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Heterogeneous Technology Diffusion and Ricardian Trade Patterns

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Abstract

Migration and trade are often linked through ethnic networks boosting bilateral trade. This study uses migration to quantify the importance of Ricardian technology differences for international trade. The framework provides the first panel estimates connecting country-industry productivity and exports, and the study exploits heterogeneous technology diffusion from immigrant communities in the United States for identification. The latter instruments are developed by combining panel variation on the development of new technologies across US cities with historical settlement patterns for migrants from countries. The instrumented elasticity of export growth on the intensive margin with respect to the exporter's productivity growth is between 1.6 and 2.4, depending upon weighting. This provides an important contribution to the trade literature of Ricardian advantages, and it establishes a connection of migration to home country exports beyond bilateral networks.

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

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Trade among countries due to technology differences is a core principle in international economics. Countries with heterogeneous technologies focus on producing goods in which they have comparative advantages; subsequent exchanges afford higher standards of living than are possible in isolation. This Ricardian finding is the first lesson in most undergraduate courses on trade, and it undergirds many

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modeling frameworks on which recent theoretical advances build (e.g., Dornbusch et al. 1977, Eaton and Kortum 2002, Costinot et al. 2012). In response to Stanislaw Ulam's challenge to name a true and nontrivial theory in social sciences, Paul Samuelson chose this principle of comparative advantage due to technology differences.

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

This study contributes to the empirical trade literature on Ricardian advantages in three ways. First, it utilizes a panel dataset that includes many countries at various development stages (e.g., Bolivia, France, South Africa), a large group of focused manufacturing industries, and an extended time frame. The 1975–2000 World Trade Flows (WTF) database provides export data for each bilateral route (exporter-importer-industry-year), and data from the United Nations Industrial Development Organization (UNIDO) provide labor productivity estimates. The developed data platform includes substantially more variation in trade and productivity differences across countries than previously feasible.

The second contribution is to provide panel estimates of the elasticity of export growth with respect to productivity development. Following the theoretical work of Costinot et al. (2012) that is discussed below, estimations include fixed effects for importer-industry-year and exporter-importer-year. The importer-industry-year fixed effects control, for example, for trade barriers in each importing country by industry segment while the exporter-importer-year fixed effects control for the overall levels of trade between countries (e.g., the gravity model), labor cost structures in the exporter, and similar. While these controls account for overall trade and technology levels by country, permanent differences in the levels of these variables across industries within a country are used for identification in most applications of this approach. This paper is the first to quantify Ricardian elasticities when further modeling cross-sectional fixed effects for exporter-importer-industry observations. This panel approach only exploits variation within industry-level bilateral trading routes, providing a substantially stronger empirical test of the theory.

The third and most important contribution is to provide instruments for the labor productivity development in exporting countries. Instruments are essential in this setting due to typical concerns: omitted variable biases for the labor productivity measure, reverse causality, and the potential for significant measurement error regarding the productivity differences across countries. The instruments exploit heterogeneous technology diffusion from past migrant communities in the United States for identification. These instruments are developed by combining panel variation on the development of new technologies across US cities during the 1975–2000 period with historical settlement patterns for migrants and their ancestors from countries that are recorded in the 1980 Census of Populations.

The foundation for these instruments is the modeling of Ricardian advantages through differences across countries in their access to the US technology frontier. Recent research emphasizes the importance of immigrants in frontier economies for the diffusion of technologies to their home countries (e.g., Saxenian 2002, 2006, Kerr 2008). These global connections and networks facilitate the transfer of both codified and tacit details of new innovations, and Kerr (2008) finds foreign countries realize manufacturing gains from stronger scientific integration, especially with respect to computer-oriented technologies. Multiple studies document specific channels sitting behind this heterogeneous diffusion.[1]

As invention is disproportionately concentrated in the United States, these ethnic networks significantly influence technology opportunity sets in the short-run for following economies. This study uses heterogeneous technology diffusion from the United States to better quantify the importance of technology differences across countries in explaining trade patterns. Trade between the United States and foreign countries is excluded throughout this study due to network effects operating alongside technology transfers. Attention is instead placed on how differential technology transfer from the United States—particularly its industry-level variation by country—influences exports from the foreign country to other nations. Said differently, the study quantifies the extent to which India's exports, for example, grow faster in industries where technology transfer from the United States to India is particularly strong. This provides an important complement in the migration literature to the typical focus on how ethnic networks boost bilateral trade.

The instrumented elasticity of export growth on the intensive margin with respect to the exporter's productivity growth is 2.4 in unweighted estimations. The elasticity is 1.6 when using sample weights that interact worldwide trade volumes for exporters and importers in the focal industry. Thus, the study estimates that a 10% increase in the labor productivity of an exporter for an industry leads to about a 20% expansion in export volumes within that industry compared to other industries for the exporter. This instrumented elasticity is weaker than Costinot et al.'s (2012) preferred estimate of 6.5 derived through producer price data for OECD countries in 1997, but it is quite similar to their 2.7 elasticity with labor productivity data that are most comparable to this study. The two analyses are also qualitatively similar in terms of their relationships to uninstrumented elasticities. This study does not find evidence of substantial adjustments in the extensive margin of the group of countries to which the exporter trades. These results are robust to sample composition adjustments and variations on estimation techniques. Extensions quantify the extent to which heterogeneous technology transfer can be distinguished from a Rybczynski effect operating within manufacturing, evaluate differences in education levels or time in the United States for past migrants in instrument design, and test the robustness to controlling for direct ethnic patenting growth by industry in the United States.

This study concludes that comparative advantages are an important determinant of trade; moreover, Ricardian differences are relevant for explaining changes in trade patterns over time. These panel exercises are closest in spirit to the industrial specialization work of Harrigan (1997) and the structural Ricardian model of Costinot et al. (2012). Other tests of the Ricardian model are MacDougall (1951, 1952), Stern (1962), Golub and Hsieh (2000), Chor (2010), Morrow (2010), Fieler (2011), Bombardini et al. (2012), Costinot and Donaldson (2012), Shikher (2012), Levchenko and Zhang (2014), Simonovska and Waugh (2014a,b), and Caliendo and Parro (2015). Recent related work on the industry dimension of trade includes Autor et al. (2013), Kovak (2013), and Hakobyan and McLaren (2016). Costinot and Rodriguez-Clare (2014) review empirical aspects and challenges of this literature. The comparative advantages of this work are in its substantial attention to non-OECD economies, the stricter panel assessment using heterogeneous technology diffusion, and the instruments built off of differential access to the US frontier. Work on migration-trade linkages dates back to Gould (1994), Head and Reis (1998), and Rauch and Trindade (2002), with Bo and Jacks (2012), di Giovanni et al. (2015), Bahar and Rapoport (2016), and Cohen et al. (2016) being recent contributions that provide references

1 Channels for this technology transfer include communications among scientists and engineers (e.g., Saxenian 2002, Kerr 2008, Agrawal et al. 2011), trade flows (e.g., Rauch 2001, Rauch and Trindade 2002), and foreign direct investment (e.g., Kugler and Rapoport 2007, Foley and Kerr 2013). The online supplement (available at https://academic.oup.com/wber) provides further references to the role of international labor mobility and other sources of heterogeneous technology frontiers (e.g., Eaton and Kortum 1999, Keller 2002).

to the lengthy subsequent literature. This paper differs from these studies in its focus on technology transfer's role for export promotion as an independent mechanism from migrant networks. In addition to contributing to the trade literature, the study documents for emerging economies an economic consequence of emigration to frontier economies like the United States.[2]

I. Estimating Framework

This section extends the basic estimating equation from Costinot et al. (2012) to a panel data setting. A simple application builds ethnic networks and heterogeneous technology diffusion into this theory. The boundaries of the framework and the statistical properties of the estimating equation are discussed.[3]

Estimating Equation

Costinot et al. (2012) develop a multi-country and multi-industry Ricardian model that has been widely studied and utilized in the trade literature. This framework builds off the model of Eaton and Kortum (2002) to articulate appropriate estimation of Ricardian advantages with industry-level data. The supplemental appendix shows how this model provides a microfoundation for studying Ricardian trade through an econometric specification of the form

$$\ln(\tilde{x}_{ij}^k) = \overline{\delta}_{ij} + \overline{\delta}_j^k + \theta \ln(\tilde{z}_i^k) + \overline{\varepsilon}_{ij}^k, \tag{1}$$

where i indexes exporters, j indexes importers, and k indexes goods. Each good k has an infinite number of subvarieties that are being bought and sold with observed trade flows being an aggregation of the subvarieties. In the estimating equation, $\tilde{x}_{ij}^k$ represents trade flows from exporter i to importer j for good k that adjust for country openness, and $\tilde{z}_i^k$ represents observed labor productivity in exporter i for good k. As described in the supplemental appendix, the theory framework requires including fixed effects for bilateral trade routes ($\overline{\delta}_{ij}$) and importer-industry fixed effects ($\overline{\delta}_j^k$) to account for unmodeled factors like consumer preferences, country sizes, and delivery costs. Finally, the estimated coefficient θ has a specific interpretation related to the Fréchet distribution that underlies this model and Eaton and Kortum (2002). Specifically, a low θ suggests a large scope for intraindustry comparative advantage, while a high θ (corresponding to large observed adjustments in exports with industry-level productivity shifts) suggests a limited scope for intraindustry comparative advantage.

Estimates of θ in the trade literature have been derived with cross-sectional regressions using equation (1). This study seeks identification of the θ parameter within the Costinot et al. (2012) setting via first differencing and instrumental variables.[4] The first step is to extend equation (1) to include time t,

$$\ln(\tilde{x}_{ijt}^k) = \overline{\delta}_{ijt} + \overline{\delta}_{jt}^k + \theta \ln(\tilde{z}_{it}^k) + \overline{\varepsilon}_{ijt}^k. \tag{2}$$

It is important to note that this extension is being applied to the fixed effect terms. Thus, the exporter-importer fixed effects in the cross-sectional format become exporter-importer-year fixed effects in a panel format. It is assumed that θ does not vary by period, although stacked versions of the Costinot et al. (2012) model could allow for this. The empirical work below estimates equation (2) for reference, but most of the specifications instead examine a first-differenced form,

2 Davis and Weinstein (2002) consider immigration to the United States, technology, and Ricardian-based trade. Their concern, however, is with the calculation of welfare consequences for US natives as a consequence of immigration due to shifts in trade patterns.

3 Dornbusch et al. (1977), Wilson (1980), Baxter (1992), Alvarez and Lucas (2007), Costinot (2009), and Costinot and Vogel (2015) provide further theoretical underpinnings for comparative advantage.

4 Daruich et al. (2016) estimate this framework encompasses about 20% of the variation in trade flows. Other studies seek to jointly model Ricardian advantages with other determinants of trade (e.g., Davis and Weinstein 2001, Morrow 2010).

$$\Delta \ln\left(\tilde{x}_{ijt}^{k}\right) = \delta_{ijt} + \delta_{jt}^{k} + \theta \Delta \ln\left(\tilde{z}_{it}^{k}\right) + \varepsilon_{ijt}^{k}, \tag{3}$$

where the fixed effects and error term are appropriately adjusted.

The motivation for first differencing is stronger empirical isolation of the θ parameter. By themselves, exporter-importer-year and importer-industry-year fixed effects in equation (2) allow identification of the θ parameter in two ways: (i) longitudinal changes in $\tilde{z}_{it}^{k}$ over time; and (ii) long-term differences in $\tilde{z}_{it}^{k}$ across industries for the exporter. In a cross-sectional estimation of equation (1), it is not feasible to distinguish between these forms. This second effect persists when extending the equation (2) to a panel setting because the exporter-importer-year fixed effects δ_{ijt} only account for the aggregate technology changes for exporters. First differencing best isolates the particular role of longitudinal changes in productivity $\tilde{z}_{it}^{k}$ over time.

Whether estimating the θ parameter through both forms of variation is appropriate depends upon model assumptions, beliefs about unmeasured factors, and measurement error. It is helpful to illustrate by considering the exports of Germany in automobiles. The study examines trade over the 1980–1999 period. Throughout this period, Germany held strong technological advantages and labor productivity for manufacturing automobiles relative to the rest of the world. Over the course of the period, this productivity also changed in relative terms. If one can feasibly isolate these productivity variables, then having both forms of variation is an advantage. A second and related issue is that first differencing the data exacerbates the downward bias that measurement error causes for estimates of the θ parameter. There are plenty of reasons to suspect non-trivial measurement error in industry-level labor productivity estimates developed from the UNIDO database.

On the other hand, removing time-invariant differences to identify the θ parameter can be an advantage. The basic identification constraint for the econometric analysis is that technology levels of exporters cannot be distinguished from other unobservable factors that also vary by exporter-industry or exporter-industry-year for the long-term technology levels and their longitudinal changes, respectively. The first is particularly worrisome given its general nature. First differencing is not foolproof against omitted factors, but it does require that the changes in these factors correlate with the changes in the focal productivity level in the exporters of $\tilde{z}_{it}^{k}$. This latter approach of panel estimation, while very common in microeconomic analyses, has yet to be extended to the Ricardian literature.[5]

Beyond this discussion, a few other notes about the estimation of (3) are warranted. The dependent variable is bilateral manufacturing exports by exporter-importer-industry-year. The lack of trade for a large number of bilateral routes at the industry level creates econometric challenges with a log specification. These zero-valued exports are predicted by the model as an exporter is rarely the lowest-cost producer for all countries in an industry. This study approaches this problem by separately testing the intensive and extensive margins of trade. Most of the focus is on the intensive margin of trade expansion, where the dependent variable is the log growth in the value of bilateral exports $\Delta \ln\left(\tilde{x}_{ijt}^{k}\right)$. The intensive margin of exports captures both quantities effects and price effects (e.g., Acemoglu and Ventura 2002, Hummels and Klenow 2005). In tests of extensive margin of trade expansion—that is, commencing exports to new import destinations—the dependent variable becomes a dichotomous indicator variable for whether measurable exports exist. Differences in the sample construction for these two tests are discussed when describing the trade dataset.

5 Estimations of the Costinot et al. (2012) model rely on fixed effects to handle delivery costs and other aspects of trade that are not due to the productivity of exporters. Thus, a cross-sectional estimation (1) requires unmodeled delivery costs be only comprised of a bilateral component and an importer-industry component ($d_{ij}^{k} = d_{ij} \cdot d_{j}^{k}$). A panel estimation (3) allows this proportionate structure to be extended to $d_{ijt}^{k} = d_{ijt} \cdot d_{jt}^{k} \cdot d_{ij}^{k}$, where the third term represents the long-term delivery costs for the exporter to the importer by industry.

Beyond the model's background, the exporter-importer-year fixed effects perform several functions. They intuitively require that Germany's technology expansion for auto manufacturing exceed its technology expansion for chemicals manufacturing if export growth is stronger in autos than chemicals. Thus, these fixed effects remove aggregate trade growth by exporter-importer pairs common across industries. These uniform expansions could descend from factors specific to one country of the pair (e.g., economic growth and business cycles, factor accumulations, terms of trade and price levels) or be specific to the bilateral trading pair (e.g., trade agreements, preferences[6]). This framework is thus a powerful check against omitted variables biases, helping to isolate the Ricardian impetus for trade from relative factor scarcities and other determinants of trade. The fixed effects also control for the gravity covariates commonly used in empirical trade studies. National changes in factor endowments may still influence industries differentially due to the Rybczynski effect, which is explicitly tested for below. The importer-industry-year fixed effects control for tariffs imposed upon an industry in the importing country. More broadly, they also control for the aggregate growth in worldwide trade in each industry, relative price changes, and the potential for trade due to increasing returns to scale (e.g., Helpman and Krugman 1985, Antweiler and Trefler 2002).

More subtly, a key difference between multicountry Ricardian frameworks and the classic two-country model of Dornbusch et al. (1977) is worth emphasizing. This difference influences how the comparative static of increasing a single country-industry technology parameter $\tilde{z}_{it}^{k}$, *ceteris paribus*, is viewed. The multicountry theoretical framework allows for increases in $\tilde{z}_{it}^{k}$ to reduce exports on some bilateral routes for the exporter-industry. This effect is due to general equilibrium pressures on input costs and extreme value distributions—while the productivity growth makes the exporter more competitive, the rising wage rates in the country may make it less competitive for a particular importer. This more nuanced pattern is different from the stark prediction of a two-country model where productivity growth in an industry for a country would never lead to declines in exports to the other country in that industry. The proper treatment effect for productivity growth is measured across all export destinations, as in the empirical work of this paper, and thus captures the general Ricardian pattern embedded in the model. This treatment effect is a net effect that may include reduction of exports on some routes.[7]

Heterogeneous Technology Diffusion and Ricardian Trade

While the Ricardian framework assigns a causal relationship of export growth to technology development, in practice the empirical estimation of specification (3) can be confounded by reverse causality or omitted variables operating by exporter-industry-year even after first differencing. Reverse causality may arise if engagement in exporting leads to greater technology adoption, perhaps through learning-by-doing or for compliance with an importer's standards and regulations. An example of an exporter-industry-year omitted factor is a change in government policies to promote a specific industry, perhaps leading to large technology investments and the adoption of policies that favor the chosen industry's exports relative to other manufacturing industries. This would lead to an upward bias in the estimated θ parameter.[8]

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

6 Hunter and Markusen (1988) and Hunter (1991) find these stimulants account for up to 20% of world trade.

7 Costinot et al. (2012) provide a more detailed discussion, including the extent to which the industry ordering of the two-country model is found in the relative ordering of exports for countries.

8 More specifically, the innovation in industrial policy support must be non-proportional across manufacturing industries. Long-term policies to support certain industries more than others are accounted for by the first differencing. Uniform changes in support across industries are also jointly accounted for by panel fixed effects.

$$\tilde{z}_{it}^{k} = \tilde{z}_{t}^{k,US} \cdot \Upsilon_{i}^{k} \cdot \Upsilon_{it} \cdot M_{it}^{k}. \tag{4}$$

$\tilde{z}_{t}^{k,US}$ is the exogenously determined US technology frontier for each industry and year. Two general shifters govern the extent to which foreign nations access this frontier. First, Υ_{i}^{k} models time-invariant differences in the access to or importance of US technologies to exporter i and industry k, potentially arising due to geographic separation (e.g., Keller 2002), heterogeneous production techniques (e.g., Davis and Weinstein 2001, Acemoglu and Zilibotti 2001), or similar factors. The shifter Υ_{it} models longitudinal changes in the utilization of US technologies common to all industries within exporter i, such as changes due to declines in communication and transportation costs, greater general scientific or business integration, and so on. In what follows, both of these shifters could further be made specific to an exporter-importer pair.

By themselves, these first three terms of model (4) describe the realities of technology diffusion but are not useful for identification when estimating specification (3). The technology frontier $\tilde{z}_{t}^{k,US}$ is captured by the importer-industry-year fixed effects, the bilateral Υ_{i}^{k} shifter is removed in the first differencing, and the longitudinal Υ_{it} shifter is captured in the exporter-industry-year fixed effects. The final term M_{it}^{k}, however, describes differential access that the migrants to the United States from exporter i provide to the technologies used in industry k. This term models the recent empirical literature that finds that overseas diaspora and ethnic communities aid technology transfer from frontier countries to their home countries. If there is sufficient industry variation in this technology transfer, after removing the many fixed effects embedded into specification (3), then this transfer may provide an exogenous instrument to the exporter productivity parameter $\tilde{z}_{it}^{k}$ in a way that allows very powerful identification for the role of Ricardian advantages in trade.

The design of this instrument combines spatial variation in historical settlement patterns in the United States of migrant groups from countries with spatial variation in where new technologies emerged over the period of the study. The instrument takes the form

$$M_{it}^{k} = \sum_{c \in C} M\%_{i,c,1980} \cdot \left[\frac{Tech_{c,t}^{k,A-S}}{Tech_{c,1980}^{k,A-S}} \right], \tag{5}$$

where c indexes US cities. $M\%_{i,c,1980}$ is the share of individuals tracing their ancestry to country i—defined in more detail below and including first-generation immigrants—that are located in city c in 1980. These shares sum to 100% across US cities. The bracketed fraction is a technology ratio defined for an industry k. The ratio measures for each city how much patenting grew in industry k relative to its initial level in 1980. The fraction exceeds one when a city's level of invention for industry k grows from the base period, and it falls below one if the city's invention for an industry weakens.

The instrument thus interacts the spatial distribution across US cities of migrants from exporter i with the city-by-city degree to which technological development for industry k grew in locations. By summing across cities, equation (5) develops a total metric for exporter i and industry k that can be first differenced in a log format, $\Delta\ln(M_{it}^{k})$, to instrument for $\Delta\ln(\tilde{z}_{it}^{k})$ in equation (3). A subtle but important point is that the instrument can only work in a first-differenced format (or equivalent panel data model with bilateral route fixed effects). This restriction is because the expression (5) does not have a meaningful cross-sectional level to it—for all countries and industries, the value of M_{it}^{k} is equal to one in 1980 by definition. As such, M_{it}^{k} cannot predict the cross-section of trade in 1980. However, M_{it}^{k} does provide insight about changes in technology opportunity sets over time that can be used for identification in estimations that consider changes in technology and trade over time.

Three other points about the instrument's design are important to bring out as they specifically relate to potential concerns about the instrument. First, the technology trend modeled in equation (5) is at the city-industry level, not at the city level. This is vital because the instrument interacts the US spatial ancestry distribution for a country with these city-industry patenting trends. As the estimations include exporter-importer-year fixed effects, any variable or instrument that would interact a city-level trend (e.g., population growth, housing prices, local public expenditures, etc.) with the city spatial distribution will be completely absorbed by the exporter-importer-year fixed effects (specifically, the exporter-year part of these fixed effects). In other words, general city-level factors like the total patenting of a location are anticipated to impact industries for a country in a proportionate way, and the estimations only use disproportionate variation over industries to identify the empirical effects.

Second, one concern would be that migrants from exporter i select cities specifically to acquire technologies useful for their home country's exports. This seems less worrisome perhaps for individual migrants, but it is quite plausible when contemplating a German automobile manufacturer opening a new facility in the United States (e.g., Alcacer and Chung 2007). The instrument seeks to rule out this concern by fixing the city distribution of migrants from exporter i at their city locations in 1980. This approach eliminates endogenous resorting, and the results below are also shown to be robust to focusing on second-generation and earlier migrants. Additional analyses also consider dropping industries for each country where the concerns could be most pronounced.

A third concern is one of reverse causality. The United States relies extensively on immigrants for its science and engineering labor force, with first-generation immigrants accounting for about a quarter of the bachelor's educated workforce and half of those with PhDs. Moreover, immigrants account for the majority of the recent growth in the US science and engineering workforce. The spatial patterns of new high-skilled immigrants frequently build upon ethnic enclaves and impact the innovation levels in those locations (e.g., Kerr and Lincoln 2010, Hunt and Gauthier-Loiselle 2010, Peri et al. 2015). Thus, a worry could be that the technology growth for cities in model (5) is endogenous. The concern would be that Germany is rapidly developing innovations and new technologies for the automobile industry, and this expansion is simultaneously leading to greater exports from Germany and the migration of German scientists that are patenting automobile technologies to the United States.

This concern is addressed in several ways throughout this study, including sample decomposition exercises, lag structure tests, and similar exercises. The most straightforward safeguard, however, is already built into model (5). The patenting data, as described below, allow us to separate the probable ethnicities of inventors in the United States. By focusing on inventors of Anglo-Saxon ethnic heritage, one can remove much of this reverse causality concern. The Anglo-Saxon group accounts for about 70% of US inventors during the time period studied, and so this group reflects the bulk and direction of US technological development. Extensions will further consider settings where patent citation records suggest that the Anglo-Saxon inventors are mainly drawing on other Anglo-Saxon inventors in their research.[9]

Addressing these concerns also provides the approach (5) with a conceptual advantage with respect to the fixed effect estimation strategy. The first differencing in specification (3) controls for the initial distributions $M\%_{i,c,1980}$, and the importer-industry-year fixed effects δ_{jt}^{k} control for the technology growth ratio for industry k. This separation is not perfect due to the summation over cities, but it is closely mimicked. Thus, the identification in these estimations comes off these particular interactions. This provides a strong lever against concerns of omitted factors or reverse causality, and the well-measured US data can provide instruments that overcome the downward bias in coefficients due to measurement error.

II. Data Preparation

This section summarizes the key data employed in this study and their preparation, with the online supplement providing further details. Table S1a describes the 88 exporting countries included, and table S1b provides similar statistics for the 26 industries, aggregating over countries.

9 Very strong crowding-in or crowding-out of natives by immigrant scientists and engineers would create a bias in the Anglo-Saxon trend itself. Kerr and Lincoln (2010) find very limited evidence of either effect at the city level for the United States during this time period and for the time horizons considered here (i.e., first differencing over five-year periods).

Labor Productivity Data

Productivity measures $\tilde{z}_{it}^{k}$ are taken from the Industrial Statistics Database of the United Nations Industrial Development Organization (UNIDO). The UNIDO data provide an unbalanced panel over countries, industries, and time periods, and the availability of these data are the key determinant of this study's sample design. Estimations consider manufacturing industries at the three-digit level of the International Standard Industrial Classification system (ISIC3). Data construction starts by calculating the annual labor productivity in available industries and countries during the 1980–1999 period. These annual measures are then collapsed into the mean labor productivity level for each five-year period from 1980–1984 to 1995–1999. This aggregation into five-year time periods affords a more balanced panel by abstracting away from the occasional years when an otherwise reported country-industry is not observed. The higher aggregation is also computationally necessary below due to the tremendous number of fixed effects considered.

These labor productivity measures are first differenced in log format for inclusion in equation (3). Thus, an exporter i and industry k is included if it is observed in the UNIDO database in two adjacent periods. Sample inclusion also requires that the country-industry be reported in two observations at least five years apart (e.g., to prevent an included observation only being present in 1989 and 1991). The main estimations consider the three change periods of 1980–1984 →1985–1989, 1985–1989 →1990–1994, and 1990–1994 →1995–1999.

Export Volumes

Bilateral exports $\tilde{x}_{ijt}^{k}$ are taken from the 1975–2000 World Trade Flows Database (WTF) developed by Feenstra et al. (2005). This rich data source documents product-level values of bilateral trade for most countries from 1980–1999. Similar to the development of the labor productivity variables, these product flows are aggregated into five-year periods from 1980–1984 to 1995–1999 and then first differenced in log format. Each productivity growth observation available with the UNIDO dataset is paired with industry-level bilateral export observations from that country. All exporting countries other than the United States are included.

The majority of export volumes for bilateral routes are zero-valued, which creates challenges for the estimation of equation (3). It is also the case that the minimum threshold of trade that can be consistently measured across countries and industries is US $100,000 in the WTF database. While Feenstra et al. (2005) are able to incorporate smaller trading levels for some countries, these values are ignored to maintain a consistent threshold across observations. To accommodate these conditions, the empirical approach separately studies the extensive and intensive margins of export expansion. Mean export volumes are taken across exporter-importer-industry observations for five-year time periods. For the extensive margin, entry into exports along an exporter-importer-industry route is defined as exports greater than US $100,000.

US Historical Settlement Patterns

The first building block for the instrument is the historical settlement patterns of migrants from each country $M\%_{i,c,1980}$. These data are taken from the 1980 Census of Populations, which is the earliest US census to collect the detailed ancestry of respondents (as distinguished from immigration status or place of birth). The detailed ancestry codes include 392 categories with positive responses, and this study maps these categories to the UNIDO records. Respondents are asked primary and secondary ancestries, but the classifications only focus on the primary field given the many missing values in the secondary field. There are multiple ancestry groups that map to the same country, but the mapping procedure limits each ancestry group to map to just one UNIDO country. Categories not linked to a specific UNIDO country are dropped (e.g., Western Europe not elsewhere classified, Ossetian). In total, 89% of the US population in 1980 is mapped.

Metropolitan statistical areas, which will be referred to as cities for expositional ease, are identified using the 1% Metro Sample. This dataset is a 1-in-100 random sample of the US population in 1980 and is designed to provide accurate portraits of cities. The set C over which $M\%_{i,c,1980}$ is calculated includes 210 cities from the 1980 census files that are linked to the US patent data described next. The primary measures of $M\%_{i,c,1980}$ include all individuals regardless of age or education level to form $M\%_{i,c,1980}$, only dropping those in group quarters (e.g., military barracks) or not living in an urban area. Extensions test variations on these themes.

US Patenting Data

The second building block for the instrument is the trend in patenting for each city $Tech_{c,t}^{k,A-S}$. These series are quantified through individual records of all patents granted by the United States Patent and Trademark Office (USPTO) from January 1975 to May 2009. Each patent record provides information about the invention (e.g., technology classification, citations of patents on which the current invention builds) and inventors submitting the application (e.g., name, city). USPTO patents must list at least one inventor, and multiple inventors are allowed. Approximately 7.8 million inventors are associated with 4.5 million granted patents during this period. The online supplement documents how the patent data are augmented in terms of city and industry definitions. Only patents with all inventors living in the United States at the time of their patent application are included, and multiple inventors are discounted so that each patent receives the same weight when measuring inventor populations. Concordances link USPTO technology classes to ISIC3 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.

The probable ethnicities of inventors are estimated through the names listed on patents (e.g., Kerr 2007). This procedure exploits the fact that individuals with surnames Gupta or Desai are likely to be Indian, Wang or Ming are likely to be Chinese, and Martinez or Rodriguez are likely to be Hispanic. The name matching work exploits two commercial databases of ethnic first names and surnames, and the procedures have been extensively customized for the USPTO data. The match rate is 98% for US domestic inventors, and the process affords the distinction of nine ethnicities: Anglo-Saxon, Chinese, European, Hispanic, Indian, Japanese, Korean, Russian, and Vietnamese. Most of the estimations in this paper only use whether inventors are of Anglo-Saxon origin, as a means for reducing the potential of reverse causality as discussed above. The Anglo-Saxon share of US domestic patenting declines from 73% in 1980–1984 to 66% in 1995–1999 (table S2). This group accounts for a majority of patents in each of the six major technology categories developed by Hall et al. (2001).

As with the productivity and trade data, the patenting series are aggregated into five-year blocks by city and industry. These intervals start in 1975–1979 and extend through 1995–1999, and the series are normalized by the patenting level of each city-industry in 1980–1984. These series are then united with the spatial distribution of each country's ancestry group using model (5) to form an aggregate for each country-industry, and the log growth rate is then calculated across these five-year intervals. The lag of this growth rate is used as the instrument for the productivity growth rate in an exporter-industry. That is, the estimated growth in technology flows from Brazil's chemical industry during 1975–1979 $\rightarrow$1980–1984 is used as the instrument for the growth in Brazil's labor productivity in chemicals for the 1980–1984 $\rightarrow$1985–1989 period. This lag structure follows the emphasis in Kerr (2008) on the strength of ethnic networks for technology diffusion during the first 3–6 years after a US invention is developed, and the comparison to contemporaneous flows is shown in robustness checks. The online supplement provides additional notes on the instrument design and its connection to patent data.

III. Empirical Results

This combined dataset is a unique laboratory for evaluating Ricardian technology differences in international trade. This section commences with ordinary least squares (OLS) estimations using the UNIDO and WTF data. The instrumental variable (IV) results are then presented.

Base OLS Specifications

Table 1 provides the basic OLS estimations. Column 1 presents the "between" estimates from specification (2) before first differencing the data; the dependent variable is the log mean nominal value of bilateral exports for the five-year period. These estimates identify the θ parameter through variation within bilateral trading routes and variation across industries of an exporter. This framework parallels most Ricardian empirical studies. Column 2 presents the "within" estimate from specification (3) that utilizes first differencing to isolate productivity and trade growth within exporter-importer-industry cells.

Estimations in panel A weight bilateral routes by an interaction of total exporter and importer trade in the industry. For example, the weight given to Germany's exports of automobiles to Nepal is the total export volume of Germany in the auto industry interacted with the total imports of Nepal in the auto industry, using averages for each component across the sample period. These weights focus attention on routes that are likely to be more important and give a sense of the overall treatment effect from

Table 1. OLS estimations of labor productivity and exports

	Between estimation (1)	FD estimation (2)
	Panel A: Weighting bilateral routes by the interaction of exporter and importer trade in industry (summed across all bilateral routes)	
	DV: Log bilateral exports	DV: Δ Log bilateral exports
Log country-industry labor productivity	0.640***	
	(0.242)	
Δ Log country-industry labor productivity		0.573***
		(0.185)
Observations	149,547	103,839
Importer-Industry-Yr FE	Yes	Yes
Exporter-Importer-Yr FE	Yes	Yes
	Panel B: Excluding sample weights	
	DV: Log bilateral exports	DV: Δ Log bilateral exports
Log country-industry labor productivity	0.361***	
	(0.091)	
Δ Log country-industry labor productivity		0.210***
		(0.041)
Observations	149,547	103,839
Importer-Industry-Yr FE	Yes	Yes
Exporter-Importer-Yr FE	Yes	Yes

Notes: Panel estimations consider manufacturing exports taken from the WTF database. Data are organized by exporter-importer-industry-year. Industries are defined at the three-digit level of the ISIC Revision 2 system. Annual data are collapsed into five-year groupings beginning with 1980–1984 and extending to 1995–1999. The dependent variable in Column 1 is the log mean nominal value (US$) of bilateral exports for the five years; the dependent variable in Column 2 is the change in log exports from the prior period. The intensive margin sample is restricted to exporter-importer-industry groupings with exports exceeding $100 k in every year. The $100 k threshold is chosen due to WTF data collection procedures discussed in the text. Labor productivity from the UNIDO database measures comparative advantages. Column 1 estimates Ricardian elasticities using both within-panel variation and variation between industries of a country. Column 2 estimates Ricardian elasticities using only variation within panels. Estimations in Panel A weight bilateral routes by the interaction of total exporter and importer trade in industry; estimations in Panel B are unweighted. Estimations cluster standard errors by exporter-industry. Importer-Industry-Yr FE are defined at the two-digit level of the ISIC system. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Source: Author's analysis based on data described in text.

Ricardian advantages. The weights, however, explicitly do not build upon the actual trade volume for a route to avoid an endogenous emphasis on where trade is occurring. Estimates in panel B are unweighted. This study reports results with both strategies to provide a range of estimates.

Estimations cluster standard errors by exporter-industry. This reflects the repeated application of exporter-industry technology levels to each route and the serial correlations concerns of panel models. Other variants are reported below, too. Finally, the combination of 88 countries, 26 industries, and three time intervals creates an enormous number of exporter-importer-year and importer-industry-year fixed effects. The number of import destinations is in fact larger than the 88 exporters, as a UNIDO data match is not required for import destinations. With such a large dataset, it is computationally difficult to include exporter-importer-year and importer-industry-year fixed effects, especially when considering IV estimations. By necessity, manual demeaning is employed to remove the exporter-importer-year fixed effects, and this procedure is applied over the importer-industry-year fixed effects. The baseline estimates also use an aggregated version of the importer-industry-year fixed effects where the industry level used for the groups is at the two-digit level of the ISIC system rather than the three-digit level (reducing this dimension from 26 industries to eight higher-level industry groups). Robustness checks on these simplifications are reported below.

Interestingly, the "between" and "within" elasticities estimated in panel A are both around 0.6 on the intensive margin. These coefficients suggest that a 10% growth in labor productivity for an exporter-industry is associated with a 6% growth in exports. The estimates in panel B are lower at 0.2–0.4, but they remain economically and statistically important. These elasticities are somewhat lower than the unit elasticity often found in this literature with OLS estimation techniques and cross-sectional data. There are many empirical reasons why this might be true, with greater measurement error for productivity estimates outside of OECD sources certainly being among them. An elasticity greater than or equal to one is also the baseline for the Ricardian theory presented earlier. The IV estimates reported below are greater than one and have a comparable level on some dimensions to those estimated with OECD countries. The next subsection continues with extensions for these OLS estimates to provide a foundation for the IV results.

Extended OLS Results

Table 2 provides robustness checks on the first-differenced estimates, which are the focus of the remainder of this study. The first column repeats the core results from column 2 of table 1. The next two columns show robustness to dropping Brazil and China. Brazil, of all included countries, displays the most outlier behavior with respect to its productivity growth rates, likely due to definitional changes, but Brazil's exclusion does not affect the results. The results are also similar when excluding China, which experienced substantial growth during the sample period. It is generally worth noting that the 1980–1999 period predates the very rapid take-off of Chinese manufacturing exports after 2000 (Autor et al. 2013). Unreported tests consider other candidates like Mexico, Germany, and Japan, and these tests, too, find the results very stable to the sample composition, reflective in large part of the underlying exporter-importer-year fixed effects.

Column 4 shows the results when excluding industry 383 (Machinery, electrical). The coefficient estimates are reduced in size by about 30% from column 1, but they remain quite strong and well-measured overall. The exclusion of industry 383 has the largest impact on the results of the 26 industries in the sample, which is why it is reported. This importance is not very surprising given the very rapid development of technology in this sector, its substantial diffusion around the world, and its associated trade. On this dimension, the industry-year portion of the importer-industry-year fixed effects play a very stabilizing role. Quantitatively similar results are also found when excluding the Tobacco and Petroleum sectors (314, 353, 354). Column 5 shows that winsorizing the sample at the 2%/98% level delivers similar results, indicative that outliers are not overly influencing the measured elasticities.

Table 2. Robustness checks on OLS specifications in Table 1

	Base estimation (Column 2, Table 1)	Excluding exports from Brazil	Excluding exports from China	Excluding electrical machinery	Using a 2%/98% winsorized sample	Using ISIC 2-digit level industry groups	Kerr (2008) sample using Imp-ISIC2-Year fixed effects	Kerr (2008) sample using Imp-ISIC3-Year fixed effects	Using exporter-level clustering
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
The dependent variable is Δ log bilateral exports on the intensive margin by exporter-importer-industry									
Panel A: Weighting bilateral routes by the interaction of exporter and importer trade in industry									
Δ Log country-industry	0.573***	0.573***	0.472***	0.390***	0.493***	0.266**	0.287**	0.281**	0.573***
labor productivity	(0.185)	(0.185)	(0.097)	(0.121)	(0.133)	(0.112)	(0.113)	(0.138)	(0.086)
Observations	103,839	103,010	101,221	97,326	103,839	51,483	23,345	23,345	103,839
Importer-Industry-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Importer-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Excluding sample weights									
Δ Log country-industry	0.210***	0.210***	0.221***	0.154***	0.264***	0.097***	0.248***	0.184***	0.210***
labor productivity	(0.041)	(0.041)	(0.041)	(0.039)	(0.043)	(0.037)	(0.066)	(0.069)	(0.048)
Observations	103,839	103,010	101,221	97,326	103,839	51,483	23,345	23,345	103,839
Importer-Industry-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Importer-Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 1.
Source: Author's analysis based on data described in text.

It was earlier noted that computational demands require that the main estimations employ the ISIC2-level industry groups when preparing importer-industry-year fixed effects. Columns 6–8 test this choice in several ways. First, column 6 shows that the results hold when estimating the full model with ISIC2-based cells, so that the importer-industry-year fixed effects exactly match the cell construction. The weaker variation reduces the coefficient estimates by half, but the results remain statistically and economically important. Columns 7 and 8 alternatively estimate the model using the sample from Kerr (2008) that focuses on a subset of the UNIDO data in the 1985–1997 period. The Kerr (2008) sample is substantially smaller in size than the present one, and so there is greater flexibility with respect to these fixed effect choices. The choice of industry aggregation for the importer-industry-year fixed effects does not make a material difference in this sample.[10]

Finally, column 9 shows the results with exporter-level clustering. The labor productivity and export development of industries within countries may be correlated with each other due to the presence of general-purpose technologies, learning-by-doing (e.g., Irwin and Klenow 1994), and similar factors, and Feenstra and Rose (2000) show how the export ranges of countries can change over time in systematic ways across industries. Clustering at the exporter level allows for greater covariance across industries in this regard, returning lower standard errors. Most papers in this literature use robust standard errors on cross-sectional data, which would translate most closely to bilateral-route clustering in a panel model. Unreported estimates consider bilateral-route clustering and alternatively bootstrapped standard errors, and these standard errors are smaller than those reported in column 9.

Further extensions are contained in tables S3 and S4. Interacting our core regressor with the GDP/capita level of the exporter suggests that the OLS link between productivity and exports is mainly through lower-income countries, suggestive of higher trade due to varieties among developed economies. It is similar to the conclusion of Fieler (2011) that trade among advanced economies links to product differentiation and variety (low θ), while trade among emerging economies links more closely to fundamental productivity levels (higher θ). By contrast, there is limited heterogeneity by country size or geographic distances, excepting the fact that the growth in exports is not simply happening to bordering countries. Additional tests further confirm that the observed role for technology within manufacturing is not due to specialized factor accumulations and a Rybczynski effect. Under the Rybczynski effect, the accumulation of skilled workers in country *i* shifts country *i*'s specialization toward manufacturing industries that employ skilled labor more intensively than other factors. When incorporating country-specific time trends for subgroups of manufacturing industries according to their capital-labor ratio, mean wage rate, and non-production worker share as evident in the United States, technology's importance is confirmed. Finally, there is limited adjustment on the extensive margin of trade routes compared to the intensive margin adjustments.

Base IV Results

Table 3 presents the core IV results. The first column reports the first-stage estimates of how $\Delta\ln\,(M_{it}^{k})$ predicts $\Delta\ln\,(\tilde{z}_{it}^{k})$. The first-stage elasticity in panel A is 0.6, suggesting a 10% increase in the technology flow metric from the United States predicts a 6% increase in labor productivity abroad at the exporter-industry level. The unweighted estimates in panel B suggest a smaller 3% increase. While the second elasticity is lower, the instrument generally performs better in the unweighted specifications due to its more precise measurement. The F statistics in panels A and B are 4.7 and 11.6, respectively. The sample weights in panel A place greater emphasis on larger and more advanced countries that have large export volumes (e.g., Germany, Japan). While this framework finds a substantial response, the weighted

10 This extra check also has the advantage of linking the two studies closer together since the Kerr (2008) paper focuses extensively on productivity growth due to technology transfer. Stability to the somewhat different data preparation steps in Kerr (2008) is comforting.

Table 3. IV estimations of labor productivity and exports

	First-stage estimation (1)	Reduced-form estimation (2)	IV estimation (3)
	Panel A: Weighting bilateral routes by the interaction of exporter and importer trade in industry		
	DV: Δ Log country-industry labor productivity	DV: Δ Log bilateral exports	DV: Δ Log bilateral exports
Δ Log estimator for technology flows from the United States	0.589**	0.938***	
	(0.272)	(0.298)	
Δ Log country-industry labor productivity			1.592**
			(0.637)
Observations	103,839	103,839	103,839
Importer-Industry-Yr FE	Yes	Yes	Yes
Exporter-Importer-Yr FE	Yes	Yes	Yes
	Panel B: Excluding sample weights		
	DV: Δ Log country-industry labor productivity	DV: Δ Log bilateral exports	DV: Δ Log bilateral exports
Δ Log estimator for technology flows from the United States	0.267***	0.648***	
	(0.078)	(0.112)	
Δ Log country-industry labor productivity			2.429***
			(0.791)
Observations	103,839	103,839	103,839
Importer-Industry-Yr FE	Yes	Yes	Yes
Exporter-Importer-Yr FE	Yes	Yes	Yes

Notes: See Table 1. The instrument combines panel variation on the development of new technologies across US cities during the 1975–2000 period with historical settlement patterns for migrants and their ancestors from countries that are recorded in the 1980 Census of Populations. The F statistics in Panels A and B are 4.7 and 11.6, respectively.

Source: Author's analysis based on data described in text.

dependency of this group on heterogeneous technology transfer from the United States is noisier than in the unweighted estimations that emphasize more developing and emerging countries.

The second column presents the reduced-form estimates where $\Delta\ln\,(M_{it}^{k})$ predicts $\Delta\ln\,(\tilde{x}_{ijt}^{k})$ using a format similar to equation (3). In both panels, there is substantial reduced-form link of technology flows to export volumes. The interquartile range in the reduced form, conditional on the fixed effects, can account for around 6% of the interquartile range of export growth using a 0.8 coefficient estimate that sits in between panels A and B.

The third column provides the second-stage estimates from equation (3) having used $\Delta\ln\,(M_{it}^{k})$ to predict $\Delta\ln\,(\tilde{z}_{it}^{k})$. In panel A's estimation, the weighted elasticity is 1.6, suggesting a 16% increase in export volumes for every 10% increase in labor productivity. In panel B's unweighted estimation, the 10% increase in labor productivity is linked to a 24% increase in export volumes. The second-stage elasticity in panel B is larger than in panel A, as the IV estimates provide the reduced-form scaled up by the first-stage effects. Thus, even though the unweighted reduced-form estimate in column 2 is smaller than the weighted reduced-form estimate, this ordering reverses once scaled-up by the first stages.

This study does not overly favor one set of estimates. The weighted and unweighted approaches both have merits and liabilities. Instead, the conclusion from this work is that the instrumented elasticity is in the neighborhood of two. While it is impossible to differentiate among the various reasons as to why the IV estimates are larger than the OLS estimates, a very likely candidate is that OLS suffers from a substantial downward bias due to measurement error in the labor productivity estimates, especially with the substantial differencing embedded in equation (3). While it is likely that omitted factors or reverse causality influenced the OLS estimations as well, these appear to have been second-order to the measurement issues.[11]

This instrumented θ elasticity is at the lower end of the estimates provided in the literature. Costinot et al. (2012) is the closest comparison given their use of industry-level regressions of productivity data and trade. Using a cross-sectional analysis of producer price data for OECD countries in 1997, they derive their preferred estimate of 6.5, which is substantially larger than this study's estimate of about two. On the other hand, Costinot et al. (2012) derive a quite similar elasticity of 2.7 when they consider labor productivity metrics, the metric considered here. They too have IV estimates that are considerably larger than OLS estimates. More broadly, Eaton and Kortum (2002) provide larger initial estimates of the θ elasticity, with a preferred estimate in the range of eight. Simonovska and Waugh (2014a) revisit these results with a new estimator and come to a preferred estimate of about four. Overall, this study's estimates are again lower than this connected work. The robustness checks described below find θ estimates that continue in this ballpark, never exceeding four. Thus, this empirical approach consistently derives θ estimates that are among the lowest in the literature, with some part of this difference due to methodology but an important part being substantive in interpretation.

It is important to identify the dual meaning of the higher IV results compared to OLS with respect to the θ parameter. In the Ricardian model, a higher θ parameter corresponds to a reduced scope for intraindustry trade due to comparative advantages across varieties. IV estimations thus suggest that OLS specifications overestimate the scope for intraindustry trade because they understate the link between country-industry productivity improvements and their associated export volumes. Both impetuses can be connected to Ricardian theories of comparative advantage for trade, but the role of the structural θ parameter needs to be carefully delineated. This partitioning can also have important consequences for views of development and export success. Compared to OLS, the IV results shift more emphasis toward fundamental country-industry productivity improvements rather than intraindustry varieties; yet, on the whole, the overall work in this paper with emerging economies provides more support for intraindustry varieties than typically found in the Ricardian literature that has focused mostly on OECD trade flows (as evidenced by the lower θ estimates compared to prior studies).

These estimates are significant in terms of their potential economic importance and explanatory power. Using an elasticity of two, the interquartile range of country-level labor productivity growth, conditional on fixed effects, can explain up to 35% and 39% of the interquartile range in conditional export growth levels using unweighted and weighted specifications, respectively.

Extended IV Results

The online supplement provides many robustness checks on these IV estimations in tables S5-S8b. The results are robust to the various specification checks conducted in table 2. Moreover, dynamic estimations find lagged productivity growth estimators consistently stronger than contemporaneous productivity growth estimators, providing comfort in the estimation design and the proposed causal direction of the results. The IV is further analyzed when: (i) considering variations on the city-industry technology trend terms and cross-sectional distributions used to weight US cities for the development of M_{it}^k; (ii) sample composition exercises that aggressively test for data quality and reverse causality concerns; and (iii) direct inclusion of ethnic patenting in the United States as a control. The online supplement also

11 Costinot et al. (2012) adjust export volumes for trade openness using the import penetration ratio for a country-industry (to link observed productivity to "fundamental productivity"). The estimates are very similar when undertaking this approach, being 1.163 (0.457) and 2.513 (1.138) for weighted and unweighted specifications, respectively. The unadjusted and adjusted first differences have a 0.93 correlation. This approach is not adopted for the main estimations due to worries about mismeasurement in the import penetration ratio when combining UNIDO and WTF data.

contains an extended discussion of the identification achieved in this study and its limitations. In the end, the paper is able to make substantial progress toward causal identification in a Ricardian model, beginning with the panel estimation approach and extending through many IV approaches. This effort remains incomplete, however, and it is hoped that future work both identifies natural experiment settings to test these arguments and also identifies other forms/impetuses for heterogeneous technology transfer that can provide identification in a setting that focuses on large country-industry samples like this one.

IV. 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 United States through ethnic migrant networks to make additional headway. Estimations find bilateral manufacturing exports respond positively to growth in observable measures of comparative advantages. Ricardian technology differences are an important determinant of trade in longitudinal changes in addition to their cross-sectional role discussed earlier.

Leamer and Levinsohn (1995) argue that trade models should be taken with a grain of salt and applied in contexts for which they are appropriate. This is certainly true when interpreting these results. The estimating frameworks have specifically sought to remove trade resulting from factor endowments, increasing returns, consumer preferences, and so on, rather than test against them. Moreover, manufacturing exports are likely more sensitive to patentable technology improvements than the average sector, and the empirical reach of the constructed dataset to include emerging economies like China and India heightens this sensitivity. Further research is needed to generalize technology's role to a broader set of industrial sectors and environments.

Beyond quantifying the link between technology and trade for manufacturing, this paper also serves as input into research regarding the benefits and costs of emigration to the United States for the migrants' home countries (i.e., the "brain drain" or "brain gain" debate). While focusing on the Ricardian model and its parameters, the paper establishes that the technology transfers from overseas migrants are strong enough to meaningfully promote exports. Care should be taken to not overly interpret these findings as strong evidence of a big gain from migration. The paper does not seek to establish a clear counterfactual in the context of immigration from the source countries' point of view (e.g., Agrawal et al. 2011). As such, the positive export elasticities due to US heterogeneous technology diffusion do not constitute welfare statements relative to other scenarios. Future research needs to examine these welfare implications further.

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