Heterogeneous Technology Diffusion and Ricardian Trade Patterns

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Abstract

This study tests the importance of Ricardian technology differences for international trade. Panel regressions find technology growth increases manufacturing exports. To establish a causal relationship between technology and trade, instrumental-variables specifications exploit uneven technology diffusion from the US through ethnic scientific networks. The instrumented elasticity of export growth to the exporter's technology development is 0.9 in the preferred specification. Supplemental specifications show this elasticity is robust to incorporating the importer's technology development and to controlling for the Rybczynski effect due to factor accumulation. An exogenous reform of US immigration law also confirms the results are not due to reverse causality. These findings suggest technology differences are an important determinant of trade patterns.

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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 still undergirds many modelling frameworks on which recent theoretical advances build (e.g., Dornbusch, Fischer, and Samuelson 1977, Eaton and Kortum 2002). In a famous response to Stanislaw Ulam's challenge to name a true and nontrivial theory in the social sciences, Paul Samuelson chose this principle of comparative advantage due technology differences.

While empirical tests of this framework date back to its original proponent David Ricardo (1817), the underlying technology differences across countries are very difficult to quantify. Proxies for technology (e.g., total factor productivity) allow substantial progress but do risk confounding heterogeneous technologies with other country-specific determinants of trade, especially in cross-sectional exercises. In principle, the relationship between technology and trade is best estimated through panel data models that remove time-invariant characteristics of each nation (e.g., distances, colonial history) and afford explicit controls of the time-varying determinants deemed important (e.g., factor accumulation, economic development, trading blocs). Of course, quantifying the dynamics of uneven technology advancement across countries is an even more challenging task, and whether the uncovered partial correlations represent causal parameters still needs to be addressed.[1]

This study develops this form of empirical environment by exploiting differences across countries in their access to the US technology frontier. Recent research emphasizes the importance of ethnic scientists and entrepreneurs living in the US for the diffusion of US technologies to their home countries. These frontier expatriates facilitate the transfer of the codified details of new innovations, but perhaps more importantly also convey the tacit knowledge required for successful adoption. In a companion study, Kerr (2005a) finds that a larger ethnic research community in the US improves technology diffusion to foreign countries of the same ethnicity. That is, new computer technologies flow faster to Chinese economies than to Latin America if the Chinese computer research community in the US is stronger than the Hispanic community. Moreover, the foreign countries realize substantial manufacturing output and productivity gains from the stronger scientific integration. As invention is disproportionately concentrated in the US, these ethnic channels significantly influence the technology opportunities of imitating economies.[2]

[1] The panel exercises in this paper are closest in spirit to Harrigan (1997b), who evaluates the importance of both technology and factor supply differences across countries for determining industry specialization. This paper differs, however, in its direct study of trade flows, its substantial attention to non-OECD economies, and in its IV analysis using heterogeneous technology diffusion. Other tests of the Ricardian model are McDougall (1951, 1952) and Stern (1962).

[2] Kerr (2005a) provides additional references on the role of ethnic networks in transmitting new technologies. 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,

This uneven technology diffusion through ethnic networks offers an empirical foothold for evaluating the importance of technology differences across countries in explaining trade patterns. The empirical specifications, however, must be carefully designed to isolate technology's role, and the next section of this paper utilizes the multi-country Ricardian model of Eaton and Kortum (2002) to guide the form of the estimating equations. Eaton and Kortum construct a special theoretical framework that relates trade flows among countries to the technology capabilities, distances, and input costs of each economy. A simple application in Section 2 replaces Eaton and Kortum's random technology parameters with country-specific technology capabilities that depend upon a frontier country's technology state and the follower's human-capital stock with respect to the frontier innovations. The human-capital stocks for each country are acquired through scientists of the following country's ethnicity who work in the frontier economy. Reduced-form expressions thereby relate the trade patterns of the technology follower to its ethnic scientific community in the technology leader.

After the appropriate estimating specifications are developed, Section 3 describes the dataset constructed for this project. Ethnic scientists working in the US are identified by applying an ethnic-name database to individual US patent records (e.g., identifies inventors with Chinese versus Hispanic names). The matched dataset describes the 1980-1997 ethnic composition of US inventors with unparalleled cross-sectional and longitudinal detail, and the sizes of ethnic research communities are determined at the industry level by aggregating individual patent records. These research communities are joined with detailed export data for foreign countries (e.g., US Chinese computer research is paired with China's trade in the computer industry) in an econometric framework that follows from theoretical model. Total factor productivity (TFP) indices are also developed as proxies for aggregate technology states.

The fourth section presents the main empirical results using bilateral manufacturing exports aggregated over industries from 1980-1997.[3] Following the reduced-form equations developed in Section 2, tests of the Ricardian theory first regress these bilateral exports on the exporter's ethnic human-capital stocks for US technologies as measured in the ethnic patenting dataset. Panel fixed effects remove time-invariant determinants of bilateral trade and global developments in technology and trade; gravity covariates are also included to isolate technology's role. Export volumes rise with an elasticity of about 0.6 to better human capital for the US technology frontier, with the coefficient statistically different from zero. The results are robust to a number of sample decomposition exercises and specification variants. The strong elasticity of exports to the exporter's integration to the US frontier is also preserved when the importer's technology integration is added as an additional regressor. Moreover, the elasticity estimates for the importer's technology regressor are smaller and not statistically different from zero. The combined

Coe, Helpman, and Hoffmaister 1997), or international patenting decisions (e.g., Eaton and Kortum 1999). Keller (2004) reviews the technology transfer literature.

[3] As discussed below, exports to the US are excluded from the trade patterns examined in this paper due to potential network effects operating alongside technology transfer. Kerr (2005b) separately analyzes the role of ethnic scientific networks in US bilateral trade.

pattern suggests countries export more manufacturing goods when they develop a comparative advantage due to uneven technology diffusion from the US.

These initial reduced-form estimations assume the following order of events: technologies are developed in the US, ethnic scientists in the US transmit the technologies to their respective countries, and trade patterns are determined. Reverse causality, however, is an important concern, with a plausible alternative being that foreign human-capital development is responsible for both the export growth, perhaps with industry reallocations due to the Rybczynski effect, and the emigration of ethnic researchers to the US. If true, the ethnic human-capital stock for US technologies measured through the patenting data would not be a valid instrument for the exporter's technology set. To begin addressing this issue, Section 4 continues by developing a second estimator using exogenous, differential changes in the sizes of US ethnic research communities following the US Immigration Act of 1990. Reduced-form regressions with this immigration quotas estimator also find positive export growth following stronger scientific integration with the US, and the strong contrast with the importer's integration is again evident. While the new elasticity estimate of 0.5 is not directly comparable to the ethnic patenting estimator, the directions of the two exercises support each other.

After establishing these two estimators for heterogeneous technology diffusion, Section 4 concludes with the full OLS and IV regressions of bilateral export volumes on the exporter's and importer's technology states. Aggregate technology capabilities are proxied with country-level TFP indices. In the OLS regressions, growth in the exporter's technology set correlates with positive export growth, but the elasticity estimates are sensitive whether the gravity covariates are included; the importer's TFP coefficients are much weaker. IV regressions instrument for technology development in both countries using the heterogeneous diffusion from the US through ethnic scientific networks. First-stage regressions with both the patent-based and quotas-based instruments find a robust growth in foreign technology levels with a stronger US ethnic research community.

The second-stage regressions exhibit instrumented elasticities of exports to the exporter's technology development that range from 0.6 to 1.1 with the patent-based instruments; the higher estimates are for specifications that exclude the (potentially endogenous) gravity covariates. The range of elasticities evident with the quotas-based instruments is 1.1 to 1.7. In all cases these elasticity estimates are statistically different from zero. By contrast, the instrumented elasticities of exports to the importer's technology state are smaller and not consistently different from zero, especially when the gravity covariates are included. The conclusion from these country-level exercises is that Ricardian technology differences are important determinants of trade patterns.

Section 5 extends these core tests of the Ricardian model by exploiting the additional industry and geographic variation available in the combined trade and ethnic patenting dataset. These extensions are of interest in their own right, and more importantly provide additional confidence that the measured role for technology development is not reflecting an omitted factor

accumulation. 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).[4] 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 significant growth in manufacturing exports due to the Rybczynski effect.

Section 5 tests this alternative hypothesis by contrasting industries within each country of similar factor input intensities. Technology's important role is preserved in these detailed matching exercises. Exploiting the within-country variation also ensures the findings are robust to other country-level explanations like nations entering trade agreements or multinational bodies (e.g., the World Trade Organization), asynchronous business cycles, and so on. Section 5 concludes by further analyzing the geographic margin of trade expansion. Export growth is strongest in bordering and nearby countries, but positive growth is evident at all distances studied.

The results of this project confirm technology is an important determinant of trade; moreover, it is relevant for explaining changes in trade patterns over time. Section 6 concludes this paper by discussing future projects that will utilize the uneven transmission of technologies through ethnic networks to characterize how Ricardian technology differences shape international exchanges.

2 Theoretical and Estimating Frameworks

This section develops the estimating equations employed in Section 4's empirical analysis. It begins by briefly sketching a recent multi-country Ricardian model of Eaton and Kortum (2002). This framework is unique in relating trade to technology differences across several countries, and a simple application builds into this theory ethnic research networks and heterogeneous technology diffusion. From this analysis, reduced-form specifications are developed that relate bilateral exports to ethnic human-capital stocks with respect to frontier technologies. The second half of this section in turn manipulates these theoretical specifications into a framework suitable for empirical analysis.[5]

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 $Q(j)$ accord-

[4] See Heckscher (1919), Ohlin (1933), and Vanek (1968). Dornbusch, Fischer, and Samuelson (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) and Davis and Weinstein (2001) also jointly explore technology and factor differences as determinants of trade.

[5] See also Alvarez and Lucas (2004). The Dornbusch, Fischer, and Samuelson (1977) approach to Ricardian trade is not readily extended to multiple countries, although some local comparative statics are feasible (e.g., Wilson 1980).

ing 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 throughout most of this discussion.

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 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.

To model heterogeneous technology diffusion through ethnic ties to the frontier economy, the technology location parameter is specified as

$$T_{it} = \tilde{T}_t \cdot \Upsilon_i \cdot (H_{it})^{\tilde{\beta}_H}. \tag{5}$$

$\tilde{T}_t$ is the exogenously determined frontier technology stock.[6] Υ_i models time-invariant differences in the access or importance of frontier technologies to country i, potentially arising due to geographic separation (e.g., Keller 2002), heterogeneous production techniques (e.g., Davis and Weinstein 2001), and so on. Finally, H_{it} is the human-capital stock of country i with respect to the frontier innovations, including both the codified and tacit knowledge required for successful adoption. This human-capital stock depreciates at a rate δ, and the population of researchers of country i's ethnicity ($\tilde{L}_i$) working in the frontier country replenishes it: $\partial H_i/\partial t = -\delta H_i + \tilde{L}_i$. If the number of expatriate researchers is constant, the steady-state human-capital stock of country i with respect to frontier inventions is $\delta^{-1}\tilde{L}_i$. The elasticity $\tilde{\beta}_H$ is empirically estimated below.

2.2 Estimating Framework

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 $\pi_{ni} = T_i(c_i d_{ni})^{-\theta} \big/ \sum_{k=1}^{N} T_k(c_k d_{nk})^{-\theta}$.[7] 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

$$\frac{X_{ni}}{X_n} = \frac{T_i(c_i d_{ni})^{-\theta}}{\sum_{k=1}^{N} T_k(c_k d_{nk})^{-\theta}}, \tag{6}$$

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 (6) also shows how trading costs d lead to deviations in the law of one price.

For the case of frictionless trade or constant trading costs ($d_{nk} = d \; \forall n, k$)[8], condition (6) can be rearranged into the structural estimating equation for year t,

$$\ln(X_{nit}) = \ln(T_{it}) - \theta \ln(c_{it}) + \ln(X_{nt}) - \ln\left(\sum_{k=1}^{N} T_{kt}(c_{kt})^{-\theta}\right). \tag{7}$$

Panel estimations of bilateral exports evaluate this structural relationship in the next section. A vector of year effects η_t will control for the world price and technology aggregate

[6] Variables referring to the frontier economy are generally denoted by a tilda.

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

[8] The assumption of constant trading costs is unimportant for the upcoming panel estimations if the number of countries is large. The numerator's bilateral distance $d_{ni}^{-\theta}$ is time-invariant and absorbed into the cross-sectional effects. The error from modelling the denominator's world price and technology aggregate with year effects is small, $\lim_{N \to \infty} [\partial \ln(\sum_{k=1}^{N} T_{kt}(c_{kt} d_{nk})^{-\theta}) / \partial \ln(T_i)] = 0$.

$\ln\left(\sum_{k=1}^{N} T_{kt}(c_{kt})^{-\theta}\right)$; the year effects also remove uniform growth in trade volumes and price changes during the period studied. A vector of cross-sectional effects ϕ_{ni} further extract time-invariant determinants of bilateral exports from country n and country i (e.g., distances, colonial ties).

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. As noted above, geographic distances are controlled for by the cross-sectional effects ϕ_{ni}. To model changes over time in the economic sizes of nations, some specifications below further incorporate the gravity covariates of the exporter's and importer's GDP and GDP per capita. These gravity covariates are interacted following Frankel (1997) and Rauch (2002).[9] The augmented estimating equation is

$$\begin{aligned} \ln(X_{nit}) &= \alpha + \beta_T \ln(T_{it}) + \gamma \ln(GDP/CAP_{it} \cdot GDP/CAP_{nt}) \\ &\quad + \zeta \ln(GDP_{it} \cdot GDP_{nt}) + \phi_{ni} + \eta_t + \epsilon_{nit}, \end{aligned} \tag{8}$$

where the theoretical elasticity of one between technology and bilateral exports is empirically evaluated with the β_T coefficient. Specification (8) also direct models the importer's aggregate expenditure X_{nt} in (7) with the importer's GDP. The exporter's GDP per capita further captures broad changes in the input costs c_{it}.[10]

The OLS specification (8) is evaluated in Section 4 with the aggregate technology parameter T_{it} measured through country-level TFP indices. While this Ricardian framework clearly assigns a causal relationship of export growth to technology development, in practice the empirical estimation of (8) can be confounded by reverse causality or omitted variable biases. Moreover, the possible simultaneous accumulation of factor endowments and new technologies is particularly worrisome for isolating the Ricardian impetus for trade from relative factor scarcities. Technology is the only channel promoting export growth in this framework due to identical factor endowments and no intertemporal factor accumulation.[11]

Anticipating these issues, this section closes with how heterogeneous technology transfer from the frontier economy (5) provides a foothold for establishing causality when these complications are introduced. The human-capital stock of country i with respect to the frontier innovations (H_i) affects country i's exports only through technology transfer and can thus serve as an instrument for country i's technology in the structural specification (8). This human-capital stock is

[9] The interaction of the gravity covariates is further discussed below. The gravity relationship in the Eaton and Kortum model arises due to technology differences interacting with distances and production costs. An alternative derivation through Armington or monopolistic competition builds on imperfect substitution among goods for consumers. The former predicts trade growth at the extensive margin with technology development, while the latter two predict trade growth at the intensive margin.

[10] Input costs can be endogenized through a specification of the labor market. This study does not undertake this step, instead measuring export growth due technology transfer net of input costs increases from general-equilibrium wage pressure.

[11] Differences in preferences or non-homothetic utility functions 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).

acquired through researchers of country i's ethnicity ($\tilde{L}_i$) working in the frontier economy, and two instruments are developed in Section 4 using ethnic scientific communities in the frontier US economy. Substituting (5) into the structural equation (8) yields the reduced-form contribution of these communities for exports from their home countries,

$$\begin{aligned} \ln(X_{nit}) &= \alpha + \beta_H \ln(H_{it}) + \gamma \ln(GDP/CAP_{it} \cdot GDP/CAP_{nt}) \\ &\quad + \zeta \ln(GDP_{it} \cdot GDP_{nt}) + \phi_{ni} + \eta_t + \epsilon_{nit}, \end{aligned} \tag{9}$$

with $\beta_H = \beta_T \cdot \tilde{\beta}_H$. The log frontier technology state $\tilde{T}_t$ is separated from the ethnic human-capital stock H_{it} and absorbed into the year effects η_t; likewise, the time-invariant differences in access for country i are absorbed into the cross-sectional effects ϕ_{ni}.[12] The empirical exercises below commence with this reduced-form relationship, and then analyze (8) in a two-stage least squares framework.

3 Dataset Preparation

To test empirically these Ricardian predictions, a dataset is prepared combining bilateral trade data, foreign-country technology measures, and US ethnic human-capital stocks. The core industry-level and country-level variation exploited in this study is dictated by the ethnic patenting metrics developed first. Once this panel foundation is established, the mapping in of trade and foreign-country TFP measures is easily motivated.

3.1 US Ethnic Human-Capital Stocks

This paper exploits technology differences across countries arising due to uneven technology diffusion from the US through ethnic scientific networks. The ethnic human-capital stocks with respect to US technologies are developed through the NBER Patent Data File (Hall, Jaffe, and Trajtenberg 2001). This dataset offers detailed records for all patents granted by the United States Patent and Trademark Office (USPTO) from January 1975 to December 1999. Each patent record provides information about the invention (e.g., technology classification, citations of prior art) and the inventors submitting the application (e.g., name, city). To estimate inventor ethnicities, a commercial database of ethnic first names and surnames is mapped into the inventor records. The match rate is 98% for US patent records, and the process affords the distinction of nine ethnicities: Chinese, English, European, Hispanic, Indian, Japanese, Korean, Russian, and Vietnamese.

Table 1 describes the 1980-1997 US sample. The trends demonstrate a growing ethnic contribution to US technology development, especially among Chinese and Indian scientists. Also matching popular perceptions, ethnic inventors are more concentrated in high-tech industries

[12] More generally, technology differences across countries orthogonal to the US ethnic human-capital stock H_{it} are absorbed into the error term ϵ_{nit} without biasing the β_H coefficient.

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 demonstrate a close correspondence of the estimated ethnic composition to the country-of-birth composition of the US science and engineering workforce in the 1990 Census.[13] 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 ethnic contributions by broad technology groups.[14]

From this matched database, the ethnic human-capital stocks H_i to the US frontier are easily developed. Recall that these stocks depend upon the number of frontier researchers undertaking inventive activity of country i's ethnicity ($\tilde{L}_i$): $\partial H_i/\partial t = -\delta H_i + \tilde{L}_i$. Define the patenting productivity of a US researcher to be $\tilde{P}$, so that the measured US patenting of ethnicity i in year t is expected to be $\tilde{P}_{it}^{Flow} = \tilde{P} \cdot \tilde{L}_{it}$. Inverting this expression suggests the size of the ethnic research community can be inferred annually using the observed number of US ethnic patent applications divided by the constant researcher productivity ($\tilde{L}_{it} = \tilde{P}_{it}^{Flow} \diagup \tilde{P}$).

With the population of US ethnic researchers quantified annually, subject to a multiplicative constant, the human-capital stocks H_i could be estimated through the perpetual inventory method. The empirical results presented below, however, take a slightly different approach. In an examination of international patent citations, Kerr (2005a) finds ethnic scientific networks aid direct communications among inventors. Inventors living outside of the US cite US inventors of their own-ethnicity approximately 50% more often than other US-based inventors, even after controlling for technology classes. Moreover, by considering different time lags between the filing dates of the cited and citing patents, the ethnic bias is shown to be most important in the first five years of the diffusion process. The human-capital stocks H_i are accordingly modelled by aggregating the number of ethnic patents over the previous five years, with the panel fixed effects controlling for any changes in patenting productivity $\tilde{P}$ of US researchers.[15,16]

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

[13] The estimated European ethnic contribution is naturally higher than the immigrant contribution measured by foreign born.

[14] Kerr (2005c) further details the ethnic patenting dataset and provides additional descriptive statistics. A quality assurance exercise matching the ethnic-name database to foreign patent records registered in the US is also presented. The ethnic-name procedure assigns ethnicities to 98% of foreign inventor records, and the average own-ethnicity contribution is 88%. Similar to the US, own-ethnicity contributions should be less than 100% due to expatriate researchers.

[15] In an influential survey, Griliches (1990) notes that annual fluctuations in US patents granted occur due to changes in USPTO personnel resources, as well as technology development. Over the last two decades, US patent grants have increased dramatically. While several explanations for this increase are put forth (e.g., Kortum and Lerner 2000, Kim and Marshcke 2004, Hall 2004, and Branstetter and Ogura 2005), it is clear that the number of patents awarded has grown faster than the growth in research scientists would suggest. The time effects account for changes in the underlying patenting productivity, effectively contrasting ethnic shares of US patents granted.

[16] Similar results are found if the perpetual inventory method is employed. The two disadvantages of this technique are the assignments of a depreciation rate δ for human capital and initial human-capital stocks. The latter is particularly burdensome since the ethnicity of inventors can only be determined after 1975.

of the US Standard Industrial Classification system. Table A1 in the appendix lists the ISIC industries employed.[17]

3.2 Export Volumes

Bilateral exports are taken from the World Trade Flows Database (WTF), compiled by Statistics Canada and Feenstra (2000). This rich data source documents the product-level values of bilateral trade for most countries from 1980-1997. These product flows are aggregated into the four-digit ISIC 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 summary characteristics.[18]

The first pair of columns present the mean 1980-1997 multilateral export volumes and growth rates for each country (in nominal US dollars). Exports to all countries other than the US are considered in this paper; trade relations with the US are excluded, however, due to the strengthening network effects — which are also thought to increase trade flows — operating alongside the heterogeneous technology transfer.[19] The base panel is thus asymmetric in the sense that exporters are limited to countries of non-English ethnicities contained in the ethnic-name database, but in many specifications their bilateral exports to other countries are included (e.g., exports to English or African countries). Variations on the base panel below restrict the sample to be only bilateral flows among the eight non-English ethnicities, particularly when the importer's technology growth is being contrasted with the exporter's technology development.

The forty-four economies account for 53% and 64% of global manufacturing exports in 1980 and 1997, respectively, with countries of English ethnicity accounting for most of the residual (the US export share is 12% in 1980 and 13% in 1997). Not surprisingly, the largest exporters are European nations (especially Germany) and Japan, while the smallest exporters are found in Latin America. Vietnam (25%), Hong Kong (15%), Korea (13%), and Mainland China (13%) experience the strongest compound annual growth in nominal exports; only Venezuela demonstrates an absolute decline in trade volumes over the seventeen years.

[17] The USPTO issues patents by technology categories rather than by industries. Combining the work of Johnson (1999) and Silverman (1999), concordances are developed between the USPTO classifications and the four-digit ISIC 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.

[18] The empirical analysis verifies the multiple country mappings do not unduly influence the results. Some country to ethnicity mappings are debatable (e.g., placing Spain and Portugal with European rather than Hispanic, including the Scandinavian countries in European), as is the inclusion of communist countries. The results are robust to these marginal reclassifications.

[19] Kerr (2005b) explores how ethnic scientific networks facilitate bilateral trade with the US. See also Rauch (2001) and Rauch and Trindade (2002).

3.3 TFP Indices and Development Indicators

This study employs country-level total factor productivity (TFP) as a proxy for the technology location parameter T_i. Section 2's theory abstracts from capital stocks by specifying a Cobb-Douglas production function of labor (with elasticity α) and intermediate inputs from the CES aggregator. Capital accumulation, however, is important for explaining economic development, particularly the rapid advances made by several East Asian economies (e.g., Young 1992, 1995; Ventura 1997). Accordingly, TFP indices are developed for each country c relative to the US frontier with a production function employing capital and labor,

$$TFP_{c,US} = \frac{Y_c}{Y_{US}} \left(\frac{L_{US}}{L_c} \right)^{\alpha} \left(\frac{K_{US}}{K_c} \right)^{1-\alpha}, \tag{10}$$

with the year subscripts omitted. This index is superlative (i.e., it is exact for the Cobb-Douglas production function).[20] As this index is also transitive (i.e., $TFP_{ac} = TFP_{ab} \cdot TFP_{bc}$), the choice of the base country is irrelevant, with the US baseline providing intuition only. The second pair of columns in Table 2 presents the country-level TFP indices calculated from the Penn World Tables (PWT) using data on aggregate GDP, workers, and capital stocks.[21]

The final pair of columns exhibit GDP per capitas for each country that are also used in the estimations below. Comparing the TFP indices to the GDP per capitas highlights several important points about the former. First, the mean country TFPs relative to the US range from <1% for Honduras, Nicaragua, and Bolivia to 34% for Germany and 46% for Japan. In the GDP per capita series, the four lowest 1980-1997 means are India ($1364), Mainland China ($1653), Honduras ($1747), and Nicaragua ($2007), while the four highest are Switzerland ($19,258), Norway ($17,829), Denmark ($17,487), and Japan ($17,120). The levels and rank correlations are 55% and 68%, respectively. The core difference between the two series is that the relative TFP metrics of larger to smaller countries (e.g., Mainland China, India, and Brazil vis-à-vis Scandinavian nations) tends to be greater than the relative GDP per capita metrics. This difference may reflect how workers are measured in the underlying PWT data or may be due to an increasing discrepancy in using the US labor share. The levels of both series are inconsequential, however, as the estimations employ cross-sectional fixed effects.

The correlation in growth rates is much higher at 94%, and their rankings are closely tied. The three fastest growing economies in both series are Mainland China, Taiwan, and Korea; Vietnam's GDP per capita also experiences a fast 10% growth rate, but TFP measures are unavailable due to insufficient capital data. Likewise, TFP metrics cannot be constructed for

[20] Caves, Cristensen, and Diewert (1982) derive the general TFP index for the translog family. The Cobb-Douglas index (10) is a special case where labor shares are constant.

[21] See Heston, Summers, and Aten (2002). Real GDP levels are adjusted for PPP differences and for price movements using the Laspeyres method (rgdpl, pop). Real capital stocks are measured beginning-of-year and calculated from aggregate investment (ki) using the perpetual inventory method. Initial stocks are developed for 1970, and a depreciation rate of 15% is employed. Worker estimates are developed by the PWT from International Labour Organization data, with linear interpolation between census or survey dates for each country (rgdpwok). The share of labor α is taken to be 0.67.

Belize, Cuba, and the former Soviet Union. While these four economies are excluded from the IV regressions, they are retained in the reduced-form exercises that form the bulk of this study.

Estimating country-level TFP indices is fraught with peril: the industrial structures of countries differ, inputs are only coarsely measured, pricing differentials and exchange rates are difficult to handle, and so on (e.g., Harrigan 1997a, 1997b). Measurement error is clearly present in the TFP metrics constructed. However, errors confined to cross-sectional levels or aggregate yearly fluctuations (e.g., due to mismeasurement in the US baseline) do not affect the analysis due to the log specification and panel fixed effects. Idiosyncratic errors across countries with time, however, are not captured by the panel effects and bias the estimated elasticities towards zero. This scope for this concern, however, is also limited in that the TFP indices are primarily used in the IV regressions, which circumvent measurement error in the endogenous regressor.

4 Country-Level Estimations

This combined dataset is a unique laboratory for evaluating Ricardian technology differences in international trade. This section evaluates country-level regressions of bilateral export volumes using the derived specification (8), while the next section concentrates more on the industry and geographic dimensions of the data. These later extensions provide a better platform for distinguishing heterogeneous technology diffusion from shifts in factor endowments than the country-level regressions. Accordingly, most discussion of the factor content of trade is postponed until then.

The study deviates from the typical arrangement of empirical papers by presenting the reduced-form specification (9) first, with the OLS and IV regressions using the exporting country's TFP index held until the section's end. This ordering takes early advantage of the richness of the ethnic patenting dataset; it further segues into the introduction of a second estimator for US ethnic human-capital stocks that exploits exogenous changes in US immigration law. Both of these estimators are used in the IV analysis. Throughout this section, technology development is found to be a strong determinant of exports.

4.1 US Ethnic Human-Capital Estimations

Table 3 evaluates the reduced-form specification (9). The dependent variable for each regression is the log dollar value of bilateral exports from country n to country i.[22] The base regression includes the log of the exporting country's human-capital stock H_i with respect to US technologies, as well as the interacted gravity covariates of the exporter's and importer's log GDP per capitas and log GDPs. Although not reported in the table, vectors of cross-sectional and year

[22] Nominal dollar values are employed, with the vector of year effects extracting aggregate price changes. This approach is motivated by the expenditure specification derived in Section 2. Section 5 demonstrates, however, that the results are robust to individually deflating each industry's trade with the NBER shipments deflators (Bartlesman and Gray 1996) before aggregating to country-wide exports.

fixed effects are included as well. Finally, to account for the multiple countries mapping into the Chinese, European, and Hispanic ethnicities, standard errors are clustered at the ethnicity level. This conservative cross-sectional clustering further addresses the serial-correlation concerns of Bertrand, Duflo, and Mullainathan (2004).

As both variables are in logs, the 0.569 coefficient in the upper-left corner finds a 0.6% increase in the value of bilateral exports with a 1% increase in the exporter's human-capital stock for US technologies. Stronger scientific integration with the US technology frontier clearly correlates with an increase in manufacturing exports to other countries. From this estimated elasticity and the measured growth in US ethnic human-capital stocks, back-of-the-envelope calculations find increasing technology transfer from the US accounts for about 15% of the total manufacturing export growth experienced by the sample countries from 1980-1997. This share is only approximate but conveys the order-of-magnitude of the trade effect stemming from ethnic scientific integration.

The gravity covariates are important for isolating technology's role, as the growth in human-capital stocks could otherwise be confounded with other sources of growth in country size or standards of living that independently promote trade. The economic development of the exporter, however, is clearly endogenous — technology transfer in Section 2's model simultaneously increases the exporter's GDP and trade. The second column finds the estimated elasticity increases to 1.3 if the gravity covariates are excluded. As strong arguments exist for both approaches, this study will continue to present and compare both specifications.

Figures 3 and 4 provide a graphic view of these two regressions if export volumes are summed across importers into single exporter-year observations,

$$\ln\left(X_{it}\right) = \alpha + \beta_H \ln\left(H_{it}\right) + \gamma \ln(GDP/CAP_{it}) + \zeta \ln\left(GDP_{it}\right) + \phi_i + \eta_t + \epsilon_{it}.$$

The data points in Figure 3 are the residuals of total non-US multilateral exports and US ethnic human-capital stocks after the country and year fixed effects and the exporter's gravity covariates are removed. The slope of the trend line through Figure 3's residuals is akin to the β_H coefficient estimated in the first column of Table 3. Figure 4, on the other hand, follows the second column and does not partial out the gravity covariates. Without the gravity covariates, the strong relationship is driven by the exceptional performance of Chinese economies, Korea, and India. Removing development levels, on the other hand, leads to a more nuanced picture with a broader set of nations contributing to the positive relationship. The sample composition exercises below directly evaluate the importance of different ethnic groups to the measured elasticity.[23]

[23]Figures 3 and 4 exclude Belize, Cuba, the former Soviet Union, and Vietnam, all of which are included in Table 3's reduced-form analysis. This done for consistency with TFP graphs examined later, when these countries are dropped due to missing TFP indices. The exports of the former Soviet Union and Vietnam also demonstrate strong correlations to their US ethnic human-capital stocks. For visual ease, the figures also exclude three other trade outliers (Panama 1988, Paraguay 1991, Venezuela 1991); the inclusion or exclusion of these observations does not have a noticeable effect on the results.

The constructed dataset builds on two rich sources for economic data, and thus trade and ethnic patenting data are available for all observations (subject to the ethnicities identifiable with the ethnic-name database). The base specification, however, excludes observations if the gravity covariates are missing or if the export volume is zero. Columns 3 and 4 evaluate whether these restrictions are overly influencing the measured elasticity. First, gravity covariates are not always available for very small importers, resulting in a 22% loss from the maximum possible sample size of non-zero bilateral exports. Column 3 demonstrates, however, that this attrition is unimportant as the elasticity estimate in the larger sample is very close to Column 2.

Second, approximately 25% of the possible bilateral exchanges have zero values. In some cases these zero values reflect explicit restrictions on trade, but most are due to a combination of geographic distance and small country sizes. Zero values are undefined in a log specification like (9), and the base regression drops these observations. To ensure this procedure is not dictating the results, Column 4 retains the zero-valued observations through recoding and including appropriate indicator variables. The results are again very close to the base regression in Column 1, indicating that ignoring zero-valued observations is not overly influencing the estimated elasticities. Moreover, Figures 3 and 4 also find a positive relationship at the exporter-year level, where zero values are not encountered.

As highlighted in the data description section, the base sample is asymmetric in the sense that it only considers bilateral exports from the forty-four countries with ethnicities identifiable with the ethnic-name database; the countries receiving the imports, however, can be of any ethnicity (including English). Column 5 restricts the base sample to consider only bilateral exports within the countries associated with the ethnic patenting dataset. There is no significant difference from Column 1.

More importantly, this balanced panel is a platform for further characterizing the direction of trade due to technology differences. Column 6 introduces the similarly constructed importer's human-capital stock with respect to the US frontier. The strong elasticity of manufacturing exports to the exporter's scientific integration is preserved. On the other hand, the elasticity to the importer's integration is smaller and not statistically different from zero. A related regression of bilateral imports on the two ethnic human-capital stocks equivalently finds that imports respond positively to the foreign country's technology development and less to own-country ethnic human-capital stocks for US technologies.

Finally, Columns 7 and 8 present two reduced-form regressions that correspond directly to the IV regressions (with gravity covariates) later in this section. Belize, Cuba, the former Soviet Union, and Vietnam are excluded from the IV regressions since TFP indices are not available. While this attrition is only 10% of the countries in the sample, the number of non-English ethnicities is reduced from eight to six. Comparing Column 7 to Column 1, the elasticity of bilateral exports to the exporter's US ethnic human-capital stocks is somewhat weaker but still statistically significant in the smaller sample. Column 8, however, finds a substantial reduction

in the measured elasticity of exports to the importer's human-capital stocks for US technologies, although the large standard errors in both cases indicate the estimate is imprecisely measured. This contrast is further discussed in the IV section.[24]

4.2 Sample Composition

The assembled dataset is a diverse set of countries and experiences. While Figures 3 and 4 suggest the unique outcomes of a single exporter or ethnicity (e.g., Mainland China, India) are not solely responsible for the positive correlations, Columns 9 through 16 formally test the robustness of the measured elasticity to sequentially dropping each ethnicity. The β_H coefficient remains strong and statistically significant throughout; the regressions are individually discussed below to highlight further the underlying features of the dataset.

First, Column 9 drops the four Chinese economies. Perhaps surprisingly, the measured elasticity strengthens when these economies are excluded (although the coefficient is not statistically different from the base regression). The US Chinese research community exhibits the strongest growth over the 1980-1997 period, and therefore receives significant attention in the fixed effect estimations. All four economies exhibit strong export growth during the period studied and contribute to a high elasticity in the regressions without the gravity covariates (evident in Figure 4). After the gravity covariates are included, however, Taiwan's export growth is weaker than the expanding US Chinese human-capital stock would have predicted (evident in Figure 3). Dropping this ethnicity thus raises the estimated elasticity from the base regression. Individually excluding each Chinese economy also results in 10% to 20% positive or negative shifts, but the results are remarkably robust to dropping this special case.

The constructed sample also includes several industrialized economies that are undertaking extensive R&D themselves. For example, Japanese inventors living in the US, who are well identified with the ethnic-name database, patented less than 10,000 inventions from 1985-1997; almost 300,000 patents were awarded to Japanese inventors living outside of the US during this period.[25] Positive correlations of export growth to US ethnic research may simply be capturing reverse technology flows, intra-company patenting, or defensive patenting from these advanced economies. Columns 10 and 13 demonstrate, however, that excluding the large European bloc or Japan only results in small increases in the estimated elasticity. Hispanic countries also account for about 45% of the sample, and Column 11 demonstrates that the results are robust to dropping these nations too. Individual European and Hispanic countries can similarly be excluded.[26]

[24] The standard errors for the importer's technology regressor in Columns 6 and 8 are calculated through dual regressions clustering on the importer's ethnicity.

[25] The estimates are sums over inventor ethnicity percentages at the patent level. Japanese inventors are associated with more patents due to multiple inventors.

[26] An alternative strategy to mapping multiple countries into the Chinese, European, and Hispanic ethnicities is to run the export regressions at the ethnicity level (thereby also removing intra-ethnicity trade). As these sample composition exercise suggest, this approach yields similar results to the country-level analysis.

The last five columns turn to the ethnicities with single country mappings. India and Korea, like the Chinese ethnicity, are widely noted for their export growth and US research presence during the 1980-1997 period. Excluding these two countries in Columns 12 and 14 leads to only small declines in the estimated elasticity. Finally, the seventeen years covered by this study witnessed the integration of the former Soviet Union and Vietnam into the world trading community. During this period, the US research presence of these two ethnicities also increased, especially Vietnamese which roughly quadrupled its ethnic share of US patent applications (from a low initial position of 0.1%). Columns 15 and 16 show these groups contribute to the estimated elasticity, but that the measured effect is not being driven by their integration alone.

Finally, unreported regressions divide the sample into two smaller, overlapping time periods: 1980-1992 and 1985-1997. The positive dependence of exports on technological advancement is clearly present in both subsamples, but the relationship is stronger in the later years (elasticities of 0.4 and 1.0, respectively). This higher elasticity stems from the stronger growth of Asian research communities in US high-tech industries and their associated export growth in the later years. Section 5's industry-level regressions further evaluate the different elasticities in high-tech versus low-tech industries. In summary, the sample composition adjustments find positive export growth from scientific integration with the US is evident throughout the panel studied.

4.3 US Immigration Reform Estimations

The reduced-form estimations demonstrate a strong correlation between the growth of US ethnic scientific communities and their home country's export development. In preparation for the IV specifications, it is important to question whether these correlations capture causal relationships. Of particular concern is reverse causality. A plausible alternative to technology transfer from the US is that foreign human-capital development leads to both export growth abroad, perhaps with industry shifts due to the Rybczynski effect, and the emigration of scientists to the US. If true, using US ethnic research communities measured through the patenting database as an instrument for foreign technology levels would not solve the endogeneity problem.[27]

US immigration law is a foothold for establishing greater confidence in the direction of causation as it only influences foreign exports (to countries other than the US) through the sizes of US ethnic research communities and their associated technology transfer. If the populations of immigrant scientists and engineers (ISEs) are exogenously determined by legal restrictions, a second reduced-form strategy for ethnic human-capital stocks with respect to the US frontier can be developed within the US quotas system. US immigration law does not control the population sizes of foreigners in the US, but it does control the inflow of new immigrants. Define the quota on ISE inflows from country c to the US to be $QUOTA_{ct}$. Assuming that only the previous

[27] Another concern may be omitted variables that simultaneously boost the productivity of US ethnic researchers and the exports of their home countries (e.g., Japanese technology diffusion through Asian business networks). The ability to contrast exporter and importer technology levels substantially weakens this concern, and most of the ensuing discussion centers on reverse causality.

three years of immigration matter for a research stock[28], a reduced-form immigration estimator for ethnic scientific integration to the US is modelled as

$$\ln(IMM_{ct}^{RF}) = \ln\left[\sum_{s=1}^{5}(QUOTA_{c,t-s} + QUOTA_{c,t-s-1} + QUOTA_{c,t-s-2})\right]. \tag{11}$$

The summation over the previous five years maintains the human-capital stock modelling technique employed with the ethnic patenting dataset. This section designs and implements an empirical version of (11) using exogenous changes in US immigration quotas from the Immigration Act of 1990 (1990 Act).

The disproportionate influence of ISEs in the US is staggering: while immigrants account for 10% of the US working population, they represent 25% of the US science and engineering workforce and 50% of those with doctorates. Even looking within the Ph.D. level, immigrant researchers have an exceptional contribution to science as measured by Nobel Prizes, election to the National Academy of Sciences, patent citation counts, and so on.[29] Yet, the US immigration system significantly restricted the inflow of ISEs from certain nations prior to its reform with the 1990 Act.

US immigration law applies two distinct quotas to numerically restricted immigrants.[30] Both of these quotas were increased by the 1990 Act, and their combined change dramatically released pent-up immigration demand from researchers in constrained countries. The first quota governs the annual number of immigrants admitted per country. This quota is uniform across nations, and the 1990 Act increased the limit from 20,000 to approximately 25,620.[31] Larger nations are more constrained by country quotas than smaller nations and benefited most from these higher admission rates. Second, separately applied quotas govern the relative admissions of family-based versus employment-based immigrants. Prior to the 1990 Act, the quotas substantially favored family-reunification applications (216,000) to employment applications (54,000). The 1990 Act shifted this priority structure by raising employment-based immigration to 120,120 (20% to 36% of the total) and reducing family-based admissions to 196,000.[32] Moreover, the relative admissions of high-skilled professionals to low-skilled workers significantly increased within the employment-based admissions.

The uniform country quotas and weak employment preferences constrained high-skilled immigration from large nations, and long waiting lists for Chinese, Indian, and Filipino applicants

[28] The immigration reform examined below focuses on a very sharp surge in immigration that makes this assumption reasonable.

[29] For example, Stephan and Levin (2001), Burton and Wang (1999), Johnson (1998, 2001), and Streeter (1997).

[30] US immigrants are admitted through numerically restricted categories, governed by the quotas discussed in this section, and numerically unrestricted categories (e.g., immediate relatives of US citizens). The reduced-form estimator centers on the numerically restricted categories that admit 75% of ISEs (versus 43% of all immigrants). Jasso, Rosenzweig, and Smith (1998) outline US immigration policy and the 1990 Act; they further discuss behavioral responses to changes in quotas. ISE inflows through the unrestricted categories are stable in the years surrounding the 1990 reform.

[31] The worldwide ceiling for numerically restricted immigration now fluctuates slightly year-to-year based on past levels; maximum immigration from a single country is limited to 7% of the worldwide ceiling.

[32] The employment limit increased to 140,000, but 120,120 corresponds to the previously restricted categories.

formed in the 1980s. When the 1990 Act simultaneously raised both of these quotas, the number of ISEs entering the US dramatically increased. Figures 5 and 6 detail the response. Figure 5 plots the number of ISEs granted permanent residency in the US from 1983-1997 for selected ethnicities (summed over countries within each ethnicity). Prior to the 1990 Act, no trends are evident in ISE immigration. The 1990 Act took effect in October 1991, and a small increase occurred in the final three months of 1991 for Chinese and Indian ISEs. Immigration further surged in 1992-1995 as the pent-up demand was released.[33]

National Science Foundation surveys of graduating science and engineering doctoral students, the group most important for developing human capital with respect to US innovations, confirm the strong responses evident in the INS data. The questionnaires ask foreign-born Ph.D. students in their final year of US study about their plans after graduation. Figure 6 exhibits the percentage intending to remain in the US for available countries. The 60% to 90% jump for Mainland China from 1990 to 1992 is striking. Substantial increases are also apparent for India and Western Europe.

The second reduced-form strategy exploits differences in the extent to which countries were affected by the 1990 reform. It is inappropriate, however, to use the outcomes exhibited in Figures 5 and 6 to determine treatment and control groups. Kerr (2005a) undertakes a formal analysis of researcher immigration responses to the legislation change, finding the constrained countries to be India, Mainland China, the Philippines, and Taiwan. The reduced-form immigration estimator (11) then takes the form

$$\ln(IMM_{ct}^{RF}) = \ln\left[\sum_{s=1}^{5}(QUOTA_{c,t-s}^{Eff} + QUOTA_{c,t-s-1}^{Eff} + QUOTA_{c,t-s-2}^{Eff})\right], \qquad (12)$$

where $QUOTA_{ct}^{Eff}$ is the effective quota for country c in year t. Raising the numerical ceilings did not change the effective quota for nations unconstrained by the former immigration regime, and their effective quota is held constant at a pre-reform theoretical limit of the 20,000 country-level quota multiplied by the 20% employment allocation. The effective quota for the four constrained countries increases to reflect both the higher country limit of 25,600 and the larger employment preference allocation of 36% (i.e., 120,120/336,000). This quota increase occurs in 1991, and the shift is moved forward to 1990 for Mainland China to account for the Chinese Student Protection Act.[34]

[33] Kerr (2005a) shows that low-skilled immigration remained constant during the 1990 reform; temporary versus permanent immigration and the responses of other skilled occupations are also discussed. ISE trends are developed from immigrant-level INS records using the Engineers, Natural Scientists, and Mathematical and Computer Scientists occupations.

[34] The extremely large Chinese response and sharp decline in Figure 5 is partly due to a second law that slightly modified the timing of the 1990 Act's reforms. Following the Tiananmen Square crisis in June 1989, Chinese students present in the US from the time of the crisis until May 1990 were permitted to remain in the US until at least 1994 if they so desired. The Chinese Student Protection Act (CSPA), signed in 1992, further granted this cohort the option to change from temporary to permanent status during a one-year period lasting from July 1993 to July 1994. The CSPA stipulated, however, that excess immigration from the CSPA, over Mainland China's numerical limit, be deducted from later admissions. The timing of the CSPA partly explains the 1993 spike, and

Table 4 documents the reduced-form specifications (9) using the immigration quotas estimator (12) in place of the ethnic patenting estimator. The format of Table 4 mirrors Table 3. Exports are found to increase with an elasticity of about 0.5 to the exporter's scientific integration with the US. Although the β_H coefficients from the two reduced-form estimators should not be directly compared, their similar qualitative directions do provide confidence that reverse causality is not responsible for the positive reduced-form elasticities evident in Table 3. The elasticity of exports to the importer's technology integration is negative with this quotas-based estimator. If the gravity covariates are excluded, however, this elasticity is instead positive and very small.[35]

4.4 TFP Estimations

With both instruments and their reduced-forms described, this subsection completes the country-level analysis with OLS and IV regressions of bilateral export volumes on the TFP indices (a proxy for the country technology-location parameter T_i). Column 1 of Table 5 estimates the structural specification (8). While the TFP indices vary by country, the standard errors are still clustered by ethnicity for comparison to the IV regressions. In contrast to Tables 3 and 4, the bilateral export elasticity to the exporter's TFP development is much weaker (0.2) and statistically insignificant when the gravity covariates are included. Column 2, however, shows a much stronger response when the gravity covariates are excluded. Figures 7 and 8 illustrate these regressions in a form similar to Figures 3 and 4.

The large coefficient swing from Column 1 to Column 2 brings to the forefront an underlying data concern. Unlike the reduced-form estimations, the TFP indices and the gravity covariates are derived from the same PWT data and are highly colinear by construction (recall the 92% correlation in growth rates for the TFP indices and the exporters' GDP per capitas). As a result, the TFP elasticity is very sensitive to small specification changes. For example, substituting the non-interacted exporter's and importer's GDPs and GDP per capitas for the two interacted covariates restores the measured elasticity to 0.8. Moreover, it is questionable whether the gravity covariates should be included in the upcoming IV regressions anyway due to their endogeneity. As shown below, the IV regressions are robust to including or excluding the gravity variables, and Table 5 maintains the same baseline estimation as the reduced-form exercises for consistency.

Examining the remainder of Table 5, the balanced panel specifications of Columns 5 and 6 find a stronger and statistically significant elasticity of exports to the exporter's TFP index, while the elasticity to the importer's TFP index is negative and statistically insignificant. Column 8 shows the positive elasticity derives from the latter part of the sample, while the sample decompositions

the ability of graduating Chinese science and engineering students to remain in the US in 1990 is factored into the timing of the reduced-form estimator.

[35] Graphs for the immigrations quotas estimator are presented in the appendix.

find the Chinese and Indian outcomes are most responsible for the partial correlations evident between export and TFP growth. As noted in Section 3, TFP indices are unavailable for the former Soviet Union and Vietnam (as well as Belize and Cuba), and these two ethnicities are dropped from the sample considered in Figures 7 and 8 and Tables 5 and 6.

The core IV regressions using the US ethnic human-capital stocks instruments are presented in Table 6A. The first four columns document again the OLS permutations with and without the importer's TFP regressor and gravity covariates. As noted earlier, the inclusion of the gravity covariates substantially reduces the coefficient on the exporter's TFP regressor. Columns 5 to 8 of Table 6A instrument for the exporter's and importer's technology development with the ethnic human-capital stocks developed from the US patenting dataset. The first-stage regressions in Panels B and C demonstrate that ethnic scientific integration with the US improves the TFPs of their home countries. The gravity covariates are included in the first-stages of Columns 6 and 8, but the coefficients are not reported to conserve space. Figures 9 and 10 plot the first-stage regressions for the exporters, highlighting that technology transfer is most evident for the Chinese, Indian, and Korean ethnicities. The first-stage relationship is weaker among European economies and is not present for Latin America or Japan unless the gravity covariates are included.

In contrast to the OLS regressions, the instrumented elasticities for the exporter's technology state are strong and statistically significant regardless of whether the gravity covariates are included. The IV specifications are able to overcome the measurement error and colinearity problems from the coarse TFP proxy. The estimated elasticity for the importer's technology state, on the other hand, is not robust to the including the gravity covariates. Unfortunately, the null hypothesis that the two elasticities are equal cannot be rejected due to the large standard errors for the importer's technology state, but the greater importance of the exporter's technology does appear to hold true.

Columns 5 through 8 of Table 6B present the IV regressions using the immigration-based instruments. The instrumented export elasticities of 1.1 to 1.7 to the exporter's technology state are 50% larger than those using the patent-based instrument; all of the elasticities but Column 8 are again statistically significant. Moreover, the importer's technology development is not found to increase export volumes and is statistically different from the exporter's contribution in Column 7. Taken together, these IV regressions find strong support for Ricardian technology differences as a source of trade.[36]

4.5 Discussion of IV Elasticities

While both of this study's instruments model the heterogeneous transfer of US technologies through ethnic networks, the properties of the two instruments are quite different. The ethnic

[36] Table A2 in the appendix shows the IV results are robust to the sample decompositions undertaken in the reduced-form analysis. The only major departure is for the immigration quotas instrument when the Chinese ethnicity is excluded.

human-capital stocks instrument calculated from the US patenting dataset is very rich in detail and well measured, but it is admittedly exposed to reverse causality concerns. The immigration quotas instrument, on the other hand, is exogenous and provides greater confidence in the direction of technology flows. The cost of this exogeneity, however, is less variation that can be exploited. Of course, no instrument is perfect, but the liabilities of these two approaches are largely orthogonal. Hence, the fact that the elasticities in Table 6 are relatively close should provide confidence in the identified results.

A definitive explanation for the larger elasticity with the immigration-based instrument cannot be given, but two hypotheses are readily identified. First, the theoretical development in Section 2 assumes both constant country sizes and that the labor resources of each country are fully employed in manufacturing. Several countries in the sample, however, have large reservoirs 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 (2005a) finds that technology transfer from the US to these emerging economies produces a larger growth in manufacturing output compared to industrialized economies due employment growth from sector reallocation complementing labor productivity gains.

In the current framework, this transition process is equivalent to an increase in effective country size. If wage equality with the agricultural sector is also maintained, general-equilibrium increases in the input costs c_i for the manufacturing sector are also depressed. Both effects further promote growth in export volumes. The immigration-based instrument focuses attention on three economies undergoing this transition. The 1980 agriculture employment share for Mainland China, India, and the Philippines are 70%, 74%, and 52%, respectively, compared to 8% in Taiwan and a sample mean of 22%.[37] Additional sector reallocation to manufacturing in these economies following technology transfer from the US may explain part of the larger elasticity.

A second candidate explanation, however, is an omitted variable bias. The reduced variation inherent in the immigration estimator's design potentially exposes it to spurious correlation with omitted factors that differentially affect the four treatment economies from the control group around the 1990 Act. To take one case, India undertook several trade reforms in the early 1990s as part of an IMF-supported adjustment program (e.g., Topalova 2004). While it is possible to argue these reforms are endogenous outcomes to facilitate the expansion of exports, it certainly conceivable that India's reforms are in fact independent and potentially bias technology's role with the immigration IV upward. The price of the exogeneity in the immigration quotas instrument is greater exposure to these types of concerns.

To summarize the material presented in this section, two estimators are developed to model heterogeneous technology diffusion from the US through ethnic scientific networks. The first uses ethnic patenting data to measure the human-capital stocks of each ethnicity with respect to

[37] Agricultural shares are from the United Nations Statistical Division and Sun, Fulginiti, and Peterson (2003).

US innovations, while the second exploits exogenous changes in the sizes of US ethnic scientific communities following the Immigration Act of 1990. In both reduced-form and IV specifications, the exporter's integration with the US frontier consistently yields growth in export volumes, while the importer's integration has an inconsistent and often negligible effect. Taken together, these country-level regressions provide strong evidence that Ricardian technology differences across countries are important for explaining trade patterns.

5 Empirical Extensions

The bilateral perspective taken in Section 4's country-level regressions affords a detailed contrast of the exporter's and importer's technology development. The large number of exporter-importer permutations, however, prohibits the use of much of the underlying industry and geographic variation available in the ethnic patenting and trade datasets. This section undertakes two extensions that highlight instead these other dimensions.

The first extension sums multilateral exports across destination countries to focus on industry-level exports for each country. Technology advancement is again found to increase exports at this disaggregated level. Moreover, this result is robust to including detailed country-level controls that remove the aggregate trends for each nation's manufacturing sector. This finding argues against alternative hypotheses for the earlier results that would operate at the country-level (e.g., entry into trading blocs). Through matching exercises that further group industries according their capital and skilled-labor intensities, the industry-level analysis also provides additional confidence that a generalized Rybczynski effect due to factor accumulation is not responsible for the positive elasticities assigned to technology growth.

The second extension returns to the bilateral trade data to explore how the elasticity estimates differ by different geographic distances to import destinations. Export growth appears to be strongest in bordering and nearby countries, but positive growth is evident at all distances.[38]

5.1 Industry Analysis

The industry-level analysis sums exports for each country i across import destinations by the ISIC industries listed in Table A1. For comparison, country i's imports from nations other than the US are also calculated. As in the bilateral exercises, some observations have zero values that are undefined in a log specification. The multiple specification checks undertaken in Table 7 (e.g., first differences, time trends) are best conducted with panels of uniform series length. Accordingly, country-industry observations are excluded if they do not maintain \$10k in non-US multilateral exports and imports throughout the 1980-1997 period. A second bar of one ethnic patent per annum is also applied. These hurdles focus the analysis on economically important

[38] Industry-level analyses do not follow directly from the Eaton and Kortum model, which requires random industry technologies around the country technology aggregate to satisfy the Fréchet distribution.

interactions, but the results are robust to raising or removing these hurdles.

The basic industry-level regressions for country i and industry j in year t take the form

$$\ln(X_{ijt}) = \alpha + \beta \ln(H_{ijt}) + \gamma \ln(GDP/CAP_{it}) + \zeta \ln(GDP_{it}) + \phi_{ij} + \eta_{jt} + \epsilon_{ijt}. \quad (13)$$

All of the industry-level specifications employ the detailed US ethnic human-capital stocks H_{ijt} that are constructed through the ethnic patenting database. The regressions retain the exporting country's gravity covariates and include vectors of country-industry fixed effects ϕ_{ij} and industry-year fixed effects η_{jt}. In Table 7, Column 1 of the top panel finds a β coefficient of 0.7 when estimating specification (13). As in the country-level regressions, positive integration with the US technology frontier increases manufacturing exports. The industry-level elasticity is statistically significant, with the standard errors now clustered at the ethnicity-industry level to reflect the more disaggregated data employed.

By itself, this industry-level regression provides two important checks on the earlier results. First, the data development in Section 3 asserts that five-year sums of US ethnic patents can proxy for the underlying sizes of ethnic research communities because changes in the patenting productivity of US researchers will be absorbed into the aggregate year effects η_t. This assumption may be cavalier, however, as the patenting rate per researcher likely increased faster in high-tech sectors than in more mundane fields. With ethnicities specializing in different industries (e.g., the US Chinese in computer research), composition effects can potentially bias the results. By narrowing the focus to within-industry variation, this liability is minimized because the patenting productivity is now controlled for at the industry-year level by the fixed effects η_{jt}. Likewise, differential changes in industry prices (e.g., the rapid decline in computer prices) in the nominal export volumes are now captured.

The second column in Panel A weights the observations by each industry's patenting level from 1980-1982. This weighting scheme focuses more attention on high-tech industries, finding a small growth in the estimated elasticity. The stability of the elasticity across Columns 1 and 2 highlights, however, how pervasive the industry-level response of exports to technology integration is.

The country-level exercises found weak export elasticities to the importer's technology development. The analogous industry-level prediction is that non-US multilateral imports should respond less to scientific integration with the US frontier than exports. This Ricardian outcome is evident in Columns 3 and 4, which present the unweighted and weighted regressions for imports using a specification similar to (13). Unreported regressions further find that multilateral imports respond more to the scientific integration of other ethnicities to the US frontier. This contrast between exports and imports again emphasizes the role of technology in determining trade patterns. Moreover, the asymmetry argues against omitted trade agreements affecting the outcomes measured.

Many empirical analyses first difference a levels specifications for estimation,

$$\Delta \ln (X_{ijt}) = \alpha + \beta \Delta \ln (H_{ijt}) + \gamma \Delta \ln(GDP/CAP_{it}) + \zeta \Delta \ln (GDP_{it}) + \eta_{jt} + \tilde{\epsilon}_{ijt}, \qquad (14)$$

where $\tilde{\epsilon}_{ijt} = \epsilon_{ijt} - \epsilon_{ijt-1}$. The efficiency of a first-differences form versus the levels specification turns on whether the error term ϵ is autoregressive. If autoregressive deviations are substantial, the first-differences form is preferred; a unit-root error is fully corrected. If there is no serial correlation, however, first differencing introduces a moving-average error component. Estimations of the autoregressive parameter in the levels specification (13) find moderate serial correlations of 0.5 to 0.6. Columns 5 through 8 of Panel A show the Ricardian findings are evident in a first-differences form too, although the measured export elasticity is weaker at 0.2 to 0.3.[39]

The lower panel in Table 7 presents a battery of specification checks to the base regressions from Panel A. The tabulated coefficients are from separate regressions that modify the base regressions as indicated in the left-hand column; the coefficients for the gravity covariates are again omitted to conserve space. The first row of Panel B excludes the computer and drug industries. Case studies of successful technology diffusion often focus on the computer and pharmaceutical industries, and the exceptional outcomes of Asian scientific communities in Silicon Valley are widely noted. While the industry-year effects control for the overall growth in each industry's research and output (e.g., Griliches 1994), it would be important to note if ethnic differences in high-tech industries alone are responsible for the positive correlations. The minor elasticity changes indicate that they are not.

More importantly, the bottom four rows introduce aggregate ethnicity-level and country-level controls. The power of the industry-level analysis is its ability to isolate within-country variation, even after removing levels differences and global industry trends. A positive β coefficient in these regressions requires that China's exports in the computer industry grow faster than its exports in the pharmaceuticals industry if Chinese integration to the US computer frontier grows faster than its integration to the pharmaceutical frontier. Strong performance in these regressions places this same burden on any competing explanations.

The elasticity estimates are remarkably stable to these country-level controls. The specifications become more stringent as one moves down the rows from the linear time trends to nonparametric country-year effects; the coefficient estimates slightly decline as the additional variation is removed. Yet, a strong elasticity of export growth to scientific integration with the US frontier is maintained even when the triple combination of country-industry, industry-year, and country-year fixed effects are introduced. Moreover, the asymmetric growth of multilateral exports over multilateral imports is maintained throughout. The robust conclusion from Table

[39] As first differencing exacerbates the downward bias in estimated coefficients due to measurement error in the regressor, the levels form remains the preferred specification in this study. GLS estimations that correct the autoregressive parameter yield elasticity estimates bounded by the levels and first-differences results presented. Lagged dependent variable specifications that test for mean reversion also demonstrate export growth with scientific integration.

7 is that Ricardian technology differences are important determinants of industry-level patterns even after aggregate country trends are removed.

5.2 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. Section 4's immigration reform exercise argues against this reverse causality explanation, and Table 7's finding of strong technology elasticities using only within-country variation again suggests a Rybczynski effect for the manufacturing sector as a whole (e.g., a shift from agriculture to manufacturing due to capital accumulation) is not responsible for the observed trade patterns. This subsection provides additional evidence that technology's role is not reflecting changes in trade patterns due to factor accumulations by using industry comparisons within the manufacturing sector itself.

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 important role is preserved after time trends are removed for these industry groups within each country. To illustrate, both the computer and pharmaceutical industries are 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 mean 1980-1997 factor intensities in the US. Three intensities are studied — the industry's capital-labor ratio, the share of non-production workers in the industry's labor force, and the industry's average wage. Table A1 lists for each industry the quintile groupings assigned. Textiles rank in the lowest quintiles in all three classifications schemes, while chemicals and industrial machinery consistently fall into the 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.

These detailed comparisons place a premium on the number of industries available for each country. Accordingly, the matching test employs a slight variant of (13) that regresses the share of country i's manufacturing exports in industry j on the share of its US ethnic human-capital

stock in industry j,

$$\left(\frac{X_{ijt}}{X_{it}}\right) = \alpha + \beta\left(\frac{H_{ijt}}{H_{it}}\right) + \phi_{ij} + \eta_{jt} + \epsilon_{ijt}. \tag{15}$$

The regression retains the vectors of country-industry fixed effects ϕ_{ij} and industry-year fixed effects η_{jt}. This regression is similar to the specification that included country-year fixed effects, but without the log transformation the zero export values can be incorporated.

The first column in Table 8 finds an unweighted β coefficient of 0.7 with this modified specification. The next three columns incorporate into (15) the ethnicity time trends interacted with each quintile group. For all three factor intensity comparisons, the positive role of technology is preserved. The robustness of technology's role in this matching exercise is also evident in the weighted regressions of Columns 5 through 8.[40]

These findings suggest an omitted factor accumulation is not confounding the strong role for technology identified throughout this study. Of course, the test is not foolproof, as specialized foreign development could produce both export shifts within intensity groups and the emigration of ethnic researchers trained in these specialized fields to the US. Nevertheless, the combined evidence from the earlier immigration quotas estimations and this stringent matching exercise suggests the results are robust to alternative factor-based explanations of trade. This study concludes that Ricardian technology differences are an important determinant of trade patterns.[41]

5.3 Geographic Expansion

This study closes with some initial findings regarding the geographic margin of export growth due to technology advances. This margin is quantified in the reduced-form specification (9) for country-level bilateral exports. Table 9 begins by repeating the basic regression with the bilateral exports for which distances are available (using the Great Circle distances between capital cities). The sample is then divided into bordering countries in Column 2 and non-bordering countries in Columns 3 through 7. Non-bordering countries are further separated into five distance categories: 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,

[40] Vietnam is excluded as its US ethnic patenting is very small in the early years of the sample, producing several outliers in this industry-comparison exercise. The coefficient estimates are lower if Vietnam is included, but they remain statistically significant and convey the same results.

[41] The ideal test would simply remove factor-based trade from the 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. See Davis and Weinstein (2001) for an application using richer OECD data.

to the capitals of Taiwan, Bangladesh, United Arab Emirates, and Spain are 1723 km., 3029 km., 5967 km., and 9229 km., respectively.

The estimated elasticities suggest export growth declines slightly with distance and in a non-linear way. The strongest elasticities are found for bordering countries, although the small sample size yields substantial standard errors, and non-bordering countries within 1500 km. The remaining groupings, however, are not very different from the average elasticity estimate and do not display an obvious trend. This latter stability is a comforting result as it suggests local shocks (e.g., regional trade agreements, macroeconomic cycles) are not responsible results. A complete characterization of the interaction between distance and export growth from technology advancement is left for future work.

6 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 using panel estimation techniques. Country-level regressions find bilateral exports respond positively to the exporter's technology development. This result is robust to 1) including the importer's technology development as a regressor, 2) instrumenting for technology development using scientific integration with the US frontier, 3) testing for reverse causality using an exogenous reform of US immigration quotas, and 4) considering industry-level specifications that focus on within-country variation and test for factor accumulation alternatives. The results strongly support the conclusion that technology differences are an important determinant of trade.

Several promising extensions are currently being pursued using the additional geographic and industry variation discussed in Section 5. The first project seeks a fuller characterization of the industry and geographic margins of export expansion (including their joint interactions for intensive and extensive growth). This research will bring specific attention to industry entry and exit decisions and characterize the importance of different country sizes. A second project is exploring the impact of technology transfer for trade policies and political institutions (and vice versa). This additional work will further refine our understanding of how Ricardian technology differences influence trading patterns among countries.

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Figure 1: US Ethnic Patenting

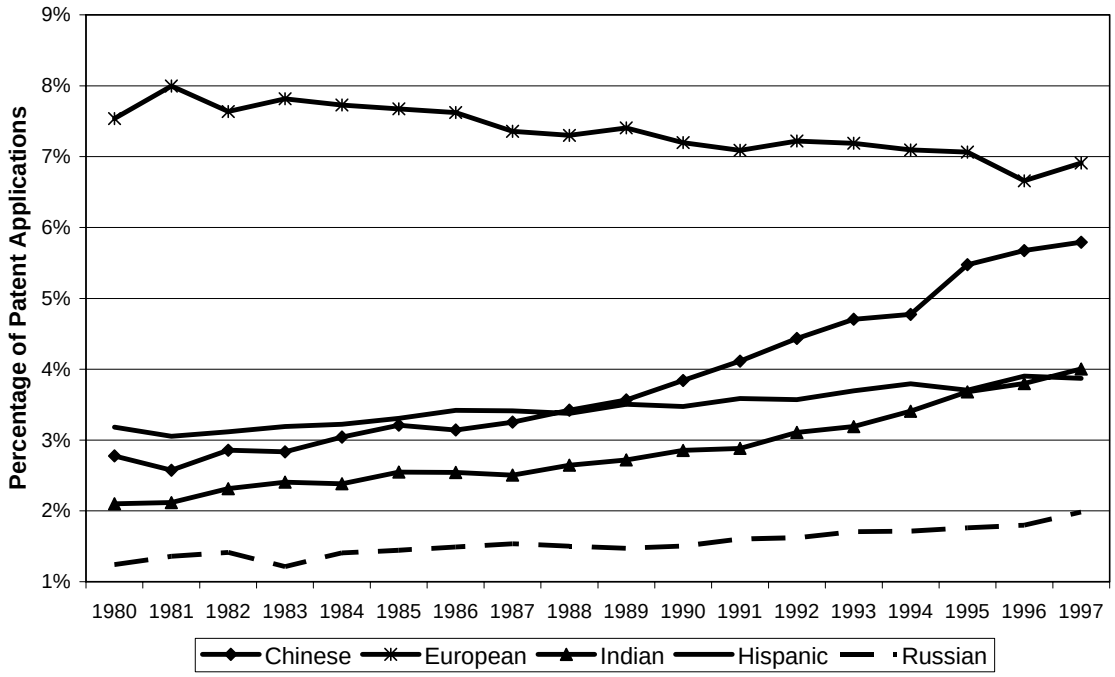

Figure 2: Ethnic Share by Technology

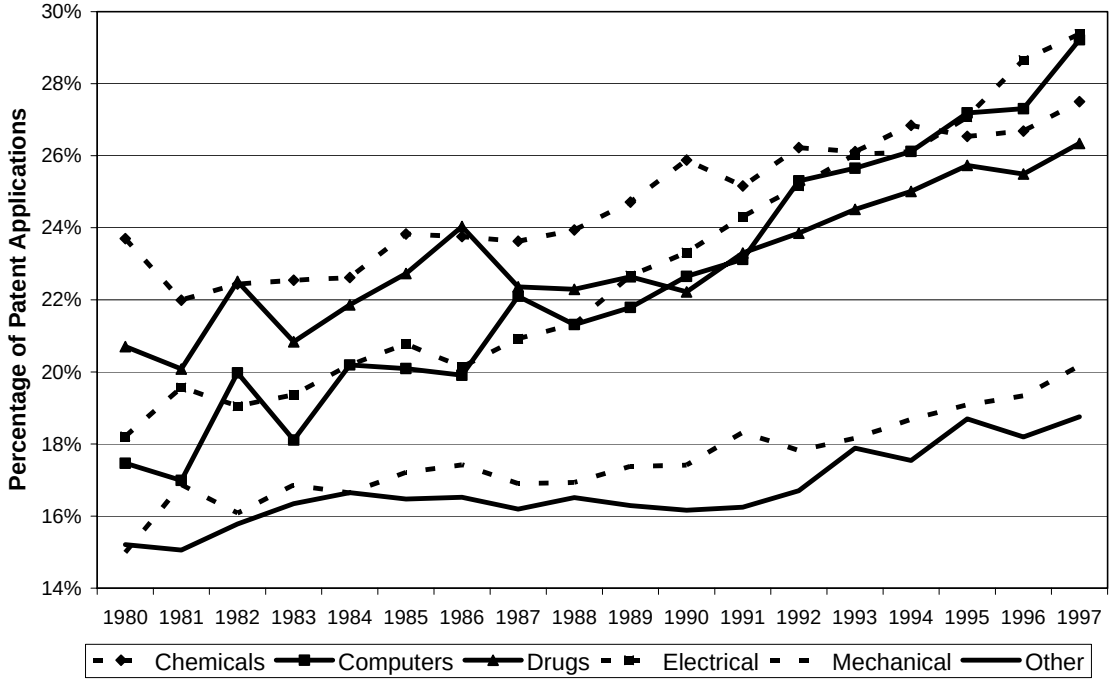

Figure 3: RF Multilateral Exports on US Ethnic HC Stocks

Panel Effects and Gravity Covariates Removed

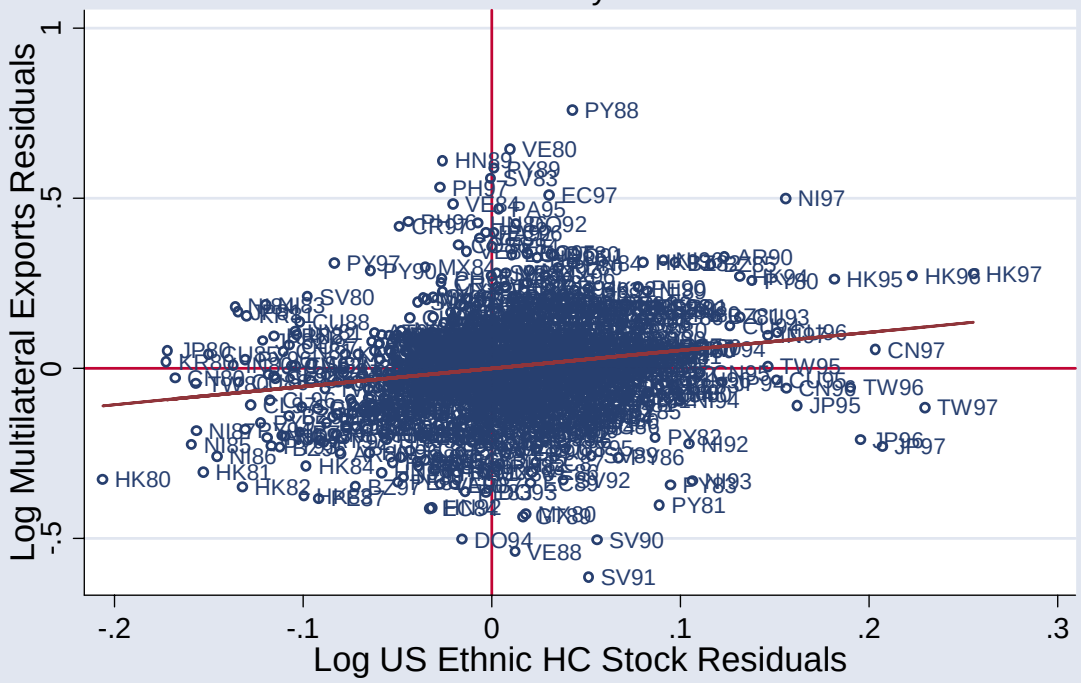

Figure 4: RF Multilateral Exports on US Ethnic HC Stocks

Panel Effects Removed

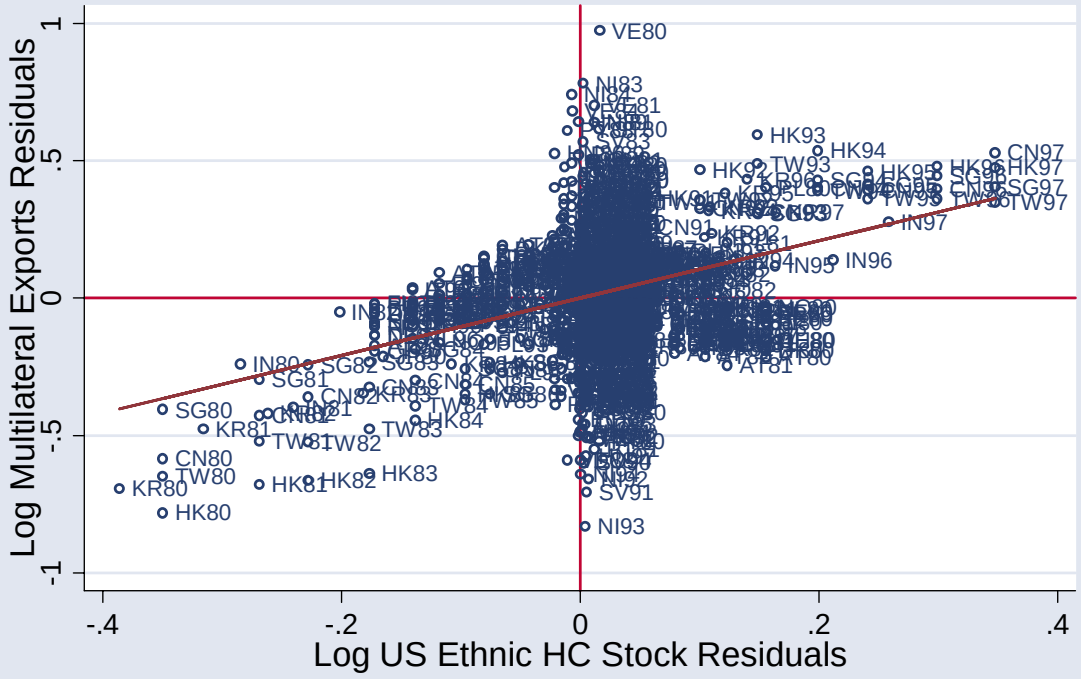

Figure 5: Science & Engineering Immigration

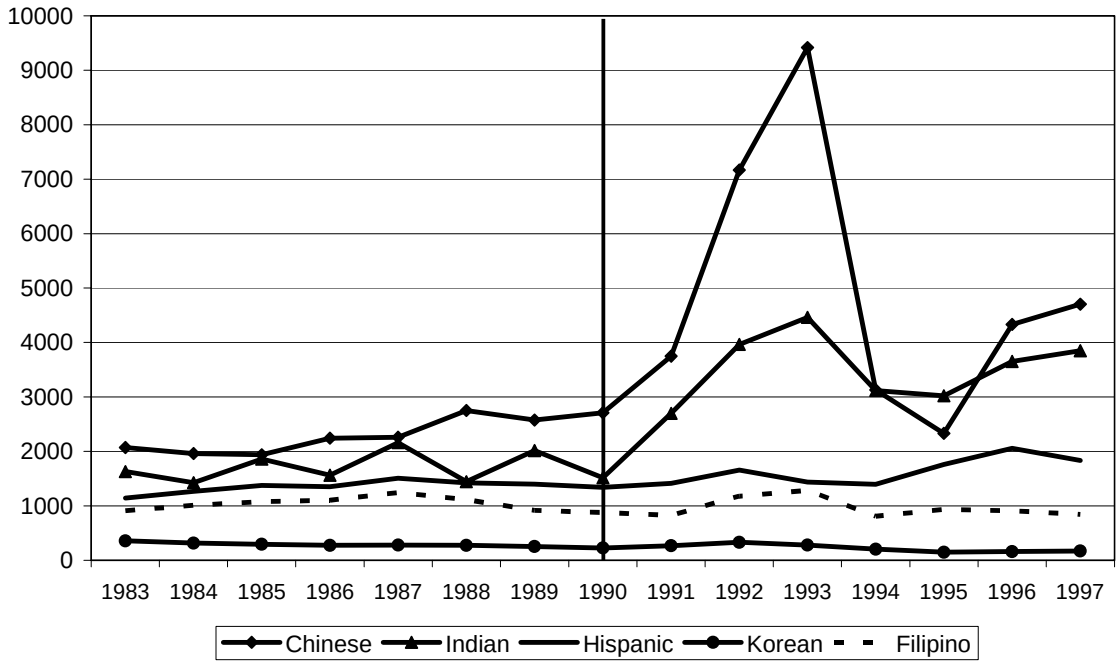

Figure 6: US SE Ph.D. Graduates Staying

Percentage of Graduates from Country Expecting to Stay in US

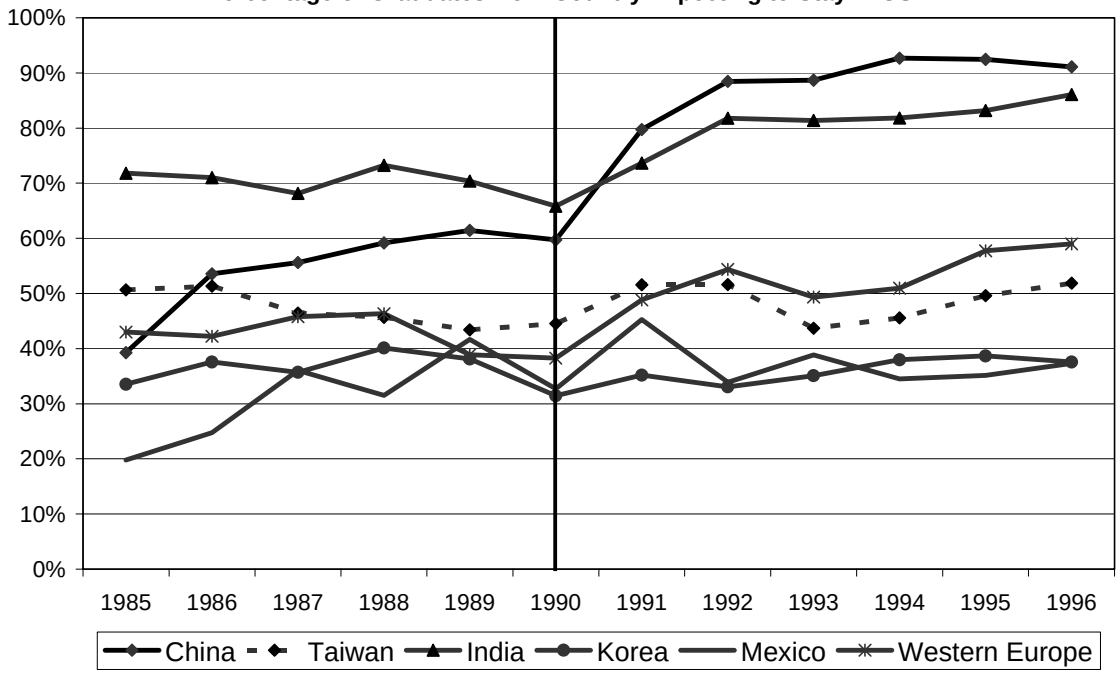

Figure 7: OLS Multilateral Exports on Exporter's TFP

Panel Effects and Gravity Covariates Removed

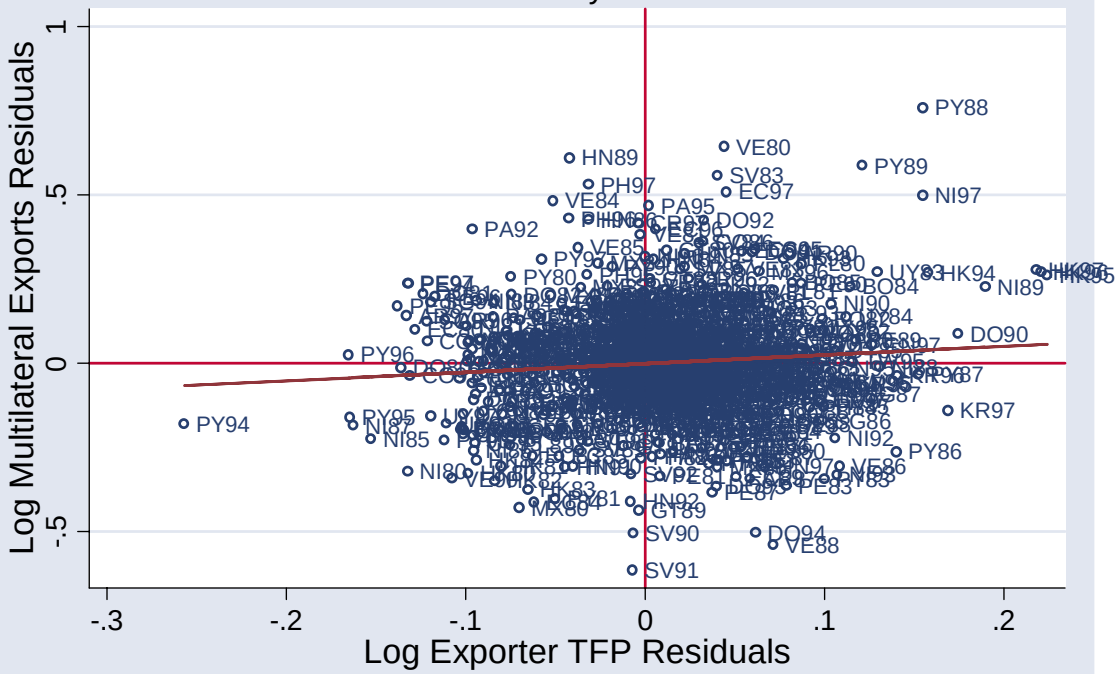

Figure 8: OLS Multilateral Exports on Exporter's TFP

Panel Effects Removed

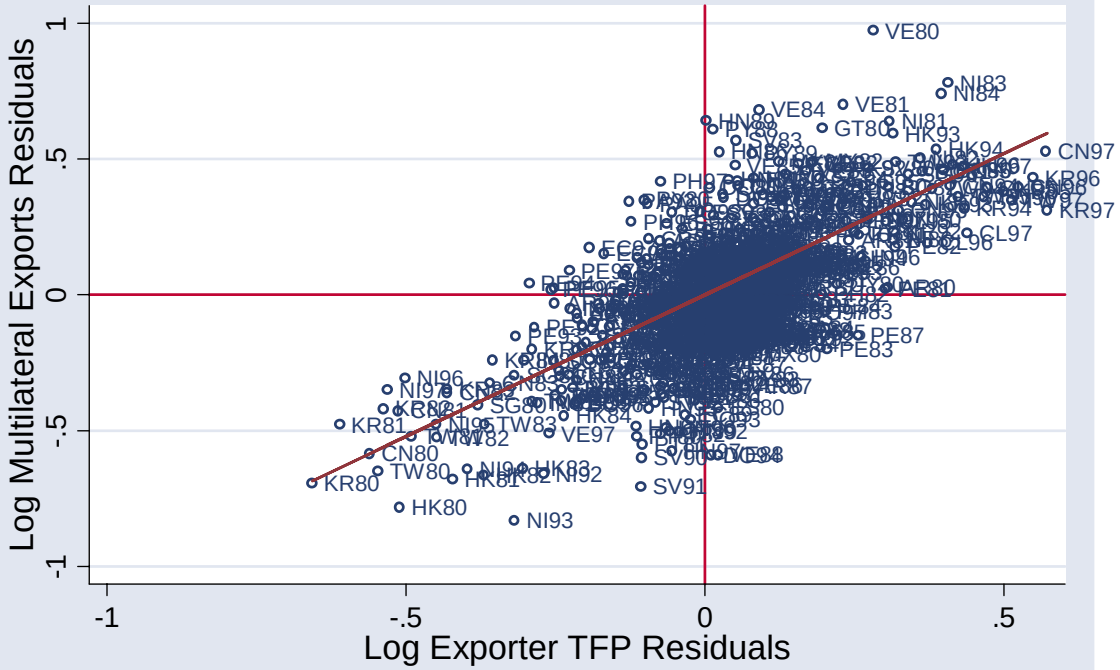

Figure 9: FS Exporter's TFP on US Ethnic HC Stocks

Panel Effects and Gravity Covariates Removed

Figure 10: FS Exporter's TFP on US Ethnic HC Stocks

Panel Effects Removed

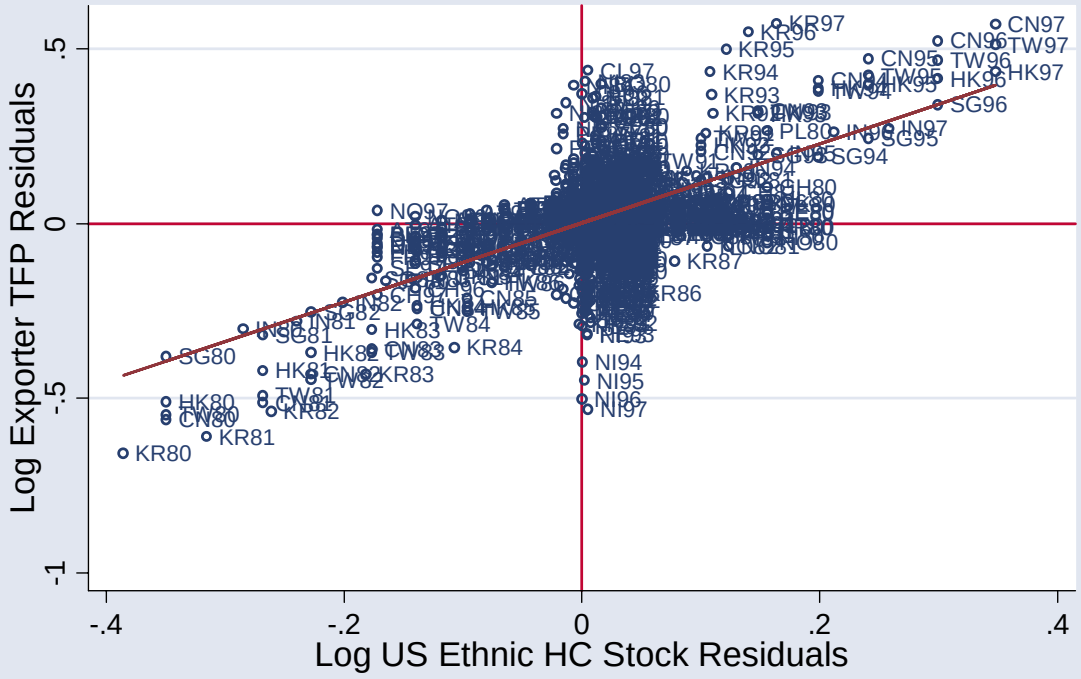

Table 1: Descriptive Statistics for Inventors Residing In US

	Ethnicity of Inventor (Percent Distribution)								
	English	Chinese	European	Hispanic	Indian	Japanese	Korean	Russian	Vietnamese
A. Ethnic Inventor Shares Estimated from US Inventor Records									
1980-1985 Share	81.0	3.0	7.7	3.1	2.4	0.7	0.6	1.3	0.1
1986-1990 Share	79.6	3.7	7.3	3.3	2.9	0.8	0.7	1.5	0.2
1991-1997 Share	76.4	5.4	6.9	3.7	3.7	0.9	0.8	1.7	0.4
Chemicals	75.0	6.1	7.7	3.5	4.0	0.9	0.8	1.6	0.3
Computers	75.9	6.0	6.3	3.4	4.4	0.9	0.8	1.7	0.6
Pharmaceuticals	75.8	5.0	7.6	4.0	3.7	1.1	1.0	1.6	0.2
Electrical	76.0	5.7	7.2	3.5	3.5	1.0	0.8	1.8	0.5
Mechanical	82.2	2.3	7.3	3.2	2.2	0.6	0.5	1.5	0.2
Miscellaneous	82.9	2.3	7.0	3.5	1.9	0.5	0.5	1.2	0.2
Top MSAs as a Percentage of MSA's Patents	KC (89) WS (89) MEM (86)	SF (12) LA (7) NYC (7)	NYC (11) NOR (11) STL (11)	MIA (17) SD (8) WPB (6)	NYC (6) BUF (6) AUS (6)	LA (2) SD (2) SF (2)	BAL (3) COL (2) SF (2)	BOS (3) NYC (3) PRO (3)	AUS (2) LA (1) SF (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: MSAs - AUS (Austin), BAL (Baltimore), BOS (Boston), BUF (Buffalo), COL (Columbus), HRT (Hartford), KC (Kansas City), LA (Los Angeles), MEM (Memphis), MIA (Miami), NOR (New Orleans), NYC (New York City), PRO (Providence), SA (San Antonio), SD (San Diego), SF (San Francisco), STL (St. Louis), WPB (West Palm Beach), and WS (Winston-Salem). MSA percentages are for 1985-1997. 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 98%. Manual recoding further ensures all patents with more than 100 citations and all city names with more than 100 patents are identified. 1990 Census statistics are calculated by country-of-birth using the groupings listed in Table 2; English provides a residual in the Census statistics.

Table 2: Bilateral Trade Sample

Country	Exports ($B) Mean Level	Exports ($B) Growth Rate	TFP Index Mean Level	TFP Index Growth Rate	GDP/Capita ($) Mean Level	GDP/Capita ($) Growth Rate
Single Ethnic Mappings:						
India	14.4	9%	5%	3%	1364	7%
Japan	193.3	7%	46%	1%	17120	6%
Korea	46.9	13%	10%	7%	8110	11%
Soviet Union	47.6	5%	na	na	7770	-3%
Vietnam	2.2	25%	na	na	1300	10%
Chinese Economies:						
China, Mainland	58.1	13%	7%	6%	1653	10%
Hong Kong	64.5	15%	5%	5%	16962	8%
Singapore	43.3	11%	4%	4%	14499	9%
Taiwan	46.5	12%	6%	6%	9042	10%
European Economies:						
Austria	32.4	6%	8%	-1%	15614	5%
Belgium	98.5	6%	10%	-1%	15536	5%
Denmark	28.7	7%	6%	-1%	17487	5%
Finland	22.2	6%	5%	-1%	14956	5%
France	167.9	6%	30%	-1%	15434	5%
Germany	312.2	6%	34%	0%	15521	5%
Italy	134.9	7%	30%	-1%	14967	6%
Netherlands	114.4	6%	12%	-2%	15625	5%
Norway	28.2	6%	6%	0%	17829	5%
Poland	14.2	3%	6%	-2%	5575	4%
Sweden	46.2	6%	8%	-2%	16224	5%
Switzerland	48.4	6%	9%	-3%	19258	5%

Country	Exports ($B) Mean Level	Exports ($B) Growth Rate	TFP Index Mean Level	TFP Index Growth Rate	GDP/Capita ($) Mean Level	GDP/Capita ($) Growth Rate
Hispanic Economies:						
Argentina	11.4	7%	8%	-3%	7711	4%
Belize	0.1	3%	na	na	4466	4%
Bolivia	0.7	1%	0%	-4%	2134	2%
Brazil	26.8	6%	14%	-2%	5327	4%
Chile	7.1	7%	2%	3%	5413	7%
Columbia	4.0	5%	3%	-1%	3974	5%
Costa Rica	1.0	7%	1%	-2%	4106	3%
Cuba	1.4	1%	na	na	5278	0%
Dom. Republic	0.3	5%	1%	0%	2846	5%
Ecuador	1.6	4%	1%	-3%	3252	2%
El Salvador	0.5	4%	1%	-2%	3000	4%
Guatemala	0.9	2%	1%	-2%	3010	3%
Honduras	0.4	0%	0%	-2%	1747	3%
Mexico	10.5	8%	12%	-2%	6296	3%
Nicaragua	0.3	2%	0%	-6%	2007	-1%
Panama	0.3	3%	1%	-2%	4481	4%
Paraguay	0.7	5%	1%	-1%	3756	4%
Peru	2.7	5%	2%	-3%	3599	3%
Philippines	6.2	8%	3%	-2%	2464	4%
Portugal	12.2	10%	4%	0%	9210	7%
Spain	48.1	10%	17%	-1%	11218	6%
Uruguay	1.5	6%	1%	-2%	6418	5%
Venezuela	8.1	-3%	4%	-4%	5773	2%

Table 3: Reduced-Form Regressions of Bilateral Exports on US Ethnic Human-Capital Stocks

Dependent Variable is Log Bilateral Export Volume (US$)	Base Regression	Excluding Gravity Covariates	Full Non-Zero Sample	Including Zero-Valued Trade Series	Excluding Non-Ethnic Importers	Including Importer HC Stock	RF for Single IV Regressions	RF for Dual IV Regressions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Exporter's US Ethnic HC Stock	0.569	1.349	1.370	0.685	0.536	0.682	0.454	0.376
	(0.201)	(0.241)	(0.298)	(0.252)	(0.254)	(0.255)	(0.188)	(0.217)
Log Importer's US Ethnic HC Stock						0.401		0.093
						(0.411)		(0.447)
Log Product of GDPs per Capita	1.032			1.823	0.333	0.499	0.942	0.159
	(0.451)			(0.247)	(0.536)	(0.578)	(0.438)	(0.539)
Log Product of GDPs	0.056			-1.020	0.725	0.442	0.156	0.906
	(0.447)			(0.159)	(0.461)	(0.540)	(0.434)	(0.493)
Observations	66358	66358	84741	88701	28850	28850	62839	25384

Dependent Variable is Log Bilateral Export Volume (US$)	Excluding Chinese	Excluding European	Excluding Hispanic	Excluding Indian	Excluding Japanese	Excluding Korean	Excluding Russian	Excluding Vietnamese
	Base Regression							
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log Exporter's US Ethnic HC Stock	0.667	0.622	0.661	0.509	0.707	0.564	0.556	0.468
	(0.364)	(0.291)	(0.241)	(0.208)	(0.191)	(0.224)	(0.200)	(0.189)
Log Product of GDPs per Capita	1.008	0.509	1.474	1.151	1.132	1.038	1.013	0.998
	(0.509)	(0.301)	(0.576)	(0.458)	(0.449)	(0.470)	(0.456)	(0.451)
Log Product of GDPs	0.112	0.536	-0.367	-0.064	-0.083	0.057	0.082	0.103
	(0.501)	(0.334)	(0.574)	(0.453)	(0.441)	(0.463)	(0.450)	(0.449)
Observations	59351	42010	38436	64445	64277	64426	65747	65814

Notes: Panel estimations consider trade patterns taken from the 1980-1997 WTF database. The dependent variable is the log nominal value (US$) of bilateral manufacturing exports for exporter-importer pairs. US Ethnic HC Stocks are estimated from the US ethnic patenting dataset. Regressions are unweighted and include exporter-importer and year fixed effects. Standard errors are clustered at the ethnicity level.

Table 4: Reduced-Form Regressions of Bilateral Exports on US Immigration Quotas Estimators

Dependent Variable is Log Bilateral Export Volume (US$)	Base Regression	Excluding Gravity Covariates	Full Non-Zero Sample	Including Zero-Valued Trade Series	Excluding Non-Ethnic Importers	Including Importer Estimator	RF for Single IV Regressions	RF for Dual IV Regressions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Exporter's US Immigration Estimator	0.520	0.985	0.908	0.624	0.538	0.515	0.530	0.600
	(0.200)	(0.296)	(0.305)	(0.042)	(0.157)	(0.205)	(0.206)	(0.206)
Log Importer's US Immigration Estimator						-0.148		-0.404
						(0.295)		(0.237)
Log Product of GDPs per Capita	0.899			1.657	0.196	0.899	0.856	0.035
	(0.351)			(0.155)	(0.458)	(0.352)	(0.354)	(0.518)
Log Product of GDPs	0.278			-0.766	0.932	0.284	0.300	1.118
	(0.315)			(0.134)	(0.388)	(0.325)	(0.321)	(0.483)
Observations	66358	66358	84741	88701	28850	66358	62839	25384

Dependent Variable is Log Bilateral Export Volume (US$)	Excluding Chinese	Excluding European	Excluding Hispanic	Base Regression Excluding Indian	Excluding Japanese	Excluding Korean	Excluding Russian	Excluding Vietnamese
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log Exporter's US Immigration Estimator	0.663	0.452	0.646	0.352	0.497	0.533	0.521	0.542
	(0.385)	(0.170)	(0.283)	(0.098)	(0.197)	(0.206)	(0.201)	(0.207)
Log Product of GDPs per Capita	0.909	0.547	1.237	1.018	0.930	0.904	0.883	0.901
	(0.421)	(0.261)	(0.599)	(0.350)	(0.331)	(0.370)	(0.359)	(0.359)
Log Product of GDPs	0.279	0.592	0.022	0.161	0.246	0.259	0.301	0.258
	(0.394)	(0.286)	(0.579)	(0.302)	(0.290)	(0.333)	(0.324)	(0.323)
Observations	59351	42010	38436	64445	64277	64426	65747	65814

Notes: Panel estimations consider trade patterns taken from the 1980-1997 WTF database. The dependent variable is the log nominal value (US$) of bilateral manufacturing exports for exporter-importer pairs. US Immigration Quotas Estimators are constructed from quotas changes due to the 1990 Act. Regressions are unweighted and include exporter-importer and year fixed effects. Standard errors are clustered at the ethnicity level.

Table 5: OLS Regressions of Bilateral Exports on TFP Indices

Dependent Variable is Log Bilateral Export Volume (US$)	Base Regression	Excluding Gravity Covariates	Full Non-Zero Sample	Including Zero-Valued Trade Series	Excluding Non-Ethnic Importers	Including Importer TFP Index	1980-1992 Sample	1985-1997 Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Exporter's TFP Index	0.164	0.938	0.887	0.289	0.411	0.319	0.012	0.343
	(0.149)	(0.127)	(0.120)	(0.199)	(0.194)	(0.118)	(0.149)	(0.299)
Log Importer's TFP Index						-0.136		
						(0.164)		
Log Product of GDPs per Capita	0.769			1.492	-0.071	-0.046	0.957	0.340
	(0.383)			(0.200)	(0.599)	(0.496)	(0.257)	(0.667)
Log Product of GDPs	0.357			-0.664	0.994	1.112	0.174	0.673
	(0.336)			(0.124)	(0.403)	(0.497)	(0.251)	(0.627)
Observations	62839	62839	78794	82047	27182	25384	43351	46893

Dependent Variable is Log Bilateral Export Volume (US$)	Excluding Chinese	Excluding European	Excluding Hispanic	Base Regression Excluding Indian	Excluding Japanese	Excluding Korean	Excluding Russian	Excluding Vietnamese
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log Exporter's TFP Index	0.041	0.220	0.406	0.113	0.200	0.139	n.a.	n.a.
	(0.193)	(0.147)	(0.083)	(0.175)	(0.140)	(0.187)		
Log Product of GDPs per Capita	0.764	0.382	1.233	0.930	0.801	0.776		
	(0.456)	(0.343)	(0.689)	(0.364)	(0.370)	(0.399)		
Log Product of GDPs	0.404	0.649	-0.104	0.201	0.300	0.364		
	(0.412)	(0.370)	(0.668)	(0.316)	(0.309)	(0.351)		
Observations	55927	39607	36070	60926	60758	60907		

Notes: Panel estimations consider trade patterns taken from the 1980-1997 WTF database. The dependent variable is the log nominal value (US$) of bilateral manufacturing exports for exporter-importer pairs. TFP Indices are constructed from the PWT. Regressions are unweighted and include exporter-importer and year fixed effects. Standard errors are clustered at the ethnicity level.

Table 6A: IV Regressions of Bilateral Exports on TFP Indices using US Ethnic Human-Capital Stocks Instruments

Dependent Variable is Log Bilateral Export Volume (US$)	OLS				US Ethnic Human-Capital Stocks IV			
	Base Regression	Including Gravity Covariates	Including Importer TFP Index	Including Gravity Covariates	Base Regression	Including Gravity Covariates	Including Importer TFP Index	Including Gravity Covariates
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. OLS and Second-Stage Regressions							
Log Exporter's TFP Index	0.887	0.164	1.047	0.319	0.946	0.623	1.118	0.705
	(0.120)	(0.149)	(0.075)	(0.118)	(0.156)	(0.222)	(0.154)	(0.367)
Log Importer's TFP Index			0.591	-0.136			0.842	0.428
			(0.078)	(0.164)			(0.429)	(0.826)
Log Product of GDPs per Capita		0.769		-0.046		1.023		-0.281
		(0.383)		(0.496)		(0.441)		(0.602)
Log Product of GDPs		0.357		1.112		-0.302		0.731
		(0.336)		(0.497)		(0.440)		(0.394)
	B. First-Stage Regressions for Exporter's TFP Index							
Log Exporter's US Ethnic HC Stock					1.096	1.009	1.120	0.764
					(0.308)	(0.238)	(0.394)	(0.230)
Log Importer's US Ethnic HC Stock							0.021	-0.336
							(0.016)	(0.159)
	C. First-Stage Regressions for Importer's TFP Index							
Log Exporter's US Ethnic HC Stock							0.007	-0.368
							(0.012)	(0.151)
Log Importer's US Ethnic HC Stock							1.102	0.726
							(0.386)	(0.237)
Observations	78794	62839	25384	25384	78794	62839	25384	25384

Notes: Panel estimations consider trade patterns taken from the 1980-1997 WTF database. The dependent variable is the log nominal value (US$) of bilateral manufacturing exports for exporter-importer pairs. TFP Indices are constructed from the PWT. US Ethnic HC Stocks instrument for TFP Indices and are estimated from the US ethnic patenting dataset. Gravity covariates are included in Columns (6)'s and (8)'s first-stage regressions but are not reported. Regressions are unweighted and include exporter-importer and year fixed effects. Standard errors are clustered at the ethnicity level.

Table 6B: IV Regressions of Bilateral Exports on TFP Indices using US Immigration Quotas Instruments

Dependent Variable is Log Bilateral Export Volume (US$)	OLS				US Immigration Quotas IV			
	Base Regression	Including Gravity Covariates	Including Importer TFP Index	Including Gravity Covariates	Base Regression	Including Gravity Covariates	Including Importer TFP Index	Including Gravity Covariates
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. OLS and Second-Stage Regressions							
Log Exporter's TFP Index	0.887	0.164	1.047	0.319	1.342	1.130	1.685	1.227
	(0.120)	(0.149)	(0.075)	(0.118)	(0.455)	(0.610)	(0.685)	(1.418)
Log Importer's TFP Index			0.591	-0.136			0.050	-0.398
			(0.078)	(0.164)			(0.304)	(0.983)
Log Product of GDPs per Capita		0.769		-0.046		0.820		-0.126
		(0.383)		(0.496)		(0.693)		(1.088)
Log Product of GDPs		0.357		1.112		-0.293		0.753
		(0.336)		(0.497)		(0.546)		(0.688)
	B. First-Stage Regressions for Exporter's TFP Index							
Log Exporter's US Immigration Estimator					0.615	0.499	0.644	0.394
					(0.255)	(0.176)	(0.250)	(0.137)
Log Importer's US Immigration Estimator							0.008	-0.248
							(0.018)	(0.104)
	C. First-Stage Regressions for Importer's TFP Index							
Log Exporter's US Immigration Estimator							-0.002	-0.249
							(0.017)	(0.103)
Log Importer's US Immigration Estimator							0.646	0.392
							(0.253)	(0.139)
Observations	78794	62839	25384	25384	78794	62839	25384	25384

Notes: Panel estimations consider trade patterns taken from the 1980-1997 WTF database. The dependent variable is the log nominal value (US$) of bilateral manufacturing exports for exporter-importer pairs. TFP Indices are constructed from the PWT. US Immigration Quotas Estimators instrument for TFP Indices and are constructed from quotas changes due to the 1990 Act. Gravity covariates are included in Columns (6)'s and (8)'s first-stage regressions but are not reported. Regressions are unweighted and include exporter-importer and year fixed effects. Standard errors are clustered at the ethnicity level.

Table 7: OLS Regressions of Industry-Level Multilateral Trade on US Ethnic Human-Capital Stocks

Dependent Variable is Log Industry Exports or Imports (US$)	Levels Regressions				First-Differences Regressions			
	Multilateral Exports		Multilateral Imports		Multilateral Exports		Multilateral Imports	
	No Weights	Industry Patent Weights	No Weights	Industry Patent Weights	No Weights	Industry Patent Weights	No Weights	Industry Patent Weights
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Base Industry-Level Regressions							
Log Exporter's US Ethnic HC Stock	0.719	0.809	0.206	0.545	0.214	0.325	-0.014	0.086
	(0.115)	(0.131)	(0.111)	(0.107)	(0.098)	(0.101)	(0.084)	(0.086)
Observations	23948	23948	23948	23948	22437	22437	22437	22437
	B. Coefficients for Exporter's US Ethnic HC Stock from Variations on Base Industry-Level Regressions							
Excluding Computer and Drug Industries	0.688	0.766	0.172	0.494	0.202	0.303	-0.019	0.075
	(0.118)	(0.133)	(0.112)	(0.103)	(0.100)	(0.108)	(0.086)	(0.090)
Including Ethnicity Time Trends	0.699	0.967	0.064	0.278	0.141	0.324	0.092	0.182
	(0.147)	(0.178)	(0.122)	(0.147)	(0.117)	(0.133)	(0.095)	(0.099)
Including Country Time Trends	0.553	0.882	-0.065	0.195	0.127	0.309	0.087	0.177
	(0.141)	(0.179)	(0.122)	(0.142)	(0.118)	(0.134)	(0.095)	(0.099)
Including Ethnic-Year Effects	0.602	0.954	-0.111	0.137	0.043	0.226	-0.018	0.032
	(0.153)	(0.200)	(0.136)	(0.156)	(0.117)	(0.129)	(0.098)	(0.086)
Including Country-Year Effects	0.435	0.847	-0.258	0.067	-0.015	0.212	-0.070	-0.017
	(0.147)	(0.209)	(0.141)	(0.158)	(0.120)	(0.134)	(0.095)	(0.089)

Notes: Panel estimations consider trade patterns taken from the 1980-1997 WTF database. The dependent variable is the log nominal value (US$) of manufacturing exports or imports at the country-industry level. US Ethnic HC Stocks are estimated from the US ethnic patenting dataset. Regressions include gravity covariates, country-industry fixed effects, and industry-year fixed effects. Standard errors are clustered at the ethnicity-industry level.

Table 8: Industry-Share Regressions to Test Rybczynski Effect

Dependent Variable is Industry Export Share of Country Exports	No Weights	Including Interaction of Ethnic Time Trends With Industry Quintiles			Industry Patent Weights	Including Interaction of Ethnic Time Trends With Industry Quintiles		
		Wage	Capital-Labor	Non-Product.		Wage	Capital-Labor	Non-Product.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of Exporter's US Patenting in Industry	0.694	0.738	0.689	0.699	0.801	0.806	0.732	0.764
	(0.382)	(0.379)	(0.361)	(0.360)	(0.412)	(0.348)	(0.332)	(0.349)
Observations	56861	56861	56861	56861	56861	56861	56861	56861

Notes: Panel estimations consider trade patterns taken from the 1980-1997 WTF database. The dependent variable is the industry's share of the country's manufacturing exports. The independent variable is the industry's share of the ethnicity's US ethnic patenting stock. Regressions include country-industry and industry-year fixed effects. Standard errors are clustered at the ethnicity-industry level.

Table 9: Geographic Distance Regressions

Dependent Variable is Log Bilateral Export Volume (US$)	Observations with Distance Data	Exports to Border Countries	Exports to Countries ≤ 1500 km	Exports to Countries 1501-3000	Exports to Countries 3001-6000	Exports to Countries 6001-9000	Exports to Countries > 9000 km	Exports to Non-Border Countries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Exporter's US Ethnic HC Stock	0.586	1.772	0.977	0.564	0.895	0.614	0.506	0.570
	(0.208)	(0.801)	(0.475)	(0.614)	(0.396)	(0.301)	(0.305)	(0.206)
Log Product of GDPs per Capita	1.055	1.011	1.461	0.380	-0.171	1.760	0.859	1.083
	(0.459)	(0.327)	(0.238)	(0.655)	(1.119)	(0.423)	(0.279)	(0.469)
Log Product of GDPs	0.022	-0.503	-0.907	0.322	0.985	-0.580	0.419	0.012
	(0.451)	(0.416)	(0.317)	(0.714)	(1.141)	(0.405)	(0.317)	(0.468)
Observations	63826	1933	3923	5575	10785	15110	26500	61893

Notes: Panel estimations consider trade patterns taken from the 1980-1997 WTF database. The dependent variable is the log nominal value (US$) of bilateral manufacturing exports for exporter-importer pairs. US Ethnic HC Stocks are estimated from the US ethnic patenting dataset. Regressions are unweighted and include exporter-importer and year fixed effects. Standard errors are clustered at the ethnicity level.

Figure A1: RF Multilateral Exports on US Imm. Estimator

Panel Effects and Gravity Covariates Removed

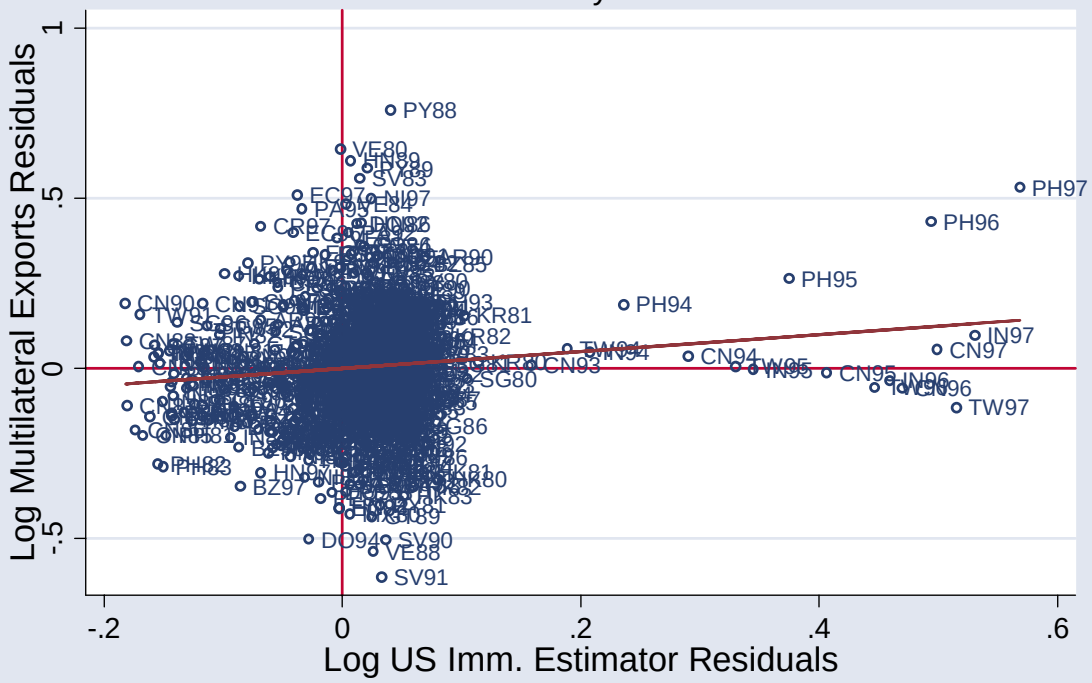

Figure A2: RF Multilateral Exports on US Imm. Estimator

Panel Effects Removed

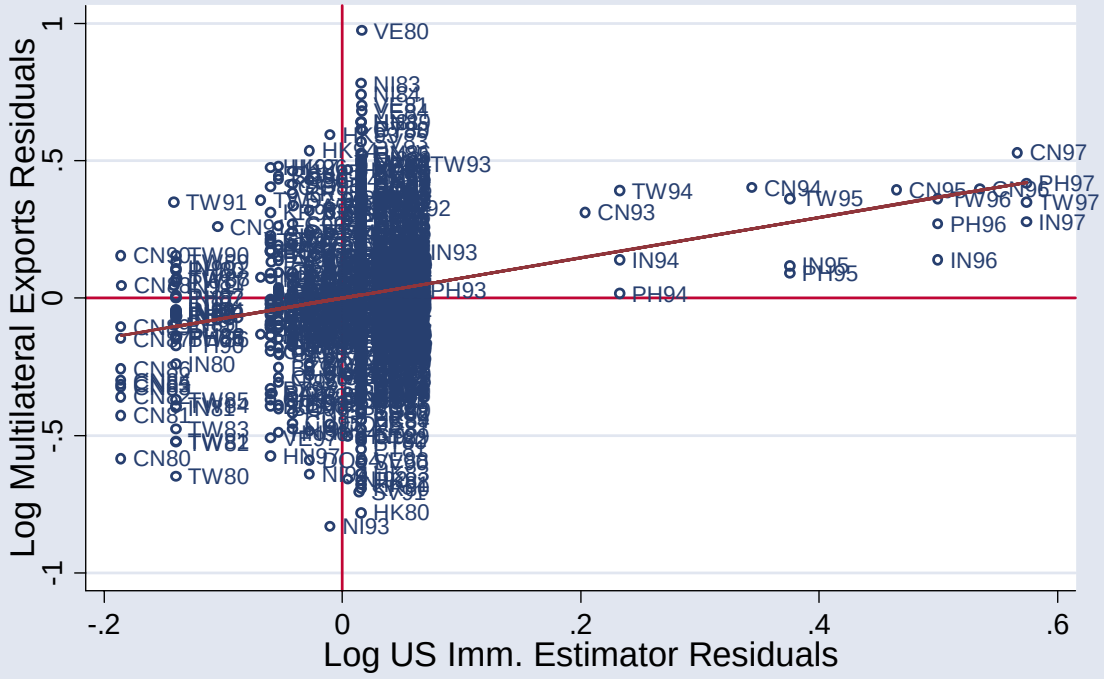

Figure A3: FS Exporter's TFP on US Imm. Estimator

Panel Effects and Gravity Covariates Removed

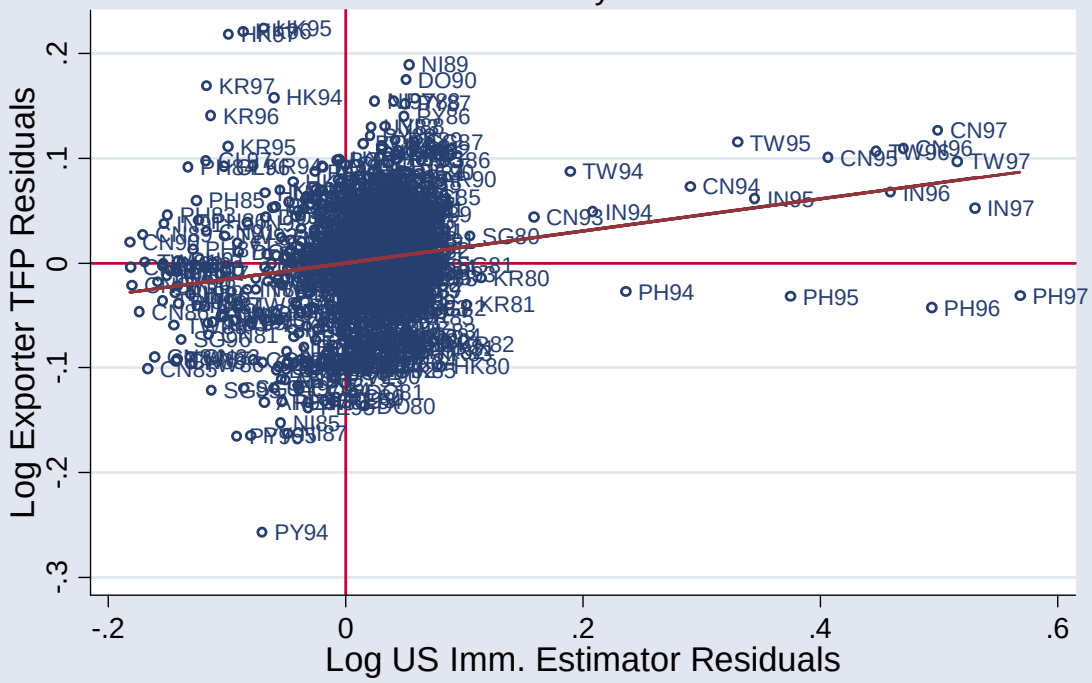

Figure A4: FS Exporter's TFP on US Imm. Estimator

Panel Effects Removed

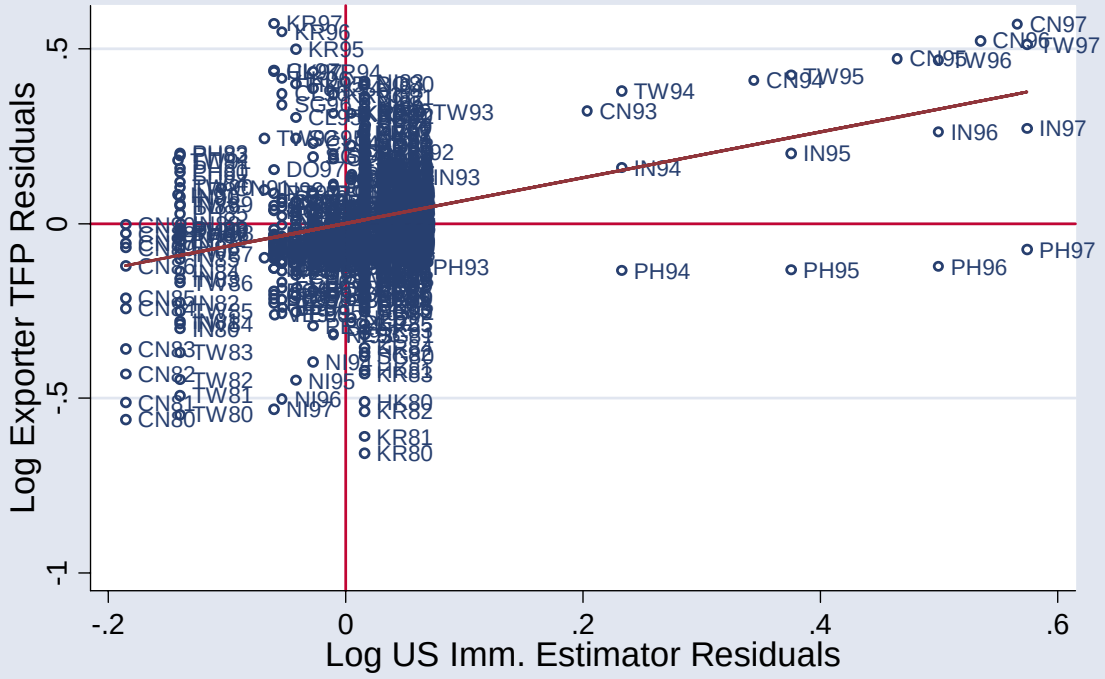

Table A1: ISIC Revision 2 Industry Codes

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

Table A1: ISIC Revision 2 Industry Codes (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.	

Table A2: IV Regressions of Bilateral Exports on TFP Indices - Sample Decomposition

Dependent Variable is Log Bilateral Export Volume (US$)	Base Regression							
	Excluding Chinese	Excluding European	Excluding Hispanic	Excluding Indian	Excluding Japanese	Excluding Korean	1980-1992 Sample	1985-1997 Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Second-Stage Coefficients using US Ethnic Human-Capital Stocks Instruments							
Log Exporter's TFP Index	0.871	0.444	0.708	0.530	0.728	0.630	0.372	0.893
	(0.634)	(0.139)	(0.159)	(0.200)	(0.259)	(0.281)	(0.203)	(0.239)
	B. First-Stage Coefficients using US Ethnic Human-Capital Stocks Instruments							
Log Exporter's US Ethnic HC Stock	0.700	1.597	1.087	1.006	1.026	0.938	0.935	1.004
	(0.380)	(0.036)	(0.080)	(0.260)	(0.242)	(0.304)	(0.229)	(0.257)
Observations	55927	39607	36070	60926	60758	60907	43351	46893
	C. Second-Stage Coefficients using US Immigration Quotas Instruments							
Log Exporter's TFP Index	3.635	1.150	1.227	0.717	1.074	1.064	n.a.	1.408
	(2.007)	(0.671)	(0.766)	(0.246)	(0.601)	(0.544)		(0.624)
	D. First-Stage Coefficients using US Immigration Quotas Instruments							
Log Exporter's US Immigration Estimator	0.209	0.420	0.597	0.513	0.502	0.549	n.a.	0.457
	(0.221)	(0.110)	(0.215)	(0.246)	(0.178)	(0.185)		(0.168)
Observations	55927	39607	36070	60926	60758	60907		46893

Notes: See Tables 6A and 6B.