Trade, Markups, and Consumer Welfare: Evidence from the Global Smartphone Industry *

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Abstract

This study investigates how trade policies impact markups and consumer welfare. Elevated trade barriers force some imported products to exit the market, reducing market competitiveness and allowing remaining products to raise markups (entry mechanism). Simultaneously, higher trade barriers cause imported goods to raise prices less than the cost hike to counter demand decline, reducing markups (cost mechanism). Utilizing data from the smartphone markets of 40 major countries, we build a supply and demand model where both firms' product portfolios and pricing strategies are endogenous. Our counterfactual analysis indicates that the tariff effect on markups varies with imported goods' market share. Furthermore, we underscore the importance of cost mechanisms in shaping markup adjustments by analyzing the impact of trade policies on markup through both mechanisms across countries. Finally, we highlight the importance of considering trade-policy-induced markup alterations on consumer welfare, under specific conditions.

JEL Codes: F11, F12, L11, L13

Keywords: variable markup, oligopolistic competition, gains from trade

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1 Introduction

In recent years, the resurgence of trade protectionism worldwide has heightened economists' focus on how increased trade barriers affect consumer welfare (Amiti, Redding, and Weinstein, 2019; Fajgelbaum et al., 2020; Flaaen, Hortaçsu, and Tintelnot, 2020; Cavallo et al., 2021). Higher tariffs imposed on products within an industry directly impact the import costs and the exit of imported varieties, ultimately affecting consumers. This mechanism has been widely considered in canonical quantitative trade models (e.g., Eaton and Kortum, 2002; Melitz, 2003; et al.). Simultaneously, higher tariffs also alter the markups of products active in the market, thereby potentially influencing consumer welfare. Ignoring the fluctuation of markups on the market under the influence of trade policies may lead to inaccurate quantification of the impact of trade policies on resident welfare.

Markups are determined by market demand, competition, and costs. Higher trade barriers and tariff levels affect the markups of products and competition in the market through both entry and cost mechanisms. To understand the entry mechanism, consider that higher tariff levels and trade barriers force some imported products to exit the market at higher costs, decrease market competition, and elevate the markups of products remaining in the market. Meanwhile, empirical research has found that changes in import costs potentially affect firm markups (De Loecker et al., 2016). For instance, higher tariff levels leading to increased final delivery costs for imported products may potentially prompt imported products to reduce markups to mitigate the decrease in market demand resulting from price hikes. Therefore, changes in trade barriers can lead to different outcomes in markup alterations. Understanding how these two mechanisms operate differently across various market environments and to what extent they determine the overall changes in market markups is crucial for better grasping the markup alterations and the trade policies' pro-competitive effect highlighted in existing literature (e.g. Atkeson and Burstein (2008), Edmond, Midrigan, and Xu (2015), and Arkolakis et al. (2019)).

In this article, we employ global smartphone data to quantitatively analyze how trade policies affect firm markups and consequently impact consumers. We build a structural model that trade policies affect firm pricing via both cost and entry mechanisms. Our model is a two-stage game, wherein firms make endogenous decisions of product portfolio in the first stage, followed by endogenous product pricing in the second stage. Then we use the model to fit the supply and demand of smartphone markets across countries and simulate the impact of higher tariff levels on product entry outcomes and the pricing equilibrium across countries. We conduct counterfactual analysis to address three key questions: 1. How does a higher tariff generally affect markups in the market? How does the impact of tariff policies on markups vary across markets with different market shares of imported products? 2. How do cost and entry mechanisms jointly determine changes in markups under higher tariff effects? 3. Beyond the mechanisms through which traditional quantitative trade entry models examine how trade policies affect consumer welfare via marginal costs and entry and exits of varieties, how do changes in markups influenced by trade policies additionally impact consumer welfare?

We obtained quarterly sales information and performance characteristics of almost all available smartphones in the markets of 40 major countries from 2010 to 2015. This rich cross-country product-level information enables us to move beyond the assumptions of monopolistic competition commonly applied in trade literature, allowing for an oligopolistic competition setting for smartphone brands' pricing strategies. Additionally, it allows us to identify firms' product portfolio strategies across different countries and estimate the entry costs associated with introducing a product into a market. This data foundation enables us to analyze in finer detail from a micro perspective how changes in trade policies affect the pricing and product portfolio strategies of firms.

With this data foundation, we build a model of supply and demand where both the set of offered smartphone products and their prices are endogenously determined. In the second stage, we utilized a nested logit model to fit market demand and Nash-Bertrand pricing competition to fit supply pricing. In the first stage, we assumed that firms decide which products to launch in a market based on the expected marginal profit generated by each product and the fixed costs of product entry. In our model mechanism, higher tariffs changing the cost of imported products influence pricing and profits for all products in the second stage. Subsequently, changes in product profits affect the entry and exit of products during the first stage. This entry and exit, in turn, alters the market competition environment, influencing the equilibrium pricing in the second stage until a new equilibrium is reached. Benefiting from the detailed mechanisms in our model, our endogenous determination of market structure and equilibrium pricing enables a better grasp, at the micro level, of how exogenous trade policies impact firm pricing through the costs of imported goods and the exit of imported products, ultimately affecting consumers. Furthermore, to ensure comparability with canonical trade entry models in quantification, in Section 3.4, we demonstrate that with appropriate adjustments, the IO nested logit demand of our second-stage firm pricing setting is essentially isomorphic to a nested CES demand widely used in trade literature.

Our empirical implementation begins by estimating the supply and demand coefficients for the second-stage market, followed by deriving the fixed entry cost coefficients for firms' product introductions in the first stage based on the results of the second stage. Employing instrumental variable estimation, we first determine the demand-side coefficients in the second stage. We estimate price elasticity coefficients for smartphone products, ranging from 1.74 to 2.9 across countries, indicating a relatively inelastic industry.[1] Subsequently, based on the demand-side results, we infer the marginal cost coefficients for the second-stage supply side under a Nash-Bertrand competition equilibrium. Next, based on the second-stage estimates, we deduce the marginal variable profits contributed by a product to its brand's existing product portfolio in a market. Assuming that the actual market outcomes represent a Nash equilibrium, where removing a product from their existing portfolio or adding a product that selling in another country does not yield higher profits for firms, we employ maximum likelihood estimation to estimate coefficients related to product entry costs.

Based on our estimated demand, marginal cost, and entry cost parameters, we conduct counterfactual analysis to answer our research questions. Using the sales data from the first quarter of 2015, we simulate counterfactual scenarios of trade protection with 25, 50, 75, and 100 percentage points higher tariffs based on the actual tariff levels at that time in each country. In the first part of the counterfactual analysis, we investigate the impact of higher tariffs and trade barriers on markup levels across countries. Under higher tariffs, the entry mechanism may raise the markup of remaining products, while the cost mechanism

[1] Fan and Yang (2020) set a consumer utility function that is linearly related to the price of smartphone products. Using data from the U.S. smartphone market from 2009 to 2013, they estimated a price coefficient of -0.007. We adopted a consumer function form that is linearly related to the log of smartphone product prices. After adjusting according to $d(logp) = dp/p$ and based on the average price of the U.S. smartphone products from 2010 to 2013 in our sample, we estimated a price coefficient of -0.006. Similarly, Fan and Zhang (2022) applied data from the Chinese smartphone market from 2007 to 2013 and estimated different price coefficients for urban and rural areas. If we apply a similar transformation to the parameters of the Chinese smartphone market in our sample from 2010 to 2013, we estimate a price coefficient that falls between their reported urban and rural price estimates.

potentially lowers the markup of imported products under higher costs. Thus, the impact of tariffs on markup in an industry is ambiguous and varies depending on the market share of imported products in a country's market. In our sample countries, higher tariffs result in a slight overall markup increase in countries with a higher market share of domestically produced goods, while causing a decrease in markup for countries more reliant on imported products.

Next, we delve into a micro-level analysis of how costs and entry mechanisms contribute to changes in markups under tariff influence. We find that in smartphone markets of countries heavily reliant on imports, the impact of costs tends to outweigh that of entry. This is because higher tariffs directly affect the costs of imported products, leading to pass-through effects on final prices. In these markets, products exiting due to increased trade barriers are often those with lower profit margins and smaller market shares, thereby exerting limited and indirect influence on the pricing of other products in the market. Simultaneously, in countries with a lower market share of imported goods in their smartphone markets, the impact of the cost mechanism remains noteworthy compared to the entry mechanism, though not as decisive as in import-intensive countries. Our findings highlight the crucial role of tariffs in altering the costs of imported products, thereby affecting markups, which, in many instances, prove to be even more critical than the entry mechanism.

Finally, our counterfactual analysis examines the additional extent to which changes in markups due to trade policy alterations affect consumer surplus, beyond the mechanisms typically addressed in classical models, such as changes in product availability and supply costs in the market. Results from our counterfactual analysis suggest that under higher tariff levels, the additional impact of markup changes on consumer surplus is ambiguous for countries heavily reliant on imports, and its effect is minor compared to the direct influences of higher costs and the exit of imported varieties. However, for countries with relatively lower market share of imported goods, the additional markup changes exacerbate the reduction in consumer surplus due to higher costs and fewer varieties, and the magnitude of the markup effect is non-negligible. This is because domestically produced products, under heightened trade barriers, experience increased markup and prices, further compromising consumer surplus, a mechanism more pronounced in countries with a higher market share of domestically produced goods.

Leveraging the rich product entry, pricing, and feature information provided by our unique cross-country sales data, our research methodology possesses two key advantages. Firstly, we focus on firm behavior regarding markups, a supply-side aspect, while our model does not include strong assumptions on the supply side. Secondly, compared to standard trade models, our oligopolistic competition framework explores, at a more granular level, the mechanisms through which trade policies influence markups via costs and entry.

This paper contributes to the quantitative analysis of the gains from trade liberalization, with a particular focus on markups. Traditional trade models and sufficient statistics have not taken into account the changes in markups resulting from trade shocks (e.g. Eaton and Kortum (2002), Melitz (2003), Chaney (2008), Eaton, Kortum, and Kramarz (2011), Arkolakis, Costinot, and Rodriguez-Clare (2012)). While recent studies by Edmond, Midrigan, and Xu (2015) and Arkolakis et al. (2019) consider the impact of trade on firm markups, they do not delve into the specific mechanisms through which trade policies affect markups at the micro-level, considering both cost and entry [2]. This paper employs cross-country data at an industry level to delve into trade and markup from a more granular perspective.

Our analysis is supported by a body of empirical literature on markups and trade.[3] Levinsohn (1993), Harrison (1994), Krishna and Mitra (1998), and Feenstra and Weinstein (2017) have revealed lower price-to-cost margins alongside increased trade exposure. Meanwhile, De Loecker et al. (2016) found a net increase in markups for Indian manufacturing firms following the tariff reduction in 1991, attributing it to an additional cost channel. In recent years, a series of articles focusing on the incidence of tariffs have estimated the pass-through of the US trade war (Amiti, Redding, and Weinstein, 2019; Fajgelbaum et al., 2020; Flaaen, Hortaçsu, and Tintelnot, 2020; Cavallo et al., 2021). Our quantitative analysis, using industry data across different countries, demonstrates that trade policies can lead to diverse outcomes on markups (complete/incomplete pass-through), depending on the forces of entry and cost mechanisms across countries with different market shares of targeted goods.

Our empirical approach draws on modeling strategies outlined in various articles. Our second-stage cross-country demand and supply settings resemble the model applied by Cosar

[2] Many studies explore the costs of markup and their welfare implications in the macro economy, with a particular emphasis on the competitive effects as well, as exemplified by the work of Edmond, Midrigan, and Xu (2023).

[3] In recent years, a series of IO articles have also addressed how markup evolves with changes in the economic environment and its impact on welfare. These studies include works by Autor et al. (2020), De Loecker, Eeckhout, and Unger (2020), Grieco, Murry, and Yurukoglu (2023), and Miller et al. (2023), among others.

et al. (2018) and the estimation of product-level entry costs in our first stage is adapted from Head and Mayer (2019). However, our emphasis on oligopolistic competition in the model due to markup considerations, alongside simplification in production decisions, diverges slightly. Our method for estimating fixed entry costs of the second stage based on the demand and supply estimates of the first stage, draws from the approaches outlined by Eizenberg (2014) and Fan and Yang (2020). Unlike their focus on whether offering additional potential products in a single market leads to increased welfare, we utilize cross-market data to underscore the impact of trade policies on markups across different countries and their effects on consumers. Finally, specifically, Head and Mayer (2023) compared the differences between IO and trade CES quantitative results using BLP's data generation process. We utilized real cross-country data from an industry and incorporated considerations regarding product entry and exit.

The remainder of this paper is organized as follows: Section 2 describes the data. Section 3 presents the model. Section 4 introduces the estimation process. Section 5 discusses counterfactual analysis. Section 6 concludes.

2 Data

A lot of influential research has utilized structural models to quantitatively analyze trade and firm markup. Typically, these studies use datasets covering all manufacturing or industrial enterprises, providing insights into the economic performance across various sectors and industries within a country. However, such datasets have drawbacks when investigating trade and markup, as they often simplify markup determination based on consumer substitution elasticity or market share and lack a theoretical foundation for micro-level firm pricing decisions. Unlike previous studies, our focus in this article is on the global smartphone market. It is noteworthy to emphasize the advantages of our data source and the utilization of multiple market data from a specific industry in studying the impact of trade policies on firm markup.

The majority of our product-level data is sourced from the Worldwide Quarterly Mobile Phone Tracker, a market research endeavor conducted by the International Data Corporation (IDC) headquartered in Massachusetts, United States. The IDC's bottom-up methodology provides quarterly product-level sales information, including prices and quantities, for all smartphone products [4] sold in 40 major countries and regions from the first quarter of 2010 to the last quarter of 2015.

Table 1 presents preliminary statistics on smartphone sales in 2015 for the 40 countries/regions in our dataset. It is noteworthy that these 40 countries/regions, listed in Column (1) of Table 1, collectively contribute to 90% of the total global GDP, according to 2016 World Bank statistics. This substantial representation in our dataset positions these countries/regions as significant indicators of global smartphone sales and trade flows. Columns (2) to (5) of Table 1 respectively display population, total smartphone sales units, GDP, and total smartphone sales value for each market in 2015. The proportion of annual smartphone shipments to the total population is considerable in various countries, with Hong Kong's smartphone sales in 2015 even surpassing its total population. Additionally, comparing the total sales value of the smartphone industry to the GDP of each country/region, the ratio is noteworthy, exceeding 1% in both the Hong Kong SAR and mainland China. This underscores the widespread consumer base and substantial profitability of the smartphone industry, making it a representative industry for studying trade and markup.

Moreover, our global industry data, compared to previous studies and utilized datasets, offers significant advantages in exploring trade and markup. The standout feature of our data lies in enabling economists to observe the sales performance of almost all major market entrants in an industry (smartphone industry) across multiple countries. This facilitates the understanding of two crucial aspects: (1) the market competition outcomes of various firms and their products in a specific industry across different countries/regions (prices and quantities), and (2) the diverse product combinations and pricing decisions of the same firms in different markets.

The first aspect of our data brings forth the primary advantage of our research methodology and model construction: the ability to construct an oligopolistic competition model to fit

[4] In the original IDC data, the definition of a product is based on the model name, such as the iPhone 6S and Samsung Galaxy Note 6. However, in the real market, even if two phones belong to the same model and share many similar product attributes, they may have very different production costs, pricing, and market demand due to differences in certain dimensions of product features, such as a clearer camera, larger storage space, or a more expensive chip. Therefore, in this paper, we define a product as follows: for two smartphones to be considered the same product, they must have the same model name (e.g., Huawei Mate 60), the same mobile operating system, whether they are 4G/3G phones, the same screen size, the same camera pixel count, the same chip, the same hard disk space, the same primary card, the same color display, the same screen and keyboard functions, the same Wifi, Bluetooth, NFC, GPS, and TV functions, as well as the same Sim card slot.

Table 1: Statistics of Smartphone Market by Countries in the Year 2015

Country/ Region	Population	Market Size	GDP	Market Value	# of Products	# of Brands	HHI
	Unit: Millions		Unit: Billions of USD				
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Argentina	43.42	11.82	584.71	3.92	164	15	0.187
Australia	23.79	8.98	1345.38	5.32	163	15	0.313
Austria	8.63	2.71	376.97	1.31	207	26	0.310
Belgium	11.27	3.06	454.99	1.28	239	27	0.174
Brazil	205.96	47.43	1803.65	11.03	283	18	0.255
Canada	35.85	11.91	1552.81	6.42	129	19	0.301
Chile	17.76	8.44	242.52	1.76	136	18	0.213
Chinese Taipei	23.49	10.24	525.24	4.05	252	18	0.177
Colombia	48.23	7.33	291.52	1.32	221	21	0.144
Denmark	5.68	2.66	301.31	1.54	152	22	0.308
Finland	5.48	1.82	232.36	0.83	149	18	0.200
France	66.62	24.54	2433.56	8.54	397	52	0.142
Germany	81.69	26.12	3363.60	11.74	337	41	0.217
Hong Kong SAR	7.31	8.87	309.40	5.96	214	17	0.334
India	1309.05	98.63	2111.75	13.14	1128	49	0.121
Indonesia	258.16	27.79	861.26	3.26	415	35	0.131
Ireland	4.68	1.85	283.72	0.77	131	18	0.204
Italy	60.73	18.86	1824.90	6.67	390	38	0.245
Japan	127.14	30.42	4383.08	15.55	105	19	0.270
Korea	51.01	16.08	1382.76	10.16	70	12	0.369
Mainland China	1371.22	422.26	11064.70	110.77	645	33	0.097
Malaysia	30.72	9.06	296.28	2.29	319	24	0.142
Mexico	125.89	34.40	1151.04	6.89	232	23	0.132
Netherlands	16.94	6.84	750.32	3.17	233	26	0.227
New Zealand	4.60	1.69	175.56	0.62	115	15	0.270
Nigeria	181.18	9.31	481.07	1.93	310	39	0.143
Norway	5.19	2.32	386.58	1.34	139	17	0.278
Pakistan	189.38	8.29	271.05	1.34	330	22	0.260
Philippines	101.72	13.32	292.77	1.94	446	25	0.103
Portugal	10.36	3.00	199.08	0.69	282	25	0.115
Russia	144.10	25.34	1365.87	4.28	383	34	0.108
Singapore	5.54	4.29	296.84	2.52	185	22	0.317
Spain	46.45	16.34	1192.96	5.17	380	39	0.182
Sweden	9.80	3.94	495.69	2.29	141	19	0.280
Switzerland	8.28	3.62	670.79	2.18	157	24	0.282
Thailand	68.66	21.49	399.24	3.77	360	24	0.142
USA	320.90	167.26	18036.60	79.33	411	24	0.231
Ukraine	45.15	3.25	91.03	0.46	331	29	0.218
United Kingdom	65.13	31.74	2861.09	15.85	312	43	0.218
Venezuela	31.16	1.77	260.09	0.28	41	8	0.322

Notes: The table presents data on smartphone sales in 40 markets for the year 2015. Specifically, column (1) lists the names of countries/regions in the sample. Columns (2) and (3) provide information on population and total smartphone sales units. Columns (4) and (5) document GDP and total smartphone sales value for each market. Columns (6) to (8) display smartphone product counts, smartphone firm counts, and the Herfindahl Index for the smartphone industry in each country/region in 2015.

the competitive pricing decisions of firms in the smartphone markets of different countries, subsequently modeling how national trade policies influence firms' competitive strategies. Columns (6) to (8) of Table 1 display smartphone product counts, smartphone brand counts, and the Herfindahl Index for the smartphone industry in each country/region in 2015. These columns reveal varying market concentration levels across different markets, with competition often concentrated, suggesting that pricing strategies often conform to an oligopoly competition mechanism. Unlike many existing international trade papers that focus on data from all manufacturing firms in a specific country, estimating markup based on demand elasticity, our data concentrates on an industry. Leveraging an oligopoly competition model from IO, we enable firms' pricing strategies to depend on the cost of introducing products, the market competition environment, and consumer demand. This modeling approach better captures how firms make pricing decisions in the face of market demand, final delivery costs, and external conditions of competition. These richer market competition insights not only enhance our analysis of how trade policies influence firm pricing strategies and the distribution of market markup, as intended in this study but also align with the trend of increasing accessibility to industry-specific data across countries in the era of big data and digital development.

Meanwhile, the dataset provides product-level information on product characteristics. These product characteristics include CPU details (processor vendor, speed band, number of cores), system specifications (operating system, RAM band, storage band), screen and display attributes (form factor, screen resolution, screen size, display type), air interface and generation information, camera specifications (camera megapixels, dual rear camera), and the availability of additional functions, such as NFC, Wi-Fi, TV, GPS, and Bluetooth. These supplementary variables related to the performance of each smartphone product enable us to better capture consumer utility and market demands on the demand side while capturing firm marginal costs and pricing strategies on the supply side.

The second aspect of our data's key information brings forth the second advantage of our research methodology: understanding how trade policies impact firms' product portfolio strategy and market competition. This is achieved by observing the complete set of products available to firms and identifying firms' product combination decisions in different countries. In contrast to most IO papers that only provide market data for a specific industry in one

Table 2: Smartphone Brands' Product Portfolio Statistics by Countries in the Year 2015

Brand	Total Sales Value (Billions of USD)	Num of Countries	Num of Products	Average Num of Products	Max Number Market	Max Num of Products
Apple	149.51	39	48	16.28	India	29
Samsung	86.85	40	337	33.33	Brazil	70
Huawei	18.06	40	199	18.28	Mainland China	64
LG	12.94	39	227	18.31	Brazil	63
Xiaomi	9.91	17	45	8.35	Mainland China	17
OPPO	9.49	11	67	14.27	Mainland China	29
Sony	9.16	39	112	16.15	Hong Kong SAR	28
vivo	7.72	5	55	17.20	Mainland China	35
Motorola	7.29	26	80	9.42	USA	21
ZTE	5.75	37	181	8.76	Mainland China	45

Notes: The table reports total sales, the number of countries/regions entered, the number of products owned, the average number of products introduced in all entered countries/regions, and the number of products introduced in the country with the highest product count for the top 10 smartphone brands in our observed 40 countries/regions for the year 2015.

country, we can observe the diverse products introduced by firms in different countries. Table 2 displays, for the year 2015, the total sales, number of countries/regions entered, number of products owned, average number of products introduced in all entered countries/regions, and the number of products introduced in the country with the highest product count for the top 10 smartphone brands in our observed 40 countries/regions. It is evident that even in the country where these major manufacturers introduce the highest number of products, the count is significantly lower than the total set of products they introduce across all countries. On one hand, this reflects the diverse product combination strategies adopted by firms in different markets. On the other hand, it implies that introducing products to a market may incur a certain degree of fixed costs.

Traditional trade and IO models in previous papers could fit market demand and firm supply costs, understand expected earnings for firms, and infer the marginal benefits a product's presence in a market brings to a firm's existing product portfolio. Building upon these results and combining them with our observed firms' entry decisions for each product in different markets, we can infer the entry cost of a product. The release of entry costs is crucial in addressing the issue in our study: in our counterfactual simulation, we can adjust product combinations (product-level entry and exit decisions) based on changes in trade policies and marginal costs faced by smartphone brands, and simulate how external trade policies impact the final pricing strategies and markup distribution through both cost and entry channels. This second feature of our data assists in integrating market supply and demand in an oligopolistic competition setting with the common entry decisions found in the international trade literature, providing a more comprehensive simulation of the impact of trade policies on firms' decisions.

Furthermore, we collect firm-level information on headquarters and manufacturing countries by searching their official websites based on their vendor name in the dataset, advertisements, factory-related news, and online product pictures[5]. Each country's wage and GDP per capita data come from the World Bank Database. The information on tariffs and regional trade agreements comes from the World Trade Organization database.

In summary, our global smartphone data provides unprecedented cross-national market competition information. The scarcity of such data has enabled us to construct more comprehensive models for firm supply and demand, as well as entry decisions. This allows us to investigate how changes in exogenous trade environments, influenced by costs, impact the market structure, pricing, and sales in a new equilibrium. This scarcity-driven research opens up possibilities for novel discoveries in understanding the economic mechanisms of international markets.

3 Model

3.1 Environment

In a given quarter t, there exist many independently-operated smartphone brands, each denoted by b (e.g., Apple), endowed with its productivity φ_b and a range of smartphone products (e.g., iPhone 6, iPhone 6S) targeted for sale in specific countries. Each product j is endowed with distinct characteristics (e.g., 1300M camera megapixels, 4.6" screen size) and is assembled in a specific location to deliver smartphones with identical configurations to each designated country. The potential markets for smartphone sales comprise N countries, and the decision of whether a brand b has entered a country n is predetermined before the commencement of the static game each quarter.

The game unfolds in two stages. In the first stage, brands entering a given country n

[5]For more details and statistics on headquarters information and production information, please see Appendix 7.1 and 7.2.

determine their product portfolio based on their observation of the market demand, unit delivery costs, and fixed entry costs for each product j incurred in delivering to consumers in country n during quarter t. As a result, the brand decides whether to introduce each product j in country n, resulting in the determination of the product portfolio J_{bn} for each brand b, shaping the smartphone market structure in country n.

Moving to the second stage, contingent on the market structure determined in the first stage, brands price their products in each country and engage in simultaneous Nash-Bertrand pricing competition. The competition is influenced by the market demand observed and the marginal costs incurred. Brands strategically set prices to maximize their profits within the market in each quarter.

In the real-world market, the operations of smartphone manufacturers in certain countries may involve negotiations with telecom carriers and distributors, as highlighted in previous studies on mobile phones (Fan and Yang, 2020; Liu and Luo, 2023). In our model, we do not treat the collaboration between smartphone brands and network carriers or distributors in these countries as a separate stage of decision-making. This is partly due to diverse operational methods in different countries—such as in the United States, where a significant portion of smartphone sales comes from telecom carriers, while in China, phones are predominantly sold through physical stores or online channels. Consequently, the role of network operators varies in different countries. Additionally, obtaining data on how manufacturers arrange distributors in each country proves challenging.

In our model, we consider different operational strategies in various countries as fixed entry costs for entering a market. Simultaneously, we measure the price of each phone product using the average selling price in each country for each quarter. We do not differentiate whether the phone is sold by the brand to a telecom carrier or directly to consumers [6], assuming that phone brands have good expectations regarding the average selling price and sales quantity of their products. By adopting this approach, we can effectively understand the pricing strategies and average markups of each product across different markets. Simultaneously, we streamline the analysis based on the available data.

Moreover, we posit that the selection of the assembly country for each product of every brand destined for each specific country is exogenously determined. This differs from a series

[6] From the available data, we cannot discern whether a phone is sold by the brand to a telecom carrier or directly to consumers.

of articles focusing on FDI location choices (Tintelnot 2017; Antras, Fort, and Tintelnot, 2017; Coşar, Grieco, Li, and Tintelnot, 2018; Head and Mayer, 2019, et al.). Instead, we focus on how exogenous trade policies influence costs, thereby impacting firms' decisions on product entry and pricing. Hence, our quantitative simulations and counterfactual policy analyses resemble a medium-term policy analysis: brands do not adjust their assembly locations in response to trade policies. This assumption is made to avoid additional computational challenges associated with finding the optimal production location set using various mathematical algorithms (e.g., Jia, 2008). Furthermore, during our sample period, the assembly choices for phone brands were notably restricted, with a predominant concentration of smartphone production in a handful of countries such as China, Vietnam, and Brazil [7][8]. The practicality of such limited data poses challenges in estimating the costs associated with relocating assembly lines to a new country, while aligning with the assumptions of our simplified model.

3.2 Demand

We base our consumer demand assumption on the canonical discrete choice model (McFadden, 1973; Berry, 1994; Berry, Levinsohn, and Pakes, 1995; Goldberg, 1995). The utility u_{ijnt} that consumer i from country n derives from purchasing smartphone product j of brand $b(j)$ in quarter t is expressed as:

$$u_{ijnt} = x_j\beta - \alpha_{nt}log(p_{jnt}) + \lambda_b + F_n + T_t + \xi_{jnt} + \zeta_{ignt} + (1-\sigma)\epsilon_{ijnt}.$$

Here, x_j represents a vector of observable product characteristics, encompassing CPU cores, camera megapixels, and other smartphone function variables detailed in the data section. The vector β represents parameters of interest governing consumers' preferences for various smartphone functions. The average selling price of smartphone product j in country n at quarter t, p_{jnt}, and the related price elasticity parameter, α_{nt}, are essential components. We allow α_{nt} to vary across countries and quarters, accommodating the diverse sensitivity of consumers from countries with varying income levels to price changes in smartphone products

[7]See Appendix 7.2 for more details.

[8]Notably, a minimal number of brands made adjustments to their assembly locations, as only nine out of the total 243 brands in our sample once shifted their assembly countries for products destined to specific countries between 2010 and 2015.

[9].

The decision to adopt a log form of the price term instead of an original price term and exclude random coefficients on β and α is motivated by three reasons: simplifying the estimation of price elasticity parameters across countries, delivering a well-fitted form to consumer demand, and most importantly, ensuring comparability of the utility function form of our model to the CES demand in trade literature, as will be demonstrated in Section 3.4.1. While our model's demand specification originates from IO literature, it yields a notably similar relationship between product market demand, prices, and quality when compared to the CES demand in a majority of trade literature. This alignment strengthens the meaningful comparison of our model with traditional trade entry models, especially when employing both approaches for counterfactual analyses to assess the impact of trade policies on firm markups and consumer surplus.

Furthermore, λ_b, F_n, and T_t denote brand, country, and quarter fixed effects in consumer utility. The term ξ_{jnt} captures unobserved product-country-quarter demand shocks, such as the exterior value of iPhone 6 in a specific country.

We conclude the treatment of consumer idiosyncratic tastes and utility by adopting a nested logit demand form following Berry (1994) to address potential cross-price elasticity threats. Specifically, we categorize smartphone products in each country into six exhaustive and mutually exclusive sets based on IDC's original classification of quality and selling prices: ultra-high-end ($600+), high-end ($400-$600), mid-range ($200-$400), low-end ($100-$200), and ultra-low-end (0-$100). The group index is denoted as $g = 0, 1, ..., 5$. The outside option $j = 0$, representing not buying a smartphone, is assumed to be the only member of group $g = 0$. We define ζ_{ignt} as consumer i's taste shock common to all products in group g, ϵ_{ijnt} as consumer i's specific taste shock to product j, and the parameter σ captures within-group correlation of utility for smartphone products.

This group nesting allows within-group products to share similar utility levels, improving the fit for substitution patterns across smartphone products [10]. For instance, an iPhone 6 has a larger substitution effect with a Samsung Galaxy Note 6 than a $300 Xiaomi 4. Our

[9] Simonovska (2015) examined pricing by Mango in countries with different income levels and found richer countries have higher markups and pricing.

[10] Many trade studies have also explored the substitution effect among different goods, as exemplified by Hottman, Redding, and Weinstein (2016).

model captures consumer behaviors in purchasing smartphones, assuming that consumers first decide to buy a flagship product among leading options and then make a decision within that group, or they decide to buy a basic, inexpensive smartphone and choose from their targeted product groups.

Under the assumption of i.i.d. Gumbel distribution for ϵ_{ijnt} and $\zeta_{ignt} + (1-\sigma)\epsilon_{ijnt}$, and after performing calculus algebra to integrate the distribution of error terms, our utility function and taste shock distribution yield a reduced form specification similar to Berry (1994)'s well-known nested logit model [11]:

$$log(s_{jnt}) = log(s_{0nt}) - \alpha_{nt}log(p_{jnt}) + x_j\beta + \sigma log(s_{jnt/gnt}) + \lambda_b + f_n + T_t + \xi_{jnt}, \quad (1)$$

where s_{jnt} is the market share of product j in country n at quarter t, and $s_{jnt/gnt}$ is the market share of product j within the group g to which it belongs. Other terms follow our previous definitions.

3.3 Supply

Each quarter, brands leverage their productivity and assembly locations to supply products to destination markets. Given the observed market demand, unit delivery costs, and fixed entry costs, brands strategically determine their product-level entry and pricing decisions. The decision-making unfolds in two stages: first, brands decide on their available products, and second, they set prices based on the market structure established in the initial stage. This subsection outlines our modeling approach, beginning with the representation of firms' endowed features and realized marginal costs, followed by their pricing decisions in the second stage, and concluding with an examination of how product-level fixed costs influence entry decisions in the first stage.

3.3.1 Marginal Cost

Each brand b is endowed with a productivity φ_b. The product design process occurs at headquarters h, following which brands either authorize their own factories or other qualified

[11] The nested logit model is also commonly featured in research examining trade policy issues, such as in Khandelwal (2010).

manufacturers in locations l for production. Configured products are then shipped from production locations l to destination markets n.

Assembly manufacturers acquire composite inputs to manufacture final goods, with brand productivity influencing production efficiency and higher-quality goods incurring greater input costs. Following Feenstra and Romalis (2014), brand b employs l_{jl} units of composite inputs to produce one unit of product j with characteristics x_j in country l:

$$l_{jl} = c_m(x_j)/\varphi_{jl},$$

where $c_m(x_j)$ represents a manufacturing cost function for a product with characteristics x_j, and $\varphi_{jl} = \varphi_{b(j)}/\gamma_{hl}$ denotes the realized productivity of brand b in producing products in country l after accounting for the productivity loss γ_{hl} during the transfer of ideas from headquarters h to the production location l. The price of the composite input in country l is denoted as ω_l. The manufacturing cost c_{jl} of product j with characteristics x_j assembled in country l before shipping to its destination country is given by:

$$c_{jl} = \omega_l l_{jl} = \omega_l c_m(x_j)\gamma_{hl}/\varphi_{b(j)}.$$

For each product j assembled in country l and delivered to consumers in country n, it also involves trade friction costs τ_{ln}, capturing tariff and shipping costs from production location l to destination market n. Lastly, an idiosyncratic cost shock ε_{jln} is also considered for each product j.

Therefore, incorporating the quarter subscript t and cost time-effect c_t, the final delivery (marginal) cost of brand b's product j designed in country h, assembled in country l, and sold in country n is expressed as:

$$c_{jnt} = c_{jlnt} = \frac{\omega_l c_m(x_j) c_t}{\varphi_{b(j)}} \gamma_{hlt}\tau_{lnt}\varepsilon_{jlnt} \tag{2}$$

This formulation applies as the assembly location l of product j is endowed.

3.3.2 Bertrand Pricing Competition

In the second stage, brands set prices for their products based on observed market demand, realized unit costs, and the market structure determined by firms' product portfolio decisions in the first stage. Specifically, brand b formulates their pricing decisions as an optimization problem:

$$\max_{p_{jnt}, j \in J_{bnt}} \quad \sum_{j \in J_{bnt}} (p_{jnt} - c_{jnt}) M_{nt} s_{jnt}$$

Here, J_{bnt} represents the set of products offered by brand b in country n at quarter t, M_{nt} is the potential smartphone market size in country n at quarter t, and c_{jnt} and s_{jnt} are cost and market share as defined before. The first-order condition yields the equilibrium conditions for the pricing stage:

$$s_{jnt} + \sum_{j \in J_{bnt}} [p_{jnt} - c_{jnt}] \frac{\partial s_{jnt}}{\partial p_{jnt}} = 0. \tag{3}$$

While this subsection on the pricing stage is concise, it is pivotal in our study. Firstly, decisions in this stage determine our research focus: firms' markups. The pricing equilibrium in our model is achieved in an oligopolistic competition setting, where pricing decisions consider costs, market demand, and the competitive market environment. This aspect of our model significantly differs from most trade literature which often relies on the elasticity of substitution to determine pricing and markups.

Secondly, in our model, the pricing stage and product-level entry decisions jointly determine market equilibrium. The equilibrium pricing along with the marginal entry values of each product for firms in the second stage, influences product entry in the first stage. Simultaneously, decisions made by firms in the first stage impact the market competition environment, influencing pricing decisions in the second stage.

3.3.3 Product Entry Decision

In the first stage, brands strategically determine their product portfolio for each entering country from the available set of designed products. The entry decision for each product is contingent on its marginal profit within the equilibrium product portfolio and the realized fixed entry cost. In our context, the realized fixed entry cost F_{jnt} for each product j encompasses the fixed costs associated with arranging assembly lines and the costs of engaging with local government, dealerships, or potential carrier networks to expose the final product to consumers at each period. Brands initially observe the realized fixed entry cost for each product, form expectations regarding the marginal variable profit of each product, and subsequently decide whether to include or exclude each product in each entered country.

Considering the actual market outcomes of each country as Nash equilibriums, any deviation from a smartphone brand's equilibrium product portfolio is unprofitable.

If a product j is already part of brand $b(j)$'s product portfolio J_{bnt} in country n at quarter t, the realized fixed cost of introducing product j should be lower than the marginal loss for brand $b(j)$ to remove product j from its equilibrium portfolio. Mathematically, this condition is expressed as:

$$\pi_{J_{bnt}} - \pi_{J_{bnt}-j} > F_{jnt} \tag{4}$$

Here, $\pi_{J_{bnt}}$ represents the total variable profit for brand b following the portfolio J_{bnt}, and $J_{bnt} - j$ denotes the portfolio obtained by removing product j from J_{bnt}.

Conversely, for a product k not included in brand $b(k)$'s product portfolio J_{bnt} in country n but appearing in any other country at quarter t, its realized fixed cost F_{knt} should be higher than the marginal benefit for brand $b(k)$ to add product k to its equilibrium portfolio in country n. This relationship is expressed as:

$$\pi_{J_{bnt}+k} - \pi_{J_{bnt}} < F_{knt} \tag{5}$$

Here, $J_{bnt} + k$ indicates the portfolio resulting from adding product k to the existing portfolio J_{bnt}. In these inequalities, we have taken into account the cannibalization effect of the marginal product on other products within the portfolio.

Our model regarding product-level fixed entry costs in this section closely aligns with the studies that integrate the BLP pricing stage with the entry stage (Eizenberg, 2014; Fan and Yang, 2020). Given that our data allows observation of product strategies for various smartphone brands across 40 major countries, we can better discern which products each brand has introduced or not in each market compared to prior studies. Combining market demand with other estimates of firms' supply, our data enables a more accurate estimation of parameters related to product-level entry costs.

Finally, it is crucial to note that in our entry decision stage, we only consider product-level entry decisions and do not address brand-level decisions for entering a country. This is partly because each brand has a multitude of products, making it nearly impossible to compute the variable revenue for a brand entering a country with different product combinations[12]. Moreover, as we will show, our counterfactual design of higher trade barriers only involves the removal of certain existing products based on the real market equilibrium, without delving into brand-level entry decisions.

3.4 Comparison with Canonical Trade Entry Models

In the counterfactual analysis, we use the model above to simulate how trade policies impact market structures, pricing, and consumer surplus within a specific industry. It is crucial to emphasize that while our model is rooted in the micro-foundations of IO, besides incorporating elements of oligopolistic competition to derive pricing decisions and markup, other features of our model closely resemble a basic Melitz (2003) trade entry model. Now, we briefly assume that if our smartphone data were applied to a canonical trade entry model, we outline our fundamental modeling approach, and we compare the similarities and differences between using the classical trade entry model and the approach presented in this paper.

3.4.1 Demand Isomorphism

We apply the issues discussed in this article to a classic Melitz (2003) trade entry model. We extend the standard CES consumer demand utility function to a Nested CES form:

$$U_n^{trade} = \left[\int_g \left(\int_{j \in \Omega_{gn}} a_{jn}^{\frac{1}{\sigma_n^{trade}}} q_{jn}^{\frac{\sigma_n^{trade}-1}{\sigma_n^{trade}}} dj \right)^{\frac{\sigma_n^{trade}}{\sigma_n^{trade}-1} \frac{\alpha_n^{trade}-1}{\alpha_n^{trade}}} dg \right]^{\frac{\alpha_n^{trade}}{\alpha_n^{trade}-1}}$$

Here, we partition all products in each country n into complementary and disjoint nests, where Ω_{gn} represents the set of all products in nest g of country n. The elasticity of substitution between nests is denoted by $\alpha_n^{trade} > 0$ and within each nest by $\sigma_n^{trade} > 0$. a_{jn} is the preference shifter of product j in country n. Consumers in country n optimize their con-

[12]For instance, as illustrated in Table 2, Apple had 48 products in 2015. Without the assumption of sequential entry in our counterfactual analysis, Apple would have had 2^{48} possible product combinations in each market, approximately 2.8×10^{14}. Even with just Apple as the sole smartphone brand globally, it would be impractical to calculate the profitability of the optimal product combination in each market among such an astronomically large number of possibilities. Simultaneously, other smartphone brands, such as Samsung, have an even greater number of available products for sale.

sumption q_{jn} to maximize their utilities. If we denote the aggregate expenditure in country n by X_n, then utility optimization implies the quantity demanded of product j at price p_{jn} in country n is given by:

$$q_{jn} = a_{jn} \frac{p_{jn}^{-\sigma_n^{trade}}}{P_{gn}^{1-\sigma_n^{trade}}} \frac{P_{gn}^{1-\alpha_n^{trade}}}{P_n^{1-\alpha_n^{trade}}} X_n \tag{6}$$

Here, the price index of nest g in country n is defined as $P_{gn} = [\int_{j \in \Omega_{gn}} a_{jn} p_{jn}^{1-\sigma_n^{trade}} dj]^{\frac{1}{1-\sigma_n^{trade}}}$ and the price index in country n is defined as $P_n = [\int_g P_{gn}^{1-\alpha_n^{trade}} dg]^{\frac{1}{1-\alpha_n^{trade}}}$. If we further define the total demand for smartphones in country n as M_n, and specify the consumer's preference shifter for product j, which is related to the observable performance variable x_j, unobservable taste ξ_{jn}, and the brand $b(j)$'s name, following a function form as:

$$a_{jn} = exp\left(\frac{\sigma_n^{trade}}{\alpha_n^{trade}} (x_j \beta + \xi_{jn} + \lambda_b) \right) \tag{7}$$

where x_j, ξ_{jn}, β, and λ_b are defined as phone characteristics, unobserved demand shocks, utility preference parameter, and brand fixed effect as before in Section 3.2. Incorporating Equation (7) into Equation (6), dividing both sides by M_n, and taking the logarithm, we obtain:

$$log(s_{jn}) = -\alpha_n^{trade} log(p_{jn}) + x_j \beta + \frac{\sigma_n^{trade} - \alpha_n^{trade}}{\sigma_n^{trade}} log(s_{jn/gn}^{trade}) + \xi_{jn} + \lambda_b + logX_n + (\alpha_n^{trade} - 1) logP_n - logM_n \tag{8}$$

where $s_{jn/gn}^{trade}$[13] is defined as the share of product j within its nest g. By segmenting the smartphone market into various nests g following Section 3.2, incorporating fixed effects for country n as $logX_n + (\alpha_n^{trade} - 1) logP_n - logM_n$, and including time effects with the time subscript t in Equation (8), this equation in this context is basically isomorphic to the reduced form expression of the nested logit demand side obtained in Equation (1) in Section 3.2.

[13] $s_{jn/gn}^{trade} = \frac{q_{jn}}{q_{gn}^{trade}} = \frac{X_{jn}/p_{jn}}{X_{gn}/P_{gn}} = \frac{P_{gn} a_{jn} p_{jn}^{1-\sigma_n^{trade}}}{p_{jn} P_{gn}^{1-\sigma_n^{trade}}} = \frac{a_{jn} p_{jn}^{-\sigma_n^{trade}}}{P_{gn}^{-\sigma_n^{trade}}}$, where X_{jn} indicates the expenditure on product j in country n and X_{gn} indicates the expenditure on products of nest g in country n. Here, $q_{gn}^{trade} = (\int_{j \in \Omega_{gn}} a_{jn}^{\frac{1}{\sigma_n^{trade}}} q_{jn}^{\frac{\sigma_n^{trade}-1}{\sigma_n^{trade}}} dj)^{\frac{\sigma_n^{trade}}{\sigma_n^{trade}-1}}$ is slightly different from the logit nest quantity.

3.4.2 Supply Isomorphism and Pricing Mechanisms

In the unit cost, our specifications align closely with common modeling in the trade literature. Equation (2) expresses our marginal cost, building upon the prevalent trade cost $\frac{c}{\varphi}\tau$ (manufacturing cost $\times$ iceberg cost), incorporating Feenstra and Romalis (2014)'s microfoundation on how product quality affects production costs and the recent attention to "Headquarters Gravity" (Head and Mayer, 2019; Wang, 2021).

During the pricing competition stage, while our model's mechanism differs significantly from the Dixit-Stiglitz (1977) markup $\frac{\sigma_n^{trade}}{\sigma_n^{trade}-1}$ in the standard trade model under monopolistic competition, our pricing mechanisms resembles an oligopolistic competition pricing strategies that considers both demand elasticity and expenditure shares of a firm's products.

The entry decision mechanism for each product in our model is essentially the same as in a basic Melitz (2003) model with fixed cost shocks—products (firms) that are more productive and profitable than their realized fixed cost can enter a country's market.

Lastly, the most significant distinction between our model and traditional trade entry models lies in whether to address a general equilibrium related to wages (sometimes including labor). Given that our data, counterfactual analysis, and focus revolve around a specific industry, trade policies in this sector typically have limited effects on wage levels and employment in a country's labor market. Recent papers that similarly utilize data from a specific industry across multiple countries and structurally investigate trade policies often discuss market outcomes within a partial equilibrium framework, as seen in studies like Head and Mayer (2019).

In this section, our goal is to clarify that although our model specifications draw from fundamental IO models, they closely resemble trade models.

4 Estimation

Our estimation process follows a traditional approach: we initially estimate parameters related to demand and marginal costs. With these parameters, we gain insights into the marginal expected profit of each product in each market. By considering the product entry choices of brands across countries, we then estimate parameters related to the fixed entry costs at the product level.

4.1 Demand Side Estimation

4.1.1 Parameterization and Identification Strategy

We employ Equation (1) to estimate parameters on the demand side.

Among these parameters, the estimation of the price elasticity α_{nt} is crucial and challenging. Given our sample covering 40 countries and 24 quarters, it is practically impossible to individually estimate a reasonable price elasticity for each country-quarter. Therefore, we refer to a series of IO literature involving cross-market price elasticity estimation (Berry, Levinsohn, and Pakes, 1999; Barwick, Cao, and Li, 2021, et al.) to further parameterize α_{nt} as follows:

$$\alpha_{nt} = \frac{\alpha}{log(GDP\ per\ capita_{nt}^{\bar{\alpha}})} = \frac{\alpha}{\bar{\alpha} log(GDP\ per\ capita_{nt})}$$

Additionally, to better characterize how the feature of each product j enters consumer utility, we incorporate not only the functional characteristic variables x_j for each product but also the relationship between the design headquarters h of product j and the country n where the final market is located. This involves *Distance*, *Language*, and *Home*. Specifically, $Home_{hn}$ is one when the consumers are located in the headquarters country of the smartphone brand. *Distance* is the average number of kilometers on a great-circle route among main cities between two countries. *Language* equals one if two countries share at least one common official language.

Subsequently, we employ instrumental variables to estimate demand parameters, including $\alpha/\bar{\alpha}$, β, σ, and fixed effects. To overcome unobservable demand shocks ξ_{jnt} affecting product pricing and within-group share and finally impact market share, we use two sets of classical BLP instrumental variables for estimation.

The first set includes the number of brands within the nested group and the number of rival products within the nested group as common instruments reflecting market competitiveness. These instruments ensure that the competition from other brands and products in the market does not influence the market share of product j through unobserved demand shocks. To address potential estimation collinearity issues, we select the number of brands and products within the nested group as instruments.

The second set comprises cost shifters, incorporating tariffs faced by product j in country n, a home dummy, a shared language dummy, and the log of the weighted distance between the assembly location and the consumer country of product j. These instruments impact product costs and, consequently, prices and within group shares, independent of unobserved demand shock ξ_{jnt}.

4.1.2 Estimation Results

Table 3 presents the estimation results of parameters on the demand side.

The estimated coefficient for $\alpha/\bar{\alpha}$ is -20.151. Considering the range of log of per capita GDP across the 40 countries/regions during our sample period is between 6.95 and 11.54, this implies that the consumption price elasticity in our model falls between 1.74 and 2.9 [14]. Such a range indicates a relatively low absolute value of price elasticity. However, when we derive the product costs based on the estimated price elasticity using Equation (3) and compare them with some collected market research, our estimated product costs closely align. For instance, according to our estimation, the average markup for Apple products in each country-quarter during our observed period ranges from 1.25 to 3.3, which is consistent with some market estimates [15]. Furthermore, the estimated value for σ is 0.445, reflecting a certain degree of substitutability among products within groups in our grouping approach, validating the reasonableness of our grouping method in capturing consumer behavior.

Most estimated coefficients in the vector of product performance parameters β are intuitively signed and statistically significant. Regarding the parameters related to the trade between market countries and brand headquarters countries, we found a significantly positive home market advantage and language advantage. Meanwhile, our estimation for distance suggests that consumers in a country may prefer products from countries that are farther away. The coefficients related to observable smartphone performance in our estimation are mostly reasonable. During our sample years, Android and BlackBerry systems were preferred, and we did not include the Apple iOS system dummy as this dummy variable is absorbed by the brand fixed effect of Apple. Additionally, consumers show a stronger preference for 4G phones, larger screens, higher camera pixel, self-designed chip, better processors, larger storage, as well as features such as wifi, NFC, dual SIMs, GPS, TV, and an external keyboard (QWERTY)—consistent with everyday intuition.

[14] $1.74 = 20.151/11.54$, $2.9 = 20.151/6.95$.

[15] Example source: https://www.bankmycell.com/blog/how-much-do-iphones-cost-to-make.

Table 3: Demand Side Estimation

Price and Nested Correlation Parameters					
$\alpha/\bar{\alpha}$	-20.151***	σ	0.445***		
	(0.933)		(0.021)		
Linear Parameters: β					
$Home_{hd}$	0.370***	$Language_{hd}$	0.082***	$Log\ of\ Distance_{hd}$	0.039***
	(0.034)		(0.016)		(0.007)
Android	0.560***	Qualcomm Chips	-0.032**	GPS	0.192***
	(0.032)		(0.013)		(0.029)
Blackberry	0.709**	Mediatek Chips	-0.173***	TV	0.429***
	(0.317)		(0.020)		(0.032)
Windows	-0.188***	Self Processor	0.120***	Primary Card	-0.223***
	(0.024)		(0.022)		(0.019)
4G	0.685***	Cores	0.105***	Color 64k	-0.103
	(0.040)		(0.004)		(0.207)
3G	0.282***	CPU Speed	0.666***	Color 256k	-0.339
	(0.027)		(0.029)		(0.207)
Screen Size	0.492***	log of Storage	0.066***	Color 16m	-0.227
	(0.029)		(0.006)		(0.207)
Camera 0	0.081	WIFI	0.522***	Full Screen	-0.059
	(0.151)		(0.031)		(0.045)
Camera 1-5M	0.183*	Bluetooth	-0.861***	Touch Screen	-0.144***
	(0.110)		(0.111)		(0.025)
Camera 5-13M	0.674***	NFC	0.245***	QWERTY	0.196***
	(0.107)		(0.016)		(0.031)
Camera 13M or More	0.815***	Dual Sim	0.083***	Constant	4.027***
	(0.109)		(0.013)		(0.627)
Brand Fixed Effect	Yes	Country Fixed Effect	Yes	Quarter Effect	Yes
Observations	92,804	No. of Countries	40	R-squared	0.708

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.2 Marginal Cost Estimation

4.2.1 Parameterization and Identification Strategy

With the estimation results from the demand side, we utilize Equation (3) to infer the costs $\hat{c}_{jlnt}$ for each product. Combining $\hat{c}_{jlnt}$ with Equation (2), we proceed to estimate cost coefficients related to marginal costs. To bridge the reduced-form specifications with actual data, we parameterize unspecified manufacturing cost function $c_m(x_j)$, trade frictions τ_{lnt} and γ_{hlt}, and cost shocks ε_{jlnt}. We first assume a log-linear form for the manufacturing cost function:

$$log(c_m(x_j)) = x_j \kappa$$

where κ represents a vector of the functional parameters influencing manufacturing costs based on smartphone performance, capturing the expected trend of higher-performance phones having higher assembly costs.

Additionally, we parameterize frictions governing headquarters productivity transfer costs (γ) and trade friction costs (τ) as exponential functions of observable determinants: $Grav_{hlt}$ and $Grav_{lnt}$. Specifically, we assume:

$$\gamma_{hlt} = exp(Grav'_{hlt} Grav^g), \ \tau_{lnt} = exp(Grav'_{lnt} Grav^f)$$

where $Grav^f$ and $Grav^g$ are vectors of the primitive friction cost parameters. The $Grav'$ vectors include standard explanatory variables in trade gravity equations as we show in the demand specification: $Distance$, $Language$, and $Home$.

Finally, we parameterize the idiosyncratic production cost shock ε_{jlnt} in Equation (2) to follow an independent and identically distributed log-normal distribution $LN(\mu_\varepsilon, \sigma_\varepsilon)$.

By incorporating these parameterizations into Equation (2) and taking the logarithm of both sides, we then estimate parameters related to marginal costs: $\{\kappa$, $Grav^f$, and $Grav^g\}$.

4.2.2 Estimation Results

Table 4 presents the estimation results of parameters related to marginal costs.

Table 4: Marginal Cost Estimation

Gravity Variables					
$Home_{hl}$	-0.037	$Language_{hl}$	0.077**	$Log\ of\ Distance_{hl}$	0.008
	(0.037)		(0.036)		(0.005)
$Home_{ld}$	-0.035**	$Language_{ld}$	-0.038***	$Log\ of\ Distance_{ld}$	0.010**
	(0.016)		(0.007)		(0.004)
Phone Features					
Android	-0.010	Qualcomm Chips	-0.031***	GPS	0.138***
	(0.007)		(0.004)		(0.007)
Blackberry	0.025	Mediatek Chips	-0.127***	TV	0.041***
	(0.026)		(0.005)		(0.009)
Windows	0.039***	Self Processor	0.124***	Primary Card	-0.096***
	(0.008)		(0.005)		(0.005)
4G	0.316***	Cores	0.033***	Color 64k	-0.121
	(0.008)		(0.001)		(0.105)
3G	0.113***	CPU Speed	0.330***	Color 256k	-0.209**
	(0.007)		(0.005)		(0.105)
Screen Size	0.245***	log of Storage	0.044***	Color 16m	-0.189*
	(0.003)		(0.001)		(0.105)
Camera 0	-0.177***	WIFI	0.154***	Full Screen	-0.234***
	(0.050)		(0.009)		(0.011)
Camera 1-5M	-0.106***	Bluetooth	-0.161***	Touch Screen	0.063***
	(0.038)		(0.035)		(0.008)
Camera 5-13M	0.116***	NFC	0.123***	QWERTY	0.002
	(0.038)		(0.003)		(0.010)
Camera 13M or More	0.289***	Dual Sim	-0.025***	Constant	4.686***
	(0.039)		(0.004)		(0.138)
Brand Fixed Effect	Yes	Assembly Fixed Effect	Yes	Country Fixed Effect	Yes
Quarter Effect	Yes				
Observations	91,875	No. of Countries	40	R-squared	0.836

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Starting with the parameters associated with trade gravity, our estimates confirm conventional expectations that the same country, shared language, and shorter distance reduce productivity losses from the headquarters country to the assembly country and shipping costs from the assembly country to the market country. The classic estimate variable here is $Log\ of\ Distance_{ld}$, reflecting the traditional trade gravity model where greater distance correlates with lower costs (increased trade volume). The only debatable point is the significant positive coefficient we estimate for $Language_{hl}$.

The estimated parameters related to product performance and manufacturing costs are mostly intuitively signed and statistically significant. Interestingly, the Windows system, once favored but later swiftly eliminated from the market, exhibits higher costs compared to the preferred Android and BlackBerry systems. Additionally, features such as 4G mode (during our sample period transitioning from 2G to 4G), larger screens, higher camera pixel resolution, self-designed chips, advanced processors, larger hard drive space, and smartphones with wifi, NFC, GPS, TV functionality, and touchscreens contribute to higher manufacturing costs.

4.3 Fixed Cost Estimation

4.3.1 Parameterization and Identification Strategy

Our data record the products that brands choose to launch in each of the 40 countries. By combining information on successful or unsuccessful product-level market entries with the estimates of demand and marginal cost parameters, we can infer the product-level entry costs that brands incur when introducing a product.

Following a series of trade entry literature (e.g., Eaton, Kortum, and Kramarz, 2011; Head and Mayer, 2019), we parameterize the product-specific entry costs. We specify that in quarter t, the fixed entry cost F_{jnt} for product j belonging to brand $b(j)$ when entering market n follows the functional form:

$$F_{jnt} = \upsilon_{jnt} f_{jnt} = \upsilon_{jnt} \frac{FC_n FT_t (Distance_{hnt}^{\alpha_{dist}})}{exp(\alpha_{home} Home_{hnt}) exp(\alpha_{lang} Language_{hnt})}$$ [16]

[16] Arkolakis, Ganapati, and Muendler (2019) set the product-level entry cost to be correlated with the number of varieties a firm introduces in a trade market to reconcile several data facts how firms make product-level entry decisions. Our simplified form of product-level entry cost still makes the model fit the data of brands' product portfolio well and introducing an additional product will reflect in the cannibalization effect of brand profit on the

Here, FC_n represents the common fixed cost base that all brands face when launching new products in country n. $Distance_{hn}$, $Language_{hn}$, and $Home_{hn}$ maintain their previous definitions, capturing that the fixed costs of launching new products in a country are lower if the brand does so in its home country, in its native language, or in a country geographically closer to its headquarters, reflecting lower costs in obtaining local market authorization or facilitating collaboration with local distributors or network operators. α_{dist}, α_{home}, and α_{lang} are the corresponding gravity parameters. FT_t accounts for the time effect on fixed entry costs. Finally, to capture the fact of brands introducing different products in different markets, we introduce a shock to product entry costs, υ_{jnt}, and specify that υ_{jnt} follows a log-normal distribution with mean μ_υ and variance σ_υ. f_{jnt} is an intermediary variable introduced for writing simplification.

For each product j launched by brand b in country n under equilibrium conditions, we can deduce the marginal variable profit $\pi_{J_{bnt}} - \pi_{J_{bnt}-j}$ for this product j based on previous demand and marginal cost estimates. In the presence of fixed entry cost shocks υ_{jnt}, the ex-ante probability of brand $b(j)$ introducing this product j in country n due to a lower realized fixed cost shock is given by:

$$
\begin{aligned}
Pr(Entry_{jnt} = 1) &= Pr(\pi_{J_{bnt}} - \pi_{J_{bnt}-j} > F_{jnt}) \\
&= Pr(log(\pi_{J_{bnt}} - \pi_{J_{bnt}-j}) > log(F_{jnt})) \\
&= \Phi(\frac{log(\pi_{J_{bnt}} - \pi_{J_{bnt}-j}) - log(f_{jnt}) - \mu_\upsilon}{\sigma_\upsilon})
\end{aligned}
$$

where $log(f_{jnt}) = log(FC_n) + log(FT_t) + \alpha_{dist} log(Distance_{hnt}) - \alpha_{home} Home_{hnt} - \alpha_{lang} Language_{hnt}$.

Similarly, for products k launched by brand $b(k)$ in other countries but not in country n, the ex-ante probability of brand $b(k)$ not introducing product k in country n due to a higher fixed entry costs at the product level is given by:

$$
\begin{aligned}
Pr(Entry_{knt} = 0) &= Pr(\pi_{J_{b(k)nt+k}} - \pi_{J_{b(k)nt}} < F_{knt}) \\
&= 1 - \Phi(\frac{log(\pi_{J_{b(k)nt+k}} - \pi_{J_{b(k)nt}}) - log(f_{knt}) - \mu_\upsilon}{\sigma_\upsilon})
\end{aligned}
$$

Unlike a product that actually appears in the market, we cannot observe demand shocks

pricing stage in our model.

ξ_{knt} and marginal cost shocks ε_{knt} for a potential product k that has not appeared in the market n. For computational purposes, we approximate the marginal profit of this product by fitting the median values of the ξ and ε distributions of a potential entrant.

Since we observe whether any product j from brand $b(j)$ in our sample is introduced in country n during quarter t conditional on brand $b(j)$ sold any products in country n at quarter t ($\mathbf{1}(B_{jnt} = 1)$), we can construct the likelihood function as follows:

$$\max_{\Theta_{fc}} \prod_{j,n,t|\mathbf{1}(B_{jnt}=1)} Pr(Entry_{jnt} = 1)^{\mathbf{1}(Entry_{jnt}=1)} Pr(Entry_{jnt} = 0)^{\mathbf{1}(Entry_{jnt}=0)}$$

Then we estimate the parameters related to fixed entry costs through maximum likelihood estimation: $\Theta_{fc} = \{\sigma_\upsilon, \mu_\upsilon, \alpha_{home}, \alpha_{lang}, \alpha_{dist}, \{FC_n\}_n, \{FT_t\}_t\}$.

4.3.2 Estimation Results

Table 5 presents the estimation results for the parameters Θ_{fc}.

Table 5: Fixed Cost Estimation

Θ_{fc}	σ_υ	μ_υ	α_{home}	α_{lang}	α_{dist}
	8.25***	14.96***	7.99***	2.03***	0.83***
	(0.128)	(0.396)	(0.110)	(0.068)	(0.0320)
Country Effect	Yes	Quarter Effect	Yes		
Observations	679,199	No. of Countries	40	Pseudo R-squared	0.0866

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

As shown in Table 5, our estimated value of $\sigma_\upsilon = 8.25$ indicates a substantial variation in the product-level entry costs, comparable to the model-level fixed cost variation ($= 5.61$) reported by Head and Mayer (2019) using IHS global automotive data. Similar to addressing collinearity concerns in reduced-form regressions, we chose Argentina as the benchmark country when estimating the country effects of fixed costs. Consequently, the interpretation of the estimated value for μ_υ is associated with Argentina, and further details on the levels of product entry costs across countries will be provided in Figure 1. The estimation results for α_{home}, α_{lang}, α_{dist} reveal substantial discounts for domestic firms, firms using their native language, and firms with headquarters closer to the market in reducing fixed costs associated with new product launches.

In Figure 1, we offer a detailed explanation of the specific ranges of fixed costs incurred by brands launching new products in each country. Based on the estimation results from Table 5, we first simulate the median fixed cost values for all active products in each country in the first quarter of 2015 [17]. We then take the logarithm of the median fixed costs for each product in each country, compute the average and minimum values at the country level, and plot these averages (blue dots) and minimums (red dots) against the log(GDP) for each country in 2015.

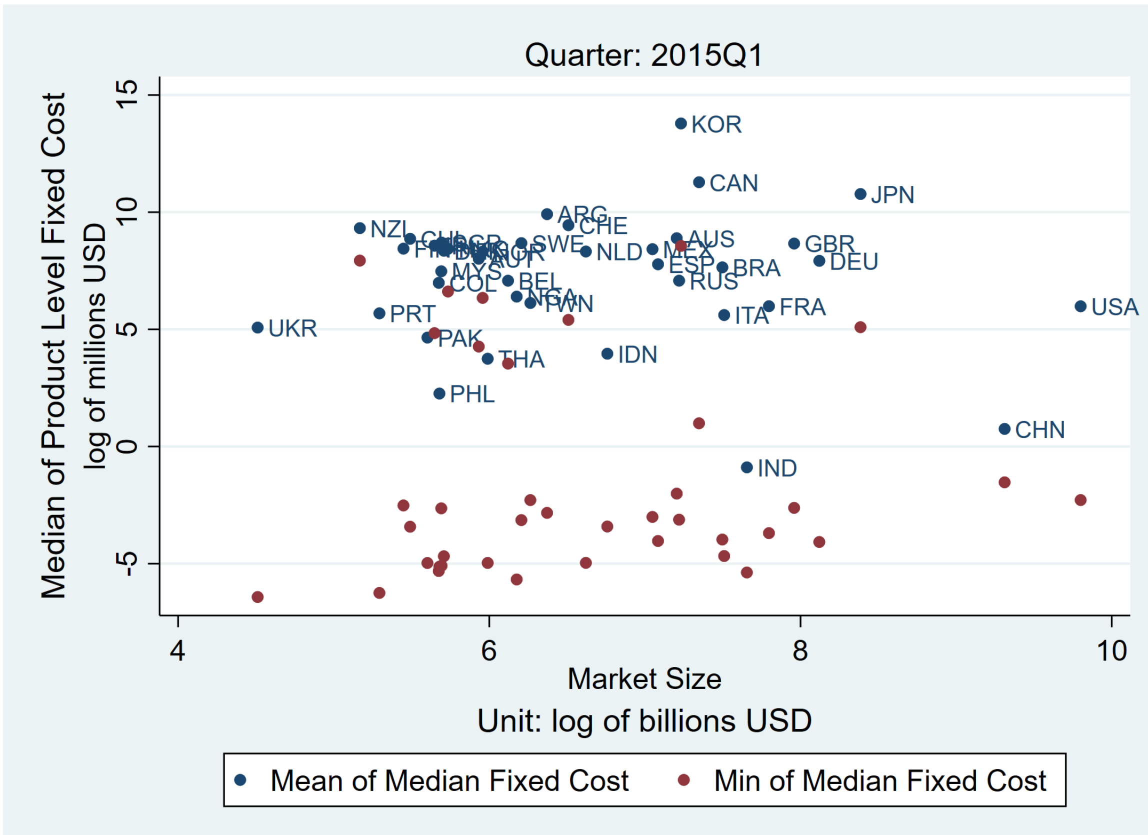


Figure 1: Product level fixed entry cost by country/region

From the graph, it is evident that, for most countries, both average and minimum log(median fixed costs) exhibit a positive correlation with log(GDP), implying that larger countries incur higher product entry costs. Countries like South Korea, Japan, and Canada exhibit higher product entry costs, supported by Column (6) - (7) of Table 1 indicating fewer products introduced in these countries conditional on their market size. Conversely, China and India show considerably lower average entry costs, attributed to the presence of numer-

[17]The determination of fixed cost values relies on the distribution of fixed cost shocks υ.

ous local brands in these countries. To gain a more nuanced understanding, we delve into specific fixed cost values; the red dots represent the minimum logged median product entry cost in a country, primarily originating from local brands (home country, native language, close proximity). For instance, our estimate indicates that the quarterly product entry cost for a domestic brand in China is $216,752$ USD [18]. Additionally, the graphical representation of Figure 1 appears reasonable if we use the blue dots and red dots to approximately estimate the product level entry costs for brands in each country.

5 Counterfactual

In this section, we apply our two-stage endogenous decision model to quantitatively analyze how changes in trade policy impact the product composition, pricing (markup), and consumer surplus in smartphone markets across countries.

5.1 Simulation Algorithm

Before presenting our counterfactual analysis results, it is essential to clarify the process of computing market equilibrium in our counterfactual analysis. As designed in the model environment (Section 3.1), our model assumes that, before deciding on product entry and pricing each period, firms' existing products are endowed with characteristics, and exogenous policy changes do not prompt firms to design new products. Additionally, our model operates within a short to medium-term decision-making framework: exogenous policies do not alter firms' decisions on the assembly location for each product provided to each country. During our sample period, the majority of smartphones, driven by cost considerations, were produced by a handful of countries such as China, Vietnam, and Brazil.

In our counterfactual simulation, we focus on how changes in trade barriers within a more trade-protected world affect firms' product choices and pricing under equilibrium. The four main scenarios we examine in the counterfactual trade policy considerations are as follows: for smartphones assembled abroad, each country increases tariffs by (1) 25 percentage points, (2) 50 percentage points, (3) 75 percentage points, and (4) 100 percentage points on top of existing tariff levels. We utilized data from the first quarter of 2015 for counterfactual anal-

[18] exp(-1.529)*1e6=216,752.31 USD.

ysis, as 2015 marked the final year of our dataset. The first quarter was randomly chosen as the period for the counterfactual analysis. In each counterfactual scenario, we are interested in understanding how the market equilibrium evolves from the initial equilibrium in the data to the final equilibrium under each policy scenario, and how market and pricing structures change in each market. We employ the following simulation algorithm when computing firm pricing and consumer surplus in the market equilibrium under each counterfactual scenario:

1. Based on the estimated demand and marginal cost parameters, calculate the marginal variable profit of each product j active in country n under the real market equilibrium for its respective brand $b(j)$: $\hat{\pi}_{J_{bnt}} - \hat{\pi}_{J_{bnt}-j}$.

2. Conditional on the true realized fixed entry cost $\hat{F}_{jnt}$ for product j being less than $\hat{\pi}_{J_{bnt}} - \hat{\pi}_{J_{bnt}-j}$, draw 10 times of fixed cost shocks $\hat{\upsilon}_{jnt}$ from a log-normal distribution with coefficients $(\hat{\mu}_{\upsilon}, \hat{\sigma}_{\upsilon})$.

3. We use the equilibrium conditions of each market in the data and the estimated unit delivery costs $\hat{c}_{jlnt}$ for each product as the initial state S_0 for the counterfactual equilibrium.

4. Compute the pricing equilibrium after increasing the tariff levels on products assembled abroad by 25, 50, 75, and 100 percentage points under market structure and demand of the state in Step 3, as a temporary equilibrium.

5. Calculate whether the marginal variable profit contributed by each product to its respective brand exceeds its realized product-level entry fixed cost in the new temporary equilibrium for each draw.

6. If, under the new equilibrium, there exists any product k in a country n whose marginal variable profit contributed to its brand $b(k)$ is lower than its realized product entry fixed cost in this draw, the product with the lowest value of marginal variable profit contribution minus its realized product entry fixed cost is removed from the market in country n under this temporary equilibrium to a new state S' (Assumptions of Sequential Entry).

7. Return to Step 4 and recalculate the market equilibrium pricing under the new market structure of State S' after removing the least profitable products identified in Step 6,

until the marginal variable profit contribution for each product in each country in each draw exceeds its realized product entry fixed cost in the draw.

8. Calculate the product decisions, markup levels, and consumer surplus for each country and each brand under each draw, and then average the market outcomes for each scenario across all draws.

9. Compare the brand decisions and consumer surplus under each counterfactual scenario.

In order to make our counterfactual analysis computable, we address potential multiple equilibria issues related to entry decisions. In Step 6 of the aforementioned simulation algorithm, we adopt a similar assumption to Berry (1992) regarding sequential entry decisions by firms and make a product-level analogous assumption: in a market, products capable of generating higher marginal returns are given priority in the entry decision process; in environments with higher costs, less profitable products exit first, leaving room for other products to reconsider their decisions. In our counterfactual analysis, all products remaining in the final market equilibrium generate positive marginal returns for their respective brands, while the last product to exit the market, reaching the final equilibrium state, yields negative marginal profits for its brand in that market. Adopting such sequential entry and exit assumptions allows our counterfactual simulations to be computationally feasible and lead to a unique equilibrium in each draw, given the multitude of product combinations each brand in each market might consider[19]. Moreover, our sequential entry assumption aligns with market dynamics: in more challenging competitive environments, a product with greater bargaining power convinces less profitable products to exit first.

Additionally, in the above simulation algorithm, to facilitate the computability of the equilibrium, we make another assumption: under market equilibrium, products not introduced to a market will not yield higher marginal returns for their brands compared to currently active introduced products. This could stem from higher product profitability or lower realized levels of entry fixed costs. This assumption is designed to make the simulation feasible while minimally impacting the final equilibrium outcomes.

[19] For instance, as shown in Table 2, Samsung had 70 smartphone products in Brazil in 2015. Without the sequential entry assumption in our counterfactual analysis, the potential product combinations for Samsung under each new equilibrium would be 2^{70}, approximately equal to 1.2×10^{14}.

We only consider scenarios involving tariff increases and do not delve into tariff reduction scenarios for two main reasons: (1) Most countries maintained a tariff level of 0 for products in the category of smartphones during our sample period (2010-2015), rendering an analysis of further tariff reduction economically irrelevant. (2) Reducing tariff levels could involve complex considerations regarding potential brand-level entry decisions for various brands entering a country, leading to computational challenges (as noted in Section 3.3.3, estimating brand-level entry costs requires impossibly extensive computation). Under our assumptions, higher tariffs merely result in brands removing products from their existing product portfolios. This design of counterfactual policy scenarios, along with our assumption of sequential entry for products, enables us to achieve our research objectives within a framework that aligns with real-world decision-making processes of firms and ensures the computational feasibility of equilibrium in counterfactual analysis.

Based on these counterfactual scenario designs and the simulation algorithm, we conducted counterfactual analyses to examine how trade policies affect equilibrium pricing and product portfolio for firms and consumer surplus in the market.

5.2 Tariff and Markups

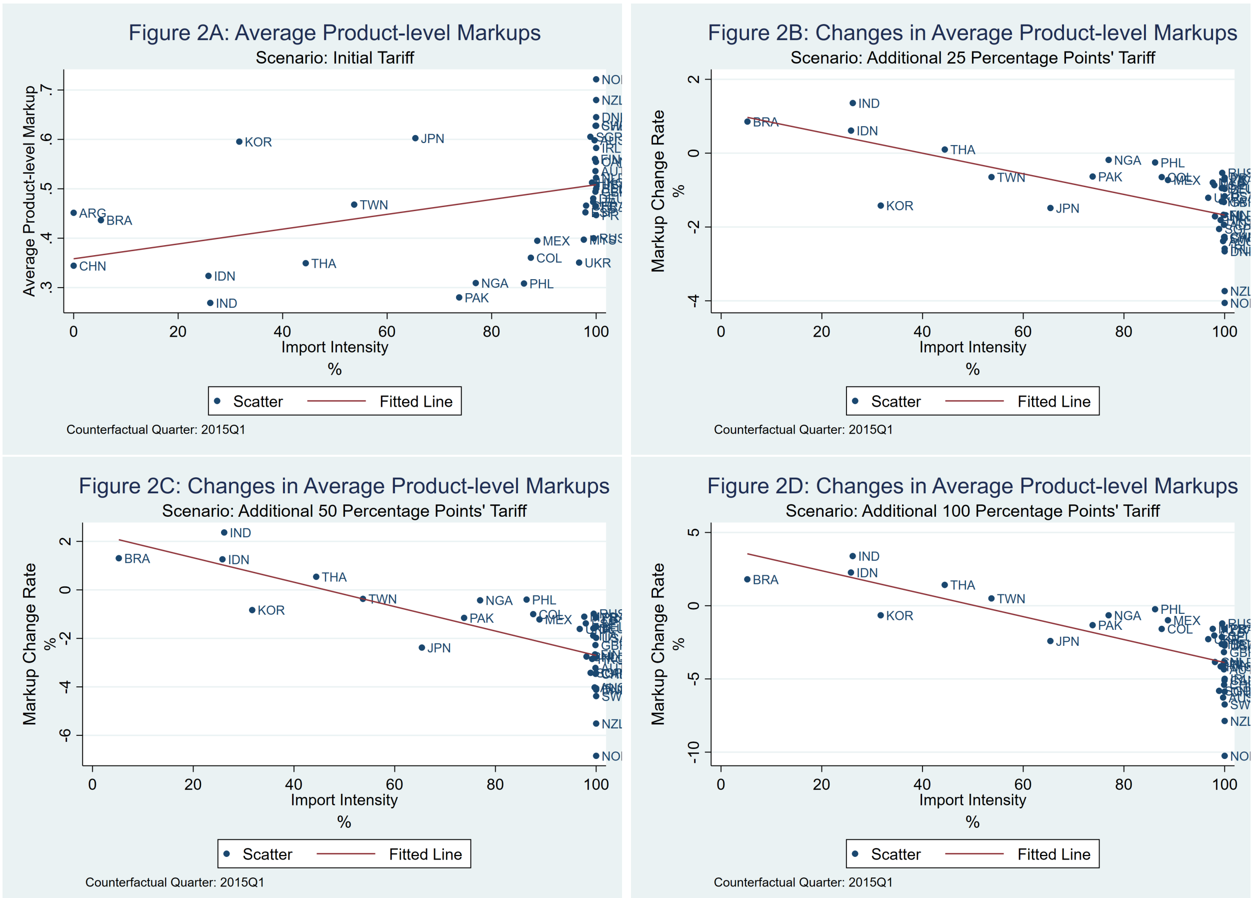
Our counterfactual analysis starts by examining how higher tariff levels and trade barriers impact the average markup of smartphone product pricing across countries. In all our subsequent counterfactual analyses, we consistently define the markup of a product j as the ratio of its final price p_{jnt} in a market to its final realized unit delivery cost c_{jlnt}, subtracted by 1, i.e., $\frac{p_{jnt}}{c_{jlnt}} - 1$.[20] We uniformly define the average markup level of a country as the average of product-level markups across all smartphone products in that country.

Figure 2 illustrates how higher tariff levels in our counterfactual policy scenario affect the average markup of smartphone products across countries. It also depicts the relationship between tariffs' impact on markups in a country and the country's market share of imported products. We define a country's smartphone import density as the ratio of the total quantity of imported smartphones to the total sales quantity of smartphones in that country, providing a metric for measuring a country's reliance (market share) on imported products in the

[20] In contrast to the common definition of markup as p/c in most literature, we deduct an additional 1 here to better reflect the ratio of unit product profit to cost.

smartphone market.

Figure 2: Markup and a Country/Region's Import Density



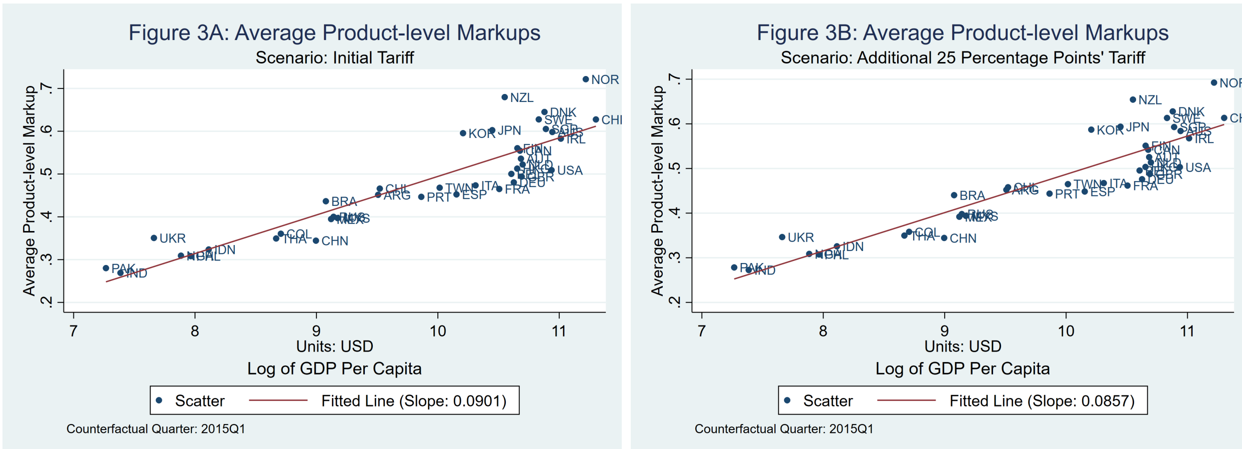
To begin, Figure 2A plots the relationship between the estimated average markup of smartphone products in various countries and the import density of smartphone products in those countries, based on the original data. It is noteworthy that between 2010 and 2015, a significant portion of smartphones in the datasets from most Western European and North American countries were imported, with major market share-holding brands such as Apple, Samsung, LG, and Huawei being primarily assembled in a handful of Asian countries such as China and Vietnam. Consequently, we observe the clustering of many Western European and North American countries in regions where import density is close to 100%. Moreover, the fitted line in Figure 2A indicates that countries with higher dependency on smartphone imports also exhibit higher average markups of smartphone products. On one hand, these countries with higher import densities often belong to the category of "rich countries," where consumers exhibit lower price sensitivity, allowing smartphone brands to charge higher prices. On the other hand, countries with lower import densities not only have globally popular brands but also offer many affordably-priced domestically produced smartphones. Consequently, those markets are more competitive, resulting in lower overall market markups. Additionally, the figure shows that some Western European and North American countries, along with Japan and South Korea, two countries with high-income levels and major players in smartphone manufacturing, have average markups exceeding 0.5. In contrast, the majority of countries with relatively lower import densities, primarily labor-cost-effective developing countries, tend to have average markups below 0.4. Figure 2A provides us with an initial statistical overview of the average markup levels of smartphones across countries, reinforcing the consistency with our intuition and experience and consolidating the robustness of our estimates.

Figure 2B illustrates the relationship between the change rate of average markup across countries and their import densities after an additional 25 percentage points of tariff imposition. Higher tariffs influence the final market markup through two mechanisms: cost and entry. In the entry mechanism, increased tariffs may lead to the exit of some imported products from the market, reducing market competition and increasing the markup of the remaining products. In the cost mechanism, imported products face higher costs, potentially causing a reduction in markup to offset the sharp decline in market demand for higher-priced products. The negative correlation shown by the fitted line in Figure 2B between the change in markup levels under higher tariffs and market import density can be explained by these two mechanisms: markets in countries with lower import density, indicating a higher prevalence of domestically produced products, may experience an increase in markup due to reduced competitiveness. Conversely, in countries where most products in the market are imported, the decision to lower markup in response to higher unit delivery costs under elevated tariffs becomes more pronounced. [21]

Examining the direction of the change in average markup, only a few countries, such as Brazil, Indonesia, India, and Thailand, experience a positive shift in average markup

[21]In the first quarter of 2015, the vast majority of smartphones in the Chinese market, including Apple and Chinese-brand phones, were assembled in China; meanwhile, the Argentine government required all smartphone brands to assemble phones in its territory, particularly in Tierra del Fuego, to boost Argentina's manufacturing sector. Therefore, the impact of our counterfactual higher tariff policy on the markets of China and Argentina is minimal and not indicated in the figure. Furthermore, we have excluded data from Venezuela beyond the year 2013 in estimation owing to a deficiency in reliable macroeconomic statistics. The subsequent counterfactual results and figures follow the same scenario.

Figure 3: Markup and a Country's GDP per capita



under a 25% additional tariff. These countries generally have a higher market share of domestically manufactured products and greater price elasticity. However, for countries relying on imported smartphone products, higher tariffs generally lead to a decrease in average markup across most cases.

In Figures 2C and 2D, the counterfactual scenarios with an additional 50 and 100 percentage points increase in tariffs are presented, showcasing how the average markup in each country's market changes. Overall, under higher tariff levels, the direction of change in markup levels across countries remains consistent with that under a 25% additional tariff, albeit with intensified magnitude. The results in Figures 2C and 2D serve as a robust analysis, reinforcing our initial exploratory findings on how changes in tariffs and trade barriers affect markup.

Next, we delve into how higher tariffs alter the cross-country disparities in markup levels. Figure 3 summarizes the average markup levels of smartphone markets in different countries and the extent of markup level changes under higher tariff imposition, relating them to each country's per capita GDP. Figure 3A plots the relationship between the estimated average markup levels of smartphone products and the per capita GDP of each country based on the original data, revealing a highly significant positive correlation with a slope of 0.09. In Figure 3B, we observe the relationship between the average markup levels of smartphone products and the per capita GDP of each country after an additional 25 percentage points tariff imposition. The correlation remains significantly positive, though the slope decreases to 0.086. It's a well-known finding that residents of higher-income countries, due to their lower price elasticity, tend to face higher markups. Our Figures 3A and 3B imply that, while there are cross-national differences in markup levels, higher tariffs and trade barriers lead firms in countries with initially higher markup levels and higher import intensity to substantially reduce their markups, due to increased costs, ultimately narrowing the cross-national gap in markup levels. This mechanism of higher tariffs and trade barriers affecting markup levels across countries also explains why, in Figures 2B to 2D, countries experiencing a more significant decline in markup are often richer countries.

In summary, in this section, we explore the impact of higher tariffs and trade barriers on markup levels across countries. Higher tariffs lead to a slight increase in the overall average markup in countries with a higher market share of domestically produced goods, while causing a decrease in markup for countries more reliant on imported products. Moreover, higher trade barriers also reduce the disparity in markup levels among countries.

5.3 Cost v.s. Entry and Exit

Trade policies influence final market markup through two channels: entry and cost. In this subsection, we decompose how entry and cost mechanisms jointly affect the extent of the final changes in average markup levels across countries.

Our specific approach to decomposing the impact of cost and entry on markup involves assuming a fixed market structure with no entry or exit of smartphone products. Take the counterfactual scenario of an additional 25% tariff as an example. First, the marginal costs of products in each country's market are adjusted to reflect an additional 25% tariff. We then calculate the pricing and markup of each product at the market equilibrium under this fixed market structure and compute the average markup levels across countries. The difference between this intermediate equilibrium and the initial data's markup levels represents the extent of cost's influence on markup. Additionally, the difference between this intermediate equilibrium and the final equilibrium of the last subsection considering product entry and exit decisions represents the influence of entry and exit on markup. The results of this analysis are presented in Figure 4.

Figure 4: Cost versus Entry and Exit

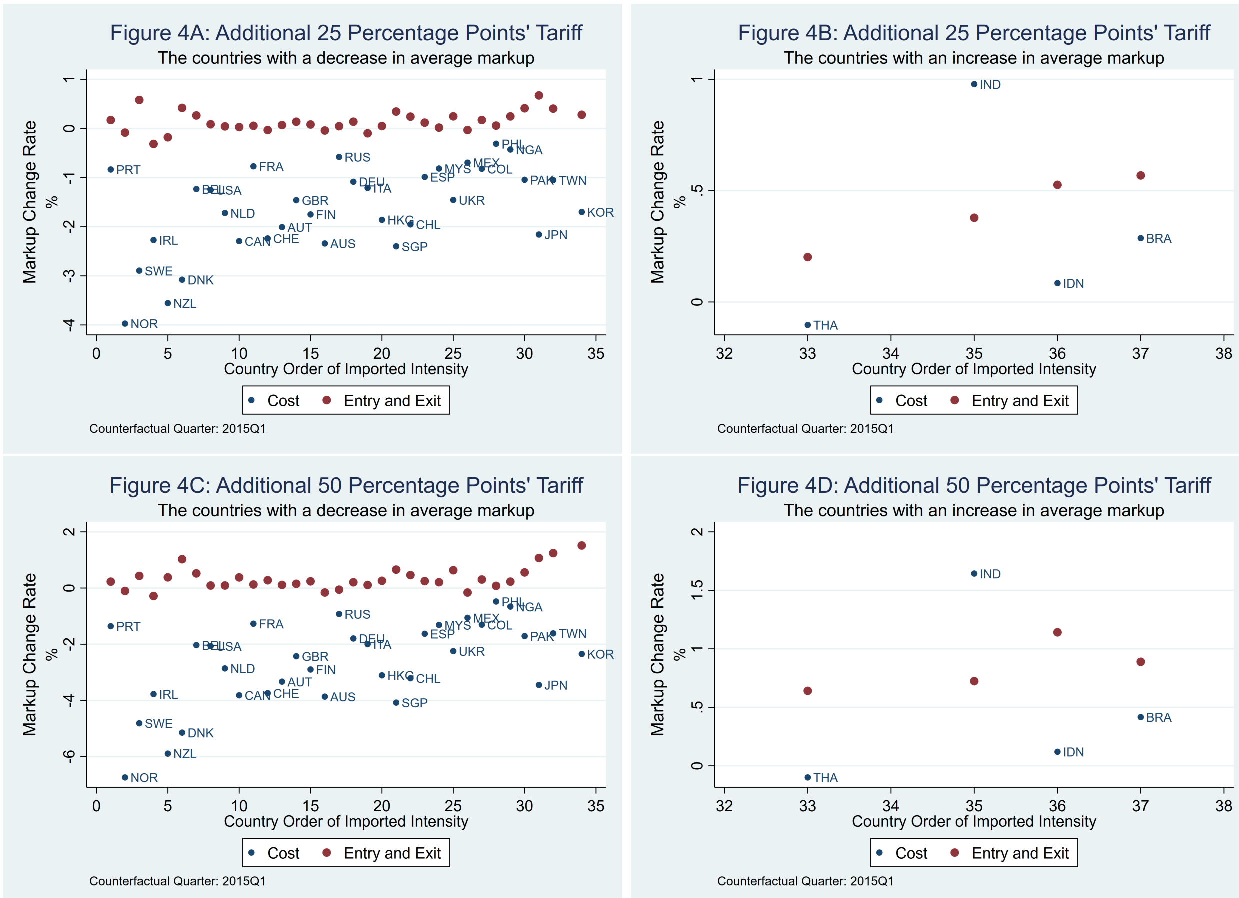


Figure 4A illustrates the extent to which cost and entry mechanisms drive changes in markup levels for countries experiencing a decrease in average markup levels in the market after a 25 percentage points tariff increase. In these countries, higher tariffs and increased costs for imported goods lead to a reduction in markup (blue dots). However, the effect of the entry and exit mechanism, resulting from changes in market structure due to some products exiting, generally pushes markup upward (red dots) in most countries. In the majority of countries, the downward force exerted by cost on markup is significantly greater than the upward force exerted by entry and exit, ultimately resulting in a decrease in markup under the 25 percentage points additional tariff. This is intuitive as these countries heavily rely on imports in the smartphone market, making the mechanism through which tariffs affect pricing and markup via costs very direct. Meanwhile, under the mechanism of entry and exit, most exiting products are low-profit and low-volume, hence their impact on pricing and markup for products dominating the market is limited. Therefore, the downward force of the cost mechanism on markup outweighs the upward force of the entry and exit mechanism.

Figure 4B displays the changes in markup levels driven by cost and entry mechanisms for countries experiencing an increase in average markup levels in the market after a 25 percentage points tariff increase. Only four countries remain in the sample: Brazil, India, Indonesia, and Thailand. Under the entry and exit mechanism, reduced market competitiveness leads to an increase in markup levels for these countries (red dots). As these countries generally have a significant presence of domestically produced smartphones, the impact of cost on imported products also contributes to the increase in markup for Brazil, India, and Indonesia, possibly reflecting domestic manufacturers responding to price higher to the higher prices of imported goods. Although Thailand's markup level exhibits a negative impact under cost influence, it's relatively mild. In these countries, the role of cost in influencing markup can still be compared in strength to the impact of entry and exit on markup.

Figure 4C and Figure 4D depict how cost and entry mechanisms drive changes in markup levels across countries in the counterfactual scenario of an additional 50 percentage points tariff increase. Overall, the extent to which cost and entry mechanisms affect markup levels aligns with the direction of results shown in Figure 4A and Figure 4B, albeit with further intensified effects.

In this section, we observe that in smartphone markets of countries heavily reliant on imports, the influence of cost mechanism tends to outweigh that of entry and exit mechanism. In countries with lower import density in their smartphone markets, the impact of the cost mechanism is also noteworthy compared to the entry and exit mechanism. The existing literature studying the pro-competitive effect of trade liberalization on a country's welfare often underscores the role of entry mechanisms in enhancing market competition from more trade exposure. Our results in this section emphasize that changes in the cost of imported goods have a significant impact on markups, which in many cases are even more critical than the entry mechanism.

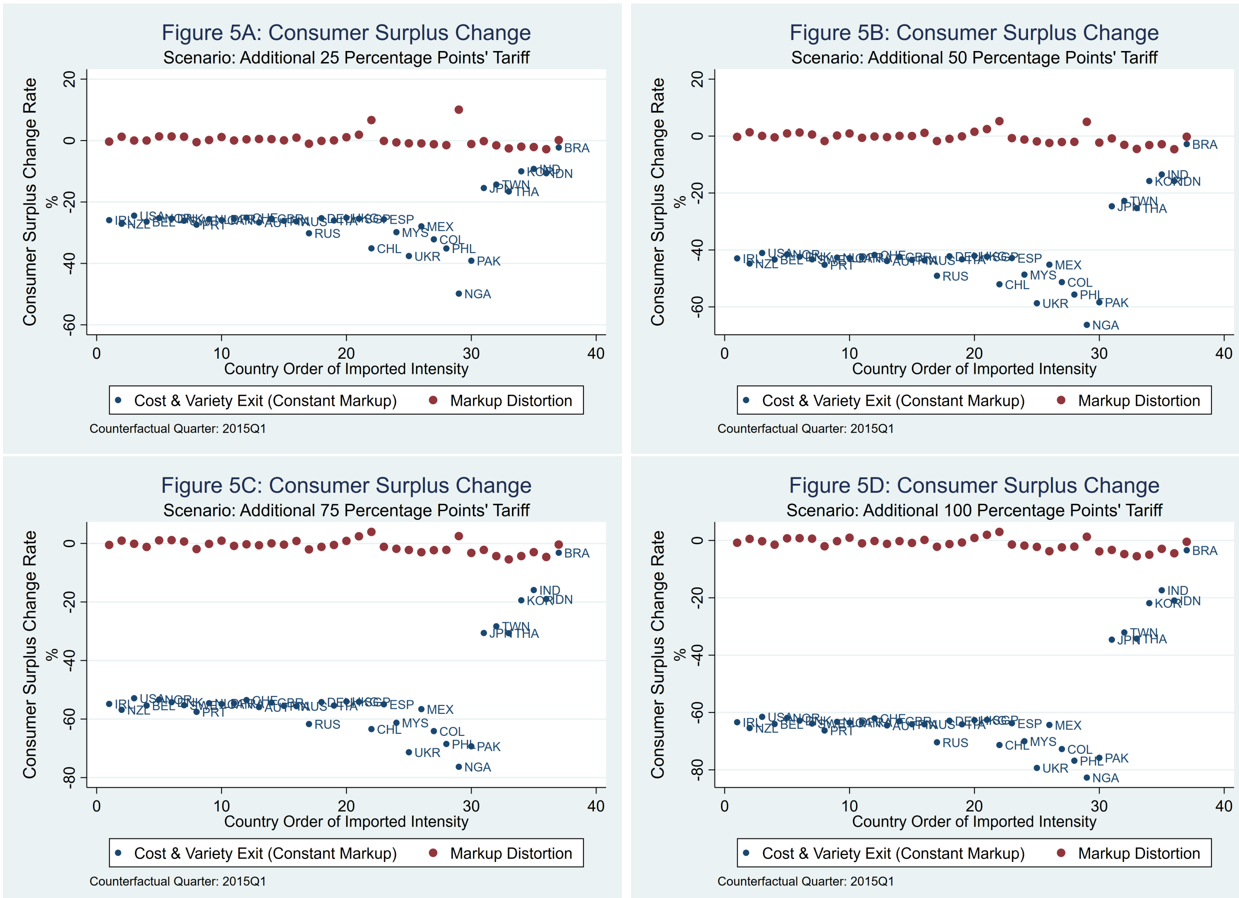
5.4 Variable Markups v.s. Constant Markups

Traditional quantitative trade models focus on general equilibrium effects on wages and price indices across countries when assessing how tariffs and trade policies affect residents' welfare. In our case, it's challenging for a policy in one industry to significantly impact a country's wages. However, similar to the standard Melitz (2003) trade entry model, changes in trade barriers and tariffs alter costs on the intensive margin, affecting the pricing of products in the smartphone industry. They also influence the entry and exit of products in each country's smartphone market on an extensive margin, thus impacting consumer surplus through market competition and variety availability. Moreover, compared to the constant markup assumption in traditional trade models, our oligopolistic pricing mechanism allows us to consider to what extent changes in markup affect the additional impact of tariffs and trade policies on consumer surplus. In this subsection, we decompose the factors affecting consumer surplus under the assumption of constant markup in traditional models – costs and variety availability – and how additional changes in markup collectively influence the overall variation in consumer surplus.

The simulation process in this subsection is as follows: We first estimate the costs $\hat{c}_{jlnt}$ of each product and their original product markup based on the model estimates. After applying additional tariffs, we assume that the markup remains constant while only the marginal cost changes, influencing new pricing, market share, profits, and product entry decisions. In this setup, we calculate how consumer surplus in the smartphone market changes in the new and also intermediate market equilibrium under the constant markup assumption. The change from the initial market consumer surplus to this intermediate equilibrium consumer surplus is considered as the impact of tariffs and trade policies on consumer surplus under the constant markup assumption of the traditional trade entry models. The change from this intermediate market equilibrium consumer surplus to the final equilibrium consumer surplus, considering flexible pricing and variable markup strategies, is regarded as the additional impact of variable markup on consumer surplus.

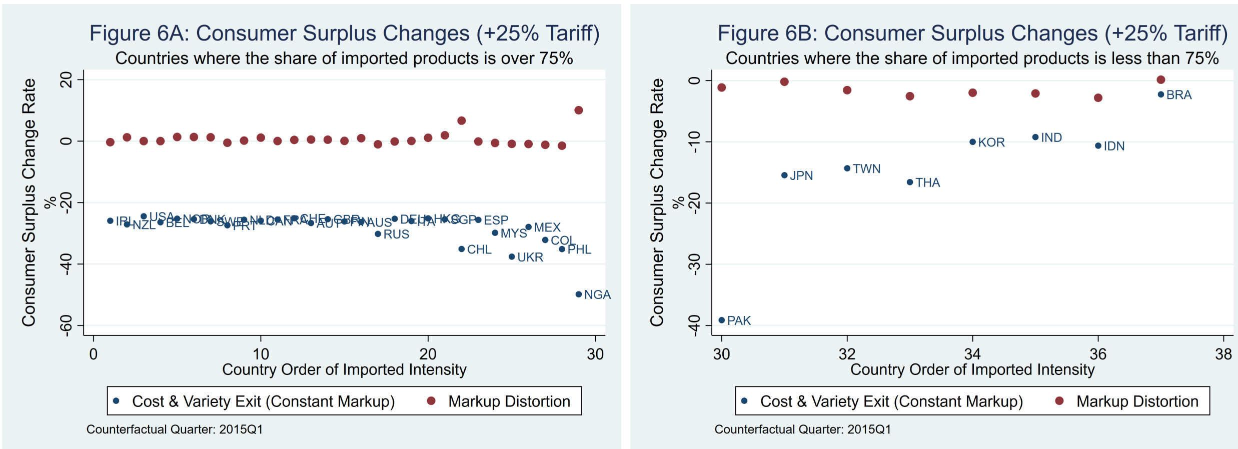
While our model's demand side originates from IO's discrete choice model, as shown in Section 3.4, our model's settings for supply, demand, and entry decisions are essentially isomorphic to traditional trade entry models, except for the setting of firms making entry and pricing decisions in an oligopolistic competition, distinct from the monopolistic competition in standard trade entry models. The model isomorphism allows us to quantitatively compare how costs and variety exit affect consumer surplus under the assumption of unchanged markup in our model with that in a standard trade entry model.

Figure 5: Constant Markup Models versus Variable Markup Models



Figures 5A to 5D depict the impact of additional tariffs at 25%, 50%, 75%, and 100% on consumer surplus through increased costs and less varieties (blue dots), along with the additional effects stemming from changes in markup (red dots). Taking the 25% additional tariff scenario in Figure 5A as an example, assuming constant product markup under the policy, the extra 25% tariff leads to a 10-40% decline in consumer surplus for most countries. The extra variation in markup has a less clear and considerably smaller impact on consumer surplus across countries. Excluding Nigeria ("NGA"), a relatively extreme simulation point, higher costs of imported goods and exits of imported varieties result in an average 24.65% decrease in consumer surplus, with markup contributing an additional 0.02%. The supplementary effect of markup on consumer surplus is less than 1% compared to the primary impact of costs and smartphone product exits. Figures 5B to 5D illustrate how consumer surplus is distorted by costs, variety exits, and additional markup adjustments under higher levels of additional tariff imposition, aligning closely with the scenario under a 25% additional tariff.

Figure 6: Constant Markup Models versus Variable Markup Models



Finally, we categorized all countries in our sample into two groups based on whether their import intensity exceeded 75%, and then compared the additional markup distortion's extra impact on consumer surplus for import-intensive countries (Figure 6A) and less import-intensive countries (Figure 6B). For countries heavily reliant on imported smartphone products (import intensity exceeding 75%), the effect of additional markup changes on consumer surplus is ambiguous and significantly lower than the direct impact of higher costs and variety exits. Conversely, for countries with relatively lower import dependence (import intensity below 75%), markup changes do lead to a further reduction in consumer surplus, possibly arising from price increases in domestic products, thereby compromising consumer surplus. Lastly, by calculating the ratio of the additional impact of markup on consumer surplus changes to the direct decrease in consumer surplus caused by costs and variety exits, we can assess how higher tariffs affect consumer surplus through markup relative to costs and variety exits. In Figure 6B, encompassing eight countries, we calculated this ratio and found an average of 11.58%. This suggests that when analyzing the impact of trade policies on consumer surplus, the additional effect of the markup, beyond the commonly considered factors of costs and exits of varieties, is notably significant in these countries with relatively lower import intensity.

In summary, in this section, we examined how consumer surplus is affected under higher tariffs by both the traditional trade entry model's considerations of costs and variety availability and the additional impact of markup changes, which we focused on in this paper.

Among the sample countries where our counterfactual policies were implemented, under higher tariff levels, the additional impact of markup changes on consumer surplus is unclear for countries heavily reliant on imports, and its effect is minor compared to the direct effects of costs and exits of varieties. However, for countries with relatively lower import dependence, the additional markup changes further exacerbate the reduction in consumer surplus due to higher costs and fewer varieties, and the magnitude of the markup effect is non-negligible.

6 Conclusion

In recent years, amidst an increasingly uncertain international environment, economists have shown particular interest in understanding the impact of trade policies on the welfare of residents in various countries. Classical trade theories often overlook changes in market markups before and after policy implementation when quantifying the effects of trade policies on welfare. This article explores the influence of trade policies on markups and examines how such influences ultimately affect consumer surplus in a country. Specifically, we focus on the micro-level mechanisms through which trade policies impact markups, considering the dual channels of cost and entry.

The theoretical foundation for examining the impact of trade policies on firms' pricing strategies at the micro-level is established by building a cross-country oligopolistic competition model to fit market outcomes in each country. Our work relies on an unprecedented cross-country sales data for all products within a specific industry. Previous trade literature that constructs structural models from the firm level mostly utilizes manufacturing enterprise data from an entire country or multiple sectors to build a Melitz (2003) model with CES demand and monopolistic competition on the supply side. Our unique dataset and oligopolistic competition setting enable us to more reasonably capture how firms consider market competition and cost comprehensively when determining final equilibrium pricing and markups. This modeling approach allows for a more detailed analysis of firms' pricing strategies at the micro-level compared to traditional models. Additionally, our model, unlike traditional trade models, does not solve a general equilibrium to further understand the impact of trade policies on labor markets across countries – our industry-specific data confines our focus to the smartphone product industry, making it challenging for policies within a single industry to substantively affect a country's overall labor market.

In summary, our modeling approach, linking oligopolistic competition with trade models, and insights into firms' pricing strategies at the micro-level benefit from rich cross-country sales data for smartphones. As digitized recording of business transactions becomes increasingly prevalent, such industry-specific cross-country data is becoming more accessible. The combination of abundant data information with models that can analyze the mechanisms through which policies affect firms at a more micro-level represents a potential future direction for research.

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