stronger than the contemporaneous effect when removing exporter-importer-year FEs in Column 6. This difference may suggest that the developed technology measures are better suited for explaining intensive adjustments than trade entry, perhaps due to absorptive capacity arguments. The lead effect on the extensive margin could also point to earlier, unmodeled technology transfer, particularly around less-advanced technology imitation, that promotes initial export entry.

Overall, these results suggest that treatment effects are reasonably modelled by the short-run empirical strategy. This result mirrors international patent citation analyses where ethnic networks are found to be most important in early phases of technology diffusion. Kerr (2008) finds inventors living outside of the US cite US inventors of their own-ethnicity 30%-50% more often than other US-based inventors. This own-ethnicity bias peaks around the fourth year of the diffusion process.

4.5 Testing for the Rybczynski Effect

In contrast to the Ricardian framework, Heckscher-Ohlin-Vanek (HOV) models describe trade as resulting from factor differences across countries (e.g., labor, capital, natural resources). During the period studied, some countries experienced significant growth in their skilled labor forces and physical capital stocks, as well as their technology sets, and the former could lead to growth in manufacturing exports due to the Rybczynski effect. Capital accumulation is particularly noted in rapid advances made by several East Asian economies (e.g., Young 1992, 1995; Ventura 1997). The inclusion of exporter-importer-year FEs suggests that a Rybczynski effect for the manufacturing sector as a whole is not responsible for the observed trade patterns. Panel B of Table 5 provides additional evidence that the observed role for technology within manufacturing is not due to specialized factor accumulations.[14]

[14] See Heckscher (1919), Ohlin (1933), and Vanek (1968). Dornbusch et al. (1980) provide a classic HOV model, while Schott (2003) and Romalis (2004) offer state-of-the-art extensions and empirical tests. Trefler (1994, 1996), Harrigan (1997b), Davis and Weinstein (2001), and Morrow (2010) jointly explore technology and factor differences as determinants of trade.

The intuition behind the proposed test is straightforward. Under the Rybczynski effect, the accumulation of skilled workers in country i shifts country i's specialization towards manufacturing industries that employ skilled labor more intensively than other factors. By grouping manufacturing industries by their skilled-labor intensities, tests examine if technology's importance is preserved after time trends are removed for these industry groups within each country. These time trends are include in addition to the fixed effects listed at the bottom of the table. To illustrate, the computer and pharmaceutical industries are both highly skill intensive. A general Rybczynski effect due to skilled worker accumulation in China would favor specialization and export growth in these industries equally. Additional confidence for technology's role is warranted if China's exports grow faster in the skill-intensive industry that receives the strongest technology transfer from the US relative to its peer industries.

To implement this matching exercise, industries are grouped into quintiles based upon their factor intensities in the US. Three intensities are studied—the industry's capital-labor ratio, the industry's mean wage rate, and the share of non-production workers in the industry's labor force. The appendix documents for each industry the quintile groupings assigned. Textiles rank in the lowest quintile in all three classifications schemes, while chemicals and industrial machinery consistently fall into top quintiles. Some differences do exist though. The correlations among quintile groupings are 76% for capital-labor and wage, 59% for wage and non-production share, and 37% for capital-labor and non-production share.

The role for technology holds up well in all three variants. Estimates in Column 1 are weaker, but it is difficult to evaluate the linear quintile trends without controlling for the overall secular trend in exporter development. Once conditioning on longitudinal FEs, the importance of Ricardian technology differences is well preserved. These findings suggest an omitted factor accumulation is not confounding the identified role for technology.[15]

4.6 Sample Heterogeneity

The assembled dataset is a diverse set of countries, industries, and experiences. Indeed, a primary strength of this sample is the extension beyond advanced economies to include developing

[15] The ideal test would simply remove factor-based trade from export volumes studied. This is test is unattainable for several theoretical and practical reasons. First, while 2x2x2 HOV models (two countries, factors, and goods) cleanly predict a country exports goods that intensely use the factors in which the country is well endowed, this prediction does not hold universally in settings with multiple goods and factors (e.g., the critique of Leamer (1980) on Leontief's (1953) paradox). Likewise, bilateral trade patterns due to factor-based differences are only determined for special cases in a multi-country world (e.g., Romalis 2004). Thus, strong assumptions would be required for distinguishing factor-based trade in this empirical setting. Practically speaking, the data constraint is also prohibitive as factor data and industry input-output matrices are very poorly measured for most of the countries and years covered by this study. Davis and Weinstein (2001) study this issue using OECD data. Morrow (2010) comparatively assesses the Ricardian and HOV models in a unified framework. Morrow finds that the two models each offer valid partial descriptions and ignoring one force for comparative advantage does not bias empirical tests of the other.

and emerging economies where manufacturing export growth has been very pronounced. Table 6 interacts the primary regressor with different features of the data to identify where treatment effects are stronger. Main effects for interactions are absorbed into panel FEs, and regressors are demeaned prior to interaction to restore main effects.

Panel A interacts with different ethnic groupings, employing Japan as the omitted interaction. Before conditioning on longitudinal effects, the strongest elasticities are evident in Indian, Korean, and Chinese cases on both intensive and extensive margins. These three ethnic groups have clearly witnessed both strong expansion in manufacturing exports and technology transfer from the US over the past three decades.

After removing longitudinal effects, Chinese interactions remain very important on both margins of expansion. This is not very surprising given the many cases studies and articles written on technology transfer to these economies and their exceptional export growth. Korean and Indian interactions remain important, albeit on a single margin of export growth only. Finally, European interactions become relatively more important in conditional estimations. Overall, these sample exercises suggest Ricardian influences operate in many parts of the sample and are strongest among rapidly industrializing economies.

Panel B of Table 6 considers a second interaction design. The exceptional characteristics of the computer manufacturing industry are frequently noted (e.g., Griliches 1994), and many observers document the special relationship of immigrant Chinese scientists and entrepreneurs in Silicon Valley to their home countries (e.g., Saxenian 2002, 2006). Panel B maintains the Chinese interaction and further incorporates an interaction for the Machinery & Equipment Sector. This industrial sector is defined as ISIC3 382 and includes computer equipment manufacturing. A joint interaction is also incorporated.

The Machinery & Equipment Sector interaction is quite strong. Its magnitude in intensive estimations is comparable to the Chinese interaction, and it is relatively stronger in extensive margin estimations. The point estimate for the triple interaction is also positive, although it is statistically precise only in extensive margin estimations. Overall, these regressions find technology transfer in computer manufacturing has special outcomes for export promotion. The effect is somewhat stronger for Chinese economies, but main interaction effects are more important quantitatively.

Unreported estimations examine differences across industries in vertical integration. Export growth following technology transfer may be easier in industries where trade in intermediate goods is feasible, which is again outside of the basic Ricardian theory. As an initial test, an interaction is formed for industries where trade in "parts" is possible. Parts trade is identified through product titles (e.g., Ng and Yeats 1999, Schott 2004). This interaction is also economically and statistically important, roughly on par with the Machinery & Equipment Sector interaction. This crude test suggests that Ricardian trade is more likely to follow in industries characterized by intermediate trade flows, although future theoretical and empirical work is needed to refine the role of intermediate goods.

Finally, the appendix documents models that consider spatial distances and export growth. Both border effects and non-parametric distance interactions between countries are tested. The results do not yield a consistent pattern across specifications. More generally, distance interactions are very small in economic size relative to those presented in Tables 4 and 6. These extensions suggest that spatial distance is a second-order factor in shaping where export growth occurs following technology expansion.

5 Conclusions

While the principle of Ricardian technology differences as a source of trade is well established in the theory of international economics, empirical evaluations of its importance are relatively rare due to the difficulty of quantifying and isolating technology differences. This study exploits heterogeneous technology diffusion from the US through ethnic scientific networks to make additional headway. Estimations find bilateral manufacturing exports respond positively to growth in observable measures of comparative advantages. Ricardian technology differences are an important determinant of trade both in the cross-section and over time.

Leamer and Levinsohn (1994) argue that trade models should be taken with a grain of salt and applied in contexts for which they are appropriate. This is certainly true when interpreting these results. The estimating frameworks have specifically sought to remove trade resulting from factor endowments, increasing returns, consumer preferences, etc. rather than test against them. Moreover, manufacturing exports are likely more sensitive to patentable technology improvements than the average sector, and the empirical focus on emerging economies like China and India heightens this sensitivity. Further research is needed to generalize technology's role to a broader set of industrial sectors and environments.

Beyond quantifying the link between technology and trade for manufacturing, this paper also serves as input into research regarding the benefits and costs for sending countries of high-skilled emigration to the US (i.e., the "brain drain" or "brain gain" debate). Interpretation of these results, however, are complex. While export growth is evidence of beneficial technology transfer from diaspora communities, strong elasticities may also be a warning. Agrawal et al. (2011) emphasize how differences may emerge between a social planner's optimal distribution of ethnic inventors and the decentralized outcome. In the context of this paper, a strong sensitivity of exports to US technology transfers in the reduced-form analysis may exceed what a social planner would desire. Future research needs to examine these welfare implications further.

References

Acemoglu, Daron, and Jaume Ventura, "The World Income Distribution", *The Quarterly Journal of Economics*, 117:2 (2002), 659-694.

Acemoglu, Daron, and Fabrizio Zilibotti, "Productivity Differences", *The Quarterly Journal of Economics,* 116:2 (2001), 563-606.

Agrawal, Ajay, Devesh Kapur, John McHale, and Alexander Oettl, "Brain Drain or Brain Bank? The Impact of Skilled Emigration on Poor-Country Innovation", *Journal of Urban Economics* 69:1 (2011), 43-55.

Alvarez, Fernando, and Robert Lucas, "General Equilibrium Analysis of the Eaton-Kortum Model of International Trade", *Journal of Monetary Economics*, 54 (2007), 1726-1768.

Antweiler, Werner, and Daniel Trefler, "Increasing Returns and All That: A View from Trade", *The American Economic Review*, 92:1 (2002), 93-119.

Baxter, Marianne, "Fiscal Policy, Specialization, and Trade in the Two-Sector Model: The Return of Ricardo?", *The Journal of Political Economy*, 100:4 (1992), 713-744.

Bombardini, Matilde, Chris Kurz, and Peter Morrow, "Ricardian Trade and the Impact of Domestic Competition on Export Performance", *Canadian Journal of Economics* 45:2 (2012), 585-612.

Branstetter, Lee, and Yoshiaki Ogura, "Is Academic Science Driving a Surge in Industrial Innovation? Evidence from Patent Citations", NBER Working Paper 11561 (2005).

Burstein, Ariel, and Jonathan Vogel, "Factor Prices and International Trade: A Unifying Perspective", Working Paper (2012).

Caliendo, Lorenzo, and Fernando Parro, "Estimates of the Trade and Welfare Effects of NAFTA", Working Paper (2012).

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

Coe, David, Elhanan Helpman, and Alexander Hoffmaister, "North-South R & D Spillovers", *The Economic Journal*, 107:440 (1997), 134-149.

Costinot, Arnaud, "An Elementary Theory of Comparative Advantage", *Econometrica* 77:4 (2009), 1165-1192.

Costinot, Arnaud, and David Donaldson, "Ricardo's Theory of Comparative Advantage: Old Idea, New Evidence", *American Economic Review Papers and Proceedings* 102:3 (2012), 453-458.

Costinot, Arnaud, David Donaldson, and Ivana Komunjer, "What Goods Do Countries Trade? New Ricardian Predictions", *Review of Economic Studies* 79:2 (2012), 581-608.

Davis, Donald, and David Weinstein, "An Account of Global Factor Trade", *The American Economic Review*, 91:5 (2001), 1423-1453.

Davis, Donald, and David Weinstein, "Technological Superiority and the Losses from Migration", NBER Working Paper 8971 (2002).

Dornbusch, Rudiger, Stanley Fischer, and Paul Samuelson, "Comparative Advantage, Trade and Payments in a Ricardian Model with a Continuum of Goods", *The American Economic Review*, 67:5 (1977), 823-839.

Dornbusch, Rudiger, Stanley Fischer, and Paul Samuelson, "Heckscher-Ohlin Trade Theory with a Continuum of Goods", *The Quarterly Journal of Economics*, 95:2 (1980), 203-224.

Eaton, Jonathan, and Samuel Kortum, "International Technology Diffusion: Theory and Measurement", *International Economic Review*, 40:3 (1999), 537-570.

Eaton, Jonathan, and Samuel Kortum, "Technology, Geography, and Trade", *Econometrica*, 70:5 (2002), 1741-1779.

Feenstra, Robert, "New Product Varieties and the Measurement of International Prices", *The American Economic Review*, 84:1 (1994), 157-177.

Feenstra, Robert, "World Trade Flows, 1980-1997", Working Paper (2000).

Feenstra, Robert, Robert Lipsey, Haiyan Deng, Alyson Ma, and Hengyong Mo, "World Trade Flows: 1962-2000", NBER Working Paper 11040 (2005).

Foley, C. Fritz and William Kerr, "Ethnic Innovation and U.S. Multinational Firm Activity", *Management Science* (2012), forthcoming.

Frankel, Jeffrey, *Regional Trading Blocs in the World Economic System* (Washington, DC: Institute for International Economics, 1997).

Golub, Stephen, and Chang-Tai Hsieh, "Classical Ricardian Theory of Comparative Advantage Revisited", *Review of International Economics*, 8:2 (2000), 221-234.

Griliches, Zvi, "Productivity, R&D, and the Data Constraint", *The American Economic Review*, 84:1 (1994), 1-23.

Griliches, Zvi, "Patent Statistics as Economic Indicators: A Survey", *Journal of Economic Literature,* 28:4 (1990), 1661-1707.

Grossman, Gene, and Elhanan Helpman, *Innovation and Growth in the Global Economy* (Cambridge, MA: MIT Press, 1991).

Hall, Bronwyn, "Exploring the Patent Explosion", *Journal of Technology Transfer*, 30 (2005), 35-48.

Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg, "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools", NBER Working Paper 8498 (2001).

Harrigan, James, "Cross-Country Comparisons of Industry Total Factor Productivity: Theory and Evidence", Federal Reserve Bank of New York Research Paper 9734 (1997a).

Harrigan, James, "Technology, Factor Supplies, and International Specialization: Estimating the Neoclassical Model", *The American Economic Review*, 87:4 (1997b), 475-494.

Harris, John, and Michael Todaro, "Migration, Unemployment, and Development: A Two-Sector Analysis", *The American Economic Review*, 60:1 (1970), 126-142.

Heckscher, Eli, "The Effect of Foreign Trade on the Distribution of Income", *Ekonomisk Tidskrift*, 21:2 (1919), 1-32.

Helpman, Elhanan, "R&D and Productivity: The International Connection", in Razin, Assaf, and Efraim Sadka, ed., *The Economics of Globalization* (Cambridge, UK: Cambridge University Press, 1999).

Helpman, Elhanan, and Paul Krugman, *Market Structure and Foreign Trade* (Cambridge, MA: MIT Press, 1985).

Hummels, David, and Peter Klenow, "The Variety and Quality of a Nation's Exports", *The American Economic Review*, 95:3 (2005), 704-723.

Hunter, Linda, "The Contribution of Non-Homothetic Preferences to Trade", *Journal of International Economics*, 30:3 (1991), 345-358.

Hunter, Linda, and James Markusen, "Per Capita Income as a Determinant of Trade", in Robert Feenstra, ed., *Empirical Methods for International Trade* (Cambridge, MA: MIT Press, 1988).

Jaffe, Adam, and Joshua Lerner, *Innovation and Its Discontents* (Boston, MA: Harvard Business School Press, 2005).

Jaffe, Adam, and Manuel Trajtenberg, "International Knowledge Flows: Evidence from Patent Citations", *Economics of Innovation and New Technology*, 8 (1999), 105-136.

Johnson, Daniel, "150 Years of American Invention: Methodology and a First Geographic Application", Wellesley College Economics Working Paper 99-01 (1999).

Kapur, Devesh, "Diasporas and Technology Transfer", *Journal of Human Development*, 2:2 (2001), 265-286.

Kapur, Devesh, and John McHale, "Sojourns and Software: Internationally Mobile Human Capital and High-Tech Industry Development in India, Ireland, and Israel", in Arora, Ashish, and Alfonso Gambardella, *From Underdogs to Tigers: The Rise and Growth of the Software Industry in Some Emerging Economies* (Oxford, UK: Oxford University Press, 2005).

Keller, Wolfgang, "Trade and the Transmission of Technology", *Journal of Economic Growth*, 7 (2002a), 5-24.

Keller, Wolfgang, "Geographic Localization of International Technology Diffusion", *The American Economic Review*, 92:1 (2002b), 120-142.

Keller, Wolfgang, "International Technology Diffusion", *Journal of Economic Literature*, 42:3 (2004), 752-782.

Kerr, William, "Ethnic Scientific Communities and International Technology Diffusion", *Review of Economics and Statistics*, 90:3 (2008), 518-537.

Kerr, William, "The Ethnic Composition of US Inventors", HBS Working Paper 08-006 (2007).

Kerr, William, "The Role of Immigrant Scientists and Entrepreneurs in International Technology Transfer", MIT Ph.D. Dissertation (2005).

Kerr, William, and William Lincoln, "The Supply Side of Innovation: H-1B Visa Reforms and US Ethnic Invention", *Journal of Labor Economics* 28:3 (2010), 473-508.

Kim, Jinyoung, and Gerald Marschke, "Accounting for the Recent Surge in U.S. Patenting: Changes in R&D Expenditures, Patent Yields, and the High Tech Sector", *Economics of Innovation and New Technologies*, 13:6 (2004), 543-558.

Kortum, Samuel, and Joshua Lerner, "Assessing the Contribution of Venture Capital to Innovation", *RAND Journal of Economics*, 31:4 (2000), 674-692.

Kugler, Maurice, and Hillel Rapoport, "International Labor and Capital Flows: Complements or Substitutes?", *Economics Letters*, 92.2 (2007), 155-162.

Leamer, Edward, "The Leontief Paradox, Reconsidered", *The Journal of Political Economy*, 88:3 (1980), 495-503.

Leamer, Edward, and James Levinsohn, "International Trade Theory: The Evidence", NBER Working Paper 4940 (1994).

Lemley, Mark, and Bhaven Sampat, "Is the Patent Office a Rubber Stamp?", Stanford Public Law Working Paper No. 999098 (2007).

Leontief, Wassily, "Domestic Production and Foreign Trade: The American Capital Position Re-examined", *Proceedings of the American Philosophical Society*, 97 (1953), 332-349.

Levchenko, Andrei, and Jing Zhang, "Ricardian Productivity Differences and the Gains from Trade", Working Paper (2012).

MacDougall, G.D.A., "British and American Exports: A Study Suggested by the Theory of Comparative Costs. Part I", *The Economic Journal*, 61:244 (1951), 697-724.

MacDougall, G.D.A., "British and American Exports: A Study Suggested by the Theory of Comparative Costs. Part II", *The Economic Journal*, 62:247 (1952), 487-521.

Morrow, Peter, "Ricardian-Heckscher-Ohlin Comparative Advantage: Theory and Evidence", *Journal of International Economics* 82:2 (2010), 137-151.

Nanda, Ramana, and Tarun Khanna, "Diasporas and Domestic Entrepreneurs: Evidence from the Indian Software Industry", *Journal of Economics & Management Strategy* 19:4 (2010), 991-1012.

Ng, Francis, and Alexander Yeats, "Production Sharing in East Asia: Who Does What for Whom and Why?", World Bank Policy Research Working Paper Series (1999).

Obukhova, Elena, "Global-Pull, State-Push, or Brain Circulation? Firm-Level Technological Upgrading in Shanghai's Semiconductor Design Industry", Working Paper (2008).

Obukhova, Elena, "Does Brain Circulation Promote International Development? High-Skilled Migration and Organizational Performance", Working Paper (2009).

Ohlin, Bertil, *Interregional and International Trade* (Cambridge, MA: Harvard University Press, 1933).

Papageorgiou, Chris, and Antonio Spilimbergo, "Learning Abroad and Technology Adoption", Working Paper (2008).

Rauch, James, "Business and Social Networks in International Trade", *Journal of Economic Literature*, 39 (2001), 1177-1203.

Rauch, James, and Vitor Trindade, "Ethnic Chinese Networks in International Trade", *The Review of Economics and Statistics*, 84:1 (2002), 116-130.

Ricardo, David, *On the Principles of Political Economy and Taxation* (London, UK: John Murray, 1817).

Romalis, John, "Factor Proportions and the Structure of Commodity Trade", *The American Economic Review*, 94:1 (2004), 67-97.

Saxenian, AnnaLee, with Yasuyuki Motoyama and Xiaohong Quan, *Local and Global Networks of Immigrant Professionals in Silicon Valley* (San Francisco, CA: Public Policy Institute of California, 2002).

Saxenian, AnnaLee, *The New Argonauts* (Cambridge, MA: Harvard University Press, 2006).

Scherer, Frederic, "Using Linked Patent Data and R&D Data to Measure Technology Flows," in Griliches, Zvi (ed.) *R & D, Patents and Productivity* (Chicago, IL: University of Chicago Press, 1984).

Schott, Peter, "Across-Product versus Within-Product Specialization in International Trade", *The Quarterly Journal of Economics*, 119:2 (2004), 647-678.

Schott, Peter, "One Size Fits All? Heckscher-Ohlin Specialization in Global Production", *The American Economic Review*, 93:2 (2003), 686-708.

Silverman, Brian, "Technological Resources and the Direction of Corporate Diversification: Toward an Integration of the Resource-Based View and Transaction Cost Economics", *Management Science*, 45:8 (1999), 1109-1124.

Stern, Robert, "British and American Productivity and Comparative Costs in International Trade", *Oxford Economic Papers*, 14:3 (1962), 275-296.

Sun, Ling, Lilyan Fulginiti, and Wesley Peterson, "Accounting for Agricultural Decline with Economic Growth in Taiwan", Working Paper (2003).

Trefler, Daniel, "International Factor Price Differences: Leontief was Right!", *The Journal of Political Economy*, 101:6 (1993), 961-987.

Trefler, Daniel, "The Case of the Missing Trade and Other Mysteries", *The American Economic Review*, 85:5 (1995), 1029-1046.

Vanek, Jaroslav, "The Factor Proportions Theory: The N-Factor Case", *Kyklos*, 21:4 (1968), 749-756.

Ventura, Jaume, "Growth and Interdependence", *The Quarterly Journal of Economics*, 112:1 (1997), 57-84.

Wilson, Charles, "On the General Structure of Ricardian Models with a Continuum of Goods: Applications to Growth, Tariff Theory, and Technical Change", *Econometrica*, 48:7 (1980), 1675-1702.

Young, Alwyn, "A Tale of Two Cities: Factor Accumulation and Technical Change in Hong Kong and Singapore", *National Bureau of Economic Research Macroeconomics Annual*, 7 (1992), 13-63.

Young, Alwyn, "The Tyranny of Numbers: Confronting the Statistical Realities of the East Asian Growth Experience", *The Quarterly Journal of Economics*, 110:3 (1995), 641-680.

Fig. 1: Ethnic Share of US Domestic Patents

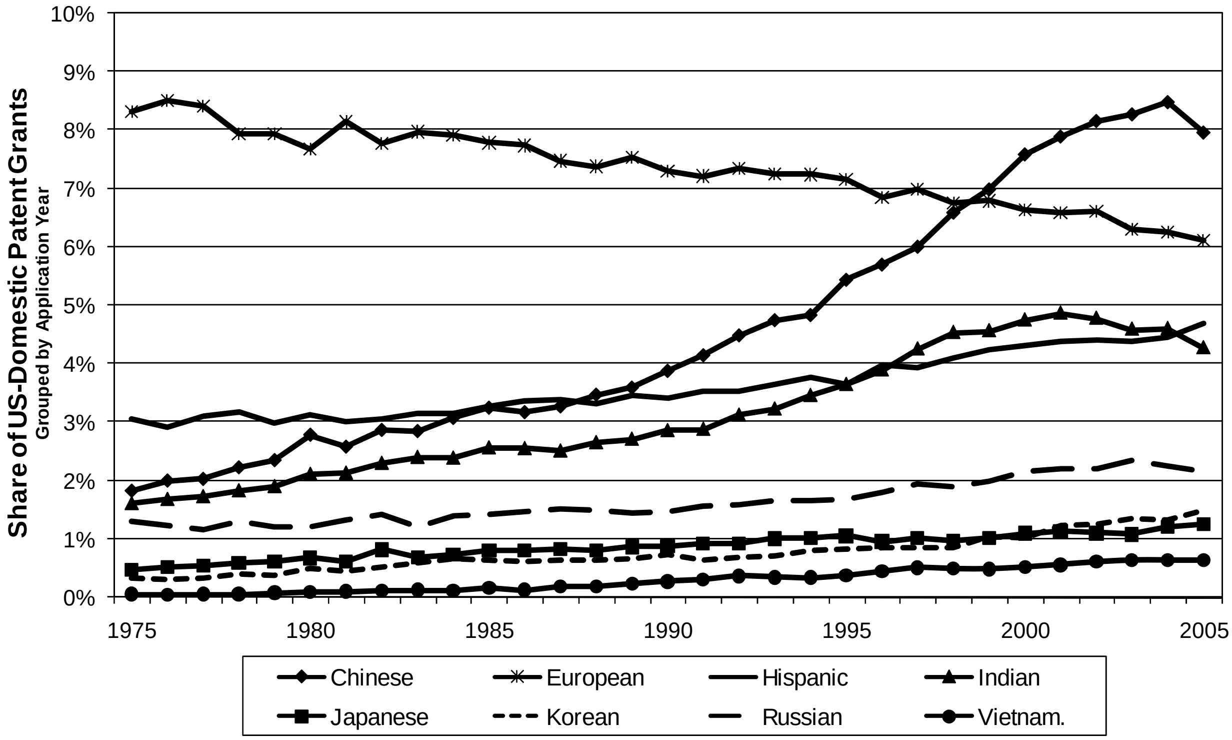

Fig. 2: US non-English Share by Technology

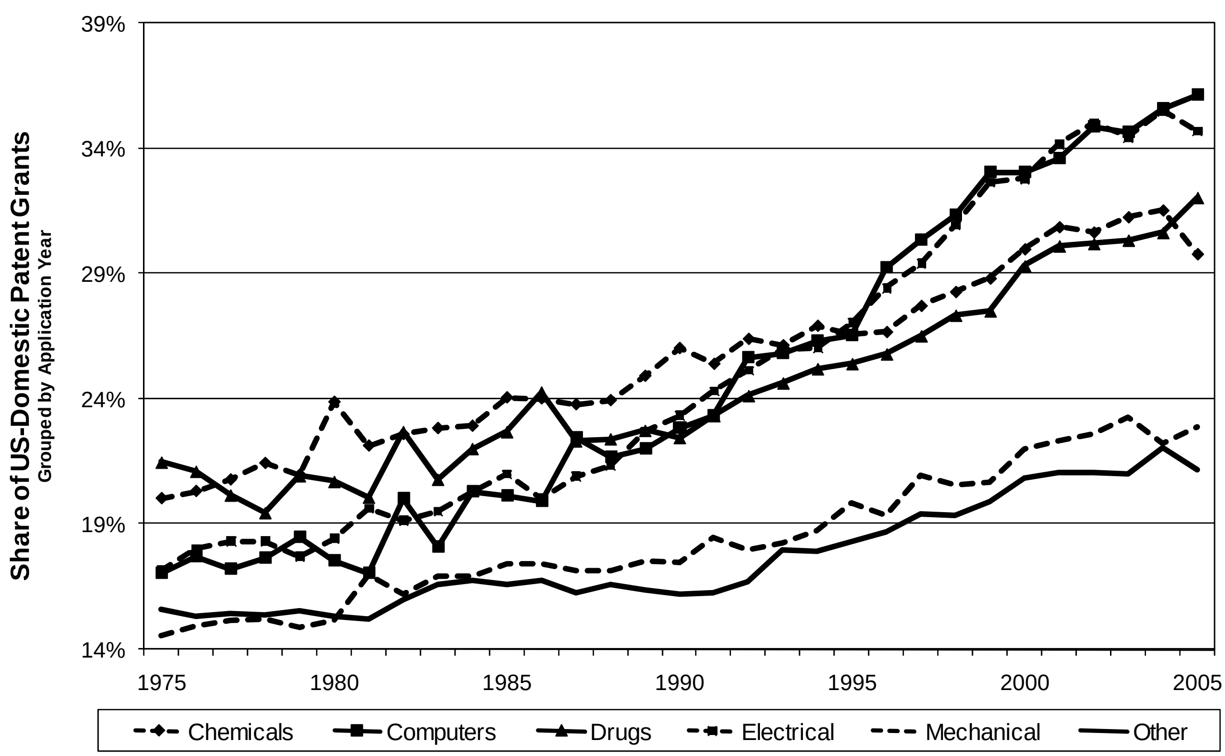

Table 1: Descriptive Statistics for Inventors Residing in US

	Ethnicity of Inventor								
	English	Chinese	European	Hispanic	Indian	Japanese	Korean	Russian	Vietnam.
	A. Ethnic Inventor Shares Estimated from US Inventor Records								
1975-1979	82.5%	2.2%	8.2%	3.0%	1.9%	0.6%	0.4%	1.2%	0.1%
1980-1984	81.1%	2.9%	7.9%	3.1%	2.4%	0.7%	0.6%	1.3%	0.1%
1985-1989	79.8%	3.6%	7.5%	3.3%	2.8%	0.8%	0.7%	1.4%	0.2%
1990-1994	77.6%	4.7%	7.2%	3.5%	3.4%	0.9%	0.8%	1.5%	0.4%
1995-1999	74.0%	6.6%	6.8%	3.9%	4.5%	0.9%	0.9%	1.8%	0.5%
2000-2004	71.0%	8.5%	6.4%	4.2%	4.8%	1.0%	1.2%	2.2%	0.6%
Chemicals	73.7%	7.1%	7.6%	3.6%	4.2%	0.9%	0.9%	1.7%	0.3%
Computers	71.3%	7.9%	6.3%	3.7%	6.1%	1.1%	1.0%	2.0%	0.7%
Pharmaceuticals	73.3%	6.9%	7.4%	4.3%	3.9%	1.1%	1.0%	1.8%	0.3%
Electrical	72.0%	8.0%	6.8%	3.7%	4.6%	1.1%	1.2%	2.0%	0.7%
Mechanical	80.6%	3.2%	7.2%	3.4%	2.4%	0.7%	0.6%	1.6%	0.2%
Miscellaneous	81.5%	2.9%	7.0%	3.8%	2.1%	0.6%	0.6%	1.4%	0.2%
Top MSAs as a	KC (89)	SF (14)	NOR (12)	MIA (16)	AUS (6)	SF (2)	BAL (2)	BOS (3)	AUS (2)
Percentage of	WS (88)	LA (8)	STL (11)	SA (9)	SF (6)	SD (2)	LA (2)	NYC (3)	SF (1)
MSA’s Patents	NAS (88)	AUS (6)	NYC (11)	WPB (7)	BUF (5)	LA (2)	SF (2)	SF (3)	PRT (1)
	B. Ethnic Scientist and Engineer Shares Estimated from 1990 US Census Records								
Bachelors Share	87.6%	2.7%	2.3%	2.4%	2.3%	0.6%	0.5%	0.4%	1.2%
Masters Share	78.9%	6.7%	3.4%	2.2%	5.4%	0.9%	0.7%	0.8%	1.0%
Doctorate Share	71.2%	13.2%	4.0%	1.7%	6.5%	0.9%	1.5%	0.5%	0.4%

Notes: Panel A presents descriptive statistics for inventors residing in the US at the time of patent application. Inventor ethnicities are estimated through inventors' names using techniques described in the text. Patents are grouped by application years and major technology fields. MSAs include AUS (Austin), BAL (Baltimore), BOS (Boston), BUF (Buffalo), KC (Kansas City), LA (Los Angeles), MIA (Miami), NAS (Nashville), NOR (New Orleans), NYC (New York City), PRT (Portland), SA (San Antonio), SD (San Diego), SF (San Francisco), STL (St. Louis), WPB (West Palm Beach), and WS (Winston-Salem). MSAs are identified from inventors' city names using city lists collected from the Office of Social and Economic Data Analysis at the University of Missouri, with a matching rate of 99%. Manual recoding further ensures all patents with more than 100 citations and all city names with more than 100 patents are identified. Panel B presents comparable statistics calculated from the 1990 Census using country of birth for scientists and engineers. Country groupings follow Table 2; the English column provides a residual in the Census country-of-birth statistics.

Table 2: Descriptive Statistics for Bilateral Trade Sample

	WTF Mfg Exports ($B)			UNIDO	1980		WTF Mfg Exports ($B)			UNIDO	1980
	Mean Level	Growth Rate	Sample Share	Output Levels	Agr. Share		Mean Level	Growth Rate	Sample Share	Output Levels	Agr. Share
Single Ethnic Mappings:						*Hispanic Economies:*					
India	18.0	9%	59%	118.0	70%	Argentina	10.3	9%	83%	66.2	13%
Japan	240.7	8%	67%	2,053.0	11%	Belize	0.1	13%	51%	n.a.	38%
South Korea	63.8	15%	70%	230.9	37%	Bolivia	0.4	0%	95%	1.5	53%
Soviet Union	13.3	1%	66%	n.a.	16%	Brazil	27.1	5%	75%	127.8	37%
Vietnam	3.0	29%	75%	n.a.	73%	Chile	6.7	11%	86%	20.6	21%
						Columbia	3.5	5%	87%	20.1	40%
Chinese Economies:						Costa Rica	0.6	14%	69%	3.3	35%
China, Mainland	107.2	20%	84%	327.2	74%	Cuba	0.9	2%	61%	10.5	24%
Hong Kong	31.2	10%	72%	30.5	1%	Dom. Republic	0.3	7%	72%	n.a.	11%
Macao	1.0	4%	89%	1.2	6%	Ecuador	0.8	9%	88%	4.4	40%
Singapore	44.3	12%	54%	37.8	2%	El Salvador	0.3	2%	83%	n.a.	43%
Taiwan	59.4	14%	77%	145.1	8%	Guatemala	0.5	4%	77%	n.a.	54%
						Honduras	0.3	7%	87%	1.0	57%
European Economies:						Mexico	9.9	16%	60%	61.6	36%
Austria	36.9	8%	77%	73.5	10%	Nicaragua	0.2	-3%	83%	n.a.	40%
Belgium	101.7	7%	78%	32.0	3%	Panama	1.4	0%	92%	1.5	29%
Denmark	29.1	6%	73%	38.2	7%	Paraguay	0.5	3%	96%	n.a.	45%
Finland	26.9	8%	70%	52.5	12%	Peru	2.3	6%	83%	13.9	40%
France	181.1	8%	71%	517.3	8%	Philippines	9.9	17%	76%	23.2	52%
Germany	334.6	7%	72%	870.6	7%	Portugal	15.1	10%	78%	36.4	26%
Italy	145.6	7%	70%	390.3	13%	Spain	55.2	11%	76%	202.0	18%
Netherlands	122.5	7%	72%	117.9	6%	Uruguay	1.5	9%	89%	4.6	17%
Norway	19.9	5%	71%	37.5	8%	Venezuela	3.9	7%	75%	24.2	15%
Poland	13.8	11%	69%	54.9	30%						
Sweden	52.0	7%	74%	93.7	6%						
Switzerland	57.1	7%	72%	37.8	6%						

Notes: Manufacturing exports are taken from the 1975-2000 WTF database and expressed in billions of dollars. Exports to the US are excluded. The first and second columns document mean levels and compound annual growth rates for national exports in manufacturing industries considered for 1984-2000, respectively. The third column documents the share of these exports included in the primary sample that restricts the importers to the economies listed in this table. The fourth column documents mean annual output levels in constant 1987 dollars derived from industry data used in the UNIDO3 panel. Production levels are under-reported relative to exports due to missing industries in the UNIDO data. The last column documents the 1980 agricultural share used in sector reallocation exercises. The Soviet Union and Vietnam are not included in the primary panel but are considered in robustness checks.

Table 3A: Intensive Margin Specifications of Productivity, Output, and Trade

	OLS Levels Specification, Between DV: Log Bilateral Exports			OLS Levels Specification, Within DV: Log Bilateral Exports			OLS FD Specification, Within DV: Δ Log Bilateral Exports		
	Full Sample	Europe and Japan	Other Economies	Full Sample	Europe and Japan	Other Economies	Full Sample	Europe and Japan	Other Economies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				A. Employing Labor Productivity Metrics					
Log Country-Industry Labor Productivity	0.605	1.296	0.586	0.256	0.311	0.175			
	(0.024)	(0.040)	(0.032)	(0.033)	(0.053)	(0.046)			
Δ Log Country-Industry Labor Productivity							0.181	0.270	0.100
							(0.034)	(0.054)	(0.047)
Observations	36,199	18,197	18,002	36,199	18,197	18,002	23,345	11,582	11,763
				B. Employing Output Metrics					
Log Country-Industry Output	0.900	1.127	0.765	0.355	0.401	0.300			
	(0.010)	(0.016)	(0.014)	(0.022)	(0.036)	(0.030)			
Δ Log Country-Industry Output							0.313	0.357	0.256
							(0.024)	(0.038)	(0.033)
Observations	36,199	18,197	18,002	36,199	18,197	18,002	23,345	11,582	11,763
Exporter-Importer-Industry FE				Yes	Yes	Yes			
Industry-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Importer-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panel estimations consider manufacturing exports taken from the 1975-2000 WTF database. Data are organized by exporter-importer-industry-year. Annual data are collapsed into five-year groupings beginning with 1985-1989 and extending to 1995-1999. Table 3A tests the intensive margin of trade. The dependent variable is the log mean nominal value (US$) of bilateral exports for the five years. The intensive margin sample is restricted to exporter-importer-industry groupings with exports exceeding $100k in every year. Table 3B tests the extensive margin of trade through linear probability models. The dependent variable is a dichotomous indicator variable taking unit value if bilateral exports exceed $100k. The $100k threshold is chosen due to WTF data collection procedures discussed in the text. In both tables, Panels A and B consider labor productivity and output, respectively, as metrics of comparative advantages. These metrics are developed from the UNIDO database. Columns 1-3 estimate Ricardian elasticities using both within-panel variation and variation between industries of a country. Columns 4-9 estimate Ricardian elasticities using only variation within panels.

Table 3B: Extensive Margin Specifications of Productivity, Output, and Trade

	OLS Levels Specification, Between DV: (0,1) Exports > US$100k			OLS Levels Specification, Within DV: (0,1) Exports > US$100k			OLS FD Specification, Within DV: Δ (0,1) Exports > US$100k		
	Full Sample	Europe and Japan	Other Economies	Full Sample	Europe and Japan	Other Economies	Full Sample	Europe and Japan	Other Economies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				A. Employing Labor Productivity Metrics					
Log Country-Industry Labor Productivity	0.033	0.100	0.034	0.001	0.035	-0.004			
	(0.003)	(0.007)	(0.003)	(0.006)	(0.014)	(0.000)			
Δ Log Country-Industry Labor Productivity							0.006	0.025	0.001
							(0.007)	(0.015)	(0.008)
Observations	95,844	32,214	63,630	95,844	32,214	63,630	61,908	20,622	41,286
				B. Employing Output Metrics					
Log Country-Industry Output	0.082	0.090	0.076	0.020	0.021	0.019			
	(0.001)	(0.003)	(0.002)	(0.004)	(0.011)	(0.004)			
Δ Log Country-Industry Output							0.018	0.010	0.018
							(0.004)	(0.012)	(0.005)
Observations	95,844	32,214	63,630	95,844	32,214	63,630	61,908	20,622	41,286
Exporter-Importer-Industry FE				Yes	Yes	Yes			
Industry-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Importer-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 3A. Estimations consider the extensive margin of exports through linear probability models.

Table 4: Reduced-Form Specifications of Technology and Trade

	Intensive Margin DV: Log Bilateral Exports			Extensive Margin DV: (0,1) Exports > US$100k		
	(1)	(2)	(3)	(4)	(5)	(6)
			A. Base Estimations			
Log Exporter's US Ethnic Technology	0.318	0.167	0.153	0.037	0.010	0.010
	(0.029)	(0.047)	(0.046)	(0.005)	(0.006)	(0.006)
Observations		132,804			736,848	
		B. Testing for Sector Reallocation Effects and Importer Technology State				
Log Exporter's US Ethnic Technology	0.109	0.136	0.114	0.029	0.010	0.010
	(0.033)	(0.047)	(0.047)	(0.005)	(0.006)	(0.006)
x Exporter's 1980 Agr Share	1.139	0.408	0.499	0.096	0.035	0.035
	(0.057)	(0.141)	(0.139)	(0.008)	(0.014)	(0.014)
Log Importer's US Ethnic Technology	0.328	0.033	0.058	0.046	0.002	0.002
	(0.022)	(0.038)	(0.035)	(0.004)	(0.006)	(0.005)
x Importer's 1980 Agr Share	-0.003	-0.376	-0.336	0.059	0.021	0.021
	(0.044)	(0.087)	(0.079)	(0.005)	(0.012)	(0.012)
Observations		132,804			736,848	
Exporter-Importer-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Yr & Importer-Yr FE		Yes			Yes	
Exporter-Importer-Yr FE			Yes			Yes

Notes: Panel estimations consider manufacturing exports taken from the 1975-2000 WTF database. Data are organized by exporter-importer-industry-year. Annual data are collapsed into three-year groupings beginning with 1975-1977 and extending to 2000; the last period of 1999-2000 is two years. The 1984-2000 period is the primary sample due to a substantial shift in WTF data collection after 1984. The appendix reports results from the full sample. Columns 1-3 test the intensive margin of trade. The dependent variable is the log mean nominal value (US$) of bilateral exports for the three years. The intensive margin sample is restricted to exporter-importer-industry groupings with exports exceeding $100k in every year. Columns 4-6 test the extensive margin of trade through linear probability models. The dependent variable is a dichotomous indicator variable taking unit value if bilateral exports exceed $100k. The $100k threshold is chosen due to WTF data collection procedures discussed in the text. US Ethnic Technology states are estimated from the US ethnic patenting dataset at the ethnicity-industry-year level. Regressions are unweighted and cluster standard errors to reflect multiple country-to-ethnicity mappings. Panel A considers the base estimation. Panel B incorporates the US importer's technology state and interacts both technology regressors with their respective foreign country's agricultural share in 1980 as a test for sector reallocation. Variables are demeaned prior to interaction to restore main effects.

Table 5: Robustness Checks on Treatment Effects

	Intensive Margin DV: Log Bilateral Exports			Extensive Margin DV: (0,1) Exports > US$100k		
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Testing for Lag Structure of Effects					
Log Exporter's US Ethnic Technology - Forward	0.126	0.007	-0.001	0.009	0.015	0.015
	(0.045)	(0.053)	(0.052)	(0.007)	(0.007)	(0.007)
Log Exporter's US Ethnic Technology	0.101	0.155	0.146	0.003	0.008	0.008
	(0.044)	(0.047)	(0.047)	(0.007)	(0.006)	(0.006)
Log Exporter's US Ethnic Technology - Lagged 1	0.126	0.074	0.052	0.012	-0.002	-0.002
	(0.039)	(0.043)	(0.042)	(0.006)	(0.006)	(0.006)
Log Exporter's US Ethnic Technology - Lagged 2	0.048	0.049	0.032	0.041	-0.008	-0.008
	(0.038)	(0.043)	(0.042)	(0.006)	(0.006)	(0.006)
Observations		132,804			736,848	
	B. Testing for Rybczynski Effect within Manufacturing					
	Including Linear Trends for Country x Industry Quintiles - K/L Ratio					
Log Exporter's US Ethnic Technology	0.141	0.213	0.197	0.009	0.007	0.007
	(0.042)	(0.044)	(0.044)	(0.006)	(0.006)	(0.006)
Observations		132,804			736,848	
	Including Linear Trends for Country x Industry Quintiles - Mean Wages					
Log Exporter's US Ethnic Technology	0.066	0.132	0.126	0.010	0.009	0.009
	(0.041)	(0.043)	(0.044)	(0.007)	(0.006)	(0.006)
Observations		132,804			736,848	
	Including Linear Trends for Country x Industry Quintiles - Skilled Emp. Share					
Log Exporter's US Ethnic Technology	0.039	0.102	0.101	0.011	0.009	0.009
	(0.042)	(0.045)	(0.045)	(0.007)	(0.006)	(0.006)
Observations		132,804			736,848	
Exporter-Importer-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Yr & Importer-Yr FE		Yes			Yes	
Exporter-Importer-Yr FE			Yes			Yes

Notes: See Table 4. Panel A extends the base estimation to include forward and lagged values of the exporter's technology regressor. Panel B tests for the Rybczynski effect within manufacturing. Industries are grouped into quintiles by their US capital-labor ratios, mean wage rates, and skilled worker wage bill shares. The appendix lists industry groupings. Linear time trends for each country by industry quintile are included in the estimation.

Table 6: Heterogeneity across Ethnicities and Industries

	Intensive Margin DV: Log Bilateral Exports			Extensive Margin DV: (0,1) Exports > US$100k		
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Ethnicity Interactions (Japan Omitted)					
Log Exporter's US	0.214	0.168	0.133	0.007	0.012	0.012
Ethnic Technology	(0.049)	(0.050)	(0.051)	(0.006)	(0.007)	(0.007)
x Chinese Economies	0.524	0.634	0.596	0.096	0.046	0.046
	(0.033)	(0.105)	(0.105)	(0.006)	(0.013)	(0.013)
x European Economies	0.417	0.316	0.262	0.074	0.048	0.048
	(0.034)	(0.075)	(0.077)	(0.006)	(0.012)	(0.012)
x Hispanic Economies	0.518	0.104	0.067	0.074	0.029	0.029
	(0.031)	(0.096)	(0.100)	(0.006)	(0.012)	(0.012)
x India	0.951	0.129	0.129	0.178	0.074	0.074
	(0.050)	(0.125)	(0.130)	(0.009)	(0.018)	(0.018)
x South Korea	0.583	0.338	0.344	0.139	0.009	0.009
	(0.059)	(0.134)	(0.132)	(0.010)	(0.018)	(0.018)
Observations		132,804			736,848	
	B. Machinery & Equipment Sector Interactions (includes Computer Mfg)					
Log Exporter's US	0.257	0.143	0.124	0.009	0.009	0.009
Ethnic Technology	(0.035)	(0.046)	(0.046)	(0.005)	(0.006)	(0.006)
x Chinese Economies	0.068	0.312	0.316	0.035	0.005	0.005
	(0.027)	(0.072)	(0.070)	(0.004)	(0.008)	(0.008)
x Machinery & Equipment Sector	0.297	0.414	0.307	0.045	0.018	0.018
	(0.131)	(0.108)	(0.113)	(0.022)	(0.016)	(0.016)
x Chinese Economies	0.120	0.096	0.119	0.003	0.019	0.019
x Machinery & Equipment Sector	(0.097)	(0.082)	(0.085)	(0.011)	(0.007)	(0.007)
Observations		132,804			736,848	
Exporter-Importer-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Yr & Importer-Yr FE		Yes			Yes	
Exporter-Importer-Yr FE			Yes			Yes

Notes: See Table 4. Panel A extends the base estimation by interacting the exporter's technology regressor with ethnic groupings. Japanese is the omitted ethnicity interaction. Panel B considers interactions with the Machinery & Equipment sector (which includes computer manufacturing) and Chinese economies. Variables are demeaned prior to interaction to restore main effects.

App. Table: ISIC Revision 2 Industries

ISIC	Industry Title	US Quintiles (5 = Highest) K/L	Wage	Skill
3111	Slaughtering, preparing and preserving meat	2	1	1
3112	Man. of dairy products	4	3	4
3113	Canning and preserving of fruits and vegetables	4	2	1
3114	Canning, preserving and processing of fish and crustaceans		n.a.	
3115	Man. of vegetable and animal oils and fats	5	3	4
3116	Grain mill products	5	4	4
3117	Man. of bakery products	3	2	5
3118	Sugar factories and refineries	4	2	2
3119	Man. of cocoa, chocolate and sugar confectionery		n.a.	
3121	Man. of food products n.e.c.	3	2	3
3122	Man. of prepared animal feeds		n.a.	
3131	Distilling, rectifying and blending spirits	5	4	5
3132	Wine industries		n.a.	
3133	Malt liquors and malt		n.a.	
3134	Soft drinks and carbonated waters industries		n.a.	
3140	Tobacco manufactures	5	5	3
3211	Spinning, weaving and finishing textiles	3	1	1
3212	Man. of made-up textile goods except wearing apparel		n.a.	
3213	Knitting mills	1	1	1
3214	Man. of carpets and rugs	2	2	2
3215	Cordage, rope and twine industries		n.a.	
3219	Man. of textiles n.e.c.	1	1	2
3220	Man. of wearing apparel, except footwear	1	1	1
3231	Tanneries and leather finishing	2	2	1
3232	Fur dressing and dyeing industries	1	1	4
3233	Man. of products of leather, except footwear and wearing apparel	1	1	2
3240	Man. of footwear, except vulcanized or molded rubber or plastic	1	1	1
3311	Sawmills, planing and other wood mills	2	1	1
3312	Man. of wooden and cane containers and small cane ware	1	1	1
3319	Man. of wood and cork products n.e.c.	1	1	1
3320	Man. of furniture and fixtures, except primarily of metal	1	1	1
3411	Man. of pulp, paper and paperboard	5	5	2
3412	Man. of containers and boxes of paper and paperboard	3	3	2
3419	Man. of pulp, paper and paperboard articles n.e.c.	3	3	2
3420	Printing, publishing and allied industries	1	3	5
3511	Man. of basic industrial chemicals except fertilizers	5	5	5
3512	Man. of fertilizers and pesticides	5	5	4
3513	Man. of synthetic resins, plastic and man-made fibers except glass	5	5	4
3521	Man. of paints, varnishes and lacquers	4	4	5
3522	Man. of drugs and medicines	5	5	5

App. Table: ISIC Revision 2 Industries, continued

ISIC	Industry Title	US Quintiles (5 = Highest) K/L	Wage	Skill
3523	Man. of soap and cleaning, preparations, perfumes, cosmetics, etc.	4	4	5
3529	Man. of chemical products n.e.c.	4	4	5
3530	Petroleum refineries	5	5	4
3540	Man. of miscellaneous products of petroleum and coal	5	4	4
3551	Tire and tube industries	5	5	1
3559	Man. of rubber products n.e.c.	2	2	3
3560	Man. of plastic products n.e.c.	2	2	2
3610	Man. of pottery, china and earthenware	1	2	2
3620	Man. of glass and glass products	4	3	1
3691	Man. of structural clay products	3	2	2
3692	Man. of cement, lime and plaster	4	3	3
3699	Man. of non-metallic mineral products n.e.c.	4	3	3
3710	Iron and steel basic industries	5	5	2
3720	Non-ferrous metal basic industries	5	4	3
3811	Man. of cutlery, hand tools and general hardware	3	3	3
3812	Man. of furniture and fixtures primarily of metal		n.a.	
3813	Man. of structural metal products	2	3	3
3819	Man. of fabricated metal products except mach. and equip. n.e.c.	3	3	3
3821	Man. of engines and turbines	5	5	4
3822	Man. of agricultural mach. and equip.	4	3	3
3823	Man. of metal and wood-working mach.	3	4	3
3824	Man. of special ind. mach./equip. except metal and wood-working	2	4	5
3825	Man. of office, computing and accounting mach.	4	5	5
3829	Mach. and equip. except electrical n.e.c.	3	4	4
3831	Man. of electrical industrial mach. and apparatus	2	3	4
3832	Man. of radio, television and communication equip. and apparatus	3	5	5
3833	Man. of electrical appliances and household goods	3	2	3
3839	Man. of electrical apparatus and supplies n.e.c.	4	4	4
3841	Shipbuilding and repairing	2	3	2
3842	Man. of railroad equip.	3	4	3
3843	Man. of motor vehicles	4	5	1
3844	Man. of motorcycles and bicycles	2	3	2
3845	Man. of aircraft	3	5	5
3849	Man. of transport equip. n.e.c	3	5	5
3851	Man. of prof. and scientific, measuring/controlling equip., n.e.c	2	4	5
3852	Man. of photographic and optical goods	4	4	5
3853	Man. of watches and clocks	2	2	3
3901	Man. of jewelery and related articles	1	2	4
3902	Man. of musical instruments	1	1	2
3903	Man. of sporting and athletic goods	2	1	3
3909	Manufacturing industries n.e.c.		n.a.	

App. Table: Base Specifications with 1975-2000 Period

	Intensive Margin DV: Log Bilateral Exports			Extensive Margin DV: (0,1) Exports > US$100k		
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Base Estimations					
Log Exporter's US	0.472	0.187	0.152	0.068	0.004	0.004
Ethnic Technology	(0.030)	(0.048)	(0.047)	(0.005)	(0.006)	(0.006)
Observations		152,874			1,105,272	
	B. Testing for Sector Reallocation Effects and Importer Technology State					
Log Exporter's US	0.286	0.165	0.122	0.065	0.004	0.004
Ethnic Technology	(0.034)	(0.049)	(0.048)	(0.005)	(0.006)	(0.006)
x Exporter's 1980 Agr Share	0.826	0.248	0.342	0.095	0.094	0.094
	(0.064)	(0.165)	(0.162)	(0.007)	(0.015)	(0.015)
Log Importer's US	0.430	-0.013	0.005	0.057	-0.008	-0.008
Ethnic Technology	(0.022)	(0.038)	(0.036)	(0.003)	(0.005)	(0.004)
x Importer's 1980 Agr Share	-0.491	-0.572	-0.561	0.036	0.022	0.022
	(0.043)	(0.123)	(0.112)	(0.004)	(0.010)	(0.010)
Observations		152,874			1,105,272	
Exporter-Importer-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Yr & Importer-Yr FE		Yes			Yes	
Exporter-Importer-Yr FE			Yes			Yes

Notes: See Table 4. This table reports results with the complete 1975-2000 period.

App. Table: Base Specifications in a First-Differences Form

	Intensive Margin DV: Δ Log Bilateral Exports			Extensive Margin DV: (0,1) Exports > US$100k		
	(1)	(2)	(3)	(4)	(5)	(6)
			A. Base Estimations			
Δ Log Exporter's US	0.166	0.075	0.079	0.019	0.005	0.005
Ethnic Technology	(0.027)	(0.031)	(0.031)	(0.005)	(0.005)	(0.005)
Observations		110,670			614,040	
		B. Testing for Sector Reallocation Effects and Importer Technology State				
Δ Log Exporter's US	0.060	0.070	0.069	0.016	0.005	0.005
Ethnic Technology	(0.027)	(0.031)	(0.032)	(0.005)	(0.005)	(0.005)
x Exporter's 1980 Agr Share	0.922	0.088	0.158	0.082	0.017	0.017
	(0.065)	(0.123)	(0.122)	(0.010)	(0.016)	(0.016)
Δ Log Importer's US	0.073	-0.009	0.011	0.012	-0.002	-0.002
Ethnic Technology	(0.026)	(0.028)	(0.028)	(0.004)	(0.005)	(0.005)
x Importer's 1980 Agr Share	-0.056	-0.350	-0.245	0.062	0.020	0.020
	(0.066)	(0.121)	(0.110)	(0.008)	(0.017)	(0.016)
Observations		110,670			614,040	
Industry-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Yr & Importer-Yr FE		Yes			Yes	
Exporter-Importer-Yr FE			Yes			Yes

Notes: See Table 4. This table reports results first-differenced estimations.

App. Table: Heterogeneity across Bilateral Geographic Distances

	Intensive Margin DV: Log Bilateral Exports			Extensive Margin DV: (0,1) Exports > US$100k		
	(1)	(2)	(3)	(4)	(5)	(6)
			A. Bordering Countries Interactions			
Log Exporter's US Ethnic Technology	0.328	0.183	0.144	0.039	0.011	0.009
	(0.029)	(0.047)	(0.046)	(0.005)	(0.006)	(0.006)
x Bordering Economies	0.053	0.203	-0.089	0.028	0.027	-0.037
	(0.028)	(0.025)	(0.043)	(0.006)	(0.005)	(0.010)
Observations		132,804			736,848	
			B. Non-Parametric Distance Interactions (0-1500 km omitted)			
Log Exporter's US Ethnic Technology	0.359	0.198	0.148	0.037	0.012	0.009
	(0.030)	(0.047)	(0.046)	(0.005)	(0.006)	(0.006)
x 1501-3000 km to Importer	0.038	-0.075	-0.006	0.030	0.012	0.019
	(0.018)	(0.016)	(0.039)	(0.003)	(0.003)	(0.007)
x 3001-6000 km	-0.075	-0.208	0.106	0.024	-0.012	0.009
	(0.026)	(0.028)	(0.060)	(0.004)	(0.004)	(0.009)
x 6001-9000 km	-0.052	-0.173	0.083	0.019	-0.011	0.023
	(0.026)	(0.024)	(0.053)	(0.004)	(0.004)	(0.008)
x 9001+ km	-0.126	-0.198	-0.087	0.000	-0.028	0.024
	(0.025)	(0.022)	(0.042)	(0.004)	(0.004)	(0.008)
Observations		132,804			736,848	
Exporter-Importer-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Yr & Importer-Yr FE		Yes			Yes	
Exporter-Importer-Yr FE			Yes			Yes

Notes: See Table 4. Panel A extends the base estimation by interacting the exporter's technology regressor with whether the importer is a bordering country or not. Panel B includes interactions by geographic distances between exporters and importers using Great Circle distances between capital cities. The five distance categories are 0-1500 km., 1501-3000 km., 3001-6000 km., 6001-9000 km., and greater than 9000 km. To give a feel for these demarcations, the distances from Beijing, China, to the capitals of Taiwan, Bangladesh, United Arab Emirates, and Spain are 1723 km., 3029 km., 5967 km., and 9229 km., respectively. The omitted distance interaction is 0-1500 km. Variables are demeaned prior to interaction to restore main effects.

App. Table: UNIDO Industry Sample

Country	1980 Agr. Share	UNIDO3 Panel	Output (m) Level	Output (m) Growth	Labor Prod. (k) Level	Labor Prod. (k) Growth	Employment (k) Level	Employment (k) Growth	Capital (m) Level	Capital (m) Growth
Single Ethnic Mappings:										
India	70%	85-97	117,950	6%	16	3%	7,354	2%	46,740	4%
Japan	11%	85-97	2,053,048	7%	206	8%	9,998	-1%	415,195	8%
South Korea	37%	85-97	230,942	14%	88	13%	2,626	1%	88,873	14%
Russia	16%	93-97	109,729	12%	10	22%	11,685	-8%		
Soviet Union	16%	85-89	1,087,914	7%	35	8%	31,434	-1%		
Chinese Economies:										
China, Mainland	74%	85-97	327,173	11%	8	9%	38,940	3%		
Hong Kong	1%	85-97	30,520	3%	66	12%	535	-9%	6,628	3%
Macao	6%	85-97	1,209	8%	26	10%	49	-2%	235	1%
Singapore	2%	85-97	37,830	16%	117	12%	309	3%	8,477	8%
Taiwan	8%	85-96	145,055	11%	68	11%	2,141	0%		
European Economies:										
Austria	10%	85-97	73,524	5%	125	5%	595	0%	22,001	5%
Belgium	3%	85-92, 95-97	31,958	5%	131	7%	247	-2%	19,809	7%
Denmark	7%	85-91	38,198	9%	93	11%	411	-1%	8,788	7%
Finland	12%	85-97	52,510	4%	141	8%	386	-4%	18,868	1%
France	8%	85-96	517,276	8%	130	10%	4,006	-2%	107,758	4%
Germany	7%	91-97	870,625	7%	147	7%	5,920	0%		
Germany, East		85-92	233,905	12%	81	12%	2,902	0%		
Germany, West		85-89	734,523	12%	115	12%	6,391	0%	51,571	-6%
Italy	13%	85-94, 96-97	390,266	7%	134	7%	2,897	0%	79,391	6%
Luxembourg	5%	85-97	2,952	3%	137	5%	22	-1%	730	1%
Netherlands	6%	85-97	117,868	6%	178	7%	670	-1%	29,146	6%
Norway	8%	85-97	37,467	4%	149	6%	256	-2%	10,402	-1%
Poland	30%	90-97	54,895	6%	21	7%	2,650	-1%	18,749	1%
Sweden	6%	85-97	93,727	6%	140	7%	678	-1%	23,192	4%
Switzerland	6%	86-96	37,827	7%	142	8%	270	-2%		

App. Table: UNIDO Industry Sample, continued

Country	1980 Agr. Share	UNIDO3 Panel	Output (m) Level	Output (m) Growth	Labor Prod. (k) Level	Labor Prod. (k) Growth	Employment (k) Level	Employment (k) Growth	Capital (m) Level	Capital (m) Growth
Hispanic Economies:										
Argentina	13%	85-90, 93-96	66,160	11%	73	14%	938	-3%		
Bolivia	53%	85-97	1,474	7%	41	1%	36	6%		
Brazil	37%	90, 92-95	127,807	11%	61	17%	2,105	-5%		
Chile	21%	85-97	20,604	10%	72	5%	278	5%	3,964	9%
Columbia	40%	85-97	20,099	5%	41	3%	487	2%	4,917	-1%
Costa Rica	35%	85-97	3,264	5%	26	1%	127	4%		
Cuba	24%	85-89	10,531	-1%	20	-3%	524	2%	6,097	0%
Ecuador	40%	85-97	4,372	3%	41	2%	107	2%	2,797	1%
Honduras	57%	90-95	989	8%	12	-10%	90	22%		
Mexico	36%	85-97	61,612	4%	60	6%	1,021	-2%	11,111	2%
Panama	29%	85-94, 96-97	1,468	4%	44	3%	33	1%	445	-3%
Peru	40%	85-92, 94-96	13,944	8%	55	9%	255	-1%	2,320	5%
Philippines	52%	85-97	23,238	11%	27	6%	857	5%	5,512	4%
Portugal	26%	85-97	36,365	8%	43	9%	816	-1%		
Spain	18%	85-97	201,951	8%	108	7%	1,858	2%	35,005	7%
Uruguay	17%	85-97	4,648	6%	37	8%	130	-1%		
Venezuela	15%	85-97	24,174	1%	59	2%	417	0%	13,775	1%

Notes: Values are in 1987 US dollars. Levels and growth rates are unweighted averages of yearly country-level aggregates derived from the industry data used in the UNIDO3 panel. Belize, Dominican Republic, El Salvador, Guatemala, Latvia, Lithuania, Nicaragua, Paraguay, and Vietnam are not included due to lack of data. For countries in the sample, insufficient observations or severe quality concerns excluded observations in Bolivia (353 in 1985, 355 and 382 in 1987), Brazil (1985), Costa Rica (371, 385 in 1997), Ecuador (352 in 1994, 354 in 1995, 313 in 1997), Honduras (1981-1989), Hong Kong (369 in 1996), Macao (314) and Venezuela (314 in 1996, 371 in 1995). Series breaks are modeled for Argentina (1990), Austria (1985), China (1989), Denmark (1989), Italy (1994), Mexico (1993), and Portugal (1989) for distinct levels shifts over the 1985-1997 period usually due to changes in variable definitions.

ISIC Rev. 2 Industries: Food products (311), Beverages (313), Tobacco (314), Textiles (321), Wearing apparel, except footwear (322), Leather products (323), Footwear, except rubber or plastic (324), Wood products, except furniture (331), Furniture, except metal (332), Paper and products (341), Printing and publishing (342), Industrial chemicals (351), Other chemicals (352), Petroleum refineries (353), Misc. petroleum and coal products (354), Rubber products (355), Plastic products (356), Pottery, china, earthenware (361), Glass and products (362), Other non-metallic mineral products (369), Iron and steel (371), Non-ferrous metals (372), Fabricated metal products (381), Machinery, except electrical (382), Machinery, electric (383), Transport equipment (384), Professional & scientific equipment (385), and Other manufactured products (390). Industry 390 is excluded.