Order of Entry and Market Performance in the Global Smartphone Industry *

Wenzhuo Lu †   Xiaochen Xie ‡

April 21, 2024

Abstract

The global cell phone market has transitioned significantly from feature phones to smartphones since 2007. This particular period of smartphone industry expansion, and a detailed product-level dataset of all the cell phones sold in 40 major economies between 2007 and 2016, give us an unprecedented chance to study how the order of entry affects the performance of the same firm in different markets. We begin with a theoretical framework wherein the order of a firm's entry affects both consumers' preferences and suppliers' delivery costs. We then document a market sales advantage for early entrants, especially those originating from developed countries, offering high-quality products, or having diversified product lines. Finally, we show that adopting radical innovation, such as the 4G wireless network, can help late followers leapfrog over formerly leading firms.

Keywords: order of entry, early-mover advantage, leapfrog, cross-country variations

*The authors thank Jie Bai, Panle Jia Barwick, Shengmao Cao, Kerem Coşar, Jonathan Eaton, Jingting Fan, Paul Grieco, Yi Lu, Rong Luo, Charles Murry, Peter Newberry, Mark Roberts, Karl Schurter, Ang Sun, Felix Tintelnot, and Shaoda Wang for insightful conversation and comments. We are grateful to seminar participants at Renmin University of China and the Penn State Alumni Academic Conference for useful feedback. All errors are of our own.

†School of International Economics and Trade, University of International Business and Economics, luwenzhuo@uibe.edu.cn.

‡Corresponding author: School of Finance, Renmin University of China, xiexiaochen@ruc.edu.cn. Address: 59 Zhong Guan Cun Ave, 831 Mingde Main Building, Haidian District, Beijing, China, 100872

1 Introduction

Over the past two decades, economists have extensively explored the sources of firm heterogeneity that contribute to varying firm performance across markets. An established strand of literature primarily focuses on features of the firm that are universal across markets, such as productivity, technology upgrading, and brand awareness, etc., aiming to explain firm-level performance in diverse markets (Melitz, 2003; Bernard et al., 2003; Chaney, 2008; etc.). This literature still leaves room to account for the vastly different performances of the same firms in different markets (Eaton et al. 2011), recognizing the role of idiosyncratic interactions between individual firms and markets.

This paper investigates how the order of a firm's entry into a market influences its subsequent performance. It is well-documented that an early-mover advantage may arise under certain conditions that create obstacles to subsequent entry, including the network externality of early accumulating consumers, switching costs, learning by doing, and economies of scale (Berger and Dick, 2007). However, this advantage comes with higher initial costs and risks compared to late followers. In contrast, later entrants can benefit from free-rider effects, the resolution of technological and market uncertainties, changing technologies, and evolving consumer needs (Lieberman and Montgomery, 1988). As these theories hold distinct implications, many corporate managers face genuine uncertainty about the impact of entry orders on profitability. As these theories hold distinct implications, many corporate managers face genuine uncertainty about the impact of entry orders on profitability. By understanding how different order sequences affect market performance, businesses can optimize their expansion strategies, mitigate risks, and ultimately enhance their competitiveness in the global market. Meanwhile, policymakers can formulate policies aimed at fostering environments conducive to innovation and economic development. Therefore, our paper uses theory and data to explore the roles of the order of market entry in explaining cross-country market performance variations of the same firm.

The relationship between the order of entry and a firm's market performance has been of great interest to economists for the last 30 years. However, there still exist three key remaining issues in empirical research. First, how to identify the market pioneers many years after the market's beginning, given that data on well-established industries can miss the start of new markets. Second, how to avoid survivor bias when non-survivors are not observed.[1] Third, although researchers have added refinements to address the endogeneity of the order of market entry, the scholarship may still concern itself with how to capture unobserved differences between business units that can affect the decision to become an early entrant or not. Specifically, do market pioneers typically start with intrinsically superior skills or resources? And is a firm's decision to enter a particular market first influenced by unobserved firm-destination-specific matching shocks?

To address the first and second challenges posed by data limitations, we shift our focus to the dynamic landscape of the smartphone industry—a sector that has experienced remarkable growth since the introduction of the first iPhone in June 2007. Over the subsequent decade, smartphones have progressively taken over from traditional feature phones. By the second quarter of 2016, an impressive 177 smartphone companies were offering a total of 2,147 models, constituting 77.32% of overall cell phone expenditures. Our dataset, while noteworthy, captures the quarterly product-level details of all cell phones (encompassing both smartphones and feature phones) sold across 40 major economies from the first quarter of 2007 to the second quarter of 2016. We then leverage this dataset to identify market pioneers, document comprehensive information on both surviving and non-surviving entities, and generate robust data on the sequence of firms entering the market.

Simultaneously, we tackle the third issue of endogeneity through two key approaches. First, multi-market firms are usually early entrants in some markets but late followers in others. Hence, our multi-market data, unlike previous studies reliant on single-market observations, portray cross-market variations in the order of entry. Therefore, we can identify the early/late mover advantages of the same firm in different markets, based on the varying market performance resulting from different entry orders. This better controls estimation biases arising from unobserved characteristics such as firm productivity.

Second, in addition to traditional observations on product price and sales, our data offers an extensive array of product characteristics (e.g., camera megapixels, screen size, operating system, storage capacity, etc.) To mitigate the estimation bias resulting from unobserved

[1]For instance, Golder and Tellis (1993) caution the reader that if a dataset – such as the PIMS database, which contains business unit data from typical Fortune 500 companies – misclassifies early followers as pioneers and includes only data on surviving pioneers, it would yield results that are potentially biased in support of an early-mover advantage.

firm-destination-specific shocks, we construct firm-destination-specific measures of market competition – measured by the average product characteristics at the time of a firm's entry into a given market – as instruments. These instrumental variables are valid because, on one hand, the endogenous and unobserved firm-market match shocks are independent of exogenous market conditions and competition, thus satisfying the exclusion property of instrumental variables. On the other hand, firms entering a market later often encounter more intense market competition, hence meeting the relevance property of instrumental variables.

To guide the empirical investigation, we build on Head and Mayer (2019) and develop a theoretical framework that nests both early- and late-mover advantages. It is well documented that market pioneers tend to shape consumer tastes and preferences, so we allow early entrants to gain the early-mover advantage by improving consumers' utility.[2] Meanwhile, since late entrants can learn from pioneers' experience, we allow late entrants to gain the late-mover advantage by saving on marginal delivery costs.

Guided by the model's testable prediction, our baseline estimation implies that the earlier a firm enters, the better its market performance relative to others. Precisely, doubling the order of a firm's entry in any given market results in a 28.20% decrease in its subsequent market revenue and a 29.34% decrease in subsequent market share.

We then conduct a heterogeneity test to explore how the magnitude of the early-mover advantage differs across firm types. First, we compare smartphone firms from China and Europe to examine whether the headquarters country affects the early-mover advantage. The empirical results suggest that European firms benefit more from the early-mover advantage than Chinese firms do. One plausible reason is that European companies often have a longer track record of international expansion, accumulating extensive experience in building global brand recognition and reputation. So, they are more adept at influencing consumer tastes and preferences in favor of their products, thus reaping greater benefits from being early movers. By contrast, Chinese firms are more likely to find cost-saving opportunities through imitation, thus gaining advantages as late movers.

[2] After analyzing two ethical drug markets in the United States, Bond and Lean (1977) conclude that the main pioneer advantage is physician preference for the established and familiar pioneering brand names, rather than patent protection. Similarly, Hurwitz and Caves (1988) point out that the market share leadership of 29 original patent holders in the United States pharmaceutical market is not driven by the pioneers' superior product quality or lower prices. One potential explanation is that consumers learn more about pioneer brands and dislike the risk of an adverse experience.

Next, we interact the order of entry with the product price to investigate whether product quality, measured by the weighted average price, affects the early-mover advantage. The results indicate that firms that offer higher-quality products benefit more from the early-mover advantage. That is because high-quality products are more likely to generate favorable customer attitudes, leading to better performance in consumer trials and a higher incidence of repeat purchases. It follows that we interact a firm's order of entry with the breadth of its product line, and we document that firms with more extensive product lines are better off entering the market earlier. Intuitively, firms with broad product lines can introduce numerous products to meet diverse market demands, allowing them to rapidly accumulate early consumers, capture market share, establish brand recognition, and thus derive greater benefits from the early-mover advantage overall.

Finally, we investigate how technological innovation impacts the early-mover advantage. Our findings suggest that early adoption of radical technology, such as the 4G wireless network, can empower late entrants to leapfrog formerly leading firms that missed timely investments in the wireless technology. However, early adoption of the Android operating system does not yield the same advantage for late followers. The transition from 3G to 4G represents a significant leap in mobile network technology, offering faster data speeds, reduced latency, and enhanced application capabilities. Notably, 4G networks enable data-intensive activities like HD video streaming and real-time applications such as online gaming and video conferencing. In contrast, while Android stands out for its integration with Google services and open-source nature fostering customization, other mobile operating systems possess unique strengths; for example, iOS is acclaimed for its user-friendly interface and robust security, while Windows Phone offered distinct features like tile-based design and Microsoft service integration. Hence, the benefits of early 4G adoption are more pronounced.

These empirical findings are important as they link to a number of stylized facts in international economics and business. Firstly, we make a substantial contribution by introducing a novel channel that profoundly influences a firm's subsequent market performance, thus explaining the cross-country variations observed in the market performances of the same firm. Secondly, our study sheds light on the intriguing phenomenon of certain firms entering "small and unpopular" markets before pursuing "large and popular" markets. We propose that these multi-market entry decisions are influenced by the recognition of early-mover advantages in these "small and unpopular" markets. This diverges from previous research, which mainly focused on complementarity among multi-markets of the same firm (Morales et al. (2019); Jia (2008)). Moreover, we address concerns related to data limitations and endogeneity to extend the scope of current research on early-mover advantages. This extension involves quantifying the magnitude of the early-mover advantage, analyzing how it varies across different firm types, and exploring how late followers can leverage radical innovations to seize early-mover advantages from pioneers.

2 Literature Review

A few empirical studies in international economics and business have explored cross-country variations in market performances of the same firm. Roberts et al. (2018) quantify the importance of three sources of firm heterogeneity – marginal production cost, export fixed cost, and demand – in explaining Chinese firm-level export performance. Their empirical results indicate that the firm-specific demand and marginal cost components account for over 30% of market share variation and 40% of sales variation among exporters. Coşar et al. (2018) find that although trade costs, foreign production costs, and taste heterogeneity all matter for market outcomes, a preference for home brands is the most important driver of home market advantage. Simonovska (2015) studies the roles that per capita income and shipping costs play in accounting for observed cross-country price variations of identical items. Relative to these papers, we contribute by introducing a new channel by which the order of a firm's entry into a market affects its performance in this particular market through its impact on consumers' demand and suppliers' delivery costs.

The existing empirical literature on the advantage of early movers is mostly based on the pharmaceutical industry (Bond and Lean, 1977; Gorecki, 1986; Hurwitz and Caves, 1988; Grabowski and Vernon, 1992) and consumer packaged goods (Urban et al., 1986; Kalyanaram and Urban, 1992), with some other applications, such as those to cigarettes (Whitten, 1979), financial innovations (Tufano, 1989), semi-submersible oil-drilling rigs (Mascrenhas, 1992), internet search engines (Gandal, 2001), and commercial banks (Berger and Dick, 2007). Our work complements these works with in-depth studies of a novel and growing industry: smartphones. This focus enables us to observe firms' entry and exit when the market originated, thus avoiding survivor bias and misclassification of pioneers many years after the market's beginning.[3]

The most common statistical procedure used to control for possible endogeneity in the order of market entry is the instrumental variable approach.[4] Specifically, Moore et al. (1991) construct the instrumental variables by accounting for control variables that may affect the expected market shares, such as the probability of being a pioneer (derived from a reduced-form logit equation), indicators of low price, high purchase frequency, low customer service importance, intensive industry advertising, etc. Boulding and Christen (2003) compile the instruments by using the average age of a business unit and a set of industry-structure variables, such as the fraction of production costs relative to revenues, and the measure of the competitive environment, the latter of which is built on Porter's framework and is shaped by a firm itself, competitors, customers, suppliers, and regulators. Relative to these studies, our work adds refinements to these endogeneity problems. Because our novel dataset provides extremely rich information on product characteristics, it enables us to construct, as instruments, firm-market-specific measures of market competition at the time of a firm's entry into a given market. Furthermore, our multi-country dataset allows us to mitigate estimation bias by analyzing the diverse market performances of the same firms across countries, stemming from their varying entry sequences in each market.

3 Model

Building on Head and Mayer (2019)'s trade gravity model, we develop a theoretical model to capture the ambiguous impacts of order of entry on firms' market outcomes. In particular, we allow early entrants to gain a first-mover advantage by improving consumers' utility because of consumer inertia, network externality and switching costs. Meanwhile, late entrants gain a late-mover advantage by reducing risks and saving production costs after observing early entrants' experience. Finally, we show that this framework provides a closed-form solution for empirical analysis.

[3]Kerin et al. (1992) argue that many studies are based on idiosyncratic industry samples; industries selected by the researcher may tend to have greater early-mover advantages. As a result, one need among the scholarship is to complement the existing literature with studies focused on other industries.

[4]Several other studies use alternative approaches, such as reverse regression (Vanhonacker and Day, 1987) and lagged firm controls (Berger and Dick, 2007).

3.1 Consumer Demand

Assume each consumer only buys one unit of smartphones to fulfill basic needs in life. That is, each consumer m in country n chooses a product i made by firm j to maximize the utility $z_{in}^{\epsilon}\psi_{mi}/p_{in}$, where z_{in} is a demand shifter of product i in country n, ϵ is a preference parameter, p_{in} is the price of product i in country n, and ψ_{mi} is the taste shock perceived by consumer m to product i. Following Head and Mayer (2019), we parameterize ψ_{mi} to follow Frechet distribution with a scale parameter η: $Pr(\psi_{mi} \leq \psi) = exp(-\psi^{-\eta})$. As a result, the probability of consumer m choosing product i (from the total product set I_n available in country n) equals to $(p_{in}z_{in}^{-\epsilon}/P_n)^{-\eta}$ with aggregate price index $P_n = (\sum_{i \in I_n}(p_{in}z_{in}^{-\epsilon})^{-\eta})^{-\frac{1}{\eta}}$. Hence, the total quantity demanded for product i in market n follows

$$Q_{in} = (\frac{p_{in}z_{in}^{-\epsilon}}{P_n})^{-\eta}Q_n,$$

where Q_n is the total market demand of smartphones in country n.

Since each product is unique, the final delivery price is a constant markup $\frac{\eta}{\eta-1}$ of the marginal delivery cost. Denote c_{in} as the final delivery cost of product i in country n, we thus can rewrite the above quantity demand function as

$$Q_{in} = (\frac{\eta}{\eta-1}c_{in})^{-\eta}z_{in}^{\epsilon\eta}Q_nP_n^{\eta}. \tag{1}$$

3.2 Firm Supply

Each firm j is endowed with a productivity φ_j. Firms first design their products in headquarters h. Next, they either authorize their own factories or other qualified manufacturers for the production in locations l. Afterward, the configured products are shipped from the production locations l to the destination markets n.

Firms purchase composite inputs to make final goods. The firm productivity determines the production efficiency, and producing higher-quality goods costs more composite inputs. Following Feenstra and Romalis (2014), firm j uses l_{iln} units of composite inputs to produce one unit i with output quality y_i in country l ultimately delivered in country n according to: $l_{iln} = y_i^{\frac{1}{\theta}}/\varphi_{jln}$, where φ_{jln} refers to the realized productivity of firm j to make products in country l for consumers in country n after deducting the productivity loss from transferring the ideas from the headquarter to the production location. Besides, $0 < \theta < 1$ reflects diminishing returns of composite inputs to quality. We denote ω_l as the price of the composite input. The manufacturing (unit) cost of product i with quality y_i in country l before sourcing to its destination country is

$$c_{il}^m = \omega_l y_i^{\frac{1}{\theta}} / \varphi_{jln}.$$

For each product i designed in its headquarters country h, produced in country l and ultimately delivered to consumers in country n, the delivery cost contains two types of friction costs: the trade friction costs, τ_{ln}, and marketing friction costs, δ_{hn}. In particular, τ_{ln} captures both tariff and shipping costs from the production location l to the destination market n. δ_{hn} captures marketing friction costs between headquarters h and destination market n. For example, selling a product to a country with the same language or culture as the headquarters would be easier than selling it to a distant and unfamiliar cultural environment. Additionally, assume each product i incurs an idiosyncratic cost shock ε_{iln}. Therefore, the delivery (unit) cost of firm j's product i that is designed in country h, produced in country l, and sold in country n follows:

$$c_{ijln} = \frac{\omega_l y_i^{\frac{1}{\theta}}}{\varphi_{jln}} \tau_{ln} \delta_{hn} \varepsilon_{iln}. \tag{2}$$

3.3 First Mover Advantage and Late Mover Advantage

Early entrants gain a first-mover advantage by improving consumers' utility because of consumer inertia, network externality and switching costs. We thus specify the demand shifter z_{in} in consumers' utility functions as [5]

$$z_{in} = o_{jn}^{\kappa} \prod_k x_{ik}^{\beta_k}, \tag{3}$$

where o_{jn} is the entry order of firm j in country n, and the parameter κ captures the effect of entry order on consumers' perceived utility. We expect κ to be negative so that the earlier a firm enters the market (i.e. smaller o_{jn}), the larger the demand shifter of that

[5] The adoption of these function forms is inspired by the way how economists set up the relationship between the productivity of each firm's product (affiliate) and the efficiency order in the firm's product (affiliate) scope; see Arkolakis, Ganapati, and Muendler (2021); Chen et al. (2021). In the empirical analysis, we consider additional function forms to consolidate the analysis.

firm's products. Besides, x_{ik} represents the kth observed smartphone characteristics such as screen size, CPU speed, number of CPU cores, etc.[6] The weight parameter β_k characterizes consumers' preference towards the kth smartphone characteristic.

Next, late entrants gain a late-mover advantage by learning from early entrants' experiences, reducing risks and saving production costs. Hence, we specify firm productivity φ_{jln} as

$$\varphi_{jln} = \varphi_j o_{jn}^{\zeta} / \gamma_{hl}, \tag{4}$$

where φ_j is the productivity of the firm j's design department at the headquarters country, and γ_{hl} captures the productivity efficiency loss transferred from the headquarters country h to the production location l. Again, o_{jn} represents the firm j's entry order in country n, and the parameter ζ characterizes the impact of entry order on firm productivity. We expect ζ to be positive because late entrants can learn from pioneers' experience, adjust their marketing strategies, and thus become more productive.

Based on Equations (1)-(4), we can derive the market share of each product i as:

$$s_{in} = \frac{Q_{in}}{Q_n} = (\frac{\eta}{\eta - 1} \frac{\omega_l y_i^{\frac{1}{\theta}}}{\varphi_j o_{jn}^{\zeta}} \gamma_{hl} \tau_{ln} \delta_{hn} \varepsilon_{iln})^{-\eta} (o_{jn}^{\kappa} \prod_k x_{ik}^{\beta_k})^{\epsilon\eta} P_n^{\eta}. \tag{5}$$

It follows that the revenue of product i in country n can be written as:

$$r_{in} = (\frac{\eta}{\eta - 1} \frac{\omega_l y_i^{\frac{1}{\theta}}}{\varphi_j o_{jn}^{\zeta}} \gamma_{hl} \tau_{ln} \delta_{hn} \varepsilon_{iln})^{1-\eta} (o_{jn}^{\kappa} \prod_k x_{ik}^{\beta_k})^{\epsilon\eta} Q_n P_n^{\eta}. \tag{6}$$

3.4 Parameterization

To connect the reduced-form specifications with the real data, we further specify the output quality measure y_i and trade friction costs $(\gamma, \tau, \delta, \varepsilon)$.

[6] In particular, the smartphone characteristics used in the estimation include whether the smartphone is operating on an IOS system, whether the smartphone is operating on an Andriod system, whether the smartphone is operating on a Blackberry system, whether the smartphone is operating on a Windows system, whether is a 4G generation phone, whether it is a 3G generation phone, the screen size of the phone, the megapixel of the camera of the phone, whether a Qualcomm processor is in use, whether a Mediatek processor is in use, whether a self-made processor is in use, the number of cores in the processor, the CPU speed of the processor, the log of the storage of the phone, whether it has Wifi, whether it has Bluetooth, whether it has NFC, whether it has dual sims, whether it has GPS, whether it has TV, the primary card of the phone, the display of the phone (64K/256K/16M), whether it has a full screen, whether it has a touch screen, and whether it has a qwerty board.

First, we specify output quality y_i of product i as,

$$y_i = \prod_k x_{ik}^{\alpha_k}, \tag{7}$$

where x_{ik} indicates the observed kth smartphone characteristics. The weight parameter α_k characterizes the share of spending on the kth phone characteristic. We expect $\alpha_k > 0$ since the output quality of smartphones increases in the quality of inputs.

Besides, we parameterize the frictions governing headquarters productivity transfer costs (γ), trade friction costs (τ), and marketing friction costs (δ) to be exponential functions of some observable determinants: $Grav_{hl}$, $Grav_{ln}$ and $Grav_{hn}$. In particular, assume that

$$\tau_{ln} = exp(Grav'_{ln} f), \gamma_{hl} = exp(Grav'_{hl} g), \delta_{hn} = exp(Grav'_{hn} d), \tag{8}$$

where f, g and d are vectors of the primitive friction cost parameters. The $Grav$ vectors include standard explanatory variables in trade gravity equations: $Distance$, $Language$, and $Home$.[7] Specifically, $Distance$ 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. $Home_{hl}$ equals one when the manufacturer is located in the headquarters country. $Home_{ln}$ equals one if the assembly manufacturer is in the same country where smartphones are sold. $Home_{hn}$ is one when the consumers are located in the headquarters country of the smartphone company.

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

3.5 Reduced-form Specifications

Incorporating the above parameterization into Equation (5) and taking a log of both sides of the equation, the market share s_{in} is a function of entry order o_{jn}, smartphone characteristics

[7] We recognize that tariffs are an important source of trade frictions between production locations and destination markets, but the effects of tariffs are absorbed by the destination-year fixed effects because of lack of multilateral trade agreements related to cell phones during the sample period.

x_{ik}, and gravity variables $Grav$:[8]

$$log(s_{in}) = CST^{(1)}+\beta_o^{(1)}log(o_{jn})+\sum_k \beta_k^{(1)}log(x_{ik})+Grav'\beta_{grav}^{(1)}+FE_j^{(1)}+FE_l^{(1)}+FE_n^{(1)}+N(0,\eta\sigma_\varepsilon), \tag{9}$$

where the gravity term $Grav'\beta_{grav}^{(1)} = Grav'_{hl}\eta g + Grav'_{ln}\eta d + Grav'_{hn}\eta f$ captures the trade frictions among headquarters, manufacturing locations, and destinations. Besides, we also control for the brand fixed effect $FE_j^{(1)}$, production-location fixed effect $FE_l^{(1)}$, and destination fixed effect $FE_n^{(1)}$.

Similarly, the revenue function r_{in} in Equation (6) can be rewritten as [9]

$$log(r_{in}) = CST^{(2)}+\beta_o^{(2)}log(o_{jn})+\sum_k \beta_k^{(2)}log(x_{ik})+Grav'\beta_{grav}^{(2)}+FE_j^{(2)}+FE_l^{(2)}+FE_n^{(2)}+N(0,(\eta-1)\sigma_\varepsilon), \tag{10}$$

with the gravity term $Grav'\beta_{grav}^{(2)} = Grav'_{hl}(1-\eta)g + Grav'_{ln}(1-\eta)d + Grav'_{hn}(1-\eta)f$.

Identifying the coefficient β_o on the order of entry is the key to this paper. We first describe our novel dataset, exhibit data patterns, and then elaborate on the identification strategies in the following sections.

4 Smartphone Industry and Data

4.1 Smartphone Industry

The smartphone industry is an excellent subject for studying the role of first-mover advantages in terms of consumer behavior, market competitiveness, and innovation. Firstly, smartphone pioneers can establish early advantages. According to The State of Mobile Internet Connectivity Report 2023 by the Global System for Mobile Communication Association (GSMA), approximately 4.3 billion individuals, accounting for 54% of the global population, own at least one smartphone. These devices operate as experience goods, enabling pioneers to shape consumer tastes and preferences in favor of their brand. Furthermore, the smart-

[8] The constant term $CST^{(1)}$ is given by $-\eta log(\frac{\eta}{\eta-1})+\eta\mu_\varepsilon$. The coefficient on the entry order o_{jn} satisfies $\beta_o^{(1)} = \zeta\eta+\kappa\epsilon\eta$, and the coefficient on product characteristic x_{ik} satisfies $\beta_k^{(1)} = \varepsilon\eta\beta_k - \frac{\eta}{\theta}\alpha_k$. Moreover, we have $FE_j^{(1)} = \eta log(\varphi_j)$, $FE_l^{(1)} = -\eta log(w_l)$, and $FE_n^{(1)} = \eta log(P_n)$.

[9] The constant term $CST^{(2)}$ is given by $(1-\eta)log(\frac{\eta}{\eta-1})+(\eta-1)\mu_\varepsilon$. The coefficient on the entry order o_{jn} satisfies $\beta_o^{(2)} = \zeta(\eta-1)+\kappa\epsilon\eta$, and the coefficient on product characteristic x_{ik} satisfies $\beta_k^{(2)} = \varepsilon\eta\beta_k + \frac{1-\eta}{\theta}\alpha_k$. Meanwhile, there are $FE_j^{(2)} = (\eta-1)log(\varphi_j)$, $FE_l^{(2)} = (1-\eta)log(w_l)$, and $FE_n^{(2)} = \eta log(P_n)+log(Q_n)$.

phone market is highly competitive, with numerous companies striving for market share. Analyzing the impact of the order of entry on market performance helps businesses and researchers understand market dynamics, competition strategies, and consumer preferences. Finally, the smartphone industry is a hub of continuous innovation, illustrating how market pioneers capture market share through cutting-edge technology and providing insights into how late followers employ radical innovation to leapfrog formerly leading firms.

4.2 Data source

Most firm-level data come from the Worldwide Quarterly Mobile Phone Tracker, a market research endeavor by the International Data Corporation (IDC) headquartered in Massachusetts, United States. The bottom-up methodology of IDC delivers the quarterly product-level data of all the cell phones sold in 40 major countries (and regions) from the first quarter of 2007 to the second quarter of 2016. These countries, as listed in Column (1) of Table 1, account for 90% of the total global GDP, according to 2016 World Bank statistics. The dataset documents whether a particular smartphone model was available in a particular market for any period between the first quarter of 2007 (2007Q1) and the second quarter of 2016 (2016Q2). Hence, we assume a smartphone company entered a market when at least one smartphone model was reported in the dataset. Since our dataset starts from 2007Q1, we assume the "start period" is 2007Q1 if a firm entered the market before 2007Q1.[10]

Meanwhile, the dataset reports product-level information on product characteristics and product-market revenue from the first quarter of 2010 until the second quarter of 2016. These product characteristics include CPU information (processor vendor, speed band, number of cores), system information (operating system, RAM band, storage band), screen and display information (form factor, screen resolution, screen size, display type), air interface and generation information, camera information (camera megapixels, dual rear camera), and the availability of other functions, such as NFC, Wi-Fi, TV, GPS, and Bluetooth. Furthermore, we collect firm-level information on headquarters and manufacturing countries by searching their official websites, advertisements, factory-related news, and online product pictures. The information on tariffs and regional trade agreements comes from the World Trade Organization database.

[10]As a benchmark, the first iPhone was released on June 29, 2007.

4.3 Data Fact

Table 1 depicts smartphone sales by market. Specifically, Column (1) lists the market names in the sample. Columns (2) and (3) report the total number of active smartphone firms at the beginning and the end of the sample period. Columns (4) and (5) document the total number of available smartphone models in selected quarters. Finally, Columns (6) and (7) exhibit the share of spending on smartphones relative to total expenditure on cell phones (including smartphones and feature phones) in each market.

The pharmaceutical and consumer packaged goods industry received the most attention in the existing literature on the early-mover advantage.[11] Hence, the first advantage of our dataset is that it brings attention to a new and rapidly expanding industry: the smartphone industry. During the sample period, smartphones were gradually replacing feature phones. Table 1 suggests that the number of smartphone companies increased by 478.38%, and the share of smartphone spending increased by 480.85% between 2010 Q1 and 2016 Q2. In addition to numerous observations on the entry of new firms, the dataset can also easily identify market pioneers, yielding reliable and robust information on the order of entry.[12]

Table 2 shows the number of countries that the 10 largest smartphone firms (according to total sales in 10 years) have entered since their first year of business. Among them, 4 smartphone firms are identified as market pioneers as they introduced smartphones before 2007. However, 3 out of 4 market pioneers – Nokia, BlackBerry, and HTC – first expanded and then gradually quit the smartphone markets. Samsung became the only surviving pioneer by the end of the sample period. Hence, the second advantage of our dataset is that it provides detailed information on survivors and non-survivors in a growing industry. Market pioneers often face a greater risk of perishing in the first few years of business. Because of this, when analyzing the early-mover advantage, it is important that researchers aim to avoid market pioneer survivor bias (a bias that generally arises from the fact that limited data are available on non-surviving firms); some market pioneers may fall out of the market and thus not be considered in empirical observations. We show later in Section 5.5.1

[11] See studies of pharmaceuticals (Bond and Lean, 1977), cigarettes (Whitten, 1979), and consumer packaged goods (Urban et al., 1986).

[12] A common concern of this strand of literature is how to identify the market pioneers many years after the market's beginning, given that data on well-established industries can miss the start of new markets. As a result, high-market-share firms can be misidentified as market pioneers. For example, one of the criticisms directed at the PIMS dataset is that it uses single-informant self-reports to identify pioneers.

Table 1: Summary Sales Statistics by Market in the Sample

Market	Num of firms		Num of models		Smartphone share(%)	
	2010Q1	2016Q2	2010Q1	2016Q2	2010Q1	2016Q2
Argentina	8	11	23	54	10.50	96.12
Australia	8	14	39	76	48.11	94.06
Austria	7	16	22	88	38.89	86.67
Belgium	9	21	36	110	23.56	90.49
Brazil	10	15	59	97	9.19	82.19
Canada	9	18	32	68	37.63	96.39
Chile	6	14	15	94	6.92	85.30
Chinese Taipei	9	13	39	98	18.10	89.79
Colombia	9	18	35	149	9.29	85.76
Denmark	8	12	34	64	40.12	94.83
Finland	5	12	27	68	24.66	92.64
France	12	36	48	176	21.36	85.52
Germany	13	32	55	158	20.85	88.28
Hong Kong SAR	13	15	54	71	49.63	96.91
India	9	39	47	475	2.53	44.29
Indonesia	9	30	39	156	11.59	57.46
Ireland	6	11	23	58	22.06	91.66
Italy	10	27	43	172	21.42	88.10
Japan	8	17	26	64	47.42	95.19
Korea	6	8	18	31	16.72	97.00
Mainland China	16	32	107	313	7.36	91.33
Malaysia	10	22	40	126	25.44	88.10
Mexico	11	22	46	141	14.04	82.34
Netherlands	9	16	40	89	43.47	95.11
New Zealand	5	12	16	51	31.94	92.14
Nigeria	5	30	25	222	3.07	37.21
Norway	6	12	27	50	31.81	95.30
Pakistan	3	19	13	175	4.49	39.57
Philippines	8	22	48	166	17.35	58.37
Portugal	9	18	43	94	15.17	78.84
Russia	12	29	61	189	10.21	68.70
Singapore	10	18	48	77	55.59	95.14
Spain	10	28	44	152	29.67	90.85
Sweden	7	15	19	72	39.52	94.02
Switzerland	7	16	25	81	32.37	89.50
Thailand	9	19	50	128	9.48	64.53
USA	12	25	71	292	31.75	89.38
Ukraine	6	23	21	101	8.33	72.45
United Kingdom	12	31	44	124	40.18	92.74
Venezuela	10	5	46	21	12.50	65.03
Total	37	177	330	2147	16.08	77.32

Notes: the table reports smartphone sales in 40 markets from the first quarter of 2010 until the second quarter of 2016. Specifically, column (1) lists the market names in the sample. Columns (2) and (3) report the total number of active smartphone firms at the beginning and the end of the sample period. Columns (4) and (5) document the total number of available smartphone models in selected quarters. Columns (6) and (7) exhibit the share of spending on smartphones relative to total expenditure on cell phones (including smartphones and feature phones) in each country. Note that the data documents firm-market revenue since the first quarter of 2007 and reports product characteristics since the first quarter of 2010.

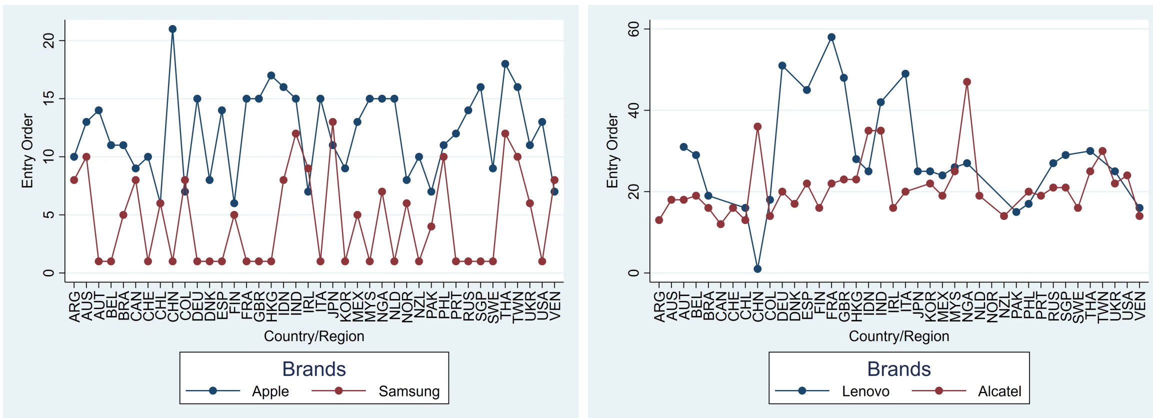
Table 2: Smartphone Firms' Expansion Speed

Firm	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Samsung	19	26	34	37	39	40	40	40	40	40
Apple	1	6	32	38	38	39	39	39	39	39
Nokia	34	38	38	39	39	39	38	38	37	2
Huawei	3	21	36	37	39	40	40			
LG Electronics	1	16	11	35	38	40	39	38	38	
BlackBerry	30	31	35	37	38	38	36	30	27	18
Xiaomi	1	1	3	16	17					
Lenovo	1	1	1	1	1	3	5	11	14	19
HTC	16	34	31	34	36	37	35	35	31	31
ZTE	1	3	3	17	27	27	29	31	30	

Notes: the table reports the number of markets the top 10 smartphone firms (according to total sales between 2007 and 2016) have entered since their first year of business.

that taking non-survivors into account generates different empirical implications from not including them.

Besides, Table 2 shows that it takes years for a firm to expand its business from home to foreign markets. Notably, Apple accomplished this expansion in six years for all markets except Argentina, where it opted not to sell products directly due to a disagreement with the local government over production location. In contrast, Lenovo took a decade to enter 19 markets. Consequently, multi-market firms tend to be early entrants in some markets while lagging behind in others. Furthermore, Figure 1(a) displays the entry order of Apple and Samsung in 40 economies. Samsung, identified as one of the four "market pioneers" in the smartphone industry for introducing smartphones before 2007, entered most markets earlier than Apple and was the first entrant in 20 out of 40 sample markets. However, Apple entered markets such as Colombia, Ireland, Japan, and Venezuela earlier than Samsung. Similarly, Figure 1(b) compares the entry timelines of Chinese company Lenovo and French company Alcatel. While Lenovo entered certain Asian markets, including China, Indonesia, Pakistan, and the Philippines, before Alcatel, it significantly lagged behind in entering European markets compared to Alcatel. To enhance the visual representation of the idea behind the paper, Figure 2 portrays the entry sequence of the ten most profitable smartphone companies (based on total sales between 2007 and 2016). In contrast to previous studies relying on single-market observations, Figure 2's intricately intertwined lines capture the third advantage of our multi-country dataset: illustrating cross-country variations in the order of firms' entry. This allows us not only to construct instrumental variables but also to control for firm fixed effects across countries, thereby mitigating estimation bias arising from unobserved, intrinsically superior strengths such as firm productivity.[13]



(a) Apple vs. Samsung

(b) Lenovo vs. Alcatel

Figure 1: the left panel plots the order of Apple and Samsung's entry into 40 markets. The right panel depicts the order of Lenovo and Alcatel's entry into 40 markets. These 40 markets account for 90% of the total global GDP, according to the 2016 World Bank statistics.

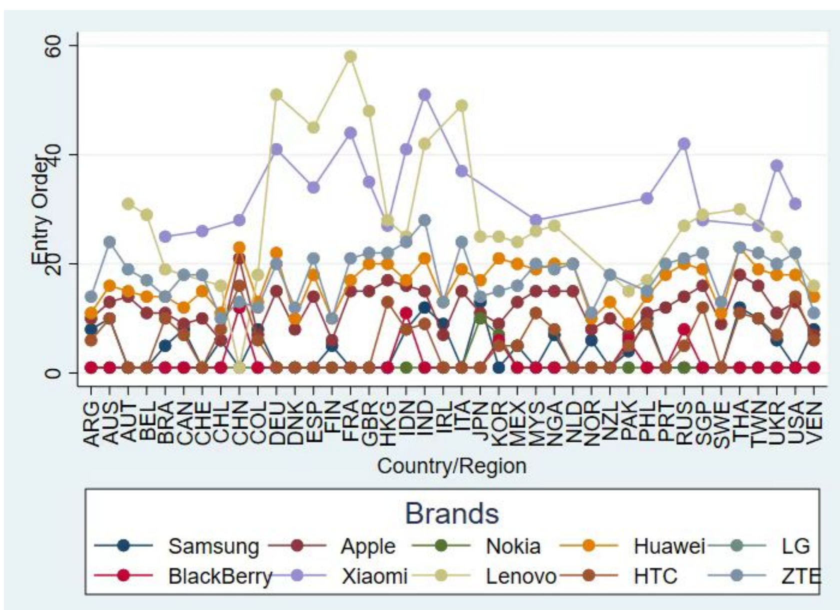


Figure 2: the figure depicts the order of the top 10 smartphone firms' entry into 40 markets.

[13]One of the estimation concerns is whether the market pioneers typically start with intrinsically superior skills and resources. We illustrate how to address these estimation concerns in greater detail in Section 5.2.

5 Empirical Analysis

Starting with the launch of the iPhone in 2007, the global cell phone market has undergone a significant change in its transition from feature phones to smartphones. The particular period of smartphone industry development, growth, and expansion examined here, as well as the detailed multi-country product-level data we analyze, give us an unprecedented research base to study early- and late-mover advantages. In this section, based on our model inferences, we apply global smartphone industry data to address the following objectives of the study. First, we explore in the baseline analysis whether there exists an early-mover advantage. Then, in the heterogeneity analysis, we explore three determinants of the effectiveness of the early-mover advantage. Also, we examine under which conditions a late follower can leapfrog over an established market leader through technological innovation.

5.1 Baseline Analysis

We first estimate the effect of the order of a firm's entry on its revenue and market share. Guided by Equations 9 and 10, we build a specification as follows to test whether there exists an early-mover advantage in the smartphone market:

$$log(y_{int}) = \beta_0 + \beta_r log(o_{jn}) + \sum_k \beta_k log(x_{ik}) + Grav'\beta_{grav} + \varphi_j + \varphi_l + \varphi_{nt} + \varepsilon_{int} \tag{11}$$

where the dependent variable y_{int} measures market performance measures: market share s_{int}, and market revenue r_{int} of product i in country n at time t. o_{jn} measures the entry order of firm j in destination market n and its parameter β_r is the focus of interest. Hence, in addition to the order of entry into the destination (in logs), we also consider a few alternative entry-order measurements. As an illustration, consider the entry order itself rather than the logarithmic terms of entry orders. Also, we group firms by whether they are pioneers (defined as a given market's very first entrant), among the first 3 entrants, among the first 5 entrants, or among the first 10 entrants.

Additionally, for the gravity variables $Grav$, we use the home (i.e., location of headquarters), language, and log of weighted distance to measure the trade frictions between headquarters, production locations, and destinations. We also use product characteristic variables x_{ik} to capture the quality level of each product, such as primary cell phone function-related indicators (e.g., operating system, signal mode, screen and display, camera function, chip, etc.). Each product characteristic variable is indexed by k. In addition, in the regressions, we include firm fixed effect, production-location fixed effect, and destination-year fixed effect.

5.2 Endogeneity Issues and Instrumental Variable Design

The biggest concern of the estimation of Equation 11 comes from the potential endogeneity between a firm's order of entry and its market performance. The first source of this potential endogeneity is reverse causality: earlier market entrants tend to be better firms. The second potential source of endogeneity is the unobserved firm-destination-specific matching shocks: a firm that enters a market earlier tends to have a higher unobserved match value with that market, such as whether a firm's managers have lived and worked in that country before the firm enters its market. Endogeneity from these two sources was generally difficult to address in previous studies on early-mover advantages.

We attempt to address the first source of endogeneity – reverse causality – by controlling for the firm fixed effects. In the phase of feature phone conversion to smartphones, it takes years for a firm to expand to multiple countries, and firms appear to follow paths of expansion that differ substantially from one another. Hence, multi-market firms are usually early entrants in some markets but late entrants in others. After controlling for the firm fixed effects, we can mitigate the estimation bias caused by firms' unobserved characteristics, including firm productivity, and thus address the matter of reverse causality.

Next, we employ instrumental variable estimation to overcome the identification threats from unobservable firm-country-specific matching shocks. Specifically, our instrumental variables consist of firm-market-specific metrics of market competition at the point of a firm's market entry. These indicators encompass the total number of smartphone products in the market, average smartphone storage, and average CPU speed. More specifically, we define the instrumental variables as follows:

$$IV_{ij}^{nmodel} = Num\ of\ Products_{j,t_{ij}(1)}$$

$$IV_{ij}^{storage} = \frac{\sum_k storage_{kj,t_{ij}(1)}}{Num\ of\ Products_{j,t_{ij}(1)}}$$

$$IV_{ij}^{CPUspeed} = \frac{\sum_k CPUspeed_{kj,t_{ij}(1)}}{Num\ of\ Products_{j,t_{ij}(1)}}$$

Here, IV_{ij}^{nmodel} denotes the number of active products in the market at the time of firm i's entry into country j. Similar definitions apply to $IV_{ij}^{storage}$ (average smartphone storage of products in the market) and $IV_{ij}^{CPUspeed}$ (average CPU speed of smartphone products in the market). Moreover, $t_{ij}(1)$ represents the quarter in which the products of firm i were first observed in country j. Thus, $Num\ of\ Products_{j,t_{ij}(1)}$ represents the number of competing products in the market when firm i entered country j in its initial quarter. The same definitions also apply to the calculation of average storage and CPU speed of smartphone products in the market. [14]

The exclusion of instrumental variables for market competition when a firm enters a market is inspired by the well-known BLP instruments. Conditional on controlling for country-time fixed effects, our constructed instrumental variables only affect the dependent variables related to firm market performance through their correlation with the order of firm entry into the market. This is because the level of market competition at a firm's market entry reflects the exogenous market environment at that time, unrelated to the firm's own match shock with the market. In addition, the channel how the market environment at the time of each firm's entry impacts the current market condition has been absorbed by the country-time fixed effects in our specification. Consequently, these instruments are independent of unobserved firm-destination-specific shocks.

Furthermore, the market environment at a firm's entry into a market and its entry order are relevant: firms entering a market earlier tend to face less intense competition. As we will demonstrate in the first stage results, our initial findings also confirm the relevance of the instrumental variables we construct.

Moreover, we anticipate that firms headquartered in the same country are likely to share similar firm-destination-specific shocks. To further mitigate biases arising from firm-country-specific match shocks, we replicate the baseline specification with firms that are originally from only China (or only Europe) in the heterogeneity analysis, yielding consistent results.

[14] For firms entering the market by 2010Q1, we assume that firm-market-specific measures of market competition are calculated as the average product characteristics of all firms (including both new entrants and continuing firms) in that market in 2010Q1. In subsection 5.4.3, we refine this assumption by excluding firms entering a particular smartphone market for the first time no later than 2010Q1 and report the results in Columns (5)-(8) of Table 5 as a robustness check.

Another concern arises from the potential upward bias in the coefficient of interest, primarily influenced by old firms present in the dataset for a longer duration. To illustrate, consider two firms entering a market at different times. The early entrant secures 100 percent market share in the first period and 40 percent in the second period, while the late entrant captures 60 percent in the second period. As the coefficient reflects the average lifetime product-level market share by order of entry, it becomes upwardly biased in this scenario. The destination-time fixed effects as controls in our econometric model address this concern. This adjustment ensures that the key coefficient compares the average effect among firms present in a given market at a specific period by order of entry.

5.3 First Stage Results of 2SLS Estimation

Given the instrumental variable design described above, we conducted a two stage least square estimation to identify the early-mover advantage. Firstly, we initiate a first-stage analysis for the following specification:

$$log(o_{jn}) = \beta_0' + \sum_m \beta_m IV_m + \sum_k \beta_k' log(x_{ik}) + Grav'\beta_{grav}' + \varphi_j' + \varphi_l' + \varphi_{nt}' + u_{int} \tag{12}$$

As set in our baseline analysis, we employ six different measures to characterize the dependent variables o_{jn}, reflecting the entry order. In addition to the covariates of interest and fixed effects included in the baseline analysis, we incorporate the three instrumental variables we designed in the first stage regression, denoted by $\sum_m \beta_m IV_m$. Furthermore, we add primes to each parameter and fixed effect to distinguish between the coefficients of the first and second stages.

We applied OLS to conduct the first-stage estimation, and Table 3 displays the first-stage regression results. As expected, the estimated coefficients of the instrumental variables are statistically significant and align with intuition: firms entering markets later face more intense competition. Our estimation results confirm the relevance of the instrumental variables we constructed. Based on our first-stage estimates, we predict $\hat{o}_{ijt}$ and proceeded with the second-stage estimation as designed in the baseline analysis:

$$log(y_{int}) = \beta_0 + \beta_r log(\hat{o}_{jnt}) + \sum_k \beta_k log(x_{ik}) + Grav'\beta_{grav} + \varphi_j + \varphi_l + \varphi_{nt} + \varepsilon_{int}. \tag{13}$$

Table 3: First Stage Results of the 2SLS Estimation

VARIABLES	(1) Log of entry order	(2) Entry order	(3) First entrant	(4) Earliest 3 entrants	(5) Earliest 5 entrants	(6) Earliest 10 entrants
Number of models	0.003***	0.074***	-0.001***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Average storage	0.127***	2.456***	-0.012**	-0.013***	-0.061***	0.038***
	(0.011)	(0.085)	(0.005)	(0.005)	(0.004)	(0.005)
Average CPU speed	0.502***	4.482***	-0.072***	-0.062***	0.106***	-0.612***
	(0.050)	(0.390)	(0.021)	(0.022)	(0.020)	(0.023)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Gravity Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Assembly FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	OLS	OLS	OLS
No. of Countries	40	40	40	40	40	40
Observations	98,576	98,576	98,576	98,576	98,576	98,576
R-squared	0.853	0.918	0.770	0.775	0.786	0.808

Notes: Columns (1)-(6) document the first stage results on the explanatory variables of entry orders. Firm-market-specific instruments encompass measures of market competition, including the number of competing models, average CPU speed, and average phone storage capacity at the time of firm entry into a market. Product characteristics variables describe the operating system, signal mode, screen and display, camera function, chip, etc. Gravity variables are home, language, and log of weighted distance to capture the trade frictions among headquarters, production locations, and destinations. In addition, we control for firm fixed effects, production-location fixed effects, and destination-year fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.4 Baseline Results

Table 4 shows the baseline regression results of order of market entry into the smartphone market. In particular, Columns (1)-(6) document the impact of order of market entry on market revenue, while Columns (7)-(12) exhibit the impact of order of market entry on market share (which is defined as the percentage of product quantities sold in a market by a particular firm; see Equation 5). The estimated results suggest that earlier entrants are associated with larger market revenue and higher market share.[15] Specifically, doubling the order of a firm's entry into the smartphone market reduces its subsequent market revenue by an average of 28.20% (i.e., $2^{-0.478} - 1$) and subsequent share by 29.34% (i.e., $2^{-0.501} - 1$).

Next, we estimate the effect of whether a firm is the 1st, or among the top 3, top 5, or top 10 entrants on market performance. The results exhibit a similar pattern: earlier leaders have, on average, a higher market share and market revenue than later entrants.

[15] In appendix A.1, we empirically document that earlier entrants are associated with higher product prices, *ceteris paribus*. Hence, earlier entrants can generate more significant market revenue because they not only sell more products but charge higher prices as well.

Table 4: Baseline Results of the Impact of Entry Order on Market Performance

	Log of Market Revenue (Millions of USD)						Log of Market Share (%)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log of entry order	-0.478***						-0.501***					
	(0.040)						(0.040)					
Entry order		-0.022***						-0.023***				
		(0.002)						(0.002)				
First entrant			3.006***						3.130***			
			(0.319)						(0.322)			
Earliest 3 entrants				3.446***						3.597***		
				(0.356)						(0.361)		
Earliest 5 entrants					3.793***						4.006***	
					(0.320)						(0.325)	
Earliest 10 entrants						1.803***						1.912***
						(0.129)						(0.131)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gravity variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Production FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576
R^2	0.531	0.549	0.417	0.378	0.334	0.498	0.431	0.454	0.282	0.231	0.169	0.387

Notes: Columns (1)-(6) document the impact of the order of entry on market revenue, while columns (7)-(12) exhibit the impact of the order of entry on market share. The main explanatory variable, Entry Order, is the order of entry among all active and inactive firms. Product characteristics variables describe the operating system, signal mode, screen and display, camera function, chip, etc. Gravity variables are home, language, and log of weighted distance to capture the trade frictions among headquarters, production locations, and destinations. Firm-market-specific instruments encompass measures of market competition, including the number of competing models, average CPU speed, and average phone storage capacity at the time of firm entry into a market. In addition, we control for firm fixed effects, production-location fixed effects, and destination-year fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.5 Robustness Checks

5.5.1 Time-varying order of market entry

Since early entrants initially face the most demand and technological uncertainty, they usually also face a greater risk of perishing in the first few years of commercialization (Boulding and Christen, 2003). Hence, we reorder firms among surviving firms at the current period to explore the impact of *time-varying* order of market entry on market performance.

Recall that in our baseline analysis, we use the *historical* order of entry, o_{jn}, as the main explanatory variable, where o_{jn} indicates the order of entry of firm j among all (active and inactive) firms in country n. We recognize that as markets evolve and some firms choose to quit, a firm's order of entry among survivors will change over time. Hence, we re-estimate the baseline specification by replacing the historical entry order o_{jn} with time-varying entry order o_{jnt}, in which o_{jnt} represents the order of market entry of firm j among all active firms in country n at t. The results, reported in Table 5, are similar to the results of the baseline analysis, especially the coefficients for "Log of Entry Order" and "Entry Order". However, the magnitude of coefficients differs from the baseline analysis when estimating the impact of whether a firm is the 1st, or among the top 3, top 5, or top 10 entrants on market performance. In particular, Table 4 suggests that early market leaders (i.e., the 4th and 5th entrants in our sample) have even better performance than market pioneers (i.e., the 1st entrant), which is consistent with an argument in Robinson et al (1994).[16] Meanwhile, Table 5 shows a positive correlation between order of entry and market share among active firms. Together, these findings suggest that the attempt to be a market pioneer involves high initial risk but also high potential returns. Intuitively, market pioneers are generally more involved in product innovation, and innovation is more costly than product imitation.

[16] As a robustness check, we further divide firms into 5 categories: the 1st, the 2nd-5th, the 6th-10th, the 11th-15th entrants, and others. Then we re-estimate the baseline specification and report the results in Table A2 in the appendix. Similarly, Table A2 suggests that there exists a market share advantage for early entrants, and moreover, that early market leaders have even better market performance than market pioneers. The coefficients for the 6th-10th and the 11th-15th entrants are negative mainly because there are fewer than 15 entrants in many markets during most of the sample periods, as illustrated in Table 1.

Table 5: Robustness Checks on Time-varying Entry Orders' Impact on Market Performance

	Log of Market Revenue (Millions of USD)						Log of Market Share (%)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log of entry order	-0.431***						-0.450***					
	(0.037)						(0.037)					
Entry order		-0.025***						-0.026***				
		(0.003)						(0.003)				
First entrant			3.033***						3.159***			
			(0.321)						(0.325)			
Earliest 3 entrants				2.112***						2.221***		
				(0.204)						(0.207)		
Earliest 5 entrants					1.912***						2.026***	
					(0.147)						(0.150)	
Earliest 10 entrants						1.057***						1.122***
						(0.065)						(0.066)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gravity variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Production FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576
R^2	0.540	0.549	0.414	0.478	0.484	0.532	0.442	0.454	0.279	0.361	0.366	0.432

Notes: the main explanatory variable, Entry Order, is the order of entry among all active firms. In addition, product characteristics variables describe the operating system, signal mode, screen and display, camera function, chip, etc. Gravity variables are home, language, and log of weighted distance. Instruments are measures of market competition at the time of a firm entry into a market, namely, the number of competing models, average CPU speed, and average phone storage capacity. Furthermore, we control for firm fixed effects, production-location fixed effects, and destination-year fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

5.5.2 Feature Phones' Intervention

Meanwhile, we acknowledge the existence of two potential types of entrants: the first type comprises firms producing feature phones before entering the smartphone market, while the second type consists of true newcomers whose initial product is a smartphone. If there are spillover effects across products, for instance, if Nokia feature phone users are more likely to buy Nokia smartphones, then the sequence of entry into the smartphone industry might be less important if older firms have already established a consumer base with other products. Consequently, in Table 6, we replicate the baseline regression, focusing on "true newcomers" whose first product is a smartphone. The instruments in this exercise remain the same as in the baseline regression, capturing the average characteristics of products sold by both types of firms. Again, the findings in Columns (1) to (4) of Table 6 indicate that early leaders, on average, exhibit better market performance.

Table 6: Robustness Checks on Feature Phones' Intervention and Entrants Before 2010Q1

	Exclude Feature Phones' Intervention				IV Before 2010Q1			
	Log (Sales)		Log (Share)		Log (Sales)		Log (Share)	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log of Entry Order	-1.801***		-1.765***		-1.340***		-1.370***	
	(0.143)		(0.143)		(0.074)		(0.075)	
Entry Order		-0.029***		-0.027***		-0.041***		-0.042***
		(0.004)		(0.004)		(0.003)		(0.003)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gravity Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Production FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
No. of Countries	40	40	40	40	40	40	40	40
Observations	36,730	36,730	36,730	36,730	37,323	37,323	37,323	37,323
R^2	0.584	0.611	0.492	0.524	0.470	0.502	0.443	0.477

Notes: Columns (1)-(4) replicate the baseline regression, focusing on true newcomers whose first product in business is a smartphone. Columns (5)-(8) focus on firms that enter a particular market for the first time after 2010Q1.

5.5.3 Instruments Before 2010

Our instrumental variables represent firm-market-specific measures of market competition, specifically defined as the average product characteristics at the time a firm enters a market. Information on product characteristics is available from 2010Q1 to 2016Q2. On the other hand, details on when a firm launched its first smartphone product in a particular market are accessible between 2007Q1 and 2016Q2. So, we arrange these smartphone companies in each market based on quarterly observations, assuming a "start period" of 2007Q1 if a firm entered a smartphone market before that period. Consequently, for firms entering the smartphone market no later than 2010Q1, we lack observations on the market competition they faced at the time of entry.

To include more observations in the baseline analysis, we propose an assumption. For firms entering the market by 2010Q1, their firm-market-specific measures of market competition are calculated as the average product characteristics of all firms (including new entrants and continuing firms) in that market in 2010Q1. In this subsection, to refine our measures and ensure consistency, we relax this assumption by excluding firms entering the smartphone market for the first time no later than 2010Q1. The results are reported in Columns (5)-(8) of Table 6, presenting arguments similar to those in the baseline analysis.

5.6 Heterogeneity in Treatment Effects

Innovation is a key source of economic growth. To encourage more innovation, an important research need is to find a way to calculate the risk-return tradeoff for a potential early market entrant. Hence, we then conduct a heterogeneity analysis of the treatment effect to explore determinants of the effectiveness of the early-mover advantage.

5.6.1 Headquarters Country

First, we focus on firms based in the same country to answer whether the headquarters country has an effect on the early-mover advantage, and meanwhile, to further mitigate the estimation bias caused by unobserved firm-destination-specific shocks, as discussed in Section 5.2. We recognize that around 18.97% and 24.11% of smartphone companies originate in China and Europe, respectively, so we explore the relationship between order of market entry and market performance among Chinese and European firms. Specifically, Columns (1) and (2) of Table 7 suggest that doubling the order of a firm's market entry reduces its subsequent market revenue by an average of 28.40% (i.e., $2^{-0.482}-1$) for a Chinese firm, and by an average of 35.92% (i.e., $2^{-0.624}-1$) for a European firm. Similarly, the later a firm enters, the smaller its market share is. Also, Table 7 indicates that the negative impact of

Table 7: Extension Results of the Impact of Entry Order on Sales by Headquarters Country

	Log of Market Sales		Log of Market Share	
	(1) China	(2) Europe	(3) China	(4) Europe
Log of entry order	-0.482***	-0.624***	-0.508***	-0.610***
	(0.039)	(0.103)	(0.040)	(0.106)
Characteristics	Yes	Yes	Yes	Yes
Gravity variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Production FE	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes
Estimation	2SLS	2SLS	2SLS	2SLS
Observations	22,892	21,669	22,892	21,669
R^2	0.563	0.527	0.347	0.475

Notes: columns (1) and (3) document an early-mover advantage for firms originating from China, and columns (2) and (4) document an early-mover advantage for firms originating from Europe. In addition, product characteristics variables describe the operating system, signal mode, screen and display, camera function, chip, etc. Gravity variables are home, language, and log of weighted distance. Instruments are measures of market competition at the time of a firm entry into a market. Furthermore, we control for firm fixed effects, production-location fixed effects, and destination-year fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

being a late entrant on market performance is more severe for a European firm than for a Chinese firm.

One plausible explanation for this observation is that European companies often have a longer track record of international expansion, accumulating extensive experience in building global brand recognition and reputation. Consequently, they are more adept at influencing consumer tastes and preferences in favor of their products, thus reaping greater benefits from being early movers.[17] In contrast, Chinese companies may encounter linguistic, cultural, legal, political, and other hurdles, hindering their ability to effectively foster network externalities among early consumers. Additionally, Chinese firms may find cost-saving opportunities through imitation, thus gaining advantages as late movers. In summary, Table 7 suggests that headquarters countries affect the early-mover advantage. Specifically, firms, particularly those from European countries, stand to gain more by entering markets earlier and shaping consumer preferences in favor of their products.

[17]See Schmalensee (1982), Hauser and Wernerfelt (1990), Kardes et al. (1993).

5.6.2 Product Quality

Next, we investigate whether product quality, as measured by the average price, has an effect on the early-mover advantage. Specifically, after controlling for the observed product characteristics, we interact the order of entry with a weighted average price as:

$$\begin{aligned} log(y_{int}) =& \beta_0 + \beta_1 log(o_{jn}) \times log(aprice_{jnt}) + \beta_2 log(o_{jn}) + \beta_3 log(aprice_{jnt}) \\ &+ \sum_k \beta_k log(x_{ik}) + Grav'\beta_{grav} + \varphi_j + \varphi_l + \varphi_{nt} + \varepsilon_{int}, \end{aligned}$$

where $aprice_{jnt}$ is an average price, weighted by quantity, sold by firm j in country n at time t. Table 8 documents these results. The negative coefficients of the interaction terms in Columns (1) and (3) of Table 8 indicate that the negative impact on market performance of being a late entrant is stronger for a firm that offers more expensive products. In other words, firms that offer products that are perceived to be of higher quality benefit more from early-mover advantage and thus are better off entering a market earlier. Intuitively, a smartphone is a relatively expensive item, and its switching cost is significant. Purchasing such a big-ticket item tends to carry a high level of perceived risk, so customers tend to rely on established and familiar brand names. As a result, the market's early entrants that offer high-quality products should benefit.

5.6.3 Product-line Breadth

Third, we investigate whether product-line breadth has an effect on the early-mover advantage. That is,

$$\begin{aligned} log(y_{int}) =& \beta_0 + \beta_1 log(o_{jn}) \times log(width_{jnt}) + \beta_2 log(o_{jn}) + \beta_3 log(width_{jnt}) \\ &+ \sum_k \beta_k log(x_{ik}) + Grav'\beta_{grav} + \varphi_j + \varphi_l + \varphi_{nt} + \varepsilon_{int}, \end{aligned}$$

where $width_{jnt}$ is the number of products sold by firm j in country n at time t,[18] and Columns (2) and (4) of Table 8 present the results. Specifically, the negative coefficient of the interaction terms indicates that the adverse effect of entering a market late is more

[18]For example, we assume that the 16 GB iPhone 5 and the 32 GB iPhone 5 are the same model but two different products.

Table 8: Extension Results of the Impact of Entry Order on Sales by Product Quality and Width

	Log of Market Sales		Log of Market Share	
	(1)	(2)	(3)	(4)
Interaction terms	-0.0971***	-0.0614***	-0.0985***	-0.0594***
	(0.00560)	(0.00509)	(0.00561)	(0.00511)
Log of entry order	0.526***	0.155***	0.532***	0.142***
	(0.0323)	(0.0147)	(0.0323)	(0.0147)
Log of average price	0.514***		-0.412***	
	(0.0174)		(0.0175)	
Log of product width		0.375***		0.365***
		(0.0135)		(0.0135)
Characteristics	Yes	Yes	Yes	Yes
Gravity variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Production FE	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	OLS
No. of Countries	40	40	40	40
Observations	98,576	98,576	98,576	98,576
R^2	0.554	0.554	0.466	0.460

Notes: columns (1) and (3) interact the order of entry with an average price weighted by quantity, and columns (2) and (4) interact the order of entry with the number of products. In addition, product characteristics variables describe the operating system, signal mode, screen and display, camera function, chip, etc. Gravity variables are home, language, and log of weighted distance. Instruments are measures of market competition at the time of a firm entry into a market. Furthermore, we control for firm fixed effects, production-location fixed effects, and destination-year fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

pronounced for firms with broad product lines. Put simply, companies offering a wide range of products reap greater benefits from being early movers, making earlier market entry more advantageous for them. Typically, firms with diverse product lines adopt a strategy of introducing numerous products to cater to various market demands, allowing them to rapidly accumulate early consumers, capture market share, and establish brand recognition. For instance, in the second quarter of 2014, OPPO, a three-year-old smartphone company, launched 21 different models globally, introducing 8 of these models simultaneously upon its debut in the Malaysian market.[19] Conversely, firms with narrower product lines typically target smaller market segments, aligning with brand proliferation models like Schmalensee (1978). As a result, early market entrants with broad product lines can swiftly seize market opportunities and thus derive greater benefits from the early-mover advantage overall. [20]

5.6.4 Technological Innovation

Finally, we examine whether technological innovation has an effect on the early-mover advantage. Throughout the birth and development of smartphones, their performance has seen significant changes, such as the launch of 4G technology and the evolution of the Android operating system. Hence, we are interested in identifying the conditions under which a late follower can wrest the early-mover advantage from established market leaders through innovation.

In particular, conditional on the order of a firm's entry into the smartphone market, we examine the impact of the order of a firm's adoption of new technology on market gains. In Columns (1) and (3) of Table 9, we observe that the order of entry into the market shows minimal significance, while doubling the adoption order of 4G technology correlates with a notable decline in subsequent market revenue by 7.47% (i.e., $2^{-0.112} - 1$) and market share by 7.47% (i.e., $2^{-0.112} - 1$). This suggests a strong positive association between early adoption of 4G technology and enhanced market performance, irrespective of entry timing. The shift from 3G to 4G signifies a substantial advancement in mobile network technology, delivering faster data speeds, reduced latency, and improved performance across various

[19]OPPO introduced Find 7, Neo, R1, N1, Joy, Find 5 mini, Find 7a, and Yoyo in Malaysia in the second quarter of 2014.

[20]Berger and Dick (2007) further illustrate this phenomenon by showing that large, geographically diversified banks can achieve market leadership relatively swiftly compared to smaller, locally-focused entrants.

Table 9: Extension Results of the Impact of Entry Order on Sales by Innovation Type

	Log of Market Sales		Log of Market Share	
	(1) 4G	(2) Android	(3) 4G	(4) Android
Log of entry order	0.011	-0.021***	0.005	-0.022***
	(0.009)	(0.008)	(0.009)	(0.008)
Log of innovation order	-0.112***	-0.134***	-0.112***	-0.135***
	(0.009)	(0.013)	(0.009)	(0.014)
Characteristics	Yes	Yes	Yes	Yes
Gravity variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Production FE	Yes	Yes	Yes	Yes
Destination-year FE	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	OLS
Observations	71,764	84,054	71,764	84,054
R^2	0.562	0.542	0.453	0.456

Notes: columns (1) and (3) examine the impact of the order of a firm's adoption of the 4G wireless network on a market share advantage for earlier entrants into the smartphone industry, and columns (2) and (4) explore the impact of the order of a firm's adoption of the Android operating system on a market share advantage for earlier entrants into the smartphone industry. In addition, product characteristics variables describe the operating system, signal mode, screen and display, camera function, chip, etc. Gravity variables are home, language, and log of weighted distance. Furthermore, we control for firm fixed effects, production-location fixed effects, and destination-year fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

applications. Notably, 4G networks utilize advanced LTE technology, enabling smoother HD video streaming and better performance for data-intensive tasks. Lower latency in 4G networks enhances user experiences, particularly for real-time applications like online gaming and video conferencing. Additionally, 4G networks facilitate simultaneous voice and data transmission, ensuring high-quality voice calls during data usage. As a result, the adoption of radical technologies such as 4G wireless networks appears to empower late entrants in the smartphone market, allowing them to leapfrog previously leading firms that did not invest in the technology promptly.

However, not every innovation enables late followers to leapfrog dominant firms. In Columns (2) and (4) of Table 9, we reveal that both the entry order and adoption order coefficients for the Android operating system are negatively significant at the 1% level. This suggests that adopting Android does not constitute the radical innovation needed to propel late entrants ahead of leading firms. Developed by Google, Android stands out from other mobile operating systems in several aspects. It offers tight integration with Google services, fostering seamless access to Google's ecosystem. Also, as an open-source platform, Android fosters innovation and offers a high degree of customization for both users and device manufacturers. However, alternative mobile operating systems also have their unique attributes; for instance, iOS is known for its user-friendly interface and robust security features, while Windows Phone featured a distinctive tile-based design and Microsoft service integration. Hence, the benefits of early adopting Android are relatively limited.

6 Conclusion

We use theory and data to explore the roles of the order of market entry in explaining cross-country market share variations and market revenue variations. The displacement of feature phones by smartphones between 2007 and 2016 provides an excellent opportunity to study this topic. We build on Head and Mayer (2019) and develop a theoretical framework that nests both early- and late-mover advantages. We apply sales data from 40 major smartphone markets, guided by the model's predictions, to estimate the impact of the order of a firm's entry on its subsequent market revenue and market share. Our baseline estimation implies that the earlier a firm enters, the better is its market performance relative to others. Precisely, doubling the order of a firm's entry in any market results in a 28.20% decrease in market revenue and a 29.34% decrease in market share. We then conduct a heterogeneity test to explore how the magnitude of the early-mover advantage differs across firm types. The empirical results suggest that firms originating from developed countries, offering higher-quality products, or having more-diversified product lines are better off entering markets earlier. Finally, we examine whether technological innovation affects the early-mover advantage and find that the adoption of some radical innovation, such as the 4G wireless network, might be capable of helping late entrants to leapfrog ahead of the formerly-leading firms that failed to invest in the same technology in time.

The relationship between order of entry and market outcomes has been of great interest to researchers for a long time. However, a few key questions still need to be answered due to data limitations. This study combined modern theories with novel data to critically explore the joint impact of the order of market entry on market performance in a growing industry. Meanwhile, this study complements the empirical literature on cross-country variations in the market performance of the same firm. Also, our analysis suggests that in exploring multi-period, multi-market entry decisions, it is critical to recognize that a firm's multi-market expansion strategy may lead to different orders of entry, ultimately thus leading to a different global market share and level of profitability.

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A Appendix

A.1 Robustness checks on product prices

Incorporating the parameterization into Equation (2) and taking a log of both sides of the Equation, the product price p_{ijln} is a function of entry order o_{jn}, smartphone characteristics x_{ik}, and gravity variables $Grav$:[21]

$$log(p_{ijln}) = CST^{(3)} + \beta_o^{(3)} log(o_{jn}) + \sum_k \beta_k^{(3)} log(x_{ik}) + Grav' \beta_{grav}^{(3)} + FE_j^{(3)} + FE_l^{(3)} + T_t + N(0, \eta\sigma_\varepsilon), \tag{14}$$

where the gravity term $Grav'\beta_{grav}^{(3)} = Grav'_{hl}\eta g + Grav'_{ln}\eta d + Grav'_{hn}\eta f$ captures the trade frictions among headquarters, manufacturing locations, and destinations. Besides, we also control for the firm fixed effect $FE_j^{(3)}$, production-location fixed effect $FE_l^{(3)}$, and year effect T_t.

Table A1 shows the 2SLS regression results of order of market entry on product prices. In particular, Columns (1)-(6) document the impact of the *historical* order of entry among both active and inactive firms in a particular market as the main explanatory variable, while Columns (7)-(12) explore the impact of *time-varying* order of market entry among only active firms. All the estimated results suggest that earlier entrants charge higher prices while late followers charge lower prices, *ceteris paribus.* In a scenario with constant markups, Table A1 further indicates there exists a late-mover advantage on the supply side where late followers pay lower production costs.

[21] The constant term $CST^{(3)}$ is given by $log(\frac{\eta}{\eta-1}) + \mu_\varepsilon$. The coefficient on the entry order o_{jn} satisfies $\beta_o^{(3)} = -\zeta$, and the coefficient on product characteristic x_{ik} satisfies $\beta_k^{(3)} = \frac{\alpha_k}{\theta}$. Moreover, we have $FE_j^{(3)} = -log(\varphi_j)$ and $FE_l^{(3)} = log(w_l)$.

Table A1: Robustness Checks of the Impact of Entry Order on Product Prices

	Historical order of entry						Time-varying order of entry					
Log of product prices	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log of entry order	-0.105***						-0.097***					
	(0.007)						(0.007)					
Entry order		-0.006***						-0.009***				
		(0.000)						(0.001)				
First entrant			1.137***						1.130***			
			(0.084)						(0.083)			
Earliest 3 entrants				1.056***						0.462***		
				(0.062)						(0.038)		
Earliest 5 entrants					0.702***						0.189***	
					(0.039)						(0.022)	
Earliest 10 entrants						0.146***						0.109***
						(0.018)						(0.014)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gravity variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Production FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576	98,576
R^2	0.841	0.846	0.708	0.731	0.800	0.845	0.844	0.846	0.710	0.825	0.844	0.845

Notes: the main explanatory variable, Entry Order, is the order of entry among all active and inactive firms in Columns (1)-(6); while it is the order of entry only among active firms in Columns (7)-(12). In addition, product characteristics variables describe the operating system, signal mode, screen and display, camera function, chip, etc. Gravity variables are home, language, and log of weighted distance. Instruments are measures of market competition at the time of a firm entry into a market. Furthermore, we control for firm fixed effects, production-location fixed effects, and year effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A.2 Robustness checks on order of entry

Table A2: Robustness Checks on Impact of Entry Order on Sales by Entry Category

	Log of Market Sales (Millions of USD)	Log of Market Share (%)
1st entrant	7.127***	7.008***
	(0.988)	(0.976)
2nd to 5th entrants	4.966***	5.180***
	(0.924)	(0.908)
6th to 10th entrants	-0.616**	-0.451
	(0.295)	(0.289)
11th to 15th entrants	-2.665***	-2.494***
	(0.533)	(0.526)
Characteristics	Yes	Yes
Gravity variables	Yes	Yes
Firm FE	Yes	Yes
Production FE	Yes	Yes
Destination-year FE	Yes	Yes
Estimation	2SLS	2SLS
Observations	98,576	98,576

Notes: firms are divided into five categories: the first, the 2nd-5th, the 6th-10th, the 11th-15th entrants, and others. The table shows that a market share advantage exists for early entrants, and early market leaders have even better market performance than market pioneers. The coefficients for the 6th-10th and the 11th-15th entrants are negative mainly because there are fewer than 15 entrants in most markets. In addition, product characteristics variables describe the operating system, signal mode, screen and display, camera function, chip, etc. Gravity variables are home, language, and log of weighted distance. Firm-market-specific instruments encompass measures of market competition, including the number of competing models, average CPU speed, average phone storage capacity, average screen size, and average CPU cores at the time of firm entry into a market. Furthermore, we control for firm fixed effects, production-location fixed effects, and destination-year fixed effects.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.