Product Bundling, Joint Markups and Trade Liberalization

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Abstract

Product bundling is a frequent practice that multi-product firms use to increase firm-level profits. This paper examines how product bundling affects a firm's markups at various levels in international trade. Joint pricing decisions for product bundling pose a challenge for previous methods in estimating markups. Utilizing the linkages across prices in the firm profit maximization problem, I propose a method to estimate transaction-level markups incorporating multi-product firms' decisions to bundle products. Focusing on Chinese exporters, multi-product firms that bundle products achieve markups that are approximately 40% higher than firms without product bundling. The markup premiums that bundling firms enjoy have been partially driven out since competition has increased due to China's WTO accession.
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1 Introduction

Multi-product firms are generally larger and hold a significant share of transactions in international trade, as shown by Bernard et al. (2012). As such, understanding the behavior of multi-product firms is central to characterizing the costs and benefits of trade policy. Naturally, there have been many studies on multi-product firms, such as their entry/exit decisions, product scope, and product quality (see Bernard et al. (2011), Lopresti (2016), and Manova and Yu (2017)). However, previous literature on multi-product firms and trade has overlooked one of the main advantages multi-product firms have over single-product firms: their ability to engage in product bundling, a practice whereby firms sell multiple goods in a single package.[1]In this paper, I study (i) how product bundling impacts a firm's markups and (ii) how the impacts of trade liberalization may differ for bundling and non-bundling firms.

Multi-product firms that engage in product bundling make pricing decisions jointly across the products they decide to bundle. Since previous methods of recovering markups rely on an implicit assumption that firms price goods independently, markups for bundling firms are not correctly captured by methods from the literature. This is especially true when the firm leverages its market power from one product market to another by bundling its goods. Thus, I first provide an alternative methodology to flexibly identify markups at the transaction level for both bundling and non-bundling firms. The multi-product firm with mixed bundling practices makes joint pricing decisions for all of its single-product goods and bundles to maximize its profit at the firm-level. Thus, the firm's first-order conditions from the profit maximization problem reflect the firm's joint pricing decision, which creates a markup linkage across goods. The expressions for markups are in terms of prices and consumer tastes across products, captured by the distribution of consumer valuations. After estimating consumer tastes with transaction data, the markups are recovered using the information from the first-order conditions.

[1]As a provider of multiple goods, multi-product firms can sell their products independently with separate pricing or jointly with product bundling. The option to buy products separately or as a bundle is referred to as *mixed bundling*. If buyers can only purchase products as a bundle, it is called *pure bundling*. Depending on the market structure and the firm's market power, a firm engaging in bundling practices can price a bundle at a higher (*bundling premium*) or lower (*bundling discount*) price. This paper focuses on mixed bundling practices with price discounts, the most prominent case in product bundling.

This paper proposes a methodology that uses demand-side information based on a firm's profit maximization problem and consumer rationality, similar to the traditional structural approach from Berry et al. (1995). This significantly departs from the widely used method of recovering markups using production-side information and a firm's cost minimization problem, proposed by De Loecker and Warzynski (2012) and De Loecker et al. (2016).[2] This paper's methodology also departs from that of Berry et al. (1995), where the dimensionality problem was solved by switching to the product characteristic space, and thus, data on sales, product characteristics, and market share are required. Instead, the consumer tastes across products are estimated herein using transaction data, which eases the burden on the data compared Berry et al. (1995). By incorporating product bundling into the framework, this paper characterizes the difference in markup strategies across independent pricing firms and bundling firms with joint pricing decisions, which previous methods cannot address.

This paper is also among the first to study strategic bundling practices by multi-product firms in an international trade context. After the basic framework of Stigler (1963), Adams and Yellen (1976), and McAfee et al. (1989) was proposed, the bundling literature focused on either theoretically extending the basic framework[3] or analyzing bundling practices in the retail, telecommunication, and software product markets[4]. However, Iyoha et al. (2022) document that product bundling is also prevalent in international markets. Specifically, they find that 37.76% of transactions are for bundles, accounting for 43.49% of import values in Columbia between 2015 and 2019. These findings

[2]While the production-side approach is widely used due to its simplicity and ease of data restrictions, there have been many challenges. For example, if the production data do not contain price information but only revenue, only revenue elasticities can be obtained, not output elasticities. With revenue elasticity, the expression for markups collapses to one, hence does not entail any information about markups. See Klette and Griliches (1996) and Bond et al. (2021). Also, there are discussions of identification issues where the markup is not identified using the proxy model (see Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015)) to estimate a production function and hence the output elasticity. See Flynn et al. (2019), Doraszelski and Jaumandreu (2019), and Jaumandreu (2018) for relevant discussions.

[3]See Zhou (2017) and Zhou (2021) for pure and mixed bundling practices in a competitive setting where there are an arbitrary number of firms and Chen and Riordan (2013) for general conditions for the profitability of product bundling where a copula is used to model the stochastic dependence of consumer values.

[4]Regarding software, see the *United States v. Microsoft Corporation, 253 F.3d 34* court case where the U.S. government accused Microsoft of illegally maintaining its monopoly position primarily through bundling PCs with Internet Explorer. Additionally, Crawford and Yurukoglu (2012) studied short-run welfare in the television channel market when á la carte policies that require distributors to offer individual channels for sale to consumers are introduced. The simulation results showed that increased input costs offset consumer benefits from purchasing individual channels.

are also present in the data sample I use for the main analysis. Specifically, out of 3,554 firms, 84% are multi-product firms that sell more than one product during the sample period. Out of 267 firms that sell both ADPMs (*automatic data procession machines*) and ADPM accessories[5], 35% engage in product bundling. By recovering markups jointly for multi-product firms with mixed bundling practices, I recover markups at the transaction level and examine systematic differences in markups among firms with different bundling decisions. The empirical analysis for Chinese exporters' electrical machines (ADPMs and ADPM accessories) from 2000 to 2006 shows that multi-product firms with product bundling enjoyed approximately 40.6% higher markups at the firm-market-year level than their counterparts without bundling practices. These differences in markups across bundling and non-bundling firms can plausibly reveal how multi-product firms use bundling practices to retain their market power. Nevertheless, to my knowledge, there has yet to be a study of product bundling in an international trade setting.

Last, this paper adds to the literature studying the relationship between markups and competition in response to trade reform. Changes in market competitiveness force firms to revisit pricing decisions, particularly when firms exert market power. De Loecker et al. (2016) study the impact of India's trade liberalization on markups, prices, and costs and find that (i) the incomplete pass-through of input costs declines to prices and (ii) there is a pro-competitive effect on markups. However, in their setting, each product's markup is assumed to be *independent* of the other products' markups even though most production occurs within multi-product firms. By recovering markups *jointly* for multi-product firms with product bundling, I determine how joint pricing affects firm profitability after trade liberalization. Empirical analysis shows that the increased competition induced by trade liberalization results in a decrease in markup dispersion across firms for computer parts. This pro-competitive effect may partly come from increased competition driving out product bundling.

The structure of this paper is as follows. Section 2 describes the data sets used in the

[5]ADPMs are machines that use logically interrelated operations performed in accordance with preestablished programs to furnish data. Computer parts such as CPUs (*central processing units*), GPUs (*graphics processing units*), and SSDs (solid state drives) fall into this category. Examples of ADPM accessories are coolers, server racks, and mounts.

empirical analysis and China's WTO accession features for products of interest. Section 3 presents an empirical framework to recover markups using information from transactions and firm pricing decisions for both bundling and non-bundling firms. In section 4, the empirical results are presented, and section 5 concludes this paper.

2 Data and Trade Policy Background

I first describe the Chinese Customs data (CCD) in section 2.1 because these data determine the base unit in which markups are recovered, how firms are classified into different types, and the product choice for the empirical analysis. Basic features of China's WTO accession, such as tariff changes are summarized in section 2.2.

2.1 *Data*

I take advantage of the Chinese Customs data that the Chinese Customs Office collects to explore markup behavior across firms, time, and international markets. The CCD record Chinese firm-level exports and imports between 2000 and 2006 at the destination market–month level with corresponding HS6 codes, quantities, values, and firm characteristics such as names, ownership, addresses, and cities.

There are a few things to note about this data set. First, because these are customs data, the entire empirical analysis is focused on exporter firms and their export transactions.[6] Second, the framework for recovering markups requires transaction data such that, ideally, transactions are recorded between each seller and buyer firm in a short period of time. While the frequency of CCD is at the monthly level, which is a good measure for international trade, there is aggregation on the buyer side. This buyer-side aggregation may lead to misclassifying multiple single–good transactions across different firms in a market into bundled–good transactions from one buyer. To check this, I

[6] De Loecker and Warzynski (2012) show that exporter firms, on average, have higher markups than domestic firms. In contrast, Yang (2021) document that Chinese exporter firms have lower markups than nonexporters because China has a comparative advantage in low-markup products. Regardless, if there is not a systematic difference across firms with different pricing strategies, then focusing on exporters will not lead to significantly different results from those of domestic firms.

introduce additional data for capturing individual transactions between China and the USA for the years 2004 and 2005.[7] Last, unlike production data where domestic and foreign quantities are aggregated, market-level transaction records allow me to incorporate demand-side characteristics into the framework and carry out the analysis by market. Hence, in the main empirical analysis, the markups are recovered at the firm-market-product-month level and aggregated to various levels, such as the firm-year level.

2.1.1 Price Imputation for Multi-Product Firms

The framework for recovering markups from the transaction side requires price information available to the buyer at the moment of the transaction. That is, while the price is observed for only the products sold during a given transaction, the prices of unsold products (including the bundle) for multi-product firms need to be imputed. These unobserved prices are imputed based on the firm's actual behaviors using the monthly feature of the customs data. The key intuition is to impute the unobserved prices using the observed price data from the closest month.

Consider a benchmark case with two products, product 1 and product 2. For firm f in market d, let (y_1, y_2) denote dummy variables for selling product 1 and product 2, and let (p_1, p_2) be the corresponding *observed* price for a transaction. Let (x_1, x_2, x_b, d) be the final *imputed* prices for product 1, product 2, both products combined, and the bundling discount for the transaction used to estimate consumer valuations and recover markups. The bundling discount is calculated as $d = (x_1 + x_2) - x_b$. If a transaction is a multi-product transaction $(y_1, y_2) = (1, 1)$, with $d > 0$, then it is classified as a transaction with product bundling. Transactions with either $(y_1, y_2) \neq (1, 1)$ or $d = 0$ are not classified as bundling transactions.[8]

[7] Firm-to-firm-level transaction data show that most transactions (80%) remain the same when seller firm-to-buyer transactions are aggregated to the seller firm-to-buyer market. The firm-to-firm-level and firm-to-market-level data both reach 3% for transactions containing both ADPMs and ADPM accessories, indicating that the chances of misclassifying non-bundling transactions as bundling transactions are slim.

[8] For example, a transaction where $(y_1, y_2) = (1, 0)$ with $d > 0$ is a transaction where the buyer buys only product 1 even though there is a discount for a bundled product. On the other hand, a transaction where $(y_1, y_2) = (1, 1)$ but $d = 0$ is simply a transaction with multiple products and is not classified as a bundled transaction.

First, for a given transaction, if the price is observed, the imputed price is simply the observed price itself, i.e., $x_j = p_j$. For example, in the case of $(y_1, y_2) = (1, 0)$, $x_1 = p_1$ and for $(y_1, y_2) = (1, 1)$, $x_b = p_1 + p_2$. If a price is not observed for product j, then $y_j = 0$ for $j = 1, 2$. Then, for a given firm-market-year, I find the closest transaction where only $y_j = 1$ and $y_{-j} = 0$, where $-j$ denotes the other good. If there is no such transaction, I find the closest transaction with $(y_1, y_2) = (1, 1)$. I use the price from the closest transaction as the imputed price, i.e., $x_j = p_j^c$, where p_j^c denotes the price from the closest transaction. For $j = b$, I find the closest transaction where $(y_1, y_2) = (1, 1)$ and impute it as $x_b = p_1^b + p_2^b$, where p_j^b are prices from the closest multi-product transaction. If there are no transactions with $(y_1, y_2) = (1, 1)$, I simply set this as $x_b = x_1 + x_2$.

Table 1 presents a basic example of the imputation procedure. To show the process more clearly, multi-product firms that sold both product 1 and product 2 to market d in a given year t are divided into five groups. Firms that sold only good j or both goods are classified into group j with $j = 1, 2$. That is, firms in group 1 have the following; $(y_1, y_2) = \{(1, 0), (1, 1)\}$. Firms that have only single-product transactions, i.e., $(y_1, y_2) = \{(1, 0), (0, 1)\}$ are in group 3. Firms that only have multi-product transactions, $(y_1, y_2) = \{(1, 1)\}$, are in group 4. Last, firms that sold all compositions of goods are classified into group 5; that is, they have $(y_1, y_2) = \{(1, 0), (0, 1), (1, 1)\}$. Note that by construction, firms in groups 3 and 4 can never be classified into bundling firms by design.[9] Out of five multi-product transactions, in this example, only three are classified as bundling transactions.

2.1.2 Firm Type Definition and Data Description

After unobserved prices are imputed, firms can be classified into single- and multi-product firms with and without bundling practices. This classification is based on sales behavior rather than production behavior. First, firms are categorized into single- or multi-product firms depending on how many goods they sell to each destination market in a given year. For example, if firm f produced multiple products but sold only ADPMs to destination market d in year t, then the firm is classified as a single-product firm in market d in year t. Once

[9]Thus, this imputation conservatively constructs bundling transactions by excluding group 4 entirely. Group 4 accounts for approximately 7% of firm–market pairs.

Table 1: Price Imputation Example

	Observed				*Imputed*				
	y_1	y_2	p_1	p_2	x_1	x_2	x_b	d	Bundle?
Group 1	1	0	80	-	80	100	170	10	No
	1	1	70	100	80	100	170	10	Yes
Group 2	0	1	-	120	70	120	170	20	No
	1	1	70	100	70	120	170	20	Yes
Group 3	1	0	80	-	80	120	200	0	No
	0	1	-	120	80	120	200	0	No
Group 4	1	1	60	100	60	100	160	0	No
	1	1	70	120	70	120	190	0	No
Group 5	1	0	80	-	80	120	170	30	No
	0	1	-	120	80	120	170	30	No
	1	1	70	100	80	120	170	30	Yes

Note: This table shows how price imputation for unobserved prices is carried out with a simple example. Firm-market-year pairs are grouped into five different groups based on their transaction behavior, i.e, (y_1, y_2). A transaction is classified as a bundling if it satisfies $(y_1, y_2) = (1, 1)$ and $d > 0$.

unobserved prices are imputed for multi-product firms that have sold products of interest, multi-product firms are further divided into bundling firms and non-bundling firms based on whether there was a bundling transaction in market d in year t.

In this paper, ADPMs and ADPM accessories are selected for analysis.[10] The products are selected based on the following criteria. First, there must be enough observations. Electrical machines were one of the most exported goods from China during the sample period. Additionally, the relationship between goods must be considered. Goods are chosen based on whether firms are likely to produce all the gods and sell them as a bundle. ADPMs and ADPM accessories are both parts of electrical machines that are frequently produced by the same manufacturers. A basic description of the data for ADPMs and ADPM accessories is summarized in Table 2.

In the upper panel, Table 2 shows that based on the transaction-side classification, multi-product firms are the majority firm type in the ADPM and ADPM accessory product markets, which aligns with findings from the multi-product firm literature. Specifically, out of 15,467 firm-market-year pairs, multi-product firms account for approximately 60% of the

[10]The products are classified at the HS6 code level. Specifically, the ADPMs are {847130, 847141, 847149, 847150, 847160, 847170, 847180}, and the ADPM accessories are {847330}.

Table 2: Summary Statistics

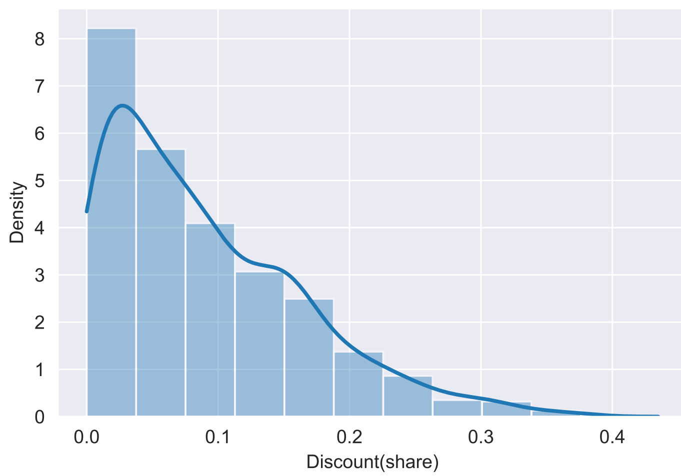
	Observation	(%)
Firm Characteristics(fdt)	15,467	100.0%
Single-Product Firms	6,265	40.51%
Multi-Product Firms	9,202	59.49%
selling either ADPMs or ADPM accessories	8,483	92.19%
selling both ADPMs and ADPM accessories	719	7.814%
with product bundling	251	34.91%
without product bundling	468	65.09%
Transaction Characteristics(fdm)		
Number of Transactions	74,247	100.0%
$MPT_{fdm} = 0$	72,880	98.16%
$MPT_{fdm} = 1$	1,367	1.84%
$Bundling_{fdm} = 1$ in $MPT_{fdm} = 1$	578	42.28%

Note: The subscripts indicate the following: f is for firms, d is for destination markets, j is for products(ADPMs or ADPM accessories), and m and t are time subscripts that stand for month and year, respectively. MPT_{fdm} is a dummy that refers to multi-product transactions that consist of both ADPMs and ADPM accessories between firm f and market d for month m.

observations.[11] Out of those multi-product firms, 719 firms sold both ADPMs and ADPM accessories to market d in year t, which accounts for approximately 7.8% of the multi-product firms. As we increase the proportion of products of interest, the ratio of multi-product firms selling those goods will increase. Out of 719 firms, approximately 35% of firms engaged in product bundling with ADPMs or ADPM accessories. The bottom panel describes the baseline transactions, defined at the firm-market-month level. There are a total of 74,247 transactions, and of those, approximately 2% sold ADPMs and ADPM accessories. Among the transactions involving both both ADPMs and ADPM accessories, 42.28% were bundled transactions. Figure 1 plots the share of bundling discounts for those bundling transactions. A power–law feature is shown for the bundling discount, where most of the discounts are 10% or less of the original price.

[11] Out of 8,139 possible firm-importer pairs, only 4% of firms changed their status during the sample period for a given market, and the majority of firms remained with their original type for a given market.

Figure 1: Bundling discount share for bundled transactions



Note: This figure plots the bundling discount share, which is the bundling discount over the sum of each component product price on the x-axis, i.e., $\frac{d_{fdbt}}{p_{fd1t}+p_{fd2t}}$. The y-axis shows the normalized density for the number of observations.

2.2 *WTO Accession and Tariff Reductions*

China's WTO accession, which took place in 2001, has induced substantial tariff reductions (see Lu et al. (2015)). In this section, I document the impact of China's trade liberalization on electric machines using tariff data from the WITS database and trade values from UN COMTRADE. To examine the impact of tariff reductions and improved overall market access, I focus on the top 30 markets where China had the most transactions for ADPMs and ADPM accessories. They account for 94.77% of the quantity exported and 97.13% of trade value.[12]

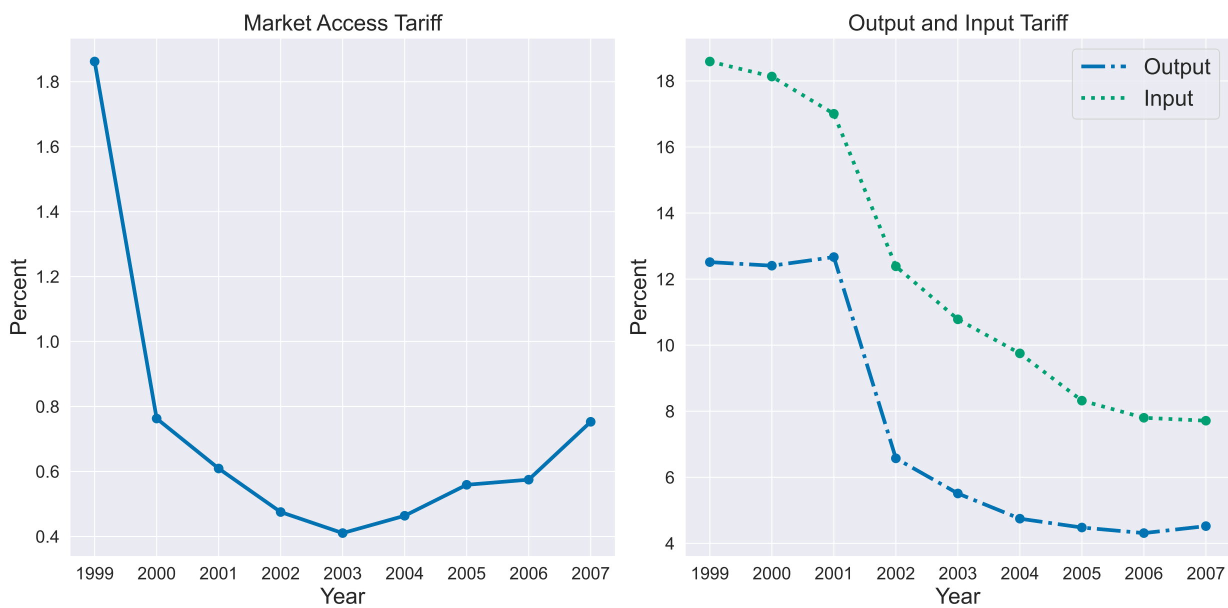
Figure 2 displays the evolution of China's aggregated market access, output and input tariffs.[13] Market access tariffs are tariffs that partner country firms face when exporting to China, whereas output tariffs are those that Chinese exporters face. Output tariffs are aggregated using each market's trade value as weights. For the input tariffs, I follow

[12]These markets are Hong Kong, the USA, Japan, Taiwan, the Netherlands, Singapore, Germany, the UK, South Korea, Australia, Malaysia, France, India, Thailand, the UAE, Canada, Italy, Spain, the Philippines, Brazil, Mexico, Belgium, South Africa, Israel, Turkey, Finland, New Zealand, Ireland, Indonesia, and Poland, in order of frequency. Aside from Taiwan, which joined the WTO alongside China, the remaining 29 markets were all WTO members before China's WTO accession.

[13]Market access, output and input tariffs for each market are displayed in the appendix.

De Loecker et al. (2016) and construct them for each market by passing the tariff data at the ISIC Rev3 level to China's input–output matrix table for 1995–2010 and then using the values as weights to create the aggregated input tariffs.[14] Figure 2 shows that trade liberalization brought a sharp decline in both output and input tariffs for ADPMs and ADPM accessory products and a modest decline in market access tariffs. Specifically, the output tariff declined from approximately 12% to 4%, and the input tariff declined significantly from approximately 19% to 8%.

Figure 2: Tariffs for ADPMs and ADPM accessories from 1998 to 2007



Note: This figure plots aggregated market access and, output and input tariffs for China from 1999 to 2007 for HS2 level 84, which contains both ADPMs and ADPM accessories.

3 A Framework for Estimating Markups

To incorporate joint markups and product bundling, I introduce an empirical model from the bundling literature. While non-bundling firms price goods independently, a bundling

[14]The formal definition of the input tariff is $\tau_{idt}^{input} = \sum_k a_{ki} \tau_{kdt}^{output}$, where τ_{kdt}^{output} is the export tariff for market d to China in industry k at time t and a_{ki} is the share of industry k in the value of industry i from the input–output table.

firm will choose prices for all of its single-product goods and bundles jointly to maximize its profit across all products simultaneously. Therefore, the firm's first-order conditions from the profit-maximizing problem reflect information on independent markups for non-bundling firms and a markup linkage across all goods for bundling firms. This information from the FOCs is expressed in terms of consumers' valuations for the individual goods and the optimal price levels that the firm chooses.

Firms choose optimal prices based on their marginal cost and demand. Using monthly transaction data and assumptions on the parametric structure for the consumer's valuations, the model recovers marginal costs and consumer valuations across goods from the information revealed in the data. Once consumer valuations across goods are obtained, markups among firms that sell goods separately can be explicitly calculated, while joint markups among bundling firms are solved numerically.

For the rest of the paper, the set of individual goods (bundles) for firm f in year t are denoted as $\mathcal{G}_{ft}(\mathcal{B}_{ft})$, and the number of components in the set are $G_{ft}(B_{ft})$. Let J_{ft} be the total number of products that the multi-product firm sells, either as individual products or as a product bundle. For example, if firm f produces two discrete products and sells three products—each individual product and one product bundle of both single products—we have the following: $J_{ft} = 3$, $\{1, 2\} \in \mathcal{G}_{ft}$ and $\{b\} \in \mathcal{B}_{ft}$. Theoretically, for a total number of individual products G_{ft}, the number of possible bundles is at most $\sum_{b=2}^{G_{ft}} \binom{G_{ft}}{b}$.

Let c_{fdjt} be firm f's constant marginal cost for a single product $j \in \mathcal{G}_{ft}$ in market d and year t.[15] The marginal cost of a bundle is the sum of the marginal costs of its single product components. The price of a bundle is potentially offered at a discount relative to the sum of its components.[16] For example, in the case of $G_{ft} = 2$, $c_{fdbt} = c_{fd1t} + c_{fd2t}$ and $P_{fdbt} = P_{fd1t} + P_{fd2t} - d_{fdbt}$ with $d_{fdbt} > 0$, where the subscript b refers to a bundled product comprising both product 1 and product 2. Multi-product firms that do not engage in bundling practices could be interpreted as having $d_{fdbt} = 0$, that is, as effectively selling both

[15] The assumption that marginal costs are constant is needed to construct the marginal cost for the bundle. This assumption can be relaxed for firms that price goods separately to incorporate nonconstant returns to scale.

[16] In this framework, a bundling premium in which a bundle is offered at a higher price than the sum of its component goods is not considered. Intuitively, consumers always have the option to buy single-product goods together rather than as a bundle when there are mixed bundling practices.

goods simultaneously. Thus, while the subsequent discussion assumes that multi-product firms bundle individual products, it could easily be applied to multi-product firms without bundling by setting $d_{fdbt} = 0$.

The model assumes that consumers for each firm desire at most one unit of each good and demand each good independently of their consumption of the other goods.[17] For these consumers, consider the consumer valuations for G_{ft} goods $\mathbf{v}_{fdt} = (v_{fd1t}, ..., v_{fdG_{ft}t})$, which are distributed according to the unknown distribution function $\Psi_{fdt}(\mathbf{v}_{fdt})$.[18] Let $\psi_{fdt}(\mathbf{v}_{fdt})$ and $\psi_{fdkt}(v_{fdkt})$ be the probability density function and marginal density function, respectively, for product k for $\Psi_{fdt}(\mathbf{v}_{fdt})$. To avoid trivial cases, a positive measure of consumers exists such that $v_{fdjt} \geq c_{fdjt}$ for all j, and resale by consumers is not possible.

This paper will focus on a benchmark case where $G_{ft} = 2$ to build on the key intuition as transparently as possible. Then, I outline how to generalize the estimation procedure for cases where $G_{ft} > 2$. Generalizing the estimation process for an arbitrary number of single products and bundles is a straightforward extension of the $G_{ft} = 2$ setting, albeit with substantially more derivations. In practice, bundled products do not typically contain many individual products, which eases the burden of derivation and any data restrictions.[19].

The next section describes the framework for recovering markups with the transaction unit based on Chinese customs data; thus, the transactions are at the firm-market-month level. However, the transactions can be defined based on the available data.[20]

[17] The unit demand assumption is relaxed in section 3.3 by utilizing quantity information from the transaction data.

[18] The consumer valuation distribution function Ψ can vary along various dimensions. The choice heavily depends on the number of observations in the data. In this paper, Ψ varies by firm, market, and year to capture demand characteristics at the firm, market, and year levels.

[19] Iyoha et al. (2022) found that most multi-product transactions have fewer than four products.

[20] The assumptions on the unit of the marginal costs, consumer valuations, and prices, and hence the markups, can be chosen appropriately based on how detailed the "transaction" is. For example, this paper defines a transaction as between an exporter firm and the destination market at the monthly level. Thus, in this paper, the marginal costs can differ by destination market, i.e., c_{fdjt}, to reflect shipping or market-specific marketing fees. However, it is not reasonable to assume that the marginal costs will differ at a monthly level; hence, the time unit remains at a yearly level. Consumer valuations for each firm's residual demand also differ by destination market and year, i.e., Ψ_{fdt}, to reflect market-specific demand characteristics. The unit price for each product follows the unit of transactions, i.e., P_{fdjm}, where m is the month.

3.1 *Recovering Markups for Non-Bundling Firms*

I first describe how to recover markups for firms that do not engage in bundling practices. Firms with independent pricing decisions maximize market-level profit by maximizing profits from each product independently.[21] Thus, the first-order conditions for each product-level profit entail information about *independent* product markups. The profit maximization problem for product j in market d for year t is

$$\underset{\mathbf{P}_{fdjm}}{\operatorname{argmax}}\, \Pi_{fdjt} = \underset{\mathbf{P}_{fdjm}}{\operatorname{argmax}} \sum_{m \in t} \Pi_{fdjm} = \underset{\mathbf{P}_{fdjm}}{\operatorname{argmax}} \sum_{m \in t} (P_{fdjm} - c_{fdjt}) Q^D_{fdjm}, \tag{1}$$

where $Q^D_{fdjm}(P_{fdjm})$ is the quantity demanded for product j in market d in month m. Given the consumer valuations for product j in market d and year t, consumers whose valuations are higher than the price will purchase the good. Thus, $Q^D_{fdjm}(P_{fdjm}) = \int_{P_{fdjt}}^{\infty} \psi_{fdjt}(x)dx$.

Note that the quantity demanded for good j is only a function of the good j characteristics such as price P_{fdjm} and its marginal distribution ψ_{fdjt} and does not depend on other products' characteristics. Then, the first-order condition (2) yields the following equation in terms of the marginal density of valuations for product j, ψ_{fdjt}, monthly prices in year t, $P_{fjdm \in t}$, and the marginal cost c_{fdjt}.[22] After the distribution of the consumer's valuations is estimated, equation (2) is used to recover the marginal cost c_{fdjt} and markups μ_{fjdm} for firms without bundling practices.

$$\sum_{m \in t} \Big(Q^D_{fdjm}(P_{fdjm}) - (P_{fdjm} - c_{fdjt}) \psi_{fdjt}(P_{fdjm}) \Big) = 0, \tag{2}$$

Equation (2) shows the identification problem of previous methods in recovering joint markups for bundling firms. Once joint pricing decisions are incorporated, the number of unknown parameters (marginal costs and markups) increases with product size, while the information (one first-order condition) remains the same.

[21] In this paper, independent pricing firms include single- and multi-product firms without bundling practices. Markups for multi-product firms without bundling can be recovered using (1) the separate pricing method and (2) the product bundling method with $d_{fbt} = 0$, setting the discount equal to zero.

[22] The intuition of equation (2) is simple. A firm should choose a price such that the marginal revenue from increasing the price by 1 unit is equal to the marginal cost of increasing the price by 1unit. If a firm increases the price by 1 unit, the firm will gain additional profits from existing customers $(1 \times Q^D_{fdjm}(P_{fdjm}))$ and lose profits from customers who were on the margin $((P_{fdjm} - c_{fdjt})\psi_{fdjt}(P_{fdjm}))$.

3.2 *Recovering Joint Markups with Product Bundling*

To identify joint markups, I introduce a framework from the bundling literature. The approach employs a model setting similar to those of McAfee et al. (1989) and Chen and Riordan (2013) in that consumer valuations are introduced to capture demand-side information. While their work focuses on finding the theoretical conditions in which it is more profitable for the firm to engage in product bundling, I focus on the joint pricing behavior of bundling firms and hence joint markups. Information regarding consumer taste is required to recover markups. I borrow the strategy for estimating consumer valuations from Letham et al. (2014), where variations in purchase behavior and prices are used.

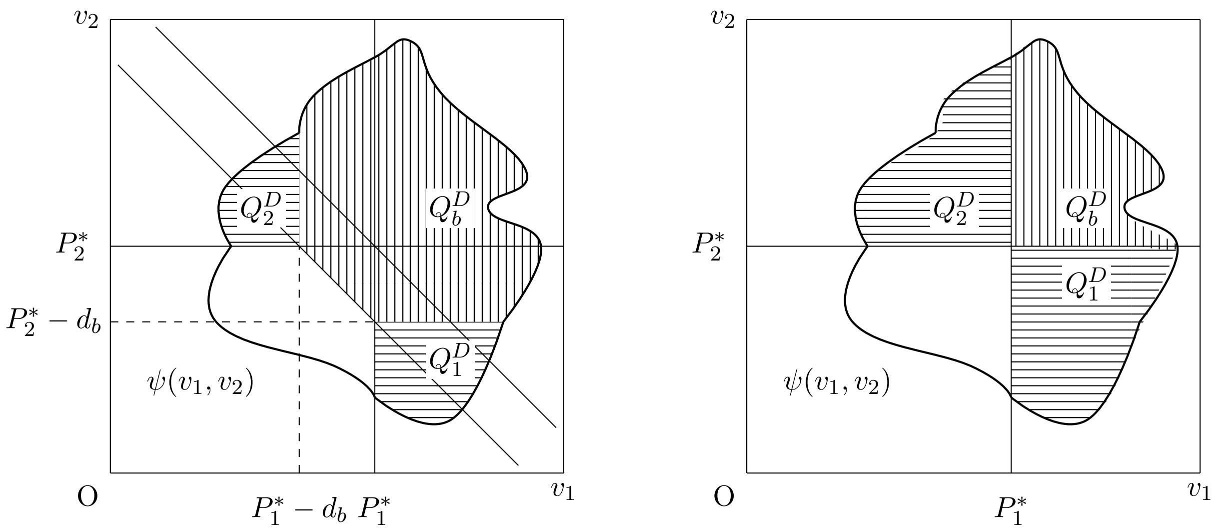
3.2.1 $G_{ft} = 2$ *Case*

Since consumers are rational, a given consumer will purchase product k from firm f only if it gives her the highest utility among all other options. This enables me to write the quantity demanded for each good j (Q^D_{fdjm}) in terms of prices and the distribution of consumer valuations. For example, when $G_{ft} = 2$,

$$\begin{aligned}
&[Q^D_{fd1m} \text{ when}] \qquad v_{fd1t} - P_{fd1m} \geq max\{0, v_{fd1t} + v_{fd2t} - P_{fdbm}\}, \\
&[Q^D_{fd2m} \text{ when}] \qquad v_{fd2t} - P_{fd2m} \geq max\{0, v_{fd1t} + v_{fd2t} - P_{fdbm}\}, \\
&[Q^D_{fdbm} \text{ when}] \qquad v_{fd1t} + v_{fd2t} - P_{fdbtm} \geq max\{0, v_{fd1t} - P_{fd1m}, v_{fd2t} - P_{fd2m}\},
\end{aligned} \tag{3}$$

Denoting the vector of prices as $\mathbf{P}_{fdm} = (P_{fd1m}, P_{fd2m}, P_{fdbm})$, combining each inequality and applying the definition of P_{fdbm} gives the following expressions for the quantity demanded in equation (4), which are graphically illustrated in the left panel of Figure 3. The consumer whose valuation falls in the area marked as Q^D_1, Q^D_2, or Q^D_b will buy good 1, good 2, or the bundled goods, respectively. Note that the quantity demanded for a single good $j = 1, 2$ is a function of not only its price but also the price of the bundled good b and hence the price of the other good, explicitly showing the linkage across goods for firms with joint pricing.

Figure 3: Graphical illustrations: Joint density functions



(a) $G_{ft} = 2$ with bundling

(b) $G_{ft} = 2$ without bundling

Note: This figure graphically depicts the quantity demanded for each good j, which depends on the joint density ψ and the price variables. The left panel depicts the case for a multi-product firm with product bundling, and the right panel shows the quantity demanded for a multi-product firm without bundling. For a multi-product firm without bundling, Q^D_{fd1m} and Q^D_{fd2m} refer to the quantities demanded for only products 1 and 2, respectively, and Q^D_{fdbm} refers to the quantity demanded for both goods without a discount. For both figures, subscripts f, d, and m or t are dropped for parsimony.

$$
\begin{aligned}
Q^D_{fd1m}(\mathbf{P}_{fdm}) &= \int_{P_{fd1m}}^{\infty} \int_{0}^{P_{fdbm}-P_{fd1m}} \psi_{fdt}(x,y)dydx, \\
Q^D_{fd2m}(\mathbf{P}_{fdm}) &= \int_{0}^{P_{fdbm}-P_{fd2m}} \int_{P_{fd2m}}^{\infty} \psi_{fdt}(x,y)dydx, \\
Q^D_{fdbm}(\mathbf{P}_{fdm}) &= \int_{P_{fd1m}}^{\infty} \int_{P_{fdbm}-P_{fd1m}}^{\infty} \psi_{fdt}(x,y)dydx + \int_{P_{fdbm}-P_{fd2m}}^{P_{fd1m}} \int_{P_{fdbm}-x}^{\infty} \psi_{fdt}(x,y)dydx,
\end{aligned} \tag{4}
$$

These expressions for the quantities demanded can be plugged into the firm's profit maximization problem. The profit-maximizing firm will simultaneously choose all prices $\mathbf{P}_{fdm}$ to maximize its profit:

$$
\begin{aligned}
\underset{\mathbf{P}_{fdm}}{\operatorname{argmax}} \, \Pi_{fdt} = & \underset{\mathbf{P}_{fdm}}{\operatorname{argmax}} \sum_{m \in t} \Pi_{fdm} = \underset{\mathbf{P}_{fdm}}{\operatorname{argmax}} \sum_{m \in t} \Big(\Pi_{fd1m} + \Pi_{fd2m} + \Pi_{fdbm} \Big), \\
& \text{where} \quad \Pi_{fdkm} = (P_{fdkm} - c_{fdkt}) Q^D_{fdkm}, \quad \text{for all } k \in \{1, 2, b\},
\end{aligned}
$$

and the analytical expression for $Q^D_{fdkm}(\mathbf{P}_{fdm})$ in terms of prices is derived from the rational consumer assumption as described above. Thus, the profit function is as follows:

$$
\begin{aligned}
\Pi_{fdt} =& \sum_{m \in t} \Big(\Pi_{fd1m} + \Pi_{fd2m} + \Pi_{fdbm} \Big), \\
=&(P_{fd1t} - c_{fd1t}) \int_{P_{fd1t}}^{\infty} \int_{0}^{P_{fdbt}-P_{fd1t}} \psi_{fdt}(x,y) dy dx, + (P_{fd2t} - c_{fd2t}) \int_{0}^{P_{fdbt}-P_{fd2t}} \int_{P_{fd2t}}^{\infty} \psi_{fdt}(x,y) dy dx \\
&+ (P_{fdbt} - c_{fd1t} - c_{fd2t}) \Bigg[\int_{P_{fd1t}}^{\infty} \int_{P_{fdbt}-P_{fd1t}}^{\infty} \psi_{fdt}(x,y) dy dx + \int_{P_{fdbt}-P_{fd2t}}^{P_{fd1t}} \int_{P_{fdbt}-s}^{\infty} \psi_{fdt}(x,y) dy dx \Bigg].
\end{aligned}
$$

The first-order conditions for the price variables give the following three equations that express the relationship among marginal costs (hence markups) across products in terms of consumer valuation $\psi_{fdt}(v_{fd1t}, v_{fd2t})$ and price variables.[23]

$$
\begin{aligned}
&\sum_{m \in t} \Big(Q^D_{fd1m}(\cdot) - (P_{fd1m} - c_{fd1t}) \mathcal{A}_{fdm} + (P_{fd2m} - c_{fd2t} - d_{fdbm}) \mathcal{B}_{fdm} \Big) = 0 \\
&\sum_{m \in t} \Big(Q^D_{fd2m}(\cdot) - (P_{fd2m} - c_{fd2t}) \mathcal{C}_{fdm} + (P_{fd1m} - c_{fd1t} - d_{fdbm}) \mathcal{D}_{fdm} \Big) = 0 \qquad (5) \\
&\sum_{m \in t} \Big(Q^D_{fdbm}(\cdot) - (P_{fd1m} - c_{fd1t})(\mathcal{D}_{fdm} + \mathcal{E}_{fdm}) - (P_{fd2m} - c_{fd2t})(\mathcal{B}_{fdm} + \mathcal{E}_{fdm}) \\
&\qquad + d_{fbm}(\mathcal{B}_{fdm} + \mathcal{D}_{fdm} + \mathcal{E}_{fdm}) \Big) = 0
\end{aligned}
$$

where $\mathcal{A}_{fdm} = \int_0^{P_{fdbm}-P_{fd1m}} \psi_{fdt}(P_{fd1m}, y) dy$, $\mathcal{B}_{fdm} = \int_{P_{fd1m}}^{\infty} \psi_{fdt}(x, P_{fdbm} - P_{fd1m}) dx$, $\mathcal{C}_{fdm} = \int_0^{P_{fdbm}-P_{fd2m}} \psi_{fdt}(x, P_{fd2m}) dx$, $\mathcal{D}_{fdm} = \int_{P_{fd2m}}^{\infty} \psi_{fdt}(P_{fdbm} - P_{fd2m}, y) dy$, and $\mathcal{E}_{fdm} = \int_{P_{fdbm}-P_{fd2m}}^{P_{fd1m}} \psi_{fdt}(x, P_{fdbm} - x) dx$.[24] Note that after the consumer's valuation distribution $\psi_{fdt}(x,y)$ is estimated, the first-order conditions provide the expression needed to identify joint markups.[25]

[23] The derivation of these equations is included in the Appendix.

[24] For multi-product firms without bundling, taking the first-order conditions with respect to only (P_{fd1t}, P_{fd2t}) or plugging $d_{fdbt} = 0$ into equation (5) yields an identical result. In this case, joint pricing from product bundling is removed; hence, product markups are independent of one another, as in previous literature.

$$
\begin{aligned}
Q^D_{fd1m}(P_{fd1m}, P_{fd2m}) + Q^D_{fdbm}(P_{fd1m}, P_{fd2m}) - (P_{fd1m} - c_{fdjt})(\mathcal{A}_{fdt} + \mathcal{D}_{fdt}) = 0 \\
Q^D_{fd2m}(P_{fd1m}, P_{fd2m}) + Q^D_{fdbm}(P_{fd1m}, P_{fd2m}) - (P_{fd2m} - c_{fdjt})(\mathcal{B}_{fdt} + \mathcal{C}_{fdt}) = 0
\end{aligned}
$$

The regression results in section 4 are robust to numerically estimating the markups of multi-product firms without bundling by plugging in $d_{fdbt} = 0$.

[25] The intuition for the first-order conditions still holds, just as it did for equation (2). If the firm increases the price for product 1 by 1 unit, it will gain additional profit from existing consumers from Q_{fd1m} and from consumers who were on the margin between Q_{fd1m} and Q_{fdbm}, which is captured by the first and third

The equations from system (5) are denoted as $\mathbf{\Gamma}(\mathbf{P}_{fdm}, \mathbf{Q}^D_{fdm}, \psi_{fdt}(\mathbf{v}_{fdt}); \mu_{fdj\in\{1,2\}m}) = 0$. Note that $\mathbf{\Gamma}(\mu_{fdj\in\mathcal{G}_{ft}m}) = 0$, is a three ($J_{ft}$) by one vector of equations. Because we have two (G_{ft}) unknown joint markup parameters and three (J_{ft}) individual equations, it is overdetermined. I propose recovering the joint markups by solving $\mathbf{\Gamma}(\mu_{fdj\in\mathcal{G}_{ft}m}) = 0$ numerically and choosing the set of $\mu_{fdj\in\mathcal{G}_{ft}m}$ that minimizes the error below a given threshold level. The existence of a sufficiently small threshold level will filter out any cases where there is no solution for $\mu_{fdj\in\mathcal{G}_{ft}m}$.

3.2.2 *General Case with* $G_{ft} > 2$

Here, I provide a general approach for deriving markup expressions across goods for cases where $G_{ft} > 2$. As noted before, once the number of single product goods exceeds two, the total number of possible combinations of single goods to make a bundled product becomes $\sum_{b=2}^{G_{ft}-1}\binom{G_{ft}}{b}$. This means that even if firms have identical $\mathcal{G}_{ft}$, i.e., the same individual goods, they might have different bundled goods, i.e., different $\mathcal{B}_{ft}$. Thus, when G_{ft} exceeds two, I treat the case as if all firms offer all possible combinations of a bundle. That is, $B_{ft} = \sum_{b=2}^{G_{ft}-1}\binom{G_{ft}}{b}$ for all firms. Then, the discount value for combinations of goods that are not bundled can be set at zero, as in the case of multi-product firms without bundling practices.

Thus, if $G_{ft} > 2$, we follow the same steps as in the $G_{ft} = 2$ case. First, I construct the following profit-maximizing problem for a firm f.

$$\underset{\mathbf{P}_{fdm}}{\operatorname{argmax}}\,\Pi_{fdt}(\mathbf{P}_{fdm}) = \underset{\mathbf{P}_{fdm}}{\operatorname{argmax}} \sum_{k\in\mathcal{G}_{ft}\cup\mathcal{B}_{ft}} \Pi_{fdkt} \tag{6}$$

where $\Pi_{fdkt} = \sum_{m\in t}(P_{fdkm} - c_{fdkt})Q^D_{fdkm}$ for all $k \in \mathcal{G}_{ft} \cup \mathcal{B}_{ft}$. Second, using the rational consumer assumption, I derive expressions for the quantity demanded, i.e., $Q^D_{fdkm}(\mathbf{P}_{fdm})$ for $k \in \mathcal{G}_{ft} \cup \mathcal{B}_{ft}$. Note that for $k \in \mathcal{G}_{ft}$, $Q^D_{fdkm}(\mathbf{P}_{fdm})$ should be expressed in terms of its price and the prices of bundled goods of which k is a component. For $k \in \mathcal{B}_{ft}$, $Q^D_{fdkm}(\mathbf{P}_{fdm})$ should be a function of its price and the prices of all of the individual products that compose bundle k. After deriving expressions for the quantity demanded, I plug them into the profit

terms. However, with the price increase, the firm will lose profit from consumers who were on the margin between Q_{fd1m} and not buying.

function to derive J_{ft} first-order conditions with joint markups. This process is denoted as $\mathbf{\Gamma}(\mathbf{P}_{fdm}, \mathbf{Q}_{fdm}, \psi_{fdt}(\mathbf{v}_{fdt}); \mu_{fdj \in \mathcal{G}_{ft}m}) = 0$, and the joint markups are recovered numerically as in the $G_{ft} = 2$ case.

3.3 *Consumer Valuation Estimation*

This section describes how the consumer valuation distribution ψ_{fdt} is estimated using the approach proposed by Letham et al. (2014). The joint probability density function, $\psi_{ft}(\mathbf{v}_{fdt})$, describes how the consumer's valuation for each product is distributed as well as how it is correlated with the valuations of other products at the firm-year level. Because it differs at the firmlevel, it can capture cross-sectional differences in firms, such as consumer types and quality (hence price). While making specific assumptions regarding the correlation structure across goods for $\psi_{fdt}(\mathbf{v}_{fdt})$ is possible,[26] if the relationship between goods affects markups in a meaningful way, specific assumptions will likely distort the estimation of markups.[27] Using transaction data, Letham et al. (2014) propose a statistically consistent inference procedure using copulas to recover correlated consumer valuations. The key intuition is to put a parametric assumption on the joint density function's marginal distributions and choose a specific copula function that will fit the overall correlation structure well. The marginal distribution will contain information on the valuation's marginal structure; hence, the demand for each product can be recovered from the marginal distribution afterward. After the parameters for the marginal distributions are estimated, the copula parameter is estimated using these marginal parameters to fit the data in a maximum likelihood sense.

A transaction is defined as a deal between a seller and buyer during a certain period of time. In a retail setting where consumers often buy goods in small amounts, days are a good choice for the time unit. In trade, where buyer firms purchase goods in large amounts from specific sellers, months or years may be an appropriate time unit choice, depending on the goods of interest. Consider a set of transaction data that consists of two components. One

[26] See Letham et al. (2014) for a survey of studies that made assumptions of either independence or perfect correlation regarding the correlation structure across goods.

[27] While it is described in terms of profits rather than markups, Letham et al. (2014) shows how imposing an independent correlation assumption could lead to very different predictions regarding possible profit when a bundled product is introduced.

component is purchase data, $\mathbf{y}^s = [y_1^s, ..., y_{G_{ft}}^s]$, where y_j^s is 1 if item j is sold in transaction s and 0 otherwise.[28] The other component is the price data for individual products in transaction s, $\mathbf{P}^s = [P_1^s, ..., P_{G_{ft}}^s]$. Let S denote the total number of transactions. Since consumers maximize utility, $y_j^s = 1$ if and only if $v_j^s \geq P_j^s$. This relationship provides a model for the relationship between the latent variable valuations v_j^s and transaction data (y_j^s, P_j^s).

The copula $\mathbb{C}_{ft}(\cdot)$ for $\Psi_{ft}(\cdot)$ is a distribution function over $[0,1]^{G_{ft}}$ with uniform margins such that $\Psi_{ft}(v_{f1t}, ..., v_{fG_{ft}t}) = \mathbb{C}_{ft}(\Psi_{f1t}(v_{f1t}), ..., \Psi_{fG_{ft}t}(v_{fG_{ft}t}))$. The copula $\mathbb{C}_{ft}$ contains all information on the dependence structure between the components of $(v_{f1t}, ..., v_{fG_{ft}t})$ and combines each marginal distribution Ψ_{fkt} to return the joint distribution Ψ_{ft}. Suppose each marginal distribution is a function of parameters $\boldsymbol{\theta}_{fjt}$, i.e., $\Psi_{fjt}(v_{fjt}; \boldsymbol{\theta}_{fjt})$, and the copula distribution belongs to a family with parameters $\boldsymbol{\phi}_{ft}$, i.e., $\Psi_{ft}(\boldsymbol{v}_{ft}; \boldsymbol{\theta}_{ft}, \boldsymbol{\phi}_{ft}) = \mathbb{C}_{ft}(\Psi_{f1t}(v_{f1t}; \boldsymbol{\theta}_{f1t}), ...\Psi_{fG_{ft}t}(v_{fG_{ft}t}; \boldsymbol{\theta}_{fG_{ft}t}); \boldsymbol{\phi}_{ft})$. Letham et al. (2014) propose an inference functions for margins (*IFM*) procedure that is similar to pseudo-maximum likelihood estimation, where we choose parametric forms for the margins $\Psi_{fjt}(\cdot)$ and copula $\mathbb{C}_{ft}$, then find the parameters for which $\mathbb{C}_{ft}(\Psi_{f1t}(v_{f1t}), ..., \Psi_{fG_{ft}t}(v_{fG_{ft}t}))$ is the closest to $\Psi_{ft}(v_{f1t}, ...v_{G_{ft}t})$ in terms of likelihood.

The optimization can be performed in two steps. First, each marginal distribution is fit independently to recover $\hat{\theta}_{fjt}$. In the second step, the estimated marginal distributions are used to fit the correlation structure ϕ_{ft}.

$$\hat{\boldsymbol{\theta}}_{fjt} \in \underset{\boldsymbol{\theta}_{fjt}}{\operatorname{argmax}}\, l_{fjt}(\boldsymbol{\theta}_{fjt}) \quad j = 1, ..., G_{ft} \tag{7}$$

$$\hat{\boldsymbol{\phi}}_{ft} \in \underset{\boldsymbol{\phi}_{ft}}{\operatorname{argmax}}\, l_{ft}(\hat{\boldsymbol{\theta}}_{ft}, \boldsymbol{\phi}_{ft}) \tag{8}$$

The likelihood function for each marginal distribution in equation (7) is derived from the observed purchase patterns of the utility-maximizing consumer. Let $\mathfrak{p}_{fj}(P_j^s)$ be the purchase probability for item j at price P_j^s, which is equivalent to the demand model for item j. Then, the demand and inverse marginal valuation distribution functions have the following

[28] Item j here is a unit product with a quantity equal to one. The unit demand assumption is relaxed by treating q units of a product sold as 1 unit of a product sold q times during the estimation procedure.

relationship.

$$\mathfrak{p}_{fj}(P_j^s) = \mathbb{P}(y_j^s = 1) = \mathbb{P}(v_j^s > P_j^s) = 1 - \Psi_{fjt}(P_j^s; \boldsymbol{\theta}_{fjt})$$

Therefore, the likelihood function can be constructed by employing the Bernoulli distribution for y_j^s such that $y_j^s \sim \textit{Bernoulli}(1 - \Psi_{fjt}(P_j^s; \boldsymbol{\theta}_{fjt}))$, resulting in the following likelihood function for given data $\{P_j^s, y_j^s\}_{s=1}^S$.

$$l_{fjt}(\boldsymbol{\theta}_{fjt}) = \sum_{s=1}^{S} (y_j^s \log(1 - \Psi_{fjt}(P_j^s; \boldsymbol{\theta}_{ft}))) + (1 - y_j^s) \log(\Psi_{fjt}(P_j^s; \boldsymbol{\theta}_{ft})) \tag{9}$$

The relationship between the marginal distribution and the demand model provides a natural selection criterion for the marginal distributions. For example, as Letham et al. (2014) stated, if the demand model is linear, the corresponding valuation distribution is a uniform distribution. If the demand model follows the normal distribution function, the corresponding marginal valuation distribution also follows a normal distribution. For empirical analysis, I follow Letham et al. (2014) in using uniform distributions for the marginal distributions and a Gaussian copula function.

Once the marginal parameters $\boldsymbol{\theta}_{ft}$ are estimated by maximizing equation (9), these estimators are used to obtain an estimate of the copula parameters $\boldsymbol{\phi}_{ft}$ along with the data.

$$\begin{aligned}
l_{ft}(\hat{\boldsymbol{\theta}}_{ft}, \boldsymbol{\phi}_{ft}) &= \sum_{s=1}^{S} \log \mathfrak{p}_f(\mathbf{y}^s | \mathbf{P}^s_{G_{ft}}, \hat{\boldsymbol{\theta}}_{ft}, \boldsymbol{\phi}_{ft}) && (10) \\
&= \sum_{s=1}^{S} \log \int \mathfrak{p}_f(\mathbf{y}^s | \mathbf{v}^s, \mathbf{P}^s_{G_{ft}}, \hat{\boldsymbol{\theta}}_{ft}, \boldsymbol{\phi}_{ft}) \mathfrak{p}_f(\mathbf{v}^s | \mathbf{P}^s_{G_{ft}}, \hat{\boldsymbol{\theta}}_{ft}, \boldsymbol{\phi}_{ft}) d\mathbf{v}^s && (11) \\
&= \sum_{s=1}^{S} \log \int_{v^{s,l}_{G_{ft}}}^{v^{s,u}_{G_{ft}}} \cdots \int_{v_1^{s,l}}^{v_1^{s,u}} \psi_{ft}(v_1^s, ..., v^s_{G_{ft}}; \hat{\boldsymbol{\theta}}_{ft}, \boldsymbol{\phi}_{ft}) dv_1^s ... dv^s_{G_{ft}} && (12) \\
&= \sum_{s=1}^{S} \log \sum_{k=0}^{G_{ft}} (-1)^k \sum_{I \subseteq \{1, ..., G_{ft}\}, |I| = k} \Psi_{ft}(\mathbf{v}^s; \hat{\boldsymbol{\theta}}, \boldsymbol{\phi}) && (13)
\end{aligned}$$

where the equality in equations (11) to (12) uses $\mathfrak{p}_f(\mathbf{v}^s | \mathbf{P}^s_{G_{ft}}, \hat{\boldsymbol{\theta}}_{ft}, \boldsymbol{\phi}_{ft}) = \mathfrak{p}_f(\mathbf{v}^s | \hat{\boldsymbol{\theta}}_{ft}, \boldsymbol{\phi}_{ft}) =$

$\psi_{ft}(\cdot;\hat{\boldsymbol{\theta}}_{ft},\boldsymbol{\phi}_{ft})$ and makes use of the lower and upper limits of the integration as follows:

$$v_j^{s,l} = \begin{cases} -\infty & \text{if} \quad y_j^s = 0 \\ P_j^s & \text{if} \quad y_j^s = 1 \end{cases} \qquad v_j^{s,u} = \begin{cases} P_j^s & \text{if} \quad y_j^s = 0 \\ \infty & \text{for} \quad y_j^s = 1 \end{cases}$$

The representation of the likelihood formula in equation (12) is intractable due to multiple integrals. Letham et al. (2014) employed the rectangular integral of the probability density function to derive equation (13), where

$$\tilde{v}_j^s(I) = \begin{cases} v_j^{s,l} & \text{if} \quad j \in I \\ v_j^{s,u} & \text{if} \quad j \notin I \end{cases}$$

Thus, the complete, statistically consistent inference procedure for estimating the consumer valuation distribution $\psi_{ft}(\mathbf{v})$ is

$$\hat{\boldsymbol{\theta}}_{fjt} \in \underset{\boldsymbol{\theta}_{fjt}}{\operatorname{argmax}} \sum_{s=1}^{S} (y_j^s \log(1-\Psi_{fjt}(P_j^s;\boldsymbol{\theta}_f))) + (1-y_j^s)\log(\Psi_{fjt}(P_j^s;\boldsymbol{\theta}_f))$$

$$\hat{\boldsymbol{\phi}}_{ft} \in \underset{\boldsymbol{\phi}}{\operatorname{argmax}}_f \sum_{s=1}^{S} \log \sum_{k=0}^{G_{ft}} (-1)^k \sum_{I\subseteq\{1,\ldots,G_{ft}\},|I|=k} \Psi_{ft}(\tilde{\mathbf{v}}^s;\hat{\boldsymbol{\theta}}_{ft},\boldsymbol{\phi}_{ft})$$

4 Empirical Analysis

In this section, I use the framework in section 3 to recover markups for Chinese exporters and test whether bundling firms, on average, have different markups. Additionally, I use China's WTO accession and the accompanying reductions in tariffs to see whether trade liberalization differentially affects markups among bundling firms. In studying the effect of bundling practices on markups, the important thing to note is that for a given firm, the decision to bundle or not purely rests on the dependence of consumer values summarized by the copula and not on marginal costs.[29]

After the consumer valuations that capture demand-side characteristics are estimated,

[29] This is because the decision to bundle or not depends on a local perturbation of the optimal price from independent pricing firms. From this optimal independent price, which should already take the marginal cost into account, the choice to bundle or not purely depends on whether the firm can attract additional purchases from the consumer by offering a slight discount, d_{fdbt}, on the bundled product. Thus, the marginal cost matters for the magnitude of additional profit from bundling but not for the decision to bundle. See Chen and Riordan (2013) for the proof.

markups for firms with and without bundling can be computed from the FOCs as described in the previous section. The recovered markup estimates and regression analysis reveal several major findings. First, I use Chinese manufacturing data (*CMD*) to recover additional markups following the De Loecker et al. (2016) method, compare them to my markups and find that incorporating the bundling feature for multi-product firms may explain one important channel that shows why multi-product firms have higher markups than single-product firms.[30] Second, I investigate the relationship between markups and firm types across markets and time. These analyses cannot be done using previous methods, where product bundling and joint pricing decisions were not incorporated into the estimation process.

4.1 Markup Descriptions

As described in section 3, markups for firms with independent pricing are calculated from first-order conditions derived from the profit maximization problem, while joint markups for the bundling firms are recovered numerically from the expressions for the first-order conditions.

Table 3: Markup (μ_{fdjt}) Results

	Total		Single-		Multi-		Bundling-	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
ADPMs	1.44	0.49	1.39	0.45	1.73	0.45	2.26	0.72
Accessories	1.44	0.52	1.40	0.48	1.78	0.51	2.37	0.76

Note: This table reports the average and median value of recovered markups by firm type. Markups are given at the firm-market-product-year level. 'Single-', 'Multi-', and 'Bundling-' each refers to single-product firm, multi-product firm without bundling, and multi-product firm with bundling. Here, the top and bottom 3% of values are trimmed.

Table 3 presents recovered markups across firm types at the firm-market-year level. Columns (1) and (2) report the mean and the standard deviations of markups for all firm types. On average, ADPMs and ADPM accessory products are priced approximately 44% higher than their original costs.[31] Within the sample, the mean values of the recovered

[30] There is a discussion of how markups from the production side are estimated using the De Loecker et al. (2016) method, and regression results are given in the Appendix.

[31] Note that a markup value of 1.5 means that the firms obtain 50% of the marginal cost as profit for each unit. For example, with an ADPM with a marginal cost of \$100, the price is set at \$150.

markups increase as we move from a single-product firm to a multi-product firm without bundling to a multi-product firm with bundling. This may indicate that product bundling is used by multi-product firms to increase their market power to price goods over their marginal costs, which was not captured by previous literature.

Figure 4 shows the histogram of recovered markups from the transaction–side approach suggested by this paper and the production–side approach from the previous literature.[32] It shows that differences in the markups across firm types are not fully captured on the production side, where bundling firms are not present. Both approaches show the power law feature of the markup distribution for non-bundling firms, while the markup distribution is dispersed for the bundling firms in panel (a). Specifically, panel (a) shows that while the markup values of non-bundling firms present a high-peaked distribution at lower levels of markups, the markup values of bundling firms are more dispersed and tilted toward the right, indicating that product bundling may affect the markup distribution. These stark differences in markups across bundling and non-bundling firms cannot be seen from the production side in panel (b) but are attenuated to single- and multi-product firm differences.

4.2 Markups, Firm Heterogeneity and Trade Liberalization

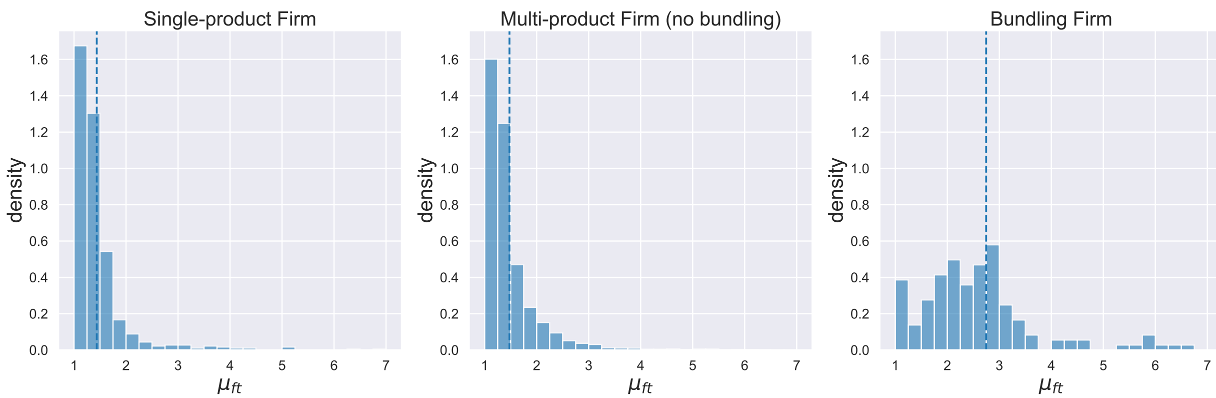
The relationship between product bundling and markups depicted in Figure 4 may explain one additional channel relevant to why multi-product firms dominate international trade, in addition to the productivity channel. To formally examine the effect of bundling on markups in international trade, I first analyze the effect of bundling on markups cross-sectionally and then across time, using China's WTO accession as a trade liberalization event. For the regression analyses, various levels of markups are used to see how not accounting for joint pricing decisions among bundling firms may lead to misleading or attenuated results.[33]

[32] Markups recovered using the lognormal distribution with the Gaussian copula instead of the uniform distribution with the Gaussian copula show similar results and are presented in the Appendix.

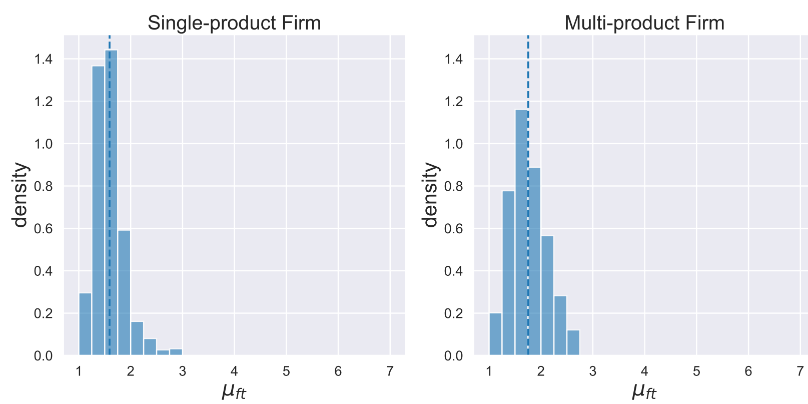
[33] The baseline markups are recovered at the firm-market-product-monthly level and aggregated to various levels of markups using values as weights. The regression results do not change much when quantities or simple averages are used as weights.

Figure 4: Markups (μ_{ft}) of ADPMs or ADPM accessories by firm type

(a) Transaction Side



(b) Production Side



Note: Figure (a) plots the histogram of firm-year level markups for ADPMs or ADPM accessories that is recovered using the transaction–side approach suggested by this paper. Figure (b) plots the histogram of firm-year level markups for ADPMs or ADPM accessories that is recovered using the production side approach. Note that the y-axis is the normalized density and the x-axis is μ_{ft}. Here, the top and bottom 3% of values are trimmed for both cases.

4.2.1 Markups and Firm Heterogeneity

I first study how markups differ across firm heterogeneity, such as in single-product firms, multi-product firms, and multi-product firms with bundling, using the following regression equation:

$$\log \mu_{fdjm} = \delta_{FE} + \delta_{MF_{fdt}} D_{MF_{fdt}} + \delta_{BF_{fdt}} D_{BF_{fdt}} + X^T \beta + \varepsilon_{fdjm} \tag{14}$$

where $D_{MF_{fdt}}$ is a multi-product firm dummy, and $D_{BF_{fdt}}$ is a dummy variable for multi-product firms that engage in bundling practices. Both $D_{MF_{fdt}}$ and $D_{BF_{fdt}}$ vary by market-year, indicating that firm type is based on the 'sales' side rather than 'production'. To capture any market, time, or ownership[34] trends, the market, year, and firm ownership fixed effects are included in δ_{FE}. To capture firm size, the quantities and number of products sold to each market in a given year are included in the covariate X as well as input, output, and market access tariffs. In this regression, $\delta_{MF_{fdt}}$ measures the percentage markup premium that a multi-product firm that does not engage in bundling has relative to single-product firms (i.e., the "multi-product premium"). The percentage premium that the multi-product firm with bundling has over multi-product firms that do not engage in bundling (i.e., the "bundling premium") is captured by $\delta_{BF_{fdt}}$. Thus, $\delta_{MF_{fdt}} + \delta_{BF_{fdt}}$ measures the percentage premium of multi-product firms with bundling over single-product firms.

Table 4 shows the results of equation (14) at various levels of markups, and the results align with economic intuition. First, the multi-product firm dummy coefficients are significantly positive and similar at the firm-market-product-monthly level (column (1)), at the firm-market-product-yearly level (column (2)), and at the firm-market-yearly level (column (3)). Specifically, for baseline transactions in column (1), the multi-product firms without bundling have 29.8% higher markups than single-product firms on average and 32.3% higher markups at the firm-market-yearly level in column (3).

The bundling dummy coefficients are all significant and positive across all specifications. For the baseline transactions in column (1), bundling firms have, on average, 21.8% higher markups than non-bundling multi-product firms and 58% higher markups than single-product firms. When monthly transactions are aggregated to the yearly level,

[34] Such as SOEs and private companies.

Table 4: Markups and Firm Heterogeneity

	(1)	(2)	(3)
	$log\mu_{fdjm}$	$log\mu_{fdjt}$	$log\mu_{fdt}$
$D_{MF_{fdt}}$	0.2605***	0.2754***	0.2801***
(*Multi-Product Firm Premium*)	(0.0053)	(0.0089)	(0.0142)
$D_{BF_{fdt}}$	0.1969***	0.2193***	0.3406***
(*Product Bundling Premium*)	(0.0094)	(0.0190)	(0.0337)
Market FE	Yes	Yes	Yes
Product FE	Yes	Yes	No
Year FE	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes
F-statistic	798.6	293.0	135.8
Observation	75,614	16,040	15,656

Note: This table reports the coefficients from the regression (14). The dependent variable is (log) markup. Each column is an OLS regression result of log markup on firm heterogeneity for observations for ADPMs or ADPM accessories with various levels. Column (1) shows the results for baseline transactions, which is the firm-market-product-monthly level, and columns (2) and (3) show the results at the firm-market-product-yearly level and firm-market-yearly level. The standard errors are in parentheses and are bootstrapped. Significance : * 10 percent, ** 5 percent, *** 1 percent.

the bundling dummy coefficient increases slightly and shows that bundling firms, on average, have 24.5% higher markups than non-bundling multi-product firms. Similarly, at the firm-market-yearly level, multi-product firms with bundling enjoyed 40.6% higher markups compared to non-bundling firms.

Firms that engage in bundling practices price goods jointly; hence, for these firms, studying markups at the product level, such as in columns (1) and (2), will not capture the true market power. In columns (1) and (2), the *product bundling premium* associates product bundling practices with firms with market power (high markups). However, once we move from column (2) to (3), where markups are aggregated at the firm-level and capture firm-level decisions, the large difference in the *product bundling premium* from column (2) to (3) shows that for multi-product firms, firm-level joint decisions such as product bundling may require analysis at both the product and firm levels to fully characterize their market power. In short, these results show that firms could potentially utilize product bundling to exercise market power and retain higher markups compared to other firms.

4.2.2 Bundling and Additional Sales

Findings from the bundling literature indicate that firms engage in bundling practices to increase their profits by increasing the probability of selling additional products via a small discount on bundled products. To investigate whether this is how bundling firms obtain higher markups than their counterparts, I follow the literature and run the following probit regression for only firms that sell both ADPMs and ADPM accessories.

$$MPT_{fdm} = \delta_{BF_{fdt}} D_{BF_{fdt}} + \delta_{\phi_{fdt}} \phi_{fdt} + X^T \beta + \epsilon_{fdm} \tag{15}$$

where MPT_{fdm} is a dummy that is equal to one when a transaction between firm f and market d in month m is a multi-product transaction with ADPMs or ADPM accessories. A positive value for the coefficient $\delta_{BF_{fdt}}$ indicates that bundling firms have a higher probability of selling goods together than other firms. I expect a positive value for $\delta_{\phi_{fdt}}$ since consumers who value ADPMs are more likely to value ADPM accessories more and thus have a higher chance of buying both goods. Vector X includes parameters related to consumer valuations such as maximum and minimum ($\theta_{\mathbf{fdt}}$), and prices ($\mathbf{p_{fdm}}$).

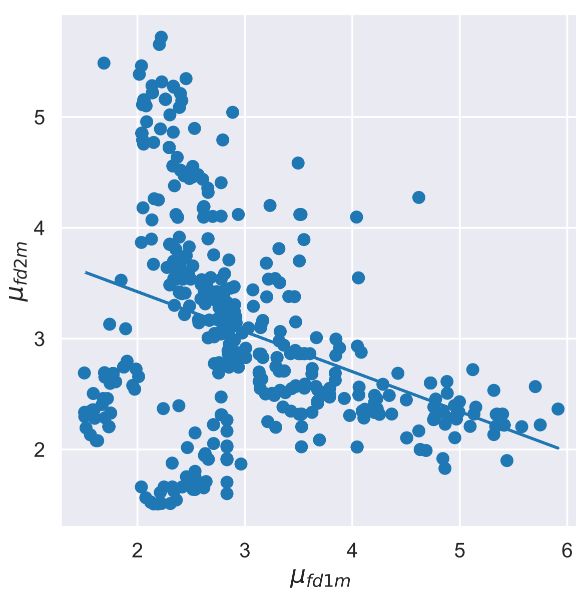
Table 5: Probit Regression for Multi-Product Purchases

		MPT_{fdm}	
$\delta_{BF_{fdt}}$	0.1347***	0.0579***	0.0597***
	(0.014)	(0.015)	(0.016)
$\delta_{\phi_{fdt}}$		0.3124***	0.3120***
		(0.016)	(0.016)
c_{fd1t}			0.0003
			(0.001)
c_{fd2t}			0.0009
			(0.001)
Other Covariates	Yes	Yes	Yes
Log-Likelihood	-3169.8	-2960.3	-2913.0
Observation	5,759	5,759	5,671

Note: The dependent variable is a dummy MPT_{fdm} that equals one when a given transaction involves both ADPMs and ADPM accessories. Other covariates such as marginal parameters ($\theta_{\mathbf{fdt}}$) and prices ($\mathbf{p_{fdm}}$) are included. The standard errors are in parentheses. Significance : * 10 percent, ** 5 percent, *** 1 percent.

Table 5 displays the marginal effect of a unit increase from zero for each regressor. First, the correlation between the consumer's values for ADPMs and APDM accessories captured by ϕ_{fdt} is positive and significant across specifications at the 1% level, as expected. If the consumers change their perception of ADPMs and their accessories from independent goods to perfect complements, multi-product sales increase by 31%. Additionally, the bundling firm coefficient is positive and significant at the 1% level across regressions. As indicated by the literature, bundling firms have a higher probability of selling more goods (both ADPMs and ADPM accessories) than others. Specifically, controlling for both the demand- (consumer taste) and supply- (marginal cost) side characteristics, being a bundling firm increases the probability of multi-product sales by 6%. This result shows that bundling firms are more likely to sell multiple goods as a bundle than other multi-product firms, increasing profit. If multi-product firms bundle products with low markups with products with high markups, then bundling firms can increase overall firm-level markups. This can be seen in Figure 5 where markups for both ADPMs and accessories are plotted. Figure 5 shows negative correlations (-0.32) between markups for ADPMs and accessories, indicating that firms bundle products with low and high markups.

Figure 5: Correlation across products for Bundling Firms



Note: This figure scatterplots the transaction-level markups for ADPMs and accessories for bundling firms. The correlation value is -0.32, indicating firms bundle low and high markup goods.

4.2.3 Markups and Trade Liberalization

As with static differences in markups, product bundling may also impact how firms and their markups react to trade liberalization. In this section, I inspect how firms react to changes in market competitiveness induced by trade policy across firm types. Overall, we would expect to see markups for Chinese exporters increase after trade liberalization due to a decrease in tariffs, but these upward trends may differ across firm types (single-product vs. multi-product vs. multi-product with bundling). To analyze this, I study the evolution of markups in response to changes in tariffs with the following equation:

$$\begin{aligned}\log \mu_{fdjm} = {} & \delta_{FE} + \delta_{access}\tau_{dt}^{access} + \delta_{access*MF_{fdt}}\tau_{dt}^{access}D_{MF_{fdt}} + \delta_{access*BF_{fdt}}\tau_{dt}^{access}D_{BF_{fdt}} \\ & + \delta_{input}\tau_{dt}^{input} + \delta_{input*MF_{fdt}}\tau_{dt}^{input}D_{MF_{fdt}} + \delta_{input*BF_{fdt}}\tau_{dt}^{input}D_{BF_{fdt}} + \mathbf{x}'\beta + \varepsilon_{fdjm} \quad (16)\end{aligned}$$

where τ_{dt}^{access} and τ_{dt}^{input} are market access and input tariffs for each market at the yearly level and δ_{FE} includes appropriate fixed effects for each level of analysis. I focus on the effects of market access tariffs and input tariffs, given that they reflect exporters' price conditions for each market and the input costs. δ_{access} captures the effect of a one–unit change in market access tariffs on markups for single-product firms, $\delta_{access} + \delta_{access*MF_{fdt}}$ captures the effect on the markups of multi-product firms without bundling, and $\delta_{access} + \delta_{access*MF_{fdt}} + \delta_{access*BF_{fdt}}$ captures the effect on multi-product firms with bundling. A similar interpretation holds for δ_{input}.

Table 6 presents the results at various levels of markups. Because both market access and input tariffs decreased, the negative sign on the coefficient corresponds to an increase in markups. Overall, a decrease in market access does not result in significant changes to the markup except for multi-product firms. Firms selling both ADPMs and ADPM accessories faced about a 1% decrease in markups when market access tariffs declined by 1 unit. However, the decrease in input tariffs remains significant across specifications and firm types, as De Loecker et al. (2016) suggests. Additionally, note that input tariff changes mitigate the markup differences across firm types, similar to findings from Lu et al. (2015). Since the magnitude of tariff reduction is significant for input tariffs, tariff reductions reduce markup dispersion across firm types. Specifically, in column (1), a 1 unit

Table 6: Markups and Trade Liberalization: Tariff Changes

	(1) $log\mu_{fdjm}$	(2) $log\mu_{fdjt}$	(3) $log\mu_{fdt}$
τ_{dt}^{access}	-0.0025^{**}	-0.0026	-0.0021
	(0.0012)	(0.0021)	(0.0023)
$\tau_{dt}^{access} D_{MF_{fdt}}$	0.0100^{***}	0.0095^{***}	0.0090^{*}
	(0.0019)	(0.0032)	(0.0054)
$\tau_{dt}^{access} D_{BF_{fdt}}$	0.0010	0.0052	0.0013
	(0.0026)	(0.0058)	(0.0090)
τ_{dt}^{input}	-0.0084^{***}	-0.0064^{***}	-0.0077^{***}
	(0.0006)	(0.0010)	(0.0011)
$\tau_{dt}^{input} D_{MF_{fdt}}$	0.0285^{***}	0.0275^{***}	0.0282^{***}
	(0.0001)	(0.0017)	(0.0025)
$\tau_{dt}^{input} D_{BF_{fdt}}$	0.0023	0.0140^{***}	0.0227^{***}
	(0.0021)	(0.0045)	(0.0089)
Market FE	Yes	Yes	Yes
Product FE	Yes	Yes	No
Ownership FE	Yes	Yes	Yes
F-statistic	527.6	139.3	74.95
Observation	75,614	16,040	15,656

Note: This table reports the coefficients from regression (16). The dependent variable is (log) markup. Each column is an OLS regression result of log markup on firm heterogeneity for observations for ADPMs or ADPM accessories with various levels. Column (1) shows the results for baseline transactions, which are at the firm-market-product-monthly level, and columns (2) and (3) show the results at the firm-market-product-yearly level and firm-market-yearly level. The standard errors are in parentheses and are bootstrapped. Significance : * 10 percent, ** 5 percent, *** 1 percent.

decrease in input tariffs results in a 0.85% increase in markups for single-product firms but a decrease in markups for multi-product firms without and with bundling by 1.99% and 2.21%, respectively. This means that if the input tariff were to decline by 10% as it did from 2000 to 2006, single-product firms would enjoy an 8.5% increase in their markups, while multi-product firms without and with bundling would lose 19.9% and 22.1% of their markups. An analysis with the more aggregated markups suggests similar findings. In column (2), with a 1 unit decrease in input tariffs, single-product firms enjoy a 0.645% increase in markups, while multi-product firms without bundling lose 2.09%, and bundling firms lose 3.45% of their original markups. At the firm-market-yearly level, a 1 unit decrease in the input tariff results in a 0.77% increase and, 2.03% and 4.24% decreases in markups for single-product firms and multi-product firms without and with bundling, respectively.

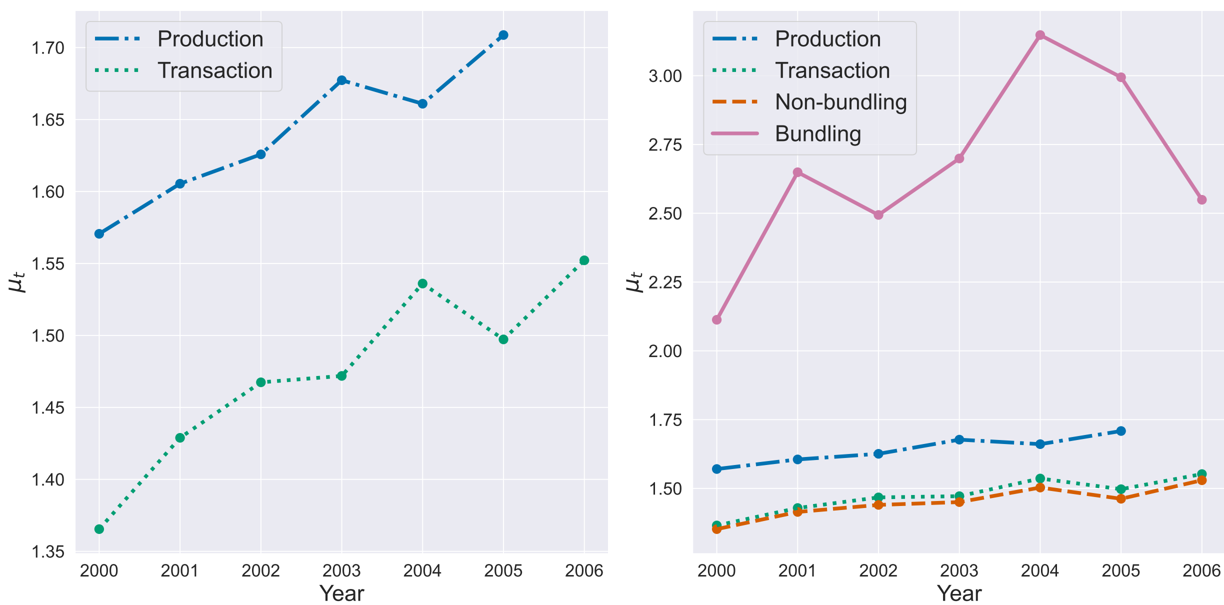
4.2.4 Aggregate Markups and Product Bundling

Last, growing empirical evidence suggests that aggregate markups are increasing (see De Loecker et al. (2020); Ganapati (2021)). In this subsection, I analyze how much volatility in aggregate markups can be attributed to bundling firms.

Figure 6 plots how the aggregate markup has evolved from 2000 to 2006. The left panel plots two aggregated markup paths that are recovered by the production approach following De Loecker and Warzynski (2012), and De Loecker et al. (2016) and by the transaction approach proposed in this paper. There are a few points to note for the left panel. First, both aggregate markups have increased over the years. Additionally, the general trend in the production approach seems to appear in the aggregated markups from the transaction approach a year later. This could be due to the time gap between production and export. Overall markup levels are also higher in the production approach. As Yang (2021) noted, this could be explained by Chinese exporters having lower markups than their non-exporting counterparts. In this case, because the transaction approach captures only exporter firms, overall markup levels may be be lower in the transaction approach.

The right panel of Figure 6 decomposes aggregate markups from the transaction approach into aggregate markups of bundling and non-bundling firms. Note that the aggregate markup for bundling firms is significantly higher. Denote $N_{b,t}$ and $\mu_{b,t}$ as the number of bundling firms and average markups for bundling firms in year t, and $N_{nb,t}$ and $\mu_{nb,t}$ as the number of non-bundling firms and average markups for non-bundling firms in year t. Define $\mu_t = \theta_{b,t}\mu_{b,t} + \theta_{nb,t}\mu_{nb,t}$, where $\theta_{b,t} = \frac{N_{b,t}}{N_{b,t}+N_{nb,t}}$ and $\theta_{nb,t} = \frac{N_{nb,t}}{N_{b,t}+N_{nb,t}}$. Consider the following variance decomposition to examine the contribution of bundling and non-bundling firms to the aggregate markup volatility at the intensive and extensive margins.

Figure 6: Evolution of Aggregate Markups



Note: This figure plots the evolution of aggregated markups (μ_t) with different approaches, the production approach and the transaction approach proposed in this paper. In the right panel, the evolution of the aggregated markups from the transaction approach is decomposed into bundling and non-bundling markups.

$$\begin{aligned} Var(\mu_t) &= Cov(\mu_t, \theta_{b,t}\mu_{b,t} + \theta_{nb,t}\mu_{nb,t}) \\ &= Cov(\mu_t, \theta_{b,t}\mu_{b,t}) + Cov(\mu_t, \theta_{nb,t}\mu_{nb,t}) \end{aligned}$$

Hence,

$$1 = \frac{Cov(\mu_t, \theta_{b,t}\mu_{b,t})}{Var(\mu_t)} + \frac{Cov(\mu_t, \theta_{nb,t}\mu_{nb,t})}{Var(\mu_t)},$$

where the first term captures the volatility from the bundling firm and the second term captures the volatility from the non-bundling firm. The contribution of each firm type can be further decomposed as follows.

$$
\begin{aligned}
\frac{Cov(\mu_t, \theta_{b,t}\mu_{b,t})}{Var(\mu_t)} &= \underbrace{\bar{\theta}_b \frac{corr(\mu_t, \mu_{b,t})std(\mu_{b,t})}{std(\mu_t)}}_{\substack{\text{intensive contribution} \\ \text{from bundling firm}}} + \underbrace{\bar{\mu}_b \frac{corr(\mu_t, \theta_{b,t})std(\theta_{b,t})}{std(\mu_t)}}_{\substack{\text{extensive contribution} \\ \text{from bundling firm}}} + C_b \\
\frac{Cov(\mu_t, \theta_{nb,t}\mu_{nb,t})}{Var(\mu_t)} &= \underbrace{\bar{\theta}_{nb} \frac{corr(\mu_t, \mu_{nb,t})std(\mu_{nb,t})}{std(\mu_t)}}_{\substack{\text{intensive contribution} \\ \text{from non-bundling firm}}} + \underbrace{\bar{\mu}_{nb} \frac{corr(\mu_t, \theta_{nb,t})std(\theta_{nb,t})}{std(\mu_t)}}_{\substack{\text{extensive contribution} \\ \text{from non-bundling firm}}} + C_{nb}
\end{aligned}
\tag{17}
$$

where C_b and C_{nb} are residual constant terms[35]. The intensive contribution terms depend on two parts. The first part, $\bar{\theta}$, is the time-averaged share of bundling (or non-bundling) firms. The second part, $\frac{corr(\mu_t,\mu_{it})std(\mu_{it})}{std(\mu_t)}$, further depends on the relative standard deviation of the average markups of bundling (or non-bundling) firms to aggregate markups as well as the correlation between the two markups. On the other hand, the extensive contributions depend on the time-averaged markups of the two types of firms, the standard deviations of the shares of firm types relative to the aggregate markup, and correlations between the shares of firms and the aggregate markup.

Table 7: Variance Decomposition of Aggregate Markups

	Intensive	Extensive	Total
Bundling	0.08	0.16	0.24
Non-bundling	0.87	-0.11	0.76
Total	0.95	0.05	1

Note: This table reports the results of variance decomposition of the aggregate markups. See equation (17) for the relevant interpretation.

Table 7 presents the contribution to aggregate markup volatility at the intensive and extensive margins for both bundling and non-bundling firms. There are a few points to note. First, the bundling firms' total contribution to the aggregate markup volatility is 24%, while the contribution from non-bundling firms is 76%. Additionally, the main contribution to the aggregate markup comes from different channels for bundling and non-bundling firms. Specifically, while the majority of the contribution for non-bundling

[35]They are products of the central moment. Specifically, $C_b = E[(\theta_{b,t} - \bar{\theta}_b)(\mu_t - \bar{\mu})(\mu_{b,t} - \bar{\mu}_b)]$. Both residual constant terms are close to zero.

firms is to the intensive margin (0.87), the extensive margin is much higher for bundling firms (0.16). Hence, for bundling firms, the contribution to aggregate markup volatility comes from the entry and exit of bundling firms and their share in the overall market. In contrast, non-bundling firms contribute mainly at the intensive margin (0.87), and their extensive margin negatively contributes to aggregate markups (-0.11). This is because while the aggregate markup increased, the share of non-bundling firms slightly decreased.

5 Conclusion

Recently, firm-level analysis has been a central focus in research attempting to understand international trade, e.g., research on multi-product firms, productivity, networks, and markups. In this paper, I examine at an important source of firm heterogeneity that has been overlooked — a multi-product firm's ability to offer product bundles—and investigate whether the effects of trade liberalization on markups differ across firm types.

In the empirical estimation, I estimate markups using transaction data and a framework that explicitly incorporates multi-product firms' joint pricing decisions, which is missing in previous literature. Comparing the estimated markups for Chinese exporters to markups recovered using the De Loecker and Warzynski (2012) method shows that the production-side approach may miss one important channel (*bundling*), which explains why multi-product firms have higher markups than single-product firms. By offering a discount, bundling firms incentivize consumers to buy more products and can leverage market power from one product to another. Thus, bundling enables firms to increase overall firm-level markups. While the main analysis focuses on two product cases for Chinese exporters, the method can be generalized to many products and individual firms in any market with market power.

My study also contributes to the literature on the relationship between markups and trade characteristics. While previous studies focused on gains from trade at the aggregate level, I study how these effects may differ across firms depending on their decision to bundle or not. Tariff reductions from trade liberalization bring pro-competitive effects by reducing the markup dispersion across firms. Analyzing the aggregate markup also reveals that while bundling firms may account for small shares in terms of numbers, their volatility accounts for approximately 24% of the aggregate markup volatility.

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Appendix

A. First–Order Conditions of Profit Maximization

A.1 Derivation of the expressions

Here, I demonstrate the steps for calculating the first-order conditions in Section 2. Recall that the profit function was

$$\begin{aligned}
\Pi_{ft}(\mathbf{P}_{ft}) &= (P_{f1t}-c_{f1t})Q^D_{f1t}(\mathbf{P}_{ft}) + (P_{f2t}-c_{f2t})Q^D_{f2t}(\mathbf{P}_{ft}) + (P_{fbt}-c_{f1t}-c_{f2t})Q^D_{fbt}(\mathbf{P}_{ft}) \\
&=(P_{f1t}-c_{f1t})\int_{P_{f1t}}^{\infty}\int_0^{P_{fbt}-P_{f1t}}\psi_f(x,y)dydx + (P_{f2t}-c_{f2t})\int_0^{P_{fbt}-P_{f2t}}\int_{P_{f2t}}^{\infty}\psi_f(x,y)dydx \\
&+(P_{fbt}-c_{f1t}-c_{f2t})\left[\int_{P_{f1t}}^{\infty}\int_{P_{fbt}-P_{f1t}}^{\infty}\psi_f(x,y)dydx + \int_{P_{fbt}-P_{f2t}}^{P_{f1t}}\int_{P_{fbt}-x}^{\infty}\psi_f(x,y)dydx\right]
\end{aligned}$$

Taking the derivative with respect to p_{f1t} results in the following equation.

$$\begin{aligned}
&\int_{P_{f1t}}^{\infty}\int_0^{P_{fbt}-P_{f1t}}\psi_f(x,y)dydx + (P_{f1t}-c_{f1t})\frac{\partial}{\partial P_{f1t}}\Big[\int_{P_{f1t}}^{\infty}\int_0^{P_{fbt}-P_{f1t}}\psi_f(x,y)dydx\Big] \\
&+(P_{fbt}-c_{f1t}-c_{f2t})\frac{\partial}{\partial P_{f1t}}\Big[\int_{P_{f1t}}^{\infty}\int_{P_{fbt}-P_{f1t}}^{\infty}\psi_f(x,y)dydx + \int_{P_{fbt}-P_{f2t}}^{P_{f1t}}\int_{P_{fbt}-x}^{\infty}\psi_f(x,y)dydx\Big] = 0
\end{aligned}$$

Note that the first term corresponds to $Q^D_{f1t}(\mathbf{P}_{ft})$. For the second term, denote $G_{f1t}(P_{f1t},P_{fbt},x) = \int_0^{P_{fbt}-P_{f1t}}\psi(x,y)dx$ and $H_{f1t}(P_{f1t},P_{fbt}) = \int_{P_{f1t}}^{\infty}G_{f1t}(P_{f1t},P_{fbt},y)dy$. Then applying the Leibniz rule gives the following for the second term.

$$\begin{aligned}
\frac{\partial}{\partial P_{f1t}}H_{f1t}(P_{f1t},P_{fbt}) &= -G_{f1t}(P_{f1t},P_{fbt},P_{f1t}) + \int_{P_{f1t}}^{\infty}\frac{\partial}{\partial P_{f1t}}G_{f1t}(P_{f1t},P_{fbt},x)dx \\
&= -\int_0^{P_{fbt}-P_{f1t}}\psi_f(P_{f1t},y)dy - \int_{P_{f1t}}^{\infty}\psi_f(x,P_{fbt}-P_{f1t})dx
\end{aligned}$$

Similarly, for the third term in the first–order condition, let $G_{f2t}(P_{fbt},x) = \int_{P_{fbt}-P_{f1t}}^{\infty}\psi_f(x,y)dy$ with $H_{f2t}(P_{f1t},P_{fbt}) = \int_{P_{f1t}}^{\infty}G_{f2t}(P_{f1t},P_{fbt},y)dy$, and for the fourth term let $G_{f3t}(P_{fbt},y) = \int_{P_{fbt}-y}^{\infty}\psi_f(x,y)dy$ with $H_{f3t}(P_{f1t},P_{f2t},P_{fbt}) = \int_{P_{fbt}-P_{f2t}}^{P_{f1t}}G_{f3t}(P_{fbt},y)dy$. Then, taking the derivative following the

Leibniz rule gives the following expressions.

$$\begin{aligned}
\frac{\partial}{\partial P_{f1t}} H_{f2t}(P_{f1t}, P_{fbt}) &= -G_{f2t}(P_{f1t}, P_{fbt}, P_{f1t}) + \int_{P_{f1t}}^{\infty} \frac{\partial}{\partial P_{f1t}} G_{f2t}(P_{f1t}, P_{fbt}, y) dy \\
&= -\int_{P_{fbt}-P_{f1t}}^{\infty} \psi_f(P_{f1t}, y) dy + \int_{P_{f1t}}^{\infty} \psi_f(x, P_{fbt} - P_{f1t}) dx \\
\frac{\partial}{\partial P_{f1t}} H_{f3t}(P_{f1t}, P_{f2t}, P_{fbt}) &= G_{f3t}(P_{fbt}, P_{f1t}) \\
&= \int_{P_{fbt}-P_{f1t}}^{\infty} \psi_f(P_{f1t}, y) dy
\end{aligned}$$

Plugging these terms into the original f.o.c. and using the definition of $Q_{f1t}(\mathbf{P}_{ft})$ yields

$$\begin{aligned}
&Q^D_{f1t}(\mathbf{P}_{ft}) - (P_{f1t} - c_{f1t})\Big[\int_0^{P_{fbt}-P_{f1t}} \psi(P_{f1t}, y) dy + \int_{P_{f1t}}^{\infty} \psi_f(x, P_{fbt} - P_{f1t}) dx\Big] \\
&+ (P_{fbt} - c_{f1t} - c_{f2t})\Big[-\int_{P_{fbt}-P_{f1t}}^{\infty} \psi_f(P_{f1t}, y) dy + \int_{P_{f1t}}^{\infty} \psi_f(x, P_{fbt} - P_{f1t}) dx + \int_{P_{fbt}-P_{f1t}}^{\infty} \psi_f(P_{f1t}, y) dy\Big] \\
&= Q^D_{f1t}(\mathbf{P}_{ft}) - (1 - \mu^{-1}_{f1t}) P_{f1t} \int_0^{P_{fbt}-P_{f1t}} \psi_f(P_{f1t}, y) dy + [(1 - \mu^{-1}_{f2t}) P_{f2t} - d_{fbt}] \int_{P_{f1t}}^{\infty} \psi_f(x, P_{fbt} - P_{f1t}) dx
\end{aligned}$$

where the equality comes from $(P_{f1t} - c_{f1t}) = (P_{f1t} - c_{f1t})\frac{P_{f1t}}{P_{f1t}} = (1 - \mu^{-1}_{f1t})P_{f1t}$ and $(P_{f1t} + P_{f2t} - c_{f1t} - c_{f2t} - d_{fbt}) = (P_{f1t} - c_{f1t})\frac{P_{f1t}}{P_{f1t}} + (P_{f2t} - c_{f2t})\frac{P_{f2t}}{P_{f2t}} - d_{fbt} = (1 - \mu^{-1}_{f1t})P_{f1t} + (1 - \mu^{-1}_{f2t})P_{f2t} - d_{fbt}$. The derivatives with respect to P_{f2t} and P_{fbt} are similar and thus omitted.

B. Regression Analysis for Production–Side Markups

B.1 Framework of the Production Side

In this section, I describe how the markups using production data (section 4) were estimated. These production–side markups were recovered by directly following the method of De Loecker et al. (2016) and the Chinese Manufacturing data. Consider the following production function for firm f producing product j at time t :

$$Q^s_{fjt} = F_{jt}(\mathbf{V}_{fjt}, \mathbf{K}_{fjt})\Omega_{ft}$$

where Q^s denotes the physical output (the quantity) of product j produced by firm f at time t. $\mathbf{V}$ denotes a vector of variable inputs that the firm can freely adjust, such as materials, and $\mathbf{K}$ is a vector of fixed inputs with adjustment costs, such as labor and capital. Combine the inputs into a vector $\mathbf{X} = \{\mathbf{V}, \mathbf{K}\}$, and denote the price of input v as W^v_{fjt}. The productivity of firm f at time t is denoted as Ω_{ft}. Lower-case variables indicate the log terms of their capitalized counterparts. Then, the firm's cost minimization problem results in the following expression for markups at the firm-product-year level.

$$\mu_{fjt} = \theta^v_{fjt}\left(\frac{P_{fjt}Q^s_{fjt}}{W^v_{fjt}V^v_{fjt}}\right) = \theta^v_{fjt}(\alpha^v_{fjt})^{-1} \tag{18}$$

where θ^v_{fjt} refers to product j's output elasticity for flexible input v.

I use single-product firms to estimate the production function and the output elasticity θ^v_{fjt} as suggested by De Loecker et al. (2016). To account for the endogeneity issue caused by unobserved productivity terms, the control function approach suggested by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015) is used to estimate the production function. To account for the bias caused by using only single-product firms, I apply a sample selection correction procedure following Olley and Pakes (1996) and De Loecker et al. (2016).

The basic idea of the control function approach is to develop an equation for the unobserved term ω_{ft} that can be used to eliminate endogeneity bias. Following De Loecker et al. (2016), I employ the Ackerberg et al. (2015) method to single-product firms to estimate the production functions. Specifically, I use the material demand function to develop an equation for ω_{ft}. Assume the material demand function for a single-product firm producing good j is

$$m_{ft} = m_t(\omega_{ft}, k_{ft}, l_{ft}, \mathbf{z}_{ft}) \tag{19}$$

where $\mathbf{z}_{ft} = \{\mathbf{L}_f, P_{ft}, EXP_{ft}, \tau^{output}_{it}, \tau^{input}_{it}\}$ with $\mathbf{L}_f$ are firm-specific exogenous factors such as age, location, ownership status, and affiliation status, $\mathbf{EXP}_{ft}$ is the export dummy, and $\tau^{output}_{it}, \tau^{input}_{it}$ are the output and import tariffs for industry i.

Inverting equation (19) gives the control function for the unobserved productivity ω_{ft} as $\omega_{ft} = h_t(\mathbf{x}_{ft}, \mathbf{z}_{ft})$. To construct the moment conditions, consider the following law of motion for productivity.

$$\omega_{ft} = \eta(\omega_{ft-1}, EXP_{ft-1}, \tau^{output}_{it-1}, \tau^{input}_{it-1}, SP_{ft}) + \xi_{ft} \tag{20}$$

where ξ_{ft} denotes the unexpected innovation to productivity and SP_{ft} is included in the law of motion to correct for selection bias in using only single-product firms.

In the first step of estimating the production function, I separate the unanticipated shocks and/or the measurement error term ϵ_{fjt} from the rest of the terms that are known to the firm.

$$q_{fjt} = \phi_{jt}(\mathbf{x}_{ft}, \mathbf{z}_{ft}) + \epsilon_{fjt} \tag{21}$$

where $\phi_{jt}(\cdot)$ is equal to $f_j(\mathbf{x}_{ft}; \boldsymbol{\beta}) + \omega_{ft}$. This allows us to express productivity ω_{ft} as a function of the data and predicted output $\hat{\phi}_{fjt}$ from the first step.

$$\omega_{ft}(\boldsymbol{\beta}) = \hat{\phi}_{fjt} - f_j(\mathbf{x}; \boldsymbol{\beta})$$

Combining this with the law of motion for productivity in equation (20), we can recover the innovation term ξ_{ft} by

$$\xi_{ft}(\boldsymbol{\beta}) = \omega_{ft}(\beta) - E[\omega_{ft}(\boldsymbol{\beta})|\omega_{ft-1}(\boldsymbol{\beta}), EXP_{ft-1}, \tau_{it-1}^{output}, \tau_{it-1}^{input}, SP_{ft}] \tag{22}$$

Then, the moment conditions in the second step that identify the parameters of the production function are

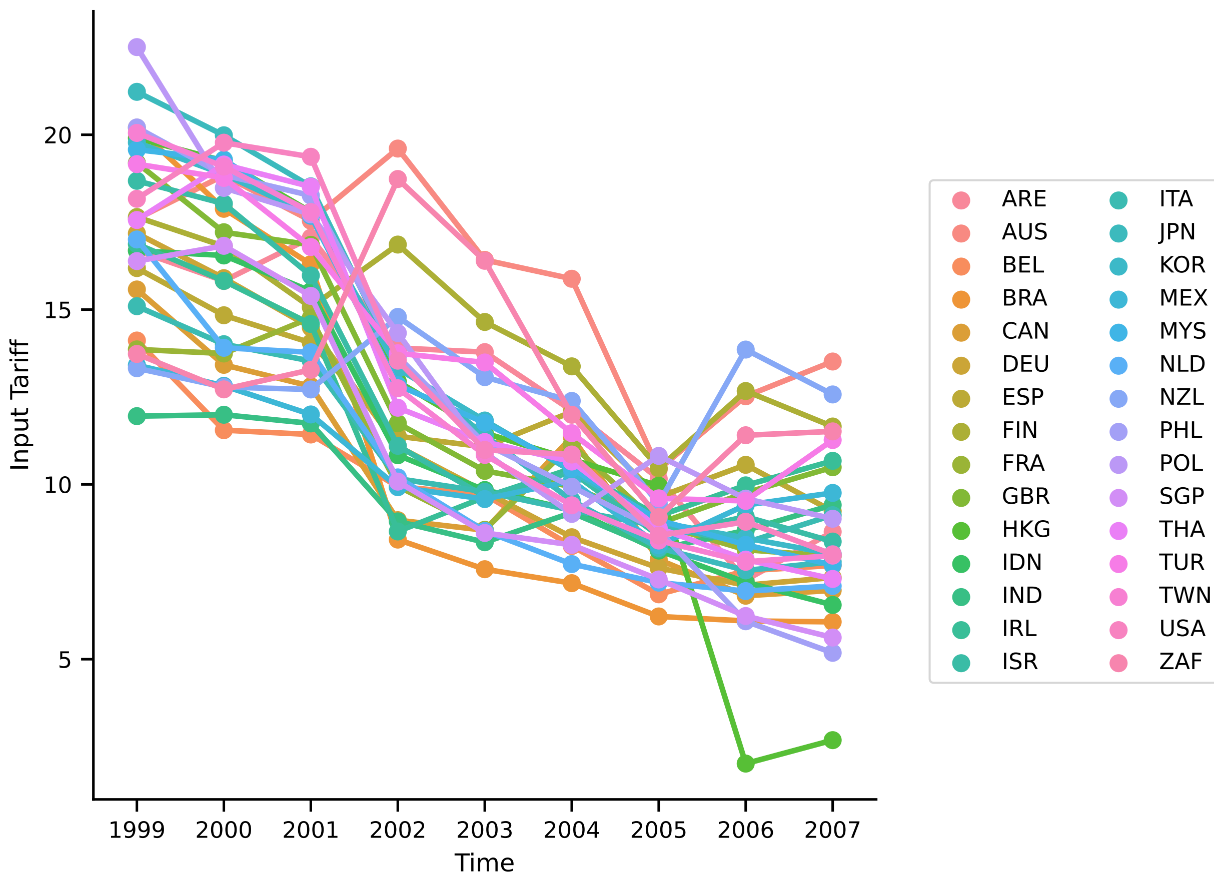
$$E[(\xi_{ft}(\boldsymbol{\beta}) + \epsilon_{fjt})\boldsymbol{Y}_{ft}] = 0 \tag{23}$$

where $\boldsymbol{Y}_{ft}$ contains all the variables that are in the firm's information set at time t such as lagged materials, current predetermined capital and, labor, and their higher–order interaction terms, as well as the lagged output prices, lagged tariffs, and their appropriate interactions with the inputs.

C. Supplementary Documentation

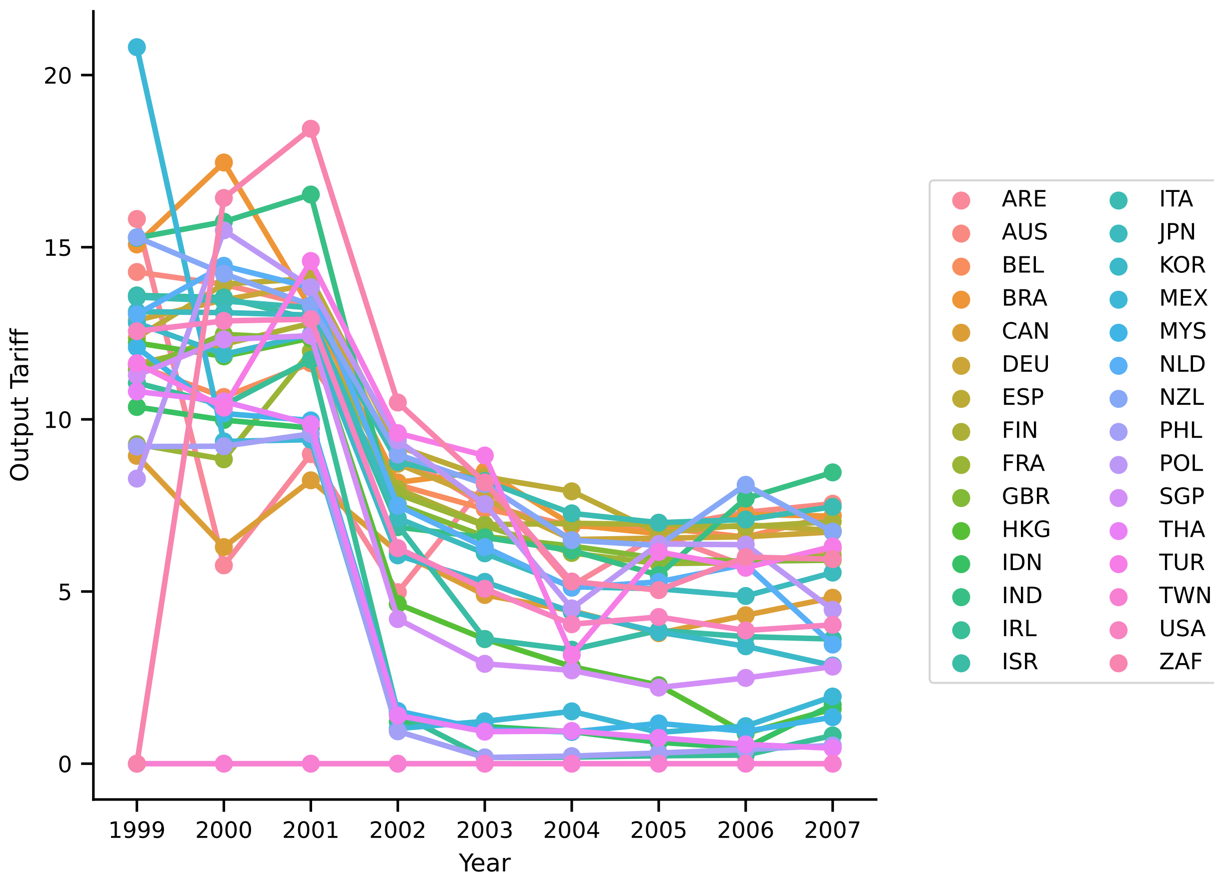
This section provides additional figures that supplement the main materials. Specifically, Figures 6 and 7 display input and output tariffs for each year at the destination market level. Figure 8 shows firm-year markups when the lognormal marginal distribution is used instead of the uniform marginal distribution.

Figure 7: Input Tariffs for ADPMs and ADPM Accessories from 1999 to 2007



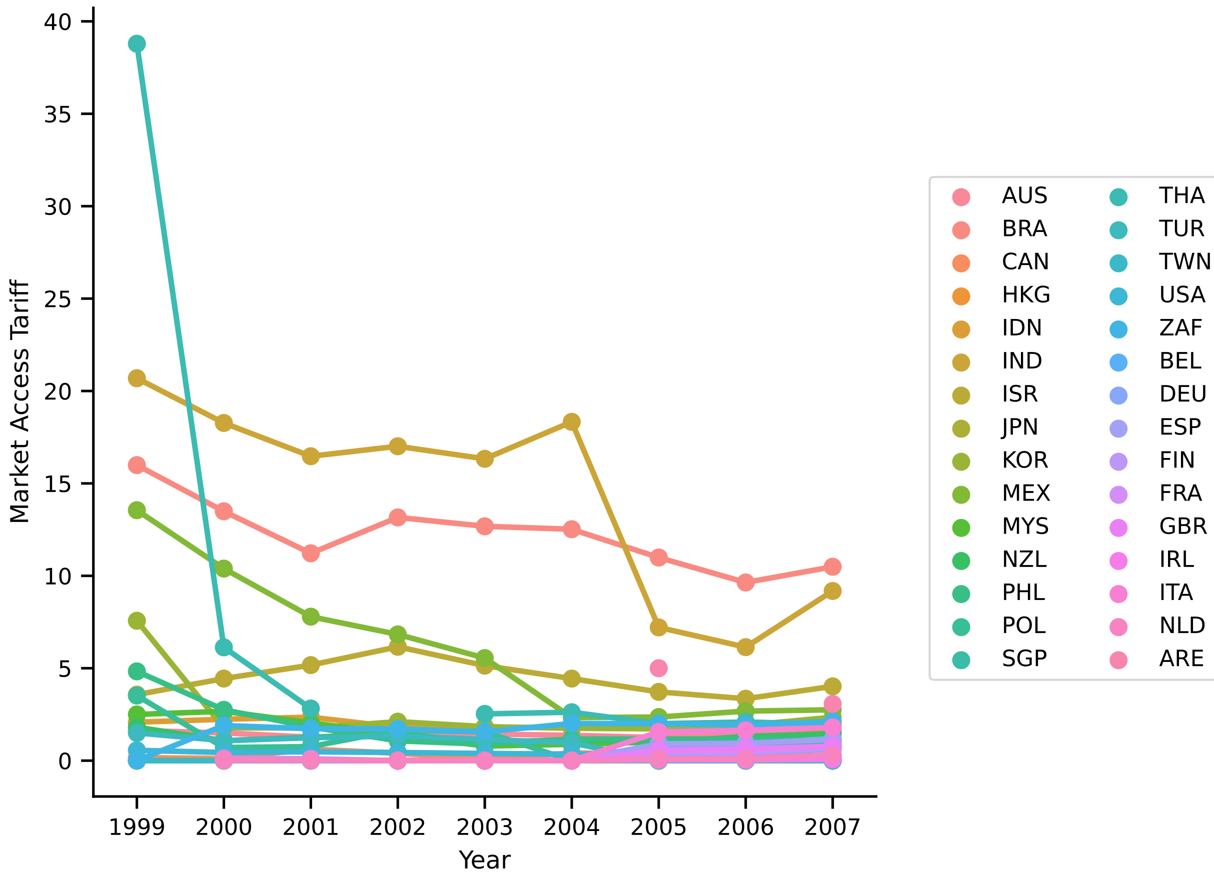
Note: This figure plots market-level input tariffs for China from 1998 to 2007 with respect to HS2 level 84, which contains ADPMs and ADPM accessories.

Figure 8: Output Tariffs for ADPMs and ADPM Accessories from 1999 to 2007



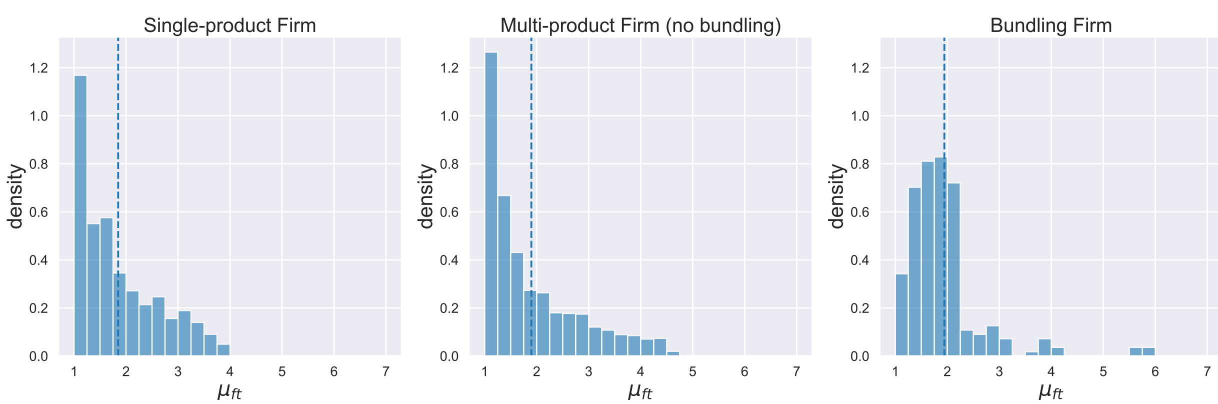
Note: This figure plots market-level output tariffs for China from 1998 to 2007 with respect to HS2 level 84, which contains ADPMs and ADPM accessories.

Figure 9: Market Access Tariffs for ADPMs and ADPM Accessories from 1999 to 2007



Note: This figure plots market-level market access tariffs for China from 1998 to 2007 with respect to HS2 level 84, which contains ADPMs and ADPM accessories.

Figure 10: Markups (μ_{ft}) of ADPMs and ADPM Accessories by Firm Type



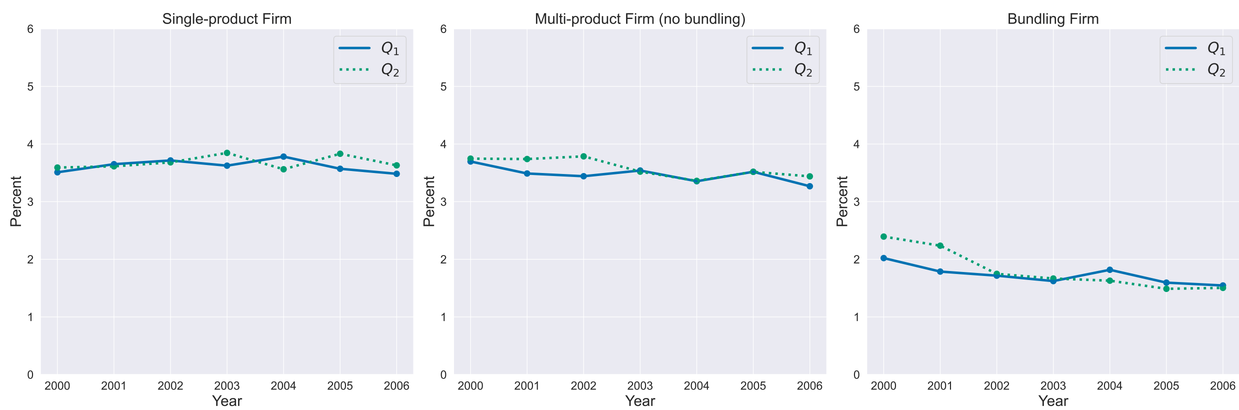
Note: This figure is the same as figure 4. However, it is recovered under the assumption that consumer valuation for each product follows a lognormal distribution rather than a uniform distribution. The overall markup distribution across firm types remains the same as in the uniform case.

Table 8: Markups and Firm Heterogeneity — Quantity Discount Robustness Check

	(1)	(2)	(3)
	$log\mu^{qs}_{fdjm}$	$log\mu^{qm}_{fdjm}$	$log\mu^{qb}_{fdjm}$
$D_{MF_{fdt}}$	0.2346***	0.2521***	0.2773***
(*Multi-Product Firm Premium*)	(0.0094)	(0.0096)	(0.0084)
$D_{BF_{fdt}}$	0.1076***	0.2473***	0.2356***
(*Product Bundling Premium*)	(0.0175)	(0.0176)	(0.0140)
F-statistic	235.1	249.0	414.2
Observation	24,957	24,955	25,713
	$log\mu^{qs}_{fdjt}$	$log\mu^{qm}_{fdjt}$	$log\mu^{qb}_{fdjt}$
$D_{MF_{fdt}}$	0.2680***	0.2872***	0.2702***
(*Multi-Product Firm Premium*)	(0.0140)	(0.0160)	(0.0173)
$D_{BF_{fdt}}$	0.2718***	0.1959***	0.2015***
(*Product Bundling Premium*)	(0.0356)	(0.0384)	(0.0290)
F-statistic	114.4	85.0	101.7
Observation	5,293	5,293	5,454
	$log\mu^{qs}_{fdt}$	$log\mu^{qm}_{fdt}$	$log\mu^{qb}_{fdt}$
$D_{MF_{fdt}}$	0.3862***	0.3418***	0.2087***
(*Multi-Product Firm Premium*)	(0.0309)	(0.0248)	(0.0202)
$D_{BF_{fdt}}$	0.2626***	0.3418***	0.3873***
(*Product Bundling Premium*)	(0.0956)	(0.0868)	(0.0391)
Market FE	Yes	Yes	Yes
Product FE	Yes	Yes	No
Year FE	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes
F-statistic	43.46	44.0	66.19
Observation	5,188	5,197	5,323

Note: This table reports the coefficients from the regression (14) with three different quantity bins to check for a quantity discount. If there is significant variation in the coefficients across quantity bins, we should be concerned about the quantity discount affecting the result. The dependent variable is (log) markup. Column (1) shows the results for transactions with small quantities, column (2) for middle quantities, and column (3) for large quantities. Overall, regardless of quantity, the coefficient does not differ significantly. The standard errors are in parentheses and are bootstrapped. Significance : * 10 percent, ** 5 percent, *** 1 percent.

Figure 11: Evolution of Demand Elasticities



Note: This figure plots the evolution of demand elasticities across firm types. Note that bundling firms have fewer elastic consumers and can charge higher prices than non-bundling firms.