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ABSTRACT

This paper studies how spillovers across complementary markets shape product variety and firm entry. We examine the Indian cell phone and wireless service markets during the 4G rollout and estimate a structural model of demand, pricing, carrier network expansion, and phone product choice. The estimation results support the economic forces through which complementarity generates spillovers. Counterfactual simulations show that banning budget Chinese phones slows 4G deployment by roughly five quarters and lowers consumer welfare without raising domestic firms' profits. Similarly, an unrestricted subsidy outperforms a domestic-only subsidy in expanding network coverage, increasing consumer welfare, and raising domestic firms' profits.

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1 Introduction

Many important industries consist of complementary markets, in which the value of a product in one market depends on the availability, price, and quality of products in another. Examples include electric vehicles and charging infrastructure, computer hardware and software, and the Internet and streaming services. In each case, products in one market become more valuable as the other market expands, and vice versa.

Such complementarity gives rise to spillovers both across markets and across firms within a market. A change in one market can affect demand in the other market, altering firms' incentives and equilibrium outcomes there. In addition, a change affecting one group of firms in a market can influence another group of firms in the same market through the complementary market, beyond the direct effect of competition between the two groups.

In this paper, we study how spillovers shape entry and product offerings in addition to demand and pricing. These extensive-margin firm decisions are important for welfare because they directly determine the options available to consumers and also affect firms' pricing competition.

Our context is the Indian cell phone and wireless service markets during the 4G rollout. In India, many consumers purchase cell phones and wireless service plans separately. A consumer needs both a phone and a plan to enjoy mobile service. In addition, consumers can enjoy many advanced features of a 4G cell phone only with 4G service, and they can enjoy the higher speeds of 4G service only with a 4G phone. Thus, the cell phone and wireless service markets are complementary, particularly for 4G phones and 4G service. In this setting, entry refers to carriers' regional entry into 4G service, whereas product offerings refer to the phones chosen by cell phone firms. A salient feature of the cell phone market is the strong presence of international firms, including both Asian and non-Asian firms.

In this context, international firms in the cell phone market can affect 4G diffusion in both the cell phone and the wireless service markets. Because technologically advantaged international cell phone firms are more inclined than their Indian counterparts to offer 4G phones, their strong presence gives wireless carriers greater incentives to build 4G networks. As 4G network coverage expands, Indian cell phone firms may find it profitable to introduce their own 4G phones. Thus, international cell phone firms can accelerate the development of the wireless service market, which in turn affects product choices by Indian firms in the cell phone market. As a result of these spillovers, consumers benefit from a faster rollout of 4G networks and a greater variety of 4G phones.

To capture these economic forces, we develop and estimate a structural model of demand, network expansion, product choice, and pricing in the Indian cell phone and wireless service

markets. On the demand side, a consumer chooses a cell phone and a service plan. Cell phones vary in their product characteristics, including whether they support 2G, 3G, or 4G technology. Service plans differ by carrier and network type (2G, 3G, or 4G). On the supply side, we model carriers' 4G network rollouts as a dynamic discrete game that determines network coverage in each period. Embedded in this dynamic game is a two-stage static game: given the current 4G networks in each period, cell phone firms decide which phones to offer in the first stage, and both cell phone firms and wireless carriers set prices in the second stage. This embedding allows us to capture the interdependence between the two markets: 4G network coverage in the wireless service market affects cell phone firms' product choices, and changes in the cell phone market can affect carriers' network expansion decisions.

We estimate the model using a newly compiled dataset covering both the cell phone and wireless service markets in India. Specifically, we obtain national-level data on the prices, characteristics, and sales of both cell phones and service plans from 2011 to 2018. We supplement these data with regional-level data on whether each carrier offers services for each technology (2G, 3G, and 4G) in each quarter. We also incorporate annual regional-level data on population and income.

Our estimates indicate a 4G phone–4G plan complementarity: consumers prefer using a 4G cell phone with 4G service, even though 4G phones are compatible with 2G and 3G networks. We also find higher markups for international 4G phones than for Indian 4G phones, consistent with international firms having an advantage in 4G phone offerings. On the supply side, we find that the marginal cost of producing cell phones decreases over time and that, while Indian cell phone firms are less efficient at producing high-quality phones, they have a cost advantage in producing low-quality phones.

Taken together, these findings support the economic forces through which complementarity generates spillovers between the cell phone and wireless service markets and across firms within a market. The 4G phone–4G plan complementarity implies interdependence between the two markets during the 4G rollout. For example, the early availability of international 4G phones in the cell phone market gives carriers incentives to begin rolling out their 4G networks in the wireless service market. The downward trend in phone marginal costs supports expansion of the cell phone market, providing continued incentives for carriers to extend their 4G networks. When 4G network coverage becomes sufficiently widespread, Indian cell phone firms' cost advantage in the low-end segment makes it possible for them to profitably introduce low-end 4G phones. Thus, the estimates point to spillovers between these two markets—from cell phones to wireless services and vice versa. As a result, a shock to some firms in a market can also spill over to other firms in the same market by affecting the complementary market.

To quantify how these spillovers shape entry, product offerings, and welfare, we use the estimated model to conduct two sets of policy counterfactuals. The first studies a hypothetical ban on Chinese cell phones priced below 12,000 INR, a policy that was considered by the Indian government as a way to push Chinese cell phone firms out of the lower end of the Indian cell phone market. Since many Chinese 4G phones were priced below the 12,000 INR threshold, Chinese cell phone firms would likely reduce their phone offerings substantially, removing a large share of the 4G products in the cell phone market and weakening the cross-market spillover that contributes to carriers' incentives to expand their 4G networks. We find that the ban would delay 4G network expansion by about five quarters, lower consumer surplus by 236 billion INR per quarter on average, and reduce carriers' discounted value by 181 billion INR. Despite facing weaker competition from Chinese firms in the low-end segment under the ban, Indian cell phone firms would not gain: the spillover benefits they lose because of the slower 4G rollout in the wireless service market outweigh the benefits of reduced competition.

In the second set of counterfactual simulations, we compare two consumer subsidy policies that have the same subsidy rate—20 percent of a 4G phone's price—but differ in their scope of eligibility. One is an unrestricted subsidy available for every 4G phone; the other is a domestic-only subsidy restricted to Indian 4G phones. Our results show that the unrestricted subsidy would deliver a substantially larger expansion of the cell phone market, increasing the average quarterly number of 4G phone models and sales of 4G phones by 54 percent and 64 percent, respectively, compared with 20 percent and 24 percent under the domestic-only subsidy. The unrestricted subsidy would also accelerate the expansion of 4G coverage by up to four quarters in urban regions and about two quarters in rural regions, compared with one quarter in urban regions and almost no acceleration in rural regions under the domestic-only subsidy. These differences translate into a much larger gain in consumer surplus (390 vs. 110 billion INR per quarter on average), while the difference in government spending on subsidies is much smaller (33 vs. 6 billion INR per quarter on average). Importantly, Indian cell phone firms would themselves be better off under the unrestricted subsidy, despite their exclusive subsidy eligibility under the domestic-only policy.

Taken together, the two counterfactuals show that policy effects depend critically on how spillovers shape carriers' regional 4G entry and cell phone firms' product-offering decisions. Policies that restrict international firms or narrowly target support to domestic firms reduce direct competition in the cell phone market, but they also weaken carriers' incentives to expand 4G networks. This cross-market effect reduces the profitability of 4G product offerings by Indian cell phone firms, offsetting any gains from reduced competition. From a single-market perspective, these policies may appear to involve a tradeoff between domestic

protection and consumer welfare. Accounting for cross-market spillovers changes this picture: because protection weakens the complementary market, it can reduce consumer welfare while failing to benefit the domestic firms it is designed to protect. The lesson is not that protection is always undesirable, but that evaluating it requires tracing how it reshapes the relevant margins in both markets; an analysis confined to the protected market alone can reach the opposite conclusion.

This paper also sheds light on the role of international firms in the Indian mobile industry. Media reports have claimed that international cell phone firms introduced 4G phones before 4G networks were widely available and thereby crowded out Indian firms. Our findings suggest that this view is incomplete because it focuses on direct competition in the cell phone market while ignoring the complementary wireless service market. By making 4G phones available early, international cell phone firms strengthened carriers' incentives to expand 4G coverage, which in turn created conditions under which Indian cell phone firms could profitably introduce their own 4G phones.

Our results extend beyond the Indian mobile industry. The finding—that the presence of technologically advanced firms in one market can increase product variety and promote technology diffusion in both markets to the benefit of consumers—may apply to many industries consisting of complementary markets. In developing countries, technologically advanced firms are often foreign, meaning that realizing these benefits requires an open market that allows international competition.

This paper relates to several strands of the literature. By studying two complementary markets simultaneously, it contributes to the literature on complementary markets. Examples include Gandal, Kende, and Rob (2000) on the diffusion of CD systems, Lee (2013) on exclusivity in game hardware and software markets, Springel (2021) on subsidies and Li (2023) on compatibility in electric vehicle and charging station markets, Heid, Remmy, and Reynaert (2024) on electricity and automobile markets during vehicle electrification, and Bollinger, Darghouth, Gillingham, and Gonzalez-Lira (2024) on complementarities in the demand for rooftop solar and battery energy storage. We contribute to this literature by studying a new topic and a new pair of complementary markets: how the presence of technologically advanced international firms in the cell phone market accelerates the development of the complementary wireless service market, which in turn affects domestic cell phone firms and benefits consumers through spillover effects.

By studying both the product choices of cell phone firms and the network expansion decisions of carriers, this paper also contributes to both the endogenous product choice literature and the dynamic entry literature. Examples include Draganska, Mazzeo, and Seim (2009), Fan (2013), Eizenberg (2014), Wollmann (2018), Fan and Yang (2020, 2025),

Chaves (2026), and Kwon (2026) on endogenous product choice, as well as Collard-Wexler (2013), Dunne, Klimek, Roberts, and Xu (2013), Sweeting (2013), Fan and Xiao (2015), and Mohapatra and Zhang (2025) on dynamic entry games. We embed a static cell phone product choice model into a dynamic network expansion model to study how spillovers link carriers' regional entry decisions to cell phone firms' product offerings.

By studying the Indian mobile industry, this paper also contributes to research on the telecommunications industry. Examples in this literature include Fan and Xiao (2015), Fan and Yang (2020), Shreeti (2024), Elliott, Houngbonon, Ivaldi, and Scott (2025), Callejas, Chatterjee, and Mohapatra (2026), and Elsas-Nicolle, Li, and Verboven (2026). While most of these papers focus on either the cell phone market or the provider market, we study both markets jointly and highlight their interdependence. Moreover, like Björkegren (2019) and Granja (2024), this paper studies the telecommunications industry in a developing country, where mobile services play a vital role in economic development and consumer well-being.

This paper also relates to a large literature on international trade and industrial policy.[1] We complement this literature by bringing the tools of empirical industrial organization to industrial policy, as in studies of shipbuilding subsidies (Kalouptsidi, 2018; Barwick, Kalouptsidi, and Zahur, 2025), automobile protectionism (Barwick, Cao, and Li, 2021), quid pro quo policy (Bai, Barwick, Cao, and Li, 2025), and firm subsidies (Rotemberg, 2019; Garg and Saxena, 2025). Relatedly, Alé-Chilet, Colson-Sihra, and Luco (2024) study the effect of the 2015 ban on Nestle's Maggi noodles in India. Unlike these papers, which focus on one market, we evaluate policy effects across two complementary markets and show that these effects hinge on firms' decisions in both markets, so that a policy intended to protect domestic firms may leave them no better off.

The remainder of the paper proceeds as follows. We describe the setting and data in Section 2 and present the model in Section 3. We explain our estimation procedure and present the estimation results in Section 4. We present the counterfactual simulation results in Section 5. Section 6 concludes.

2 Industry Background and Data

In this section, we describe the industry, summarize the data, and present data patterns for both the cell phone and wireless service markets.

[1] Examples include Lane (2025) on temporary targeted interventions and Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2020) and Flaaen, Hortaçsu, and Tintelnot (2020) on broad import restrictions. Papers studying exposure to foreign inputs, competition, and investment find that such exposure can either raise or lower domestic firms' productivity and variety (Aitken and Harrison, 1999; Javorcik, 2004; Amiti and Konings, 2007; Goldberg, Khandelwal, Pavcnik, and Topalova, 2010; Bloom, Draca, and Van Reenen, 2016).

2.1 Industry Background

The Indian mobile industry consists of two markets: the cell phone market and the wireless service market. A consumer must purchase both a cell phone and a wireless service plan in order to use mobile service. Many consumers in India purchase cell phones and service plans separately. An exception is the JioPhone line, introduced by the carrier Jio in 2017Q3, whose models are restricted to Jio's service plans.

The cell phone market consists of both domestic and international cell phone firms. In our sample, there are four Indian firms (Intex, Jio/LYF, Lava, and Micromax), six other Asian firms (Gionee, Lenovo, Oppo, Samsung, Vivo, and Xiaomi), and two non-Asian firms (Apple and Microsoft/Nokia).

The wireless service market consists of eight carriers: Airtel, Vodafone, Idea, BSNL (Bharat Sanchar Nigam Limited), Jio, Reliance Communications, Aircel, and MTNL (Mahanagar Telephone Nigam Limited). The Department of Telecommunications divides India into 22 telecommunications regions. These regions are further divided into four categories (Metro, Category A, Category B, and Category C) according to their infrastructure facilities and income levels, with Metro regions being the most developed and Category C regions being the least developed. We present a map of India showing the 22 telecommunications regions and their classifications in Appendix A.

2.2 Data

We compile a new dataset on both the cell phone and wireless service markets in India between 2011 and 2018. We obtain cell phone sales and price data from Counterpoint Research and supplement them with hand-collected data on phone characteristics. We obtain carrier sales and price data from GSMA Intelligence and supplement them with hand-collected data on each carrier's network coverage. See Appendix B for details on sample construction.

Our cell phone data contain information on sales, prices, and phone characteristics. The data cover all cell phones sold in India between 2011 and 2018. For each cell phone in our data, we observe its firm identity, technology (2G, 3G, or 4G), screen size, camera resolution, storage, RAM, and battery capacity. The national sales and price data are available at the annual level between 2011 and 2014 and at the monthly level between 2015 and 2018. We aggregate the monthly data to the quarterly level to be consistent with the frequency of the carrier data.

Our carrier data contain information on sales, prices, and network coverage. We observe whether a given carrier offers a particular technology (2G, 3G, or 4G) in each region in each quarter. For simplicity, we refer to a carrier-technology combination as a plan. We

observe the number of subscribers at the national level for each plan in each quarter. We also observe average monthly revenue per user for each carrier in each quarter, which we treat as the monthly price. While it is not ideal that we do not observe more detailed plan price information, we note that the average monthly price of a plan is only about 1/100 of the average cell phone price.

For each region, we measure market size as the population aged 15 or older and income as per capita state domestic product. To obtain market size for each region-year combination, we first combine annual data on national population from the United Nations Population Division with data on the share of the population in each region from the 2011 Census to obtain population at the region-year level. We then multiply this measure by 69%, which is the share of the total population aged 15 or older according to the 2011 Census. As in many developing countries, income is not well measured or defined in India. Therefore, we proxy income by per capita domestic product and obtain the data for each region-year combination from the Reserve Bank of India, India's central bank. We use CPI data to deflate prices and income to 2015 INR.[2]

2.3 Data Patterns

We present summary statistics in Appendix C. In this section, we highlight three data patterns in the cell phone and wireless service markets.

First, international cell phone firms, especially other Asian firms, play an important role in the cell phone market. To see this, we compute each cell phone firm's total sales of 3G and 4G phones in the sample and report the ratio of a firm's total sales to the sum of all firms' sales in Table 1. The table shows that Indian cell phone firms, other Asian firms, and non-Asian firms account for 28%, 64%, and 8% of sales, respectively, indicating that international firms are important players in the cell phone market.

Second, while Indian cell phone firms do well in the lower end of the market, international cell phone firms dominate the higher end. Table 2 shows the sales shares of cell phone firms by origin and price range for 4G cell phones. Specifically, we consider three price ranges defined by terciles. The table shows that while Indian cell phone firms account for 59% of total 4G phone sales in the low-price range, their share drops sharply to 5% and 1% in the medium- and high-price ranges. The opposite is true for other Asian firms: their total share increases from 41% in the low-price range to 95% and 89% in the two higher price ranges. Non-Asian firms are present only in the high-price range, with a total share of 10% in this market segment.

[2]CPI data are obtained from Federal Reserve Economic Data ([Link to Data]).

Table 1: Cell Phone Firms and Sales Shares

Origin	Firm	Sales Share	Total
Indian	Intex	3.3%	
Indian	Jio/LYF	15.7%	
Indian	Lava	3.2%	
Indian	Micromax	6.0%	28%
Other-Asian	Gionee	1.3%	
Other-Asian	Lenovo	4.9%	
Other-Asian	Oppo	4.8%	
Other-Asian	Samsung	33.0%	
Other-Asian	Vivo	6.2%	
Other-Asian	Xiaomi	13.7%	64%
Non-Asian	Apple	1.7%	
Non-Asian	Microsoft/Nokia	6.1%	8%

Notes: This table lists the cell phone firms in our sample. Sales share is the ratio of "total 3G and 4G phone units sold by a firm in our sample" to "total 3G and 4G cell phone units sold in our sample."

Table 2: 4G Cell Phone Sales Shares by Firm Origin and Price Range

Origin	Low Price	Medium Price	High Price
Indian	59%	5%	1%
Other Asian	41%	95%	89%
Non-Asian	-	-	10%

Notes: This table shows the sales shares of 4G phones by phone firm origin and price range. The price ranges are defined by terciles. The sales share is the ratio of "total 4G phone units sold by all firms of a given origin in a given price range" to "total 4G phone units sold in that price range."

Third, there are comovements in the cell phone and wireless service markets. Panel (a) of Figure 1 presents the number of urban and rural regions covered by 4G networks over time.[3] This panel shows that 4G network coverage in India started in 2013,[4] gradually expanded first in urban regions and then in rural regions, and reached all 22 regions by

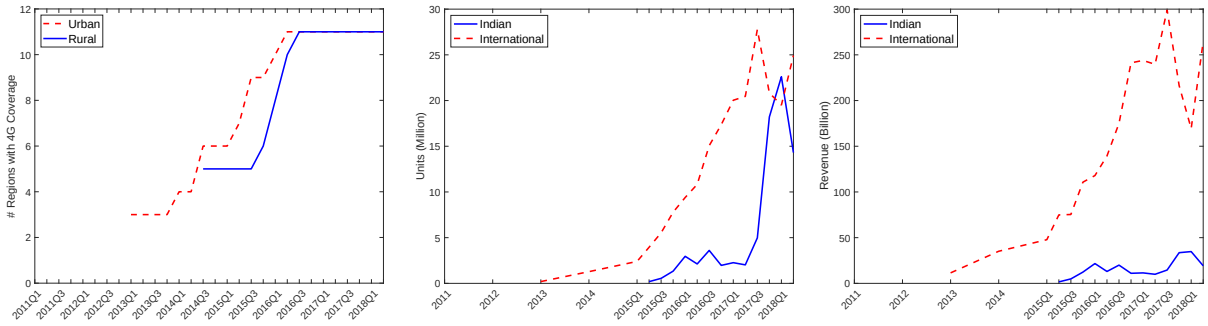
[3]We classify the 11 highest-income telecommunications regions as urban and the remaining 11 as rural.

[4]In 2012Q2 and 2012Q4, Airtel launched its 4G network in two cities, Kolkata and Pune, respectively, but only on an experimental basis.

2016Q3. Panel (b) plots 4G phone sales by firm origin over time and shows that, as the 4G network expanded, sales of 4G phones increased. International cell phone firms started offering 4G phones in 2013. Indian cell phone firms entered the 4G market later. Their sales were initially low and then increased sharply in 2017. However, Panel (c), which plots revenue from 4G phone sales rather than the number of phones sold, shows that the increase in Indian cell phone firms' revenue from 4G phone sales was much more muted. This is consistent with the second data pattern: Indian cell phone firms largely concentrated on the low end of the cell phone market.

Figure 1: 4G Network Coverage and 4G Cell Phone Sales Over Time

(a) # 4G Regions (b) 4G Phone Unit Sales (c) 4G Phone Revenue



Notes: Panel (a) plots the number of urban and rural regions with 4G coverage over time. Panels (b) and (c) plot, respectively, 4G phone unit sales and revenue by Indian and international cell phone firms over time. In Panel (a), we have quarterly data. In Panels (b) and (c), we have annual data before 2015 and quarterly data between 2015Q1 and 2018Q2.

In summary, our data show that international firms play an important role in the cell phone market. They are the first to offer 4G phones. Indian cell phone firms introduce 4G phones later and focus largely on the low end of the cell phone market. The growth of 4G phone sales and the rollout of 4G networks coincide over time.

3 Model

In this section, we develop a structural model of consumer demand, carrier network expansion, cell phone firm product choice, and pricing in the Indian cell phone and wireless service markets.

3.1 Demand

We describe demand using a discrete-choice model. Consumers choose a cell phone and a wireless plan, or the outside option of not using mobile service. A consumer needs both a

phone (indexed by j) and a plan (indexed by k) to enjoy mobile service. Let $\mathcal{J}_t$ be the set of phones at time t and $\mathcal{K}_{rt}$ be the set of plans in region r at time t. Let $\mathcal{B}(\mathcal{J}_t, \mathcal{K}_{rt})$ denote the set of phone-plan combinations available to consumers in region r at time t. It includes all combinations (j, k) such that $j \in \mathcal{J}_t$ and $k \in \mathcal{K}_{rt}$, except that 3G phones are not compatible with 4G plans, 2G phones are not compatible with 3G or 4G plans, and JioPhones are not compatible with non-Jio plans.

Consumer i gets the following indirect utility from buying phone j and plan k at time t:

$$u_{ijkt} = x_{jkt}\beta + \alpha_{r(i)t}(p_{jt} + \psi p_{kt}) + \xi_{jt}^{(ph)} + \xi_{kt}^{(pl)} + \varepsilon_{ijkt}, \tag{1}$$

where the vector x_{jkt} contains observable phone and plan characteristics, p_{jt} is the price of phone j, p_{kt} is the monthly price of plan k, and ψ is a multiplier to be estimated. We allow consumer price sensitivity to depend on average income in her region $r(i)$: $\alpha_{r(i)t} = \alpha_0 + \alpha_1 y_{r(i)t}$, where y_{rt} is the logarithm of average income in region r at time t (in 1,000 INR). We include the terms $\xi_{jt}^{(ph)}$ and $\xi_{kt}^{(pl)}$ to capture unobservable characteristics of the phone and the plan, where the superscripts (ph) and (pl) stand for "phone" and "plan", respectively. The idiosyncratic taste shocks ε_{ijkt} are assumed to be i.i.d. and to follow a type-1 extreme value distribution. The utility of the outside option is normalized to $u_{i0t} = \varepsilon_{i0t}$.

The vector x_{jkt} includes three sets of covariates. First, it includes a quality index of phone j, which is a function of observable product characteristics x_j defined as $q_j = x_j\rho$, where ρ is a vector of parameters to be estimated and the first element of ρ is normalized to 1. In other words, following Fan and Yang (2020), who also study the cell phone market, we assume that consumer utility depends on phone characteristics only through the quality index. This parsimonious specification allows us to characterize a phone by its quality index and later define potential products based on their quality indices. Second, the vector x_{jkt} includes phone technology fixed effects, plan technology fixed effects, and a dummy variable $\mathbb{1}(4G_j, 4G_k)$ that equals 1 if and only if phone j is a 4G phone and plan k is a 4G plan. By including the variable $\mathbb{1}(4G_j, 4G_k)$, we allow consumers to derive additional utility from using a 4G phone on a 4G network, beyond the benefits of a 4G phone and a 4G plan captured by their corresponding covariates. Third, in addition to phone and plan technology fixed effects, we include cell phone firm fixed effects, carrier fixed effects, and time fixed effects to account for systematic differences at various levels. We also include a dummy variable for the Jio plan during its first year of introduction to capture promotions, such as cashbacks, during that period.

The market share of combination jk in region r at time t is

$$
\begin{aligned}
& s_{jkrt}(\boldsymbol{p}_{rt}, \boldsymbol{x}_{rt}, \boldsymbol{\xi}_{rt}; \mathcal{B}(\mathcal{J}_t, \mathcal{K}_{rt})) \\
=& \frac{exp(x_{jkt}\beta + \alpha_{rt}(p_{jt} + \psi p_{kt}) + \xi_{jt}^{(ph)} + \xi_{kt}^{(pl)})}{1 + \sum_{j'k' \in \mathcal{B}(\mathcal{J}_t, \mathcal{K}_{rt})} exp(x_{j'k't}\beta + \alpha_{rt}(p_{j't} + \psi p_{k't}) + \xi_{j't}^{(ph)} + \xi_{k't}^{(pl)})},
\end{aligned} \tag{2}
$$

where $\boldsymbol{p}_{rt} = \{(p_{jt}, p_{kt}),\ jk \in \mathcal{B}(\mathcal{J}_t, \mathcal{K}_{rt})\}$, $\boldsymbol{x}_{rt} = \{x_{jkt},\ jk \in \mathcal{B}(\mathcal{J}_t, \mathcal{K}_{rt})\}$, and $\boldsymbol{\xi}_{rt} = \{(\xi_{jt}^{(ph)}, \xi_{kt}^{(pl)}),\ jk \in \mathcal{B}(\mathcal{J}_t, \mathcal{K}_{rt})\}$.

To match our national-level market share data, we aggregate the market shares above to the phone and plan levels. Specifically, for each phone j, we first sum the market share in (2) over all compatible plans within each region, and then aggregate across all regions $r = 1, \ldots, R$. Similarly, the national-level market share of plan k is obtained by aggregating over all regions and all phones compatible with that plan. Let w_r denote the population weight of region r in the national population. The market shares of phone j and plan k at time t are given by:

$$
s_{jt}^{(ph)}(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{\xi}_t; \mathcal{J}_t, \boldsymbol{\mathcal{K}}_t) = \sum_{r=1}^{R} w_r \cdot \sum_{k:(j,k) \in \mathcal{B}(\mathcal{J}_t, \mathcal{K}_{rt})} s_{jkrt}(\boldsymbol{p}_{rt}, \boldsymbol{x}_{rt}, \boldsymbol{\xi}_{rt}; \mathcal{B}(\mathcal{J}_t, \mathcal{K}_{rt})), \tag{3}
$$

$$
s_{kt}^{(pl)}(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{\xi}_t; \mathcal{J}_t, \boldsymbol{\mathcal{K}}_t) = \sum_{r=1}^{R} w_r \cdot \sum_{j:(j,k) \in \mathcal{B}(\mathcal{J}_t, \mathcal{K}_{rt})} s_{jkrt}(\boldsymbol{p}_{rt}, \boldsymbol{x}_{rt}, \boldsymbol{\xi}_{rt}; \mathcal{B}(\mathcal{J}_t, \mathcal{K}_{rt})), \tag{4}
$$

where $\boldsymbol{\mathcal{K}}_t = \{\mathcal{K}_{rt},\ r = 1, \ldots, R\}$ denotes plan availability across all regions, and $(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{\xi}_t)$ denote the collections of prices, observable characteristics, and unobservable characteristics for all phones and plans nationwide. In equations (3) and (4), the time period t refers to a quarter. For the part of the sample where only annual data on phone sales are available, we further aggregate the quarterly phone market shares in (3) over the four quarters of each year.[5]

3.2 Supply

On the supply side, carriers make decisions about their 4G network expansion. Since establishing a 4G network in a region is an absorbing state, the network expansion decision is inherently dynamic. In this dynamic game, each carrier's per-period profit is determined by the outcome of a static game in which cell phone firms choose the set of phones to offer, conditional on carriers' network coverage. Intuitively, greater 4G network coverage increases

[5] In this case, the unobservable demand shock $\xi_{jt}^{(ph)}$ is defined at the phone-year level rather than the phone-quarter level.

the profits that cell phone firms earn from selling 4G phones. Conversely, changes in the cell phone market that boost or reduce phone sales can incentivize or discourage carriers from expanding their networks. Because we embed cell phone firms' product choice game in carriers' network expansion game, our model captures this interdependence between the cell phone and wireless service markets.

We model the product choices of cell phone firms as a static decision problem. This assumption is made for three reasons. First, it would be computationally prohibitive to solve a dynamic game involving two sets of interdependent firms, each making a discrete decision with a large choice set: carriers choosing subsets of regions for 4G network deployment and cell phone firms choosing subsets of potential products to offer. Second, the static assumption is partly justified by the setting: phones in the Indian market are either sold globally, rather than designed specifically for India, or are technologically below the frontier. As such, offering these phones in India likely does not involve substantial sunk costs of innovation. Third, although we model cell phone firms' product decisions as static, the integration of this static model with our dynamic model of 4G network expansion enables us to capture the key spillover effects at the center of the paper.

In what follows, we first describe the static game of product choice and pricing and then the dynamic discrete game of 4G network expansion.

3.2.1 Static Game of Product Choice and Pricing

The static game consists of two stages. In the first stage, cell phone firms decide which products to offer, taking the current 4G network configuration as given. In the second stage, given both the realized set of phones and the current network configuration, cell phone firms and carriers simultaneously choose prices. We present these two stages in reverse order, beginning with the pricing stage.

Stage 2. Pricing Decisions. At the pricing stage, cell phone firms and carriers observe the set of available phones in India and the available plans in each region, as well as the demand and marginal cost shocks for each phone and each plan. Based on this information, they choose prices to maximize profits.

Specifically, cell phone firm f chooses the prices of its phones (denoted by $\mathcal{J}_{ft}$) to maximize its profit:

$$\max_{\{p_{jt}: j \in \mathcal{J}_{ft}\}} \sum_{j \in \mathcal{J}_{ft}} M_t s_{jt}^{(ph)}(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{\xi}_t; \mathcal{J}_t, \boldsymbol{\mathcal{K}}_t)(p_{jt} - c_{jt}^{(ph)}), \tag{5}$$

where M_t is the market size and $c_{jt}^{(ph)}$ denotes the marginal cost of phone j at time t. We

parameterize marginal cost as follows:

$$\log(c_{jt}^{(ph)}) = [\lambda_0 + \lambda_1 \mathbb{1}(Indian)_j] + [\tau_0 + \tau_1 \mathbb{1}(Indian)_j] q_j + \eta_1 \mathbb{1}(Indian)_j t + \eta_2 \mathbb{1}(Int'l)_j t + \chi \mathbb{1}(JioPhone)_j + \omega_{jt}^{(ph)}, \tag{6}$$

where $\omega_{jt}^{(ph)}$ is a marginal cost shock. We allow the level of marginal cost, the slope of marginal cost with respect to quality q_j, and the time trend to differ between international and Indian cell phone firms.[6] Finally, we also allow for a JioPhone dummy.

Similarly, carrier c chooses the prices of its plans (denoted by $\mathcal{K}_{ct}$) to maximize its profit:

$$\max_{\{p_{kt}: k \in \mathcal{K}_{ct}\}} \sum_{k \in \mathcal{K}_{ct}} M_t s_{kt}^{(pl)}(\boldsymbol{p}_t, \boldsymbol{x}_t, \boldsymbol{\xi}_t; \mathcal{J}_t, \boldsymbol{\mathcal{K}}_t)(p_{kt} - c_{kt}^{(pl)}), \tag{7}$$

where $c_{kt}^{(pl)}$ is the marginal cost of plan k at time t, decomposed into a plan fixed effect and a cost shock: $c_{kt}^{(pl)} = Plan_k + \omega_{kt}^{(pl)}$.

The case of Jio is an exception to the profit-maximization problems in (5) and (7). While Jio sells a standalone 4G plan that any compatible cell phone owner can purchase, it also sold phones in certain periods: Jio sold cell phones under the brand name LYF between 2015Q4 and 2017Q1 and has sold JioPhones since 2017Q3. We assume that Jio maximizes joint profit across the two markets during these periods.

Let $p_{jt}^*(\mathcal{J}_t, \boldsymbol{\mathcal{K}}_t, \boldsymbol{\xi}_t, \boldsymbol{\omega}_t)$ and $p_{kt}^*(\mathcal{J}_t, \boldsymbol{\mathcal{K}}_t, \boldsymbol{\xi}_t, \boldsymbol{\omega}_t)$ be the equilibrium prices for phone j and plan k, respectively, where $\boldsymbol{\omega}_t$ is the collection of marginal cost shocks. The corresponding equilibrium profits for a cell phone firm f and a carrier c are denoted by[7]

$$\pi_{ft}^{(phone)}(\mathcal{J}_t, \boldsymbol{\mathcal{K}}_t, \boldsymbol{\xi}_t, \boldsymbol{\omega}_t) \quad \text{and} \quad \pi_{ct}^{(carrier)}(\mathcal{J}_t, \boldsymbol{\mathcal{K}}_t, \boldsymbol{\xi}_t, \boldsymbol{\omega}_t). \tag{8}$$

Stage 1. Cell Phone Product Choice. At the product choice stage, cell phone firms observe each carrier's network, which determines the set of plans available in each region, i.e., $\boldsymbol{\mathcal{K}}_t = \{\mathcal{K}_{rt},\, r = 1, \ldots, R\}$. They also observe the set of potential products that each cell phone firm can offer (denoted by $\mathcal{H}_{ft}$ for firm f at time t), along with the fixed cost associated with each product (denoted by C_{jt} for potential product j at time t). Each firm

[6] The differential time trend allows us to capture potential productivity spillovers from international to Indian firms in a reduced-form way. We do not model such productivity spillovers for two reasons. First, the literature finds mixed evidence regarding such productivity spillovers. See Harrison and Rodríguez-Clare (2010) for a survey. Second, we do not observe rich variation in international firms' entry for identifying productivity spillovers separately from a general time trend in productivity. Because we only capture such productivity spillovers in a reduced-form way, to the extent that they exist, our counterfactual analyses below would understate the positive effects of international cell phone firms.

[7] For Jio, we use $\pi_{ct}^{(carrier)}(\mathcal{J}_t, \boldsymbol{\mathcal{K}}_t, \boldsymbol{\xi}_t, \boldsymbol{\omega}_t)$ to denote its joint phone and plan profit when it sells both.

then chooses a subset $\mathcal{J}_{ft} \subseteq \mathcal{H}_{ft}$ to offer in order to maximize its expected profit.

We define the expected variable profit for cell phone firm f as follows:

$$\Pi_{ft}^{(phone)}(\mathcal{J}_{ft}, \mathcal{J}_{-ft}, \boldsymbol{\mathcal{K}}_t) = \mathbb{E}_{(\boldsymbol{\xi}_t, \boldsymbol{\omega}_t)}\Big[\pi_{ft}^{(phone)}(\mathcal{J}_t, \boldsymbol{\mathcal{K}}_t, \boldsymbol{\xi}_t, \boldsymbol{\omega}_t)\Big], \tag{9}$$

where the expectation is taken over demand shocks $\boldsymbol{\xi}_t$ and marginal cost shocks $\boldsymbol{\omega}_t$ that are realized in the second stage. In (9), we separate $\mathcal{J}_t$ into firm f's product portfolio $\mathcal{J}_{ft}$ and its competitors' products $\mathcal{J}_{-ft}$.

Then, the profit-maximization problem for cell phone firm f at the product choice stage is

$$\max_{\mathcal{J}_{ft} \subseteq \mathcal{H}_{ft}} \Pi_{ft}^{(phone)}(\mathcal{J}_{ft}, \mathcal{J}_{-ft}, \boldsymbol{\mathcal{K}}_t) - \sum_{j \in \mathcal{J}_{ft}} C_{jt}. \tag{10}$$

The equilibrium of this stage is the product portfolio chosen by each cell phone firm, conditional on the carriers' network configurations, or equivalently, plan availability $\boldsymbol{\mathcal{K}}_t$. Let $\mathcal{J}_t^*(\boldsymbol{\mathcal{K}}_t, \boldsymbol{C}_t) = \{\mathcal{J}_{ft}^*(\boldsymbol{\mathcal{K}}_t, \boldsymbol{C}_t), f = 1, \ldots, F\}$ denote the equilibrium product portfolios for the F cell phone firms, where $\boldsymbol{C}_t$ denotes the vector of fixed costs C_{jt} for all potential products.

Plugging the product choice equilibrium $\mathcal{J}_t^*(\boldsymbol{\mathcal{K}}_t, \boldsymbol{C}_t)$ into the carrier's profit function and taking expectations over demand shocks $\boldsymbol{\xi}_t$, marginal cost shocks $\boldsymbol{\omega}_t$, and fixed costs $\boldsymbol{C}_t$ yields the carrier's expected profit given $\boldsymbol{\mathcal{K}}_t$:

$$\Pi_{ct}^{(carrier)}(\boldsymbol{\mathcal{K}}_t) = \mathbb{E}_{(\boldsymbol{\xi}_t, \boldsymbol{\omega}_t, \boldsymbol{C}_t)}\Big[\pi_{ct}^{(carrier)}(\mathcal{J}_t^*(\boldsymbol{\mathcal{K}}_t, \boldsymbol{C}_t), \boldsymbol{\mathcal{K}}_t, \boldsymbol{\xi}_t, \boldsymbol{\omega}_t)\Big]. \tag{11}$$

This profit function $\Pi_{ct}^{(carrier)}(\boldsymbol{\mathcal{K}}_t)$ is precisely the per-period profit for a carrier in the dynamic game of 4G network expansion, which we describe next.

3.2.2 Dynamic Game of 4G Network Expansion

In the dynamic game, we study carriers' 4G rollout decisions. We treat each carrier's 2G and 3G networks as exogenous because they were stable during the sample period, while 4G networks were being established and expanded. Therefore, henceforth, we use the word "entry" to refer to providing 4G services. For example, entering a region means starting to provide 4G services in that region.

We focus on the four largest carriers (Airtel, Idea, Jio, and Vodafone) and treat the networks of the four smaller fringe carriers as exogenous. These four larger carriers account for 95% of 4G services, while the smaller carriers either offered only 2G and 3G services or had

very limited 4G services.[8] For computational reasons, we focus on 12 telecommunications regions, which represent about 70% of the total population and include all 3 Metro regions, all 5 Category-A regions, and the 4 largest Category-B regions.[9]

We model carriers' 4G network expansion decisions as a finite-period dynamic discrete game. The finite-period assumption is consistent with the observation that all four carriers had entered almost all of the 12 regions by the end of our sample and that expanding a 4G network into a region is an absorbing state.[10] Specifically, we assume that the game starts in 2012Q4, one period before the 4G network was first deployed in the data, and ends in 2018Q2, the last period in the sample.

In what follows, we explain the actions a carrier can take in each period, the cost of an action, the timing, the Bellman equations, and the definition of equilibrium. We start with some useful notation.

Notation. Let $\mathcal{R}_{ct}$ be the set of regions that carrier c has entered with 4G services, i.e., carrier c's 4G network, at the beginning of time t. When $\mathcal{R}_{ct} = \emptyset$, carrier c has not started its 4G network. When $\mathcal{R}_{ct} = \mathcal{R}$, where $\mathcal{R}$ is the full set of regions, carrier c has expanded its 4G network to all regions.

We denote the per-period profit for carrier c at time t by $\Pi_{ct}(\mathcal{R}_t)$ where $\mathcal{R}_t = (\mathcal{R}_{1t}, \ldots, \mathcal{R}_{4t})$. This per-period profit was expressed above as $\Pi_{ct}^{(carrier)}(\boldsymbol{\mathcal{K}}_t)$ in equation (11), where $\boldsymbol{\mathcal{K}}_t = \{\mathcal{K}_{rt}, r = 1, \ldots, R\}$ represents the set of plans in each region. We can equivalently write it as a function of each carrier's 4G network, i.e., $\Pi_{ct}(\mathcal{R}_t)$, because whether carrier c offers 4G services in region r (i.e., $r \in \mathcal{R}_{ct}$) uniquely determines whether the "carrier-c/4G" plan is available in region r (i.e., "carrier-c/4G" $\in \mathcal{K}_{rt}$).

Actions. We model the decisions of Airtel, Idea, and Vodafone separately from Jio's decision. This is because the first three carriers expanded their 4G networks gradually, whereas Jio entered all regions at once, according to our data.

For Airtel, Idea, and Vodafone, each carrier's action in a given period is a 3×1 vector $a_{ct} = (a_{ct}^M, a_{ct}^A, a_{ct}^B)$, where a_{ct}^g $(g = M, A, B)$ represents the number of new category-g regions that carrier c enters at time t. Each element a_{ct}^g is naturally bounded below by 0 and above

[8] Specifically, BSNL and MTNL offered only 2G and 3G services during our sample period. Aircel and Reliance Communications operated mostly 2G and 3G networks and provided limited 4G services before exiting the market in 2018.

[9] We treat 4G coverage in the remaining 10 regions as exogenous and hold it at its observed value. Thus, the dynamic state variable governs 4G expansion in the 12 focal regions, while the remaining regions enter demand and profit calculations through their observed network configurations. Appendix A shows a map of India with the 12 regions highlighted.

[10] By the end of our sample, Airtel and Jio had entered all 12 regions, while Idea and Vodafone had entered 11 of them.

by the number of category-g regions that carrier c has not yet entered. Therefore, a carrier's action space at time t is determined by $\mathcal{R}_{ct}$, its 4G network at the beginning of time t. Correspondingly, we denote carrier c's action space at time t by $\mathcal{A}_c(\mathcal{R}_{ct})$. We impose certain restrictions on the action space such as no entry into Category-B regions before entering at least one Metro or Category-A region. All restrictions we impose are consistent with the data. See Appendix D for these restrictions.

Given each carrier's action a_{ct}, which specifies the number of new regions, a corresponding set of new regions is drawn randomly. We assume a uniform distribution over the possible sets. For example, if a carrier has not entered any Metro regions before time t and chooses $a_{ct}^M = 2$ at time t, it will enter two of the three Metro regions, each pair being equally likely with probability 1/3. Sets of new Category-A and Category-B regions are similarly drawn. The union of these new regions constitutes the set of new regions that a carrier enters at time t, denoted by $\mathcal{N}_{ct}(a_{ct})$.

In summary, our dynamic network expansion model explains the number of new regions in each category (Metro, A, or B) in each period for Airtel, Idea, and Vodafone. Modeling the exact set of new regions for each carrier in each period would result in an infeasibly large outcome space: for these three carriers, there are up to $(2^{12})^3 = 2^{36}$ possible outcomes, or more than 68 billion. It seems overly demanding to require our dynamic model to explain why one of more than 68 billion possible outcomes is realized. On the other hand, modeling only the total number of added regions would ignore regional heterogeneity. By modeling the number of added regions by category, we view our model as a parsimonious way to capture carrier expansion across different categories of regions.

Unlike Airtel, Idea, and Vodafone, Jio was a new carrier, provided only 4G services, and entered all regions with 4G services at once in 2016Q3. We assume that its decision is binary—to enter all regions at once or not at all—and that it starts making this decision in 2015Q3. Therefore, Jio's action is either a_{ct} = "no entry" or a_{ct} = "entry", and the corresponding set of new regions is either $\mathcal{N}_{ct}(a_{ct}) = \emptyset$ when a_{ct} = "no entry" or $\mathcal{N}_{ct}(a_{ct}) = \mathcal{R}$ when a_{ct} = "entry".

Costs. Let $f_{ct}(\mathcal{N}_{ct}(a_{ct}), \theta)$ denote the cost for Airtel, Idea, or Vodafone to expand its 4G network into a non-empty set of new regions, $\mathcal{N}_{ct}(a_{ct})$, which is parameterized as follows:

$$\ln f_{ct}(\mathcal{N}_{ct}(a_{ct}), \theta) = \theta_{0c} + \theta_{1c}\mathbb{1}(\mathcal{R}_{ct} = \emptyset) + \theta_{2c} \ln t + \theta_3 \ln\left(1 + M(\mathcal{N}_{ct}(a_{ct}))\right). \tag{12}$$

In (12), we allow for an additional cost of launching a carrier's 4G network with the dummy variable $\mathbb{1}(\mathcal{R}_{ct} = \emptyset)$ taking the value 1 if and only if carrier c has no 4G presence before

time t and the coefficient θ_{1c} capturing this additional cost. We allow the network expansion cost to change over time, with the coefficient θ_{2c} capturing the time trend. We also allow the network expansion cost to depend on the total market size of the newly entered regions, denoted by $M(\mathcal{N}_{ct}(a_{ct}))$. We normalize $f_{ct}(\emptyset, \theta) = 0$.

Jio's entry cost is specified separately. It is given by $\kappa_t = \kappa_1$ before 2016Q3, Jio's observed time of entry, and decreases by κ_2 to $\kappa_t = \kappa_1 - \kappa_2$ thereafter. We adopt a simpler specification for Jio's entry cost because Jio makes a binary entry decision, and we observe only the timing of its entry, not the extent of expansion in each period. In fact, even a cost function with just these two parameters is not well identified: any sufficiently large value of the initial entry cost κ_1 can explain why Jio does not enter before 2016Q3, and any sufficiently large value of the cost reduction κ_2 can explain why it enters in 2016Q3. In our estimation, we choose the smallest values of κ_1 and κ_2 that are consistent with the observed timing of Jio's entry. We provide additional details when we describe the estimation procedure.

Timing. At the beginning of each period, carriers observe the current network configuration $\mathcal{R}_t = (\mathcal{R}_{1t}, \ldots, \mathcal{R}_{4t})$. They also observe their own action-specific shocks $\boldsymbol{\epsilon}_{ct} = \{\epsilon_{ct}(a_{ct}), a_{ct} \in \mathcal{A}_c(\mathcal{R}_{ct})\}$, where $\epsilon_{ct}(a_{ct})$ captures unobserved factors influencing the payoff from each potential action and is assumed to be private information that follows a type-1 extreme value distribution with location 0 and scale parameter θ_ϵ.

Given information on $(\mathcal{R}_t, \boldsymbol{\epsilon}_{ct})$, carriers simultaneously choose their actions a_{ct}. Next, for each carrier, the set of new regions $\mathcal{N}_{ct}(a_{ct})$ is drawn. In the following period, the network configuration updates to $\mathcal{R}_{t+1}$, where $\mathcal{R}_{ct+1} = \mathcal{R}_{ct} \cup \mathcal{N}_{ct}(a_{ct})$.

Bellman Equations. For Airtel, Idea, and Vodafone, let $V_{ct}(\mathcal{R}_t, \boldsymbol{\epsilon}_{ct})$ denote the value function of carrier c at time t. The Bellman equation is given by

$$V_{ct}(\mathcal{R}_t, \boldsymbol{\epsilon}_{ct}) = \max_{a_{ct} \in \mathcal{A}_c(\mathcal{R}_{ct})} \mathbb{E}_{\mathcal{N}_{ct}(a_{ct})} \Big\{ \Pi_{ct}(\mathcal{R}_t) - f_{ct}(\mathcal{N}_{ct}(a_{ct}), \theta) + \epsilon_{ct}(a_{ct}) + \mu \mathbb{E}_{(\mathcal{R}_{t+1}, \boldsymbol{\epsilon}_{ct+1})} \left[V_{ct+1}(\mathcal{R}_{t+1}, \boldsymbol{\epsilon}_{ct+1}) \mid \mathcal{R}_t, \mathcal{N}_{ct}(a_{ct}) \right] \Big\}, \tag{13}$$

where μ is the discount factor. Because $\mathcal{R}_{t+1}$ is determined by each carrier's updated network $\mathcal{R}_{ct} \cup \mathcal{N}_{ct}(a_{ct})$, the expectation over $\mathcal{R}_{t+1}$ conditional on $(\mathcal{R}_t, \mathcal{N}_{ct}(a_{ct}))$ is taken over $a_{c't}$ and then $\mathcal{N}_{c't}(a_{c't})$ conditional on $a_{c't}$ for all $c' \neq c$.

With a slight abuse of notation, we denote the expected value function as $V_{ct}(\mathcal{R}_t) = \mathbb{E}_{\boldsymbol{\epsilon}_{ct}}[V_{ct}(\mathcal{R}_t, \boldsymbol{\epsilon}_{ct})]$. Under the assumption that the shocks $\epsilon_{ct}(a_{ct})$ are i.i.d. and follow a type-1

extreme value distribution with location 0 and scale θ_ϵ, the Bellman equation simplifies to:

$$V_{ct}(\mathcal{R}_t) = \theta_\epsilon \gamma + \theta_\epsilon \ln\Bigg(\sum_{a \in \mathcal{A}_c(\mathcal{R}_{ct})} \exp\Big(\mathbb{E}_{\mathcal{N}_{ct}(a)}\Big\{ \Pi_{ct}(\mathcal{R}_t) - f_{ct}(\mathcal{N}_{ct}(a), \theta) + \mu \mathbb{E}_{\mathcal{R}_{t+1}}[V_{ct+1}(\mathcal{R}_{t+1}) \mid \mathcal{R}_t, \mathcal{N}_{ct}(a)] \Big\} / \theta_\epsilon \Big) \Bigg), \tag{14}$$

where γ is the Euler constant.

For Jio, since it makes a binary decision and faces no action-specific shock, its Bellman equation is as follows:

$$V_{ct}(\mathcal{R}_t) = \max\Big\{ -\kappa_t + \mu \underbrace{\mathbb{E}_{\mathcal{R}_{t+1}}[V_{ct+1}(\mathcal{R}_{t+1}) \mid \mathcal{R}_t, \mathcal{N}_{ct}(a_{ct}) = \mathcal{R}]}_{\text{value of entry}}, \quad \mu \underbrace{\mathbb{E}_{\mathcal{R}_{t+1}}[V_{ct+1}(\mathcal{R}_{t+1}) \mid \mathcal{R}_t, \mathcal{N}_{ct}(a_{ct}) = \emptyset]}_{\text{value of waiting}} \Big\}. \tag{15}$$

Carriers have no further actions once they have entered all regions, i.e., $\mathcal{R}_{ct} = \mathcal{R}$. In this case, the Bellman equation is

$$V_{ct}(\mathcal{R}_{ct}) = \Pi_{ct}(\mathcal{R}_t) + \mu \mathbb{E}_{\mathcal{R}_{t+1}}[V_{ct+1}(\mathcal{R}_{t+1}) \mid \mathcal{R}_t, \mathcal{N}_{ct}(a_{ct}) = \emptyset]. \tag{16}$$

For all carriers, we define the value function in period $T+1$ as

$$V_{cT+1}(\mathcal{R}_{T+1}) = \frac{\Pi_{cT}(\mathcal{R}_{T+1})}{1-\mu}. \tag{17}$$

Equilibrium. An equilibrium is a vector of policies indexed by c and t. Each policy maps a state $\mathcal{R}_t$ such that $\mathcal{R}_{ct} \neq \mathcal{R}$ into a distribution over the action space, $\Pr(a_{ct} \mid \mathcal{R}_t)$ for $a_{ct} \in \mathcal{A}_c(\mathcal{R}_{ct})$, and the vector of the policies constitutes a fixed point of the following system of equations. For Airtel, Idea, and Vodafone, the probability of choosing an action a_{ct} is

$$\Pr_{ct}(a_{ct} \mid \mathcal{R}_t) = \frac{\exp\Big(\mathbb{E}_{\mathcal{N}_{ct}(a_{ct})}\Big\{ \Pi_{ct}(\mathcal{R}_t) - f_{ct}(\mathcal{N}_{ct}(a_{ct}), \theta) + \mu \mathbb{E}_{\mathcal{R}_{t+1}}[V_{ct+1}(\mathcal{R}_{t+1}) \mid \mathcal{R}_t, \mathcal{N}_{ct}(a_{ct})] \Big\} / \theta_\epsilon \Big)}{\sum_{a \in \mathcal{A}_c(\mathcal{R}_{ct})} \exp\Big(\mathbb{E}_{\mathcal{N}_{ct}(a)}\Big\{ \Pi_{ct}(\mathcal{R}_t) - f_{ct}(\mathcal{N}_{ct}(a), \theta) + \mu \mathbb{E}_{\mathcal{R}_{t+1}}[V_{ct+1}(\mathcal{R}_{t+1}) \mid \mathcal{R}_t, \mathcal{N}_{ct}(a)] \Big\} / \theta_\epsilon \Big)}, \tag{18}$$

and the choice probability for Jio is degenerate:

$$\Pr_{ct}(\text{entry} \mid \mathcal{R}_t) = \mathbb{1}\Big\{-\kappa_t + \mu \underbrace{\mathbb{E}_{\mathcal{R}_{t+1}}[V_{ct+1}(\mathcal{R}_{t+1}) \mid \mathcal{R}_t, \mathcal{N}_{ct}(a_{ct}) = \mathcal{R}]}_{\text{value of entry}} > \mu \underbrace{\mathbb{E}_{\mathcal{R}_{t+1}}[V_{ct+1}(\mathcal{R}_{t+1}) \mid \mathcal{R}_t, \mathcal{N}_{ct}(a_{ct}) = \emptyset]}_{\text{value of waiting}}\Big\}. \tag{19}$$

The equilibrium policies are such that the probabilities on the left-hand side of equations (18) and (19) equal the probabilities used to compute the expectations on the right-hand side of these equations.

4 Estimation and Results

In this section, we explain our estimation procedure and present the estimation results. We provide more details on estimation in Appendix D.

4.1 Estimation Procedure

We estimate the demand and marginal cost parameters following Berry, Levinsohn, and Pakes (1995). To deal with the endogeneity of phone and plan prices, we use two sets of instruments: the standard instruments proposed by Berry, Levinsohn, and Pakes (1995) and the differentiation instruments developed by Gandhi and Houde (2019). The validity of our identification strategy relies on the timing assumption that cell phone firms and carriers do not observe demand shocks when choosing their product offerings and networks. This assumption is also made, for example, in Eizenberg (2014), Wollmann (2018), and Fan and Yang (2020, 2025). Our demand specification includes a rich set of fixed effects to control for systematic variation across phone technologies, plan technologies, cell phone firms, carriers, and time. Thus, although imperfect, it seems reasonable to assume that firms do not know time-varying, transitory, technology- and firm-specific shocks when they choose products. On the demand side, we are particularly interested in the coefficient on the dummy variable $\mathbb{1}(4G_j, 4G_k)$, which captures whether consumers derive additional utility from combining a 4G phone with a 4G network. This coefficient is identified by how phone sales respond to variation in carrier 4G network coverage and how plan sales respond to variation in the availability of 4G phones, where both 4G network and 4G phone availability are uncorrelated with demand and marginal cost shocks under our timing assumption. To estimate the marginal cost parameters, we back out marginal costs using the first-order conditions with respect to prices.

We obtain bounds for phone fixed costs C_{jt} by exploiting the no-profitable-deviation condition implied by the Nash equilibrium of the product choice game. Specifically, the Nash equilibrium implies that neither dropping nor adding a product increases a firm's profit. In other words, for any phone $j \in \mathcal{J}_{ft}$,

$$\Pi_{ft}^{(phone)}(\mathcal{J}_{ft}, \mathcal{J}_{-ft}, \boldsymbol{\mathcal{K}}_t) - C_{jt} \geq \Pi_{ft}^{(phone)}(\mathcal{J}_{ft} \backslash j, \mathcal{J}_{-ft}, \boldsymbol{\mathcal{K}}_t), \tag{20}$$

and for any phone $j \notin \mathcal{J}_{ft}$,

$$\Pi_{ft}^{(phone)}(\mathcal{J}_{ft}, \mathcal{J}_{-ft}, \boldsymbol{\mathcal{K}}_t) \geq \Pi_{ft}^{(phone)}(\mathcal{J}_{ft} \cup j, \mathcal{J}_{-ft}, \boldsymbol{\mathcal{K}}_t) - C_{jt}. \tag{21}$$

Therefore, we obtain an upper bound on the fixed cost for any phone $j \in \mathcal{J}_{ft}$:

$$C_{jt} \leq \Pi_{ft}^{(phone)}(\mathcal{J}_{ft}, \mathcal{J}_{-ft}, \boldsymbol{\mathcal{K}}_t) - \Pi_{ft}^{(phone)}(\mathcal{J}_{ft} \backslash j, \mathcal{J}_{-ft}, \boldsymbol{\mathcal{K}}_t) \triangleq C_{jt}^{U}, \tag{22}$$

and a lower bound for any phone $j \notin \mathcal{J}_{ft}$:

$$C_{jt} \geq \Pi_{ft}^{(phone)}(\mathcal{J}_{ft} \cup j, \mathcal{J}_{-ft}, \boldsymbol{\mathcal{K}}_t) - \Pi_{ft}^{(phone)}(\mathcal{J}_{ft}, \mathcal{J}_{-ft}, \boldsymbol{\mathcal{K}}_t) \triangleq C_{jt}^{L}. \tag{23}$$

We denote the upper and lower bounds in (22) and (23) by C_{jt}^{U} and C_{jt}^{L}, respectively, which we use to compute the per-period profit function in the dynamic network expansion game.

We estimate the parameters of carriers' network expansion costs using a maximum likelihood approach. With a slight abuse of notation, we denote all parameters governing Airtel's, Idea's, and Vodafone's entry costs, including the scale parameter of the action-specific shock, by θ. We denote Jio's entry cost parameters by $\kappa = (\kappa_1, \kappa_2)$. To construct the likelihood function, we note that for any given value of θ, we can find values of κ that match Jio's observed entry timing. Specifically, for a sufficiently large value of κ_1 (Jio's initial entry cost), Jio does not enter before 2016Q3; and for a sufficiently large value of κ_2 (the subsequent decrease in entry cost), Jio enters in 2016Q3. Let $\kappa(\theta)$ denote the smallest pair of values (κ_1, κ_2) that rationalize the observed timing of Jio's entry in 2016Q3.[11]

Because for any value of θ, we can find a corresponding $\kappa(\theta)$ that matches Jio's observed entry timing, we define our likelihood function as the likelihood of observing the actions taken by Airtel, Idea, and Vodafone in each period. We index these carriers by $c = 1, 2, 3$.

[11] Essentially, we choose the smallest value of κ_t before 2016Q3 and the largest value after 2016Q3 that are consistent with Jio's observed entry timing. Under this calibration, our counterfactual simulations predict delayed entry by Jio. If the true value of κ_t is higher before 2016Q3 and lower after 2016Q3 than the values we choose, our calibration biases the counterfactual results against finding such a delay.

The log-likelihood function is then given by

$$\mathcal{L}(\theta) = \sum_{c=1}^{3} \sum_{t=1}^{T_c} \log \Pr_{ct}(a_{ct} \mid \mathcal{R}_t, \theta), \tag{24}$$

where T_c is either T, the last period of the game, or the period in which carrier c has entered all regions according to the data. The term $\Pr_{ct}(a_{ct} \mid \mathcal{R}_t, \theta)$ represents the equilibrium choice probability in the carrier network expansion game, as defined in equation (18), with its dependence on θ now made explicit.

We compute the likelihood function in two steps. First, we calculate the per-period profits $\Pi_{ct}(\mathcal{R}_t)$ in the Bellman equations "offline," that is, prior to optimizing over θ. These profits are carriers' expected profits in the equilibrium of the product-choice and pricing game, computed using the algorithm developed by Fan and Yang (2020). Second, for each trial value of the entry-cost parameter vector θ, we solve for the equilibrium choice probabilities of the dynamic network expansion game, $\Pr_{ct}(a_{ct} \mid \mathcal{R}_t, \theta)$, using backward induction. We provide details on these two steps in Appendix D. We set the discount factor to 0.9740, which corresponds to an annual discount factor of 0.9.

4.2 Estimation Results

Table 3 shows the results of the demand estimation. The estimates indicate that consumers dislike higher prices and that price sensitivity decreases with income. With an average income of 122,117 INR, the average price coefficient is -11.04 ($= -36.8 + 5.36 \times \log(122.117)$). We also find that consumers prefer phones with larger screens, higher camera resolution, more storage, and more RAM. For example, increasing storage from 16GB to 32GB is equivalent to a price decrease of 1,435 INR on average ($= 0.99 \times 1.6/11.04 \times 10K$), which is about 13% of the average price of a 4G phone. Consumers also gain additional utility from using a 4G phone on a 4G network. The estimated coefficient on $\mathbb{1}$(4G Phone) $\times$ $\mathbb{1}$(4G Network) is 4.72, equivalent to a willingness to pay of 4,275 INR given the average price coefficient ($= 4.72/11.04 \times 10K$). This result is intuitive: even though 4G phones are compatible with 2G and 3G networks, consumers can enjoy many advanced features of a 4G phone only with a 4G network. Such complementarity between 4G phones and 4G networks leads to the interdependence between the cell phone and wireless service markets, which is the basis for the spillover effects we highlight. Overall, the demand estimation results yield a median own-price elasticity of -7.04 for phones and -5.80 for plans.

Table 4 reports the estimated marginal cost parameters for cell phones. We find that marginal costs increase with quality ($\hat{\tau}_0 > 0$) and that Indian firms' marginal costs rise more

Table 3: Estimation Results: Demand

	Est.	Std. Error
Price (10K INR)	-36.8***	11.5
Price × Log-income	5.36***	1.88
Screen Size (Inch)	0.70***	0.21
Camera (MP)	0.09*	0.05
Storage (10GB)	0.99***	0.19
RAM (GB)	0.70**	0.29
Battery Capacity (Ah)	0.29	0.26
Plan Price Multiplier	56.7***	7.42
$\mathbb{1}$(4G Phone)×$\mathbb{1}$(4G Network)	4.72***	1.31
Phone Technology FE	Yes	
Plan Technology FE	Yes	
Cell Phone Firm FE	Yes	
Carrier FE	Yes	
Time FE	Yes	
Jio First Year FE	Yes	

Notes: This table reports the estimated demand parameters and their standard errors. Consumer utility depends on a phone quality index, which is defined as a linear combination of phone characteristics: $q_j = x_j\rho$. In this table, we report $\beta_q\rho_l$ where β_q is the coefficient on quality in the utility function and ρ_l is the weight of the l^{th} characteristic in the quality index. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

steeply with quality ($\hat{\tau}_1 > 0$). However, Indian firms have a cost advantage in the low-end segment of the cell phone market ($\hat{\lambda}_1 < 0$). This finding implies that Indian cell phone firms can profitably introduce low-end 4G phones when 4G network coverage becomes sufficiently widespread.

We also find a downward trend in marginal costs for cell phones. The estimated coefficients on the time trend for both Indian and international phones are negative and statistically significant. This downward trend in marginal costs for cell phones incentivizes the continued expansion of 4G networks. This is because decreasing marginal costs can lead to lower prices and greater product variety, thereby expanding the cell phone market, which in turn gives carriers in the complementary wireless service market stronger incentives to deploy their 4G networks.

Table 4: Estimation Results: Phone Marginal Cost Parameters

	Est.	Std. Error
Constant (λ_0)	-0.44***	0.14
Quality (τ_0)	0.14***	0.02
$\mathbb{1}$(Indian) (λ_1)	-1.80***	0.36
Quality$\times\mathbb{1}$(Indian) (τ_1)	0.17***	0.06
Time Trend $\times\mathbb{1}$(Indian) (η_1)	-0.06***	0.01
Time Trend $\times\mathbb{1}$(International) (η_2)	-0.07***	0.01
$\mathbb{1}$(JioPhone) (χ)	-0.07	0.05

*** $p < 0.01$.

Table 5: Estimated 4G Phone Markups (INR)

Quantile	25%	50%	75%
Indian 4G Phones	1,011	1,044	1,096
International 4G Phones	1,132	1,259	1,738

Table 5 presents the quantiles of markups for Indian 4G phones and international 4G phones separately and shows that international 4G phones have higher markups than Indian 4G phones: the median markup is 1,259 INR for an international 4G phone versus 1,044 INR for an Indian 4G phone, and both the 25th and 75th percentiles are higher for international phones. This finding is consistent with international firms having an advantage in 4G phone offerings.

Table 6 reports the estimates of carriers' network expansion cost parameters. The estimates show that a carrier incurs an additional cost to launch its 4G network ($\hat{\theta}_{1c} > 0$) and that the entry cost decreases over time ($\hat{\theta}_{2c} < 0$) and increases with the total market size of the newly entered regions ($\hat{\theta}_3 > 0$). For Jio, we find that the minimum pre-2016Q3 entry cost (κ_1) that rationalizes its non-entry prior to 2016Q3 is 14.81 billion INR, and the minimum decrease in entry cost from 2016Q3 onward (κ_2) that rationalizes its entry in 2016Q3 is 1.12 billion INR. These numbers imply an entry cost of 13.69 billion INR for Jio to enter all 12 regions studied in the entry game. In comparison, the realized total entry cost is 199 billion INR for Airtel, 57 billion INR for Idea, and 58 billion INR for Vodafone.

Despite the parsimonious entry cost specification, our estimated dynamic network expansion model fits the data reasonably well. To assess model fit, we conduct a factual simulation

Table 6: Estimation Results: Carrier Entry Cost Parameters

	Est.	Std. Error
Constant (θ_{0c})		
Airtel	5.50***	0.004
Idea	4.94***	0.002
Vodafone	7.68***	0.004
Additional First Entry Cost (θ_{1c})		
Airtel	0.06***	0.005
Idea	4.70***	0.017
Vodafone	2.96***	0.004
Time Trend (θ_{2c})		
Airtel	-2.00***	0.010
Idea	-2.84***	0.006
Vodafone	-3.21***	0.013
$\log(1 + \text{Total Market Size})$ (θ_3)	0.30***	0.001
Scale Parameter (θ_ϵ)	9.56***	0.006

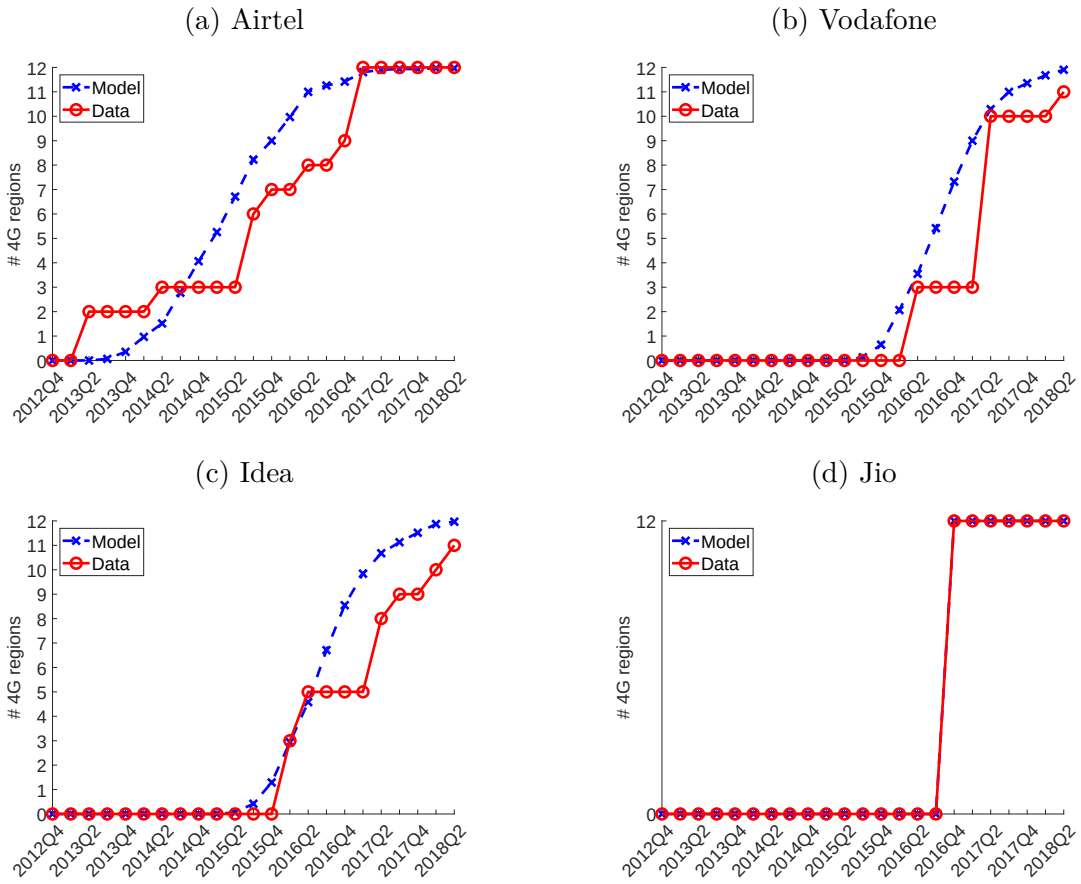
*** $p < 0.01$.

following the procedure in Appendix E and plot the average number of regions with 4G coverage, averaged across simulations, in each period for each carrier in Figure 2. This figure also plots the observed number for comparison. The figure shows that the model-simulated average number of 4G regions is, as expected, smoother than the observed number. However, the two time series are reasonably close.[12]

In summary, our estimation results support the economic forces through which complementarity generates spillovers. First, the estimated complementarity between 4G phones and 4G plans links the cell phone and wireless service markets during the 4G rollout. Second, the higher estimated markups for international 4G phones indicate that international firms had an advantage in 4G phone offerings, making their product choices important for carriers' incentives to expand 4G networks. Third, the decline in marginal costs over time supports continued expansion of the cell phone market, which strengthens carriers' incentives to extend 4G coverage. Finally, the finding that Indian firms have a cost advantage in the low-end segment implies that, once 4G coverage becomes sufficiently widespread, domestic firms can profitably introduce low-end 4G phones. Taken together, these estimates discipline

[12]The fit for Jio's entry timing is perfect because, as mentioned above, we choose the Jio entry cost parameters (κ_1, κ_2) to match the observed timing of Jio's entry (into all regions).

Figure 2: Model Fit: Observed vs. Simulated Number of 4G Regions over Time by Carrier



the cross-market spillovers from cell phone product offerings to carriers' regional 4G entry and vice versa. These spillovers then determine how shocks to international cell phone firms spill over to domestic cell phone firms through affecting 4G network expansion.[13]

5 Counterfactual Simulations

We conduct two sets of counterfactual simulations, both of which are designed to quantify how changes in 4G phone availability propagate across the two markets. In each case, a policy changes product offerings or sales in the cell phone market. Through the complementarity

[13]It is natural to ask whether Jio alone drives the spillovers across the cell phone and wireless service markets, since Jio operates in both markets and restricts the connectivity of JioPhones to its own network. Both the timing in the data and the counterfactual simulations suggest otherwise. First, the comovement of 4G plans and 4G phones predates JioPhones: Jio launched its 4G network in 2016Q3 but began selling JioPhones only in 2017Q3, whereas the joint growth of 4G networks and 4G phone sales started in 2013. Second, as our counterfactual simulations in Section 5 show, the policies we study primarily affect non-Jio firms in the two markets, and these effects have significant welfare implications.

between the two markets, this change affects carriers' incentives to expand 4G networks. The resulting network rollout then feeds back into cell phone firms' product-choice decisions.

For each counterfactual scenario, we simulate three key endogenous outcomes in each period—4G networks, cell phone product offerings, and cell phone and plan prices—while treating the 2G and 3G networks and each cell phone firm's potential products as exogenous.[14] Specifically, we solve for the equilibrium of the dynamic 4G network expansion game under the counterfactual policy, which nests the equilibrium of the static game of product choice and pricing under the counterfactual policy. We then forward-simulate the network rollout paths implied by this equilibrium, and compute the equilibrium product offerings and prices on each simulated path. We report averages across simulations. Appendix E provides details on the simulations.

5.1 Ban on Budget Chinese Phones

In the first counterfactual simulation, we restrict the availability of low-cost Chinese phones, which were a large source of 4G product variety. This counterfactual corresponds to a policy considered by the Indian government that would have prevented Chinese firms from selling phones priced below 12,000 INR in an effort to push Chinese cell phone firms out of the lower end of the Indian cell phone market (Al Jazeera (2022)). Such a policy would be a significant restriction on Chinese cell phone firms. In 2018Q2, for example, 70% of Chinese phones were priced below 12,000 INR. In this counterfactual simulation, we ask what would have happened if this policy had been implemented starting in 2012Q4, the first period of the dynamic network expansion game.

This policy directly affects Chinese cell phone firms by imposing a price floor of 12,000 INR on their products. It can change Chinese firms' product offerings because products that are profitable below the threshold may not be profitable at or above the threshold. It also affects other cell phone firms' product choices through a direct competition effect. Moreover, due to the interdependence between the two markets, it can also affect carriers' regional entry into 4G service, which in turn affects cell phone offerings.

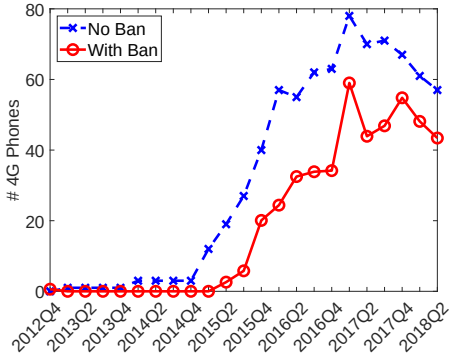
We simulate the outcomes in both markets with and without the ban and report the averages across simulations in Figure 3. In panels (a)–(d), we plot the number of 4G phones and 4G regions with and without the ban. In panels (e)–(g), we plot changes in welfare measures due to the ban.

From Figure 3, we find that the ban significantly reduces the number of 4G phones available in the market (panel (a)) despite Indian cell phone firms introducing more 4G

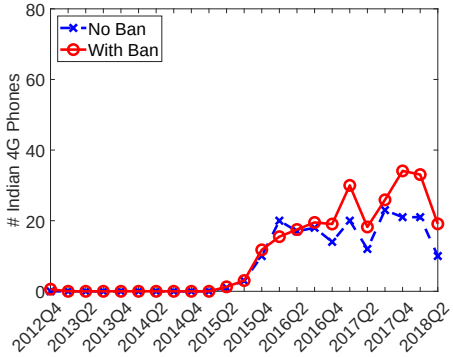
[14] We fix the 2G and 3G networks at their observed values and each cell phone firm's potential products as defined in Appendix D.

Figure 3: Effects of the Ban on Budget Chinese Phones

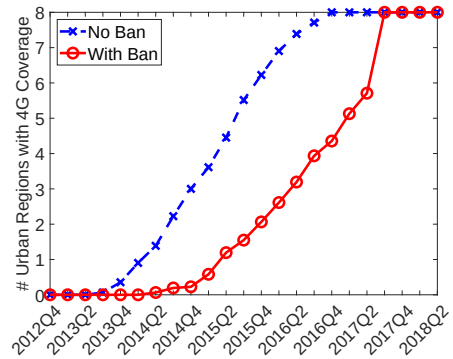
(a) # 4G Phones



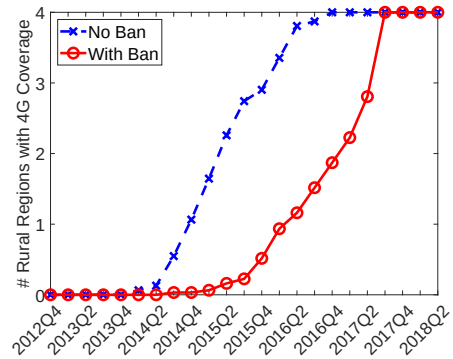
(b) # Indian 4G Phones



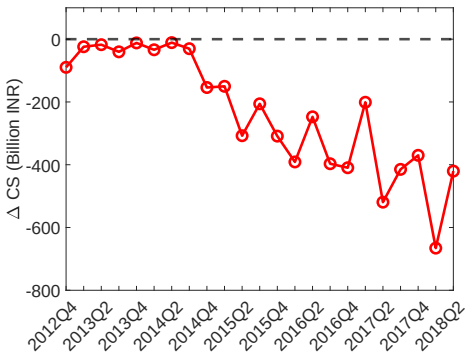
(c) # Urban Regions with 4G Coverage



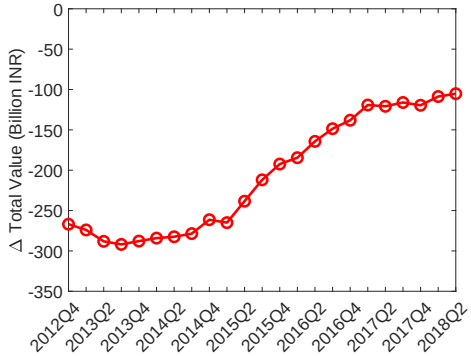
(d) # Rural Regions with 4G Coverage



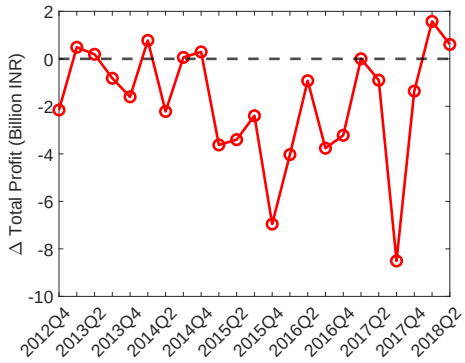
(e) Δ(Consumer Surplus)



(f) Δ(Total Value of Carriers)



(g) Δ(Total Profit of Indian Cell Phone Firms)



phones in later periods (panel (b)). This reduction in 4G product variety weakens cross-market spillovers and leads to slower expansion of 4G networks in both urban regions (panel (c)) and rural regions (panel (d)). In particular, under the ban, it takes roughly five quarters longer to reach the same number of regions with 4G coverage.

The combination of reduced 4G product offerings in the cell phone market and a slower 4G network rollout in the wireless service market reduces consumer surplus by an average of 235.7 billion INR per quarter (panel (e)).[15] Carriers are also worse off because the ban restricts an important group of firms in the complementary cell phone market: the sum of the four carriers' discounted total values falls by 181.4 billion INR on average (panel (f)).[16]

Interestingly, even though the ban disadvantages some competitors of Indian cell phone firms, Indian cell phone firms are not necessarily better off (panel (g)). This is because there are two countervailing forces. On the one hand, Indian cell phone firms face less competition when some competitors can no longer profitably offer budget cell phones. On the other hand, they face a slower rollout of the 4G network in the wireless service market, which reduces their profits given the complementarity between these two markets. This result indicates that the direct competition effect is dominated by the spillover effect.

In sum, the ban illustrates how reducing 4G product variety in the cell phone market propagates to the wireless service market. By making many low-cost Chinese 4G phones unavailable in equilibrium, the ban causes some consumers to substitute toward 2G or 3G phones or the outside option. This reduces carriers' incentives to expand 4G coverage. The slower rollout then feeds back into the cell phone market by lowering the profitability of offering 4G phones, including those offered by Indian firms. Thus, the ban affects domestic firms through two opposing forces: less direct competition in the cell phone market and a weaker cross-market spillover from 4G network expansion. In our simulations, the lost spillover dominates.

5.2 Subsidy Scope

In the second set of counterfactual simulations, we study how the scope of a 4G phone subsidy affects product offerings, network expansion, and welfare. Specifically, we compare two subsidy policies in the cell phone market. Under the unrestricted subsidy, starting in 2012Q4, all 4G phones—both domestic and international—are eligible for a subsidy equal to 20% of their prices. Under the domestic-only subsidy, only Indian 4G phones are eligible

[15] For comparison, average total revenue in these two markets is 605 billion INR per quarter.

[16] For panel (f), we compute the value function for each carrier evaluated at the state corresponding to a simulated path, take the sum over carriers, and then average across simulations. The sum is taken over three carriers before Jio becomes a potential entrant in 2015Q3 and over four carriers after 2015Q3.

for the same subsidy rate. Figure 4 shows the simulated outcomes under these two policies as well as those under the benchmark scenario of no subsidy. In panels (a)–(d), we plot the levels under all three scenarios. In panels (e)–(h), we plot the difference relative to the no-subsidy benchmark.

The subsidy counterfactual works through the same cross-market feedback as the ban counterfactual, but in the opposite direction. A subsidy increases 4G phone adoption. Through the complementarity between the two markets, higher 4G phone adoption gives carriers stronger incentives to expand their 4G networks, which in turn makes 4G phone offerings more profitable. The question is which subsidy design better activates this feedback and is more cost-effective at accelerating 4G diffusion and improving welfare.

We find that both subsidy policies increase 4G phone product offerings (panel (a) of Figure 4) and 4G phone sales (panel (b)), but the unrestricted subsidy generates larger increases. On average across quarters, it raises the number of 4G phones by 53.8% and 4G phone sales by 63.5%, compared with 19.8% and 23.7%, respectively, under the domestic-only subsidy.

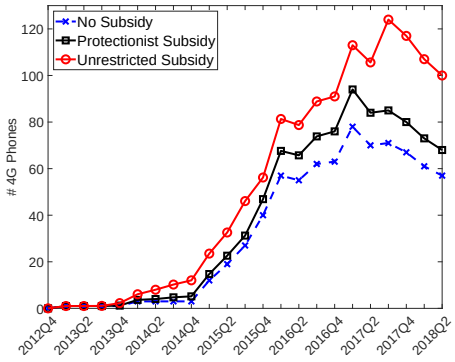
Panels (c) and (d) of Figure 4 show that both subsidy policies also speed up 4G deployment in the wireless service market, with the unrestricted subsidy accelerating 4G expansion more than the domestic-only subsidy in both urban and rural regions. Specifically, while the domestic-only subsidy speeds up 4G network expansion in urban regions by about one quarter (i.e., it takes one quarter less to reach the same coverage), the unrestricted subsidy can reduce the time needed by up to four quarters. Similarly, the domestic-only subsidy barely affects 4G deployment in rural regions, whereas the unrestricted subsidy speeds it up by roughly two quarters. This difference arises because the unrestricted subsidy induces greater 4G phone adoption and thus gives carriers stronger incentives to expand their 4G networks. In rural regions, which are less profitable to enter, the domestic-only subsidy barely induces carriers to expand 4G coverage, while the unrestricted subsidy does.

Turning to welfare effects, we find that the unrestricted subsidy benefits both consumers and carriers more than the domestic-only subsidy does (panels (e) and (f)). The unrestricted subsidy has a larger positive effect on consumer surplus because it applies more broadly, increases product offerings in the cell phone market more, and accelerates 4G network expansion more. It also has a larger positive effect on carriers due to positive cross-market spillovers: carriers in the wireless service market benefit from a more vibrant complementary market with more cell phone offerings and sales.

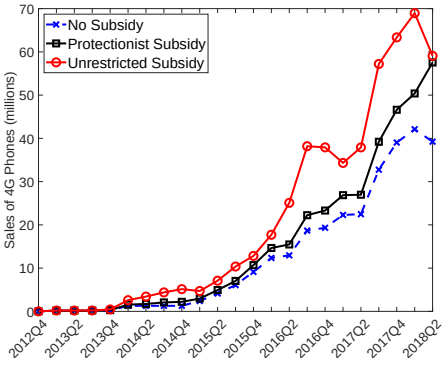
We next compare these welfare gains with government spending under the two subsidy designs. Panel (g) shows that government spending is higher under the unrestricted subsidy than under the domestic-only subsidy, at 33.3 billion INR per quarter on average compared

Figure 4: Effects of Unrestricted and Domestic-Only Subsidies

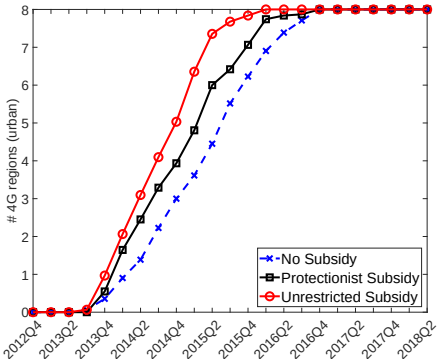
(a) # 4G Phones



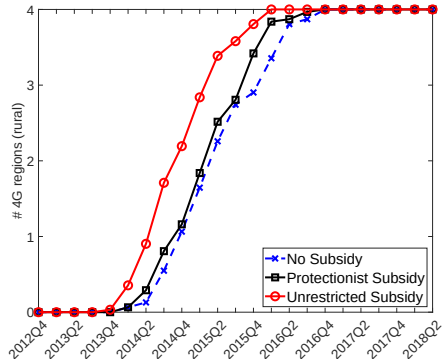
(b) Sales of 4G Phones



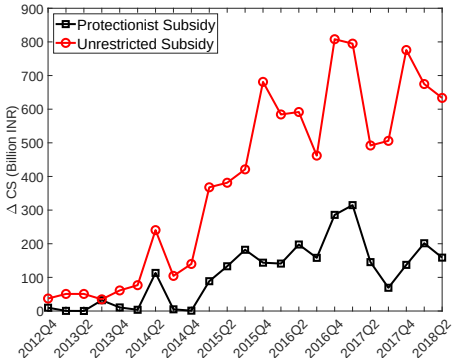
(c) # Urban Regions with 4G Coverage



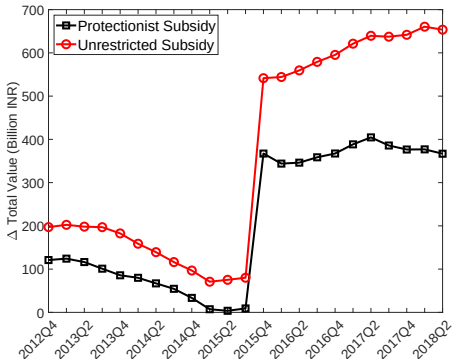
(d) # Rural Regions with 4G Coverage



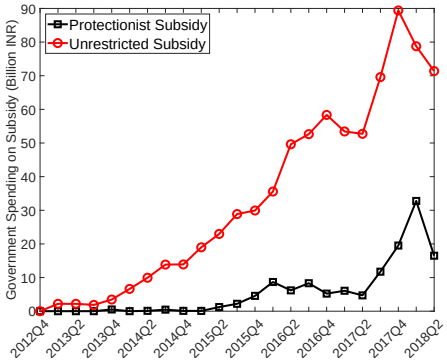
(e) Δ(Consumer Surplus)



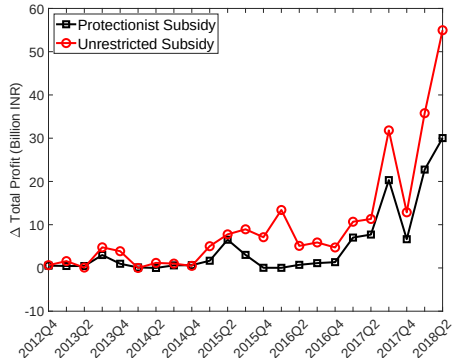
(f) Δ(Total Value of Carriers)



(g) Government Spending



(h) Δ(Total Profit of Indian Cell Phone Firms)



with 5.6 billion INR. However, this difference in government spending is much smaller than the difference in consumer surplus: on average, the unrestricted subsidy raises consumer surplus by 390 billion INR per quarter, compared with 110 billion INR under the domestic-only subsidy. In other words, the unrestricted subsidy delivers a much larger consumer benefit at only a modestly higher cost, so it is more cost-effective.

Finally, panel (h) shows that, like consumers and carriers, Indian cell phone firms are also better off under the unrestricted subsidy than under the domestic-only subsidy. Thus, although only their products are eligible under the domestic-only subsidy, Indian cell phone firms are ultimately worse off than under the unrestricted subsidy because of the slower 4G network rollout. This result again indicates that the direct competition effect is dominated by the spillover effect. This counterfactual delivers the same message as the counterfactual in Section 5.1: policies that reduce the contribution of international firms to 4G phone availability weaken carriers' incentives to expand 4G networks and, through this cross-market feedback, can lower the profitability of domestic firms' own 4G offerings.

6 Conclusion

This paper studies how spillovers across two complementary markets shape firms' entry and product choice decisions and welfare. In the Indian mobile phone industry during the 4G rollout, carriers' regional entry into 4G service and cell phone firms' product offerings are linked across markets: the availability of 4G phones affects carriers' incentives to expand 4G networks, and the expansion of 4G networks affects cell phone firms' incentives to offer 4G phones. Through this interdependence, international competition in one market can benefit domestic firms and consumers by accelerating the development of the complementary market.

Both policy counterfactuals we study point to the importance of these spillovers. The first is a ban on budget Chinese phones. The second is a subsidy for 4G phones limited to Indian 4G phones, which we compare with the same subsidy offered to all 4G phones. Each policy curbs the role of international firms in the cell phone market — the ban by restricting their budget phones, the domestic-only subsidy by excluding them from eligibility — but both also weaken the spillover to carriers' 4G network rollout. In our counterfactual analysis, this lost spillover offsets the gains that Indian cell phone firms receive from reduced competition. The ban would lower consumer surplus and carriers' value without raising Indian cell phone firms' profits. Similarly, the domestic-only subsidy would generate a smaller gain in consumer surplus while leaving Indian cell phone firms worse off than under an unrestricted subsidy.

These findings apply more broadly to settings with complementary markets and to the design of industrial policy in developing countries. When markets are complementary, tech-

nologically advanced firms can affect welfare not only through direct competition but also by accelerating the development of the complementary market. In developing economies, these firms are often foreign, so policies that restrict international competition may have unintended effects on domestic firms, product variety, and consumer welfare. More generally, our results show that evaluations of trade and industrial policies can change substantially when they account for spillovers across complementary markets rather than treating each market in isolation.

References

Aitken, Brian J., and Ann E. Harrison. 1999. "Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela." *American Economic Review* 89 (3): 605–618.

Al Jazeera. 2022. "India aims to restrict sale of Chinese cheap smartphones: Report." [Link to the Report], Published on: Aug 8, 2022, Accessed: June, 2026.

Alé-Chilet, Jorge, Eve Colson-Sihra, and Fernando Luco. 2024. "Product Bans as Protectionism: The Maggi Scare." working paper, Universidad de los Andes.

Amiti, Mary, and Jozef Konings. 2007. "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia." *American Economic Review* 97 (5): 1611–1638.

Bai, Jie, Panle Jia Barwick, Shengmao Cao, and Shanjun Li. 2025. "Quid Pro Quo, Knowledge Spillovers, and Industrial Quality Upgrading: Evidence from the Chinese Auto Industry." *American Economic Review* 115 (11): 3825–3852.

Barwick, Panle Jia, Shengmao Cao, and Shanjun Li. 2021. "Local Protectionism, Market Structure, and Social Welfare: China's Automobile Market." *American Economic Journal: Economic Policy* 13 (4): 112–151.

Barwick, Panle Jia, Myrto Kalouptsidi, and Nahim Bin Zahur. 2025. "Industrial Policy Implementation: Empirical Evidence from China's Shipbuilding Industry." *Review of Economic Studies* 92 (6): 3611–3648.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica* 63 (4): 841–890.

Björkegren, Daniel. 2019. "The Adoption of Network Goods: Evidence from the Spread of Mobile Phones in Rwanda." *The Review of Economic Studies* 86 (3): 1033–1060.

Bloom, Nicholas, Mirko Draca, and John Van Reenen. 2016. "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity." *The Review of Economic Studies* 83 (1): 87–117.

Bollinger, Bryan, Naim Darghouth, Kenneth Gillingham, and Andres Gonzalez-Lira. 2024. "Valuing Technology Complementarities: Rooftop Solar and Energy Storage." Working Paper 32003, National Bureau of Economic Research.

Callejas, Jeronimo, Chirantan Chatterjee, and Debi Prasad Mohapatra. 2026. "Domestic Tariffs and Consumer Welfare in Developing Countries: Evidence from India." *The RAND Journal of Economics*.

Chaves, Daniel. 2026. "Market Power, Taxation and Product Variety in the Brazilian Automobile Industry." *The RAND Journal of Economics*, Forthcoming.

Collard-Wexler, Allan. 2013. "Demand Fluctuations in the Ready-mix Concrete Industry." *Econometrica* 81 (3): 1003–1037.

Draganska, Michaela, Michael Mazzeo, and Katja Seim. 2009. "Beyond Plain Vanilla: Modeling Joint Product Assortment and Pricing Decisions." *Quantitative Marketing and Economics* 7 (2): 105–146.

Dunne, Timothy, Shawn D Klimek, Mark J Roberts, and Daniel Yi Xu. 2013. "Entry, Exit, and the Determinants of Market Structure." *The RAND Journal of Economics* 44 (3): 462–487.

Eizenberg, Alon. 2014. "Upstream Innovation and Product Variety in the U.S. Home PC Market." *The Review of Economic Studies* 81 (3): 1003–1045.

Elliott, Jonathan T, Georges V Houngbonon, Marc Ivaldi, and Paul T Scott. 2025. "Market Structure, Investment, and Technical Efficiencies in Mobile Telecommunications." *Journal of Political Economy* 133 (5): 1401–1459.

Elsas-Nicolle, Ambre, Shiyuan Li, and Frank Verboven. 2026. "Who Bears the Costs of Technology Sanctions? Evidence from Global Smartphone Markets." Working Paper DP21405, Centre for Economic Policy Research.

Fajgelbaum, Pablo D., Pinelopi K. Goldberg, Patrick J. Kennedy, and Amit K. Khandelwal. 2020. "The Return to Protectionism." *The Quarterly Journal of Economics* 135 (1): 1–55.

Fan, Ying. 2013. "Ownership Consolidation and Product Characteristics: A Study of the US Daily Newspaper Market." *American Economic Review* 103 (5): 1598–1628.

Fan, Ying, and Mo Xiao. 2015. "Competition and Subsidies in the Deregulated US Local Telephone Industry." *The RAND Journal of Economics* 46 (4): 751–776.

Fan, Ying, and Chenyu Yang. 2020. "Competition, Product Proliferation, and Welfare: A Study of the US Smartphone Market." *American Economic Journal: Microeconomics* 12 (2): 99–134.

Fan, Ying, and Chenyu Yang. 2025. "Estimating Discrete Games with Many Firms and Many Decisions: An Application to Merger and Product Variety." *Journal of Political Economy* 133 (6): 1886–1931.

Flaaen, Aaron, Ali Hortaçsu, and Felix Tintelnot. 2020. "The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines." *American Economic Review* 110 (7): 2103–2127.

Gandal, Neil, Michael Kende, and Rafael Rob. 2000. "The Dynamics of Technological Adoption in Hardware/Software Systems: The Case of Compact Disc Players." *The RAND Journal of Economics* 31 (1): 43–61.

Gandhi, Amit, and Jean-François Houde. 2019. "Measuring Substitution Patterns in Differentiated Products Industries." Working Paper 26375, National Bureau of Economic Research.

Garg, Shresth, and Sagar Saxena. 2025. "Mixing Tariffs and Subsidies for Industrial Policy Objectives in Oligopolistic Markets."

Goldberg, Pinelopi Koujianou, Amit Kumar Khandelwal, Nina Pavcnik, and Petia Topalova. 2010. "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India." *The Quarterly Journal of Economics* 125 (4): 1727–1767.

Granja, Joao. 2024. "Regulation and Service Provision in Dynamic Oligopoly: Evidence from Mobile Telecommunications." working paper, UCL.

Harrison, Ann, and Andrés Rodríguez-Clare. 2010. "Trade, Foreign Investment, and Industrial Policy for Developing Countries." In *Handbook of Development Economics*, Volume 5. 4039–4214, Elsevier.

Heid, Pascal, Kevin Remmy, and Mathias Reynaert. 2024. "Equilibrium Effects in Complementary Markets: Electric Vehicle Adoption and Electricity Pricing." TSE working paper.

Javorcik, Beata Smarzynska. 2004. "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages." *American Economic Review* 94 (3): 605–627.

Kalouptsidi, Myrto. 2018. "Detection and Impact of Industrial Subsidies: The Case of Chinese Shipbuilding." *The Review of Economic Studies* 85 (2): 1111–1158.

Kwon, Hyuk-soo. 2026. "Subsidies Versus Tradable Credits for Electric Vehicles: The Role of Market Power in the Credit Market." working paper, University of Chicago.

Lane, Nathan. 2025. "Manufacturing Revolutions: Industrial Policy and Industrialization in South Korea." *The Quarterly Journal of Economics* 140 (3): .

Lee, Robin. 2013. "Vertical Integration and Exclusivity in Platform and Two-Sided Markets." *American Economic Review* 103 (7): 2960–3000.

Li, Jing. 2023. "Compatibility and Investment in the U.S. Electric Vehicle Market." working paper, Tufts University.

Mohapatra, Debi Prasad, and Yang Zhang. 2025. "Rx-to-OTC Switch, Market Exclusivity, and Consumer Welfare: A Study of the US Anti-Ulcer Drug Markets." *The RAND Journal of Economics* 56 (4): 587–606.

Rotemberg, Martin. 2019. "Equilibrium Effects of Firm Subsidies." *American Economic Review* 109 (10): 3475–3513.

Shreeti, Vatsala. 2024. *Tracing the Adoption of Digital Technologies.* Bank for International Settlements, Monetary and Economic Department.

Springel, Katalin. 2021. "Network Externality and Subsidy Structure in Two-Sided Markets: Evidence from Electric Vehicle Incentives." *American Economic Journal: Economic Policy* 13 (4): 393–432.

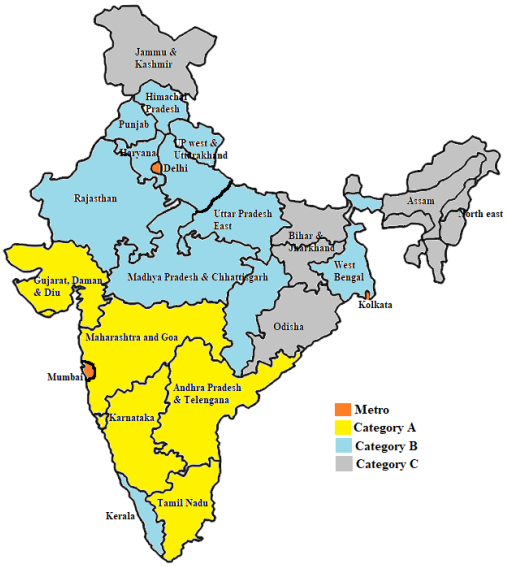
Sweeting, Andrew. 2013. "Dynamic Product Positioning in Differentiated Product Markets: The Effect of Fees for Musical Performance Rights on the Commercial Radio Industry." *Econometrica* 81 (5): 1763–1803.

Wollmann, Thomas G. 2018. "Trucks Without Bailouts: Equilibrium Product Characteristics for Commercial Vehicles." *American Economic Review* 108 (6): 1364–1406.

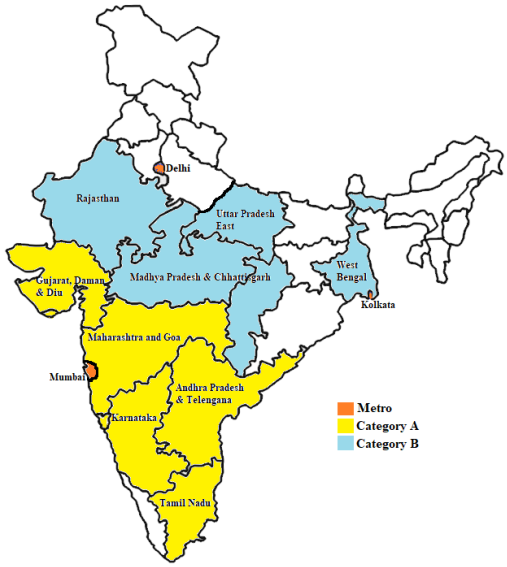
Appendices

A Telecommunications Regions in India

(a) 22 Telecommunications Regions



(b) 12 Regions Used in the Dynamic Estimation



B Sample Construction

Cell Phone Sample. We drop a firm from the 3G segment of the cell phone market if its 3G phone sales are less than 5% of all 3G phone sales. We drop a firm from the 4G segment of the cell phone market if its 4G phone sales are less than 1% of all 4G phone sales.

Measurement of Plan Market Shares. A consumer needs both a phone and a plan to enjoy mobile service. Our model implicitly assumes that a consumer actively chooses a plan only when she actively chooses a phone. However, whereas our phone sales data measure units sold rather than the number of consumers holding a particular phone, our plan data record the number of connections. Therefore, rather than measuring the plan market share directly as $Q_{kt}^{(pl)}/M_t$, where $Q_{kt}^{(pl)}$ is the number of connections and M_t is the market size, we adjust it by the ratio of total phone sales $\tilde{Q}_t^{(ph)}$ to total wireless service connections $\tilde{Q}_t^{(pl)}$

in period t. The plan market share is therefore $s_{kt}^{(pl)} = \frac{Q_{kt}^{(pl)}}{M_t} \frac{\tilde{Q}_t^{(ph)}}{\tilde{Q}_t^{(pl)}}$. With this measurement of plan market shares, the ratio of the market shares of two plans equals the ratio of their numbers of connections in that period, i.e., $\frac{s_{kt}^{(pl)}}{s_{k't}^{(pl)}} = \frac{Q_{kt}^{(pl)}}{Q_{k't}^{(pl)}}$.

C Summary Statistics

In this section, we report summary statistics on cell phones, plans, and telecommunications regions.

Table C.1 reports summary statistics for 3G and 4G cell phones. An observation is a phone-year combination for 2011–2014 and a phone-quarter combination for 2015Q1–2018Q2. We divide annual sales between 2011 and 2014 by four when reporting sales statistics.

Table C.1: Summary Statistics: Cell Phones

	Mean	S.D.
Price (INR)	11,297	11,118
Sales (Million)	0.35	0.55
Screen Size (Inch)	4.79	0.82
Camera Resolution (Megapixel)	8.47	4.29
Internal Memory (GB)	17.08	17.04
RAM (GB)	1.66	1.11
Battery Capacity (Ah)	2.50	0.83
Number of Obs	1,106	

Table C.2 reports summary statistics for the wireless service plans. An observation is a plan-quarter combination.

Table C.2: Summary Statistics: Plans

	Mean	S.D.
Monthly Price (INR)	121	41
Sales (Million)	2.83	3.58
Number of Obs	489	

Table C.3 reports summary statistics for the 22 telecommunications regions. The first column gives the category for each region. The second column reports the population from the 2011 Census. The last column reports average income for each region, averaged over

time and expressed in 2015 INR. We proxy income by per capita state domestic product, using data obtained from the Reserve Bank of India.

Table C.3: Summary Statistics: Regions

Region	Category	Population	Avg Income
Delhi	Metro	16,787,941	296,709
Kolkata	Metro	4,486,679	225,688
Mumbai	Metro	12,478,447	495,791
Andhra Pradesh & Telangana	A	84,580,777	118,678
Gujarat & Daman & Diu	A	60,682,939	137,067
Karnataka	A	61,095,297	144,777
Maharashtra & Goa	A	101,354,431	145,467
Tamil Nadu	A	72,147,030	139,201
Haryana	B	25,351,462	163,762
Kerala	B	33,470,534	146,118
Madhya Pradesh & Chhattisgarh	B	98,172,007	66,068
Punjab	B	27,743,338	117,132
Rajasthan	B	68,548,437	81,513
UP (West) & Uttarakhand	B	70,029,994	67,823
Uttar Pradesh (East)	B	139,868,639	31,698
West Bengal	B	86,789,436	75,704
Assam	C	31,205,576	58,972
Bihar & Jharkhand	C	137,087,586	37,288
Himachal Pradesh	C	6,864,602	132,110
Jammu and Kashmir	C	12,541,302	69,644
North East	C	14,566,612	84,396
Orissa	C	41,974,218	68,541

D Estimation Details

D.1 Treatment of 2G Phones

During our sample period, which covers the 4G rollout, the market still contains inexpensive 2G phones. We aggregate all 2G cell phones in a period into a single composite product and represent the utility that a consumer derives from it as the sum of a mean utility $\delta_{2G,t}$ and an idiosyncratic taste shock. For demand estimation, we follow Berry, Levinsohn, and

Pakes (1995), define the mean utility for each phone δ_{jt} and each plan δ_{kt}, and invert them out by matching the observed market shares. We normalize δ_{jt} for the 2G composite phone to be zero because u_{ijkt} depends on δ_{jt} and δ_{kt} only through their sum, and thus their levels cannot be separately identified. On the supply side, we treat the 2G composite product as exogenous and do not study the product-choice or pricing decisions regarding this product.

D.2 Definition of Potential Products

We treat the availability of Apple's iPhones and Jio's JioPhones as exogenous and thus do not define potential products for them. Apple does not produce cell phones specifically for India, and its product portfolio is largely driven by the global market. As for JioPhones, Jio did not introduce them when it launched its 4G network, largely for reasons outside our model.

We define potential products for other cell phone firms as follows. A product is a triple consisting of firm, technology, and quality. We define the set of potential products separately for each technology.

Potential 3G Products. For each cell phone firm f, let $\underline{q}_f^{3G}$ represent the minimum quality of all its 3G phones in the sample and $\overline{q}_{ft}^{3G}$ represent the maximum quality of all its 3G phones up to and including time t.

For each cell phone firm f, we define its potential 3G products at time t as follows.

1. Define a vector of grid points between $\underline{q}_f^{3G} - 5$ and $\overline{q}_{ft}^{3G} + 5$ with increments of 1.
2. Remove a grid point from this vector if the quality of an observed 3G phone of firm f (i.e., q_j for $j \in \mathcal{J}_{ft}$) is within 0.5 of that grid point.
3. Define the set of potential 3G products for cell phone firm f at time t as the union of the remaining grid points and the qualities of its observed 3G products.

In our data, some international cell phone firms never sold 3G phones in India. For these firms, both $\underline{q}_f^{3G}$ and $\overline{q}_{ft}^{3G}$ are undefined, and we define their set of potential 3G products as empty. Moreover, all international cell phone firms stopped selling 3G phones after 2017Q1. Therefore, we define this set as empty after 2017Q1 for all international cell phone firms. Finally, two Indian cell phone firms started selling 3G phones later than the first period. For each of these firms, in periods before it first offered a 3G phone, we define its set of potential 3G products as the set in the first period in which it offered 3G phones.

Potential 4G Products. To define the set of potential 4G products for each firm f, we define $\underline{q}_f^{4G}$ and $\overline{q}_{ft}^{4G}$ analogously and follow the same Steps 1–3 above.

For any firm and any period before the firm first offered 4G phones, we define its set of potential 4G products as its set in the first period in which it offered 4G phones. This rule allows firms to introduce 4G phones earlier than observed if doing so is profitable in a counterfactual scenario, while avoiding the use of product qualities beyond those available when the firm first offered 4G phones.

D.3 Details on Estimating the Dynamic Network Expansion Game

Restrictions on the Action Space. We impose three restrictions on the action space $\mathcal{A}_c(\mathcal{R}_{ct})$, all of which are consistent with the data. First, a carrier does not expand into a Category-B region unless it has already deployed its 4G network in at least one Metro or Category-A region. Second, a carrier does not enter more than two Metro regions, more than three Category-A regions, or more than three Category-B regions in a single period. Third, Airtel and Idea do not enter more than four regions across all categories at a time.

Computing the Per-Period Profit Functions. We calculate the per-period profit $\Pi_{ct}(\mathcal{R}_t)$ in the Bellman equations "offline," that is, prior to optimizing over θ. As explained earlier, $\Pi_{ct}(\mathcal{R}_t)$ corresponds to $\Pi_{ct}^{(carrier)}(\mathcal{K}_t)$ in equation (11), the carrier's expected profit obtained by integrating over demand shocks ξ_{jt}, marginal cost shocks ω_{jt}, and fixed costs C_{jt}. To compute this expectation, we draw demand and marginal cost shocks from their empirical distributions, and draw C_{jt} from a uniform distribution over $[0.8C_{jt}^U, C_{jt}^U]$ for $j \in \mathcal{J}_t$ and over $[C_{jt}^L, 1.2C_{jt}^L]$ for $j \notin \mathcal{J}_t$.[17] For each draw, we compute the equilibrium of the static product-choice and pricing game using the heuristic algorithm developed by Fan and Yang (2020). We then evaluate each carrier's profit at the resulting equilibrium and average across all draws to obtain the per-period profit $\Pi_{ct}(\mathcal{R}_t)$.

Value Function Approximation. Estimating the equilibrium of the dynamic network expansion game is challenging because the state space is large. The state variable in the dynamic expansion game is $\mathcal{R}_t = (\mathcal{R}_{1t}, \ldots, \mathcal{R}_{4t})$, where $\mathcal{R}_{ct}$ is the set of regions in which carrier c offers 4G services in period t. For Jio, $\mathcal{R}_{ct}$ is either the empty set or the full set

[17] As explained above, we obtain upper bounds C_{jt}^U for observed products ($j \in \mathcal{J}_t$) and lower bounds C_{jt}^L for unobserved products ($j \notin \mathcal{J}_t$). We draw fixed costs for potential products from ranges consistent with these bounds, similar to Fan and Yang (2020). Alternatively, one could specify and estimate a parametric fixed-cost function, as in Fan and Yang (2025). However, this approach typically yields set identification instead of point identification of the fixed-cost parameters. This complicates estimation of the dynamic game because it nests the product-choice game, for which fixed-cost parameters are important primitives.

of 12 regions. For the other three carriers, $\mathcal{R}_{ct}$ is a subset of the 12 regions. Therefore, the number of possible values for the state variable $\mathcal{R}_t$ is up to $(2^{12})^3 \times 2$.

To address the large state space, we follow Sweeting (2013) to compute the value function for a subset of possible values of the state variable and approximate the value function for other values of the state variable with a flexible (nonparametric) function of a set of summary statistics of the state variable. Specifically, for each period $t = 1, \ldots, T$, we randomly draw a set of values for $\mathcal{R}_t$, add the observed values of $\mathcal{R}_t$ to this set, and denote the union by $\mathscr{R}_t$. We compute the value function $V_{ct}(\mathcal{R}_t^d, \theta)$ for each $\mathcal{R}_t^d \in \mathscr{R}_t$. We then fit a regression tree of $V_{ct}(\mathcal{R}_t^d, \theta)$ on a set of summary statistics of the state variable $s_t(\mathcal{R}_t^d)$, defined below, using the observations $\mathcal{R}_t^d \in \mathscr{R}_t$. We fit this regression tree separately for each carrier c and for each time period t. Let $\hat{V}_{ct}(\theta, \cdot)$ be the fitted regression tree for carrier c in period t. We approximate the value function $V_{ct}(\mathcal{R}_t, \theta)$ for $\mathcal{R}_t \notin \mathscr{R}_t$ by $\hat{V}_{ct}\Big(\theta,\, s_t(\mathcal{R}_t)\Big)$.[18] As for period $T+1$, we need to approximate $\pi_{cT}(\cdot)$ in order to compute $V_{cT+1}(\cdot)$, which we do following the same procedure.

Given a state $\mathcal{R}_t = (\mathcal{R}_{1t}, \ldots, \mathcal{R}_{4t})$ and time t, the summary statistics $s_t(\mathcal{R}_t)$ are: (i) $(\text{Region Characteristics})_r \times \mathbb{1}(r \in \mathcal{R}_{ct})$ for each region r and each carrier $c = 1, 2, 3$, where "Region Characteristics" includes population, income, area, and population density; (ii) total market size and average regional income across regions in $\mathcal{R}_{ct}$ for each carrier $c = 1, 2, 3$; (iii) number and total population of regions with one, two, three, or four 4G carriers; and (iv) an indicator for Jio's entry status, i.e., $\mathbb{1}(\mathcal{R}_{4t} = \mathcal{R})$.

Solving the Dynamic Network Expansion Game. We solve the dynamic network expansion game for each carrier's equilibrium policy, $\Pr_{ct}(a_{ct} \mid \mathcal{R}_t, \theta)$, using backward induction as follows. Following the notation in Section 3, we suppress θ here.

First, we compute $V_{cT+1}(\mathcal{R}_{T+1}^d)$ in (17) for states $\mathcal{R}_{T+1}^d \in \mathscr{R}_{T+1}$ and approximate $V_{cT+1}(\mathcal{R}_{T+1})$ for states $\mathcal{R}_{T+1} \notin \mathscr{R}_{T+1}$ as described above.

Then, for each period going backward in time $t = T, T-1, \ldots, 1$, we carry out the following two steps:

- For each $\mathcal{R}_t^d \in \mathscr{R}_t$, we compute the equilibrium vector of choice probabilities $\Pr_{ct}(a_{ct} \mid \mathcal{R}_t^d)$ for $a_{ct} \in \mathcal{A}_c(\mathcal{R}_{ct}^d)$ for all c as a fixed point of equations (18) and (19), where $V_{ct+1}(\cdot)$ on the right-hand side of the equations has been computed. We start with an initial guess for the choice probability vector and iterate until the probabilities on the left-hand side of these equations equal the probabilities used to compute the expectations

[18] Because the value function is approximated with a regression tree rather than a linear projection, exact or near collinearity among the summary statistics does not affect the approximation.

on the right-hand side.[19]

- We compute $V_{ct}(\mathcal{R}_t^d)$ in (14) and (15) for $\mathcal{R}_t^d \in \mathscr{R}_t$, evaluating the expectations in these equations under the equilibrium probabilities obtained above. We approximate $V_{ct}(\mathcal{R}_t)$ for states $\mathcal{R}_t \notin \mathscr{R}_t$.

Before this backward-induction process, we compute the per-period profits $\Pi_{ct}(\mathcal{R}_t^d)$ for $\mathcal{R}_t^d \in \mathscr{R}_t$ for $c = 1, \ldots, 4$ and $t = 1, \ldots, T$ as described above.

E Details on Simulations

We use similar simulation procedures to evaluate the model fit and conduct counterfactual simulations. The procedure consists of three steps.

Step 1. For each counterfactual scenario, we solve the dynamic network expansion game for each carrier's equilibrium policy function in each period using the backward-induction procedure described in Appendix D.3. In this procedure, we need to compute the per-period profits $\Pi_{ct}(\mathcal{R})$ for $\mathcal{R}_t^d \in \mathscr{R}_t$, and we do so by applying the relevant counterfactual policy, either the ban on budget Chinese phones or the subsidy. For the factual simulation used to evaluate the model fit, Step 1 is unnecessary because we have already solved these policy functions at the estimated parameter values in estimating the dynamic carrier network expansion game.

Step 2. Based on the equilibrium policy functions obtained in Step 1, we forward-simulate 100 network rollout paths, denoted by $\mathcal{R}_t^{(m)}$ for $m = 1, \ldots, 100$. We start from the network configuration observed in the first period of the dynamic game, that is, we set $\mathcal{R}_1^{(m)} = \mathcal{R}_1$ for all m. Then, for $t = 2, \ldots, T$, given $\mathcal{R}_{t-1}^{(m)}$, we draw each carrier's action from its equilibrium entry policy $\Pr_{ct-1}(a_{ct-1} \mid \mathcal{R}_{t-1}^{(m)}, \hat{\theta})$ using the inverse-cumulative-distribution method, with independent uniform draws generated before the forward simulation, using a fixed seed, and reused across scenarios. Denote the drawn action by $a_{ct-1}^{(m)}$. Given this action, a specific set of new regions $\mathcal{N}_{ct-1}^{(m)}(a_{ct-1}^{(m)})$ is drawn uniformly from the admissible sets, as described in Section 3.2.2. We then update the network configuration for time t to $\mathcal{R}_{ct}^{(m)} = \mathcal{R}_{ct-1}^{(m)} \cup \mathcal{N}_{ct-1}^{(m)}(a_{ct-1}^{(m)})$.

[19] Due to the incomplete-information nature of the game, multiple equilibria are less of a concern. Nonetheless, we use different starting values in the fixed-point iteration to numerically check for multiple equilibria and find that, at our estimated parameters, they lead to the same equilibrium.

Step 3. For the model fit, the simulated paths obtained in Step 2 are sufficient. For counterfactual simulations, we also compute outcomes such as phone offerings, prices, sales, consumer surplus, government spending, and firm profits along each simulated path. To this end, we solve the static product-choice and pricing equilibrium at the simulated network configuration $\mathcal{R}_t^{(m)}$, applying the relevant counterfactual policy.