Adoption of Digital Technologies: The Case of Smartphones in India

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Abstract

Smartphones have become the primary device through which people in developing countries can access the benefits of widespread digitalisation. However, most mobile phone users in developing countries continue to use low-quality feature phones. This paper develops a structural model of consumer demand and supply to understand the main drivers of smartphone adoption. It then uses the estimates of the model to investigate how to best design pro-adoption policies. I find that gains in device quality, changes in income distribution and expansion of network coverage are the main factors behind the growth of smartphone sales in India. Given the central role of income in driving adoption, I simulate the impact of targeted subsidies for smartphones. I find that, compared to ad valorem tax reductions and uniform subsidies, targeted subsidies are the least costly for the government and are the most effective for redistribution, being (almost) fully appropriated by consumers.

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1 Introduction

In the last two decades, access to mobile telecommunication services has rapidly expanded in developing countries, leading to well-documented positive impacts on economic development (Jensen, 2007; Aker and Mbiti, 2010; Jack and Suri, 2016). More recently, emerging markets have been making the transition to internet-based digitalisation but access to digital technologies is often concentrated among the rich, urban and literate households (World Bank, 2021). [1] What are the factors that explain the adoption of digital technologies in emerging markets? Which policy measures can be useful in furthering digitalisation and bridging the digital divide? This paper focuses on understanding the adoption of smartphones, the backbone of internet-based digitisation in emerging markets.

Fostering smartphone adoption in emerging markets is important for a number of reasons. First, in the absence of widespread wired internet connectivity and expensive computers, smartphones can provide the first access to the internet for a large majority of people.[2] Second, as governments around the world push for digitisation, more and more public services are moving online, with the aim of reducing transaction costs and corruption. Smartphones are crucial to access these services and reap the benefits of digitalisation. Third, smartphones have been shown to be positively correlated with household income (Hartje and Hubler, 2016) and with the business income of small enterprises (GSMA, 2017). The urgency underlining the problem of insufficient adoption was brought to light during the recent Covid-19 pandemic.[3] A large proportion of the population in developing countries had limited or no access to online schooling, public and citizen-led health initiatives due to limited smartphone penetration.[4,5] To realize the full extent of the benefits of digital technologies, the pace of adoption of necessary digital hardware like smartphones needs to be faster.

Tracing the adoption of smartphones in an emerging economy is challenging for three main reasons. First, many factors (income of consumers, prices, characteristics and quality of devices,

[1] Narrowing the digital divide can foster inclusion and increase jobs, World Bank, 2021

[2] As of 2022, nearly 96% of internet access in India is wireless. TRAI Performance Indicator Report, December 2022

[3] "New front in India's digital divide exposed by India's COVID-19 meltdown". The Wire. April 2021

[4] "About 56% of children have no access to smartphones for e-learning."Indian Express, June 2020.

[5] "Bangladesh Schools Reopen After 18 Month covid Shutdown." September 2021.

entry of new brands, market competition, network coverage) affecting smartphone adoption change simultaneously, making it difficult to determine their relative contribution in driving adoption. Second, in a country where income inequality has been increasing (Chancel and Piketty, 2019), there is likely to be substantial income-based heterogeneity in consumer preferences for handsets. Any policy that aims to encourage smartphone adoption would need to take into account this heterogeneity. Third, systematic data linking device purchases and consumer demographics are difficult to obtain in India but also in many other developing countries.

In this paper, I address these challenges by using new handset level data from India, which is the second largest telecommunications and internet services market in the world.[6] I study the evolution of the handset market in India between 2007 and 2018 to answer two main research questions: i) What are the main drivers of smartphone adoption? ii) Which policies can be effective to encourage adoption of smartphones? The smartphone market in India has seen important changes over the last decade: decreasing prices, increasing quality of products, entry of foreign firms, as well as a substantial expansion of network coverage. Despite these changes, the market for handsets continues to be dominated by feature phones that accounted for more than 57% of total sales of handsets in 2018. Feature phones provide basic services like voice calling, SMS, and basic Internet browsing, often at low speeds. They typically do not have additional applications like smartphones do. There have been only a few policy efforts in India to spur smartphone adoption. The only pro-adoption government program was started by an Indian state, Chhatisgarh in 2018 and provided free devices to rural poor women. This has since been discontinued following a change in the state government. In fact, recently policy has taken the opposite direction: in 2020, the value added tax on mobile phones was increased from 12% to 18%, leading to an increase in smartphone prices paid by consumers.

I estimate a structural model of discrete choice to represent consumer demand and supply for handsets. The model i) allows me to separately identify the contribution of different factors to the adoption trajectory and ii) combine aggregate data on handset sales and prices with data on income distribution to capture consumer heterogeneity in preferences. The model incorporates income-heterogeneity in preferences by allowing for individuals with different incomes to have different

[6] List of countries by number of Internet users

price sensitivities. Allowing price sensitivities to vary with income allows me to measure the heterogeneous effects of pro-adoption policies, as well as to simulate targeted pro-adoption policies. The model also allows for handsets to have a high degree of horizontal differentiation. This is particularly important to capture since there have been substantial gains in product variety and product quality in the twelve-year period between 2007 and 2018.

To recover the structural parameters of consumer preferences, I estimate handset demand under a random coefficients nested logit model using non-linear GMM. Using estimates of the demand model, I compute the marginal cost and markups for each handset. I combine three different datasets for this analysis: i) a novel handset level dataset published by the International Data Corporation (IDC) which provides information on the sales, prices and characteristics of all handsets sold at the national level between 2007-2018, ii) percentile wise annual income distribution from the World Inequality Database (WID), and iii) data on mobile network coverage from GSMA which provides the proportion of the population having access to 3G and 4G coverage over time. On the supply side, I model a Bertrand-Nash game in a multiproduct oligopoly setting.

Results from the estimation show that smartphone demand is fairly price elastic: a 1% increase in price leads to an 11% reduction in demand on average over the whole period. Individuals in the bottom 60% of the income distribution are nearly 4 times as price sensitive as individuals in the top 40%. Additionally, I find that smartphones are much closer substitutes to each other than they are to feature phones. On the supply side, I find that marginal costs for firms decline over time for both smartphones and feature phones. Markups for smartphones also decline on average over this period. Markups and marginal costs are both higher for smartphones than for feature phones.

Next, I use the estimates of the structural parameters of utility to quantify the drivers of smartphone adoption in India. I simulate the smartphone market under several different counterfactual scenarios by changing the potential determinants of adoption, one at a time. First, to understand the role of income in driving the smartphone market, I fix the income distribution in every period to the baseline distribution of 2007. I recompute the market equilibrium, letting all other factors vary as in the observed data. Similarly, to gauge the importance of device quality improvements, I fix the quality of devices to the baseline level of 2007. Next, I focus on the impact of changes in market competition on the smartphone market by fixing the number of firms to the baseline level, and by not allowing the entry of Chinese firms. Finally, in the last simulation, to understand the impact of changes in the complementary mobile services market, I look at market outcomes in the absence of 3G and 4G network expansion. In all of these exercises, I allow the firms to reset their prices by recomputing the Bertand-Nash equilibrium.

I find that total size of the smartphone market contracts on average (over the whole period) by i) 35% if the device quality is fixed at the baseline level (of 2007); ii) 20% if the income distribution is fixed at the baseline level; iii) 12% if 3G and 4G network expansion did not take place; iv) 8% if market competition is fixed at the baseline level; and v) 2.3% had the Chinese brands not entered the market. Accordingly, quality improvements in smartphones and changes in the income distribution over time are the most important factors driving adoption.

I then turn to the second research question to study the effectiveness of potential government policies in encouraging smartphone adoption. The structural model with heterogeneous consumer preferences is especially suitable for this purpose as it allows me to capture the heterogeneous effects of any potential policy across the income distribution. Moreover, by explicitly including the firms' response to policy changes, it is possible to measure the effectiveness of the policy by quantifying the pass-through of taxes/subsidies to consumer prices. I compare three potential policies to encourage smartphone adoption: a reduction in the ad valorem tax on budget smartphones, a uniform subsidy for budget smartphones, and a subsidy targeted to individuals below the sixtieth percentile of the income distribution. I find that a 10% expansion in the size of the smartphone market can be achieved through a reduction in the tax rate to 3%. The same magnitude of expansion in the smartphone market can be achieved through an \$ 7 flat subsidy, or through a \$10 targeted subsidy. Of the three policies, the targeted subsidy has the most redistributive effects, increasing the share of the poorest 60% of individuals in the total smartphone market by 7%. The revenue loss for the government for the targeted subsidy is 13%, compared to 43% from the tax reduction and 30% from the uniform subsidy. With the targeted subsidy, the average pass through is nearly 100%, meaning that almost all of the subsidy is passed through to the consumers.

Finally, I provide evidence that the recent tax increase on mobile phones (from 12% to 18%) would lead to a contraction in the smartphone market by 5.7%. This tax increase would almost entirely be passed through to consumers by an increase in prices. Further, the tax increase would lead to a larger reduction in the probability of smartphone purchase of poorer individuals as they are more price elastic.

The existing literature on smartphone adoption is limited. Bjorkegren (2019) is the closest in spirit to this paper. It considers the entire network of mobile phone users in Rwanda until 2009 and emphasizes the importance of including network effects in evaluating the welfare consequences of tax policies. It models the utility of owning a mobile phone as a function of its usage, the consumer's social network and cost of usage. However, it does not consider consumer heterogeneity in preferences based on income, or the extensive horizontal product differentiation among handsets. Chatterjee, Fan and Mohapatra (2022) also study the Indian handset market but consider a different research question. They quantify the spillover effects arising from the presence of technologically-advanced international companies in the handset market on expanding network coverage in the mobile services market. Most of the other academic work so far has concentrated on the economic and social impact of having access to telecommunications services. Jensen (2007) evaluates the impact of efficiency gains in information sharing through mobile phone connectivity in the fisheries sector in Kerala, India. Garbacz and Thompson (2007) study the demand for telecommunication services in developing countries. A related strand of literature looks at the impact of services like mobile money that can be used on feature phones. For example, Jack and Suri (2016) evaluate the impact of mobile money on poverty in Kenya. Abiona and Koppensteiner (2020) study the impact of mobile money adoption on consumption smoothing, poverty and human capital investment in Tanzania. Most of this strand of literature concentrates on the impact of using financial services through feature phones.[7] Methodologically, this paper relates to a large literature on demand estimation in Industrial Organisation starting with Berry, Levinhson and Pakes (1995), Nevo (2002), Petrin (2002), Grigolon and Verboven (2014) and others. In particular, I adapt the random coefficient nested logit demand model of Grigolon and Verboven (2014) for the analysis. The model proposed in this paper differs from Grigolon and Verboven (2014) by relaxing some parametric

[7] Papers that do study the smartphone market do so in the context of developed economies like the US (Fan and Yang 2019; Wang 2018; Yang 2019) and focus on questions of innovation and product proliferation.

assumptions and including observed consumer heterogeneity.

In light of this, this study makes several contributions to the literature. To the best of my knowledge, this is the first paper to trace the transition from low quality feature phones to smartphones. This is an important topic to study, especially in developing countries, as smartphones are an essential tool in harnessing the benefits of digital technologies for development and addressing the digital divide. Next, by using a structural model of consumer preferences to answer a question important in development economics, this paper is able to shed light on the role of market and demographic factors behind consumer technology adoption in a developing country context. In a setting where several of these factors are changing simultaneously, the model allows me to separately quantify the contribution of each of these factors to smartphone adoption. This approach is also useful to overcome the data limitations common in a developing country context. The paper links three different sources of aggregate data to take into account consumer heterogeneity in income and changes in the complementary market of telecom services. I do not rely on parametric assumptions for the income distribution, instead using the time varying empirical distribution of income to quantify smartphone adoption across different income groups. Finally, I contribute to the policy literature by providing i) an ex-post evaluation of a recent handset tax policy in India and ii) ex-ante evaluations and comparisons of policies that can be used to spur smartphone adoption (or adoption of other digital technologies, more generally). Ex-ante policy evaluations are especially important for studying digitisation since policy is often outpaced by rapid technological change.

The rest of the paper is organized as follows: in Section 2, I discuss the data used for this work. In Section 3, I provide a brief background of the handset market in India. I then describe the demand and supply model in Section 4 and the estimation method and specification in Section 5. I discuss the counterfactual simulations in Section 6 and conclude in Section 7.

2 Data

Handset data The main data set that I use is published by the International Data Corporation (IDC) and provides quarterly prices, sales and characteristics of mobile handsets sold in India over a 12 year period between 2007 until the second quarter of 2018. Data collection is bottom up- sales and price data are collected from major vendors across the country. The data is provided at the handset level, where a model refers to a unique bundle of handset characteristics and company. There are a total of 9,534 models, 89 companies, and 27,730 observations (model-quarter) over the twelve year period.[8] The data set provides information on the following characteristics of handsets- operating system, embedded memory, screen size, screen resolution, communication technology (2G, 2.5G, 3G or 4G), processor speed band, camera megapixels, RAM band, input method, dual sim, and form factor.[9]

Real prices The prices of handsets in the dataset are deflated by using the consumer price index (CPI). The data for CPI is obtained from the IMF database.[10] I do this to capture the real purchasing power of consumers and to ensure that the analysis is not affected by nominal fluctuations in prices. The base year for the deflation is 2010. Although the data set provides prices reported in US dollars as well as the Indian rupee, in the paper I report all figures in 2010 real US dollars.

Market size and Outside Option I use data on the annual population and the proportion of the working population from World Bank Open Data to define the market size and the size of the outside option. I provide details on construction of the outside option in the Estimation section. [11]

Data on income One of the key objectives of the demand model in this paper is to capture the heterogeneous response to prices based on consumer's incomes. To do this, I construct the income distribution of the population at the national level using data from the World Inequality Database (WID).[12] The WID provides the average income of each percentile of the population for the years 2007 to 2015 in nominal dollars. For consistency with the handset and data prices, I convert the average incomes to real USD 2010. I use this information in the simulated draws of consumers. I provide more details on how I use this data in the section on Estimation.

[8] In the original data set, there are a group of very small companies (producing feature phones) clubbed together in a category called "Others". Together they account for less than 1% of the total sales. Since there is no additional information available about the companies that are a part of this category, I drop these observations from the analysis.

[9] Input method refers to whether the phone is touchscreen or requires alphanumeric/QWERTY input through a physical keyboard, or a combination of the two.

[10] IMF database on inflation last accessed on 14.10.2020

[11] World Bank Open Data last accessed on 14.10.2021

[12] World Inequality Database last accessed on 16.10.2020

Data on coverage I obtain the data on coverage from the Global System for Mobile Communications Association (GSMA).[13] This data tracks the percentage of the population living in areas that have access to mobile internet services. It includes 3G and 4G coverage separately over time.

3 Background of the Industry

In this section, I provide details of the structure of the market using the handset level data from IDC. I also provide details on changes in coverage and changes in the income distribution over the period of consideration.

3.1 Market level descriptive evidence

As of 2017, there are 47 brands and 951 models of mobile phones available in the market suggesting a large choice set for consumers (Table 1). The market can be segmented into two groups - smartphones and feature phones. Feature phones are basic handsets that run on the 'RTOS' operating system, and can be used for voice calls, sending text messages, and a limited capacity for internet browsing.[14] Smartphones, on the other hand, have more sophisticated operating systems, partial or full touchscreens, and a wide variety of internet enable applications. Over the 12-year period between 2007 and 2018, the ranking (by volume and value of sales) of companies has been continuously changing (table 9 and table 10). There has been considerable entry and exit over most of the period. However, entry, exit and churn rates have declined over time, pointing to a more stable market towards the end of the period of analysis.[15]

3.1.1 Sales[16]

At the beginning of the period in 2007 and until 2010, three firms accounted for approximately 70% of the total sales, with Nokia emerging as the market leader. Subsequently, the market became less concentrated in terms of total sales, with 6–8 companies accounting for the same 70% of total sales. The sales data also show a significant increase in the market shares of Indian companies,

[13] I thank David Salant and Daniel Ershov for making this data available to me

[14] RTOS stands for real time operating system.

[15] Churn rate is the sum of entry and exit rates and is a crude indicator of the dynamics of the industry.

[16] Since the data does not cover the entire year of 2018, the descriptive statistics are provided only until 2017 in this section and the next.

Table 1: Total number of companies and models by year

Year	Companies	Models
2007	27	405
2008	30	597
2009	37	691
2010	37	1007
2011	40	997
2012	43	1527
2013	42	1544
2014	50	2257
2015	50	2234
2016	50	1825
2017	47	951
2018	40	497
Total		27370

Source: Author's compilation from IDC data

particularly between 2012 and 2015. Most of these Indian companies entered the market in 2009 and by 2015 accounted for over 30% of the total sales of the market. Prior to entering the market as independent firms, all of them were distribution partners of established global firms, and offered a cheaper alternative to the existing smartphones as well as to existing feature phones. Between 2007 and 2017, the share of feature phones relative to total sales of all handsets declined, even though it still accounted for over 50% of the market (see Figure 1). Interestingly, following the expansion of 4G coverage and an associated reduction in prices of mobile internet, the share of feature phones increased in the last year of the period. This increase was largely driven by the entry of a new type of product (hybrid 4G feature phones) in 2017.[17]

3.1.2 Chinese Entry

Since their entry in 2014, new Chinese companies (Oppo, Vivo, Xiaomi, Oneplus) have steadily gained market share, accounting for nearly 49% of the handset market by the end of period. As opposed to established Chinese companies (Huawei and Lenovo) that were present in the market before 2014, the firms entering in 2014 targeted the mid-price segment of smartphones, vastly expanding the choice set as well as quality of smartphones. Currently, they account for more than

[17] In addition to the basic functionalities (voice calling, SMS, limited internet browsing), these hybrid 4G feature phones were bundled with the services of Reliance Jio and come with a few pre-installed mobile applications and offer a walled-garden experience to accessing the internet. In terms of hardware, they are still keyboard based with small screen sizes and do not have touch screen capabilities.

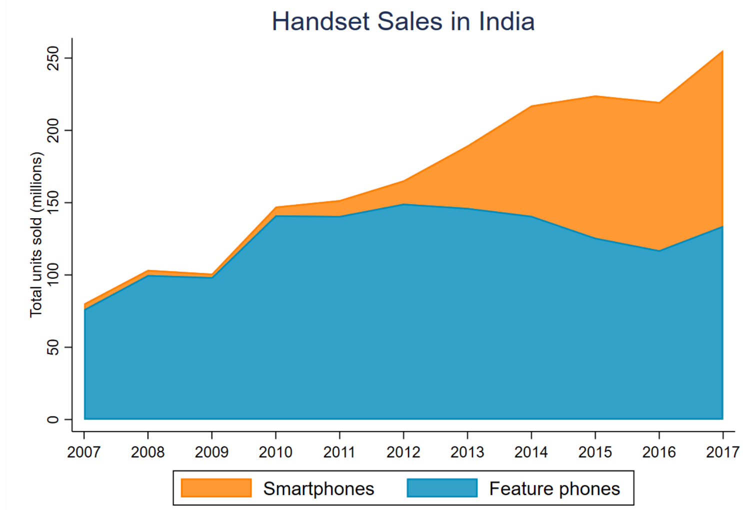

Figure 1: Volume of sales of handsets

75% of the smartphone market.[18] [19]

3.1.3 Prices of Handsets

Prices vary considerably over the 12-year period over time and across models. I normalize all the prices to 2010 real US dollars. The average real selling price (ASP) of a handset has decreased from USD 291 in 2007 to USD 107 in 2018 (see Figure 2 and Table 11). The ASP of smartphones decreased from USD 618 in 2007 to USD 125.23 in 2018. Feature phones also got cheaper over this time period with the ASP decreasing from USD 150 in 2007 to USD 11 in 2018. The ASP of smartphones as a proportion of the annual per capita real income has declined from nearly 40% in 2007 to 8% in 2017. The median price of smartphones follows the trend of mean prices quite closely, indicating increasing affordability. Moreover, the number of smartphone models that cost less than 5% of the annual per capita real income has increased in number, with as many as 567 in 2017. While these facts suggest that smartphones have become more affordable in general, the trend in affordability might differ across different income levels of consumers as income inequality has increased significantly over this period.

[18] Chinese Smartphone Brands Expanded Market Shares in India, Reuters, January 2021, last accessed on 3.05.2021

[19] Xiaomi - The Chinese Brand dominating India's Smartphone Market, BBC news, October 2019, last accessed on 3.05.2021

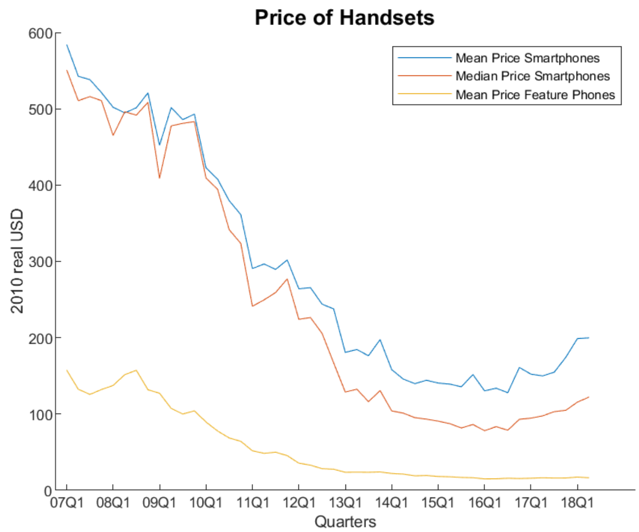

Figure 2: Price of Handsets (2010 real USD)

3.1.4 Changes in Mobile Internet Coverage

During this 12 year period, there have been significant changes in the complementary mobile services market. Notably, the network coverage of 3G and 4G services, both important for mobile internet use, has consistently increased over time (see Figure 3). This expansion of mobile network coverage, and the transition to faster 2G and 3G networks, is likely to affect the utility of purchasing a handset but especially a smartphone. With increase in coverage and network speed, more services can be accessed using smartphones and thus, the utility of purchasing a smartphone is expected to increase.

In 2016, a new 4G provider, Reliance Jio, entered the market which greatly increased 4G coverage. This entry also led to a shock to the price of mobile internet, which decreased from \$ 11/GB in 2015 to \$ 0.10 in 2018. While this shock is likely to have had an effect on the utility of purchasing smartphones, handset or plan level data on mobile internet usage and prices is not readily available.

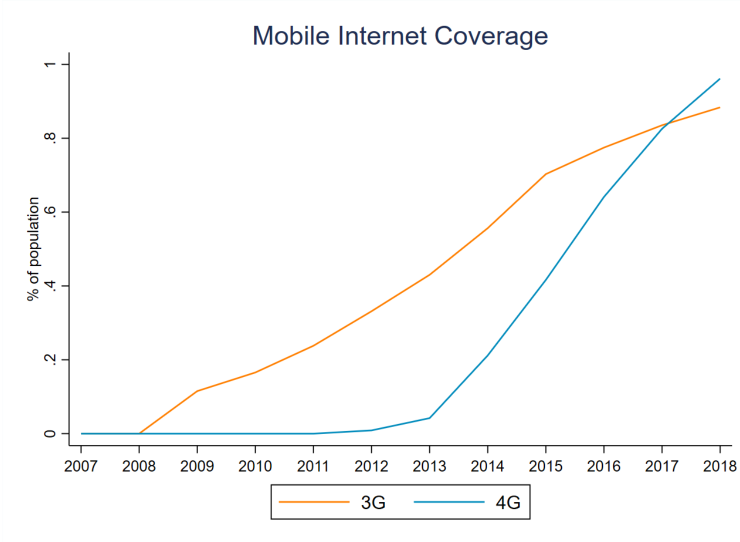

Figure 3: Network coverage over time

3.1.5 Income and Affordability

The income of individuals has been increasing over the time period of consideration but so has the inequality (see Figure 4). The mean annual real income of an individual was \$ 1338 in 2007 and increased to \$ 2256 in 2018. The standard deviation of the income distribution was \$ 2840 in 2007 and this increased to \$ 5457 in 2018, pointing to increasing inequality. These changes in the income distribution are likely to be important drivers of smartphone adoption.

On average, smartphones have become more affordable over time. The average price of a smartphone was 40% of the average per capita annual income in 2007 and this has decreased to 8.8% in 2018. However, these numbers hide substantial heterogeneity among individuals at different levels in the income distribution. As seen in Figure 5, the average price of a smartphone (\$199) is 30% of the annual income for an individual at the 25th percentile of the income distribution in 2018 Q2. Even for the median individual at the 50th percentile, the average smartphone costs 20% of their annual income in 2018 Q2.

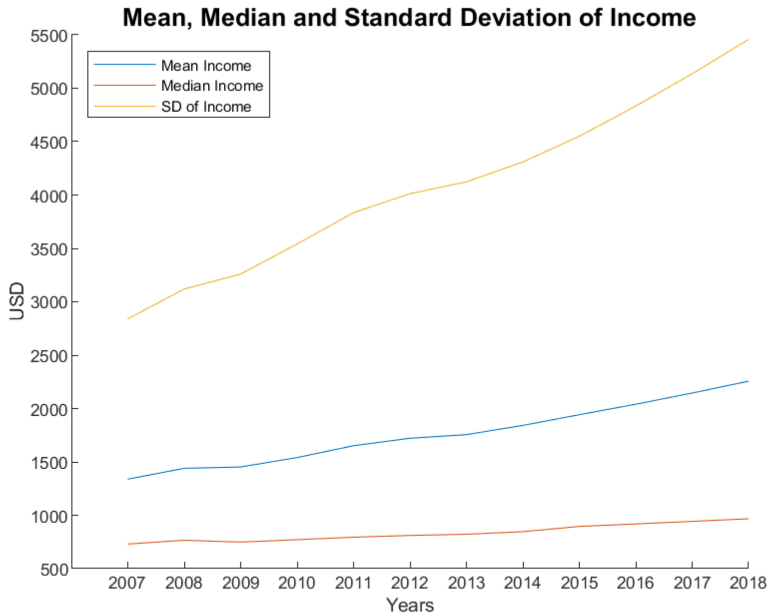

Figure 4: Income and Income Inequality in India

4 Model

I adapt the random coefficients nested logit (RCNL) model proposed by Grigolon and Verboven (2014). The RCNL model of demand allows for consumers to be heterogenous in their preferences and for the market to be segmented. This should be the case in the handset market where consumers first decide the segment of their purchase (feature phone or smartphone) and then decide which model to buy within these segments.[20] The model presented in Grigolon and Verboven (2014) does not include observed consumer heterogeneity and relies on parametric assumptions to include unobserved consumer heterogeneity. Instead, I focus on incorporating income driven heterogeneity, arguably one of the most important sources of consumer heterogeneity in developing countries with high inequality. Further, I do not rely on parametric assumptions to incorporate consumer heterogeneity, instead using the time varying empirical income distribution of income.

[20]Market segmentation can be captured using the standard mixed-logit demand model with a random coefficient and a segment dummy, however it is computationally more costly compared to the RCNL model (Grigolon and Verboven, 2014).

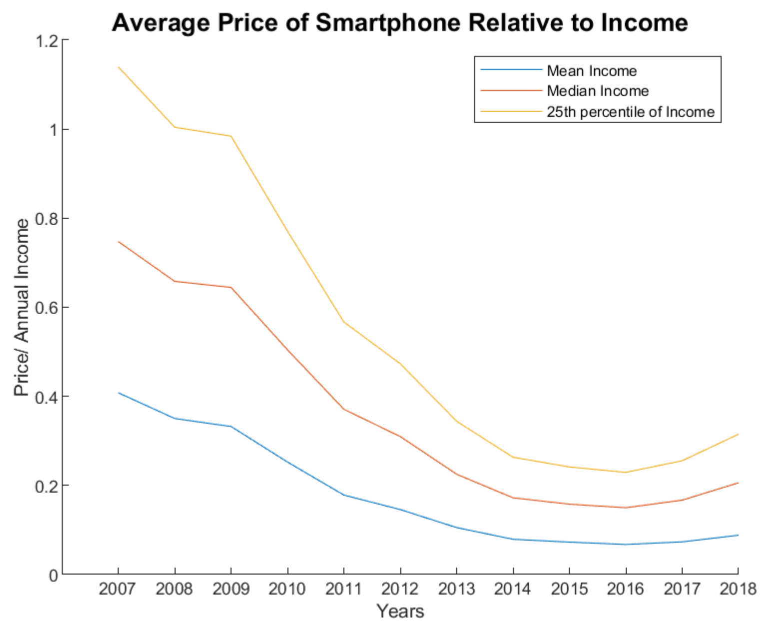

Figure 5: Affordability of smartphones

4.1 Demand

Consider T markets defined as each quarter of the period 2007Q1-2018Q2. The potential market size of each market t is denoted by M_t. Each consumer i chooses between a handset j in segment g or the outside option of not buying a new phone. If the consumer decides to purchase a handset, she gets the following indirect utility u_{ijt}:

$$u_{ijt} = \beta x_{jt} + \alpha_i p_{jt} + \gamma c_{jt} + \xi_{jt} + \lambda_f + \lambda_t + \bar{\epsilon}_{ijt}, \tag{1}$$

where,

$$\alpha_i = \frac{\sigma}{Y_{it}}, \tag{2}$$

and

$$\bar{\epsilon}_{ijt} = \zeta_{igt} + (1-\rho)\epsilon_{ijt}. \tag{3}$$

Consumer i's utility of purchasing handset j depends on a vector of product characteristics x_{jt}, its price p_{jt} in quarter t, the coverage c_{jt} in quarter t, company fixed effects λ_f that capture the average utility of buying from a particular firm, quarter fixed effects λ_t, and a vector of unobserved demand shocks ξ_{jt}. A product j is defined as a unique bundle of handset characteristics. The model allows for heterogeneity in the response of the consumer to price changes through the term $\sigma \frac{P_{jt}}{Y_{it}}$. Y_i denotes the income of individual i. This functional form implicitly assumes that richer people are more price elastic than poorer people.[21] The non-linear parameter σ measures the marginal utility of income.

The error term $\bar{\epsilon}_{ijt}$ takes into account market segmentation (g) and allows products within each segment to be correlated with each other. This correlation is captured by the parameter ρ. ϵ_{ijt} is assumed to follow an extreme value type I distribution and ζ_{igt} has the unique distribution such that $\bar{\epsilon}_{ijt}$ is also extreme value type I. In this application, there are two market segments (denoted by g)- feature phones and smartphones. Intuitively, this means that the consumer first chooses the market segment and receives a draw ζ_{igt} specific to the segment, and then chooses a product within that segment with a draw ϵ_{ijt} specific to the product. Finally, an outside option is specified so that the consumer can choose not to make a purchase in period t. The demand shock for the outside option is normalized to zero[22]:

$$u_{i0t} = \bar{\epsilon}_{i0t} = \epsilon_{i0t}.$$

The utility can be rewritten as a sum of three terms – the mean valuation of the handset δ_{jt}, the individual specific heterogeneity μ_{ijt} and an idiosyncratic consumer valuation $(1-\rho)\epsilon_{ijt}$:

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + (1-\rho)\epsilon_{ijt} + \zeta_{igt}, \tag{4}$$

where

$$\delta_{jt} = \beta x_{jt} + \gamma c_{jt} + \lambda_f + \lambda_t + \xi_{jt}, \tag{5}$$

and

$$\mu_{ijt} = \frac{\sigma}{Y_{it}} p_{jt}. \tag{6}$$

[21]For robustness, I estimate the model with more flexible functional forms including $\alpha_i = \bar{\alpha} + \sigma \log Y_i$; $\alpha_i = \bar{\alpha} + \sigma Y_i$. I find that the estimates of $\bar{\alpha}$ and σ also imply that richer people are less price elastic than poorer people. I also estimate the model with other functional forms that make use of the same assumption like $\alpha_i = \frac{\sigma}{\log Y_i}$ or $\alpha_i = \sigma \log(Y_i - P_j)$. I find that compared to all of these other functional forms, with the current functional form $\alpha_i = \frac{\sigma}{Y_{it}}$, the estimates of price-cost margins are closest to the figures quoted in an industry report.

[22]I make the assumption that consumers can change their handsets or choose the outside option every two years (or 8 quarters). More details on how the market size and outside option are defined follow in the estimation section.

Using the extreme value distribution assumption, the probability that consumer i purchases a product j in segment g in time period t is given as:

$$\pi_{ijt} = \frac{\exp(\frac{\delta_{jt}+\mu_{ijt}}{1-\rho})}{\exp(\frac{I_{igt}}{1-\rho})} \times \frac{\exp(I_{igt})}{\exp(I_{it})} \tag{7}$$

where

$$I_{igt} = (1-p)\ln\left[\sum_{m=1}^{J_{gt}} \exp\left(\frac{\delta_{mt}+\mu_{imt}}{1-\rho}\right)\right]$$

and

$$I_{it} = \ln\left(1 + \sum_{g=1}^{G} \exp(I_{igt})\right)$$

Note that J_{gt} is the number of products in segment g so that we have

$$\sum_{g=1}^{G} J_{gt} = J_t$$

Integrating the choice probabilities π_{ijt} over the empirical distribution of income (P_Y), we obtain the aggregate market share of product j in period t:

$$s_{jt}(x_t, p_t, \xi_t; \theta) = \int_{\tilde{Y}_t} \pi_{ijt} dP_Y(\mathrm{Y}_t) \tag{8}$$

Here θ refers to the vector of non-linear parameters (σ and ρ) of the utility function.

4.2 Supply

The supply of handsets is modeled under a Bertrand-Nash framework. A firm f produces a subset of products J_{ft} and chooses the price for these products in every period t so as to maximize its profits. It faces a vector of marginal cost c_f. The objective function of the firm then becomes :

$$\arg\max_{p_j : j \in J_f} \sum_{j \in J_f} (p_j - c_j).s_j(\mathbf{p})$$

The first order condition of this maximization problem in matrix form is:

$$(\mathbf{p} - \mathbf{c}) = \Delta(\mathbf{p})^{-1} s(\mathbf{p})$$

Here, Δ is the block diagonal $J_t \times J_t$ matrix of intra-firm demand derivatives. Once demand has been estimated, and given the vector of equilibrium prices $\mathbf{p}^*$, this first order condition can be used to recover estimates of marginal cost as follows:

$$\mathbf{c} = \mathbf{p}^* - \Delta(\mathbf{p}^*)^{-1} s(\mathbf{p}^*) \tag{9}$$

5 Estimation

In the data, I observe the sales of each handset in each quarter. I use this to construct aggregate market shares (s_{jt}) from the left hand side of equation (8). Since I do not observe individual level purchases of handsets, the main challenge of the estimation is to link consumer heterogeneity in income with aggregate market shares. I follow the vast literature on demand estimation with aggregate data (Berry, Levinhson and Pakes (1995), Nevo (2000) and Grigolon and Verboven (2014)) to address this challenge. The estimation steps are outlined in the next subsection.

5.1 Estimation Algorithm

To link the aggregate data with consumer demographics, in the first step, I simulate 100 consumers so that there is one representative consumer for each percentile of the income distribution. To these consumers, I assign the mean income of the percentile they belong to using the empirical distribution of income. Then using the model, I construct the probability of purchase of a handset j for a consumer with income Y_i (from equation (7)). In the next step, for a given set of initial values of the non linear parameters, I find a unique δ_{jt} (equation (5)) for each product through a contraction mapping (see Grigolon and Verboven (2014) for details). To find this unique δ_{jt}, the contraction mapping relies on setting the observed market shares exactly equal to the market shares predicted by the model. Next, I use the δ_{jt} to compute ξ_{jt}, the vector of unobserved demand shocks (equation (5)). I use this vector to construct demand side moments and in the final step, compute the empirical counterpart of the moment conditions.

Step 1: Draw consumers from the empirical income distribution, set initial values for σ, ρ

Step 2: Compute i's probability of choosing j using extreme value type I distribution of errors.

Step 3: Compute aggregate market shares for j implied by the model as function of δ_{jt}

Step 4: Recover δ_{jt} by inverting this function using a contraction mapping

Step 5. Obtain $\xi_{jt} = \delta_{jt} - \beta x_{jt}$

Step 6. Compute the empirical counterpart of moment conditions

Step 7. Find parameter values σ, ρ which minimize demand side moments using non linear GMM

5.2 Empirical Distribution of Income

I construct the empirical distribution used in Step 1 from data on average income by percentile from the WID. Since this data is only available until 2015, I calculate the average income of all 100 percentiles for the years 2016, 2017 and 2018 by assuming that incomes grow at the average rate of growth of the period 2007-15. In effect, this means that the rate of growth of mean income between 2016-18 is assumed to stay constant. Allowing income heterogeneity to vary over years, albeit with the constant growth assumption for the years 2016-18, is especially important for the Indian context since mean income and income inequality have both been increasing over the years.

5.3 Aggregate market shares and outside option

To construct the aggregate (observed) market shares which are used in step 3 of the estimation, the total market size needs to be defined. The market (M_t) is defined as $\frac{1}{8}$ of the total adult working population of that year.[23] Intuitively, this translates into the assumption that consumers can change their handsets or choose the outside option every two years (or 8 quarters). The observed market share for each product is then simply the sales of that product divided by the market size.

[23] As with most other static discrete choice models, the results of the estimation are sensitive to the market size and the size of the outside option (the share of people without a phone). I choose this definition of the market size based on a survey from 2017 by LirneAsia, which reports that the share of individuals having a smartphone is 17.3%. The model predicts this share to be 23 %.

5.4 Demand Moments and Instruments

The unobserved demand shocks ξ_{jt} are observed by both consumers and producers. Producers are expected to take these into account when they set their prices and thus prices are endogenous to the demand system. To correct for the bias arising from endogeneity, I use instruments for handset prices. Following the literature, these instruments are functions of the characteristics of competitor's products and I denote them by $h(z)$. Specifically, I use own-product characteristics and the sum of other products' characteristics within each segment. These are relevant instruments for price as they affect the mark up of differentiated products. More intuitively, characteristics of products of close competitors are likely to affect the market share (demand) of a product, but only through its price. To avoid issues arising from multicollinearity, only one out of any set of instruments that have a correlation greater than 0.9 are selected.

These instruments allow me to construct moments that can be minimized to estimate the parameters of the model (Step 67. As in BLP(1995) and Grigolon and Verboven (2014) I retrieve the linear parameters of utility using a linear projection. I conduct a search for the non-linear parameters($\theta = (\sigma, \rho)$) so as to minimize the GMM objective function with an optimal weighting matrix Ω:

$$\min_{\theta} \xi_j(\theta)' h(z_j) \Omega h(z_j) \xi_j(\theta) \tag{10}$$

5.5 Empirical Specification of the utility

To construct the demand moments of step 6, the three terms of equation (4) need to be specified. As per equation (5), the first term δ_{jt} contains a vector of device characteristics x_{jt}, coverage γ_{jt}, brand fixed effects, λ_c and quarter-year fixed effects λ_t. The device characteristics include the screen size, operating system type, camera type, dual sim capacity, technology generation (2G, 3G, 4G), screen type (touchscreen or bar) and memory. The coverage varies over time and across device type (2G, 3G or 4G).

The second part of equation (4) introduces heterogeneity among consumers based on their income, specifically allowing consumers with different incomes to have different responsiveness to the price of a handset. In equation (6), Y_{it} refers to the income of individual i in year t, which is drawn from the empirical income distribution constructed using data from the World Inequality Database.

Finally, the third part of equation (5), the idiosyncratic error term $(1-\rho)\epsilon_{ijt}$ is assumed to follow an extreme value type I distribution.

5.6 Identification of Parameters

The mean utility parameters $\bar{\beta}$ are estimated by a linear projection, which is substituted into the GMM objective function. $\bar{\beta}$ can be recovered from the variation in the correlation between the market shares of the products and their characteristics over time. The variation in the combined market share of each segment over time is used to identify the parameter ρ. The price sensitivity (which is a function of income and prices) is identified using instruments for price described in sub-section 5.4 and using the variation in the income distribution of consumers. Formally, the identification assumption can be written as:

$$\mathsf{Cov}(\xi_{jt}, Z_{jt}) = 0$$

where Z_{jt} is a matrix of instruments $h(z_{jt})$ and exogenous regressors (x_{jt}).

5.7 Marginal Costs

Once the demand is estimated, I use the firm's profit maximization condition (equation (9)) to obtain the marginal cost of each product. In equation (9), prices are observed from the data, the market shares and the matrix of intra-firm demand derivatives are obtained from the demand estimates. I then use the marginal costs to conduct counterfactual policy simulations (section 7).

6 Results

The main results of the demand estimation are provided in Table 2. The key parameter estimates of interest are σ on $\frac{p_{jt}}{Y_{it}}$, the nest coefficient ρ and γ on coverage c_{jt}. I do not report the estimates of other characteristics (screensize, operating system, memory, camera megapixels, bluetooth, gps, dualsim, technology generation) in Table 2 and the full results of the demand estimation can be found in the appendix (Table 13).

Price sensitivity The coefficient on P_{jt}/Y_{it} (σ) is negative and precisely estimated. A value of $\sigma = -36.3$ implies a mean price sensitivity ($\frac{\sigma}{Y_t}$) of -0.06 at the beginning of the period in 2007Q1 and -0.04 at the end of the period in 2018Q1. Compared to a model of nested logit demand (σ= -0.004) which does not incorporate income heterogeneity of consumers, the absolute value of the sensitivity to price is higher. This is consistent with the literature; models that do not incorporate consumer heterogeneity underestimate the price sensitivity of demand. The sensitivity to price decreases over time as the market expands and incomes grow. In the last period, 2018Q2, the price sensitivity of the poorest percentile of income is -0.25, which is several times higher than the price sensitivity of the richest percentile of income at -0.007.

Table 2: RCNL demand estimation

Price/Income (σ)	-36.31***
	(4.25)
Nest	0.84***
	(0.02)
Coverage (γ)	0.33***
	(0.07)
Company FE	Yes
Quarter-Year FE	Yes
Other characteristics	Yes
N	27,730

Nesting parameter A value of ρ close to 1 implies strong within group correlations in substitution patterns, and a value of $\rho = 0$ implies that there is no significant market segmentation. From table 2, the nesting parameter is estimated precisely at $\rho = 0.84$. This means that segmentation of the market is important - in other words, smartphones are much closer substitutes of other smartphones than they are of feature phones, and vice-versa.

Coverage The parameter estimate for γ is positive and precisely estimated. Consistent with intuition, this means that as the coverage of mobile internet (3G or 4G) increases, the overall utility of purchasing a mobile phone (either smartphone or feature phone) also increases.

Other characteristics Parameter estimates for other characteristics are precisely estimated, and have the expected sign (see Table 13). Having Dual SIM functionality has a positive effect on the utility of purchasing a handset. Compared to other designs (touchscreen), the bar form factor is negatively related to utility. Having a higher memory capacity is associated with higher utility, as is having a better quality camera. 4G phones have a higher utility compared to 2G phones but consumers prefer 2G phones over 3G phones. Surprisingly, conditional on all other factors in the model, a smaller screen size is associated with higher utility.

Elasticites The mean own price elasticity of smartphones implied by these estimates over the whole period is -11.1 and the corresponding value for feature phones is -6.6. The price elasticity of smartphones increases over time and the price elasticity of feature phones decreases over time (Figure 11 in appendix). To put some context to these numbers, Fan and Yang (2020) report own price elasticities for smartphones in the US market in the range of -7 to -6. Since India is a country with lower per capita incomes, it is reasonable to expect the price elasticity to be higher than in the US.

Marginal Costs and Margins With the demand estimates, equation (9) from the supply model can be used to retrieve the marginal costs of all products. Over the whole period, the average marginal cost is \$ 75.3. The average marginal cost for smartphones is \$ 140.8 and for feature phones is \$ 33.1. The marginal costs of both smartphones and feature phones decrease over time, presumably due to technological advancement (Figure 6). The average margin $(P - C)$ over the whole period is \$ 28.2, for feature phones this value is \$ 12.3, and for smartphones, it is \$ 52. With the entry of new companies and products, as competition increases, margins decrease over time for both feature phones and smartphones (see Figure 7).

The estimates of per unit profit (or margin) are validated by an industry report from 2017.[24] The industry reports per unit profits in 2017 for Apple, Samsung, Huawei and Oppo as \$ 241, \$ 50, \$ 24 and \$ 22 respectively (expressed in 2010 real dollars for consistency). The model estimates the per unit profit to be \$ 308, \$ 73, \$ 39, and \$ 52 respectively. The two sets of estimates are reasonably close to each other with the caveat that the model systematically overestimates the per unit profit by a small magnitude. This can be attributed to fixed costs or marketing costs that are observed by the industry and included in their total costs.

[24] Apple earns five times higher per unit profit than Samsung; last accessed on 12.10.2021

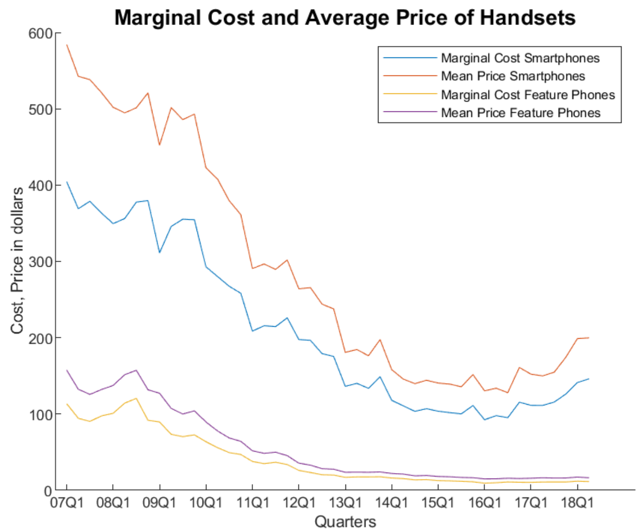

Figure 6: Marginal Cost and Average Price in 2010 real USD

Income and Smartphone Adoption Using the estimated model, it is possible to calculate the individual probability of purchasing a smartphone. This probability varies with the income of the individuals. The results show that, in the last period of analysis (2018 Q2), smartphone adoption is heavily concentrated in the top 30% of the income distribution. The top 30% richest individuals account for 68% of the entire smartphone market. The top 40% account for nearly 80% of the market(see table 3). Policies that address smartphone adoption would thus need to address this inequality in smartphone adoption. The counterfactual simulations discussed in the next sections provide evaluations of some policy instruments that can be used to do this.

Table 3: Income decile wise smartphone market in 2018 Q2

Decile of income	% of smartphone market
p0 to p10	0.28
p10 to p20	1.08
p20 to p30	2.13
p30 to p40	3.55
p40 to p50	5.44
p50 to p60	7.94
p60 to p70	11.34
p70 to p80	15.73
p80 to p90	21.66
p90 to p100	30.80
Total	100

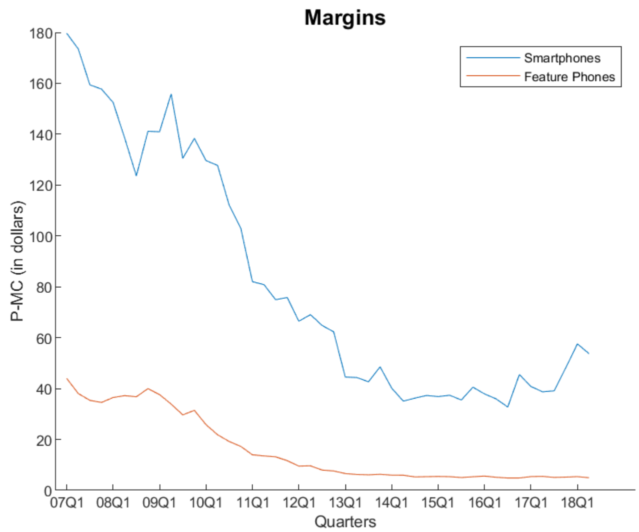

Figure 7: Margins over time in 2010 real USD

7 Counterfactual Simulations

I implement two sets of counterfactual exercises - the first set corresponds to the first research question and quantifies the contribution of key factors shaping the trajectory of the smartphone market in India. The second set of counterfactual policy simulations correspond to the second research question and compare policy strategies to spur smartphone adoption in India.

7.1 Decomposition of smartphone adoption

In this section, I use the estimated structural parameters of utility in order decompose the determinants of smartphone adoption in India. More specifically, I quantify the effect of the following factors on the size of the smartphone market : income distribution, competition in the handset market, changes in network coverage, changes in the quality of devices, and the entry of Chinese phones.

In order to implement the simulations in this section, I recompute the market equilibrium under the counterfactual assumptions. This means that in response to the counterfactual setting, firms are allowed to adjust their prices and consumers make choices based on these new prices.

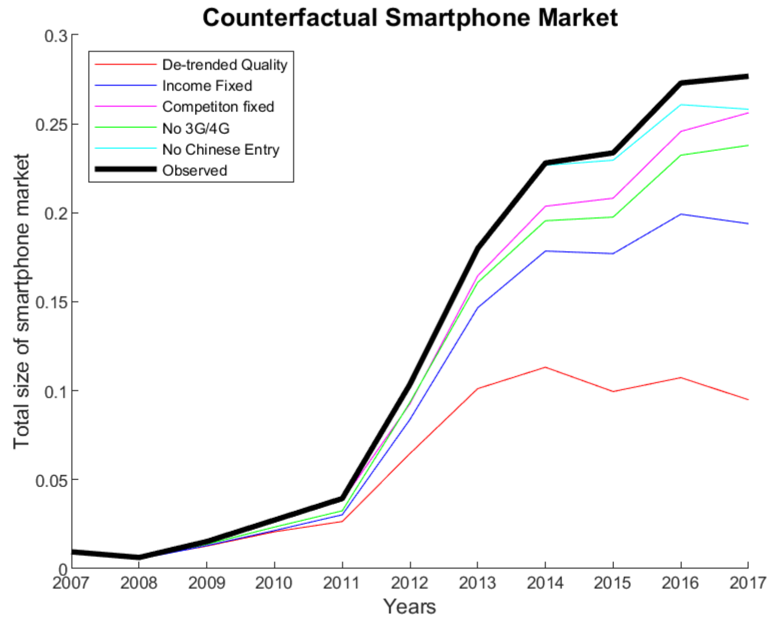

Figure 8: Smartphone market under counterfactual assumptions

7.1.1 Income and Smartphone Adoption

Affordability is one of the most important determinants of the size of the smartphone market. During the period of study, the average per capita income (in real 2010 USD) has increased from \$ 1,338 in 2007 to \$ 2,256 in 2018. At the same time, inequalities have also increased, as seen in Figure 4. To measure the impact of the changes in income distribution on the smartphone market, I fix the income distribution to the one in the base period (2007) and recompute the market equilibrium using the firms' first order conditions in every period thereafter. The difference between the observed trajectory and the counterfactual trajectory is then attributable to changes in the income distribution between 2007-2018. With the income distribution fixed to the one in 2007, the total size of the smartphone market would decrease by 20% on average. The total size of the handset market and the size of the feature phone market would decrease by 7.5% and 2% on average, respectively. This is directly attributable to the income effect on market outcomes. The magnitude of the decrease in adoption and market size differ over time which can be seen in Figure 8.

7.1.2 Coverage and Smartphone Adoption

As mentioned previously, during the period of analysis, there were important changes in the coverage of mobile internet (3G and 4G networks). The estimation results show that expanding coverage (measured as the proportion of population having access to the network) did indeed increase the utility of purchasing mobile phones (Table 2). Since smartphone users are more likely to use mobile internet, the expansion in coverage is likely to have had a relatively larger effect on the smartphone market than the feature phone market.

In this counterfactual policy simulation, the objective is to measure the evolution of market outcomes in the absence of 3G and 4G network expansion. The development of 3G and 4G networks went hand in hand with the popularity of 3G and 4G handsets.[25] In the implementation of the counterfactual, I set I set the proportion of the population having access to 3G and 4G networks to zero (as was the case at the beginning of the period) and also subtract the average utility of a 3G and 4G handset from consumer's utility function. I then re-simulate market outcomes. I find that in the absence of 3G and 4G network, the smartphone market would have contracted by 12% on average. This contraction is as large as 15% by the end of the period of analysis (2018 Q2). The total size of the handset market would decrease by 1.25% on average. The size of the feature phone market would increase by 2.2% on average, implying that smartphone users would have substituted to feature phones in the absence of network expansion of 3G and 4G.

7.1.3 Firm Entry and Smartphone Adoption

Since the beginning of the period of analysis in 2007, the number of firms entering the market, and thus the level of competition, has gradually increased (Table 1). In 2007, there were a total of 27 firms competing in the market, this nearly doubled in 2016 when there were 50 firms in the market. In the last period of analysis (2018), 40 firms offered handsets in the market. In this counterfactual, to understand the effect of firm entry on the size of the smartphone market, I fix the set of firms in every period to the baseline number of firms in 2007 and recompute the market equilibrium for every period thereafter. This is equivalent to not allowing entry of new firms, and thus reducing market competition in the counterfactual scenario. Note that firms existing in 2007

[25] Chatterjee, Fan and Mohapatra (2022) document extensive spillover effects between the two markets. I do not model the spillovers directly due to data limitations.

are still allowed to upgrade or diversify their product offerings in the counterfactual.[26]

I find that removing competitors from the market between 2008 and 2018 leads to a reduction in the size of the total market by an average of 8% over the whole period. The size of the feature phone market decreases by an average of 8.5% over the whole period. The effects of market competition on smartphone adoption become important starting from 2012. The size of the smartphone market increases until 2012Q1 by 1.1% and then decreases by 9% on average until the end of the period. Correspondingly, between 2012 and 2018, without new entrants, the average price of a smartphone increases by 49% and that of feature phones increases by 50%. The reduction in market competition has a substantial negative effect on the size of the smartphone market, though the effect is larger for the feature phone market.

7.1.4 Product Quality and Smartphone Adoption

The characteristics of handsets available to consumers have changed substantially over this 12-year period. For smartphones in particular, the range of features available has increased dramatically due to technological progress in the market. To measure quality of devices, I use the estimation results to construct a product quality index. This index is a weighted linear combination of product characteristics where the weights are the estimated coefficients of these characteristics (βx_{jt} in equation (1)). The quality of a product is defined as the difference from the lowest quality handset over the whole period. As seen in Figure 9, this index indeed shows a sizeable improvement in quality for smartphones over the period of analysis. On the other hand, the quality of feature phones stayed nearly constant between 2007 and 2011, and declined slightly thereafter.

[26] This exercise abstracts from the effect of reducing entry on the diversity of the product portfolio of the incumbents.

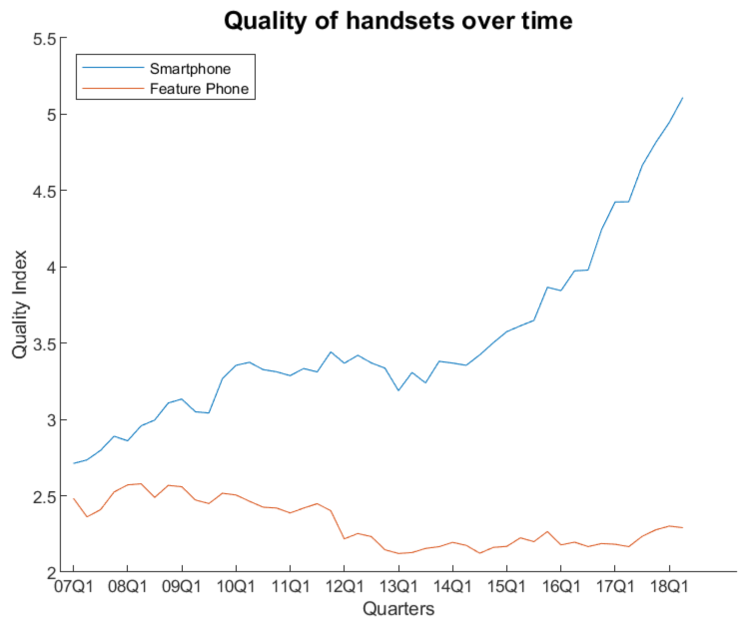

Figure 9: Decomposition of smartphone adoption

To understand the effects of this rapid increase in the quality of smartphones on the size of the smartphone market, I proceed in two steps. First, I estimate a quadratic time trend for quality of smartphones (Table 14). Then, in the counterfactual simulation, I subtract this quadratic trend from the mean utility of smartphones ($X\beta$) and recompute the market equilibrium under this modified mean utility. Intuitively, this translates into evaluating the market outcomes in the absence of the increasing trend in smartphone quality. The difference between the observed outcomes and counterfactual outcomes can then be attributed to improvements in smartphone quality.

I find that without the increasing trend in smartphone quality, on average, the total market size would decrease by an average of 6% over the whole period. The size of the smartphone market would decrease by 35% in the same period, though the decrease is more sizeable at 60% between 2016 and 2018. The size of the feature phone market would increase by 23.2% on average, and by 46.5% between 2016 and 2018. Thus, technological improvement and the resulting increase in smartphone quality was a significant factor driving smartphone adoption over this period.

7.1.5 Chinese Entry and Smartphone Adoption

The entry of four Chinese handset companies (Oppo, Vivo, Xiaomi and RealMe) starting in 2014Q1 has been important for the mid-range smartphone market in India. In fact, in the current period (2021Q1), these Chinese brands held 75% of the total smartphone market, and the only non Chinese company in the top five selling brands was Samsung.[27] As Apple is not very popular in India due to it's high prices, these Chinese brands offer cheaper alternatives to iPhones while retaining some of their most important characteristics. In this counterfactual simulation, I recompute the market equilibrium without the entry of these four Chinese brands in 2014Q1 and thereafter.

I find that on average, over the period between 2014Q1 to 2018Q2, in the absence of Chinese entry, the size of the smartphone market would decrease by 2.3 % and the size of the feature phone market would increase by 1%. The total size of the market would decrease by 0.5%. The average price of a smartphone would decrease by 0.9% and the average price of feature phones increases by 0.2%. The positive impact of Chinese entry on the size of the smartphone market was larger in magnitude 2017 onward, than between 2014 and 2017 (Figure 8).

7.1.6 Other Factors Affecting Adoption

Other factors that can be potentially important in driving smartphone adoption include changes in digital literacy, changes in usage costs and increase in services compatible with smartphones. Due to insufficient data on these, they are not explicitly included in the analysis. However, a large part of variation in digital literacy, usage costs and service availability is over the time dimension (instead of the handset model dimension) and these are included in the model implicitly through time fixed effects.[28]

[27] India Smartphone Shipments See Record Q1 in 2021. Counterpoint Research, April 2021

[28] It is likely that there is income and device based heterogeneity in the sensitivity to the cost of usage. However, systematic individual level data measuring usage costs (through prices of mobile internet) is not readily available for India. In ongoing work, I attempt to construct an empirical distribution of usage costs by combining cross-sectional individual level survey data on monthly expenditures on mobile internet usage with aggregate data on telecom operator's mobile internet revenue. This individual level distribution can then be incorporated in the utility function to shed light on the explicit relationship between changes in usage cost and smartphone adoption.

7.1.7 Summary and Discussion

The counterfactual simulations presented in sections 7.1.1 – 7.1.5 shed light on the factors driving the smartphone market in India over the 12 year period between 2007 and 2018. As seen from Figure 8, the most important factor contribution to smartphone adoption in this period has been the improvement in quality of smartphones. Without the increasing trend in smartphone quality, the size of the smartphone market would contract by 35% on average over the whole period. The next important factor driving the smartphone market is the change in the income distribution over time. Fixing the income distribution to initial levels would lead to a contraction in the smartphone market by 20% on average over the whole period. Following income, the next important factors are changes in coverage and entry of new firms in the market. In the absence of the expansion of 3G and 4G networks, the smartphone market would have contracted by 6% on average. Removing new entrants from the market would have led to an 8% contraction in the size of the smartphone market. Finally, if the Chinese firms had not entered the market, the magnitude of this contraction would have been 2.3%.

To summarize, this set of counterfactual simulations quantifies and ranks the contribution of key economic factors in driving smartphone adoption over 2007 to 2018. The two most important factors driving the smartphone market in this period are improvement in quality of smartphones, and changes in the income distribution. Among the factors analyzed in this section, the income distribution, through taxes and subsidies, can be a potential policy lever for the planner to spur adoption. The next section discusses these policy levers in greater detail.

7.2 Policies to encourage smartphone adoption: Ad Valorem Taxes

One possible policy instrument to expand access to smartphones is reducing the goods and services tax (GST), which is a value-added tax levied on all mobile phones in India. The counterfactual simulations presented in this section quantify the relationship between the GST rate on mobile phones and the size of the smartphone market. Additionally, I evaluate the impact of a recent policy of increasing the GST tax rate on the smartphone market and prices. Like in the previous section, in all of the counterfactual simulations that follow, firms are allowed to readjust prices in response to the tax changes.

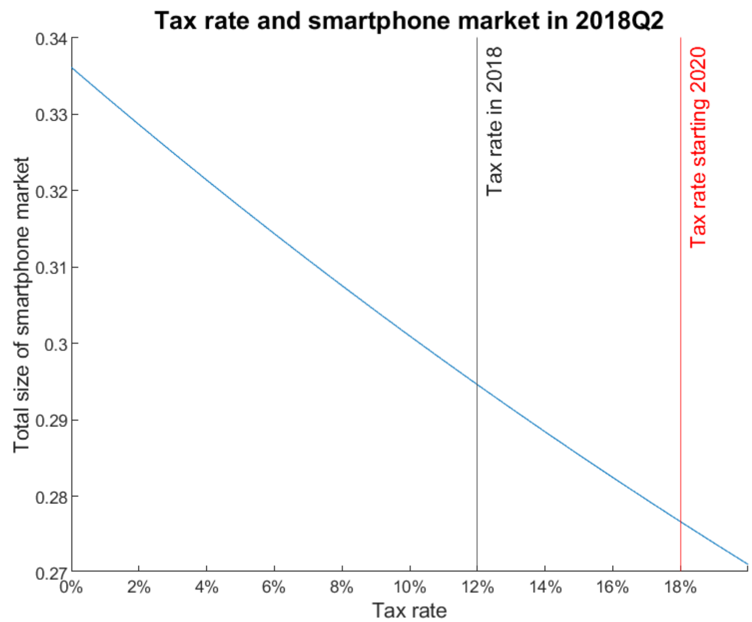

Figure 10: GST rate and smartphone market

In this sub section, I provide a schedule of GST rates and the corresponding size of the smartphone market. I find that reducing or waiving off the GST on smartphones phones would lead to substantial gains in adoption. For example, if the GST rate was reduced from 12% to 5% (the next tax bracket for consumer goods, see Figure 10), the total smartphone market would expand by 7.9% and the feature phone market would contract by 3.7%. There would also be an effect on the extensive margin as the total size of the mobile phone market would increase by 2%. The tax reduction would also be progressive, increasing the probability of smartphone purchase of poorer individuals by more than that of richer individuals.

7.2.1 Tax-free budget smartphones

In this counterfactual I consider the impact of reducing the GST rate only for budget smartphones that cost less than $ 200. I choose to consider subsidies only for budget smartphones since subsidizing expensive smartphones would mean subsidies for richer people that already have a high willingness to pay for smartphones. So, the tax rate on smartphones that cost more than $ 200 and all feature phones remains at the observed level of 12%. I find that in order to have a 10% expansion in the size of the smartphone market, the tax on budget smartphones needs to be reduced by 9

Table 4: Pass through of taxes and subsidies in 2018 Q2

Policy	**Δ Govt. Revenue***	**Δ Consumer Price**	**Δ Firm Price**
Tax increase to 18%	10.7	10.8	-0.10
Tax reduction to 3%	-8.4	-8.3	0.1
Uniform subsidy of $ 7	-7	6.6	0.40
Targeted subsidy of $ 10	-10	-10.07	-0.06

*Change in government revenue per unit in 2010 US dollars. The table can be read as follows: Take row 2, if the tax rate is decreased to 3%. For each smartphone sold, the government revenue decreases by $8.4. Of this, the firm keeps $0.1 and the consumer gets $ 8.3 in form of lower prices. This provides an intuitive understanding of the pass-through to consumers being almost 1.

percentage points (from 12% to 3%). This tax reduction would lead to a contraction in the size of the feature phone market by 5%. There are also positive effects on the external margin - the size of the total handset market would increase by 2.3%. The redistributive effects of the policy are positive but small: the share of the richest 30% in the smartphone market decreases from 68.2% to 67.7%.

Pass-Through In response to the tax reduction, firms modify their prices taking into account the change in consumer demand. Whether and how much they increase/decrease the price depends on the curvature of the demand curve. The pass through then is the proportion of the tax reduction that accrues to the consumer after firms adjust their prices.[29] I find that the average pass through for budget smartphones is close to 1: consumers capture 98% of the tax reduction (Table 4).

7.2.2 Government policy on GST on mobile phones

In March 2020, the GST rate on all mobile phones was increased from 12% to 18%. Electronic manufacturing associations and industry bodies have called for a repealing the increase, citing concerns that any increase in tax rates cannot absorbed by manufacturers, and is bound to lead to an increase in consumer prices.[30]

Though the change in the GST rate on mobile phones occurred outside the period of analysis (in 2020 Q1), the strength of using a structural model of consumer utility is that it is still possible to single out the effects of this policy. I use data from the last period of analysis (2018 Q2) to do

[29] More precisely, pass through is the difference between the post-tax price and the original price (that the consumer pays) divided by the tax rate.

[30] Electronics sector seeks tax relief amid rising input costs. LiveMint, January 2021, last accessed on 15.10.2021

this.[31] I recompute the market equilibrium in 2018 Q2 considering a GST rate of 18% on all mobile phones instead of the 12% which prevailed in this period.

The results of the counterfactual suggest that an increase of 6% in the GST rate (from 12% to 18%) would lead to a contraction in the total market of phones by 2.1%. The size of the smartphone market would decrease by 5.7%, which corresponds to 2 p.p. fall in the share of smartphones as a proportion of all the phones sold. The size of the feature phone market would increase by 0.9%.

Pass-Through I find that the pass-through of this tax increase is nearly 1. This means that firms do not absorb any of the tax increase, instead passing the burden to consumers through higher prices (Table 4). Thus, a large majority burden of this change in policy is likely to be borne by consumers, hurting affordability of smartphones and expansion of adoption. Moreover, the policy also has negative consequences for redistribution - the probability of purchasing a smartphone for poorer consumers declines a lot more for poorer people than for richer ones (Table 5). The result on pass-through is consistent with industry expectations of the effect of the policy on consumer prices.[32] Industry experts claim that the tax hike and supply shocks will especially hurt the affordability of budget smartphones that cost less than $ 200.[33]

Table 5: Change in probability of purchasing smartphones due to tax increase in 2018 Q2

Percentile of income	Δ probability (%)
p0 to p10	-16.9
p10 to p20	-14.5
p20 to p30	-14.5
p30 to p40	-13.5
p40 to p50	-12.1
p50 to p60	-10.5
p60 to p70	-8.8
p70 to p80	-6.7
p80 to p90	-4.1
p90 to p100	-0.5

[31] The model allows me to identify the probable effect of this policy ex-ante, with the caveat that in reality time varying factors might affect the size of the effect.

[32] Ibid.

[33] Semiconductor shortage triggers a rise in Smartphone Prices. Money Control, May 2021

7.3 Policies to encourage smartphone adoption: Unit Subsidies

Another policy instrument available to governments is a subsidy directly given to consumers for purchasing smartphones. In this section, I consider start by considering a uniform subsidy on the purchase of budget smartphones. Then, I consider subsidies targeted to consumers in the bottom 60% of the income distribution. As in the previous sections, I allow firms to change equilibrium prices in response to the subsidy policy.

7.3.1 Flat subsidy on budget smartphones

In this counterfactual simulation, I evaluate the impact of a flat subsidy on smartphones that cost less than$ 200 on adoption. Providing a uniform subsidy on all smartphones is analytically equivalent to a reduction of marginal cost for firms producing smartphones (Durrmeyer(2018)). Fixing the period of analysis to 2018 Q2, the last period when data is available, I find that a subsidy of $ 7 is required for a 10% increase in the size of the smartphone market. This corresponds to a 3.6 percentage point increase in the relative share of smartphones in the market (from 47% to 50.6%). The size of the feature phone market would contract by 4.6%. Compared to the tax reduction (section 7.3), this policy would have bigger positive effects on redistribution. The share of the richest 30% individuals in the smartphone market decreases from 68.2% to 64%.

Pass-through Since firms readjust their prices in response to the new demand function of consumers that includes the subsidy, the price paid by consumers may not decrease by the amount of the subsidy. The subsidy creates a wedge between the price paid by the consumer and the price recieved by the firm. Indeed, I find that for a $ 7 subsidy, consumer price decreases on average by $ 6.6 and firm price increases by $ 0.40 (Table 4). Even though consumers don't receive the full benefit of the subsidy, they receive the vast majority of it - the pass through is nearly 1 (0.92).

7.3.2 Targeted subsidy for budget smartphones

Instead of a flat subsidy on budget smartphones given to everyone, the planner might want to target poorer individuals to prevent subsidizing individuals that would adopt even in the absence of a subsidy. In this counterfactual, I simulate subsidies on budget smartphones (price less than $ 200) targeted to individuals below the 60th percentile of the income distribution. I find that in order to have a 10% increase in the size of the smartphone market, a targeted subsidy of $ 14 per person is required on budget smartphones. Not surprisingly, targeting has the biggest positive redistributive effects, the share of the richest 30% individuals in the smartphone market decreases from 68.2% to 62% (Table 6).

Table 6: Change in probability of purchasing SP due to targeted subsidy in 2018 Q2

Percentile of income	Δ probability (%)
p0 to p10	147.7
p10 to p20	81.7
p20 to p30	55.0
p30 to p40	39.2
p40 to p50	27.4
p50 to p60	17.7
p60 to p70	-6.6
p70 to p80	-8.7
p80 to p90	-8.8
p90 to p100	-8.8

7.4 Discussion

In the previous subsections, I evaluate the impact of different tax and subsidy policies on market outcomes. I find that a 10% increase in the size of the smartphone market can be achieved through i) a reduction in the GST rate from 12% to 3% on budget smartphones, or ii) a flat $ 7 subsidy on all budget smartphones, or iii) a $10 subsidy on budget smartphones targeted to individuals in the bottom 60% percentile of the income distribution. Out of these three policies, the targeted subsidy leads to the biggest gains in redistribution, the lowest tax revenue loss and the least distortions (pass-through is 1). At the same time, it must be noted that these calculations for revenue loss do not include the administrative costs of targeting. However, recently, the government has already been investing in the infrastructure that allows targeted subsidy payments to be transferred seamlessly. The "India Stack" infrastructure, that links mobile phone numbers with bank details and biometric identity cards, can be utilized to deliver these targeted handset subsidies.[34] This infrastructure is already in use for the rural employment guarantee subsidy scheme (MNREGA) in India.

[34]Stacking Up Financial Inclusion Gains in India. IMF, last accessed on 15.10.2021

Table 7: Tax/Subsidy Policies & Smartphone market

Policy	**Share of poorest 60%***	**Pass-Through**	**Tax Revenue Loss**
Observed	31.7%	-	-
↓ VAT to 3%	32.3%	98%	43%
$7 Subsidy	36%	92%	30%
$ 10 Targeted Subsidy	37.8%	100%	13%

*Share of poorest 60% in the total smartphone market. All policies simulated for budget smartphones.

8 Conclusion

This paper is the first study on the adoption of smartphones using a developing country context. Smartphones have become the primary device through which people in developing countries can access the widespread benefits of digitisation. The paper uses a structural model of consumer demand and supply of mobile handsets using novel data sources. In a growing market like India, where several factors are changing simultaneously, the model allows us to disentangle the factors that shape consumer demand for smartphones. I find that the most important factors driving smartphone adoption are improvements in product quality, changes in the income distribution and expansion of 3G and 4G network coverage. This is followed by increasing market competition and entry of foreign (Chinese) brands in the market. Finally, I provide possible policy strategies to spur smartphone adoption. A 10% expansion in the size of the smartphone market can be achieved either through a reduction in the VAT on smartphones to 3%, or through a uniform subsidy of $7 on all budget smartphones, or $ 10 subsidy targeted to individuals between the twentieth and sixtieth percentile of the income distribution. Of these, the targeted subsidy is the most redistributive, least distortionary and the least costly to the planner.

References

Abiona, O. and Koppensteiner, M.F., 2020. Financial Inclusion, Shocks, and Poverty: Evidence from the Expansion of Mobile Money in Tanzania. Journal of Human Resources, pp.1018-9796R1.

Aker, Jenny C., Christopher Ksoll and Travis J. Lybbert. 2012. “Can Mobile Phones Improve Learning? Evidence from a Field Experiment in Niger.” American Economic Journal: Applied Economics. Vol 4(4): 94-120.

Ameen, N. and Willis, R., 2019. Towards closing the gender gap in Iraq: understanding gender differences in smartphone adoption and use. Information Technology for Development, 25(4), pp.660-685.

Aker, J.C. and Mbiti, I.M., 2010. Mobile phones and economic development in Africa. Journal of Economic Perspectives, 24(3), pp.207-32.

Berry, S.T., 1994. Estimating discrete-choice models of product differentiation. The RAND Journal of Economics, pp.242-262.

Berry, S., Levinsohn, J. and Pakes, A., 1995. Automobile prices in market equilibrium. Econometrica: Journal of the Econometric Society, pp.841-890.

Bharadwaj, P., Jack, W. and Suri, T., 2019. Fintech and household resilience to shocks: Evidence from digital loans in Kenya (No. w25604). National Bureau of Economic Research.

Björkegren, D., 2019. The adoption of network goods: Evidence from the spread of mobile phones in Rwanda. The Review of Economic Studies, 86(3), pp.1033-1060.

Chancel, L. and Piketty, T., 2019. Indian Income Inequality, 1922[U+2010]2015: From British Raj to Billionaire Raj?. Review of Income and Wealth, 65, pp.S33-S62.

Chatterjee, C., Fan, Y. and Mohapatra, D.P., 2022. Spillover Effects in Complementary Markets: A Study of the Indian Cellphone and Wireless Service Markets. Working Paper.

Durrmeyer, I., 2022. Winners and losers: The distributional effects of the French Feebate on the automobile market. The Economic Journal, 132(644), pp.1414-1448.

Björkegren, D. and Karaca, B.C., 2020. The Effect of Network Adoption Subsidies: Evidence from Digital Traces in Rwanda. arXiv preprint arXiv:2002.05791.

Fan, Y. and Yang, C., 2016. Competition, product proliferation and welfare: A study of the us smartphone market.

Garbacz, C. and Thompson Jr, H.G., 2007. Demand for telecommunication services in developing countries. Telecommunications policy, 31(5), pp.276-289.

Grigolon, L. and Verboven, F., 2014. Nested logit or random coefficients logit? A comparison of alternative discrete choice models of product differentiation. Review of Economics and Statistics, 96(5), pp.916-935.

Grigolon, L., Reynaert, M. and Verboven, F., 2018. Consumer valuation of fuel costs and tax policy: Evidence from the European car market. American Economic Journal: Economic Policy, 10(3), pp.193-225.

Hübler, M. and Hartje, R., 2016. Are smartphones smart for economic development?. Economics Letters, 141, pp.130-133.

https://data.worldbank.org/

https://economictimes.indiatimes.com/industry/telecom/telecom-news/the-jio-e\ffect/articleshow/65694564.cms

https://www.financialexpress.com/industry/technology/reliance-jio-impact-volte-smartphone-dema
435286/

https://www.imf.org/en/Data

https://telecom.economictimes.indiatimes.com/news/the-year-chinese-smartphone-players-dominate
62160418

https://www.bgr.in/news/apple-earns-five-times-higher-per-unit-profit-than-samsung-547102/

https://trai.gov.in/release-publication/reports/performance-indicators-reports

Jensen, R., 2007. The digital provide: Information (technology), market performance, and welfare in the South Indian fisheries sector. The quarterly journal of economics, 122(3), pp.879-924.

Langer, A. and Lemoine, D., 2018. Designing dynamic subsidies to spur adoption of new technologies (No. w24310). National Bureau of Economic Research.

Nevo, A., 2000. A practitioner's guide to estimation of random coefficients logit models of demand. Journal of economics management strategy, 9(4), pp.513-548.

Suri, T. and Jack, W., 2016. The long-run poverty and gender impacts of mobile money. Science, 354(6317), pp.1288-1292.

Tack, Jesse B. and Jenny C. Aker. 2014. "Information, Mobile Telephony and Traders' Search Behavior in Niger." 96(5): American Journal of Agricultural Economics. 1439-1454.

Wang, P. "Innovation Is the New Competition: Product Portfolio Choices with Product Life Cycles." Mack Institute Working Paper.

Yang, C., 2020. Vertical structure and innovation: A study of the SoC and smartphone industries. The RAND Journal of Economics, 51(3), pp.739-785.

A Background of Industry

Table 8: Sales by category in %

Product	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
FP	95.02	97.05	97.99	96.56	94.16	92.56	82.94	69.02	59.18	56.14	52.50	57.20
SP	4.98	2.95	2.01	3.44	5.84	7.44	17.06	30.98	40.82	43.86	47.5	42.80
2.5G	60.27	62.70	61.46	73.20	71.07	73.75	68.76	49.90	41.32	29.14	19.70	10.90
2G	36.80	31.72	35.48	21.96	18.12	14.10	12.61	24.22	18.73	25.23	27.42	18.44
3G	2.92	5.57	3.05	4.82	10.79	12.02	18.00	24.14	26.34	12.36	12.57	0.04
4G						0.08	0.45	1.44	12.01	31.4	51.63	70.62

Table 9: Top 8 firms by yearly sales

2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Nokia	Nokia	Nokia	Nokia	Nokia	Others	Others	Samsung	Samsung	Samsung	Samsung	Jio
Classic	Others	Others	Others	Others	Nokia	Samsung	Others	Micromax	Micromax	Transsion	Samsung
Sony	LG	Samsung	Samsung	Samsung	Samsung	Nokia	Micromax	Others	Intex	Xiaomi	Xiaomi
LG	Samsung	LG	G-Five	Micromax	Micromax	Micromax	Nokia	Intex	Lava	Micromax	Transsion
Lenovo	Sony	Micromax	Micromax	G-Five	Karbonn	Karbonn	Karbonn	Lava	Others	Lava	Nokia
Samsung	Huawei	Spice	LG	Karbonn	ZTE	Lava	Lava	Karbonn	Karbonn	Jio	Lava
Huawei	Vodafone	Haier	Spice	Spice	Lava	Intex	Intex	Nokia	Lenovo	Nokia	Vivo
Vodafone	Haier	Huawei	Karbonn	Lava	Spice	Spice	Spice	Lenovo	Transsion	Vivo	Oppo

Table 10: Top 8 firms by value of sales

2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Nokia	Nokia	Nokia	Nokia	Nokia	Samsung	Samsung	Samsung	Samsung	Samsung	Samsung	Samsung
Sony	Samsung	Samsung	Samsung	Samsung	Nokia	Nokia	Micromax	Micromax	Lenovo	Xiaomi	Xiaomi
Lenovo	Sony	LG	G-Five	G-Five	Micromax	Micromax	Microsoft	Apple	Apple	Vivo	Vivo
Samsung	LG	Micromax	Micromax	Micromax	Karbonn	Karbonn	Lava	Lenovo	Oppo	Apple	Oppo
LG	Lenovo	Sony	LG	Blackberry	Sony	Sony	Apple	Intex	Xiaomi	Oppo	Jio
Classic	Spice	Spice	Blackberry	HTC	Apple	Lava	Karbonn	Lava	Micromax	Lenovo	Apple
Huawei	Huawei	Karbonn	Spice	Karbonn	HTC	Apple	Sony	Nokia	Vivo	Micromax	Transsion
Spice	Vodafone	G-Five	Maxx	Apple	Blackberry	Intex	HTC	HTC	Intex	Transsion	One Plus

Table 11: Average real price in USD across years and categories

Product Category	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Feature Phone	150.56	144.93	105.80	73.15	46.21	26.10	19.31	15.68	12.74	10.66	11.62	11.01
	(129.06)	(167.77)	(125.10)	(57.22)	(30.09)	(20.83)	(10.49)	(7.69)	(4.94)	(3.10)	(4.50)	(5.20)
Smartphone	618.56	538.13	452.84	391.93	302.27	205.53	145.39	112.93	101.47	94.18	107.52	125.23
	(218.24)	(201.20)	(181.07)	(166.40)	(158.06)	(176.91)	(127.34)	(105.66)	(109.68)	(108.51)	(119.3)	(129.23)
2G	63.65	58.48	44.01	37.16	28.48	20.4	15.89	14.53	11.89	10.31	10.66	9.63
	(25.42)	(25.88)	(20.83)	(14.45)	(9.02)	(7.53)	(5.60)	(6.04)	(4.67)	(2.63)	(3.94)	(4.07)
2.5G	265.21	187.10	112.06	70.80	46.65	26.66	24	22.44	16.74	11.91	13.53	11.83
	(234.22)	(196.48)	(131.82)	(46.7)	(29.00)	(17.54)	(17.69)	(16.38)	(14.03)	(5.20)	(5.68)	(5.30)
3G	627.27	545.07	430.55	340.12	283.83	201.05	143.32	111.10	69.94	44.20	36.10	29.12
	(240.28)	(219.44)	(191.11)	(177.51)	(162.59)	(169.23)	(104.25)	(79.00)	(49.03)	(20.67)	(16.56)	(5.04)
4G						577.54	472.89	342.80	216.92	141.76	122.46	126.09
						(195.54)	(140)	(144.90)	(156.36)	(141.76)	(125.81)	(129.56)
Total	291.54	252.94	170.09	117.47	101.17	60.45	64.14	55.71	61.62	57.20	95.62	107.30
	(268.53)	(249.65)	(192.26)	(137.18)	(130.83)	(106.50)	(97.34)	(83.15)	(92.61)	(90.98)	(116.05)	(107.30)

Note: The table provides average price across time with standard deviation in parentheses both in USD

B Survey evidence on ownership and usage

I provide evidence on smartphone uptake and usage based on micro data at the individual level. I use the nationally representative LirneAsia After Access Survey conducted in 2017. Around 61% of the population has a mobile phone, of these 29.5% have smartphones, and 97% have pre-paid connections. The estimates of mobile phone and smartphone penetration are lower than in the aggregate data because the latter over-estimates adoption – aggregate sales data don't account for the same individual buying multiple devices or individuals that replace their devices very frequently. Evidence from the survey point to a substantial degree of heterogeneity in smartphone ownership and smartphone usage. In table 3, I provide correlations between the probability of owning a smartphone and individual demographics. I find that people with higher monthly incomes, more number of years of schooling, and people living in urban areas are more likely to have a smartphone. On the other hand, women, older people and married people are less likely to have smartphones. Of the people that use the internet, the most common uses are for social media (27.1%), email (19.5%), entertainment (15.7%), education (15.41 %), and work (9.4%).

Table 12: Probability of owning a smartphone

	P(Smartphone)
Women	-0.327*
	(0.156)
Age	-0.0544***
	(0.00725)
Married	-0.367*
	(0.172)
Years of schooling	0.165***
	(0.0185)
Total monthly Income	0.00207**
	(0.000702)
Bank Access	0.351
	(0.182)
Urban	0.679***
	(0.142)
N	2542
adj. R^2	0.2242

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Results

Table 13: RCNL demand estimation

Price/Income (σ)	-36.31***
	(4.25)
Nest	0.84***
	(0.02)
Coverage (γ)	0.33***
	(0.07)
Dual SIM	0.06 ***
	(0.01)
Screen Size	-0.01 ***
	(0.005)
3G	-0.1 ***
	(0.03)
4G	0.23 ***
	(0.03)
Form factor (Bar)	-0.14***
	(0.01)
	(0.012)
Memory (4GB)	0.36***
	(0.02)
Memory (8GB)	0.37***
	(0.02)
Memory (16GB)	0.55***
	(0.03)
Memory (64GB)	1.18***
	(0.04)
Memory (256GB)	1.56***
	(0.046)
Camera (1-2MP)	0.60***
	(0.02)
Camera (5-6MP)	1.2***
	(0.04)
Camera (12-13MP)	2.56***
	(0.06)
Camera (20-21MP)	2.69***
	(0.12)
Company FE	yes
Time FE	yes
N	27,730

Table 14: Quality of smartphones regressed on quadratic time trend

	Quality Index
Time trend squared	0.001***
	(0.00001)
Constant	-0.05***
	(0.017)
N	10734
adj. R^2	0.20

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 11: Price Elasticity of Handsets (2010 real USD)

D Taxes

Table 15: Goods and Services Tax (GST) and Pass-Through

Δ tax	Δ in SP market (%)	Δ in SP price (%) consumer price
0	15.6	-4.5
2	12.9	-3.7
4	10	-3.4
5	8.7	-3
6	7.4	-2.6
8	4.9	-1.8
10	2.4	-0.9
14	-2.3	0.7
16	-4.5	1.1
18	-6.7	1.6
20	-8.8	2.5

The observed GST rate in the period of analysis in 12%.
All figures for quarter 2 of 2018.

E Including Unobserved Heterogeneity

It is possible that in addition to income based heterogeneity, there is also unobserved heterogeneity among consumers in their sensitivity to price. To take this possibility into account, I estimate the demand model with unobserved heterogeneity that follows a standard normal distribution. In this case, equation (2) is modified as follows:

$$\alpha_i = \frac{\sigma}{Y_{it}} + \eta \nu_{it}, \tag{11}$$

where $\nu_{it} \sim \mathcal{N}(0, 1)$.

Table 16: RCNL demand estimation

Price/Income (σ)	-36.38***
	(4.31)
Nest (ρ)	0.84***
	(0.02)
Unobserved heterogeneity (η)	-0.0049
	(0.06)
Company FE	Yes
Quarter-Year FE	Yes
Other characteristics	Yes
N	27,730

I find that the parameter estimate that measures unobserved heterogeneity (η) is imprecisely estimated (see table 16). This might be because aggregate data is not sufficient to identify this coefficient (in practice) and more disaggregated data on consumer choice is required. Nevertheless, even with this specification of the price sensitivity, the other coefficients of interest remain similar in magnitude and sign.