Social Network and Product Characteristics Design in the Chinese Kids Smartwatch Market*

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Abstract

Firms increasingly leverage proprietary social networks as a core product characteristic to entrench market power, yet empirical evidence on how these design choices shape competition remains scarce. We study this dynamic in the Chinese kids smartwatch market from 2015 to 2023, where brands developed unique chat apps fostering closed, exclusive networks. Our findings show that larger exclusive networks boost product sales and subsequently increase brand-level prices. In 2019, the entry of a third-party leading Chinese social networking platform –Tencent's QQ/WeChat – offered a natural experiment in cross-brand connectivity. Difference-in-differences analysis shows platform access raises prices by 5 percent with a limited effect on sales. A structural model disentangles exclusive and compatible networks, revealing consumers value both. Counterfactuals indicate full platform coverage requires massive subsidies ($4.4–$19.1 million) for minimal consumer surplus gains and negligible impact on XTC's dominance. However, bilateral alliances among rival brands can amplify platform effects indirectly, potentially eroding the leader's position over time. These findings highlight the potency of proprietary networks as competitive barriers and the practical challenges of using interoperability to discipline tipping markets.

Keywords: Network Effects, Product Characteristics, Tipping, Smartwatch

JEL Classification: L11, L14, L63

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1 Introduction

Firms increasingly embed social functionalities directly into product design to harness proprietary network effects.[1] Unlike traditional quality differentiation, these embedded network create self-reinforcing advantages: each additional user raises the value for the entire base, building a substantial competitive barrier that rivals cannot easily replicate through pricing or quality improvements alone. While this strategy is now central to global antitrust debates[2], there is limited empirical evidence on how these design choices fundamentally reshape the dynamics of market competition.

This paper studies (1) how firms strategically exploit proprietary social networks in product design and how this shapes market competition, and (2) whether rivals can share network effects through a compatible platform and tip the market in their favor.

We address the two research questions in the context of the Chinese kids smartwatch market using a market-level data over eight years from Q1 2015 to Q2 2023. One prominent feature of the Chinese kids smartwatch market is that each brand develops its unique chat application for the smartwatch, through which kids can add friends and chat. It induces a brand-exclusive or closed network among its consumers by preventing them from adding friends or chatting with users from other brands. Such closed networks grant firms a pricing advantage and accelerate the customer base growth. We first investigate the effect of network size on product sales and pricing. We begin with a reduced-form analysis that relates the price and sales of a product to the cumulative sales of products from the same brand with a chat app. Our findings suggest that the introduction of a larger social network size increases product sales and subsequent brand-level prices. Increasing the number of users by one standard deviation ($817.6*10^4$) would on average increase same-brand product price by 14.2 USD, 18 percent of the mean (79 USD).

[1] For example, AliPay integrates friend-adding into its payment interface; Peloton embeds leaderboards and live-ride communities directly into its bike hardware; Apple Watch enables activity-sharing competitions among friends. The practice extends well beyond products traditionally associated with social networking.

[2] Article 7 of European Union's Digital Markets Act (DMA) specifically mandates that gatekeeper platforms must allow rival messaging services to interoperate with their own. See: https://www.eu-digital-markets-act.com/Digital_Markets_Act_Article_7.html; China's ongoing platform regulation to bring interoperation between kids' smartwatches, see https://news.pconline.com.cn/2074/20745813.html.

The pioneer and dominant firm, Xiaotiancai (XTC), is the clearest example of this strategy's success. XTC's "knock and add" function became a social phenomenon in Chinese primary schools. By the end of 2018, XTC accounted for 24 percent of total unit sales. In an effort to challenge XTC's dominance, Tencent launched smartwatch-compatible versions of QQ in August 2019, offering rival brands a shared social platform. This platform expands the network accessible to participating products but also dilutes their own closed-network advantage. Using Tencent's launch as a quasi-experiment and a doubly robust difference-in-differences estimator, we find that platform access increases product prices by approximately 5 percent (4.5 USD), with no significant effect on unit sales. Yet XTC's share continued to rise, reaching 46 percent by 2023. To understand why interoperability failed to tip the market, we build and estimate a structural model of demand and supply that disentangles the two network channels, and explore possible remedies in the counterfactual.

Specifically, we build and estimate a structural model of consumer demand and firm decisions to join a compatible platform and set prices. On the demand side, consumers value not only product characteristics but also the number of users they can reach through both the brand-exclusive chat app and the compatible social app offered by the platform. On the supply side, firms play a two-stage game under complete information. In Stage 1, firms observe the full vector of product-specific fixed cost shocks and simultaneously choose which products to place on the platform. In Stage 2, given the platform configuration, firms observe demand and cost shocks and compete in prices. In addition to the standard endogeneity concerns for prices and the nonlinear parameters governing consumer heterogeneity, network sizes pose a further identification challenge: they are endogenous equilibrium objects, as market shares determine network sizes, which feed back into utility. We instrument for prices and the random coefficients using BLP-style instruments, and differentiation IVs (Gandhi and Houde, 2019). For the network sizes, we exploit lagged market structure as a source of exogenous variation, including characteristics of recently exited products and mean product characteristics from five quarters prior, which shift the predetermined component of network size without directly affecting current-quarter demand shocks.

We estimate demand using GMM, and marginal costs using a two-step procedure that incorporates the equilibrium conditions of the pricing game. Solving the pricing equilibrium is nonstandard in our setting: a price change alters market shares, which shifts network sizes, which feeds back into utility, requiring a double fixed point over prices and network sizes that we solve using a tiered Anderson Acceleration algorithm. The price coefficient is precisely estimated at -0.175, which implies reasonable price sensitivity. We find that consumers value both the exclusive network and the compatible network. An exclusive network of 1,000,000 users increases the mean utility of a brand's product by 8.58, comparable in magnitude to the effect of adding a 4G feature. This confirms the strong role of proprietary chat-app networks in driving brand-level demand. A compatible network of 1,000,000 users increases the mean utility of a brand's product by 10.15, suggesting that consumers value cross-brand social connectivity slightly more than same-brand social features. The marginal cost estimates are precisely estimated and are consistent with expectations. Adding functionalities such as a 4G feature, higher battery capacity, enabling waterproof, biometric sensor and better camera resolution will increase the marginal cost.

We estimate the fixed cost of joining the platform using moment inequalities based on necessary conditions for Nash equilibrium in the Stage 1 adoption game, following Eizenberg (2014) and Wollmann (2018). The fixed cost of joining the Tencent platform lies between 54,900 and 136,100 USD per product-quarter. This range rationalizes the staggered adoption pattern in the data, where firms weigh substantial integration costs against the benefits of expanded network effects. Notably, the fixed cost increased following Tencent's Q3 2021 release of WeChat Kids, with the lower bound rising from 36,400 USD in the early period to 92,400 USD thereafter, suggesting possible heightened compliance or engineering demands as the platform matured.

Finally, we conduct two counterfactual exercises. The first asks whether Tencent could have tipped the market by achieving full platform coverage at launch. We find that universal adoption in 2019Q3 would require Tencent to subsidize between \$4.4 million and \$19.1 million across all products, while generating only about \$330,000 in additional consumer surplus. Even under full coverage, XTC's profit declines by merely 0.04 percent. The conclusion is robust to timing: mandating full coverage two years earlier, when XTC's advantage was less entrenched, yields a larger proportional gain in consumer surplus, yet the required subsidy remains prohibitively large. The compatible network channel is simply too weak relative to integration costs to sustain universal interoperability.

The second counterfactual examines bilateral cross-brand alliances, motivated by the 2025 Xunkids–Huawei partnership that enabled mutual friend-adding across brands. We simulate short-run equilibria across every quarter from Q4 2018 to Q2 2023. The alliance yields a modest average profit gain of 0.10 percent for the partners, distributed asymmetrically between them, and a negligible 0.004 percent impact on XTC. However, the partnership generates an indirect effect. By drawing consumers to alliance products that are also on the Tencent platform, it expands the compatible network available to all platform members, and produces measurable consumer surplus gains. Moreover, these effects grow over time. As the combined network of the allies expands, the spillover to platform bystanders becomes more sizable, and the competitive pressure on XTC intensifies. Bilateral alliances alone cannot overturn the dominant firm's installed-base advantage, but as the market matures, they can meaningfully amplify platform network effects and begin to erode the leader's position.

This paper contributes to three strands of the literature. First, it contributes to the literature on network effects. The theoretical work begins with Katz and Shapiro (1985). They use a static Cournot model to show how firms can use incompatible networks to achieve market dominance. Later work attempts to investigate further implications of network effects in an oligopoly context. Farrell and Klemperer (2007) presents an excellent survey of this literature. Cabral (2011) considers both dynamic pricing strategies of firms and forward-looking consumers. He finds that larger networks generally set higher prices, but whether they achieve market dominance depends on the magnitude of the network effect. Chen et al. (2009) combines dynamic pricing with compatibility choices. They find that firms with similar installed bases make their products compatible to expand the market. The theoretical work generates testable results, but the related welfare implications depend on the size of the network effect, the competition among suppliers, and the heterogeneity of consumers.

The empirical literature on network effects can be traced back to Greenstein (1993), Gandal (1994), and Saloner and Shepard (1995). These papers evaluated the impact of network size in reduce-form equations. Rysman (2004) estimates consumer demand, advertiser demand, and the first-order condition of the yellow page publisher to internalize the network effect generated from the two-sided market. Most existing literature focuses on the indirect network effect between hardware and software. Dubé et al. (2010) provide an empirical measure of tipping based on dynamic pricing competition and forward-looking consumers. Corts and Lederman (2009) shows empirically that software non-exclusivity softens the competition in the home video game industry. However, Lee (2013) finds that exclusivity favored the entrant platforms in the home video game industry. Our work extends the empirical analysis to the direct network effect on the consumer base and examines the impact of compatibility choice in the smartwatch market.

Second, this paper is related to a growing literature on the study of equilibrium market outcomes and competition when firms choose more than one characteristic. Fan (2013) analyzes the effects of ownership consolidation in the newspaper industry and shows that ignoring the adjustments in newspaper quality results in substantial changes in the ex-post outcomes. Eizenberg (2014) studies how CPU choices lead to inefficiently eliminating basic personal computers and the related welfare impact. Wollmann (2018) shows the importance of allowing endogenous product offerings in the US commercial vehicle market to accurately measure the welfare effect of policy interventions. Our paper is closely related to Allende (2019) by introducing network effects in the standard endogenous product choice framework. Her paper studies the quality and price competition among schools where students sort under social interactions. Due to the strategic complementaries among consumers created by social interactions, the first-order condition of pricing is non-standard. It adds additional computation complexity because prices affect demand directly and affect the utility of products by affecting the demand. Existing empirical work focuses on the network effect among consumers within the same company (Dubé et al., 2010; Jenkins et al., 2021; Liu and Luo, 2023).

Our paper extends the model to a general setup where the network effect is shared among firms joining the same social platform. The generalization is computationally nontrivial and empirically relevant. Pricing strategy is more complicated because firms have to internalize that prices will additionally affect the relative position of products by affecting other products' demand. It is also naturally connected to the platform literature. The platform is often modeled as increasing the matching efficiency between the two sides of the market, pioneered by Caillaud and Jullien (2001, 2003), Rochet and Tirole (2003, 2006), and Armstrong (2006).

We provide a framework for analyzing the social function provided by the platform and how it interacts with the social function provided by the firm itself.

Finally, this paper relates to the literature on competition in the two-sided market. Caillaud and Jullien (2001, 2003) show that the market tips to one platform under homogeneous platform assumptions. Rochet and Tirole (2003, 2006), and Armstrong (2006) show that platform differentiation can prevent tipping from happening. The focus of these papers is on cross-group externalities between two sides of the market but not on competition between users within a group. Karle et al. (2020) shows that the correlation between product market competition and platform competition is negative. When product market competition is tough, sellers avoid competitors by choosing different platforms and thus creating differentiated platforms. It indicates that competition regulations on the platform should incorporate the competition among platform users. Our paper is one of the first few papers to extend the insights from the theoretical literature to an empirical setup. We utilize the structural demand estimation tools to allow rich consumer heterogeneity. We also carefully model the competition among the sellers who are multi-product firms and incorporate their platform choices. By building a tractable framework, we hope to measure the welfare impact of different platform fee arrangements.

This paper proceeds as follows. In Section 2, we introduce the industry background and describe the data. Section 3 presents reduced-form evidence on network effects and the impact of the Tencent platform. Section 4 sets up a structural model of consumer demand and a two-stage game of platform adoption and pricing. Section 5 describes the identification, estimation, and results for the demand, supply, and fixed cost parameters. Section 6 describes two counterfactual exercises. Section 7 concludes.

2 Industry Background and Data

2.1 Kids Smartwatch Industry in China

Resembling traditional wrist-worn watches, the smartwatch is a wearable device designed for human body with a microprocessor and can run third-party applications on the device itself. The Chinese kids smartwatch industry starts in 2015 and grows rapidly till 2019. Kids age between 5 and 12 are the main consumers. The phone call and geo-locating functions cater consumers' demand for kids safety. However, one salient feature is the social function that kids can add friends and chat with their friends through the watch. The social function emerges from Xiaotiancai (XTC), the leading firm in the industry and becomes one of the most important product characteristics for its market expansion. For example, XTC's "knock and add" – adding friends by knocking two watches – becomes trendy among primary school students and reports suggest that kids form different social circles by the watch brand and may feel social pressure without a XTC watch in school.[3] XTC keeps its dominant position in Q2 2023, followed by other major brands Huawei, Xiaomi and 360 as in Table 1.

In an attempt to break the dominance created by XTC's exclusive network, Tencent introduced a platform compatible with smartwatches powered by its leading social networking apps QQ and WeChat in August 2019. Smartwatch version Tencent apps offer the basic chat function, also allowing the "knock and add" function and payment code. It requires the smartwatch to meet certain standards, including the Android 6.0 version or above and at least 512 MB RAM. Firms can choose to install the Tencent app on their products. Prominent brands like Huawei, Xunkid, and Xiaomi have enabled their products to support smartwatch versions of QQ or WeChat. This move allows for friend-adding and chatting functionalities to no longer be brand exclusive. Interestingly, Tencent's apps are not allowed be installed on XTC products.

2.2 Data and Summary Statistics

Quarterly Kids Smartwatch Tracker The primary data is the market-level data from IDC Research covering all kids smartwatch sales in China between Q1 2015 and Q2 2023.[4] We observe quarterly sales, the average national price (ASP), brand, and product characteristics for each model. It captures sales from various channels from where the end users purchase new devices, including retail stores, telesales, vendor sales, and Internet etc.

[3]Beware of hidden comparisons and social circles in children's smartwatches. September 2022 https://finance.sina.cn/tech/2022-09-06/detail-imqmmtha6100787.d.html?fromtech=1&from=wap

[4]IDC specializes on data and analytics on ICT market. It becomes the top 1 data source in industry marketing analysis and media coverage in China in 2018 https://www.idc.com

Hand-Collected Device Attributes We supplement the IDC data with hand-collected data from the major online electronics listing and rating website: ZOL. For each model, we obtain a comprehensive set of attributes, including 4G connectivity, battery capacity, GPS locating levels, description of the social function, health monitoring, etc. In terms of social function, we observe whether they have a chat app (WeChat, QQ or brand-exclusive chat app).

Table 2 reports the product characteristics of kids smartwatches in the data. There are 223 smartwatches ever released during the sample period. The introductory price, on average, is 88.8 USD. 56.5 percent are operating through the Android system. In terms of connectivity, 82 percent watches are compatible with Wifi connection. 61 percent are compatible with 4G networks. 23.8 percent have GPS locating features inside buildings, while only 0.9 percent have advanced GPS ability to locate to floor level indoor. Most watches incorporate waterproof ability, with variations from the basic (12.1 percent), medium (82.1 percent) to advanced (5.4 percent) level.

In terms of the social function, 94 percent of watches have a built-in brand-exclusive chat app, while 34 percent of the products install Tencent chat apps (QQ or WeChat). In terms of health monitoring, 3.6 percent of smartwatches contain a sensor to detect ultraviolet (UV) radiation or biometric information, including heart rate and body temperature.

3 Reduced-Form Evidence

This section documents two sets of reduced-form findings that motivate our structural model. We first investigate the impact of network effects generated from brand-exclusive chat apps on pricing and sales. We then examine the impact of Tencent's open platform on products that gained access to compatible social functions.

3.1 Brand-Exclusive Network Effects

Each kids smartwatch brand can introduce its social function through a built-in chat application on its watch. The chat app induces direct and exclusive (or closed) network effects since users can only add friends and chat with users adopting the same brand. Thus, the chat app becomes a useful tool to build brand loyalty and accumulate user base. To show the impact of the brand exclusive chat app on consumers' demand for smartwatches and pricing, we regress the product sales and price on the lagged brand network sizes using the following model:

$$y_{jt} = \beta NS_{f(j),t-1} + \boldsymbol{X}_j + f_j + \lambda_t + \varepsilon_{jt} \tag{1}$$

where y_{jt} denotes the outcome variables log sales and price of product j in period t respectively, $NS_{f(j),t-1}$ is the lagged cumulative sales of same-brand products with chat function. $\boldsymbol{X}_j$ is a vector of product characteristics including operating system, cameras megapixels, whether compatible with wifi, 4G network connectivity, NFC and Bluetooth function, waterproof level, GPS level, and if contain any sensors (heart rate, skin temperature or UV sensor). To control for brand level unobserved characteristics, we include brand fixed effects f_j. To capture market seasonality, we also include year fixed effects and quarter fixed effects.

There is an endogeneity issue with the model above. On the one hand, there could be a correlation between prices and unobserved demand shocks, given that firms set prices with the knowledge of demand shocks. On the other hand, the lagged same-brand network size could be correlated with the unobserved shocks if the common demand shocks are serial correlated. We instrument the lagged network size with supply side factors reflecting the competition between firms and in the product characteristic space, including the number of products of the rival brands in the same quarter, number of products in the same brand in the same quarter, average characteristics of the products released in the same quarter by the same brand and by all brands according to (Berry et al., 1995), and differentiation IVs constructed from characteristics listed above according to (Gandhi and Houde, 2019).

Results Table 3 shows the reduced-form evidence for the network effects of brand exclusive chat app on sales and pricing. Columns 1 and 2 examine the effect of the closed network size on product prices using OLS and 2SLS respectively. Similarly, columns 3 and 4 show the effect of closed network size on product sales. It suggests that having an increase of 1,000,000 units in the cumulative sales of same-brand products with chat app would increase price by 1.7 USD (2 percent of mean 79 USD). Having one standard deviation increase (817.6*10^4) would on average increase same-brand product price by 18 percent (0.0174*817.6/79=14.2/79=18%). However, the network effect on sales remain positive but modest.

3.2 Impact of the Tencent Open Platform

In an effort to enter the kid's social market, Tencent launched the Kids Smartwatch version of its flagship products QQ in August 2019 and WeChat in August 2021. As we can see from Figure 1 and Figure 2, brands like Huawei, Xiaomi, and 360 are gradually adding more products to join this new compatible social platform. However, the penetration rate varies. Huawei gradually adds all its products to this open social network, while other players like Xiaomi and 360 only select a certain amount of products for this network. The adoption fraction is slightly higher if we look at the percentage of products joining the Tencent platform by revenue, indicating that more expensive products are more likely to join the platform.

However, the market leader XTC has not opened up third-party social apps such as WeChat or QQ to enter its ecosystem. Brands like Teemo, which joined the Tencent platform very aggressively, exited the market in Q4 2021. On the one hand, accessing the Tencent platform increases the social network size. On the other hand, firms lose market power from a closed network because social functions are more compatible. Therefore, we next check the effect of Tencent's launching the Kids Smartwatch version of its chat app on prices and sales.

We treat the launch as a quasi-natural experiment and only include products entering the market before Q3 2019 to allow a panel structure in our difference-in-differences setup. D_j denotes whether product j is treated or not. Since firms self-select to enter the platform, we also add the product characteristics X_j as controls to satisfy the conditional parallel trend assumption. By controlling X_j, we hope to compare "close" products facing a similar competition environment. Therefore, we construct a doubly robust DID estimator to estimate the treatment effect following Sant'Anna and Zhao (2020).

$$\tau = E[(\frac{D_j}{E(D_j)} - \frac{\frac{(1-D_j)p(X_j)}{1-p(X_j)}}{E[\frac{((1-D_j)p(X_j)}{1-p(X_j)}]})(Y_{j,2} - Y_{j,1} - E[Y_{j,2} - Y_{j,1}|D_j = 0, X_j]] \qquad (2)$$

where $p(X_j)$ is the propensity to join the platform, and we use X_j to predict the propensity. The propensity score method will generally be consistent for the average treatment effect on the treated (ATT), when $p(X_j)$ is correlated specified. $(Y_{j,2}-Y_{j,1}-E[Y_{j,2}-Y_{j,1}|D_j = 0, X_j]]$ is the regression approach to proxy the time trend using the control group. $E[Y_{j,2}-Y_{j,1}|D_j = 0, X_j]$ is to estimate the conditional expectation of the outcome among untreated units and then average these "predictions" using the empirical distribution of X_i among treated units. The outcome regression approach will generally be consistent for the ATT, when the outcome model used to estimate $E[Y_{j,2} - Y_{j,1}|D_j = 0, X_j]$ is correlated specified. DR methods will generally be consistent if either of these models is correctly specified.

Results Table 4 shows the treatment effect of Tencent chat app on products adopting the app in 2019Q3. The price for the treated group is 4.503 USD higher (5.7% of mean 79 USD). There is no significant effect on sales. We also use an event study to show the pre-trend and the dynamic effect on prices. In Figure 3, we plot the effects at quarters before and after the introduction of the Tencent platform. There is no pre-trend, as both the treated and control groups experienced similar time trends between Q1 2019 and Q2 2019. The introduction quarter has an immediate price response, and the effect disappears in the next quarter. Since we only consider products introduced before Q3 2019, the confidence band is becoming wider as more products exited the market from Q3 2019 on. As one can see from Figure 1, more products began to join the Tencent platform after Q3 2019. The result also indicates that as more products are joining the compatible platform, the competition within products on the same platform will drive down the prices and profits.

4 A Model of the Chinese Kids Smartwatch Market

The reduced-form evidence in the preceding section establishes the presence of network effects and documents how the open platform reshaped competition. We now develop a structural model that quantifies these forces and enables counterfactual analysis. The model has two key ingredients. On the demand side, a random-coefficient logit specification incorporates two distinct network channels: an exclusive within-firm network and a compatible cross-firm network mediated by the open platform. On the supply side, firms play a two-stage game in which they first choose which products to place on the platform and then compete in prices. The model primitives—consumer preferences, marginal costs, and platform adoption costs—are jointly identified from the observed market outcomes.

4.1 Consumer Demand

Following Berry et al. (1995) and Liu and Luo (2023), we model demand using a random-coefficient logit specification. In each quarter t, a set J_t of kids smartwatch products is offered. Each household chooses at most one product or the outside option, which comprises continuing to use an existing watch or purchasing a brand not in our dataset. The indirect utility that household i derives from product j in quarter t is:

$$\begin{aligned} u_{ijt} = {} & \text{Major}_{jt} \cdot \left(\boldsymbol{X}_{jt} \boldsymbol{\beta} + \tau_e N_{ft} + \tau_c ON_{jt} \right) \\ & + \text{Fringe}_{jt} \cdot \left(\kappa_0 + \kappa^{adv} Adv_{jt} + \kappa^t t \right) \\ & + \alpha p_{jt} + \nu_{i0} \beta_\nu^0 + \nu_{iF} \beta_\nu^C \text{Camera}_{jt} + \lambda_t + \xi_{jt} + \epsilon_{ijt} \end{aligned} \tag{3}$$

The vector $\boldsymbol{X}_{jt}$ contains product characteristics: camera megapixels, 4G connectivity, waterproof level, GPS level, and product age. We include year-quarter fixed effects λ_t to capture market seasonality.

The two network variables are central to our analysis. The *exclusive network* N_{ft} measures the number of consumers who purchase any product from firm f in quarter t; it captures the value of same-brand social connectivity through proprietary chat apps. The *compatible network* ON_{jt} measures the number of consumers purchasing products from *other* firms that have joined the open platform; it captures the cross-brand social connectivity enabled by the Tencent platform. Importantly, $ON_{jt} = 0$ for any product that has not joined the platform—only platform members gain access to the shared network. The parameters τ_e and τ_c govern the strength of the exclusive and compatible network effects, respectively.

The demand shock ξ_{jt} is unobserved by the econometrician and captures product-quarter-level unobservable quality. The idiosyncratic taste shock ϵ_{ijt} is i.i.d. Type I extreme value. We normalize the mean utility of the outside option to zero.

We allow for consumer heterogeneity through two channels. First, ν_{i0} is a random coefficient on the constant term, drawn from a normal distribution, which captures unobserved heterogeneity in the baseline preference for purchasing a smartwatch. Second, ν_{id} captures heterogeneous tastes over product characteristics. These random coefficients generate realistic substitution patterns that go beyond the restrictive independence-of-irrelevant-alternatives property of the plain logit.

The products in the "fringe" group—smaller brands that produce more homogeneous, lower-quality watches—enter utility with a separate specification. Fringe products are differentiated primarily through Adv_{jt}, a dummy variable indicating advanced features such as the health sensors, and a time trend that captures gradual quality improvements in this segment.

The model-predicted market share of product $j \in J_t$ is:

$$s_{jt} = \int \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{m \in J_t} \exp(\delta_{mt} + \mu_{imt})} \, dF_\nu(\nu_i) \, dF_d(Y_i) \tag{4}$$

where δ_{jt} collects all terms common across consumers and $\mu_{ijt} = \nu_{i0}\beta_\nu^0 + \nu_{iF}\beta_\nu^F \text{Fringe}_{jt}$ captures consumer-specific deviations.

A distinctive feature of our model is that shares, network sizes, and utility are jointly determined in equilibrium. Both N_{ft} and ON_{jt} depend on market shares, which in turn depend on network sizes through the utility function. Specifically, the exclusive and compatible network sizes must satisfy:

$$N_{ft} = \sum_{j \in J_{ft}} s_{jt}(\boldsymbol{\delta}_t, \boldsymbol{\mu}_t, \mathbf{N}_t, \mathbf{ON}_t) \cdot D_t \tag{5}$$

$$ON_{jt} = \left(\sum_{k \in O_t, k \notin J_{ft}} s_{kt}(\boldsymbol{\delta}_t, \boldsymbol{\mu}_t, \mathbf{N}_t, \mathbf{ON}_t) \right) \cdot D_t \tag{6}$$

where D_t is the total market size and O_t denotes the set of products on the platform. We require consumers to hold rational expectations: they correctly anticipate the equilibrium network sizes when making their purchase decisions. Equations (5)–(6) therefore define a fixed-point problem in the vectors $\mathbf{N}_t$ and $\mathbf{ON}_t$, which we solve via contraction mapping.

4.2 Supply

We assume that, in each quarter, each firm is endowed with a predetermined set of product lines. This assumption is justified by the long hardware development cycles in the smartwatch industry, where product design and manufacturing decisions are made well in advance of the sales quarter. The strategic interaction among firms is modeled as a two-stage game played in each quarter.

In Stage 1, all firms observe the complete vector of product-specific fixed cost shocks, including their own and their rivals', and simultaneously choose which products to place on the open platform. These fixed cost shocks are unobserved by the econometrician. In Stage 2, given the platform configuration determined in Stage 1, firms observe realizations of demand and marginal cost shocks and simultaneously set prices in Bertrand-Nash competition.

Let $\mathcal{F}$ denote the set of firms and J_{ft} the product portfolio of firm f in quarter t. For each product $j \in J_{ft}$, the firm chooses $d_{jt} \in \{0, 1\}$, where $d_{jt} = 1$ indicates that product j joins the platform. We denote firm f's vector of platform decisions as $\mathbf{d}_{ft} = (d_{jt})_{j \in J_{ft}}$ and the full market configuration as $\mathbf{d}_t = (\mathbf{d}_{ft})_f$.[5]

Stage 1: Platform adoption. At the beginning of Stage 1, firms observe the realization of product-specific fixed cost shocks. The fixed cost of placing product j on the platform in quarter t is:

$$FC_{jt} = F_f + \nu_{jt}, \quad E[\nu_{jt}] = 0 \tag{7}$$

where F_f is the baseline fixed cost for a given firm f, and ν_{jt} is a mean-zero product-specific shock. Following Draganska et al. (2009) and Eizenberg (2014), we impose additivity in the fixed costs across products within a firm, which avoids relying on functional form assumptions for identification.

Upon observing ν_{jt}, firms simultaneously choose their platform portfolios to maximize expected profits. At this stage, firms know the distribution of demand and cost shocks (ξ_t, ω_t)

[5]Platform adoption is an absorbing state: once a product joins, it remains on the platform in all subsequent quarters. Firms therefore make the adoption decision for each product only once.

but not their realizations, so the Stage 1 payoff is an expectation over Stage 2 outcomes:

$$\Pi_{ft}(\mathbf{d}_t) = \underbrace{\mathbb{E}_{(\xi,\omega)}\left[\sum_{j\in J_{ft}} (p^*_{jt}(\mathbf{d}_t) - mc_{jt}) \cdot s^*_{jt}(\mathbf{d}_t) \cdot D_t\right]}_{\text{Expected variable profit } \mathbb{E}[VP_{ft}(\mathbf{d}_t)]} - \sum_{j\in J_{ft}:d_{jt}=1} FC_{jt} \tag{8}$$

where $p^*_{jt}(\mathbf{d}_t)$ and $s^*_{jt}(\mathbf{d}_t)$ are the Stage 2 equilibrium prices and shares under platform configuration $\mathbf{d}_t$.

Stage 2: Pricing. Given the platform configuration $\mathbf{d}_t$ from Stage 1, firms observe the realized demand and cost shocks (ξ_t, ω_t) and simultaneously set prices to maximize variable profits:

$$\pi_{ft} = \sum_{j\in J_{ft}} (p_{jt} - mc_{jt}) \cdot s_{jt}(\mathbf{p}_t) \cdot D_t \tag{9}$$

We assume that, given any Stage 1 configuration, Stage 2 prices are determined by a pure-strategy, interior Nash-Bertrand equilibrium. The first-order condition for product j is:

$$s_{jt} + \sum_{k\in J_{ft}} \frac{ds_{kt}}{dp_{jt}}(p_{kt} - mc_{kt}) = 0 \tag{10}$$

The presence of network effects means that $\frac{ds_{kt}}{dp_{jt}}$ is not the standard partial derivative holding all else fixed. When firm f raises the price of product j, some consumers switch away, which reduces firm f's exclusive network N_{ft} and potentially the compatible network ON_{jt}. These network changes feed back into the utility of all products in the market, further shifting demand. Moreover, because the demand system features random coefficients, the total derivative must be derived at the individual consumer level and then integrated over the consumer distribution. By the chain rule, for each consumer type i:

$$\frac{ds_{ijt}}{dp_{kt}} = \sum_{m\in J_t} \frac{\partial s_{ijt}}{\partial u_{imt}} \cdot \frac{du_{imt}}{dp_{kt}} \tag{11}$$

where utility derivative $\frac{d\mathbf{u}_{imt}}{d\mathbf{p}_{kt}}$ captures how a price change propagates through three channels:

$$\frac{du_{imt}}{dp_{kt}} = \underbrace{\mathbf{1}_{[m=k]} \cdot \alpha}_{\text{direct price}} + \underbrace{\tau_e D_t \sum_{n \in J_{f(m)t}} \frac{ds_{int}}{dp_{kt}}}_{\text{exclusive network}} + \underbrace{\tau_c D_t \sum_{\ell \in O_t \setminus J_{f(m)t}} \frac{ds_{i\ell t}}{dp_{kt}}}_{\text{compatible network}} \tag{12}$$

The first term is the direct price effect: only product $m = k$ is affected. The second is the exclusive network feedback: a price increase for product k reduces same-firm sales, shrinking the exclusive network $N_{f(m)t}$ and lowering utility for all of the firm's products. The third is the compatible network feedback: changes in platform members' sales alter the shared network ON_{mt} available to other members. Because the total derivative $\frac{ds_{int}}{dp_{kt}}$ appears on both sides, equations (26)–(12) define an implicit system that must be solved via the implicit function theorem for each consumer type, and then integrated over the distribution of (ν_{i0}, ν_{iC}) to obtain the aggregate $\frac{d\mathbf{s}_t}{d\mathbf{p}_t}$. The full derivation and matrix formulation are provided in Appendix A.

Solution concept. The Stage 1 game is played under complete information: all firms observe the full vector of fixed cost shocks before choosing their platform portfolios simultaneously. The equilibrium concept is Subgame Perfect Nash Equilibrium (SPNE) in pure strategies. An SPNE consists of platform adoption decisions $\mathbf{d}^*$ and a pricing function $\mathbf{p}^*(\mathbf{d})$ such that: (i) for every possible Stage 1 configuration $\mathbf{d}$, prices $\mathbf{p}^*(\mathbf{d})$ constitute a Nash-Bertrand equilibrium; and (ii) each firm's platform portfolio maximizes its expected profit given the equilibrium pricing rule and other firms' adoption choices.

5 Estimation, Identification, and Results

The model is estimated in two steps, working backward from the equilibrium structure. We first estimate the demand parameters and recover marginal costs from the Stage 2 pricing game. We then use the estimated primitives to recover the fixed cost of platform adoption from Stage 1 revealed preference inequalities. We present results alongside each estimation step.

5.1 Demand Estimation

We estimate the demand system using the generalized method of moments (GMM) framework of Berry et al. (1995). The mean utility δ_{jt} is recovered by inverting the market share equation, and the demand parameters are identified from the orthogonality conditions $E[\xi_{jt}|\mathbf{z}_{jt}] = 0$, where $\mathbf{z}_{jt}$ are instruments.

A key challenge in our setting is that both the exclusive network size N_{ft} and the compatible network size ON_{jt} are endogenous. They are equilibrium outcomes that depend on all products' characteristics, prices, and demand shocks. Prices are also endogenous, as they are correlated with the demand shock ξ_{jt} through standard channels. We construct two sets of instrumental variables to address these concerns.

The first set of instruments for price. Following the BLP approach, we use the number of own-firm and rival products offered in the same quarter, mean own-firm characteristics at product release (leave-one-out), and mean rival characteristics at release. We supplement these with differentiation-based instruments (Gandhi and Houde, 2019), computed as the sum of squared distances between product j's characteristics and those of other own-firm or rival products. Finally, we include a predicted price from a hedonic cost regression of price on hardware attributes, which provides a supply-side shifter.

The second set instruments for the network sizes. Because network sizes are determined by equilibrium market shares, we exploit lagged market structure as a source of exogenous variation. Specifically, we use the mean characteristics of products that exited the market in the preceding one to four quarters (with imputation for quarters with no exits), the mean own-brand and market-wide product characteristics from five quarters prior, and the differentiation-based instruments computed from the five-quarter-lagged product landscape. These lagged instruments shift the predetermined component of the network size without directly affecting current-quarter demand shocks.

The potential market size D_t in each quarter is the number of children aged 5–14 in China, obtained from national population statistics. Given that the smartwatch penetration rate among this demographic is approximately 30% based on industry reports[6], we adjust the raw

[6] Report of Market Prospective and Investment Strategy Planning On China Wearable device Industry (2016-2018). See: https://bg.qianzhan.com/report/detail/458/180719-f16ebd64.html

population to reflect the plausible set of purchasers. However, not all children are equally likely to enter the market. Using data from the UNICEF 2020 report on China's child population[7], which tabulates children by residency status from the 2020 national census, we exclude rural left-behind and migrant children, as these groups exhibit low purchase likelihood across both online and offline channels due to structural constraints. These groups account for 37.9% of all children aged 0–17, leading us to define the relevant market size as $D_t = \text{Pop}_{5\text{-}14,t} \times (1 - 0.379)$. The outside option in each quarter thus represents households with an age-eligible child who, despite being part of this adjusted market, do not purchase any smartwatch product recorded in our dataset.

The outside option in each quarter represents households with an age-eligible child who purchase through the online channel but do not buy any product in our dataset.

The empirical specification for the mean utility follows the model in equation (3). We implement the estimator using the PyBLP package (Conlon and Gortmaker, 2020). The demand system is estimated via two-step GMM with a 2SLS weight matrix in the first step. Starting values for the nonlinear parameters are drawn from a grid search over combinations of initial (σ_0, σ_F) values to guard against local optima.

Demand results. Table 5 reports the demand estimation results. The price coefficient is -0.175, precisely estimated and implies moderate price sensitivity, consistent with a market where most products retail for 200–1,000 CNY.

The exclusive network coefficient $\hat{\tau}_e = 8.58 \times 10^{-6}$ is positive and statistically significant at the 1% level. The magnitude implies that an exclusive network of 1,000,000 users increases the mean utility of a brand's product by 8.58, comparable in magnitude to the effect of adding a 4G feature ($\hat{\beta_{4G}} = 8.44$). This confirms the strong role of proprietary chat-app networks in driving brand-level demand.

The compatible network coefficient $\hat{\tau}_c = 10.15 \times 10^{-6}$ is precisely estimated and slightly larger than $\hat{\tau}_e$. This suggests that consumers value both the cross-brand social connectivity provided by the Tencent platform and same-brand social features.

Among the product attributes, 4G cellular connectivity (8.44) is the most valued feature,

[7]What the 2020 Census Can Tell Us About Children in China: Facts and Figures. See: https://www.stats.gov.cn/zs/tjwh/tjkw/tjzl/202304/P020230419425670560273.pdf

followed by multi-satellite GPS (5.02), and waterproof (4.92). This suggests that consumers value the function to call and location monitoring for kids' safety. The coefficient on camera resolution is negative, together with a positive random coefficient, suggesting consumers' heterogeneous preferences towards the camera function. The quarters-since-release is not statistically different from zero. Among fringe products, the baseline shift $\hat{\kappa}_0 = -1.69$ indicates that fringe brands have substantially lower mean utility than major brands after controlling for observables, while the positive coefficient on their interaction with the advanced dummy $\hat{\kappa}^{Adv} = 13.14$ suggests a higher value attached with advanced features.

The random coefficient on the constant $\hat{\sigma}_0 = 5.16$ is large and precisely estimated, indicating substantial heterogeneity in the baseline propensity to purchase a smartwatch.

5.2 Marginal Cost Recovery

Given the demand estimates, we recover marginal costs from the Stage 2 first-order conditions. The total derivative of shares with respect to prices accounts for both the direct price effect and the indirect feedback through network sizes (see Appendix A for the full derivation and matrix formulation). Given the total derivative matrix $\frac{d\mathbf{s}_t}{d\mathbf{p}_t}'$ and the ownership structure $\mathbf{\Omega}_{\text{own}}$, the implied marginal costs are:

$$\mathbf{s}_t + \left(\frac{d\mathbf{s}_t}{d\mathbf{p}_t}' \odot \mathbf{\Omega}_{\text{own}} \right) (\mathbf{p}_t - \mathbf{mc}_t) = 0$$

We then estimate a log-linear marginal cost function:

$$\ln mc_{jt} = \mathbf{X}_{jt}^{mc} \boldsymbol{\gamma} + \eta_f + \eta_t + \omega_{jt} \tag{13}$$

where $\mathbf{X}_{jt}^{mc}$ includes sensor type, camera megapixels, 4G capability, waterproof level, and battery capacity; η_f are firm fixed effects; η_t are quarter fixed effects; and ω_{jt} captures unobserved cost factors. We estimate equation (13) by OLS. Because the cost shifters $\mathbf{X}_{jt}^{mc}$ are hardware design choices determined well before the sales quarter—typically during the product development cycle 6–12 months prior—they are plausibly predetermined with respect to the contemporaneous cost shock ω_{jt}. The firm and quarter fixed effects absorb persistent cost differences across manufacturers and common cost trends such as declining component prices over time.

Marginal cost results. Table 6 shows the results of marginal cost estimates. The coefficients are precisely estimated and suggest that adding functionalities increase the marginal cost. The leading cost component is the 4G feature. Enabling 4G connectivity would increase marginal cost by approximately 80 percent ($e^{0.587} - 1$). Increasing battery capacity by 1 mAh would increase cost by 43 percent ($e^{0.356} - 1$), followed by the waterproof ability which increases the marginal cost by 41 percent ($e^{0.342} - 1$). Improving the resolution of sensor and camera by 1 megapixel generate an increase of 34 and 15 percent, respectively.

5.3 Fixed Cost of Platform Adoption

The fixed cost of platform adoption is identified from revealed preference inequalities, following the methodology of Eizenberg (2014) and Wollmann (2018). The key identification idea is that the observed platform adoption decisions—which products each firm places on the platform and which it keeps off—reveal bounds on the fixed cost through local deviations.

For each product j that stays off the platform ($d_{jt} = 0$), the firm's decision reveals that the fixed cost exceeds the variable profit gain from adding j:

$$FC_j \geq \Delta\pi_{ft}^{+j} \equiv VP_{ft}(\mathbf{d}_{ft}^{+j}, \mathbf{d}_{-f,t}) - VP_{ft}(\mathbf{d}_{ft}, \mathbf{d}_{-f,t}) \tag{14}$$

For each product j that joins the platform ($d_{jt} = 1$), the profit gain from keeping j on must exceed the fixed cost:

$$\Delta\pi_{ft}^{-j} \equiv VP_{ft}(\mathbf{d}_{ft}, \mathbf{d}_{-f,t}) - VP_{ft}(\mathbf{d}_{ft}^{-j}, \mathbf{d}_{-f,t}) \geq FC_j \tag{15}$$

Computing $\Delta\pi_{ft}^{+j}$ requires re-solving the Stage 2 Bertrand-Nash pricing equilibrium under the counterfactual platform configuration. Because both the baseline and counterfactual equilibria depend on demand and cost shocks (ξ_t, ω_t) that the firm observes but the econometrician does not, we integrate over the shock distribution using paired Monte Carlo simulation with $S = 1000$ draws. The shocks are drawn from the empirical distribution using firm-level resampling to preserve within-firm correlation. Pricing equilibria are solved using a tiered Anderson Acceleration algorithm (Anderson, 1965; Walker and Ni, 2011). Details of the simulation and equilibrium computation procedures are provided in Appendices B and C.

We exclude XTC from the Stage 1 estimation and treat its platform status as a fixed feature of the environment. XTC is the dominant firm and never places any product on the open platform, so it only generates uninformative one-sided bounds. Its products remain in the Stage 2 pricing game, where they affect equilibrium outcomes through the exclusive network channel.

We parameterize the fixed cost as:

$$FC_{jt} = \gamma_0 + \gamma_{\text{post}} \cdot \mathbf{1}[t \geq 2021\text{Q3}] + \nu_{jt}, \quad E[\nu_{jt}] = 0 \tag{16}$$

where γ_0 is the baseline fixed cost, and γ_{post} captures the change in fixed cost after Tencent's release of the WeChat Kids version in 2021Q3. The time split is motivated by the fact that WeChat Kids substantially expanded the platform's value proposition, potentially changing the effective cost or subsidy for adoption.

Under a bounded support assumption on the idiosyncratic shock ν_{jt} (Eizenberg, 2014), taking unconditional sample averages of the inequalities eliminates the selection bias from conditioning on observed decisions, yielding:

$$\underbrace{\frac{1}{|\mathcal{S}^1|} \sum_{(j,t)\in\mathcal{S}^1} \Delta\pi_{ft}^{-j}}_{\text{avg } \Delta\pi \text{ of joiners}} \;\leq\; \gamma_0 \;\leq\; \underbrace{\frac{1}{|\mathcal{S}^0|} \sum_{(j,t)\in\mathcal{S}^0} \Delta\pi_{ft}^{+j}}_{\text{avg } \Delta\pi \text{ of stayers-off}} \tag{17}$$

where $\mathcal{S}^1$ is the set of joiner product-quarters and $\mathcal{S}^0$ is the set of stayer-off product-quarters. The lower bound reflects that joiners' profit gains must on average exceed the fixed cost, while the upper bound reflects that stayers-off's profit gains must on average fall below it. For formal inference, we will construct confidence sets using the modified method of moments criterion of Chernozhukov et al. (2007) with generalized moment selection following Andrews and Soares (2010).

Fixed cost results. Table 7 presents the estimated bounds on the fixed cost of platform adoption. We report results pooled across all post-launch quarters as well as separately for the early period (2019Q3–2021Q2, before WeChat Kids) and the late period (2021Q3–2023Q2, after WeChat Kids). All estimates restrict to simulation draws for which the pricing equilibrium converged, as non-converging draws can produce extreme profit values that distort the bounds.[8]

The pooled estimates place the fixed cost in the interval $\gamma_0 \in [5.49, 13.61]$ (in units of 10,000 USD), implying that a firm must earn between approximately 55,000 and 136,000 USD in additional variable profit per product-quarter to justify joining the platform. This range is economically plausible: it is large enough to rationalize the substantial number of firms that remain off the platform, yet small enough to explain why most branded firms eventually adopt.

The early-period bounds are relatively tight at $\gamma_0 \in [3.64, 8.47]$, reflecting a moderate adoption cost during the platform's initial growth phase. In the late period, the bounds shift upward to $\gamma_0 + \gamma_{\text{post}} \in [9.24, 27.02]$. Notably, the late-period lower bound (9.24) exceeds the early-period upper bound (8.47), so the two intervals do not overlap. It provides strong evidence that fixed costs increased after the WeChat Kids version launch. This finding is consistent with several complementary mechanisms. First, Tencent may have raised integration standards and compliance requirements as the platform matured and attracted regulatory scrutiny in the children's technology space. Second, compatibility with the WeChat Kids ecosystem likely demanded additional engineering investment, which were not required in the early period. Third, the increased prominence of the platform may have strengthened Tencent's bargaining position, enabling it to extract higher fees or impose more stringent technical requirements on prospective adopters.

As a robustness check, we exclude two Huawei products (IDs 36 and 37) that may face strategic or hardware constraints, which prevent them from running Tencent's platform applications. These products are mechanically constrained stayers-off whose large positive $\Delta\pi$ values reflect the demand they *would* gain from adoption, potentially biasing the lower

[8] Across all deviations, the average convergence rate is 92.2%. Results using all simulation draws (including non-converged) yield qualitatively similar pooled and early-period bounds but produce empty identified sets in the late period, where the smaller number of observations amplifies the influence of outlier draws.

bound upward. Excluding them has minimal effect: the pooled bounds shift to $[5.17, 13.61]$, and the early-period bounds to $[3.44, 8.47]$. All qualitative conclusions are preserved, and the lower bound of γ_{post} remains positive, confirming that the increase in fixed costs is not driven by these hardware-constrained products.

6 Counterfactual Exercises

6.1 Full Coverage at Platform Launch

Our first counterfactual asks: what would have happened if Tencent had achieved full platform coverage when it launched the open platform in 2019Q3? Specifically, we examine a scenario where *all* non-XTC, non-fringe products join the platform simultaneously at launch, rather than the gradual adoption observed in the data.

This counterfactual is motivated by the observation that platform adoption in the data is staggered, firms gradually add products over multiple quarters. The staggered adoption may reflect coordination failures, information frictions, or strategic delay. Full immediate coverage would maximize the platform's network effects from the start, potentially generating a strong enough network to tip the market.

To evaluate whether full coverage is a Nash equilibrium, we perform the following check. Let $\mathbf{d}^{\text{full}}$ denote the configuration where all eligible products are on the platform. We solve the Stage 2 pricing equilibrium under $\mathbf{d}^{\text{full}}$ to obtain $VP_{ft}(\mathbf{d}^{\text{full}})$ for each firm f. We then check, for each firm f, whether unilateral deviation is profitable: we toggle each of firm f's products off the platform one at a time, re-solve the pricing equilibrium, and compute:

$$\Delta\pi_f^{\text{full}}(j) = VP_{ft}(\mathbf{d}^{\text{full}}) - VP_{ft}(\mathbf{d}^{\text{full},-j})$$

If $\Delta\pi_f^{\text{full}}(j) \geq FC_j$ for all products j and all firms f, then no firm has an incentive to deviate from full coverage, confirming it as a Nash equilibrium. This check uses the fixed cost estimates from Section 5.3 to assess whether the variable profit gain from staying on the platform exceeds the adoption cost for each product.

We compare the full-coverage equilibrium with the observed baseline along several dimensions: equilibrium prices, market shares, firm-level variable profits, and consumer surplus. Consumer surplus is computed using the standard log-sum formula:

$$CS_t = \frac{-1}{\alpha} \cdot \frac{1}{K} \sum_{i=1}^{K} \ln \left(1 + \sum_{j \in J_t} \exp(\delta_{jt} + \mu_{ijt}) \right) \cdot D_t$$

where α is the price coefficient and K is the number of simulation draws for demographic integration.

Results. Table 8 presents the results for two timing scenarios: Q11 (2017Q3), two years before the platform launched, and Q19 (2019Q3), the actual launch quarter. Comparing the two periods illuminates how the timing of intervention interacts with the market's competitive structure.

Panel A reports aggregate market outcomes. Full coverage generates a consumer surplus gain of 0.60 percent at Q3 2017 and 0.27 percent at Q3 2019. The relative effect is more than twice as large in the earlier period, when XTC's exclusive network was less entrenched. In both cases, total units and average prices change only slightly: the compatible network effect shifts consumer welfare primarily through the utility channel rather than through quantity or price adjustments.

Panel B reports firm-level variable profit changes at both dates. XTC loses in both periods: -1.44 at Q3 2017 (-0.13%) and -1.18 at Q3 2019 (-0.04%). The percentage loss is larger at 2017, when XTC's network advantage was smaller and thus more vulnerable to competitive erosion from universal interoperability. Notably, Firm 360 switches from losing at 2017 (-0.10) to gaining at 2019($+0.96$), reflecting how the distribution of winners and losers depends on the market structure at the time of intervention. Xiaomi loses consistently at both dates, suggesting its competitive position is structurally disadvantaged by broader platform participation.

Panel C quantifies the subsidy Tencent would need to sustain full coverage. For each product j, the required subsidy is $\max\{0, FC_j - \Delta\pi_j^{\text{full}}\}$, where $\Delta\pi_j^{\text{full}}$ is the incremental variable profit from staying on the platform under full coverage. At Q3 2019, every single product's $\Delta\pi^{\text{full}}$ falls far below the estimated fixed cost of $[5.49, 13.61]$ (in 10,000 USD,

Table 7). The largest per-product gain is only 0.38 (in 10,000 USD), an order of magnitude below even the lower FC bound.

These results carry a clear policy implication. The compatible network channel (τ_c) is fundamentally too weak to sustain universal interoperability. The per-product value of joining the platform, even when all other firms are already on it, is an order of magnitude below the integration cost, and this conclusion is robust to timing. Earlier intervention at 2017 produces a larger relative CS gain, but the subsidy requirement remains prohibitive. This is not a coordination failure that targeted subsidies could efficiently resolve. The staggered adoption pattern observed in the data reflects a rational response to the limited value of cross-brand connectivity in the early stage.

6.2 Cross-Brand Interoperability

The first counterfactual established that platform-mediated interoperability through the compatible network channel (τ_c) is too weak to sustain universal coverage or justify the integration costs. A natural follow-up question is whether interoperability through the *exclusive* network channel (τ_e) can achieve what the platform could not. Our second counterfactual examines exactly this possibility: a bilateral partnership between Xunkids and Huawei that produced the first cross-brand friend-adding capability.[9]

We model this bilateral interoperability as coexisting with any existing Tencent platform membership, rather than replacing it. The rationale is that the partnership and the platform operate through technically distinct channels: the alliance extends the proprietary chat system (friend-adding via device-to-device "knock-and-add"), while the Tencent platform provides a separate app-based communication layer. A Xunkids product that is both in the alliance and on the platform can therefore access its partner's user base through τ_e and other platform members' user bases through τ_c simultaneously. Modeling the alliance as replacing platform links would amount to downgrading those connections, since the cross-brand communication enabled by the partnership is functionally equivalent to the within-

[9]The original new states that the Xunkids M7 and Huawei Kids Watch 5 Pro are the first models supporting cross-brand friend-adding, allowing watches from two different brands to add friends via a "bump-to-add" gesture.

brand chat experience. XTC's exclusive network remains intact throughout, the partnership does not force XTC to open up.

A key subtlety arises in the supply-side implications of the partnership. The expanded exclusive network enters the total derivative of shares with respect to prices through the implicit function theorem: when a Xunkids product changes its price, the resulting shift in market shares now feeds back through the partner's network as well, altering demand for both Xunkids and Huawei products. However, the two firms continue to set prices independently to maximize their own profits as the partnership does not extend to pricing coordination. We implement this distinction by using the expanded ownership matrix $\boldsymbol{\Omega}_{\text{network}}$ (which includes cross-firm links between Xunkids and Huawei) for the network feedback in the total derivative, while retaining the original ownership matrix $\boldsymbol{\Omega}_{\text{own}}$ for the pricing markup. Therefore we update equation 12 in the following way:

$$\frac{d\mathbf{u}}{d\mathbf{p}} = \alpha\mathbf{I} + \left(\boldsymbol{\Omega}_{\text{own}} \odot \tau_e D_t \cdot \mathbf{1}_N\right)\frac{d\mathbf{s}}{d\mathbf{p}} + \left(\boldsymbol{\Omega}_{\text{alliance}} \odot \tau_e D_t \cdot \mathbf{1}_N\right)\frac{d\mathbf{s}}{d\mathbf{p}} + \left(\boldsymbol{\Omega}_{\text{plat}} \odot \tau_c D_t \cdot \mathbf{1}_{ON}\right)\frac{d\mathbf{s}}{d\mathbf{p}}$$

where $\boldsymbol{\Omega}_{\text{alliance}}$ has entries equal to one for cross-firm pairs between Xunkids and Huawei. All three network channels enter the implicit function theorem that determines the equilibrium total derivative $d\mathbf{s}/d\mathbf{p}$, but only $\boldsymbol{\Omega}_{\text{own}}$ enters the first-order condition for pricing:

$$\mathbf{s} + \left(\boldsymbol{\Omega}_{\text{own}} \odot \frac{d\mathbf{s}}{d\mathbf{p}}\right)'(\mathbf{p} - \mathbf{mc}) = \mathbf{0}$$

This formulation captures the economic content of the partnership: consumers benefit from a larger network when calling friends across brands, but firms do not internalize the externality their pricing decisions impose on their partner's profits.

The Xunkids–Huawei partnership counterfactual is attractive for several reasons. It reflects an actual market development rather than a hypothetical regulatory mandate, making the results directly policy-relevant. It also isolates the effect of bilateral interoperability, allowing us to ask whether a targeted partnership between two mid-sized firms can generate sufficient network scale to meaningfully compete with XTC's dominant exclusive network. Moreover, because the partnership does not require the Tencent platform, there is no fixed cost of adoption. The interoperability is achieved through a direct technical agreement between the two firms.

We note that this exercise captures the short-run equilibrium effect of the partnership, holding firms' platform adoption decisions fixed at their observed values. In the long run, the altered competitive landscape could induce some firms to change their platform participation. For instance, if the alliance erodes the returns to platform membership for bystander firms, or if it increases the incentive for additional bilateral agreements, firms would reoptimize their plafform joining decision. Enriching the model to endogenize such responses is a natural extension that we leave for future work.[10]

Results. We evaluate the partnership by simulating the counterfactual equilibrium in each quarter from Q4 2018 through Q2 2023, spanning both the pre- and post-WeChat Kids periods. Figure 4 reports the percentage change in variable profit, market share, average price, and consumer surplus relative to the observed baseline.

The results reveal several findings. First, the combined Xunkids–Huawei entity experiences a modest average profit gain of 0.10 percent across all quarters. However, this gain is distributed asymmetrically across the two partners: the direction and magnitude of profit changes differ between Xunkids and Huawei in most quarters, reflecting the fact that the alliance alters the competitive position of each firm's product portfolio differently. Because the two firms differ in their number of products, price points, and position relative to other competitors, the additional network value from the partnership translates unevenly into demand and profit gains. This asymmetry suggests that bilateral network agreements may involve non-trivial distributional negotiations between the partners.

Second, XTC's average profit change across all quarters is 0.004 percent, with the sign varying by quarter. In some periods XTC loses slightly as the alliance draws away marginal consumers, while in others XTC gains as the competitive reshuffling increases overall market activity. The modest magnitude of these effects reflects two reinforcing forces: the combined Xunkids–Huawei exclusive network, even after the partnership, remains smaller than XTC's installed base, and the exclusive network coefficient τ_e limits how much additional network

[10] Because the fixed cost parameters are only partially identified (as intervals rather than point estimates), we follow Eizenberg (2014) and work with the set of *potential equilibria*. We focus on configurations that cannot be ruled out as a pure-strategy NE given the estimated fixed cost bounds.

value the alliance can generate. The partnership shifts the competitive landscape, but not enough to erode XTC's accumulated network advantage.

Third, the effects differ between the pre- and post-platform periods. Before the introduction of WeChat Kids, the partnership generated an average consumer surplus change of approximately zero, as the exclusive-channel gains are small and partially offset by competitive reallocation. After WeChat Kids launches, the average consumer surplus change rises, especially towards the end of the sample period. The mechanism behind this shift is an indirect platform spillover: as the partnership draws additional consumers to Xunkids and Huawei products, total enrollment on the Tencent platform increases, which expands the compatible network ON_{jt} for all platform members through the coefficient τ_c. In this sense, the bilateral partnership generates a positive externality for platform bystanders, firms that are on the platform but not party to the alliance.

7 Conclusion

This paper studies how firms strategically use social network features in the Chinese kids smartwatch market and examines the implications for platform competition and market tipping. We find significant exclusive network effects that grant the dominant firm XTC a substantial pricing advantage. The introduction of Tencent's open platform provides an alternative channel for smaller firms to access shared network effects, though the staggered adoption pattern suggests non-trivial costs of platform integration.

Using a structural model of demand with network effects and a two-stage game of platform adoption and pricing, we estimate the fixed cost of platform adoption via moment inequalities based on revealed preference. Our counterfactual exercises evaluate two platform policies. The first examines whether Tencent could have achieved full platform coverage at launch by subsidizing adoption, quantifying the cost of accelerating network growth and the potential for market tipping. The second evaluates cross-brand interoperability of two top brands, assessing whether such openness could break the dominant firm's network advantage and improve consumer welfare.

While immediate adoption could accelerate the compatible network growth, eroding the market leader XTC's profits, it sustains at a high cost of subsidy. In contrast, the Xunkids-Huawei partnership yields modest but asymmetric profit gains for the allies, minimal impact on the market leader XTC, and increasing consumer surplus post-WeChat Kids launch, driven by indirect spillovers to platform bystanders.

These findings contribute to the growing literature on platform competition and network effects by providing one of the first empirical analyses of how firms' compatibility choices interact with direct network effects in a consumer electronics market. The framework and results have implications for competition policy in markets where proprietary social networks create competitive barriers.

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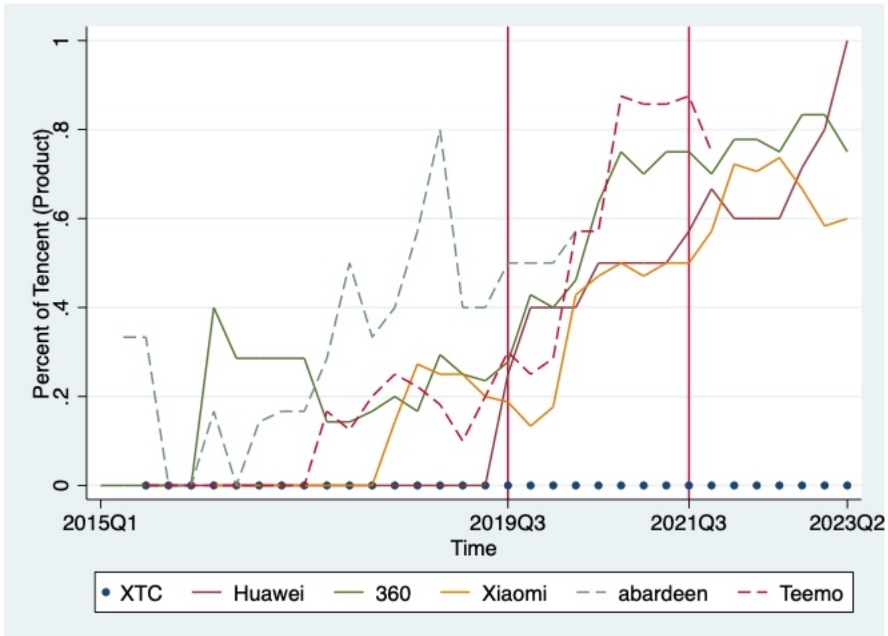
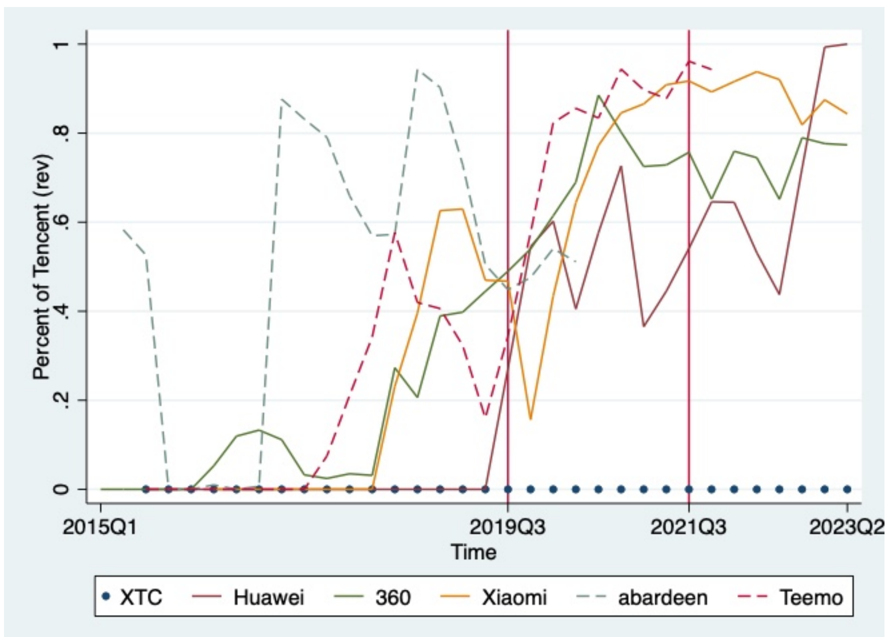
Figure 1: Percent of Products Joining Tencent Platform (by Product)



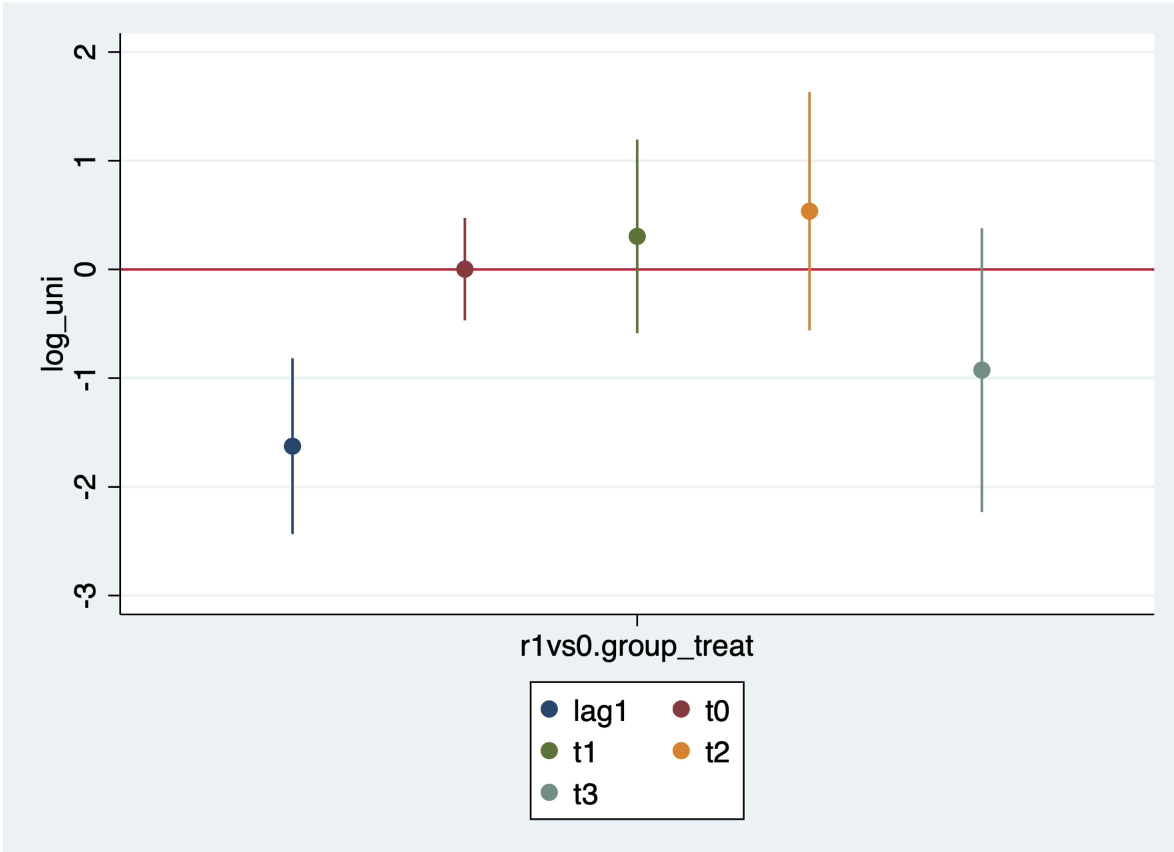
Notes: This figure shows the fraction of products joining the QQ and WeChat Kids Smartwatch platform. The percentage is computed by the number of products equipped with QQ or WeChat software divided by the total number of products sold by a company in a given quarter. Before 2019.8, some brands had already established unofficial relationships with Tencent QQ, but Tencent had not launched the Kids Smartwatch product yet.

Figure 2: Percent of Products Joining Tencent Platform (by Revenue)



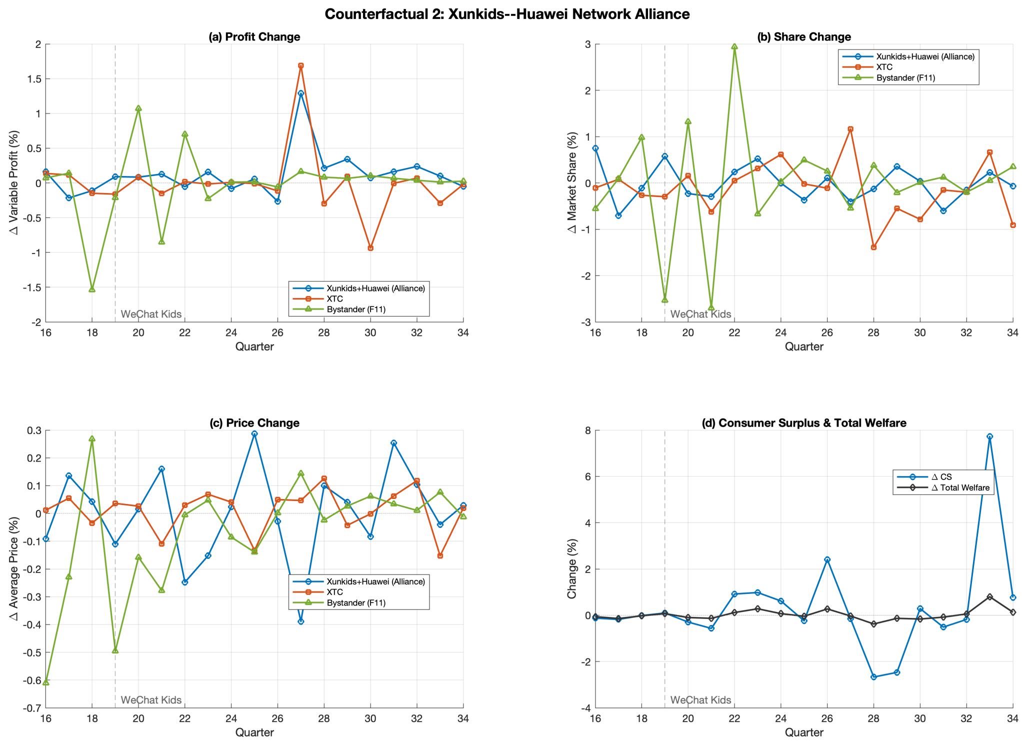
Notes: This figure shows the fraction of products joining the QQ and WeChat Kids Smartwatch platform measured by revenue. The percentage is computed by the revenue collected from watches equipped with QQ or WeChat software divided by the total revenue from products sold by a company in a given quarter. Before 2019.8, some brands had already established unofficial relationships with Tencent QQ, but Tencent had not launched the Kids Smartwatch product yet.

Figure 3: Event Study of Introduction of Tencent Platform on Prices



Notes: This figure shows the event study of the introduction of the Tencent platform on prices. "lag1" is computed by comparing 2019Q1 and 2019Q2 before the launch. "t1" to "t3" is computing some long-term dynamic effect from 2019Q3 on. Since we only consider products introduced before 2019Q3, the confidence band is becoming wider as more products were exiting the market towards the end.

Figure 4: Effects of Xunkids–Huawei Network Alliance



Notes: Each panel reports the percentage change in the outcome variable relative to the observed baseline, computed quarter by quarter from Q16 (2018Q4) to Q34 (2023Q2). The counterfactual expands the exclusive network so that Xunkids and Huawei products share within-network users, while retaining independent pricing. Panel (a) plots the change in variable profit for the alliance (Xunkids+Huawei), XTC, and a platform bystander (ReadBoy). Panel (b) plots the corresponding change in total market share. Panel (c) plots the change in share-weighted average price. Panel (d) plots the change in consumer surplus and total welfare. The dashed vertical line marks Q19 (2019Q3), the quarter of the WeChat Kids platform launch. All equilibria are computed by re-solving the Bertrand–Nash pricing game with 1,000 simulation draws per quarter; platform adoption decisions are held fixed at observed values.

Table 1: Top Brands Market Share: Q2 2023

Brand	Market Share in Q2 2023
XTC	0.0209
Others	0.0086
Huawei	0.0076
Xiaomi	0.0051
Xunkids	0.0014
360	0.0013
Readboy	0.0003

Notes: The table reports the top brands in Q2 2023. Market share is calculated as the number of sales over the national population between age 6 and 12. "Others" is a combined group of small competing fringe firms.

Table 2: Summary Statistics: Product Characteristics

	Mean	SD	N
Release price (USD)	88.785	50.217	223
Android	0.565	0.497	223
Connectivity			
If wifi	0.821	0.385	223
2G	0.354	0.479	223
3G	0.036	0.186	223
4G	0.610	0.489	223
Bluetooth	0.368	0.483	223
Camera			
No camera	0.296	0.458	223
Camera resolution: VGA	0.193	0.395	223
Camera resolution: 1-2MP	0.004	0.067	223
Camera resolution: 2-3MP	0.274	0.447	223
Camera resolution: 3-4MP	0.009	0.094	223
Camera resolution: 5+MP	0.224	0.418	223
GPS			
GPS to indoor	0.238	0.427	223
GPS to floor level	0.009	0.094	223
Waterproof			
Waterproof: basic	0.121	0.327	223
Waterproof: medium	0.821	0.385	223
Waterproof: advanced	0.054	0.226	223
Battery capacity	660.595	178.091	210
NFC	0.045	0.207	223
Contain any sensor	0.036	0.186	223
Social			
With brand exclusive chat app	0.940	0.239	215
With QQ or WeChat	0.344	0.476	215

Notes: The table reports the product characteristics at the product level. Sensors include heart rate, skin temperature and UV sensor.

Table 3: Brand Exclusive Chat-App Network Effects on Price and Sales

Dependent variable	(1) Price OLS	(2) Price 2SLS	(3) Log Sales OLS	(4) Log Sales 2SLS
Cum.Brand Network Size_t-1 (x10^4)	0.006**	0.0174***	0.0005***	0.0002
	(0.003)	(0.005)	(0.0001)	(0.0003)
ASP (USD)			-0.009***	-0.009***
			(0.002)	(0.002)
Observations	1,399	1,354	1,399	1,354
R-squared	0.778	NA	0.578	NA
Brand FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
CD F-stat	NA	14.61	NA	14.61
KP F-stat	NA	77.74	NA	44.42

Notes: The table examines the effect of the lagged brand exclusive chat-app network size on price and sales. Dependent variables are prices in columns 1-2 and log sales in columns 3-4. The independent variable is the cumulative sales of same-brand products with chat function till one quarter before. Odd number columns report the OLS estimates and even number columns report the corresponding 2SLS estimates. Controls include dummies for Android OS, 6 levels of cameras megapixels, whether compatible with wifi, 4G network connectivity, whether include NFC and Bluetooth function, waterproof level, GPS level and if contain any sensors (heart rate, skin temperature or UV sensor). Standard errors are clustered by brand-year pair and reported in parentheses.

Table 4: Introduction of Tencent Platform on Prices and Sales

Dependent variable	(1) Price Doubly-Robust	(2) Log Sales Doubly-Robust
τ	4.503**	0.003
	(2.153)	(0.241)
Observations	114	114
Product FE	Yes	Yes
Controls	Yes	Yes
Time FE	Yes	Yes

Notes: The table examines the treatment effect of the introduction of Tencent Chat APP in 2019Q3. The dependent variables are prices and sales. We use a doubly robust method to compute the treatment effect. For the propensity score matching, we follow Sant'Anna and Zhao (2020) to use stabilized inverse probability weighting. Standard errors are reported in parentheses.

Table 5: Demand Estimation Results

	Estimate	Std. Error
Panel A: Mean Utility Parameters (β)		
Price (α)	-0.1748	(0.0162)
Within network size (τ_e)	8.5801×10^{-6}	(1.3259×10^{-6})
Open network size (τ_c)	10.149×10^{-6}	(2.3023×10^{-6})
Camera	-34.1399	(7.9085)
4G cellular	8.4444	(1.0891)
Waterproof (IPX8)	4.9219	(1.4087)
Multi-satellite GPS	5.0247	(0.6458)
Quarters since release	0.0955	(0.0833)
Fringe (κ_0)	-1.6866	(3.8276)
Fringe $\times$ Advanced (κ^{adv})	13.1368	(4.6209)
Fringe $\times$ Trend (κ^{t})	-0.1415	(0.2446)
Panel B: Random Coefficients		
σ_0 (Constant)	5.1602	(1.0841)
σ_{cam} (Camera)	17.4577	(3.7630)
Quarter fixed effects	Yes	
Markets (quarters)	34	
Products (total obs.)	1,574	

Notes: The table reports estimates from a random-coefficient logit demand model estimated via two-step GMM using PyBLP (Conlon and Gortmaker, 2020). Robust standard errors in parentheses. The exclusive network N_{ft} measures the total number of users purchasing products from firm f; the compatible network ON_{jt} measures the total number of users from other firms on the open platform. Both network variables are in raw user counts. Random coefficients are integrated using product-rule quadrature with 9 nodes per dimension. Instrumental variables include BLP-style product counts, mean characteristics at product release, differentiation-based instruments (Gandhi and Houde, 2019), a predicted price from a hedonic cost regression, and lagged market-structure variables for network sizes. Quarter fixed effects are absorbed.

Table 6: Supply-Side Marginal Cost Results

	Estimate	Std. Error
Sensor	0.2953	(0.0526)
Camera (MP)	0.1383	(0.0039)
4G cellular	0.5871	(0.0373)
Waterproof (IPX8)	0.3423	(0.0404)
Battery capacity	0.3555	(0.0849)
Firm fixed effects	Yes	
Quarter fixed effects	Yes	
Observations	1,547	
Adjusted R^2	0.711	

Notes: The dependent variable is log marginal cost, $\ln(mc_j)$, recovered from the estimated demand model and the multi-product Bertrand–Nash first-order conditions. Standard errors in parentheses and clustered at the market level. Firm and quarter fixed effects are absorbed.

Table 7: Estimated Bounds on the Fixed Cost of Platform Adoption (10,000 USD)

	Lower Bound	Upper Bound
Panel A: Pooled (all post-launch quarters), γ_0		
Baseline	5.49	13.61
Excl. hardware-constrained	5.17	13.61
Panel B: Early period (2019Q3–2021Q2), γ_0		
Baseline	3.64	8.47
Excl. hardware-constrained	3.44	8.47
Panel C: Late period (2021Q3–2023Q2), $\gamma_0 + \gamma_{post}$		
Baseline	9.24	27.02
Excl. hardware-constrained	8.85	27.02

Notes: Bounds are computed from moment inequalities based on revealed preference, following Eizenberg (2014). The lower bound is the average $\Delta\pi$ across stayers-off; the upper bound is the average $\Delta\pi$ across joiners. All estimates restrict to Monte Carlo draws where the pricing equilibrium converged (average convergence rate: 92.2%). Panel D reports the identified set for γ_{post}, computed as the difference between late- and early-period bounds; positive values indicate that fixed costs increased after the WeChat Kids launch. "Excl. hardware-constrained" drops two Huawei products (IDs 36 and 37) that face hardware constraints preventing platform adoption. Units are in 10,000 USD.

Table 8: Full Platform Coverage

	Q11 (2017Q3)	Q19 (2019Q3)
Panel A: Aggregate Market Outcomes		
Eligible products	30	60
Δ CS (10K USD)	+6.37	+32.82
Δ CS (%)	+0.60%	+0.27%
Δ PS (10K USD)	+0.51	+1.41
Δ Total units (000s)	+1.4	+1.6
Δ Avg price (USD)	+0.00	+0.03
Panel B: Firm-Level ΔVP (10K USD)		
XTC (F13)	−1.44 (−0.13%)	−1.18 (−0.04%)
XunKids (F15)	—	+0.28 (+0.02%)
Temoo (F12)	+0.01 (+0.01%)	+1.00 (+0.19%)
Huawei (F5)	—	−0.04 (−0.02%)
F7	+0.42 (+0.27%)	+0.46 (+0.55%)
Readboy (F11)	+1.10 (+0.36%)	+0.27 (+2.10%)
Xiaomi (F14)	−0.40 (−1.13%)	−1.04 (−1.01%)
360 (F1)	−0.10 (−0.18%)	+0.96 (+1.09%)
Panel C: Subsidy Required to Achieve Full Coverage		
Total Subsidy	[2.22, 9.54]	[4.43, 19.06]
of which: retain ON products	—	[1.33, 5.72]
of which: attract OFF products	[2.22 , 9.54]	[3.10, 13.34]

Notes: Full coverage places all non-XTC, non-fringe products on the platform. Stage 2 prices are re-solved under $S = 1000$ Monte Carlo draws. Q11 precedes the actual platform launch (no products on-platform in the baseline); Q19 is the launch quarter (18 products already on-platform). Panel C: FC range from Table 7 (converged, pooled); since Max $\Delta\pi^{\text{full}} \ll FC$, no product sustains membership voluntarily. Panel D: subsidy per product is $\max\{0, FC - \Delta\pi_j^{\text{full}}\}$; "retain/attract" split shows subsidy for ON vs OFF baseline products ([low FC ,high FC]).

Appendix

A Total Derivatives of the Share under Network Effect

This appendix provides a detailed derivation of the total derivative of market shares with respect to prices in the presence of network effects. The key complication is that prices affect shares both directly and indirectly through changes in equilibrium network sizes, creating feedback loops that must be accounted for in the first-order conditions of the pricing game.

A.1 Model Setup

Recall from Section 4 that the indirect utility of consumer i for major product j in quarter t is:

$$\begin{aligned} u_{ijt} = \text{Major}_{jt} \cdot \left(\boldsymbol{X}_{jt}\boldsymbol{\beta} + \tau_e N_{ft} + \tau_c ON_{jt}\right) \\ + \text{Fringe}_{jt} \cdot \left(\kappa_0 + \kappa^{adv} Adv_{jt} + \kappa^t t\right) \\ + \alpha p_{jt} + \nu_{i0}\beta_\nu^0 + \nu_{iF}\beta_\nu^C \text{Camera}_{jt} + \lambda_t + \xi_{jt} + \epsilon_{ijt} \end{aligned} \tag{18}$$

where $N_{ft} = \sum_{j \in J_{ft}} s_{jt} \cdot D_t$ is the exclusive network (total users of firm f) and $ON_{jt} = \left(\sum_{k \in O_t \setminus J_{ft}} s_{kt}\right) \cdot D_t$ is the compatible network (platform users from other firms), with O_t denoting the set of on-platform products. The individual choice probability for consumer i conditional on (ν_{i0}, ν_{iF}) is the standard logit:

$$s_{ijt} = \frac{\exp(u_{ijt})}{1 + \sum_{m \in J_t} \exp(u_{imt})} \tag{19}$$

and the market share integrates over consumer heterogeneity:

$$s_{jt} = \int s_{ijt} \, dF_\nu(\nu_{i0}, \nu_{iF}) \tag{20}$$

The network sizes and shares are jointly determined in a fixed-point equilibrium:

$$N_{ft} = \sum_{j \in J_{ft}} s_{jt}(\boldsymbol{\delta}_t, \boldsymbol{\mu}_t, \mathbf{N}_t, \mathbf{ON}_t) \cdot D_t \tag{21}$$

$$ON_{jt} = \left(\sum_{k \in O_t \setminus J_{ft}} s_{kt}(\boldsymbol{\delta}_t, \boldsymbol{\mu}_t, \mathbf{N}_t, \mathbf{ON}_t) \right) \cdot D_t \tag{22}$$

We require consumers to hold rational expectations: they correctly anticipate the equilibrium network sizes when making purchase decisions, so $\mathbf{N}_t$ and $\mathbf{ON}_t$ satisfy these fixed-point conditions.

A.2 The Pricing Problem

Each firm f sets prices for its products $j \in J_{ft}$ to maximize variable profits:

$$\pi_{ft} = \sum_{j \in J_{ft}} (p_{jt} - mc_{jt}) \cdot s_{jt}(\mathbf{p}_t) \cdot D_t \tag{23}$$

The first-order condition for product j is:

$$s_{jt} + \sum_{k \in J_{ft}} \frac{ds_{kt}}{dp_{jt}} (p_{kt} - mc_{kt}) = 0 \tag{24}$$

The key object in this equation is the *total* derivative $\frac{ds_{kt}}{dp_{jt}}$, which must account for the fact that a price change for product j alters market shares, which in turn change the equilibrium network sizes N_{ft} and ON_{jt}, which feed back into shares through utility. The remainder of this appendix derives this total derivative rigorously from the individual-level choice model.

A.3 Individual-Level Derivation via the Chain Rule

We work at the individual consumer level and then aggregate. By the Leibniz integral rule, the total derivative of the market share passes inside the integral:

$$\frac{ds_{jt}}{dp_{kt}} = \int \frac{ds_{ijt}}{dp_{kt}} \, dF_\nu(\nu_{i0}, \nu_{iF}) \tag{25}$$

It therefore suffices to derive $\frac{ds_{ijt}}{dp_{kt}}$ for each individual i and then integrate. By the multivariate chain rule, the total derivative of individual i's choice probability with respect to any price

p_k is:

$$\frac{ds_{ijt}}{dp_{kt}} = \sum_{m \in J_t} \frac{\partial s_{ijt}}{\partial u_{imt}} \cdot \frac{du_{imt}}{dp_{kt}} \tag{26}$$

The first factor is the standard logit Jacobian. From equation (19), differentiation yields:

$$\frac{\partial s_{ijt}}{\partial u_{imt}} = \begin{cases} s_{ijt}(1 - s_{ijt}) & \text{if } j = m \\ -s_{ijt} \cdot s_{imt} & \text{if } j \neq m \end{cases} \tag{27}$$

which can be written compactly in matrix form as $\frac{\partial \mathbf{s}_{it}}{\partial \mathbf{u}_{it}} = \text{diag}(\mathbf{s}_{it}) - \mathbf{s}_{it}\mathbf{s}'_{it}$.

The second factor, $\frac{du_{imt}}{dp_{kt}}$, captures how a price change for product k affects the utility of product m. This operates through three channels: (i) the direct price effect on product k itself; (ii) the change in the exclusive network of the firm that owns m, which depends on the change in all of that firm's sales; and (iii) the change in the compatible network available to m, which depends on the change in sales of other on-platform firms. Formally:

$$\frac{du_{imt}}{dp_{kt}} = \underbrace{\mathbf{1}_{[m=k]} \cdot \alpha}_{\text{direct price}} + \underbrace{\mathbf{1}_{[N_{f(m)}>0]} \cdot \tau_e D_t \sum_{n \in J_{f(m)t}} \frac{ds_{int}}{dp_{kt}}}_{\text{exclusive network}} + \underbrace{\mathbf{1}_{[ON_m>0]} \cdot \tau_c D_t \sum_{\ell \in O_t \setminus J_{f(m)t}} \frac{ds_{i\ell t}}{dp_{kt}}}_{\text{compatible network}} \tag{28}$$

where $f(m)$ denotes the firm that owns product m, and $\mathbf{1}_{[N_{f(m)}>0]}$, $\mathbf{1}_{[ON_m>0]}$ are indicators for whether product m has positive exclusive and compatible network sizes, respectively.

Equations (26)–(28) reveal that the total derivative $\frac{d\mathbf{s}_{it}}{d\mathbf{p}_t}$ appears on both sides of the system—it enters the left-hand side directly and the right-hand side through the network feedback terms. This is the defining feature of our model: the total derivative must be solved as a linear system rather than evaluated in closed form.

A.4 Matrix Formulation

We now express the system in matrix notation, which clarifies the structure and maps directly to the computational implementation. For a given consumer i, the total derivative matrix

$\frac{d\mathbf{s}_{it}}{d\mathbf{p}_t} \in \mathbb{R}^{n\times n}$ (where $n = |J_t|$) can be decomposed using the chain rule as:

$$\frac{d\mathbf{s}_{it}}{d\mathbf{p}_t} = \frac{\partial \mathbf{s}_{it}}{\partial \mathbf{u}_{it}} \times \frac{d\mathbf{u}_{it}}{d\mathbf{p}_t} \tag{29}$$

Written out explicitly, this is:

$$\underbrace{\begin{bmatrix} \frac{ds_{i1}}{dp_1} & \frac{ds_{i1}}{dp_2} & \cdots & \frac{ds_{i1}}{dp_n} \\ \frac{ds_{i2}}{dp_1} & \frac{ds_{i2}}{dp_2} & \cdots & \frac{ds_{i2}}{dp_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{ds_{in}}{dp_1} & \frac{ds_{in}}{dp_2} & \cdots & \frac{ds_{in}}{dp_n} \end{bmatrix}}_{\frac{d\mathbf{s}_{it}}{d\mathbf{p}_t}} = \underbrace{\begin{bmatrix} s_{i1}(1-s_{i1}) & -s_{i1}s_{i2} & \cdots & -s_{i1}s_{in} \\ -s_{i2}s_{i1} & s_{i2}(1-s_{i2}) & \cdots & -s_{i2}s_{in} \\ \vdots & \vdots & \ddots & \vdots \\ -s_{in}s_{i1} & -s_{in}s_{i2} & \cdots & s_{in}(1-s_{in}) \end{bmatrix}}_{\frac{\partial \mathbf{s}_{it}}{\partial \mathbf{u}_{it}}} \times \underbrace{\begin{bmatrix} \frac{du_{i1}}{dp_1} & \frac{du_{i1}}{dp_2} & \cdots & \frac{du_{i1}}{dp_n} \\ \frac{du_{i2}}{dp_1} & \frac{du_{i2}}{dp_2} & \cdots & \frac{du_{i2}}{dp_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{du_{in}}{dp_1} & \frac{du_{in}}{dp_2} & \cdots & \frac{du_{in}}{dp_n} \end{bmatrix}}_{\frac{d\mathbf{u}_{it}}{d\mathbf{p}_t}}$$

The utility derivative matrix $\frac{d\mathbf{u}_{it}}{d\mathbf{p}_t}$ decomposes into three components corresponding to the three channels in equation (28):

$$\frac{d\mathbf{u}_{it}}{d\mathbf{p}_t} = \alpha \mathbf{I}_n + (\mathbf{\Omega}_{\text{own}} \odot \tau_e D_t \cdot \mathbf{1}_N) \frac{d\mathbf{s}_{it}}{d\mathbf{p}_t} + (\mathbf{\Omega}_{\text{plat}} \odot \tau_c D_t \cdot \mathbf{1}_{ON}) \frac{d\mathbf{s}_{it}}{d\mathbf{p}_t} \tag{30}$$

where the matrices and vectors are defined as follows:

Price derivative. The first term $\alpha \mathbf{I}_n$ captures the direct effect of a price change on utility. Only product k's own utility responds directly to p_k, so this term is diagonal.

Exclusive network feedback. The second term involves:

- $\mathbf{\Omega}_{\text{own}} \in \{0,1\}^{n\times n}$: the *ownership matrix*, where $[\mathbf{\Omega}_{\text{own}}]_{jk} = 1$ if products j and k belong to the same firm. This ensures that only same-firm products contribute to the exclusive network.

- $\mathbf{1}_N \in \{0,1\}^{n\times 1}$: an indicator vector where $[\mathbf{1}_N]_j = \mathbf{1}[N_{f(j)} > 0]$, equal to one if product j's firm has a positive exclusive network.

- $\tau_e D_t$: the exclusive network coefficient scaled by market size, converting share changes into network-size changes.

Written out in full:

$$(\mathbf{\Omega}_{\text{own}} \odot \tau_e D_t \cdot \mathbf{1}_N) = \begin{bmatrix} \mathbf{1}_{[N_1>0]}\tau_e D & \mathbf{1}_{[N_1>0]}\tau_e D & \cdots & 0 \\ \mathbf{1}_{[N_2>0]}\tau_e D & \mathbf{1}_{[N_2>0]}\tau_e D & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{1}_{[N_n>0]}\tau_e D \end{bmatrix}$$

where the block structure reflects the ownership grouping: rows and columns corresponding to same-firm products have nonzero entries, while cross-firm entries are zero. The Hadamard product $\odot$ broadcasts the indicator-scaled coefficient onto the ownership structure.

Compatible network feedback. The third term involves:

- $\mathbf{\Omega}_{\text{plat}} \in \{0,1\}^{n\times n}$: the *platform matrix*, where $[\mathbf{\Omega}_{\text{plat}}]_{jk} = 1$ if product k is on the platform and products j and k belong to *different* firms. This ensures that only cross-firm, on-platform products contribute to the compatible network.

- $\mathbf{1}_{ON} \in \{0,1\}^{n\times 1}$: an indicator vector where $[\mathbf{1}_{ON}]_j = \mathbf{1}[ON_j > 0]$, equal to one if product j is on the platform and has a positive compatible network.

- $\tau_c D_t$: the compatible network coefficient scaled by market size.

Written out in full:

$$(\mathbf{\Omega}_{\text{plat}} \odot \tau_c D_t \cdot \mathbf{1}_{ON}) = \begin{bmatrix} 0 & 0 & \cdots & \mathbf{1}_{[ON_1>0]}\tau_c D \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{1}_{[ON_n>0]}\tau_c D & 0 & \cdots & 0 \end{bmatrix}$$

where nonzero entries appear only at cross-firm, on-platform positions.

A.5 Solving the Linear System via the Implicit Function Theorem

Substituting equation (30) into the chain-rule decomposition (29):

$$\frac{d\mathbf{s}_{it}}{d\mathbf{p}_t} = \frac{\partial \mathbf{s}_{it}}{\partial \mathbf{u}_{it}} \left[\alpha \mathbf{I}_n + \mathbf{N}_{\text{own}} \frac{d\mathbf{s}_{it}}{d\mathbf{p}_t} + \mathbf{N}_{\text{plat}} \frac{d\mathbf{s}_{it}}{d\mathbf{p}_t} \right]$$

where we use the shorthand $\mathbf{N}_{\text{own}} \equiv \boldsymbol{\Omega}_{\text{own}} \odot \tau_e D_t \cdot \mathbf{1}_N$ and $\mathbf{N}_{\text{plat}} \equiv \boldsymbol{\Omega}_{\text{plat}} \odot \tau_c D_t \cdot \mathbf{1}_{ON}$. Distributing the multiplication and collecting terms:

$$\frac{d\mathbf{s}_{it}}{d\mathbf{p}_t} = \alpha \frac{\partial \mathbf{s}_{it}}{\partial \mathbf{u}_{it}} + \frac{\partial \mathbf{s}_{it}}{\partial \mathbf{u}_{it}} \left(\mathbf{N}_{\text{own}} + \mathbf{N}_{\text{plat}} \right) \frac{d\mathbf{s}_{it}}{d\mathbf{p}_t}$$

Rearranging to isolate $\frac{d\mathbf{s}_{it}}{d\mathbf{p}_t}$:

$$\left[\mathbf{I}_n - \frac{\partial \mathbf{s}_{it}}{\partial \mathbf{u}_{it}} \left(\mathbf{N}_{\text{own}} + \mathbf{N}_{\text{plat}} \right) \right] \frac{d\mathbf{s}_{it}}{d\mathbf{p}_t} = \alpha \frac{\partial \mathbf{s}_{it}}{\partial \mathbf{u}_{it}} \tag{31}$$

This is a linear system of the form $\mathbf{A}_i \frac{d\mathbf{s}_{it}}{d\mathbf{p}_t} = \mathbf{B}_i$, where:

$$\begin{aligned} \mathbf{A}_i &= \mathbf{I}_n - \frac{\partial \mathbf{s}_{it}}{\partial \mathbf{u}_{it}} \left(\mathbf{N}_{\text{own}} + \mathbf{N}_{\text{plat}} \right) \\ \mathbf{B}_i &= \alpha \frac{\partial \mathbf{s}_{it}}{\partial \mathbf{u}_{it}} = \alpha \left[\text{diag}(\mathbf{s}_{it}) - \mathbf{s}_{it} \mathbf{s}'_{it} \right] \end{aligned}$$

The solution is $\frac{d\mathbf{s}_{it}}{d\mathbf{p}_t} = \mathbf{A}_i^{-1} \mathbf{B}_i$. The matrix $\mathbf{A}_i$ is the *feedback matrix*: it captures how a unit change in shares propagates through the network and feeds back into shares. When network effects are absent ($\tau_e = \tau_c = 0$), $\mathbf{A}_i = \mathbf{I}_n$ and the total derivative reduces to the standard partial derivative $\alpha \frac{\partial \mathbf{s}_{it}}{\partial \mathbf{u}_{it}}$ with no feedback.

A.6 Aggregation

The individual-level total derivative $\frac{d\mathbf{s}_{it}}{d\mathbf{p}_t} = \mathbf{A}_i^{-1} \mathbf{B}_i$ captures the three feedback channels—direct price, exclusive network, and compatible network—for a single consumer type i, as shown in equations (26)–(28). The aggregate total derivative matrix is obtained by integrating over the consumer distribution:

$$\frac{d\mathbf{s}_t}{d\mathbf{p}_t} = \int \frac{d\mathbf{s}_{it}}{d\mathbf{p}_t}\, dF_\nu(\nu_{i0}, \nu_{iF}) = \int \mathbf{A}_i^{-1}\mathbf{B}_i\, dF_\nu(\nu_{i0}, \nu_{iF}) \tag{32}$$

In practice, this integral is computed numerically using the same quadrature rule employed in the demand estimation. For each quadrature node, we form $\mathbf{A}_i$ and $\mathbf{B}_i$ using the individual choice probabilities $\mathbf{s}_{it}$, solve the linear system (31) via LU factorization, and accumulate the weighted sum across nodes. Note that because $\mathbf{A}_i$ depends on the individual shares $\mathbf{s}_{it}$ (which in turn depend on the equilibrium network sizes), the total derivative must be recomputed whenever prices or network sizes change—for example, at each iteration of the pricing fixed-point algorithm described in Appendix B.

A.7 Marginal Cost Recovery

Given the total derivative matrix, the first-order conditions (24) can be written in matrix form as:

$$\mathbf{s}_t + \left(\frac{d\mathbf{s}_t}{d\mathbf{p}_t}' \odot \boldsymbol{\Omega}_{\text{own}}\right)(\mathbf{p}_t - \mathbf{mc}_t) = 0$$

which yields the markup equation:

$$\mathbf{p}_t - \mathbf{mc}_t = -\left(\frac{d\mathbf{s}_t}{d\mathbf{p}_t}' \odot \boldsymbol{\Omega}_{\text{own}}\right)^{-1}\mathbf{s}_t$$

We recover marginal costs from observed prices and shares using this equation. Products in the fringe group are treated as a composite fringe that does not engage in joint profit maximization and sets prices equal to marginal costs ($p_{jt} = mc_{jt}$ for $j \in$ Fringe). The fringe does not respond strategically to other products' prices in the Bertrand game, but other products do react to the fringe's prices through the demand system.

We parameterize the log of marginal cost as a linear function of observed cost shifters:

$$\ln mc_{jt} = \mathbf{X}_{jt}^{mc}\boldsymbol{\gamma} + \eta_f + \eta_t + \omega_{jt} \tag{33}$$

where $\mathbf{X}_{jt}^{mc}$ includes sensor type, camera megapixels, 4G capability, waterproof level, and battery capacity; η_f are firm fixed effects; η_t are quarter fixed effects; and ω_{jt} is the unobserved cost shock.

B Solving for New Price Equilibrium

Computing counterfactual price equilibria in our model requires solving a *double fixed point*. The outer fixed point is over prices: we seek a price vector $\mathbf{p}^*$ that satisfies the first-order conditions of the Bertrand-Nash pricing game. The inner fixed point is over shares and network sizes: for any candidate price vector $\mathbf{p}$, the equilibrium shares must be consistent with the network sizes they generate, because both N_{ft} and ON_{jt} depend on shares through equations (21)–(22), while shares depend on network sizes through the utility function (18). Neither fixed point can be solved in isolation—evaluating the FOC at a given $\mathbf{p}$ requires first solving for the share-network equilibrium at that $\mathbf{p}$.

B.1 The Double Fixed-Point Structure

The first-order condition for firm f's pricing of product j in market t is:

$$s_{jt} + \sum_{k \in J_{ft}} \frac{ds_{kt}}{dp_{jt}} (p_{kt} - mc_{kt}) = 0 \tag{34}$$

where $\frac{ds_{kt}}{dp_{jt}}$ is the total derivative accounting for network feedback (see Section A). Following Morrow and Skerlos (2011), we reformulate the system of first-order conditions as a fixed-point problem. Define the total derivative matrix Δ with entries $\Delta_{jk} = \frac{ds_{jt}}{dp_{kt}}$, and let Ω denote the ownership matrix where $\Omega_{jk} = 1$ if products j and k belong to the same firm. The pricing map is:

$$G(\mathbf{p}) = \mathbf{mc} - (\Delta'(\mathbf{p}) \odot \Omega)^{-1} \mathbf{s}(\mathbf{p}) \tag{35}$$

A fixed point $\mathbf{p}^* = G(\mathbf{p}^*)$ corresponds to a Nash-Bertrand price equilibrium. Evaluating $G(\mathbf{p})$ at any candidate $\mathbf{p}$ requires three nested steps:

1. **Inner fixed point (shares and networks).** Given prices $\mathbf{p}$, solve for equilibrium shares and network sizes via contraction mapping. Initialize with zero network sizes

$(\mathbf{N}^{(0)} = \mathbf{0}$, $\mathbf{ON}^{(0)} = \mathbf{0})$ and compute initial shares $\mathbf{s}^{(0)}$ from the demand system without network effects. Then iterate for $\ell = 0, 1, 2, \ldots$:

$$\mathbf{N}^{(\ell)} = D_t \cdot (\mathbf{\Omega}_{\text{own}}\, \mathbf{s}^{(\ell)}) \odot \mathbf{1}_{\text{within}}, \qquad \mathbf{ON}^{(\ell)} = D_t \cdot (\mathbf{\Omega}_{\text{plat}}\, \mathbf{s}^{(\ell)}) \odot \mathbf{1}_{\text{platform}}$$

$$s_{jt}^{(\ell+1)} = \int \frac{\exp\big(\delta_{jt}(\mathbf{p}, N_{f(j)t}^{(\ell)}, ON_{jt}^{(\ell)}) + \mu_{ijt}\big)}{1 + \sum_{m \in J_t} \exp\big(\delta_{mt}(\mathbf{p}, N_{f(m)t}^{(\ell)}, ON_{mt}^{(\ell)}) + \mu_{imt}\big)} dF_\nu(\nu_i)$$

where $\mathbf{1}_{\text{within}}$ and $\mathbf{1}_{\text{platform}}$ are indicator vectors for products with active exclusive and compatible network features. The network update exploits the linearity of N_{ft} and ON_{jt} in shares: multiplication by the ownership matrix $\mathbf{\Omega}_{\text{own}}$ sums same-firm shares, and multiplication by the platform matrix $\mathbf{\Omega}_{\text{plat}}$ sums cross-firm on-platform shares. We iterate until $\|\mathbf{s}^{(\ell+1)} - \mathbf{s}^{(\ell)}\| < 10^{-12}$, with a maximum of 500 iterations. This yields equilibrium shares $\mathbf{s}(\mathbf{p})$ and network sizes $\mathbf{N}(\mathbf{p})$, $\mathbf{ON}(\mathbf{p})$ consistent with $\mathbf{p}$, as well as the individual-level shares $\{s_{ijt}\}$ needed for the total derivative computation in Step 2.

2. **Total derivative.** Given the equilibrium shares from Step 1, compute the total derivative matrix $\Delta(\mathbf{p})$ using the IFT as derived in Section A.

3. **Pricing map update.** Evaluate $G(\mathbf{p})$ using equation (35).

Fringe products are treated as price-takers and set prices equal to marginal costs ($p_{jt} = mc_{jt}$ for $j \in$ Fringe). For numerical stability, we regularize the markup matrix $(\Delta' \odot \Omega)$ when it is ill-conditioned (adding a small diagonal perturbation when rcond $< 10^{-12}$), and we impose the constraint $p_{jt} \geq mc_{jt}$ after each pricing update.

B.2 Tiered Anderson Acceleration Algorithm

Directly iterating $\mathbf{p} \leftarrow G(\mathbf{p})$ may converge slowly or diverge, especially in markets with many products or strong network effects. We employ a tiered Anderson Acceleration (AA) approach (Anderson, 1965; Walker and Ni, 2011) to solve for the fixed point efficiently.

Anderson Acceleration. Given the residual function $\mathbf{f}(\mathbf{p}) = G(\mathbf{p}) - \mathbf{p}$, Anderson Acceleration with memory m and mixing parameter β updates the iterate as follows. At iteration

k, we maintain the most recent $m+1$ residuals $\{\mathbf{f}_{k-m}, \ldots, \mathbf{f}_k\}$ and iterates $\{\mathbf{p}_{k-m}, \ldots, \mathbf{p}_k\}$. We compute the differences $\Delta \mathbf{F}_k = [\mathbf{f}_{k-m+1} - \mathbf{f}_{k-m}, \ldots, \mathbf{f}_k - \mathbf{f}_{k-1}]$ and solve

$$\boldsymbol{\gamma}_k = \arg\min_{\boldsymbol{\gamma}} \|\mathbf{f}_k - \Delta \mathbf{F}_k \boldsymbol{\gamma}\|_2$$

via QR factorization. The next iterate is:

$$\mathbf{p}_{k+1} = \mathbf{p}_k + \beta \mathbf{f}_k - (\Delta \mathbf{P}_k + \beta \Delta \mathbf{F}_k)\boldsymbol{\gamma}_k$$

where $\Delta \mathbf{P}_k$ contains the corresponding differences in iterates.

Tiered strategy. We employ a three-tier approach to balance speed and robustness:

1. **Tier 1 — Full Anderson** ($\beta = 1.0$, $m = 5$, up to 200 iterations): aggressive acceleration that converges quickly for well-behaved markets.
2. **Tier 2 — Dampened Anderson** ($\beta = 0.3$, $m = 5$, up to 500 iterations): the dampened mixing parameter prevents divergence in markets where Tier 1 is unstable.
3. **Tier 3 — `fmincon` rescue**: for the rare markets where both Anderson tiers fail, we reformulate the problem as a minimization of the squared FOC residual:

$$\min_{\mathbf{p}} \frac{1}{2}\|\mathbf{p} - G(\mathbf{p})\|^2 \quad \text{s.t.} \quad mc_{jt} \leq p_{jt} \leq 10 \cdot mc_{jt}$$

   solved with MATLAB's `fmincon` using an interior-point algorithm.

Each tier is triggered only if the previous tier fails to achieve the acceptance tolerance. Within each Anderson tier, we implement safeguards: if the residual increases by more than a factor of 10 in a single step (a "blowup"), we halve the mixing parameter β (with a floor of 0.05) and reset the history. NaN/Inf guards are similarly handled.

For the Monte Carlo simulation exercise (Section C), we use a relaxed convergence tolerance of $\|\mathbf{f}(\mathbf{p})\|/\|\mathbf{p}\| < 5 \times 10^{-2}$, which is sufficient for computing expected profits that will be averaged across 1000 simulation draws. For single-market counterfactuals, we tighten the tolerance to 10^{-8}.

C Simulating Demand and Cost Shocks

To compute expected profits under a given platform configuration (needed for the Stage 1 entry game), we simulate demand and cost shocks and solve for equilibrium prices under each realization.

The demand shock ξ_{jt} is recovered from the BLP estimation as the mean-utility residual. The cost shock ω_{jt} is the residual from the log-linear marginal cost function. For each firm f, we pool all estimated residuals $\{(\xi_{jt}, \omega_{jt}) : j \in J_{ft},\ \text{all } t\}$ across quarters and draw with replacement to construct simulated shock vectors. This firm-level resampling preserves the within-firm correlation structure of shocks while providing sufficient variation for Monte Carlo integration.

For each simulation draw $s = 1, \ldots, S$, we solve for the pricing equilibrium and compute firm profits. The expected profit change from a platform deviation is:

$$\Delta\pi_{ft}^{+j} = \frac{1}{S}\sum_{s=1}^{S}\left[VP_{ft}^{(s)}(\mathbf{d}_t^{+j}) - VP_{ft}^{(s)}(\mathbf{d}_t)\right]$$

We use $S = 1000$ simulation draws and parallelize across draws. Importantly, we use *paired* simulation: the same shock draw $(\xi^{(s)}, \omega^{(s)})$ is used for both the baseline and deviated equilibria, which reduces the variance of the profit difference estimator.

We also track convergence rates across simulation draws. Our preferred estimates restrict to draws where the pricing equilibrium converged under both the baseline and deviated configurations. Non-converging draws, which tend to occur in markets with many small-share products and strong network effects, can generate extreme profit values that distort the bounds.

D Estimating Fixed Cost of Platform Adoption

This appendix provides the technical details underlying the fixed cost estimation summarized in Section 5. We focus on the selection bias correction, the computational procedure for the profit differences, and formal inference.

D.1 Selection Bias and Bounded Support

A subtlety arises when moving from the product-level revealed preference inequalities (equations 14–15 in the main text) to identification of the fixed cost parameters. Substituting the parameterization $FC_{jt} = \gamma_0 + \gamma_{\text{post}} \cdot \mathbf{1}[t \geq 2021\text{Q3}] + \nu_{jt}$ into the "stay off" inequality and taking conditional expectations over products that stayed off gives:

$$\gamma_0 + \gamma_{\text{post}} \cdot \mathbf{1}[t \geq 2021\text{Q3}] + E[\nu_{jt} \mid d_{jt} = 0] \geq E[\Delta\pi_{ft}^{+j} \mid d_{jt} = 0]$$

The conditional expectation $E[\nu_{jt} \mid d_{jt} = 0]$ is *not* zero: under complete information, the firm observes ν_{jt} when making its platform decision, so products that stay off the platform are selected to have higher fixed cost shocks. This is the selection bias identified by Eizenberg (2014).

Following Eizenberg's strategy, we impose a bounded support condition on ν_{jt}: the product-specific cost shock has bounded support $\nu_{jt} \in [\underline{\nu}, \bar{\nu}]$ with $-\infty < \underline{\nu}$ and $\bar{\nu} < \infty$. Under bounded support, we construct bounds that apply to *any* product j, regardless of its observed platform status:

$$L_{jt}(\boldsymbol{\theta}) \leq FC_{jt} \leq U_{jt}(\boldsymbol{\theta}) \tag{36}$$

where

$$L_{jt} = \begin{cases} \underline{\nu} + \gamma_0 + \gamma_{\text{post}} \cdot \mathbf{1}[t \geq 2021\text{Q3}] & \text{if } d_{jt} = 0 \\ \Delta\pi_{ft}^{-j} & \text{if } d_{jt} = 1 \end{cases}, \quad U_{jt} = \begin{cases} \Delta\pi_{ft}^{+j} & \text{if } d_{jt} = 0 \\ \bar{\nu} + \gamma_0 + \gamma_{\text{post}} \cdot \mathbf{1}[t \geq 2021\text{Q3}] & \text{if } d_{jt} = 1 \end{cases}$$

Taking *unconditional* expectations over all products within each period group:

$$E[L_{jt}] \leq \gamma_0 + \gamma_{\text{post}} \cdot \mathbf{1}[t \geq 2021\text{Q3}] \leq E[U_{jt}] \tag{37}$$

Since the expectation is unconditional, $E[\nu_{jt}] = 0$ and the selection bias vanishes. The inequalities define the identified set for $(\gamma_0, \gamma_{\text{post}})$.

D.2 Estimation via Sample Averaging

As described in the main text, taking unconditional sample averages of the inequalities within each period yields direct bounds. For the early period ($t < 2021\text{Q3}$), let $\mathcal{S}^0_{\text{early}}$ and $\mathcal{S}^1_{\text{early}}$ denote the stayers-off and joiners:

$$\underbrace{\frac{1}{|\mathcal{S}^1_{\text{early}}|} \sum_{(j,t)\in\mathcal{S}^1_{\text{early}}} \Delta\pi^{-j}_{ft}}_{\text{avg } \Delta\pi \text{ of early joiners}} \;\leq\; \gamma_0 \;\leq\; \underbrace{\frac{1}{|\mathcal{S}^0_{\text{early}}|} \sum_{(j,t)\in\mathcal{S}^0_{\text{early}}} \Delta\pi^{+j}_{ft}}_{\text{avg } \Delta\pi \text{ of early stayers-off}} \tag{38}$$

For the late period ($t \geq 2021\text{Q3}$), the same averaging gives bounds on $\gamma_0 + \gamma_{\text{post}}$:

$$\frac{1}{|\mathcal{S}^1_{\text{late}}|} \sum_{(j,t)\in\mathcal{S}^1_{\text{late}}} \Delta\pi^{-j}_{ft} \;\leq\; \gamma_0 + \gamma_{\text{post}} \;\leq\; \frac{1}{|\mathcal{S}^0_{\text{late}}|} \sum_{(j,t)\in\mathcal{S}^0_{\text{late}}} \Delta\pi^{+j}_{ft} \tag{39}$$

The time-shift parameter γ_{post} is identified by differencing the late-period and early-period bounds, exploiting the fact that Tencent's release of the WeChat Kids app in 2021Q3 plausibly changed the effective cost of platform adoption.

D.3 Computing the Profit Differences

The key computational object is $\Delta\pi^{+j}_{ft}$, the change in firm f's expected variable profit from switching product j's platform status. For each at-risk product-quarter (j, t):

1. Construct the counterfactual configuration $\mathbf{d}^{+j}_t$ (or $\mathbf{d}^{-j}_t$) by toggling product j's platform status.

2. For each of $S = 1000$ Monte Carlo draws of $(\xi^{(s)}, \omega^{(s)})$ from the empirical shock distribution (Section C), solve the Stage 2 pricing equilibrium under both configurations using tiered Anderson Acceleration (Section B).

3. Compute the expected profit change as a paired difference:

$$\Delta\pi^{+j}_{ft} = \frac{1}{S}\sum_{s=1}^{S}\left[VP^{(s)}_{ft}(\mathbf{d}^{+j}_t) - VP^{(s)}_{ft}(\mathbf{d}_t)\right]$$

The pairing ensures that random variation in (ξ, ω) cancels out in the difference, substantially reducing the Monte Carlo variance. Xiaotiancai's products remain in the Stage 2 equilibrium computation—its exclusive network and pricing behavior affect $\Delta\pi_{ft}^{+j}$ for all other firms—even though Xiaotiancai is excluded from the Stage 1 estimation sample.