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China's Local Comparative Advantage

James Harrigan and Haiyan Deng

3.1 Introduction

China's trading pattern is often seen as an illustration of the power of the Heckscher-Ohlin approach to explaining world trade: labor abundant China specializes in exporting labor-intensive goods. A broader Heckscher-Ohlin worldview is also perfectly consistent with China's role in performing the labor-intensive tasks in complex international supply chains.

In this paper, we draw attention to a different determinant of China's comparative advantage: her geographical location. We present theoretical models of global bilateral trade that build on the work of Eaton and Kortum (2002) and Harrigan (2006), which show how China's location influences her competitiveness in different markets around the globe, that is, China's "local comparative advantage." The model also shows how the rise of China differentially affects the competitiveness of other low-wage economies.

A key prediction of the theory is that relative transport costs by product and export destination influence China's export success. In particular, the model predicts that China will tend to export "heavy" goods (those with a high transportation cost as a share of value) to nearby export destinations and will export "light" goods to more distant markets. Furthermore, heavy

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goods will be sent by ship, while light goods may be shipped by air. Our empirical analysis, which looks at highly detailed Chinese export data in 2006, confirms this prediction of the model: the weight of China's exports is strongly related to distance.

The gravity equation, a relationship between aggregate trade volumes, country size, and distance, is extremely well established empirically and theoretically. Recent research on the trade-distance nexus has started to move beyond the aggregate gravity model and looks at disaggregated trade in theory and in the data. Relevant papers include Baldwin and Harrigan (2007), Deardorff (2004), Evans and Harrigan (2005), Harrigan (2006), Harrigan and Venables (2006), Hummels (2001), Hummels and Klenow (2005), Hummels and Skiba (2004), and Limão and Venables (2002). This line of research has two related purposes: better understanding the effects of distance and transport costs and enriching our models of comparative advantage. The current paper shares these purposes, along with the goal of better understanding China's comparative advantage in particular. In this it is, we hope, complementary to the other papers in this volume.

3.2 Theory

In this section, we present a general equilibrium model of bilateral trade in a multilateral world where relative distance is a key determinant of comparative advantage. Before moving to an exposition of the model, we introduce the interaction between specific trade costs and trade flows in partial equilibrium.

3.2.1 Partial Equilibrium

The simplest explanation for a relation between export prices and distance is the so-called Washington apples effect, which is the basis of the paper by Hummels and Skiba (2004). The theory starts with the observation that per-unit transport costs depend primarily on physical characteristics rather than value; that is, they are specific rather than ad valorem.

Focusing on a single exporting country, the relationship between import and export prices is given by

$$(1) \qquad p_{ic}^{M} = (1 + t_{ic})\, p_{ic}^{X},$$

where p_{ic}^{M} is the cost, insurance, and freight (c.i.f.) import price of good i shipped to country c, p_{ic}^{X} is the free-on-board (f.o.b.) export price, and $t_{ic} \geq 0$ is the cost of transport per dollar of value shipped.[1] The usual "iceberg" assumption is that t_{ic} is a function of distance only. This implies that per-unit

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[1] The constant returns-to-scale assumption that per-unit transport costs are independent of the number of units shipped is inessential.

transport costs are proportional to value and independent of weight, but Hummels and Skiba (2004, table 1) show that the opposite assumption is closer to the truth. Thus, a more realistic assumption about transport costs per dollar of value shipped is that they are given by

$$t_{ic} = \frac{t(w_i, d_c)}{p_{ic}^X}, \tag{2}$$

where w_i is weight per unit, d_c is the distance between the exporter and country c, and the function t is nondecreasing in both arguments. In the remainder of the paper, it is appropriate to interpret w as any physical characteristic of the good (such as volume and perishability, in addition to weight in kilos) that affects shipping costs. The specification in equation (2) has the key implication that shipping costs as a share of f.o.b. price are smaller for higher-priced goods, controlling for weight.

Now consider a high-priced good H and a low-priced good L, and let $\tilde{p} = p_H/p_L$ denote the price of H in terms of L. Equations (1) and (2) imply that the relative import price of the two goods in country c is

$$\tilde{p}_c^M = \tilde{p}^X \frac{(1 + t_{Hc})}{(1 + t_{Lc})} = \tilde{p}^X \frac{[1 + t(w_H, d_c)/p_H^X]}{[1 + t(w_L, d_c)/p_L^X]}. \tag{3}$$

If the two goods weigh the same, then the high priced good has lower transport costs as a share of f.o.b. price, and the ratio of transport factors in equation (3) will be less than 1, so $\tilde{p}_c^M < \tilde{p}^X$. The law of demand then implies that relative consumption of H will be higher in country c than at home. This is precisely the "shipping the good apples out" effect: good apples and bad apples weigh the same, but it is cheaper as a share of value to ship out the good apples.[2]

The strength of the Washington apples effect is increasing in distance.[3] The intuition is simple: as per-unit transport costs increase with distance, the importance of any difference in f.o.b. prices shrinks.

A similar comparison can be made by reinterpreting the subscripts in equation (3). Now let H and L stand for "heavy" and "light," respectively. Then H will be relatively more expensive in c than at home ($\tilde{p}_c^M > \tilde{p}^X$), with obvious effects on relative consumption. The effect of increasing distance on the strength of this weight effect is, in general, ambiguous and depends

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[2] The antique textbook by Silberberg (1978, chapter 11) has a clear discussion of the Washington apples effect, including some caveats when there are more than two goods.

[3] To see this, note that

$$\frac{\partial \tilde{p}^M}{\partial d_c} = \frac{p_L^X - p_H^X}{(p_L^X + t)^2} \frac{\partial t}{\partial d_c} \le 0.$$

In the limit as transport costs go to infinity, f.o.b prices are irrelevant, and the c.i.f. relative price is unity.

on details of the transport cost function $t(w_i, d_c)$.[4] In the case where $t(w_i, d_c)$ has constant elasticities with respect to distance and weight, the effect of greater distance is to amplify the importance of any differences in weight for import prices. Economic intuition suggests that this will be the normal case, unless $t(w_i, d_c)$ increases more rapidly with distance when evaluated at w_L than when evaluated at w_H in some relevant range.

These results about the effect of transport costs on import prices can be restated in terms that will be relevant to our empirical analysis, where we look at variation in export prices from China to different destinations. In our analysis, we will consider narrowly defined product categories that, nonetheless, may comprise many different goods with differing unit values and different weights per unit.

First, the Washington apples effect implies a composition effect: because high-quality goods will be relatively less expensive at greater distances, we should expect higher average unit values across countries as a function of distance.

Second, goods with the same value per unit that differ in weight are subject to the weight-composition effect: distance raises the relative price of heavy goods, which will cause the value-weight ratio to be increasing in distance. Clearly the Washington apples effect and the weight-composition effect are closely related. Indeed, if goods within a category differ only in their value and not their weight, then unit values are proportional to the value-weight ratio, and the two effects are identical.

A final composition effect comes from differences in demand across importers. If higher-income countries demand proportionately more higher-quality goods, or if Chinese exporters price discriminate against high-income importers, then we would also expect a positive association between importer per capita income and average export unit values from China. See Hallak (2006) for evidence on the relation between income per capita and the demand for quality and Feenstra and Hanson (2004) for some evidence on price discrimination in Chinese exports.

3.2.2 General Equilibrium

The Washington apples effect offers a useful starting point for thinking about the effect of specific trade costs on trade patterns, but because it takes f.o.b. prices as given, it cannot be considered a model of trade. Here, we embed the partial equilibrium mechanism in a general equilibrium model

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[4] The relevant cross second derivative is

$$\frac{\partial^2 \tilde{p}^M}{\partial w_H \partial d_c} = \frac{-1}{[p_L^X + t(w_L, d_c)]^2}\left[\frac{\partial t(w_H, d_c)}{\partial w_H}\,\frac{\partial t(w_L, d_c)}{\partial d_c}\right] + \frac{1}{p_L^X + t(w_L, d_c)}\,\frac{\partial^2 t(w_H, d_c)}{\partial w_H \partial d_c}.$$

The first term is negative, and the second term is positive, so this derivative cannot be signed.

to address the question: how does China's position on the globe influence its trade pattern?

Our model has N countries, one factor of production (labor), and a continuum of final goods produced under conditions of perfect competition. Goods are symmetric in demand and in expected production cost. Physical geography is unrestricted and summarized by the matrix of bilateral distances with typical element d_{cb} denoting the distance between countries b and c. As in Eaton and Kortum (2002), firms located in each country compete head-to-head in every market in the world, with the low-cost supplier winning the entire market. A firm's cost in a particular market depends on its f.o.b. price and on transport costs between the firm's home and the market (this cost is normalized to zero if the market in question is the home market). By perfect competition, f.o.b. price equals the wage divided by unit labor productivity, which is stochastic. Firms located in c have productivity distributed according to the Fréchet distribution with parameters $T_c > 0$ and $\theta > 1$.

As in Harrigan (2006), consumers value goods that are delivered by air more than goods delivered by ship. Some of the reasons for such a preference are analyzed by Evans and Harrigan (2005) and Harrigan and Venables (2006), but for the purposes of this model, we will simply suppose that utility is higher for goods that arrive by air. Let the set of goods shipped by air be A, with measure also given by A. Utility is

$$U[x(z)] = \int_{z\in A} a \ln x(z)dz + \int_{z\notin A} \ln x(z)dz, \tag{4}$$

where $a > 1$ is the air-freight preference, x is consumption, and $z \in [0,1]$ indexes goods. An implication of equation (4) is that for a given good, the relative marginal utility if it arrives by air versus ship is a.

We now consider the problem of an exporter in c choosing the optimal shipping mode for selling in b. Let $\tau^A_{cb}[w(z), d_{cb}] \geq 1$ be the iceberg shipping cost for air shipment of good z from c to b, with $\tau^S_{cb}[w(z), d_{cb}]$ defined similarly for surface shipment. Given the premium a that consumers are willing to pay for air shipment, the optimal shipping mode is

$$\tau_{cb}\,(z, d_{cb}) = \tau^A_{cb}[w(z), d_{cb}] \text{ if } \frac{\tau^A_{cb}[w(z), d_{cb}]}{a} \leq \tau^S_{cb}[w(z), d_{cb}] \tag{5}$$

$$\tau_{cb}\,(z, d_{cb}) = \tau^S_{cb}[w(z), d_{cb}] \text{ otherwise.}$$

What are the properties of the transport cost functions? First, order goods by weight, with $z = 0$ being the lightest and $z = 1$ the heaviest. We will make three assumptions about the transport cost functions $\forall b, c, z \in [0,1]$:

Air shipping is expensive

$$\tau^S_{cb}[w(z), d_{cb}] \leq \tau^A_{cb}[w(z), d_{cb}] \tag{6}$$

Air shipping is proportionately more expensive for heavier goods

$$(6') \qquad \frac{\partial \ln \tau^{S}_{cb}}{\partial \ln z} \leq \frac{\partial \ln \tau^{A}_{cb}}{\partial \ln z}$$

The cost disadvantage of air shipment declines with distance

$$(6'') \qquad \frac{\partial \ln \tau^{S}_{cb}}{\partial \ln d_{cd}} \geq \frac{\partial \ln \tau^{A}_{cb}}{\partial \ln d_{cd}}$$

The truth of the first assumption, that air shipment is always more expensive than surface shipment, is obvious to anyone who has ever traveled or shipped a package. The second assumption, that surface shipping costs increase more slowly with weight than air costs, is also reasonable and is consistent with light goods being much more likely to be shipped by air (see Harrigan [2006, table 10] for statistical confirmation of this commonplace observation). The final assumption is consistent with the fact that air shipment is almost never used on short distances. Assumption (6″) is also consistent with a model of a demand for timely delivery: for short distances, timely delivery can be assured by (cheap) surface shipment, while for longer distances only (costly), air shipment can ensure timeliness.

For any pair of countries, the optimal shipping mode will be a function of weight. It is possible that even the lightest goods will be shipped by surface, and it is also possible that even the heaviest goods will be shipped by air. But the normal case in world trade is that some goods are shipped by each mode (e.g., for U.S. trade in 2005, every exporter except Sudan sent some goods by air and some by surface). Let $\bar{z}_{cb}$ denote the dividing line between air-shipped goods ($\bar{z} \leq z_{cb}$) and goods shipped by surface ($\bar{z}_{cb} < z$) in trade between c and b. By assumption (6″), the cutoff will be lower for nearby countries than for faraway countries. These relationships are illustrated in figure 3.1 for exports from China to two countries, one near and one far. In the figure, we illustrate assumption (6′) by having surface transport costs unrelated to weight, while air transport costs are increasing in weight.

As noted in the previous section, the iceberg assumption is not realistic and rules out the important Washington apples effect on relative c.i.f. prices. It was also noted that the Washington apples effect and the weight-composition effect are very closely related. In the specification used in the current section, a Washington apples-like effect appears through the influence of weight on transport costs. Because of symmetry in supply and demand, expected f.o.b. prices from a given exporter are the same for all goods, but c.i.f. prices differ due to differences in weight.

We now turn to a discussion of the trade equilibrium. As discussed in Harrigan (2006), wages in each country c are endogenous and will be determined by the aggregate productivities T_c, labor supplies, and bilateral distances. In this paper, we analyze a single country's exports across its trading partners and, thus, can treat wages as fixed.

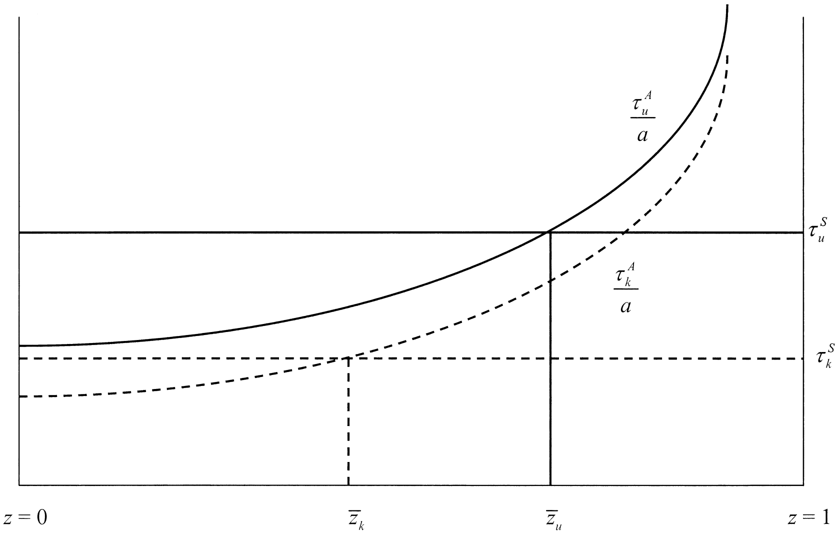

Fig. 3.1 Optimal transport mode choice for Chinese exporters

Notes: The vertical axis is iceberg transport cost factor, and the horizontal axis indexes weight from lightest ($z = 0$) to heaviest ($z = 1$). Country k (Korea) is relatively close to China, while country u (United States) is further away. The horizontal lines are surface transport costs, and the upward sloping lines are air transport costs relative to the air preference parameter a. The vertical lines show the division between optimal mode choices for the two destinations. See text for further discussion.

In keeping with the focus of the paper, we will consider China's probability of successfully competing in different markets and in different goods. In the Eaton-Kortum (2002) model, the probability that China will supply a given market b is the same for all goods (their equation (8), 1748). In the current model, the probability varies and will depend on $\tau_{cb}(z, d_{cb})$ for all countries c. With this modification, the Eaton-Kortum logic goes through otherwise unchanged, so the probability that China will supply good z to country b is

$$(7) \qquad \pi_{Cb}(z) = \frac{T_C[w_C\tau_{Cb}(z, d_{Cb})]^{-\theta}}{\sum_{c=1}^{N} T_c[w_c\tau_{cb}(z, d_{cb})]^{-\theta}} = \frac{T_C[w_C\tau_{Cb}(z, d_{Cb})]^{-\theta}}{\Phi_b(z)}.$$

The summation in the denominator $\Phi_b(z)$ in equation (7) includes country b, which reflects the fact that good z might be produced domestically rather than imported.[5] The economics of equation (7) is fairly simple. The probability that China successfully captures the market for good z in country b depends positively on China's absolute advantage T_C and negatively on

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[5] Here and in what follows, we let C stand for China, while c is a generic index for any country.

China's wage and transport cost to b, relative to an average of world technology levels and wages weighted by transport costs to the same market.

3.2.3 Implications of Chinese Growth for China's Competitors

A great virtue of the Eaton-Kortum (2002) model is that it is a fully competitive general equilibrium model. Alvarez and Lucas (2007) point out that this implies that all the properties that are known about such models in general can be applied to Eaton and Kortum's model. However, the Eaton-Kortum model has no general analytical solution for equilibrium wages, which makes comparative static analysis problematic. In this section, we show that despite its analytical complexity, the model can be used to answer some important questions about how the rise of China affects the trade performance of China's competitors.

We begin by assuming costless trade. In this case, Alvarez and Lucas (2007) show (1744, equation [6.3]) that equilibrium wages are

$$w_c = \left(\frac{T_c}{L_c}\right)^{1/(1+\theta)},$$

where L_c is country c's labor force. National income is

$$Y_c = w_c L_c = T_c w_c^{-\theta} = \left(\frac{T_c}{L_c}\right)^{1/(1+\theta)} L_c = T_c^{1/(1+\theta)} L_c^{\theta/(1+\theta)} \tag{8}$$

Thus, national income is a geometric average of a country's technology level and its labor supply. Setting all transport factors = 1, substitution of equation (8) into equation (7) implies

$$\pi_{Cb}(z) = \frac{Y_C}{\sum_{c=1}^{N} Y_c}.$$

Thus, we have that in the frictionless case, the probability that China supplies a given good z to any country is simply China's share in global gross domestic product (GDP).

Now reintroduce transport costs, adopting for the purposes of this section the Eaton-Kortum (2002) assumption that transport costs do not differ across goods. For small transport costs, this will not affect national income much, so we can replace $T_c w_c^{-\theta}$ by Y_c in equation (7). This gives the following approximation to equation (7),

$$\pi_{Cb} \cong \frac{Y_C \tau_{Cb}^{-\theta}}{\sum_{c=1}^{N} Y_c \tau_{cb}^{-\theta}} \simeq \frac{Y_C \tau_{Cb}^{-\theta}}{\Phi}. \tag{9}$$

Since equation (9) is independent of z, we can integrate over z and reinterpret equation (9) as giving China's market share in country b. This result is useful because it links China's market share to observables. Because a change of subscripts makes equation (9) applicable to every country's sales in every other country, it also allows us to analyze how international competition is affected by Chinese growth.

By the same reasoning used to derive equation (9), we have the approximation

$$\Phi_b \cong \sum_{c=1}^{N} Y_c \tau_{cb}^{-\theta}.$$

This term is very similar to the country price indexes derived by Anderson and van Wincoop (2003). It is also close to what Harrigan (2003) defines as a country's "centrality" index, which is a GDP-weighted average of a country's inverse bilateral trade costs. It is larger the closer b is to big countries: Belgium will have a large value of Φ_b, while New Zealand will have a small value.

A natural way to consider the impact of China's growth on its neighbors in this model is to ask how an improvement in China's technical capability T_C affects China's export market share. The full general equilibrium effects on global wages and trading patterns of an increase in T_C cannot be found analytically, but we can get an approximate answer by treating China as a small country and by using the preceding approximations. Substituting equation (8) into equation (9), we have

$$(10) \qquad T_C \frac{\partial \pi_{Cb}}{\partial T_C} \cong \frac{1}{1+\theta} \pi_{Cb} (1 - \pi_{Cb}).$$

This expression says that a 1 percent improvement in T_C raises China's market share in all markets, but the largest gain comes where China's share is already large.[6] The effect on some other country k's market share in b when China grows is given by

$$(11) \qquad T_C \frac{\partial \pi_{kb}}{\partial T_C} \cong -\frac{1}{1+\theta} \pi_{Cb} \pi_{kb}.$$

Equation (11) states that the biggest market share losses are felt by countries that have large market share where China also has large market share.

Equations (10) and (11) show the impact effect of an increase in T_C before equilibrium adjustments in world wages and trade flows. As noted in the preceding, analytical solutions for these general equilibrium effects are not available, but we can conjecture some effects. Because the impact effect of Chinese growth is largest in markets where China already has a substantial presence, the increased competition from China will be felt most keenly in precisely these markets. By equation (7), these locations will be markets that are close to China and far from the rest of the world, such as East and Southeast Asia. With China's market share rising in these markets, other countries that sell there will suffer loss of market share given by equation (11), with consequent reductions in factor demand. These negative factor demand effects in export markets are, of course, balanced by the consumption gains from cheap Chinese imports at home, plus increased sales of home

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[6] To see this, note that $\pi_{Cb}(1 - \pi_{Cb})$ is increasing in π_{Cb} for $\pi_{Cb} < 0.5$, a condition that holds in the data $\forall b$.

produced products in the Chinese market, with the net effect on real income uncertain. This is an application of an old but sometimes neglected point from trade theory: in a multicountry trade model, technological progress in one country may lower real income in some other countries even as it raises global real income.

3.2.4 Testable Predictions for Chinese Export Data

The theory developed in the previous two sections generates testable predictions about Chinese export data. The simplest are given by equations (10) and (11), which predict how aggregate bilateral trade patterns will change with rapid growth in China. The predictions given by equations (10) and (11) are made holding transport costs and other countries' technology fixed, so even if the model were literally true, the change in trade patterns would be more complex than given by these partial derivatives. However, as we will see in the following, these simple equations turn out to be remarkably useful predictors of changing bilateral trade patterns in markets where China already had a foothold in the mid-1990s.

Turning to product-level data, we can use equation (7) to generate testable predictions about China's export unit values. For a given good z, increases in distance reduce the probability of export success. This is simply the usual gravity effect operating through the extensive margin.

Now consider some set of goods $Z \subseteq [0,1]$. For every good $z \in Z$, the extensive margin effect of distance is operative. However, given our characterization of trade costs in assumptions (6), (6′), and (6″), it is clear that the extensive margin effect is stronger for heavier goods. That is, as distance increases, the probability that a heavy good will be successfully exported decreases faster than the same probability for a lightweight good.

Next consider a heavy good and a light good $z^H, z^L \in Z$. If both goods are exported from China to some group of markets, the weight-composition effect discussed in section 3.2.1 is operative: the more distant the market from China, the greater the relative c.i.f. price of z^H and, thus, the greater the share of z^L in local consumption. If goods weigh the same $\forall z \in Z$, the (very similar) Washington apples logic will apply: high-quality goods will be "light" in the sense of having low shipping costs as a share of f.o.b. value, and, thus, their relative c.i.f. price will be lower, and consumption higher, in more distant markets. These are intensive margin effects because they describe how relative consumption of goods actually exported changes with distance.

With an understanding of how the extensive and intensive margins for goods $z \in Z$ operate as a function of distance, we can now answer the following question: how does the average unit value of exports vary with distance? From what we have just elucidated in the previous two paragraphs, the answer is clear, and we highlight it as the key empirical prediction that we will test when we look at disaggregated export data:

PREDICTION. *For a given set of goods, the average unit value of Chinese exports will be nondecreasing in distance, controlling for other determinants of the demand for quality.*

3.3 Data Analysis

We use two different data sources. Testing the aggregate predictions of equations (10) and (11) requires data on all bilateral trade flows in the world, and our source for this data is the International Monetary Fund (IMF) Direction of Trade Statistics. The IMF does not report data on Taiwan, so we supplement the IMF data from Taiwanese government sources.

To test the predictions about export unit values, we used highly disaggregated Chinese export data from 2006 (China Customs Statistics 1997–2007). Exports are reported by eight-digit Harmonized System (HS) code, importing country, province of origin, type of exporting firm (seven categories that we aggregate as state or collective-owned and private), type of trade (eighteen categories that we aggregate as ordinary, processing, and other), and transport mode (air and sea). Export destinations are classified by the location of the final consumer.

3.3.1 Market Share Changes

Our aggregate data includes bilateral trade among 212 countries, for potentially $212 \times 211 = 44{,}732$ bilateral relationships, many of which are tiny to the point of insignificance. Because our focus is on the rise of China, we restrict most of our attention to the twenty largest markets for Chinese exports, listed in table 3.1.

The model underlying equations (10) and (11) is a static, long-run model, so it is appropriate to test it using long-run changes in trade patterns. We look at changes between 1996 and 2006. The initial date was chosen because it is after the major changes in China's foreign trade regime that were implemented in 1993 to 1994, and before the 1997 Asia crisis that temporarily disrupted trade patterns. This ten-year period covers the era when China continued to liberalize trade, joined the World Trade Organization (WTO), grew at a fantastically rapid rate, and became a major factor in global trade.

The most effective way to evaluate the predictions of equations (10) and (11) is with a series of bivariate scatter plots. Figures 3.2 and 3.3 compare the actual change in China's share of export markets between 1996 and 2006 with the level predicted by China's market share in 1996. We calculate this predicted level neglecting the constant of proportionality $(1 + \theta)^{-1}$ because we have no data on θ. An implication is that the horizontal scale and magnitude of the slope in these charts is not meaningful.

Figure 3.2 shows that the simple model does a startlingly good job of predicting China's export expansion in her top twenty markets, with most of China's big markets lining up on almost a straight line through the origin.

Table 3.1 China's top twenty export markets, 2006

	Distance from Beijing	Exports ($ billions)	% exports sent by air
United States	11,154	203	19
Hong Kong	1,979	155	12
Japan	2,102	92	15
Korea	956	45	14
Germany	7,829	40	33
The Netherlands	7,827	31	22
United Kingdom	8,146	24	15
Singapore	4,485	23	35
Taiwan	1,723	21	26
Italy	8,132	16	9
Russia	5,799	16	7
Canada	10,458	16	12
India	3,781	15	17
France	8,222	14	26
Australia	9,025	14	14
Malaysia	4,351	14	35
Spain	9,229	12	9
United Arab Emirates	5,967	11	7
Belgium	7,969	10	14
Thailand	3,301	10	16

The simple correlation in this chart is 0.48, and the correlation weighted by 2006 export value is 0.77. The two biggest negative outliers are Hong Kong and Russia, where China had small falls in market share. A group of three large East Asian markets (Malaysia, Taiwan, and Thailand) are large positive outliers, probably reflecting their participation in processing trade that boosts gross trade far above the levels predicted by models of trade in final goods such as Eaton-Kortum (2002).

Figure 3.3 includes all of China's export destinations, and the basic message is the same as that of figure 3.2. The unweighted and value-weighted correlations between predicted and actual are 0.35 and 0.46, respectively. The two northeast outliers are Yemen and Mongolia, respectively.

Equation (11) in principle gives predictions for how every bilateral relationship in the world responds to the rise of China. According to the equation, the effect is increasing in China's market share, so we restrict our attention to changes that occur in China's top twenty markets. Figures 3.4, 3.5, and 3.6 show how the other big East Asian exporters (Korea, Taiwan, and Japan) saw their export shares change in China's top twenty markets between 1996 and 2006. In each case, the correlation between predicted and actual is positive, but the relationship is weaker than when looking at China's trade directly.

Figure 3.4 shows that Korea lost market share in Europe, Japan, Austra-

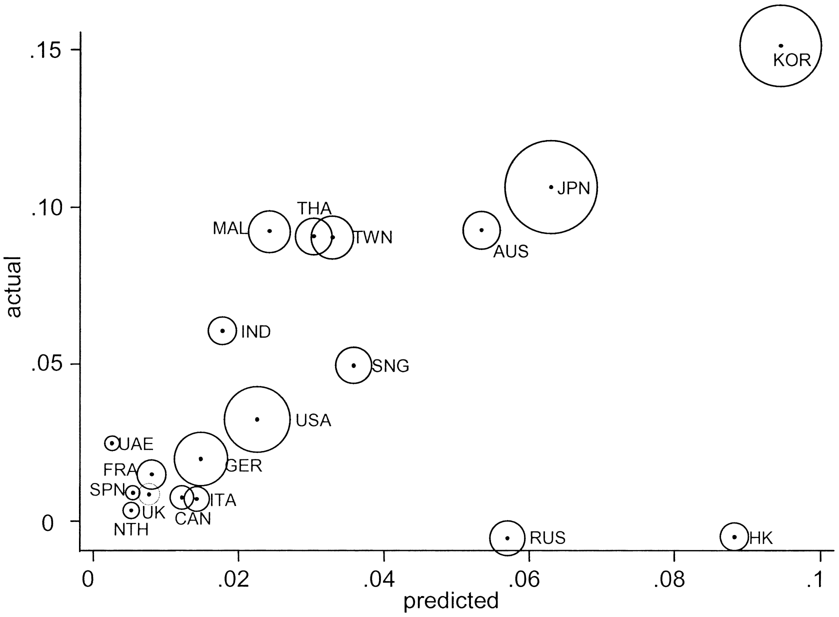

Fig. 3.2 Change in China's export market shares, 1996 to 2006, actual versus predicted, top twenty markets

Notes: Data is total bilateral trade, from International Monetary Fund (IMF) Direction of Trade Statistics (Taiwan data from Taiwan Government sources). Export market share is defined as the exporters share of the importer's aggregate imports. The size of circles is proportional to bilateral trade volume in 2006. Predicted values computed from 1996 trade shares, as given by equations (10)—figures 3.2 and 3.3—and (11)—figures 3.4, 3.5, and 3.6—in the text. Country abbreviations are as follows: USA = United States; UK = United Kingdom; BEL = Belgium; FRA = France; GER = Germany; ITA = Italy; NTH = The Netherlands; CAN = Canada; JPN = Japan; SPN = Spain; AUS = Australia; UAE = United Arab Emirates; TWN = Taiwan; HK = Hong Kong; IND = India; KOR = Korea; MAL = Malaysia; SNG = Singapore; THA = Thailand; RUS = Russia.

lia, and the United States, but had a big increase in trade with Taiwan and the United Arab Emirates. Figure 3.5 shows that Taiwan lost market share everywhere except Italy, but Taiwan's market share losses were much smaller than predicted with respect to Korea and Singapore and, to a lesser extent, Japan. As with figure 3.2, the Korea and Taiwan results are suggestive of the growing importance of processing trade among the middle-income East Asian countries.

Figure 3.6 shows that Japan lost market share in all of China's big export markets, with only trade with Australia holding up substantially better than predicted.

On the whole, the results illustrated in these charts show that the Eaton-Kortum (2002) model is a useful tool for organizing our thinking about

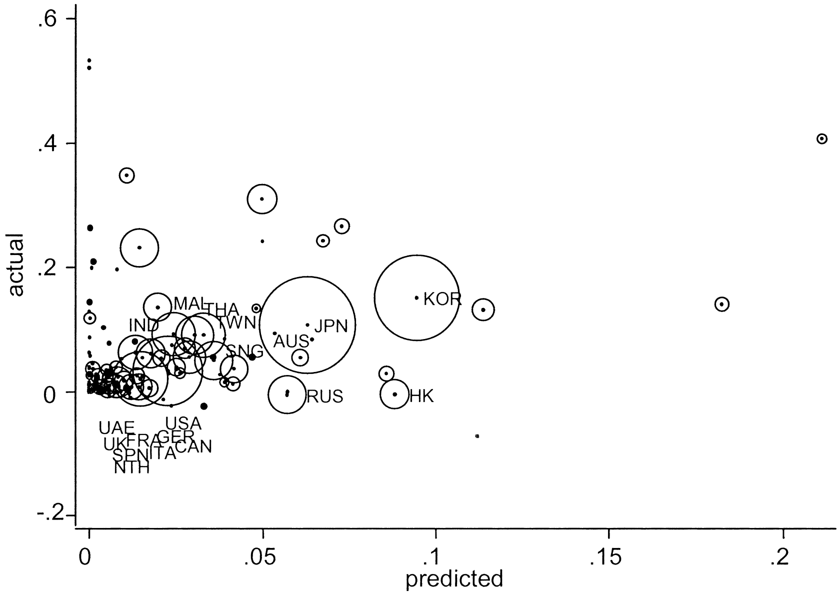

Fig. 3.3 Change in China's export market shares, 1996 to 2006, actual versus predicted, all markets

Note: See notes to figure 3.2.

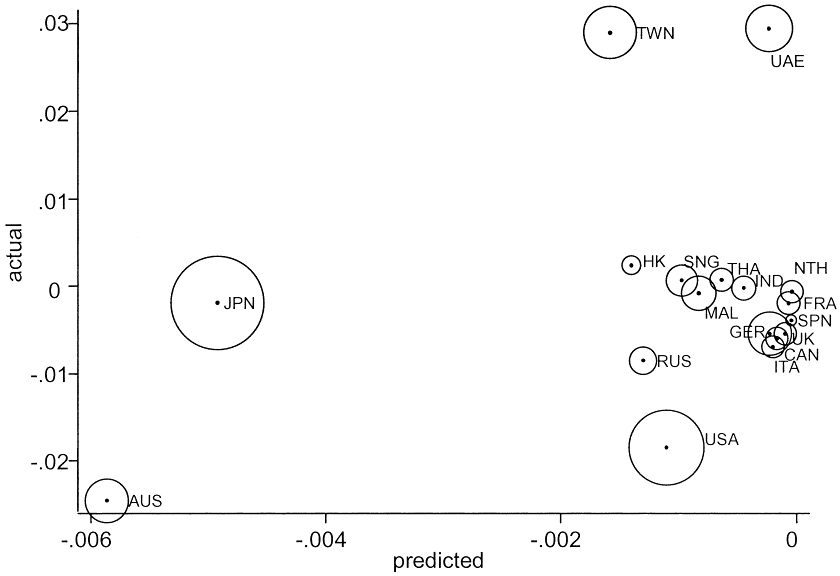

Fig. 3.4 Change in Korea's export market shares, 1996 to 2006, actual versus predicted, China's top twenty export markets

Note: See notes to figure 3.2.

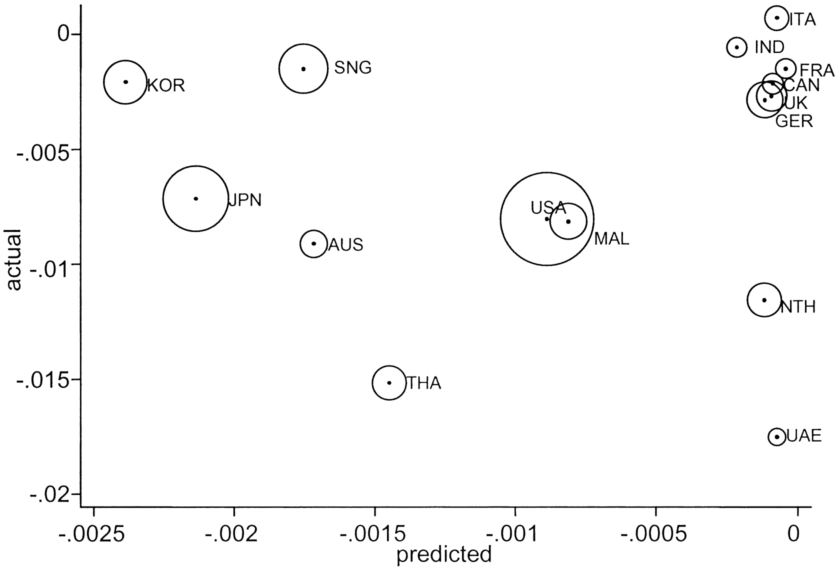

Fig. 3.5 Change in Taiwan's export market shares, 1996 to 2006, actual versus predicted, China's top twenty export markets (excluding Hong Kong)

Note: See notes to figure 3.2.

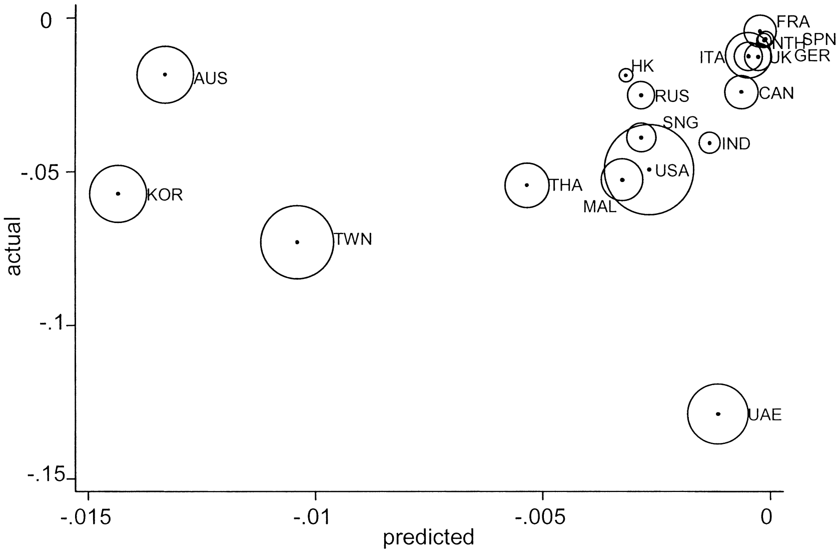

Fig. 3.6 Change in Japan's export market shares, 1996 to 2006, actual versus predicted, China's top twenty export markets

Note: See notes to figure 3.2.

changes in bilateral trade patterns. China's rise has had effects on its own market shares, and the market shares of its principal competitors, that are broadly consistent with the predictions of the model. The notable exceptions to this good fit are countries where China is involved in processing trade, where trade shares rose by more, or fell by less, than the Eaton-Kortum model would predict.

3.3.2 Specification of the Unit Value–Distance Relationship

As discussed in section 3.2.4, we are primarily interested in variation in Chinese export unit values across importing countries. The theory is silent about the appropriate degree of aggregation across products, and we would expect the composition effects to work across broad product categories: China should export heavy products to nearby markets and lighter goods to more distant markets. Nonetheless, there are two compelling reasons to analyze the predictions of the model using the most disaggregated data possible. The first reason is simply that different HS eight-digit categories are measured using different units, and it is literally meaningless to compare unit values measured as (for example) dollars/kilos and dollars/(number of shirts). The second reason is related, which is that there are systematic differences in unit values and per-unit transport costs even among goods measured in common physical units (e.g., dollars/[kilos of diamonds] and dollars/[kilos of coal]). Thus, in all specifications we will include product fixed effects that remove product-specific means and identify remaining parameters using solely cross-country variation.

Province of origin, transport mode, firm type, and trade type are characteristics of exports that are quite likely to be jointly determined with unit value and so cannot be considered exogenous to an equation that explains unit values. Feenstra and Spencer (2005) provide a model and analysis of Chinese export data that support this supposition although they focus on geographical variation within China rather than across China's export markets. These concerns motivate the following specification, where we pool across all characteristics of exports except product and destination:

$$\nu_{ic} = \alpha_i + \beta_d d_c + \beta_y y_c + \text{error}, \tag{12}$$

where

ν_{ic} = log unit value of exports of product i from China to country c.

α_i = fixed effect for eight-digit HS code i.

d_c = distance of c from Beijing.

y_c = log real GDP per capita of c in 2004.

The fixed effect α_i will remove any average differences in unit values across products so that the estimated distance elasticity is meaningful. Note that export values are measured f.o.b, so they do not include transport charges.

The model predicts $\beta_d > 0$: across importers within an eight-digit commodity category, China will sell higher unit value goods to more distant importers. As an additional control motivated by the results of Schott (2004), we include per capita GDP of the importing country.

Notwithstanding the preceding comments about the endogeneity of customs regimes and firm types, preliminary data mining reveals large differences in unit values associated with these categories. This suggests that pooling across all such categories as done in equation (12) may cause aggregation bias. To address this issue, we estimate a model that has separate intercepts and slopes for different customs regimes and firm types. Letting these categories be indexed by *j*, this model is

$$v_{ijc} = \alpha_i + \alpha_j + \sum_j (\beta_{jd} d_c) + \beta_y y_c + \text{error}. \tag{13}$$

We do not specify interactions on the GDP per capita variable because this effect is not our primary focus. Because of the endogeneity of the firm and trade type classifications, interpretation of the β_{jd}s in equation (13) will be more reduced form than the interpretation of β_ds in equation (12).

We measure distance in two ways. The first is simply log kilometers from Beijing to the capital of the importing country, using great-circle distance. The second breaks distance down into two categories:

1–2,500 km	Korea, Taiwan, Hong Kong, Japan
2,500+ km	Rest of world

The motivation for this split can be seen in figure 3.7 which compactly illustrates a number of patterns in China's exports. Because of the Pacific Ocean, there is a natural break in distance at 2,500 kilometers, with four large trading partners (Korea, Taiwan, Japan, and Hong Kong) being less than this distance from Beijing and most other important trading partners, in particular the United States and Western Europe, being at least 5,000 kilometers away. Note that the limitations of our great-circle distance data makes Western Europe seem much closer than it would be for an ocean-going freighter. This caveat is not relevant in regressions where we use the binary distance indicator.

As noted in the preceding, interpretability of regression coefficients is problematic in equations (12) and (13) as we are pooling across such disparate goods. To address this, we split the sample in a number of ways:

1. All observations
2. Observations where unit is a count and where the count is at least two
3. Observations where unit is kilos
4. All of the preceding cuts restricted to manufactured goods

In addition, for each regression, we drop trade flows below \$10,000 to dampen the measurement error that always plagues unit values.

Appropriate estimation of equations (12) and (13) requires careful atten-

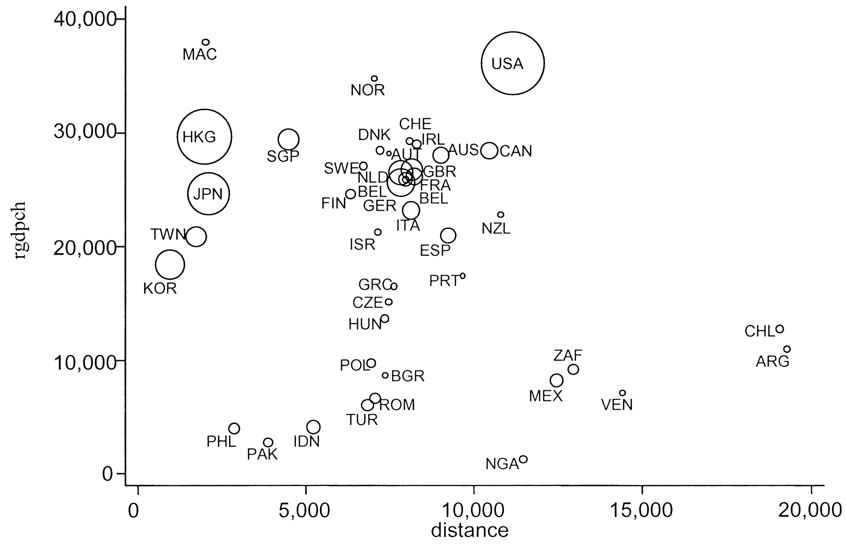

Fig. 3.7 China's export markets, 2006

Notes: The vertical axis is real GDP per capita, and the horizontal axis is distance in kilometers from Beijing. The size of circles is proportional to China's exports to indicated country. All markets where China sold at least $1 billion in 2006 are depicted.

tion to the structure of the data, which is an unbalanced panel with many (at least 1,500) products and relatively few (92) countries. The country-specific data are repeated many times in the sample, but the data does *not* have the structure of a "cluster sample" because each unit *i* has observations across many countries *c*. As discussed by Moulton (1990) and Wooldridge (2006), the appropriate estimator in such a model is random effects generalized least squares (GLS), where the random effects are country-specific. A refinement to GLS suggested by Wooldridge is to use a fully robust covariance matrix rather than assume spherical residuals, and we implement this in the following. Because we also have product fixed effects, our equations are estimated in a four-step procedure as follows:

1. Remove product-specific means from all the data using the within transformation.
2. Run pooled ordinary least squares (OLS) on the transformed data.
3. Quasi-difference the transformed data with respect to country-specific means, where the random effects quasi-differencing parameter $\phi \in [0,1)$ is a function of the OLS residuals from step 2.
4. Estimate the model on the quasi-differenced data by OLS, and calculate a robust covariance matrix.

Hansen (2007) shows theoretically that the robust covariance matrix for this mixed fixed effects-random effects model is consistent regardless of the relative size of the two dimensions of the panel. Hansen's Monte Carlo simulations confirm that the asymptotic formula is quite accurate for data dimensions substantially smaller than in our application.

In applying the preceding estimator to equation (13), we found that in every case, the estimated GLS quasi-differencing parameter ϕ was zero. Thus, for equation (13), the estimation technique is simply OLS with product fixed effects and a robust covariance matrix. We also estimated this equation using a different GLS procedure that allows for the error variance to differ by country. The GLS results were very close to the results of OLS with product fixed effects, so we do not report the GLS results to save space.

3.3.3 Estimation Results

Table 3.1 reports China's top twenty export destinations in 2006. While only 16 percent of Chinese exports are sent by air, there is wide variation across markets. The largest share of exports by air, 35 percent, goes to Malaysia and Singapore, a result that is suggestive of China's role in time-sensitive international production networks. A surprisingly (and suspiciously) high share of exports also goes to Hong Kong by air. See Feenstra et al. (1999) for a discussion of the difficulties of separating Chinese exports *to* Hong Kong and exports *through* Hong Kong. As always with aggregate international trade data, the importance of gravity (distance and country size) is clearly visible in table 3.1. We return to an analysis of the share of China's exports that are shipped by air in section 3.4.

Table 3.2 reports results of estimating various versions of equation (12). Focusing first on the full sample, the distance elasticity is 0.074, which is economically significant given the large variation in distance. But this effect is fragile across specifications ranging from 0.044 and statistically insignificant to 0.077. The indicator variable for distance greater than 2,500 kilometers is more consistent: in the full sample, the effect is to raise export unit values by 14.8 percent, and the effect ranges between 9.2 percent and 15.6 percent, depending on the sample. This effect is economically important but somewhat smaller than the distance effect on U.S. import unit values found by Harrigan (2006) and on U.S. export unit values by Baldwin and Harrigan (2007).

While it is not our main focus here, the small size and fragility of the effect of importer GDP per capita on unit values is striking, although consistent with the results of Baldwin and Harrigan (2007) on U.S. data. The overall effect of 0.04 to 0.06 is driven by a fairly large effect of 0.12 on goods measured in kilos and a near-zero effect for goods measured as a count.

Table 3.3 reports results of estimating two versions of equation (13). In the top panel, we show results with firm type interacted with the dummy "far," which is distance $>$ 2,500 kilometers (the excluded dummy is near x state and collective firms). The second panel show results with customs regime interacted with far (the excluded dummy is near x other trade). The effect of importer real GDP per capita on export unit values is consistent with table 3.2.

Table 3.2 **China export unit value regressions, 2006**

	All products					
	All units		Unit = count, >1		Unit = kilos	
Log importer GDP per capita	0.059	0.061	–0.038	–0.033	0.122	0.126
	(5.82)	(6.08)	(–1.88)	(–1.65)	(12.3)	(12.6)
Log distance	0.074		0.050		0.077	
	(6.09)		(1.39)		(6.54)	
Distance > 2,500 km		0.148		0.144		0.156
		(6.61)		(2.14)		(6.91)
Random effects ϕ	0.92	0.92	0.88	0.88	0.89	0.88
HS eight-digit fixed effects	6,820		1,951		4,334	
N	155,419		55,280		87,868	
	Manufacturing products only					
	All units		Unit = count, >1		Unit = kilos	
Log importer GDP per capita	0.040	0.043	–0.045	–0.040	0.117	0.120
	(2.81)	(3.03)	(–2.00)	(–1.78)	(7.86)	(8.03)
Log distance	0.058		0.044		0.039	
	(2.94)		(1.02)		(2.08)	
Distance > 2,500 km		0.135		0.143		0.092
		(3.52)		(1.75)		(2.43)
Random effects ϕ	0.91	0.91	0.89	0.89	0.86	0.86
HS eight-digit fixed effects	3,608		1,538		1,644	
N	95,534		43,477		41,497	

Notes: Independent variable is log Chinese bilateral export unit value by Harmonized System (HS) eight-digit code and importer. The statistical model controls for fixed product effects and random country effects. The median partial differencing parameter for the random effects transformation is ϕ. Robust *t*-statistics are in parentheses. Observations with export value less than $10,000 excluded from sample. GDP = gross domestic product.

The coefficients on the interactions in table 3.3 are somewhat hard to interpret, so we turn immediately to table 3.4, which reports the linear combinations of interest and associated test statistics from table 3.3. The top panel shows that the distance effect is positive and statistically significant for both types of firms, with the effect a bit larger for state/collective firms than for foreign/private firms. The second panel shows a relatively large and robust effect for ordinary trade of around 0.10. The effect for processing trade is small and positive for goods measured as a count and zero for goods measured in kilos. There is a large negative effect of distance for the trade regime category "other," which accounts for just 4 percent of total exports.

Summarizing the results of this section, we conclude that there is a small but robust positive relationship between distance and export unit values. The

Table 3.3 **China export unit value regressions, 2006, with trade type and firm type controls**

	All observations			Manufacturing observations		
	All	Count	Kilos	All	Count	Kilos
			Type of firm (state-collective and private-foreign)			
Log importer GDP per capita	0.067	–0.010	0.117	0.048	–0.023	0.113
	(27.3)	(–1.9)	(49.8)	(14.8)	(–3.9)	(34.0)
Far × state and collective firms	0.095	0.087	0.101	0.066	0.082	0.049
	(12.1)	(4.8)	(12.0)	(6.2)	(4.0)	(3.9)
Far × private and foreign firms	0.103	0.100	0.118	0.065	0.066	0.083
	(13.2)	(5.6)	(14.0)	(6.1)	(3.2)	(6.6)
Near × private and foreign firms	0.029	0.068	0.024	0.029	0.029	0.059
	(3.0)	(3.0)	(2.3)	(2.1)	(1.1)	(3.7)
HS eight-digit fixed effects	6,817	1,946	4,332	3,576	1,508	1,643
N	240,473	87,262	134,285	148,637	68,078	64,247
			Type of customs regime (ordinary, processing, and other)			
Log importer GDP per capita	0.053	–0.028	0.111	0.033	–0.037	0.103
	(19.3)	(–4.8)	(42.1)	(9.0)	(–5.6)	(27.1)
Far × ordinary trade	–0.498	–0.480	–0.506	–0.542	–0.392	–0.690
	(–30.2)	(–15.7)	(–26.2)	(–25.5)	(–11.9)	(–24.1)
Near × ordinary trade	–0.615	–0.570	–0.641	–0.627	–0.491	–0.760
	(–35.4)	(–17.1)	(–31.8)	(–27.8)	(–13.5)	–25.4
Far × processing trade	–0.267	–0.195	–0.334	–0.273	–0.158	–0.392
	(–15.9)	(–6.4)	(–16.9)	(–12.6)	(–4.7)	–13.3
Near × processing trade	–0.315	–0.304	–0.321	–0.331	–0.258	–0.402
	(–16.8)	(–8.6)	(–14.8)	(–13.5)	(–6.6)	–12.4
Far × other trade	–0.217	–0.226	–0.215	–0.227	–0.149	–0.311
	(–12.2)	(–7.0)	(–10.3)	(–10.0)	(–4.3)	–10.2
HS eight-digit fixed effects	6,817	1,949	4,331	3,575	1,511	1,642
N	230,937	88,823	125,089	144,104	68,714	61,013

Notes: This table reports results from twelve regressions. Independent variable is log Chinese bilateral export unit value by Harmonized System (HS) eight-digit code and importing country. All regressions have product fixed effects and importer random effects. Robust *t*-statistics are in parentheses. Observations with export value less than $10,000 are excluded from sample. GDP = gross domestic product.

relationship only disappears for processing trade where the units are kilos. We hesitate to overinterpret the results of tables 3.3 and 3.4 because customs regime, trade type, and export unit value are jointly determined.

3.4 Air Shipment and Chinese Exports

The model developed in sections 3.2.1 and 3.2.2 highlighted the importance of shipping mode choice in determining bilateral trade patterns. The keys to the mechanism are the assumptions on the transport cost functions given by equations (6), (6′), and (6″). Our empirical analysis of export unit

Table 3.4 **Effects of distance on China export unit value, 2006**

	All observations			Manufacturing observations		
	All	Count	Kilos	All	Count	Kilos
Far × state and collective firms	0.095	0.087	0.101	0.066	0.082	0.049
	(12.1)	(4.8)	(12.0)	(6.2)	(4.0)	(3.9)
(Far – Near) × private foreign firms	0.075	0.033	0.094	0.036	0.037	0.024
	(4.2)	(2.0)	(12.1)	(3.7)	(2.0)	(2.0)
(Far – Near) × ordinary trade	0.116	0.089	0.135	0.085	0.099	0.070
	(16.9)	(5.7)	(18.1)	(9.1)	(5.6)	(6.4)
(Far – Near) × processing trade	0.048	0.109	–0.014	0.058	0.101	0.010
	(4.4)	(5.3)	(1.1)	(4.0)	(4.3)	(0.5)
Far × other trade	–0.217	–0.226	–0.215	–0.227	–0.149	–0.311
	(–12.2)	(–7.0)	(–10.3)	(–10.0)	(–4.3)	(–10.2)

Notes: This table is based on table 3.3. Each cell represents the point estimate of a linear combination, and the test statistic (square root of a χ^2 test statistic) for the null that the linear combination equals zero. Robust *t*-statistics are in parentheses.

Table 3.5 **Shipment mode for Chinese exports, 2006**

	All firms	State and collective	Private and foreign
	A: Share of exports shipped by air		
All trade types	0.16	0.05	0.20
Ordinary	0.06	0.05	0.07
Processing	0.24	0.03	0.27
Other	0.14	0.11	0.17
	B: Share of total air shipments		
All trade types	1.00	0.07	0.93
Ordinary	0.16	0.05	0.12
Processing	0.80	0.01	0.79
Other	0.04	0.01	0.03

values in the previous section does not control for shipping mode because the core message of the model is that shipping mode and export unit value are jointly determined. Nonetheless, it is instructive to see how the air shipment choice is correlated with firm characteristics, which we do in table 3.5.

Panel A of table 3.5 is a cross-tab of firm type and customs regime and reports the share of exports in each cell that is shipped by air. Panel B of table 3.5 shows the share of total air shipments accounted for by each cell. The overall share of Chinese exports sent by air is fairly small at 16 percent, but this number masks a stark pattern: over 80 percent of air shipment is processing trade by private and foreign firms. Over a quarter of the value of trade in this cell is sent by air, while the air share in other cells is negligible.

Clearly, timely delivery is very important for this type of trade. We conjecture that the reason for this revealed preference for timely delivery is that with a multistage production process, the cost of delay increases very rapidly in the number of stages and the complexity of production.[7]

3.5 Conclusion

There is little doubt that China has an overall comparative advantage in labor-intensive goods. In this paper, we have argued that understanding Chinese trade also requires accounting for *local* comparative advantage: products where China has a competitive advantage in some locations but not others.

In our formulation of Deardorff's (2004) concept of local comparative advantage, we focus on cost differences due to differences in transport costs and the transport intensity (weight) of goods. In the theory section, we showed that China could be expected to have a comparative advantage in heavy goods in nearby markets and lighter goods in more distant markets. This theory motivates a simple empirical prediction: within a product, China's export unit values should be increasing in distance. We find strong evidence for this effect in our empirical analysis. Splitting up China's export markets into two groups, one nearby (Korea, Taiwan, Hong Kong, and Japan) and one further away, we find that the average unit value of exports sent beyond the nearby group is about 15 percent higher.[8]

We also showed that the Eaton-Kortum (2002) model implies that as China grows, it will gain market share most quickly in markets where it is already competitive, a prediction strongly supported by looking at the growth in China's aggregate bilateral export market shares between 1996 and 2006. A corollary is that China's competitors in export markets will be most squeezed where China starts out with a high market share, a prediction that finds some support in our analysis of how Korea, Taiwan, and Japan export performance has fared in the face of the China's expansion.

Beyond its relevance to Chinese trade, we believe this paper makes the broader point that trade economists should strive to escape the powerful field exerted by the gravity model. Understanding the effect of distance on economic activity is an important intellectual and policy issue, and much can be accomplished outside the simple gravity framework.

[7] Harrigan and Venables (2006) model this effect in detail.

[8] We refer here to the coefficients in the top panel of table 3.2.

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Comment

Chong Xiang

The explosive growth in China's trade with the rest of the world has been one of the hallmark events for globalization over the last decade. Looking ahead, will this growth continue? How will this growth affect China's neighboring countries and trading partners? In addition, which country and which industry will be affected the most? The authors have delivered timely and convincing answers to these questions that have gripped the attention of economists and policymakers alike from a novel angle: the role of geography and trade costs in shaping China's patterns of trade. Geography and trade costs are especially relevant for China's neighboring countries because these countries have different geographical locations relative to China and so are likely to face different degrees of competition from China.

To illustrate the role of geography, the authors consider trade costs that are proportional to weight and independent of value. There are "light," or high-quality goods, and "heavy," or low-quality goods. A super-premium delicious apple and a rotten apple may have very different values, but they cost the same to ship if they weigh the same. This suggests that light goods are more immune to the effects of trade costs over long distances so that China has a comparative advantage in light goods relative to heavy goods in distant markets. The authors deliver this point clearly and concisely in a partial-equilibrium setting.

The authors then consider a general-equilibrium setting à la Eaton and Kortum (2002), where every national market around the world is contended by firms located in each country and the lowest-cost firm wins the entire national market. The authors then rigorously show that as distance increases, the probability that China exports a heavy good decreases relative to the probability of exporting a light good; conditional on being successfully exported, the price of a heavy good increases relative to the price of a light good. Both imply that over long distances, light goods account for larger

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