Firm-level Response to Anti-dumping Duties: Evidence from China∗

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Very Very Preliminary and Incomplete and Please do not circulate!

Abstract

In this paper, I investigate how Chinese firms respond to the market-specific tariff shocks that arise from the US anti-dumping measures. Using Chinese trade and firm-level data between 2000 and 2006, I analyze how targeted firms’ productivity, export volume, price and markup are affected by these measures. I also examine whether these measures cause trade restriction and trade deflection. Furthermore, I evaluate the intensity and duration of both restriction and deflection effects.

Keywords: anti-dumping; difference-in-difference; Chinese exporters; total factor productivity; firm heterogeneity

JEL Classifications: F12; F13;

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1 Introduction

Despite the growing trend of trade liberalization, the use of temporary trade barriers such as anti-dumping (AD), countervailing duties and safeguards are on the rise. AD measure is particular important as it is among one of the most intensively used forms of trade restrictions. AD measures are an instrument that countries can use against unfair imports. An importing country can restrain a trade partner by levying duties if imported products are dumped and causing injury to domestic import-competing industries (WTO AD Agreement, article 3). The proliferation of using AD measures has stimulated the research on its effects on targeted products, firms and industries, as these effects are essential to evaluate the effectiveness of current instrument.

While the literature has gained significant insights regarding the impact of AD measures on the protected import competing firms, a much scarce literature looks at the corresponding effects on affected foreign firms. The effects of AD measures on the productivity of the exporting firms is not well understood. Do firms react differently in the face of such market-specific tariff shocks? How do AD measures affect trade flows? In this paper, I attempt to fill these gaps by exploring the impact of the US AD measures on the behavior of Chinese exporters. The analysis of how targeted foreign exporters response to AD measures could provide us the story from the flip side of the coin and complete picture of the effectiveness of such measures.

I provide a comprehensive analysis of the US AD measures on Chinese products, looking at their impact on trade flows and how these measures affect firm productivity, price and markup. I extract the AD cases filed by the US against Chinese products from 2000 to 2006 and estimate their impacts in determining firm export behavior. I concentrate on this research setting for several reasons. First, China has become one of the most targeted countries of AD investigations, along with its growing importance in international trade. Meanwhile, the US ranks as the second largest initiator of AD cases against China, because of its increasing trade deficit with China and the loss of manufacturing employment (see, for example David et al. 2013; Pierce and Schott 2012). In addition, given the heterogeneous productive structure of Chinese firms, my analysis of the US AD measures on Chinese products is particularly interesting since it takes into account both the impact at the product-level on the bilateral trade flows and the effect at the micro-level on firm productivity.

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1For example, according to WTO notifications, between 1995 and 2010 a total of 2503 AD measures were imposed worldwide, while in the same period safeguards and countervailing (CV) duties accounted for only 101 and 158 measures, respectively.

2This includes Konings and Vandenbussche 2008; Pierce 2011.
To carry out the empirical investigation, I utilize three datasets: the Global Antidumping Database, product-level trade data and firm-level production data from China. From the Global Anti-dumping Database, I compile all the AD investigations carried out by the US against Chinese products at the US HS 10-digit level. From the product-level trade data, I obtain the export transactions to the US at Chinese HS-8 digit product category by the universe of Chinese exporters to the US, including export volume, value and exporter identity. I combine these two datasets at the HS 6-digit product level which is common to both China and the US.

With this merged data, I first assess the possible trade damping effect (extensive margin versus intensive margin) of the US AD measures on Chinese products. That is, I investigate how AD measures distort bilateral trade flows between US and China, and whether these measures deflect Chinese exports to third markets. I then examine the exporters’ price adjustments of the concerned products. In particular, I exploit the heterogeneity of AD rates across products to measure their effects on unit price and markup. I look at the FOB unit price at product and firm-product level to examine the possible price adjustment associated with AD measures.

Furthermore, I evaluate the effect of the AD duties on firm performance using firm-level production data. In particularly, I examine the firm productivity, export propensity and the survival rate of firms by comparing the behavior of a treatment group of firms that receive AD measures to a control group of firms in similar industries that do not receive these punishments. The basic idea is to estimate the treatment effect of a policy change on a variety of firm choice using a difference-in-difference (DID) approach. In addition, I differentiate between exporters and non-exporters, multi and single-product firms and investigate their heterogeneous response to AD investigations.

More specifically, I first estimate firm-level total factor productivity (TFP) using the methodology of Olley and Pakes (1996) to correct for the simultaneity in the choice of inputs and firms exit. Second, I use DID approach to evaluate the differential productivity effects of AD measures. That is, I compare various sets of treatment versus control groups. In the first comparison, I study how firms that are specifically targeted in the AD measures differ from those that investigated but did not get any punishment. Next, I construct another control group to firms in HS 6-digit level were involved in AD investigations but not imposed AD duties. I then compare the firms producing the targeted products that are imposed AD duties with the control group. Finally, I adopt Konings and Vandenbussche (2008) approach

3This data contains the information about the inputs (i.e., labor, capital and materials), which allows me calculating firm productivity.
to construct "matched control groups", which are formed by estimating the probability of a product being subject to AD investigation.

My empirical analysis studying the trade effect of AD polices fits broadly into the literature on temporary trade barriers. In their influential paper, Bown and Crowley (2007) reveal that the US trade restrictions against Japan both deflect and depress Japanese export flows to third countries. Other couple of recent paper also document similar distortionary effects caused by AD duties. Specifically, Baylis and Perloff (2010) find that the US AD investigations result in Mexico to ship more tomatoes to Canada (trade deflection) and Canada to ship more tomatoes to the US (trade diversion). Cohen-Meidan (2013) examines the impact of the US imposition of AD duties on Japanese and Mexican imports of Portland cement, and reveals heterogeneous trade and market impacts within the US market. In this regard, my paper provides insight as to where the targeted Chinese products by the US petition go, since they are no longer being exported to the US market.

Another branch of literature explores the firm-level responses of AD actions, mainly looking at the effect on producers and exporters. Pierce (2011) studies the effect of AD duties on the performance and behavior of US manufacturers. He documents that AD protection reduces physical productivity and slows the resources reallocation from less productive to more productive plants. Using a large panel dataset of EU firms, Konings and Vandenbussche (2005) find that AD filing has a positive and significant effects on domestic markups. Applying the same data set, Konings and Vandenbussche (2008) reveal that laggard firms is associated with positive productivity gains, while the frontier firms experience productivity loss during the protection. These papers focus on the behavior of the domestic firms protected by AD. In contrast, my analysis contributes to the literature by looking at the effects on foreign firms targeted with these measures.

My research closely relates to recent several studies which look at the effects of AD measures on exporters from the targeted countries. Lu et al. (2013) use the HS 6-digit product level Chinese trade data and find that the substantial negative impact of AD protections on export volume is essentially driven by a decrease in the number of exporters. That is, the least productive firms are forced to exit the export market, increasing the market power and the productivity of surviving firms. Similarly, Shen and Fu (2014) also document that the US AD actions against China decrease China-US bilateral trade and leading to trade diversion from other sources. My paper differs from these research by focusing the impact of AD measures on firm productivity. Moreover, compared to Brambilla et al. (2012), which look at the impact of US AD duties on Vietnamese catfish, my research investigates all targeted products across industries.
In addition, my examination of firms’ reactions to AD measures contributes to the literature analyzing the impact of trade on firm-level productivity (e.g. Lileeva and Trefler 2010). While this paper deals with trade liberalization, I explore how trade protection and decreased export market access affect firm performance.

The paper is organized as follows. The next section describes the data used in the empirical analysis. Section 3 provides a brief summary of the AD investigation process in the US. Section 4 discusses the estimation strategy.

2 Data

This analysis uses data from the following sources: the Global Antidumping Database, firm-level production data and product-level trade data, to explore how Chinese firms react to the US AD measures.

The AD data comes from the Global Antidumping Database (GAD) of the world bank, covers all AD cases by all user countries in the world with each investigation mapped to the targeted HS codes (Bown, 2015). For each AD case, the GAD includes detailed information such as the product information (classified at the HS 10-digit level), initiation date, preliminary and final determination dates and decisions. It also specifies the names of the firms that had a firm-specific AD duty. I extract all US AD investigations against China and aggregate these products from HS 10-digit level to HS 6-digit level between 2000 and 2006. There are a total of 48 cases initiated sometime during my sample period.

2.1 Firm-level Production Data

The firm-level census data comes from annual surveys conducted by the National Bureau of Statistics (NBS). It covers two types of firms: all state-owned enterprises (SOEs) and non-SOEs with annual sales above 5 million yuan in manufacturing sector. This is a very rich firm-level panel dataset that covers between 162,885 firms (in 2000) and 301,961 firms (in 2006). The database contains information on firm’s characteristics, such as employment, capital stock, gross output, value added, four-digit industry code (484 categories), firm identification (e.g. firm name, age, zip code, address, et cetera.), and complete information on the three major accounting statements (i.e. balance sheets, profit & loss accounts, and cash flow statements). The information that I use to calculate productivity are the firm’s industry

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4 The unit of analysis is a firm, not the individual plant, more than 95% of observations in this data set are single-plant firms.

5 This is equivalent to 0.6 million USD based on the USD-CNY exchange rate in 2005.
code, age (based on reported birth year), ownership, value added, and capital stock.

I follow Brandt et al. (2012) instructions and the General Accepted Accounting Principles to discard observations with missing, zero, or negative values of the key financial variables (e.g., total assets, net value of fixed assets, sales, gross value of industrial output); I treat firms with missing employment similarly, and drop all firms with less than 8 employees as they fall under a different legal regime. I further exclude observations if their total assets is lower than the liquid assets or smaller than the fixed assets.

2.2 Product-level Trade Data

The disaggregated product-level trade transaction data are obtained from China’s General Administration of Customs. It records monthly import and export transactions of all Chinese firms with universal trading partners between 2000 and 2006. Each trade is measured by a product at the HS 8-digit level, a quantity, a value, and a unit value as the ratio of the value over the quantity. Quantity is measured by 1 of 12 different units of measurement (such as kilograms, square meters, et cetera). Value and unit value are in current US dollar. In addition, a trade regime variable identifies if the trade is an ordinary or processing trade and a transportation mode variable identifies if the trade is shipped by sea or air. Moreover, each firm is associated contact information: company name, address, zip code, contact person name, telephone number, and email. This dataset also contains firm ownership structure, i.e., if it is a state-owned, a privately-owned, or a foreign enterprise. As my analysis focuses on AD investigations taken by the US against China, I extract information regarding the monthly export transaction by Chinese exporters to the US.

Notably, there is a presence of large number of trade intermediaries in Chinese customs data. These are the firms that only offer services to facilitate trade but do not involve any manufacturing activities. To this end, I follow Ahn et al. (2011) suggestion and identify trade intermediaries in the data if firms’ names contain Chinese characters (i.e., ”Jinchukou”, ”Jingmao”, and ”Maoyi”) with the English-equivalent meaning of importer, exporter, and/or trading. Since I am interested in analyzing how manufacturing exporters react to market-specific cost shocks, I drop these trade intermediaries.

I first sum the monthly customs data to quarterly level in order to avoid the seasonality and lumpiness in the monthly data, as most firms do not export a given product to the

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6 Product classification is consistent across countries at the HS 6-digit level. The number of distinct product codes in the Chinese 8-digit HS classification is comparable to that in the 10-digit HS trade data for the US.

Ma et al. (2014) estimate that over 20 percent of Chinese exports were intermediated by trading firms.
US in every month. I also aggregate the export product from HS-8 digit level to the HS-6 digit level. I then merge the Chinese product-level trade data with the US AD investigations against China. In order to link with the production data, I aggregate the monthly customs data to annual level.

2.3 Matching Customs and NBS Data Sets

Firm-level production data are crucial in measuring TFP, whereas product-level trade data are essential in identifying the export unit price. Therefore, my empirical analysis relies on combining data from both sources. While each dataset is organized around firm registration numbers, the authorities have not released a unique firm identifier. Hence, the firm’s identification number cannot serve as a bridge to match the two data sets.

I merge the firm-level data to the customs records based on an algorithm of matching firm name and key contact information, including contact person, addresses and phone numbers. Specifically, I first match the two datasets by using each firm’s Chinese name and year. That is, if a firm has the exact same Chinese name in both datasets in a particular year, I match them as the same firm. Second, to increase the number of qualified matching firms to as many as possible, I adopt the fuzzy match technique to merge the imperfect firm names. By doing so, the matching success rate is highly comparable to that in other studies that use the same datasets. About one-third of the exporters in the trade dataset is merged with NBS dataset. These merged firms accounts for 33 to 37 percent (depending on the year) of values of aggregate Chinese exports.

3 A Primer on US AD Procedures

...To Be Add Later...

8In particular, the firm’s codes in the product-level trade data are at the 10-digit level, whereas those in the firm-level production data are at the 9-digit level, with no common elements inside.

9The year variable is necessary as an auxiliary identification variable since some firms could change their name in different years and newcomers could possibly take their original name.

10Often you have two datasets to merge but the variable you need to merge on does not relate perfectly in the two datasets. This is very common when you have people’s names, school names, or business names. For instance, one data set will have ”ABC Incorporated” and another ”ABC InCorp” or ”ABC Inc.”. The fuzzy merge is typically employed in this situation.

11There are at least two reasons why the merge is far from perfect. First, the NBS data set contains only manufacturing firms while the customs data contain a significant fraction of trade intermediaries that are considered as service firms by the NBS. Second, the NBS has a minimal threshold of 5 million yuan (approximately 600,000 USD during our sample period). The small processing exporters are not included in the NBS sample.
4 Empirical Framework

4.1 Definition of Treatment and Control Groups

I evaluate the possible trade dampening effects of AD measures by comparing the behavior of products in a treatment group that imposed the punishment to products in a control group that do not. The treatment group consists of products that levied AD duties. Each product in the treatment group is assigned a date of treatment and an ad-valorem duty rate.

I construct three alternative control groups. I first limit the control group to products that got the AD investigations, but whose investigations were either terminated, withdrew or received negative decisions (referred as Control Group 1). Notably, both of these two groups of products have been involved in AD investigation. This alleviates the concern that products that are investigated are different from those that do not. The second control group is all unaffected products within the HS-4 digit product category to which the affected products belong (referred as Control Group 2). This procedure, therefore, constructs a set of products that are similar to the treated group in terms of product characteristics. I adopt Konings and Vandenbussche (2008) approach to construct ”matched control groups” (referred as Control Group 3), which are formed by estimating the probability of a product being subject to AD investigation. The variables that are used to predict this probability includes the import value of the product, the real GDP growth rate in the US, an exchange rate index, a dummy variable indicating whether the product was previously investigated or not, and an HS 4-digit product dummy, similar to those used by Blonigen and Park (2004).

4.2 Empirical Strategy

I pursue a difference-in-difference (DID) approach to evaluate the effect of AD measures on product-level trade volume by following specification: \[ y_{gt} = \gamma_t + \delta_g + \gamma_t \times year + \sum_{j=-m}^{q} \beta_j D_{gt}(t = k + j) + \varepsilon_{gt}, \] (1)
where \( y_{gt} \) represents export volume of product \( g \) at time \( t \). Time fixed effect, \( \gamma_t \), captures any macro-level shocks affecting all products. Similarly, product fixed effect, \( \delta_g \), captures time-invariant product characteristics. \( D_{gt} \) indicates whether product \( g \) has imposed AD duties by date \( t \). However, instead of a single treatment effect, I have included \( m \) leads (\( \beta_{-1}, \beta_{-2}, \ldots, \beta_{-m} \)) and \( q \) lags (\( \beta_{+1}, \beta_{+2}, \ldots, \beta_{+q} \)) of the treatment effect. Let \( k \) be the time at which the treatment is being switched on in product \( g \). That is, I include the time dummies and

\[ \text{This part draws heavily from } \text{David (2003).} \]
treatment indicator to test whether the treated and control groups have the common trend before the treatment occurs, as the validity of DID estimation hinges on this assumption. If the coefficients on all leads of the treatment are close to zero and insignificant, it verifies the parallel trend assumption. In addition, I allow for product-specific time trend, $\gamma_t \times year$, to control for the possibility that different product may follow different time trend in control and treatment group.

Equation 1 uses a binary variable to define the treatment status, which implicitly assumes that AD duties are equally levied across products. However, products are charged with various level of duties in practice. That is, firms producing products such as pure magnesium receive 305.56 percent AD duties may respond differently than those producing products that receive 36.42 percent AD duties, such as non-alloy steel pipe. Therefore, I measure the effects of heterogeneity in AD rates by following specification:

$$y_{gt} = \gamma_t + \delta_g + \gamma_t \times year + \beta_1 Treatment_g \times Post_{gt} + \beta_2 Rate_{gt} \times Post_{gt} + \epsilon_{pt}. \quad (2)$$

The term $Treatment_g$ is a dummy variable taking value of 1 if product $g$ belongs to the treatment group. The term $Post_{gt}$ is a dummy equal to 1 for the product $g$ receive treatment in date $t$. The coefficient of interest in this study is $\beta_1$, which capture the essence of DID approach since it estimates the differential effects that AD investigation has on the firm-level outcome. $Rate_{gt}$ is the ad-valorem AD duty rate on product $g$ at time $t$. The interaction term $Rate_{gt} \times Post_{gt}$ allows me to disentangle the effect of varying rates of duty from the mean response of all firms receiving AD duties.

## 5 Estimation Findings

### 5.1 Product-level Quantity Response

I first assess the dynamic impact of AD measures by contrasting the product export volume in punished and non-punished products. Regression results corresponding to Equation 1 are reported in Table 1, where Control Group 1 and Control Group 2 are used, respectively. Specifically, I add indicator variable for 1, 2 and 3 quarters before the product imposed AD punishment, quarter 0-2 after the AD measures, and quarter 3 forward. Of these seven indicator variables, not that the first six are equal to one only in the relevant quarter, while the final variable is equal to on in each quarter, starting with the third quarter of imposed punishment.

The second column of Table 1 presents the preferred specification augmented with lags, leads and linear product trends using Control Group 1. The coefficient on the treatment
leads are close to zero, showing little evidence of an anticipatory response within the product about to impose for the AD duties. One quarter after the imposed AD measures, export volume decreases substantially 43 log points; then it averages 100 log points in quarter 3 forward. Subsequent columns (col.3-4) repeat these estimates when using Control Group 2. The pattern of coefficient is each case, providing robust evidence that AD duties severely distort trade flows. In the preferred specification using Control Group 2 that include linear product trend, the estimated impact is 98 log points at quarter 3. This pattern is depicted by Figure [1]

Table 1: The Estimated Impact of AD Duties on Product Export Volume

<table>
<thead>
<tr>
<th></th>
<th>Control Group 1</th>
<th>Control Group 2</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>3 Quarters Prior</td>
<td>0.290</td>
<td>0.072</td>
<td>0.294</td>
<td>0.083</td>
</tr>
<tr>
<td></td>
<td>(0.186)</td>
<td>(0.135)</td>
<td>(0.189)</td>
<td>(0.130)</td>
</tr>
<tr>
<td>2 Quarters Prior</td>
<td>0.209</td>
<td>0.055</td>
<td>0.166</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td>(0.187)</td>
<td>(0.153)</td>
<td>(0.183)</td>
<td>(0.144)</td>
</tr>
<tr>
<td>1 Quarter Prior</td>
<td>0.170</td>
<td>0.034</td>
<td>0.107</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(0.239)</td>
<td>(0.202)</td>
<td>(0.231)</td>
<td>(0.191)</td>
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<tr>
<td>Treatment Time</td>
<td>0.256</td>
<td>0.196</td>
<td>0.176</td>
<td>0.186</td>
</tr>
<tr>
<td></td>
<td>(0.237)</td>
<td>(0.219)</td>
<td>(0.231)</td>
<td>(0.214)</td>
</tr>
<tr>
<td>1 Quarter After</td>
<td>-0.465*</td>
<td>-0.433**</td>
<td>-0.506*</td>
<td>-0.405*</td>
</tr>
<tr>
<td></td>
<td>(0.299)</td>
<td>(0.217)</td>
<td>(0.290)</td>
<td>(0.214)</td>
</tr>
<tr>
<td>2 Quarters After</td>
<td>-0.618**</td>
<td>-0.698***</td>
<td>-0.637**</td>
<td>-0.649***</td>
</tr>
<tr>
<td></td>
<td>(0.277)</td>
<td>(0.246)</td>
<td>(0.274)</td>
<td>(0.241)</td>
</tr>
<tr>
<td>3 or More Quarters After</td>
<td>-1.071***</td>
<td>-0.987***</td>
<td>-1.155***</td>
<td>-0.975***</td>
</tr>
<tr>
<td></td>
<td>(0.153)</td>
<td>(0.109)</td>
<td>(0.300)</td>
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<tr>
<td>Product Trend</td>
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<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Time FE</td>
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<td>Yes</td>
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<td>Product FE</td>
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<tr>
<td>Observations</td>
<td>2718</td>
<td>2718</td>
<td>5935</td>
<td>5935</td>
</tr>
</tbody>
</table>

Standard errors cluster at product level in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01
Figure 1: Estimated impact of AD duties on product export volume for quarters before, during and after the measures, 2000q1-2006q4.

Notes: Estimates are from column (4), Table 1.
I also plot time trend of export volume for treatment and Control Group 2 over the pre- and post-antidumping investigation in Figure 2. The vertical line marks the date of final injury determination (the end of the AD investigation).

A few results emerge from this figure. First, there is an upward trend in the export volume of both treatment and control group before the AD investigation. Second, it seems that before the investigation, the treatment and control groups do not exhibit differential time trend, extrapolating that the per-existing trend are similar for both groups. Third, AD measures have a clearly dampening effect on the export volume of the treatment group.

Figure 2: Time trend of product-level export volume, Control Group 2

Notes: This figure reports the time trend of treatment group and control group 2. The vertical line mark the date of AD duties were finally determined by ITC.
References


