Foreign Competition and Quality Sorting: Overlaps in U.S. and Chinese Exports

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Abstract

Using disaggregated data on U.S. exports for the period 1989-2006, unit values are calculated to assess the impact of Chinese third-party competition. Qualitative predictions are derived from a heterogeneous firms model where quality differences shape average price patterns in alternative ways (Johnson, 2012). Only a small fraction of products (accounting for a cumulative share of about 5.0% in U.S. exports) reveals significant results. Price competition appears to prevail if the effects are estimated both pooled over all products, and separately for each HS6 product category. Overall, effects seem to cancel out and be smaller in product categories with relatively high shares in the U.S. export basket. The primary transmission channel through which Chinese competition exhibits is thus the domestic economy.

JEL-Classification: C33, F12, F14, F6, L1
Keywords: China, Foreign competition, Unit values, Quality, High-dimensional fixed effects

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1 Introduction

China’s economic rise with two-digit growth rates for more than a decade and its expansion in international trade until it became the largest exporting nation of manufacturing products was accompanied by substantial changes also in its economic structure. Amiti and Freund (2010) document how the skill-content of China’s manufacturing exports increases although much of it goes back to processing trade. Nevertheless, the structure of China’s export basket looks more like that of a high-income country and overstates its actual level of GDP per capita (Rodrik, 2006). Popular debates raised concerns on how long the United States (and other high-income economies) can compete with China’s low-cost production, and whether they will eventually be surpassed. That discussion was also initiated by Samuelson (2004) and his claim that there could be adverse terms-of-trade effects if China develops its comparative advantage in high-skill and technology-intensive products. Empirical studies find adverse employment effects in the U.S. manufacturing industry due to Chinese competition (Autor et al., 2012), and that many firms have to struggle while the best firms innovate to escape competition (Bernard et al., 2006). This paper looks at systematic changes in U.S. export unit values conditional on China’s presence in foreign product-destination markets.

The approach of this paper follows the literature on spatial patterns of export unit values and applies their framework to within-market dynamics. A panel dataset containing information on U.S. and Chinese exports at the HS6 product level for the years 1989-2006 is used for the empirical analysis. While a significant negative effect of Chinese presence on U.S. export unit values can be found, it appears to be economically small. Only a cumulative average share of 5% of U.S. exports is affected at all. Individual products reveal positive and negative effects allowing to classify these goods as price- or quality-competing. Counting positive and negative effects reveals that they are more or less balanced so that direct competition within product-destination markets is negligible. Nevertheless, the average competitive intensity in a product category is another channel through which unit values are affected. Average U.S. exporters appear to sell at higher prices in products that are exported to many destinations also by China.

Besides extending the scope of the low-wage competition literature by comparing two large manufacturing exporters at different stages of economic development, the
paper seeks to take a next step also in the literature on price- and quality competition. While Baldwin and Ito (2011) and Johnson (2012) group products into competition modes across countries, a similar exercise is done for the within market dynamics. The paper therefore begins with a review of these literatures in Section 2, and of related data patterns in Section 3. A theoretical model is briefly introduced in Section 4. Section 5 describes the empirical procedure and alternative specifications. Results are presented in Section 6, followed by a short discussion and the conclusion (Section 7 and 8).

2 Related literature

Two strands of literatures are referred to in this paper. The first mostly features empirical evidence on low-wage country competition, while the second relates to the theory of firms in international trade.

2.1 Low-wage country competition

Scenarios in which competition effects are analyzed vary in terms of the type of data used and in terms of the dependent variables that are expected to be affected. In this paper, the scenario is most similar to that of Schott (2008): Chinese exports compete with exports of high-income countries. Schott compares product-level U.S. imports from China and OECD countries and finds the former selling at systematically lower prices (i.e. unit values). This is interpreted as a relatively lower sophistication of Chinese exports, and increasing unit values of imports from the OECD indicate quality upgrading by exporters from these countries. Schott concludes that standard measures of export similarity suggest a higher-than-actual degree of competition between the two groups of countries.

My approach uses U.S. export unit values as the dependent variable and compares their levels within product-destination markets in periods of Chinese presence and Chinese absence. Different levels in the two scenarios would confirm that Chinese and U.S. exports compete with each other. The comparison of Chinese with other countries’ exports yet mostly focused on other low- and middle-income, labor abundant exporters

1Kamin et al. (2006) and Broda and Weinstein (2010) find that Chinese market penetration lowers the importing country’s import-price index.
All of them find significant displacement effects through Chinese export growth and entry into similar product categories. China’s increasing skill-intensity and sophistication of exports, however, might affect also the patterns of exports in capital abundant high-income countries.

On the importer side, Chinese competition with domestic producers in high-income countries was analyzed by Bernard et al. (2006) for the U.S. and Bloom et al. (2011) for Europe. Firm level data allows identification of firm characteristics determining their ability to successfully compete. Size, age, capital- and skill-intensity, and the intensity in using information and communication technologies (ICT) are found to be critical. Firms’ ability to innovate (i.e. R&D spendings and patenting) or switching their product mix to less exposed categories increases the probability to survive. At the product level the number of firms would decrease and unit values would change accordingly to represent the average price of the remaining firms. Domestic competition with low-wage imports is an indirect channel through which export unit values can be affected. Stylized facts and a theory of firms in international trade helps to formulate a hypothesis for the direct effect exhibiting through low-wage third-party competition in export markets.

2.2 Firms in international trade

The documentation of firm level data, beginning with Bernard and Jensen (1995), paved the way for a new generation of theoretical models. Heterogeneity of firms in size, wages, productivity, sales, prices, and exporting status reveal stylized patterns. Larger firms are more likely to export, are more productive, pay higher wages, have higher sales, and charge higher prices. Only about 20 percent of the U.S. firms actually engage into exporting, while 90 of the shipments go to domestic destinations (Eaton and Kortum, 2010). Evidence from French firms suggests a negative relationship between the number of firms selling in a market and the distance of that market (Eaton et al., 2011). Similar findings are presented in Eaton et al. (2007) for Colombian exporters. At the product level, Baldwin and Harrigan (2011) point out a positive relationship between U.S. export unit values and distance to destination markets. Manova and Zhang (2012) confirm this pattern also for Chinese exports. Differentiating industries and individual products
Johnson (2012) and Baldwin and Ito (2011) show that coefficient signs for distance are not always positive. While on average distant markets are served with higher-price (i.e. higher quality) products, some sub-categories of exports sell at lower prices in more distant markets.

The workhorse models extend the framework of Melitz (2003) to include asymmetric countries in terms of their fixed entry costs, and quality valuation by consumers (Baldwin and Harrigan, 2011; Johnson, 2012). As product quality cannot be observed directly, a positive correlation between prices and quality is assumed or results from firms’ endogenous decision on the quality of their output by choosing a more expensive input mix. Consumers evaluate quality adjusted prices which correlate negatively with observed prices. To put the firm selection mechanism at work, firms are assumed to be in monopolistic competition, charging a constant mark-up over their unit costs, and facing a fixed cost of exporting. Variable cost of exporting are passed through to consumers so that a product has different prices in different destinations (C.I.F.) but the same price as it leaves the factory gate (F.O.B.). In distant markets the product is less competitive than in nearby markets because its price is relatively higher. For some firms it is therefore not worth exporting to distant markets because higher prices lower demand and eventually prevent firms from breaking even with the fixed exporting costs.

Selecting firms into exporting and inferring associated unit values of exports in product categories focuses mostly on cross-sectional patterns. The dynamics within markets are barely studied although the models feature variables that change over time and affect the competitive environment firms face in product-destination markets. Increasing third-party competition may affect respective local price levels or the fixed costs of exporting through higher marketing costs and force less competitive firms to exit.

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2 Positive price-quality correlation finds support from firm level studies on varying input prices. Firms purchasing more expensive inputs also charge higher prices for their outputs, which is assumed to reflect the better quality of the inputs used for production. Related evidence is documented for Colombia (Kugler and Verhoogen, 2012) and China (Manova and Zhang, 2012).

3 An exception is the study by Bas and Bombarda (2012) on the effects of China’s trade liberalization on the export patterns of French firms.
3 A glance at the data

I use data from the Center of International Data at UC Davis and the UN Comtrade database. The former provides information about U.S. exports at the disaggregate 10-digit HS level for the years 1989-2006 and allows calculation of unit values using the included quantity and unit measure information. The UN Comtrade database provides a record of countries’ reports about imports from China at the 6-digit HS level. U.S. exports are therefore aggregated to that level after unit value have been calculated. Combining the two datasets entails potential coding errors from using different generations of HS6 codes. I use concordance tables from the United Nations Statistics Division to map old into new codes whenever a HS6 category appears in the Chinese export record but has been discontinued in the U.S. data. The corrections works against an understatement of export overlaps due to different coding of identical product categories.

For the final sample, I removed observations where U.S. unit values could not be computed either because the U.S. did not export at all, or because the quantity information for an HS6 code was incomplete at the HS10 level, or because the quantity information was complete but measurement units differed across HS10 codes under a common HS6 header. In order to focus on manufacturing exports, I further removed observations with HS2 codes outside the interval 28-96, which corresponds to the sectors analyzed by Johnson (2012). Finally, partner country information was added from the CEPII gravity dataset, and only those countries remained in the sample which had complete records of GDP, GDP per capita, and distance in the years 1989 through 2006. These treatments leave an unbalanced panel with 2,130,880 observations of U.S.

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4The export values are reported in F.A.S. (free alongside ship), which includes the factory gate values plus the shipping cost from the location of the plant to the U.S. port of export.

5Generations refer to the revisions made by the World Customs Organization. A revision may split up former HS6 codes into several new codes or summarize several old codes under a common new category. Revisions are mandatory for all reporting countries and came in effect in the years 1992, 1996, and 2002 during the sample period.

6Concordance tables map new into old codes but they work also for forward mapping, if assignments are unambiguous. An arbitrary element emerges when HS codes are split into several new codes. In that case I apply the rule used in Feenstra et al. (2005), where the new code listed numerically first is chosen. Alternatively, Pierce and Schott (2010) suggest an algorithm that traces goods over time by giving them a generic code that remains the same through all years. While their procedure is important to compute the margins of trade (Bernard et al., 2012), it does not outperform the numerical assignment rule in terms of aggregation bias and appropriate assignments of coinciding categories.
and Chinese exports to 126 destinations between 1989 and 2006. A total of 3,961 HS6 codes are featured in the dataset.

The share of total manufacturing exports represented in the final dataset varies annually between 60 and 70 percent for both China and the United States. However, while the coverage for U.S. exports increases over time, that for Chinese exports falls since 1995. By 2005, about 40 percent of China’s manufacturing exports go to product-destination markets that are not part of the sample. Either because not served by the United States or because unit values could not be computed.

3.1 Export structures and overlapping exports

Structural patterns documented here include the full set of manufacturing exports for both countries. Figure 1 shows different dynamics of cumulative shares in eleven sectors. U.S. exports change little with an increasing share for ‘Chemicals’ (HS2 codes 28-38) replacing ‘Machinery and Electronics’ (HS2 84-85) in the 2000s. The other large sector, ‘Transportation and Equipment’ (HS2 86-89), has constant shares in export revenues throughout. Chinese exports at the beginning of the 1990s have the largest share in ‘Apparel and Footwear’ (HS2 61-67), followed by ‘Textiles’ (HS2 50-60) and ‘Machinery and Electronics’. Over time, the latter grows strongly and becomes the largest sector earning 40% of export revenues. This growth reduces the weight of the other two large sectors and reveals the structural transition that makes Chinese exports appear more similar to U.S. exports.

Figure 1: Export sector composition U.S. and China, 1989-2006
Counting annual observations $N_t$ of U.S. exports and dividing by these the number of observations where U.S. and Chinese exports coincide gives the overlap ratio (OR) as a measure of relative Chinese presence in U.S. export markets: $OR_{t}^{Cn,us} = \frac{N_{t}^{Cn,us}}{N_{t}^{us}}$.

Figure 2 shows that this simple binary measure suggests a similar trend as the well-known Export Similarity Index (ESI) developed by Finger and Kreinin (1979).\(^7\)

![Figure 2: Export similarity U.S. and China, 1989-2006](image)

The left panel shows the OR at three margins. The solid line indicates overlaps at the HS6-destination level. The long-dashed line, on top, indicates the OR at the HS6 margin, while the short-dashed line shows the corresponding measure at the destination level. The right panel shows how the ESI computed at the HS6-destination margin evolves. By 2006, more than 60 percent of U.S. product-destination markets are also served by China, while the OR started below 10 percent in 1989. Most of this increase occurred at the geographical margin, while the ratio of overlapping HS6 codes ranges between 80 and 90 percent throughout. The number of countries reporting imports from China increases until it reaches a peak in the early 2000s.\(^8\) Weighting these overlaps by their relative shares (ESI) shows a lower similarity at the end of the period but a

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\(^7\)The ESI is computed as the sum of export shares of product-destination pairs $zd$ for two countries, where always the lower share is taken: $ESI_{t}^{Cn,us} = \sum_{zd} \min\{s_{zd,t}^{cn}, s_{zd,t}^{us}\}$. Both measures are bound between zero and one, where a value of zero indicates no overlaps (i.e. completely dissimilar exports), and a value of one identical product-destination markets (and an identical distribution of export revenues for $ESI = 1$).

\(^8\)Countries who did not report in the first half of the 1990s are mostly African countries and the former communist states that were part of the Soviet Union or Yugoslavia. It is plausible to expect that there has been trade with China even in this period. Since 1995 all countries have reported at least once so that the geographic expansion can still be observed.
Taking together the figures on structural dynamics within export baskets and increasing similarity between export baskets invites to speculate that the OR has increased the most in 'Machinery and Electronics'. Instead, this is not the case. The sectoral structure of ORs remains basically unchanged (not shown here). On average, the largest ORs can be observed for 'Apparel and Footwear' industries, and in minor sectors like 'Hides and Leather' (HS2 41-43), and 'Stone and Glass' (HS2 68-71). In absolute numbers, the overlaps in 'Machinery and Electronics’ out-compete all other sectors but its average OR of 0.41 is equal to the sample average.\footnote{This information available on request. For comparison, also see Table 1.}

With the descriptive statistics in mind, I now turn to patterns that illustrate why the theoretical setup introduced in the second part of Section 2 is a useful starting point also for analyzing price dynamics within export markets.

### 3.2 Static patterns and variation of export unit values

Calculating China’s remoteness from a potential export market uses information on the bilateral distance between the two partners and the size of the destination market:

\[
R_{cn}^d = \frac{\text{distance}_{cn}}{\text{GDP}_d}
\]

I use the term remoteness to indicate that this measure is analogue to its use in the gravity literature as a measure of multilateral trade costs (see Baldwin and Harrigan, 2011, for a discussion). Because the bilateral distance between two countries does not change over time, but GDP does, \(R_{cn}^d\) represents the arithmetic mean of the sample period 1989-2006.\footnote{Using instead any single year in the sample does not change anything regarding the result and their implications.} In Figure 3, I plot the log of China’s bilateral remoteness against the average number of overlaps counted within a destination country. Countries are clustered along a negatively sloped line and the correlation coefficient is -0.82. Most overlaps can be observed in Canada; other large or nearby economies follow: Japan, Korea, Germany, and the United Kingdom. The fewest overlaps are on average counted in Chad, Libya, Djibouti, and the Central African Republic, where the number of coinciding HS6 codes ranges between 11 and 26. The high correlation supports a
gravity relationship and the role of relative trade costs. Comparative advantage shapes the diffusion of products around the world. In nearby and large economies exporters find sufficient demand that make even less competitive products worth exporting. In small and distant economies, trade costs are higher, relative demand is lower and only the most competitive products are shipped.

A similar relationship is established by linking export unit values to market distance. If only the more productive firms export also to the more distant markets, observed export unit values should change accordingly. In Figure 4, I plot the (logged) average unit value of a standard U.S. export good against the (logged) distance to the market.\textsuperscript{11} Canada and Mexico, direct neighbors and NAFTA members since 1994, face the lowest prices for U.S. exports, while the highest prices are charged for exports to Kiribati and Macao. The correlation coefficient is 0.54 and unit value variation increases with distance. In fact, Baldwin and Harrigan (2011) point out a non-linear relationship between export prices and distance, and also other determinants might be relevant as well. Nevertheless, the HS6 product level data does not reject the quality-sorting

\textsuperscript{11}To compare unit values of different goods across destinations, I divide every individual unit value by its HS6-specific annual average. In a second step, the product-year demeaned unit values are averaged over all years within their respective export destination.
Returning to the within country dynamics, Table 1 summarizes patterns of export unit values within different categories of products. HS6 codes are grouped into HS2 sectors as in Johnson (2012). Columns show variation over time for U.S. export unit values, Chinese market presence (i.e. the OR), the share of markets in U.S. exports where China is present, and the share of U.S. exports as represented in the sample. Within product-destination markets, unit values vary the most in 'Apparel and Footwear', 'Machinery and Electronics', and in 'Transportation'; sectors that are important for at least one of the two exporters. The greatest increases in OR can be observed for 'Transportation and Equipment' where the min-max ratio is about 13.4. The sector, however, adds little to China’s export revenues and thus overlaps start from a low level (see columns 8 and 9, and Figure 1). The sector with the highest observed OR is 'Apparel and Footwear', where it peaks at more than 80% of the observations within a year. The highest cumulative shares of U.S. exports facing Chinese market presence are observed in China’s fastest growing export sector. U.S. exports in the 'Machinery and Electronics' sector that coincide with Chinese exports in a HS6-destination market account for up to one fifth of total export revenues. The sample itself assigns a share of one fourth of total export revenues to that sector. While only two thirds of the
Table 1: U.S. Exports Unit Values and Chinese Overlaps; 1989-2006

<table>
<thead>
<tr>
<th>Sector</th>
<th>HS2 code</th>
<th>Unit Values</th>
<th>OR</th>
<th>Cum. OL</th>
<th>Cum. Smpl.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>S.D.</td>
<td>Min</td>
<td>Max</td>
<td>Min</td>
</tr>
<tr>
<td>Chemicals</td>
<td>28-38</td>
<td>0.06</td>
<td>0.93</td>
<td>1.16</td>
<td>0.11</td>
</tr>
<tr>
<td>Plastics/Rubbers</td>
<td>39-40</td>
<td>0.08</td>
<td>0.89</td>
<td>1.18</td>
<td>0.07</td>
</tr>
<tr>
<td>Hides/Leather</td>
<td>41-43</td>
<td>0.11</td>
<td>0.81</td>
<td>1.11</td>
<td>0.21</td>
</tr>
<tr>
<td>Wood Products</td>
<td>44-49</td>
<td>0.07</td>
<td>0.90</td>
<td>1.12</td>
<td>0.09</td>
</tr>
<tr>
<td>Textiles</td>
<td>50-60</td>
<td>0.08</td>
<td>0.88</td>
<td>1.17</td>
<td>0.13</td>
</tr>
<tr>
<td>Apparel/Footwear</td>
<td>61-67</td>
<td>0.15</td>
<td>0.82</td>
<td>1.24</td>
<td>0.23</td>
</tr>
<tr>
<td>Stone/Glass</td>
<td>68-71</td>
<td>0.10</td>
<td>0.85</td>
<td>1.20</td>
<td>0.13</td>
</tr>
<tr>
<td>Metals</td>
<td>72-83</td>
<td>0.07</td>
<td>0.89</td>
<td>1.13</td>
<td>0.09</td>
</tr>
<tr>
<td>Machinery/Electrical</td>
<td>84-85</td>
<td>0.09</td>
<td>0.79</td>
<td>1.17</td>
<td>0.11</td>
</tr>
<tr>
<td>Transportation</td>
<td>86-89</td>
<td>0.09</td>
<td>0.85</td>
<td>1.23</td>
<td>0.04</td>
</tr>
<tr>
<td>Other Manufactures</td>
<td>90-96</td>
<td>0.17</td>
<td>0.75</td>
<td>1.30</td>
<td>0.15</td>
</tr>
<tr>
<td>Full Sample</td>
<td></td>
<td>0.08</td>
<td>0.88</td>
<td>1.14</td>
<td>0.11</td>
</tr>
</tbody>
</table>

Note: Data uses U.S. Exports (Center for international data UC Davis) and UN Comtrade. The first two columns define manufacturing sectors and their respective HS2 headers within which HS6 codes are summarized. Columns 3-5 document the variation of U.S. export unit values between 1989 and 2006, within HS6 destination markets, and after product time effects were removed. Columns 6 and 7 document the how the share of sector-level observations with Chinese market presence changes over time. Columns 8 and 9 document the cumulative share of HS6-destination markets in U.S. manufacturing that are confronted with Chinese presence, and that are reported in the sample. For comparison, the last two columns report variation of the cumulative share of HS6-destination markets that is reported in the sample.

Observations in ‘Machinery and Electronics’ report overlaps with China, these overlaps occur in markets that earn 80 percent of its revenues.

Variation in unit values, overlaps, and China’s export structure motivate the inference of direct competition effects on U.S. exports in narrow product-destination markets. The expansion of Chinese exports affects markets that account for up to 50% of U.S. manufacturing export revenues. Also, China increasingly earns similar shares in these markets (ESI, Figure 2). The next section sketches a short version of the Johnson (2012) model in order to derive the estimation equation and discuss mechanisms to be specified for empirical inference.

4 Theoretical framework

In the model of Johnson (2012), firms are heterogeneous in terms of their ‘ability’ to export to destinations with different entry barriers. Although the empirical analysis
is going to focus on the within-market adjustments, I outline Johnson’s model in its original cross-sectional design.

4.1 Consumption and preferences

Including quality into the utility function requires it to be observable for consumers. They gain utility from consuming a continuum of varieties \( j \) of good \( z \), \( j \in \Omega_z \):

\[
U_z = \left[ \int_{j \in \Omega_z} (\tilde{x}_j)^{(\sigma_z-1)/\sigma_z} d j \right]^{\sigma_z/(\sigma_z-1)}; \sigma_z > 1 \forall z. \tag{4.1}
\]

\( \tilde{x}_j = x_j q_j \) measures consumption in utility units of a variety, where quality \( q \) substitutes for quantity \( x \). If \( p_j \) is the price for one physical unit of variety \( j \), then its quality-adjusted price follows as \( \tilde{p}_j = p_j / q_j \). Aggregate demand for variety \( j \) in physical units is a function of the unit price and quality of \( j \), proportional to the average quality-adjusted price index \( \bar{P} \) and the share of income \( E \) devoted to \( z \):\(^{12}\)

\[
x_j(p_j, q_j) = q_j^{\sigma_z-1} p_j^{-\sigma_z} \bar{P}_z^{\sigma_z-1} E_z. \tag{4.2}
\]

A lower unit price, higher quality, expenditures \( E_z \), and a higher average price, \( \bar{P}_z = \left( \int_{j \in \Omega_z} [\tilde{p}_j] d j \right)^{1/(1-\sigma_z)} \) increase demand for variety \( j \).

4.2 Production

Monopolistic firms produce a single variety \( j \) using labor with CRS technology. Heterogeneity among firms in a country originates from differences in unit production costs \( c \) and output quality \( q \). Unit costs measure the amount of labor used to produce one physical output unit. The ability of firms to enter a given market is given by its quality-cost ratio \( a_j \equiv q_j / c_j \).

Selling to a given destination market \( d \in \Omega_D \) requires firms to pay fixed costs \( f_{zd} > 0 \) and iceberg costs \( \tau_{zd} > 1 \).\(^{13}\) Monopolists set prices as a constant mark-up over

\(^{12}\) In utility units, demand is: \( \tilde{x}_j(\tilde{p}_j) = \tilde{p}_j^{-\sigma_z} \bar{P}_z^{\sigma_z-1} E_z. \)

\(^{13}\) Domestic sales are not considered here since we look only at exports of the United States to multiple export destinations. The iceberg cost of trade implies that \( \tau_{zd} \) units of a good must be shipped for one unit to arrive. For simplicity, trade costs are assumed to be product-specific rather than individually firm specific.
marginal costs, and pass through variable trade costs: \( p_{jd} = \frac{\sigma_z}{(\sigma_z - 1)} c_j \tau_{zd} \). The quality-adjusted price set by a firm selling to \( d \) is hence

\[
\tilde{p}_{jd}(a) = \left( \frac{\sigma_z}{\sigma_z - 1} \right) \frac{1}{\bar{a}_j} \tau_{zd}.
\] (4.3)

### 4.3 The ability threshold and sorting

Whether a firm exports to destination \( d \) or not depends on operating profits. Revenues of firm \( j \) in market \( d \) are

\[
r_{jd} = p_{jd}(c, q) x_{jd}(c, q) = (\tilde{p}_j(a) \tau_{zd})^{1-\sigma_z} \tilde{P}_{zd}^{-1} E_{zd}.
\] (4.4)

Profits are positive if \((1/\sigma_z)r_{jd}(a) \geq f_{zd}\) holds, which gives the quality-adjusted price charged by the marginal firm:

\[
\tilde{p}_{jd} = \frac{\tilde{P}_{zd}}{\tau_{zd}} \left( \frac{E_{zd}}{\sigma_z f_{zd}} \right)^{1/(\sigma_z-1)},
\] (4.5)

and the implied ability

\[
a_{jd}^* = \left( \frac{\sigma_z}{\sigma_z - 1} \right) \frac{\tau_{zd}}{\tilde{P}_{zd}} \left( \frac{\sigma_z f_{zd}}{E_{zd}} \right)^{1/(\sigma_z-1)}.
\] (4.6)

Given fixed costs, a higher price index, larger markets and lower variable trade costs allow less able firms to export. Conversely, a lower price index exhibits pressure on the least able firms and prevents those from exporting.

### 4.4 Quality, prices, and aggregation

As in Baldwin and Harrigan (2011) and Johnson (2012), observed unit prices are linked to output quality through a positive monotonic relationship to ability: \( q = a^\theta \). The price equation can then be rewritten as a function of ability alone, where the size of \( \theta \) determines the sign of the correlation between firm’s unit prices and the quality-adjusted price:

\[
p_j = \frac{\sigma_z}{\sigma_z - 1} c = \frac{\sigma_z}{\sigma_z - 1} q/a = \frac{\sigma_z}{\sigma_z - 1} a^{\theta_z - 1}.
\] (4.7)
Recall that quality-adjusted prices are negatively correlated with ability $a$, so that the correlation between quality-adjusted prices and observed unit prices is also governed by the size of $\theta$. This model property is the key to allowing different products featuring different patterns of average prices after controlling for competition.\(^{14}\)

Aggregate revenues of firms $j \in \Omega_z$ are equivalent to observed export values in product-level data. Assuming the cumulative distribution function (cdf) $G(a)$ of firm abilities $a$ to be Pareto with support $[a_L, a_H]$, ensures that average unit prices (i.e. export unit values) vary according to the competitive environment in $d$.

Exports can be written as

$$EX_{zd} = \int_{a^*_d}^{a_H} r_{jd}(a) N_{zd} dG(a) = N_{zd} r_{jd}(a_H) \tilde{V}_{zd}, \quad (4.8)$$

where $N$ is the number of firms exporting to $d$, and $\tilde{V}$ is a scaling parameter that resembles the shape of the distribution of exporting firms. If $\tilde{V} = 1$ all firms have the same $a$ (i.e. homogeneous) and exporting would be profitable for either all firms or for no firm at all. Similar to the value of exports, quantities are

$$Q_{zd} = \int_{a^*_d}^{a_H} \tau_{zd} x_{jd}(a) N_{zd} dG(a) = N_{zd} \tau_{zd} x_{jd}(a_H) \ddot{V}_{zd}. \quad (4.9)$$

And export unit values at the product level follow as:

$$\frac{EX_{zd}}{Q_{zd}} \equiv \frac{uv_{zd}}{V_{zd}} = p(a_H)V_{zd}. \quad (4.10)$$

The average unit value of exports is given by the unit price of the best firm $a_H$, weighted by the scaling factor $V = \ddot{V} / \tilde{V}$. Inference of quality or price competition in a product category follows from comparing the most-able firm’s price with average export unit values. A higher average price compared to the best-capable price implies price competition because all other exporters are less able and charge higher prices. Through $\theta - 1 < 0$ observed and quality-adjusted prices are positively correlated. In turn, a lower average price relative to the most-able firm implies quality competition, and with $\theta - 1 > 0$ observed and quality-adjusted prices are negatively correlated.

\(^{14}\)Johnson (2012) discusses benchmark cases of this parameter in greater detail, and how correlations between quality and costs govern the correlation between the two types of prices.
5 Empirical procedure

Without information on firm’s exports a comparison of highest-ability prices and average prices is not feasible. However, the comparison of export unit values at the product level in two scenarios reveals the relationship equivalently. Noting from (4.6) that the ability of the marginal firm is negatively related to average local product prices $\tilde{P}$, the average ability of exporting firms rises as this price index is lowered, i.e. competition gets tighter. Expressing the equation in logs gives

$$\ln a^* = \ln \left( \frac{\sigma_z}{(\sigma_z - 1)} \right) + \ln \left( \frac{\tau_{zd}}{P_{zd}} \right) + \frac{1}{\sigma_z - 1} \ln \left( \frac{\sigma_z f_{zd}}{E_{zd}} \right)$$

(5.1)

which translates directly into product-level unit values using (4.10)

$$\ln uv_{zd} = \phi_z + \phi_{zd} - \ln \tilde{P}_d - \ln E_d.$$  

(5.2)

The parameter $\phi_z = \ln[\sigma_z/(\sigma_z - 1)] + \ln \sigma_z[1/(\sigma_z - 1)]$ is a product fixed effect which captures, for instance, different measurement units or the comparative advantage of the exporting country. $\phi_{zd} = \ln(\tau_{zd}/\beta_{zd}) + \ln(f_{zd}/\alpha_{zd})[1/(\sigma_z - 1)]$ is a product-destination specific intercept that captures bilateral fixed and unit trade costs, preferences, the sectoral structure, and the average competitive environment in the destination country. $\alpha$ and $\beta$ are product-destination specific parameters that assign the elasticity of product-specific expenditure (price indices) with respect to their aggregates.\(^{15}\)

Given that unit values are positively correlated with ability, observed and quality-adjusted prices are negatively correlated. Larger markets $E$ and higher average price levels $\tilde{P}$ allow less able firms to enter so that export unit values will be lower. In the case of price competition lower prices are associated with higher ability, such that larger markets and higher average prices increase average observed unit values.

5.1 The empirical model

The empirical model is not a one-to-one application of the theoretical model, where firms have to make a one-time sunk investment to start exporting to a given destination. Here, $\sum z \alpha_z = 1$.
the focus lies on continuing to export to a destination so that firms decide every period on selling abroad or not. To keep the sorting mechanism at work, these periodical costs must be independent from the volume of exports which otherwise would be passed through to consumers. Marketing costs, re-contracting and -licensing costs, or wage payments in the destination markets or for country management could be examples for recurring fixed costs of exporting. I use the following general specification:

\[ \ln w_{zdt} = \phi_{zd} + \phi_{zt} + \gamma'X_{dt} + \delta CN_{zdt} + \varepsilon_{zdt}, \]

(5.3)

Product fixed effects now have also a time dimension (for reasons explained below) and the destination specific variables are summarized in a vector \( X_{dt} \) of control variables.

Chinese market presence \( CN_{zdt} \) varies in all three dimensions — product, destination, and time —, and is included without any lag structure. Including Chinese market presence into the empirical model offers no immediate explanation through which channel a potential effect exhibits. Empirical studies mentioned above suggest a negative effect on the import price index (Broda and Weinstein, 2010; Schott, 2008; Kamin et al., 2006), but possibly also advertising and market research costs may be affected. The timing when sales actually deteriorate due to Chinese presence is therefore \textit{a priori} unclear and allows firms’ exit from a market be simultaneous with China’s appearance.

Adding a time dimension to the product fixed effect allows a finer distinction of time effects, and thereby also to control for potential sources of endogeneity and omitted variable bias. Product-time effects control for all kinds of dynamics that affect the product-specific firm composition of U.S. exports. These can come from industrial policies, foreign outsourcing (i.e. reallocation of production into foreign countries), or changes of the competitive environment in the domestic market. Also aggregate changes in China’s sectoral structure are accounted for that way, which seems relevant given the changing product composition of China’s exports shown in Figure 1. It should be noted that an interpretation of causality remains nevertheless difficult. Since multinational enterprises may relocate production on purpose to serve specific markets, the product-time effect captures only the general intensity of production relocation over time. However, correlations still allow conclusions on the average earnings of U.S. firms in export markets as their competitive environment changes.
5.2 Estimation

To estimate (5.3) I use the data described in Section 3 with information on U.S. export unit values, Chinese market presence, and country specific variables. Real GDP measures the size of the market, $E_d$, representing the budget constraint for aggregate demand. Real per capita GDP and remoteness are included to measure the local price level, $\tilde{P}_d$. The remoteness of the destination market is computed from the CEPII Gravity dataset using the formula suggested by Baldwin and Harrigan (2011)

$$R_{dt} = \left( \sum_{o \neq d} \frac{GDP_{ot}}{\text{distance}_{od}} \right)^{-1},$$

where $o$ denotes the potential origin country that may also trade with $d$. The more distant the destination country is from all other countries, and the smaller the relatively nearby countries are, the more remote is $d$. For example, contrast Belgium and New Zealand: The former is small, has direct borders with France and Germany, and has many other large economies relatively nearby. In turn, New Zealand is small too, has no common borders, and only Australia is relatively nearby. The average price level is therefore expected to be higher in New Zealand as compared to Belgium.\footnote{The effect of 'multilateral resistance' on bilateral trade flows was emphasized by Anderson and van Wincoop (2003).} Chinese presence is included as a dummy variable, $CN = \{0, 1\}$ so that I compare two scenarios within each product-destination market. Hongkong re-exports are included in separate estimations to reveal potential underestimation of a 'China-effect'.

**Pooled samples**

Pooling across all goods and estimating (5.3) implicitly assumes that the expected effect of Chinese market presence on U.S. export unit values is uniform: $\hat{\delta}_z = \delta \forall z$. For spatial sorting it has been shown that this is not true (Baldwin and Ito, 2011; Johnson, 2012), and that the obtained coefficient reflects an average effect.

I nevertheless estimate the pooled sample in three different ways in order to emphasize the inclusion of product-time effects $\phi_{zt}$. In the first regression, I treat product
and time effects separately, i.e.

\[ \ln uv_{zdt} = \phi_t + \phi_{zd} + \gamma'X_{dt} + \delta CN_{zdt} + \varepsilon_{zdt}, \]  

(5.4)

where \( \phi_{zd} \) takes care for all stationary product-specific effects such as measurement units. In the second estimation, I follow Wooldridge (2002) and include the calculated product-time averages of all variables into the regression equation. That is, instead of inserting dummies for each product-year, I divide the sum of all variable values within a product-time group by its number of observations, \( \bar{x}_{zt} = (\sum_d x_{zdt})/N_{zt} \), and include them as regressors into the equation:

\[ \ln uv_{zdt} = \phi_{zd} + \gamma'X_{dt} + \delta CN_{zdt} + \xi_1 \ln \overline{uv}_{zt} + \xi_2'\overline{X}_{zt} + \xi_3'\overline{CN}_{zt} + \tilde{\varepsilon}_{zdt}. \]  

(5.5)

The error term remains i.i.d. and captures both the \( zt \)-error and the \( zdt \)-error: \( \tilde{\varepsilon}_{zdt} = \bar{\varepsilon}_{zt} + \varepsilon_{zdt} \). Product-time averaged export unit values and average destination characteristics \( \hat{\xi}_1, \hat{\xi}_2 \) then show how changes independent of the destination country drive the variation in market-specific export unit values. Most interesting is the coefficient estimate \( \hat{\xi}_3 \), which has a direct interpretation. The average presence of China in U.S. markets is low, if China exports a good to just one destination but the U.S. to many destinations. This implies that China is not a typical exporter of that good, but the U.S. is. In contrast, the average presence is high, if many markets served by the U.S. with a given product are also served by China. In that case both countries are similarly typical exporters of that good. Average presence of China thus evaluates the role of comparative advantage and its evolution over time. The coefficient reveals the role of the structural assimilation between the two countries’ export baskets. Instead, the estimated coefficient \( \hat{\delta} \) reports the direct effect of China’s presence within a particular market.

The downside of this approach is that Equation (5.5) does not include all product-time effects. Moreover, \( \phi_{zt} \) and \( \phi_{zd} \) are high-dimensional so that \( \hat{\phi}_{zt}^{zd} \) cannot be computed.\(^{17}\) The dataset is hierarchically structured with product-destination pairs on the first level (individual level) and product-years on the second level (group level). In

\(^{17}\)High-dimensionality does not allow to include dummy variables for individual-effects estimations because the number of created variables exceeds the matrix-storage capacity of statistical software packages.
an unbalanced panel, the number of individual-level observations varies within groups so that an appropriate structure of the product-destination effects has to be found when product-time effects want to be fully included. I follow the method proposed by Guimarães and Portugal (2009) who show that an iterative algorithm (the 'zig-zag' or full Gauss-Seidel algorithm) produces column vectors \( \bar{D} \) which exactly represent the size of the individual effects. These vectors can be included instead of large diagonal dummy-matrices into OLS or fixed effects regressions and deliver coefficients \( \hat{\rho} = 1 \).\(^{18}\)

\[
\ln uv_{zt} = \gamma'X_{zt} + \delta CN_{zt} + \rho_1 \bar{D}_{zt} + \rho_2 \bar{D}_{zd} + \varepsilon_{zt} \tag{5.6}
\]

Cross-sectional correlation of the residuals is accounted for by standard error clustering at the product-destination level.

**Individual products**

In order to obtain a more differentiated picture of the effects of Chinese market presence, I also estimate single equations for each product \( z \). Unit values of U.S. exports are regressed on country variables and the China dummy, including time and country effects.

\[
\ln uv_{zt} = \phi_z t + \phi_{zd} + \gamma z X_{zt} + \delta CN_{zt} + \varepsilon_{zt} \tag{5.7}
\]

Dimensionality of matrices does no longer play a role since \( T_z \leq 18 \) and \( D_z \leq 126 \). The focus then lies on the distribution of coefficient estimates \( \hat{\delta}_z \) to see if \( \delta_z \neq \delta_k \) for \( z \neq k \). It is then possible to group products into \( \theta^+ > 1 \) and \( \theta^- < 1 \), i.e. classifying goods into price and quality competition as in Baldwin and Ito (2011) and Johnson (2012).

### 6 Results

This section presents the results from regressing U.S. export unit values on Chinese market presence. The unbalanced panel features a total of 2,130,880 observations for flows to 126 destinations in 3,961 HS6 product categories over 18 years. The panel identifier is a distinct product-destination which defines 268,100 U.S. export markets.\(^{18}\)

\(^{18}\)Although this procedure is time consuming, it produces efficient and unbiased estimators with multiple high-dimensional fixed effects and has computationally minimal requirements.
6.1 Pooled samples

The three specifications estimated in the pooled sample are presented in Table 2. In the left panel, Chinese market presence is identified as reported by importing partner countries. The right panel also includes Hongkong re-exports which are assigned to observations of Hongkong imports from China and Hongkong re-exports to destinations within the same product-year. Columns (1) through (3) represent Equations (5.4) through (5.6) respectively. The country specific control variables reveal consistent signs across columns, while the China effect exhibits a switch from positive insignificant to negative significant when product-time effects are included. Semi- and fully transformed specifications do not produce significantly different coefficient estimates for Chinese market presence. Together with Hongkong re-exports, the results are basically the same so that further distinction between the two sets of overlaps is omitted and only Chinese exports as reported by importing partner countries are focused on.

Table 2: (log) unit values of U.S. exports and direct overlaps with Chinese exports, 1989-2006

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>t-dummies</td>
<td>zt-means</td>
<td>Full zt</td>
<td>t-dummies</td>
<td>zt-means</td>
<td>Full zt</td>
</tr>
<tr>
<td>GDP</td>
<td>-0.239***</td>
<td>-0.114***</td>
<td>-0.184***</td>
<td>-0.239***</td>
<td>-0.111***</td>
<td>-0.184***</td>
</tr>
<tr>
<td></td>
<td>(0.0285)</td>
<td>(0.0202)</td>
<td>(0.0178)</td>
<td>(0.0285)</td>
<td>(0.0201)</td>
<td>(0.0178)</td>
</tr>
<tr>
<td>GDPpc</td>
<td>0.218***</td>
<td>0.0984***</td>
<td>0.162***</td>
<td>0.217***</td>
<td>0.0964***</td>
<td>0.161***</td>
</tr>
<tr>
<td></td>
<td>(0.0294)</td>
<td>(0.0223)</td>
<td>(0.0207)</td>
<td>(0.0294)</td>
<td>(0.0221)</td>
<td>(0.0206)</td>
</tr>
<tr>
<td>R</td>
<td>0.304***</td>
<td>0.281***</td>
<td>0.283***</td>
<td>0.304***</td>
<td>0.280***</td>
<td>0.281***</td>
</tr>
<tr>
<td></td>
<td>(0.0287)</td>
<td>(0.0254)</td>
<td>(0.0250)</td>
<td>(0.0287)</td>
<td>(0.0254)</td>
<td>(0.0250)</td>
</tr>
<tr>
<td>CN</td>
<td>0.00434</td>
<td>-0.0123***</td>
<td>-0.0122***</td>
<td>0.00545**</td>
<td>-0.0106***</td>
<td>-0.0106***</td>
</tr>
<tr>
<td></td>
<td>(0.00267)</td>
<td>(0.00258)</td>
<td>(0.00241)</td>
<td>(0.00265)</td>
<td>(0.00258)</td>
<td>(0.00239)</td>
</tr>
<tr>
<td>CN (mean)</td>
<td>0.0249***</td>
<td>(0.00735)</td>
<td>(0.0075)</td>
<td>0.0215***</td>
<td>(0.00701)</td>
<td>(0.00732)</td>
</tr>
<tr>
<td>N</td>
<td>2,130,880</td>
<td>2,130,880</td>
<td>2,130,880</td>
<td>2,130,880</td>
<td>2,130,880</td>
<td>2,130,880</td>
</tr>
<tr>
<td>N (cluster)</td>
<td>268,100</td>
<td>268,100</td>
<td>268,100</td>
<td>268,100</td>
<td>268,100</td>
<td>268,100</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.0103</td>
<td>0.0960</td>
<td>0.103</td>
<td>0.0103</td>
<td>0.0960</td>
<td>0.103</td>
</tr>
<tr>
<td>CF</td>
<td>-0.00169</td>
<td>0.00478</td>
<td>0.00474</td>
<td>-0.00225</td>
<td>0.00439</td>
<td>0.00438</td>
</tr>
</tbody>
</table>

Standard errors in parentheses, clustered at product-destination level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The negative coefficient $\hat{\delta}$ predicts that upon China’s market presence U.S. export unit values in an average product-destination market go down by 0.01 percent. The

19Hongkong is generally excluded as an export destination.
economic effect is small, also given the low reported goodness of fit. In the counterfactual scenario shown in the last row of the table, Chinese absence from all U.S. export markets would have left U.S. export unit values to be 0.005 percent higher. Pooled across all goods and destinations, the direct effect of Chinese market presence appears exhibit competition at the price margin, i.e. $\theta = \theta^- < 1$. In turn, the indirect effect through China’s expansion to more destination countries (products for which China and the U.S. become similarly typical exporters) suggests that U.S. exporters on average charge higher prices ($\xi_3 = 0.025$). This result is familiar to the findings of Schott (2008) and Bernard et al. (2006) where strongly competing products motivate firms to upgrade their products in order to improve their perceived quality. This effect, however, does not come from China’s presence in a particular market but rather from the overall intensity of competition within that product category.

Table 3: (log) unit values of U.S. exports and direct overlaps with Chinese exports, 1989-2006

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td>-0.334***</td>
<td>0.0150</td>
<td>-0.0225</td>
<td>-0.289***</td>
<td>-0.260***</td>
</tr>
<tr>
<td>GDPpc</td>
<td>0.332***</td>
<td>-0.0705</td>
<td>-0.0336</td>
<td>0.291***</td>
<td>0.259***</td>
</tr>
<tr>
<td>R</td>
<td>0.309***</td>
<td>0.227***</td>
<td>0.301***</td>
<td>0.345***</td>
<td>0.260***</td>
</tr>
<tr>
<td>CN</td>
<td>-0.000308</td>
<td>-0.0121</td>
<td>-0.0115**</td>
<td>-0.0175***</td>
<td>-0.0164***</td>
</tr>
</tbody>
</table>

| N           | 500,257                | 216,862       | 487,571       | 614,513                    | 568,124          | 1,467,364        |
| N (cluster) | 69,826                 | 28,449        | 51,993        | 69,346                     | 78,195           | 178,754          |
| $R^2$ (within) | 0.102                | 0.0962        | 0.0927        | 0.117                      | 0.116            | 0.101            |
| CF          | 0.000120               | 0.00472       | 0.00447       | 0.00680                    | 0.00638          | 0.00372          |

Standard errors in parentheses, clustered at product-destination level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Results for product subsamples are reported in Table 3. Columns split the sample according to the UNCTAD Skill- and Technology Intensity Dataset (columns (1)-(4), Basu, ming) and the well-known Rauch (1999) classification. All columns show results from the fully transformed specification in Equation (5.6). In the UNCTAD classification, statistical significance concentrates in medium- and high-skill intensive manufacturing industries — a pattern that fits well into the observations of China’s structural
transition and its documentation in the literature (e.g., Rodrik, 2006; Amiti and Freud, 2010). The size of the coefficients is the same as in the full sample. The effect on homogeneous goods is only slightly larger than for differentiated products, and it is negative for both.

The small size of the effects suggests that only few products are actually affected by Chinese presence while most of the U.S. exports are sufficiently different so that competitive pressures do not exhibit. Pooling across all products may, however, promote attenuation of the actual effects. Chinese market presence seems to force firms having lower prices so that quality alone cannot save the market shares necessary to export profitably. Nevertheless, uniform elasticities to the competitive environment might be a too strong assumption and actual effects potentially cancel out in the pooled samples. In the next subsection the effects in individual product categories are analyzed to clarify what drives the pattern observed here.

6.2 Individual products

Effects of Chinese competition at the individual HS6 product level are estimated with Equation (5.7). 77 HS6 codes did not have sufficient observations so that 3,884 regressions remained for estimation. From the results, information on signs and significance of the estimated coefficients $\hat{\delta}_z$ was collected and those having p-values for the t- and F-statistics below the 5% level were selected. This group constitutes a small sample of 245 HS6 products which corresponds to 6.31 percent of the product range, and has an average cumulative share 4.99 percent in U.S. exports. The within-$R^2$s in product categories with statistically significant effects range between 0.02 and 0.84 with median 0.11 and mean 0.14.

Table 4 shows the distribution of signs among the product subsamples used earlier. In almost all categories the number of positive and negative price effects is balanced. Medium-skill intensive goods have slightly more positive coefficients, while price competition (i.e., negative coefficients) dominates in high-skill intensive categories. The Rauch (1999) classification is not conclusive about the direction of the effects.

Using industry classifications at the HS2 level allows to contrast estimated China effects with other estimates of price/quality competition (Table 5). Johnson (2012, Panel B of Table 1) finds a dominance of positive correlations between observed export unit
Table 4: Correlation of U.S. export unit values and Chinese market presence, product classifications

<table>
<thead>
<tr>
<th>Category</th>
<th>Sign positive</th>
<th>Sign negative</th>
<th>Total positive</th>
<th>Total negative</th>
<th>Significant 5% positive</th>
<th>Significant 5% negative</th>
<th>Export share Total</th>
<th>Export share Significant</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>UNCTAD Classification</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resource int.</td>
<td>524</td>
<td>544</td>
<td>1,068</td>
<td>38</td>
<td>32</td>
<td>5.83%</td>
<td>0.50%</td>
<td></td>
</tr>
<tr>
<td>Low-skill int.</td>
<td>205</td>
<td>211</td>
<td>416</td>
<td>6</td>
<td>7</td>
<td>3.57%</td>
<td>0.02%</td>
<td></td>
</tr>
<tr>
<td>Medium-skill int.</td>
<td>278</td>
<td>300</td>
<td>578</td>
<td>21</td>
<td>17</td>
<td>19.07%</td>
<td>0.05%</td>
<td></td>
</tr>
<tr>
<td>High-skill int.</td>
<td>438</td>
<td>537</td>
<td>975</td>
<td>33</td>
<td>43</td>
<td>28.68%</td>
<td>1.54%</td>
<td></td>
</tr>
<tr>
<td><strong>Rauch 1999 Classification</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Homogeneous</td>
<td>645</td>
<td>717</td>
<td>1,362</td>
<td>42</td>
<td>43</td>
<td>15.66%</td>
<td>1.42%</td>
<td></td>
</tr>
<tr>
<td>Differentiated</td>
<td>1,106</td>
<td>1,207</td>
<td>2,313</td>
<td>77</td>
<td>77</td>
<td>54.89%</td>
<td>3.52%</td>
<td></td>
</tr>
<tr>
<td>All goods</td>
<td>1,818</td>
<td>1,995</td>
<td>3,813</td>
<td>119</td>
<td>126</td>
<td>80.86%</td>
<td>4.99%</td>
<td></td>
</tr>
</tbody>
</table>

Note: Table reports numbers of estimated coefficients $\delta_z$, grouped into categories. The last two columns report the weight of these categories in total U.S. manufacturing exports (average 1989-2006). See text for specification details.

values and export thresholds in cross-sections of countries. Negative signs appear predominantly for 'Apparel and Footwear', as well as for 'Machinery and Electronics' and 'Transportation' industries. My results show a prevalence of positive unit-value effects

Table 5: Correlation of U.S. export unit values and Chinese market presence, HS2 industries

<table>
<thead>
<tr>
<th>Category</th>
<th>Sign positive</th>
<th>Sign negative</th>
<th>Significant 5% positive</th>
<th>Significant 5% negative</th>
<th>Export share Total</th>
<th>Export share Significant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chemicals</td>
<td>337</td>
<td>413</td>
<td>27</td>
<td>27</td>
<td>11.35%</td>
<td>0.72%</td>
</tr>
<tr>
<td>Plastics/Rubbers</td>
<td>98</td>
<td>91</td>
<td>3</td>
<td>11</td>
<td>4.22%</td>
<td>0.41%</td>
</tr>
<tr>
<td>Hides/Leather</td>
<td>37</td>
<td>37</td>
<td>1</td>
<td>1</td>
<td>0.64%</td>
<td>0.00%</td>
</tr>
<tr>
<td>Wood Products</td>
<td>110</td>
<td>131</td>
<td>9</td>
<td>10</td>
<td>4.66%</td>
<td>0.91%</td>
</tr>
<tr>
<td>Textiles</td>
<td>227</td>
<td>309</td>
<td>17</td>
<td>17</td>
<td>2.28%</td>
<td>0.26%</td>
</tr>
<tr>
<td>Apparel/Footwear</td>
<td>195</td>
<td>144</td>
<td>13</td>
<td>9</td>
<td>1.36%</td>
<td>0.06%</td>
</tr>
<tr>
<td>Stone/Glass</td>
<td>62</td>
<td>72</td>
<td>4</td>
<td>4</td>
<td>2.48%</td>
<td>0.06%</td>
</tr>
<tr>
<td>Metals</td>
<td>292</td>
<td>284</td>
<td>11</td>
<td>14</td>
<td>4.77%</td>
<td>0.22%</td>
</tr>
<tr>
<td>Machinery/Electr.</td>
<td>302</td>
<td>353</td>
<td>24</td>
<td>23</td>
<td>32.27%</td>
<td>1.96%</td>
</tr>
<tr>
<td>Transportation</td>
<td>58</td>
<td>46</td>
<td>4</td>
<td>2</td>
<td>14.36%</td>
<td>0.19%</td>
</tr>
<tr>
<td>Other</td>
<td>100</td>
<td>115</td>
<td>6</td>
<td>8</td>
<td>2.50%</td>
<td>0.19%</td>
</tr>
<tr>
<td>All goods</td>
<td>1,818</td>
<td>1,995</td>
<td>119</td>
<td>126</td>
<td>80.86%</td>
<td>4.99%</td>
</tr>
</tbody>
</table>

in 'Footwear and Apparel' and 'Transportation' and balanced counts in 'Machinery and Electronics'. In total, price competition slightly dominates at the 5% significance level. The highest count of significant effects is found in 'Chemicals' and in 'Machinery and Electronics'.

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and Electronics’ where also relatively large shares of U.S. exports are affected. However, China seems to compete most effectively in the minor ‘Woods Products’ industry where it affects about one fifth of the export value represented in this sample. Overall, the impression remains that overlaps between Chinese and U.S. exports have only a marginal direct effect on U.S. export unit values, and that these eventually cancel out.

6.3 Economic interpretation

So far, this section has shown that statistically meaningful effects of Chinese presence in U.S. export markets concentrate on a narrow range of 245 HS6 product categories. Signs of lower unit values with Chinese presence are almost as often observable as higher unit values. The overall share of these affected products in total U.S. exports is low at an average of about 5 percent. To further evaluate the economic impact, Figure 5 plots coefficients against products’ relative export share: \( RES_z = s_{zus} / \bar{s}_{us} \). It shows a negative correlation between the estimated size of the effect \( \hat{\delta}^z \) and the relative importance of the affected products. The zero-lines indicate the benchmarks, e.g. observations above the horizontal zero-line are HS6 products that had a higher share than the average HS6 product in U.S. exports. Most observations lie below this threshold. The larger the estimated effect the further observations lie below the average U.S. export good. Except for two outliers, coefficients larger than 1 (i.e. \( \log(1) = 0 \)) were estimated for products that have a relatively low weight in overall annual U.S. exports.

7 Discussion

7.1 Identification of Chinese competition

The statistical inference of overlapping trade flows between China and the United States reveals little evidence of competition. Indirect effects seem to provide incentives for U.S. exporters to offer superior product varieties which allows them to charge higher prices. Including Hongkong re-exports does not alter these results. The use of HS6 product categories and the concordance problems mentioned in the data section may lead to an overstatement of export similarity and potential competition between the
two countries. Also, the use of a binary variable as the identification strategy is a rather rough measure. Besides presence, also the size and persistence of overlaps may play a role so that the observations of ‘meaningful’ overlaps would further decrease. Going from the results to an economic interpretation would then imply that a more sophisticated measurement of Chinese competition scales the impact further down, so that the results presented here can be taken as an ‘upper bound’ of the effects.

It should be noted, however, that the effects identified here concentrate exclusively on Chinese presence in a U.S. export market. As shown in the first part of Section 6, effects of China’s expansion in the global economy transmit also through other channels. The overall concentration of product categories in China’s export basket, and growing market shares also in domestic market of competing exporters seem to be the primary

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20Within a HS6 product category up to 74 HS10 product codes are distinguished in the U.S. data. Other codes do not differentiate further below the 6-digit level.
channels.

7.2 Models of sorting and measurement of quality

The theoretical framework makes predictions on observed average prices at the product level following unobserved selection of firms in a changing economic environment. As outlined in section 4, non-competitive firms simply drop out of the market as their environment undergoes changes. This mechanism is not rejected, but other mechanisms are plausible, too. The trapped-factor model developed by Bloom et al. (2010) and other empirical studies on the effects of increasing competition on firm-level behavior (Aghion et al., 2005; Bernard et al., 2006; Bloom et al., 2011) emphasize that firms endogenously undertake changes to escape these pressures. Switching output to less contested market segments or increasing spending on R&D followed by innovation are relevant strategies. Also, the implicit assumption that firms remaining in the market are passive in their pricing behavior can be relaxed if alternative assumptions are made on the form of the utility function. (Ottaviano et al., 2002) propose a quadratic utility function, where the elasticity of substitution increases as market structures change in their composition of available varieties of goods and price levels. All these mechanisms and transmission channels, however, remain under the surface when product level data is used.

7.3 Policy implications

Given the low incidence rates of statistically significant unit-value effects, paired with a low implied impact on U.S. exports, direct competition between Chinese and U.S. exports seems to be irrelevant during the period 1990-2006. Although an assimilation of broad patterns can be observed over time, products from both countries coexist in export markets with almost no frictions. This altogether lines up with the findings of Bernard et al. (2006) and Schott (2008). The fact that exporters belong to a group of high-performing firms in a country provides a reasonable explanation for the resistance of U.S. firms to Chinese exports in foreign markets. In contrast to other low- and middle-income economies with export structures similar to China’s, the United States (and also other OECD countries) operate at the technology frontier and can therefore rely on a broader menu of strategies to avoid direct competition.
Competition in domestic markets does nevertheless exhibit as recently documented by Autor et al. (2012), but they should not be expected to translate equivalently for increasing competition in foreign markets. The relatively small share of firms engaged into exporting and those firms’ small fractions of revenues earned from selling abroad (Eaton and Kortum, 2010) let incentives to innovate or layoff labor remain in the domestic economy.

8 Conclusion

The paper investigated patterns of U.S. export unit values conditional on the simultaneous presence of Chinese exports. As more and more markets are penetrated only a few of these reveal quantitatively significant adjustments, while the overall economic impact remains low. A rich panel dataset spanning 18 years and 126 U.S. export destinations was used to carry out the analysis. The theory that seems useful to predict and evaluate firm level behavior cannot produce consistent results for quality sorting or price competition at the HS6 product level of exports. Goods classified as quality-competing in a cross-section appear to face price competition as China starts serving the same market. In most product categories the direction of the effects is balanced. From a policy view these results are encouraging because they do not identify any meaningful displacement effects from Chinese competition. The exact transmission channels at the firm level, however, remain under the surface, and should not neglect the indirect effects of competition in the domestic economy.
References


