Smartphone adoption, technology subsidies and complementary markets

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Abstract

A vast majority of mobile phone users in developing countries continue to use low quality devices(feature phones) despite increasing affordability of smartphones, rising per capita income and declining cost of telecom services. Digitization of the economy is one of the main policy goals of many governments and the persistence of feature phones is especially problematic as more public services move online. By using a structural model of consumer demand of mobile handsets in a mixed logit framework, this paper tracks the adoption of smartphones in India between 2007 and 2018. Specifically, this paper evaluates two research questions i) What are the key barriers to smartphone adoption in India? ii) What types of policies can be used to spur adoption? I use the estimated structural parameters of utility to conduct two counterfactual simulations to answer these questions. I find that increasing competition in the services market (and thus reducing data expenditures) led to a 12.7 percentage point increase in smartphone adoption. As a preliminary answer to the second research question, I find that in order to have a 10 percentage point increase in smartphone adoption, a subsidy of $ 16 is required. Crucially, the gains from the same level of subsidy are higher in later periods.

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Introduction

Digital communication technologies have emerged as the new vehicle for development in the last two decades in many of the emerging economies of the world. Governments as well as stakeholders from the private sector have taken a keen interest in developing infrastructure for the transition to a well-functioning digital economy. India has followed the same path and is now the second largest market in the world for mobile telephony as well as internet services.[1] While the mobile phone revolution in India has been one of the biggest successes of the last decade, the migration from low quality feature phones to smartphones has not taken off as widely as expected, despite the increasing affordability (on average) and increasing variety of smartphones, and declining costs of telecommunication services. The market for handsets continues to be dominated by feature phones[2] that accounted for more than 57% in 2018 by volume of sales[3], driven largely by the rural and semi-urban populations.

In this paper, I study the evolution of the handset market in India between 2007 and 2018. I use a structural model of discrete choice to estimate consumer demand for handsets over this period. To do this, I make use of novel proprietary handset level data published by the International Data Corporation (IDC). I allow consumers' choice of handsets to depend on their income through heterogeneous price elasticities of demand. To do this, I combine the IDC data set with percentile wise data on income distribution from the World Inequality Database (WID). Additionally, to incorporate the effects of competition in the complementary market of mobile services and capture usage of the device, I employ data on the cost of mobile internet from the Telecom Regulatory Authority of India (TRAI). To obtain the structural parameters of consumer utility, I estimate consumer demand under a random coefficients nested logit model using non-linear GMM. In ongoing work, I use micro data from a new household survey provided by LIRNEAsia to incorporate income-based heterogeneity on usage of devices.

[1] https://en.wikipedia.org/wiki/Listofcountriesbynumberofinternetusers

[2] Feature phones provide basic services like voice calling, SMS, and basic Internet browsing often at low speeds. They typically do not have additional applications in the way that smartphones do.

[3] Author's calculation from aggregate sales data, recent household survey evidence from Financial Inclusion Insights and LIRNEAsia puts this number even higher at 71%.

I use these parameters of utility to conduct counterfactual simulations to answer two main research questions: i) What are the main barriers to smartphone adoption in India? ii) What type of subsidy policies can be implemented in order to encourage adoption of smartphones? In order to answer the first, I implement counterfactual policy simulations that allow me to decompose the contribution of income, product variety, competition in the complementary data services market and entry of Chinese products to the smartphone adoption trajectory (**ongoing**). To answer the second research question, I conduct counterfactual policy simulations that evaluate subsidy programs. I consider the following types of subsidy programs - a flat subsidy for all smartphones, and a targeted subsidy for smartphones for the bottom 30% of the income distribution, and a targeted subsidy only for certain types of smartphones **(ongoing)**.

According to preliminary results, I find that competition in the services market had an important role to play in increasing smartphone demand. In particular, increasing competition in the services market in 2015Q1 (and thus reducing data expenditures) led to a 12.7 percentage point increase in smartphone adoption. As a preliminary answer to the second research question, I find that in order to have a 10 percentage point increase in smartphone adoption, a subsidy of $ 16 is required. Crucially, the gains from the same level of subsidy are higher in later periods.

Insufficient smartphone adoption is an important issue not just in India but most of the developing world. Countries in East Africa and South Asia lag behind the developed world in smartphone penetration, as well as behind the world average(GSMA, 2017).[4] Smartphone adoption in the developing world is all the more important because mobile devices provide the first access to the internet for most people.[5] Additionally, governments around the world are increasingly trying to move public services online to facilitate more efficient utilisation of services by citizens. Efforts for digitisation of the economy are only as good as the devices on which they can take place and thus, persistence of low quality feature phones in the developing world requires further scrutiny.

The case of India is particularly interesting as it lags behind in smartphone penetration compared to countries like South Africa, Brazil, Mexico, Nigeria, which are at similar or lower stages of eco-

[4]https://www.gsma.com/mobilefordevelopment/wp-content/uploads/2018/08/Accelerating-affordable-smartphone-ownership-in-emerging-markets-2017$_{w}e.pdf$

[5]For example, in India, 97% of all internet access takes place through mobile devices.

nomic development.[6]The ongoing Covid-19 pandemic has brought the consequences of insufficient smartphone adoption to light. Since the beginning of the pandemic last year, most of the schools in India have been closed to physical presence and a large proportion of students (between 27% to 56%) have no access to online schooling because they don't own smartphones.[7] More recently, as the health infrastructure has crumbled during the second wave of the pandemic in India, many citizens have primarily relied on social media and mobile applications to access resources online. The majority of citizens that do not have access to smartphones or the internet are largely excluded from these citizen-led relief efforts.[8] These issues have made the question of insufficient smartphone adoption all the more relevant and urgent for policy makers.

The existing literature on the adoption of smartphones is limited. Most of the 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. Bjorkengren (2019) studies network effects in the adoption of mobile phones in Rwanda until 2009, but does not evaluate the handset market. Aker and Mbiti (2010) focus on the channels that link telecommunication connectivity to economic development in Africa. In a similar analysis, Aker (2010) evaluates the impact of mobile phone connectivity on price dispersion. 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. Bharadwaj, Jack and Suri (2019) evaluate the impact of taking loans using mobile phones in Kenya. Most of this strand of literature concentrates on the impact of using financial services that can be used on feature phones. As more sophisticated mobile applications and platforms become are becoming relevant for the development process, it may not be enough to concentrate only on the limited set of activities that can be undertaken using feature phones. Ameen and Willis (2018) look at factors that shape gender differences in

[6]https://venturebeat.com/2019/02/05/pew-south-korea-has-the-worlds-highest-smartphone-ownership-rate

[7]https://indianexpress.com/article/education/about-56-pc-of-children-have-no-access-to-smartphones-for-e-learning-study-6457247/; https://www.hindustantimes.com/education/at-least-27-students-do-not-have-access-to-smartphones-laptops-for-online-classes-ncert-survey/story-sp8nb0QZoBXXJ8ZsCLb3yJ.html

[8]https://thewire.in/rights/india-covid-19-social-media-twitter-instagram-hospitals-beds-oxygen

smartphone usage in Iraq, but do not estimate demand for smartphones. The focus of governments in developing countries has also been predominantly on mobile services and network infrastructure, and less on the nature of devices being used in the digital economy. Papers that study the handset 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.

In light of this, this paper makes three contributions. First, to the best of my knowledge, this is the first paper to look at the transition from low quality feature phones to smartphones using a novel panel data set over 12 years. Second, this paper contributes towards understanding complementary markets by analyzing the impact of increased competitiveness in the mobile services market on smartphones and having a demand model flexible enough to include heterogeneity in usage. Finally, this paper contributes to the policy literature by evaluating (ex-ante) different subsidy schemes to encourage smartphone adoption. The findings of the paper can thus inform policy in developing countries to spur the digital economy.

The paper is organised as following: Section 1 maps the background of the industry between 2007 to 2018. Section 2 outlines the structural model of demand and provides a supply model of a multi product oligopoly. Section 3 discusses the data and sample selection. Section 4 discusses the estimation method. Section 5 provides the results of the estimation. Section 6 provides preliminary results from ongoing counterfactual policy evaluations. Section 7 gives details of ongoing work and section 8 concludes.

1 Background of the Industry

1.1 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. 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. Smartphones, on the other hand, have sophisticated operating systems, partial or full touchscreens, and a wide varity of internet enable applications.[9] Over the 12 year period between 2007 and 2018, the pecking order of companies has been continuously changing.[10] There has been considerable entry and exit over most of the period, although entry, exit and churn rates[11] have declined over time, pointing to a more stable market towards the end of the period of analysis[12]. There have been two noteworthy events that have affected the trajectory of the market- the entry of new Chinese firms in the mid-price segment of smartphones starting in 2014, and the entry of a new 4G provider in the data services market in 2016.

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		14532

Sales[13] The main data source for this section is market level data on sales, prices and characteristics of handsets between 2007Q1 to 2018Q2 published by the International Data Coporation (IDC). At the beginning of the period in 2007 and until 2010, between two and 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.[14] The sales data also show a significant increase in the market shares of Indian companies, particularly between 2012 and 2015.[15],[16] Most of these Indian companies entered

[9] RTOS stands for real time operating system

[10] Table 4 and 5 in the appendix provide details of company rankings by sales and value

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

[12] Details in Figure 3 in the appendix

[13] 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.

[14] Tables 9 and 10 in the appendix provide the ranking by sales of the top 8 companies.

[15] The Indian companies are marked in red and the Chinese companies are marked in blue in tables 4, 5 6 in the appendix.

[16] Micromax, Intex, Lava, Spice, Karbonn- marked in red in tables 4 and 5 in the appendix.

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 has been declining, even though it still accounts for over 50% of the market. Interestingly, following the entry in the telecom services market, 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.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 (notably Whatsapp, Facebook) 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.

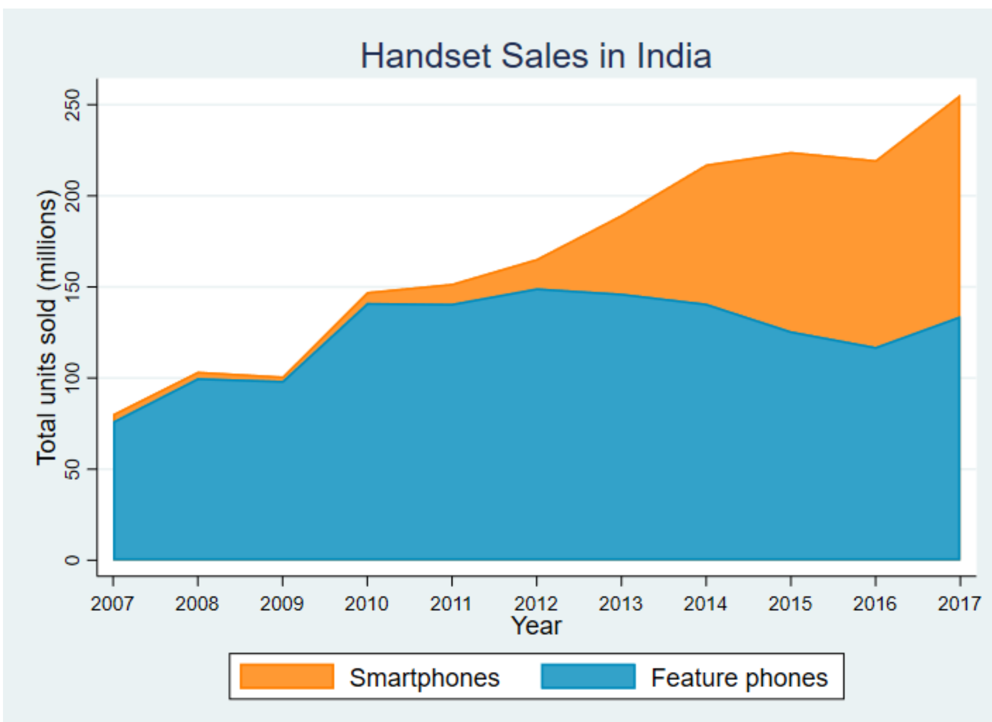

Figure 1: Volume of sales of handsets

Chinese Entry Since their entry in 2014, 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 of smartphones. Through aggressive marketing, careful product selection and exclusive contracts with retailers, these companies have managed to account for 75% of the smartphone market today.[17] [18]

Table 2: Sales by category in %

Product	2007	2009	2011	2013	2015	2017	2018
Feature phone	95.02	97.99	94.16	82.94	59.18	52.50	57.20
Smartphone	4.98	2.95	3.44	7.44	40.82	47.50	42.80

Prices Prices vary considerably over the 12 year period over time and across models. In the paper, 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 (figure 2; table 11 in appendix). 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. Additionally, in figure 2, we notice that towards the end of the period, the prices of smartphones start to increase again.

[17] https://www.reuters.com/article/india-smartphones-idUSKBN29W1X3, last accessed on 3.05.2021

[18] https://www.bbc.com/news/world-asia-india-50135050, last accessed on 3.05.2021

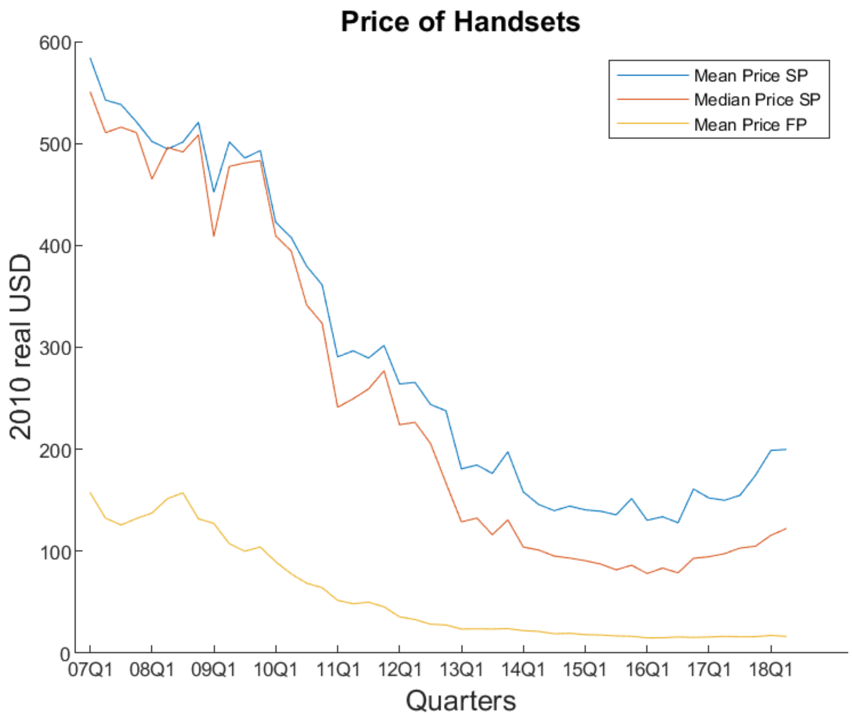

Figure 2: Price of Handsets (2010 real USD)

Entry in telecom services market In September 2016, with the entry of a new 4G service provider (Reliance Jio) in the mobile internet services market, the landscape of the telecom sector in India changed dramatically. Reliance Jio was the first operator to provide 4G mobile broadband and internet based voice services. With near-zero pricing of its services, this led to the exit of all but three incumbents (two of which subsequently merged)and a sharp increase in average data consumption per subscriber and over 215 million new mobile broadband subscribers.[19] The prices of 2G and 3G mobile internet also dropped significantly in response to this entry. To put the magnitude of the impact of this entry on internet prices in perspective, the average price of 1GB of data dropped from USD 11 in 2015 to USD 5 in 2016 and USD 0.51 in 2018. Furthermore, India jumped 154 places to be ranked the country with the maximum data consumption shortly after September 2016.[20] The fall in the prices of mobile internet was followed by product innovations in the handset market (hybrid 4G feature phones) and introduction of device-operator bundling by the entrant. These changes in the mobile services market are potentially important for smartphone

[19] https://economictimes.indiatimes.com/industry/telecom/telecom-news/the-jio-effect/articleshow/65694564.cms

[20] https://economictimes.indiatimes.com/industry/telecom/telecom-news/the-jio-effect/articleshow/65694564.cms

adoption as they directly altered the cost of using mobile devices.

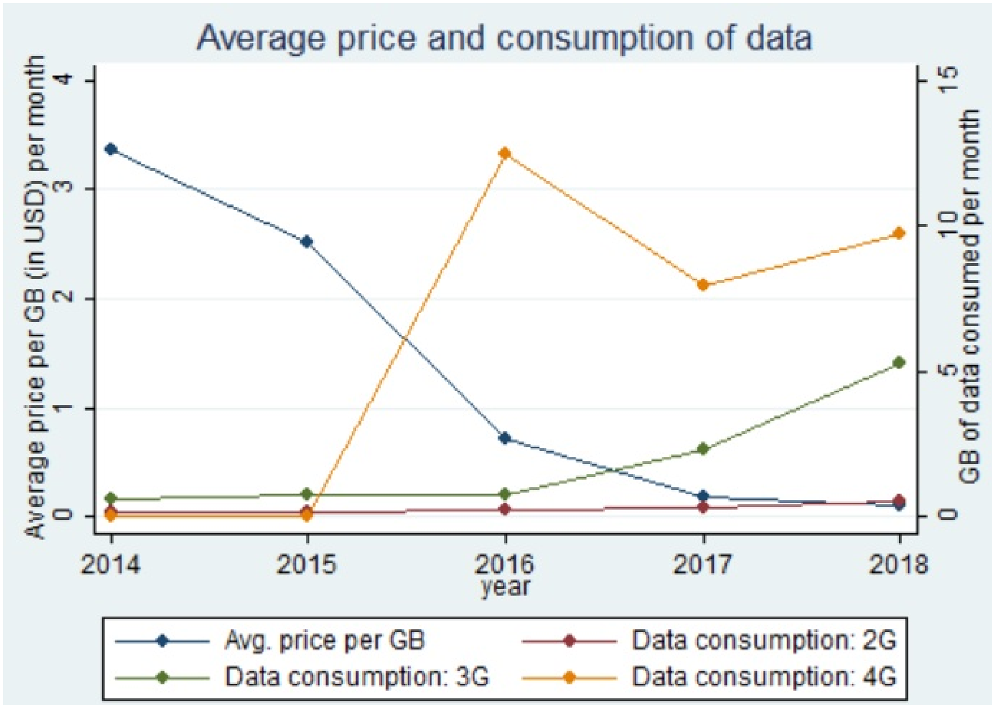

Figure 3: Average price and consumption of mobile internet

Income The income of individuals has been increasing over the time period of consideration but so has the inequality. Based on data from the world inequality database, 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 too increased to \$ 5457 in 2018, pointing to increasing inequality.

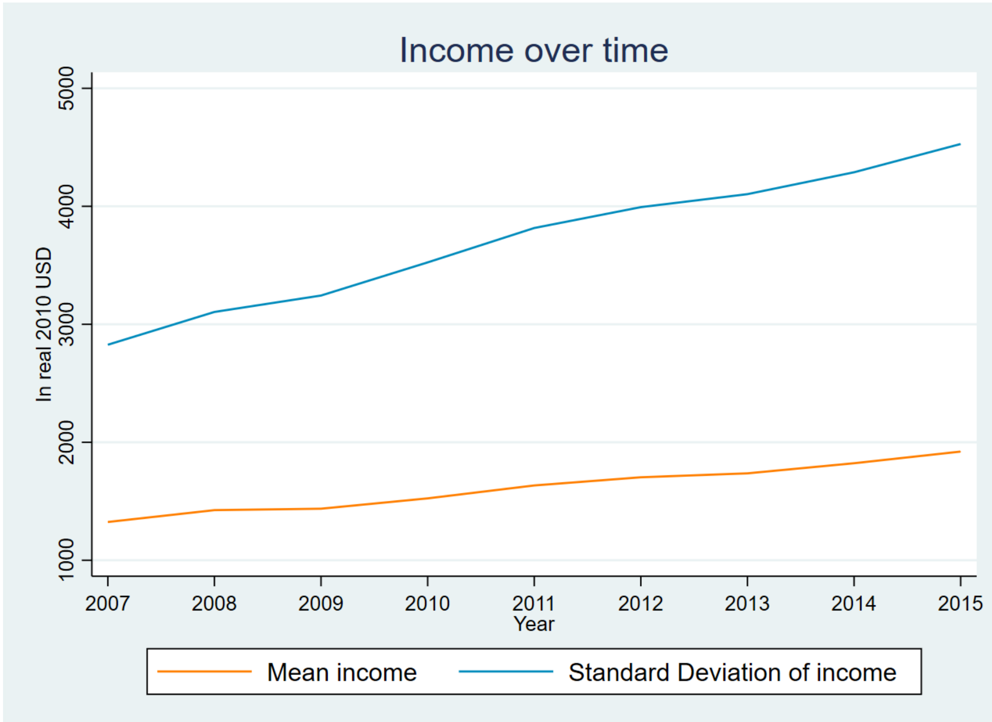

Figure 4: Income and Income Inequality

1.2 Survey evidence on ownership and usage

While the previous section relied on aggregate data on prices and sales, in this section 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 disposable income, years of schooling, usage expenditure, having a debit/credit card, having multiple SIM cards, having a computer, and network effects are positively correlated with the probability of owning a smartphone.[21] Usage of

[21]Network effects are measured by the number of people in the respondent's friend circle that have a smartphone (maximum 5).

the device (measured by monthly data expenditure) is positively correlated with income, years of schooling, having a smartphone, and residing in an urban area.[22] Only 18% of the people, and 25% of mobile phone users have used the internet. 60% of internet users use it at least once a day. 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%).

For the purpose of this paper, I concentrate on heterogeneity among consumers based on income. India is an emerging economy with an expanding middle class, and both income and income inequality have increased over the time period of consideration. Income-driven heterogeneity is thus likely to play an important role in understanding the adoption of smartphones and how people use them, as suggested by figures 5 and 6.

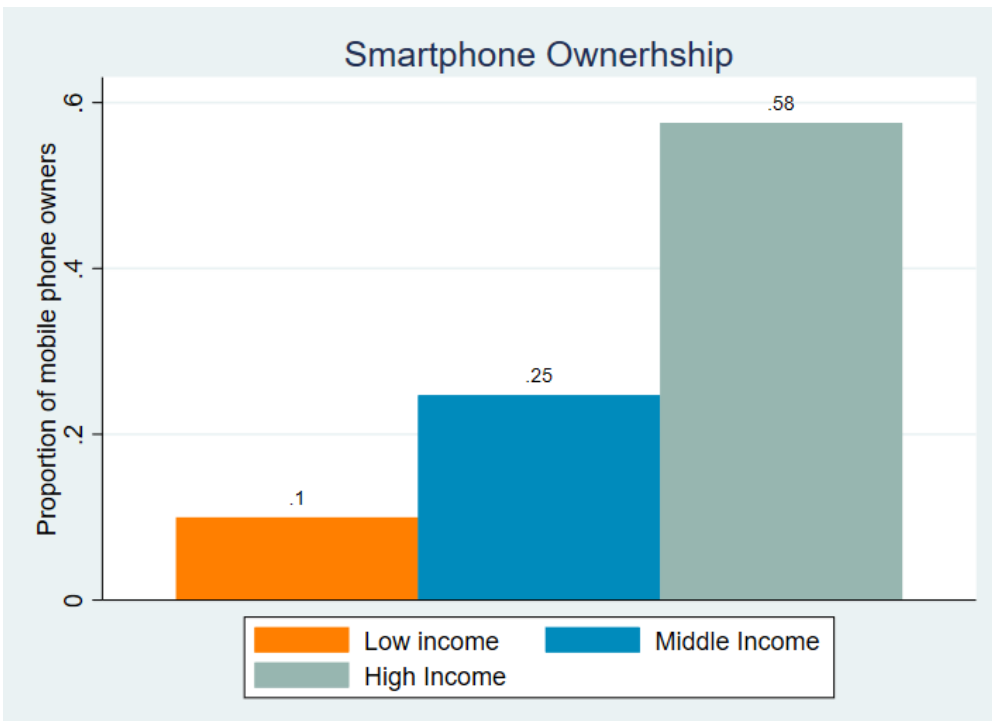

Figure 5: Smartphone ownership across income classes in 2017

[22]Table in appendix.

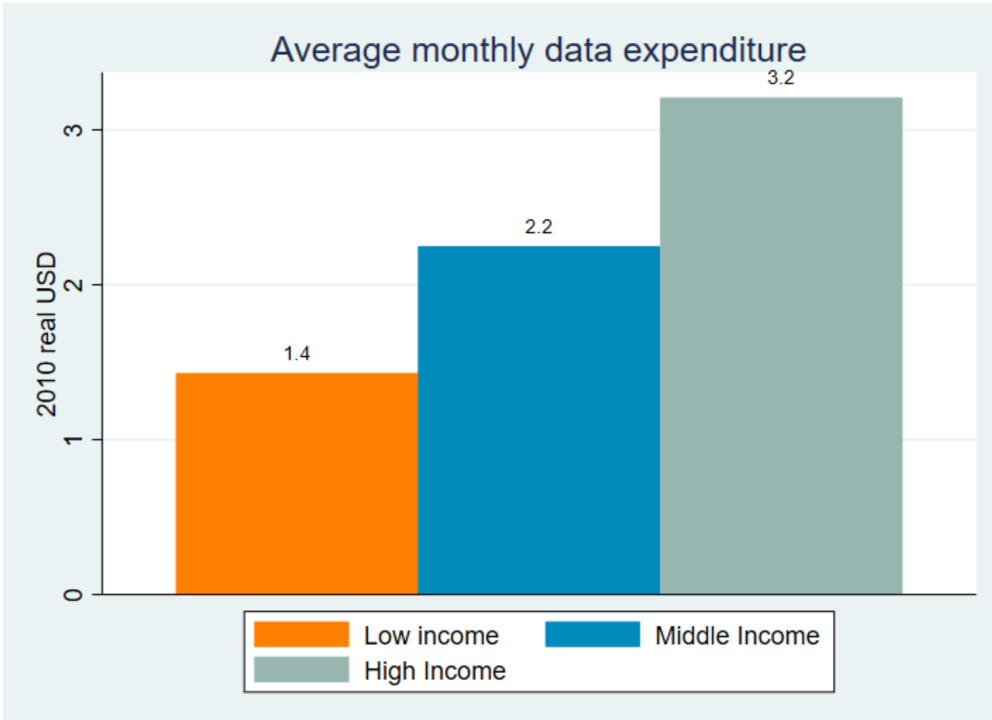

Figure 6: Data expenditure across income classes in 2017

Table 3: Probability of owning a smartphone

	Smartphone
Women	0.0364
	(0.227)
Age	-0.0600***
	(0.00970)
Married	-0.363
	(0.224)
Years of Schooling	0.102***
	(0.0212)
Disposable Income	0.000101***
	(0.0000386)
Hours worked	0.00307
	(0.00364)
Bank account access	-0.0412
	(0.258)
Employed in agriculture	-0.824***
	(0.224)
Data expenditure	0.609***
	(0.112)
Total telecom expenditure	-0.00372
	(0.0527)
Debit or Credit Card	0.295**
	(0.109)
Number of SIMs	0.704***
	(0.165)
Computer Ownership	0.983***
	(0.277)
Network Effect	0.289***
	(0.0664)
N	1975
pseudo R^2	0.355

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

2 Model

2.1 Demand Model

The adoption of a new technology like smartphones is affected by many factors (prices, income, usage costs, time varying unobserved heterogeneity) and a structural model of consumer utility is require in order to disentangle the effects of each of them. In this spirit, I adapt the random coefficients nested logit (RCNL) model proposed by Grigolon and Verboven (2014). The RCNL model of demand is useful when market segmentation is important in capturing unobserved heterogeneity. 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.[23]

I consider T markets defined as each quarter of the period 2007Q1-2007Q2. The potential market size of each market t is denoted by M_t. Each consumer i chooses a handset j in segment g sold by company c in quarter t and gets the following indirect utility u_{ijt} from this purchase:

$$u_{ijt} = \beta x_{jt} - \alpha_{it} p_{jt} + \gamma D_{igt} + \lambda_c + \lambda_t + \xi_{jt} + \bar{\epsilon}_{ijt} \tag{1}$$

Here,

$$\alpha_{it} = \frac{\sigma}{Y_{it}} \tag{2}$$

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 in quarter t, the segment specific usage cost (captured by the data expenditure) D incurred by the consumer in quarter t, company fixed effects λ_c that capture the average utility of buying from a particular company, quarter fixed effects λ_t, and a measure of unobserved product quality ξ_{ijt}. The unobserved product quality might include characteristics like the color of the phone, the shape of the phone etc which are not observed by the econometrician but are observed by the consumer and the producer. A product j is defined as a unique bundle of handset characteristics.

[23] Market segmentation can be captured using the standard mixed-logit demand model, however it is computationally more costly compared to the RCNL model (Grigolon and Verboven, 2014)

The model allows for individual level heterogeneity in the response to price changes through the term α_i specified by equation 2, Y_i denotes the income of individual i. The non-linear parameter $sigma$ 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 - feature phones and smartphones, so g can take two values. Finally, an outside option is specified so that the consumer can choose not to make a purchase in period t. The utility of the outside option is normalized to zero:

$$u_{i0t} = \xi_{0t} + \epsilon_{i0t} = 0$$

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

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

where

$$\delta_{jt} = \beta x_{jt} + \lambda_c + \lambda_t + \xi_{jt} \tag{5}$$

and

$$\mu_{ijt} = \frac{\sigma}{Y_{it}} p_{jt} + \gamma D_{igt} + \zeta_{igt} \tag{6}$$

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:

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

where

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

and

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

Note that J_g is the number of products in segment g so that we have

$$\sum_{g=1}^{G} J_g = J$$

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

$$s_{jt}(x_t, p_t, \xi_t; \theta) = \int_{Y_t} \pi_{jt} P^*_Y(Y) \tag{7}$$

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

2.2 Supply

The profits of firm f producing products J_f in period t with a marginal cost c are given by:

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

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 $J_t \times J_t$ matrix of intra-firm demand derivatives. Once demand has been estimated, this first order condition can be used to recover estimates of marginal cost as follows:

$$\mathbf{c} = \mathbf{p}^* - \Delta(\mathbf{p}^*)^{-1} s(\mathbf{p}^*) \tag{8}$$

3 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. The data set provides information on the following characteristics of handsets- operating system, operating system variant, embedded memory, screen size, screen resolution, air interface, communication technology (2G, 2.5G, 3G or 4G), processor speed band, processor core, processor vendor, camera megapixels, RAM band, input method, GPS capacity, dual sim, form factor, bluetooth capacity, waterproofing, primary memory card, dual rear camera, fingerprint reader, display type, and NFC capacity.[24]

Sample Selection In the original data set, there are a group of very small companies (producing feature phones) clubbed together in a category called "Others". Since there is no additional information available about the companies that are a part of this category, these observations are dropped from the analysis.

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.[25] This is done in order to capture the real purchasing power of consumers and to ensure that the analysis is not affected by time trends in prices. The base year for the deflation is 2010. The prices are reported in US dollars as well as the Indian rupee, and for most of the analysis the prices in US dollars are used.

Market size and Outside Option The potential market (M_t) is defined as $\frac{1}{8}$ of the total adult working population of that year. Intuitively, this translates into the assumption that consumers change their handsets every two years. The data for the annual population and the proportion of the working population is obtained from World Bank Open Data.[26]

Expenditure on usage of device I proxy the usage of the device by the annual expenditure on mobile internet. The monthly expenditure is the product of the amount of data consumed in

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

[25] https://www.imf.org/en/Data

[26] https://data.worldbank.org/

gigabytes (GB) and the price paid per GB of data. I obtain the average cost of 1GB data for a user from the Telecom Regulatory Authory of India's (TRAI) report on wireless data services.[27]. Since this data is published annually, for the purpose of my analysis, I assume the price of 1 GB data to be the same across all quarters of the year.[28] TRAI also records information on the average gigabytes of mobile data consumed per month classified by technology generation (2G, 3G and 4G).[29] As with the price of mobile data, I assume that data consumption does not change across quarters in the same year. The data expenditure, thus, varies across years and across the technology type of device (2G, 3G and 4G).

Table 4: Average monthly expenditure on mobile data in USD

Device type	2014	2015	2016	2017	2018
2G	0.47	0.50	0.17	0.05	0.05
3G	2.10	1.90	0.57	0.41	0.53
4G	0	0	8.94	1.43	0.97

This data is only available starting in 2014. In fact, the market for mobile internet gained momentum only after the 3G spectrum auctions in India which were held in 2010. This is further corroborated by figure 4 which shows that the amount of data consumed per subscriber was negligible before 2011. This is taken into account in the demand model by including an interaction term between the data expenditure and an indicator variable for the years after 2014.

Survey data on mobile internet expenditure To allow for heterogeneity in data expenditure, I use the After Access Survey provided by LIRNEAsia.[30]. This is a nationally representative cross-section of 5069 households and individuals, conducted in 2017. One of the primary goals of the survey is to record the device ownership and device usage behaviour. I use information on individual income and monthly expenditure on data in order to model heterogeneity in usage of devices.

[27] https://trai.gov.in/notifications/press-release/trai-releases-report-wireless-data-service-india, last accessed on 16.10.2020 at 2.30 p.m.

[28] While proxy-measures for the cost of 1GB data (like Average revenue per user of operators from data services) at the quarterly level are published by TRAI, these are often not entirely reflective of the cost of data that the user faces.

[29] https://main.trai.gov.in/sites/default/files/Wireless$_{D}ata_{S}ervice_{R}eport_{2}1082019_{0}.pdf$

[30] LIRNEasia. 2019. AfterAccess Asia (data set). Colombo: LIRNEasia. The findings and opinions in this paper are the author's and not of LIRNEAsia

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).[31] 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 mean incomes to real USD 2010. I use this information in the simulated draws of consumers - I simulate 100 consumers and assign to each the mean income of each of the 100 percentiles from the empirical distribution. Each consumer is therefore assigned the mean income of this percentile. Since the WID 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.

4 Estimation

I follow Nevo (2000) and Grigolon and Verboven (2014) to estimate model given in section 2.1. Since producers take into account the unobserved product quality (ξ_{jt} in the demand model) when they set prices, prices are endogenous to the demand system. To correct for the bias arising from this endogeneity, I use instruments for price. Following the literature, these instruments 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 instruments. Only one out of any set of instruments that have a correlation greater than 0.9 are selected to avoid issues arising from multicollinearity. The main identifying assumption with a vector of instruments Z_{jt} is:

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

I construct demand moments based on these instruments $h(z)$ and estimate the demand model

[31] https://wid.world/, last accessed on 16.10.2020 at 4 p.m.

using non-linear GMM. A two stepped algorithm, as in BLP(1995), is used to retrieve the linear parameters of utility in the first step and then conduct a search for the non-linear parameters($\theta = (\sigma, \rho)$) so as to minimize the objective function:

$$\min_{\theta} \xi_j \theta' h(z_j) \Omega h(z_j) \xi_j(\theta) \tag{9}$$

These parameters are then used to compute Δ, the matrix of intra-firm demand derivatives, which is in turn used to retrieve the marginal costs from equation 8.

Estimation Algorithm The estimation algorithm follows BLP (1995) with one modification. In the first step, for a given set of initial values of the non linear parameters, a unique δ_{jt} is found through a contraction mapping by setting the observed market shares exactly equal to the market shares predicted by the model. I use the modified contraction mapping proposed by Grigolon and Verboven(2014) for the special case of RCNL. The δ_{jt} is used to construct ξ_{jt} from equation (3), which is then used to construct the demand moments as in equation (6). In the final step, the GMM objective function is minimized to estimate the parameters. Details of the estimation algorithm and its implementation can be found in Nevo (2002).

Empirical Specification To construct the demand moments, 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}, brand fixed effects λ_c and quarter 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. I also include an interaction between the technology generation of the device and a linear time trend to control for changes in network coverage over time.

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; and different usage (data expenditure) based on their income. 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. D_{igt} is the empirical distribution of usage that assigns a level of data expenditure to each individual based on their income. Finally, the third part if equation(4), the idiosyncratic error term $(1-\rho)\epsilon_{ijt}$ is assumed to follow an extreme value type I distribution.

Note that in the current draft, I do not provide results and counterfactual policy simulations for the case that includes income based heterogeneity in data expenditures since it is work in progress. Instead, the results presented allow data expenditure to vary across quarters and market segment.

Identification of parameters Following Nevo (2002), the mean utility parameters $\bar{\beta}$ abd γ are estimated by a linear projection, which is substituted in the GMM objective function. $\bar{\beta}$ can be recovered from the correlation between the market shares of the products and their characteristics over time. The income distribution of consumers in the market changes substantially over 2007-2018 as do the prices of products and this is the variation used to pin down the random coefficient σ on the price variable. The variation in the combined market share of each segment over time is used to identify the parameter ρ.

5 Results

The main results of the demand estimation are provided in table 5. The key parameter estimates of interest are (σ), the nest coefficient (ρ) and the mean data expenditure coefficients for smartphones and feature phones. A table containing the full results of the demand estimation can be found in the appendix.

Price sensitivity The coefficient on P_{jt}/Y_{it} (σ) is negative and precisely estimated. A value of $\sigma = -3.45$ implies a mean price sensitivity ($\bar{\alpha}$) 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 ($\bar{\alpha}$= -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. Additionally, the model specification and parameter estimate of σ implies that individuals with higher income are less price elastic than individuals with lower incomes. The price sensitivity of the poorest percentile of income is -0.28, which is several orders of magnitude than the price sensitivity of the richest percentile of income at -0.009. A value of the nesting parameter this high suggests a high degree of substitution within nests(feature phone and smartphone) as opposed to across nests. In other words, consumer tastes for products within each nest are highly correlated with each other.

Table 5: RCNL demand estimation

Price/Income (σ)	-35.4***
	(4.16)
Nest	0.85***
	(0.02)
Data Expenditure × SP	0.01***
	(0.002)
Data Expenditure × FP	-0.57***
	(0.03)
Company FE	yes
Time FE	yes
Time trend × techology	yes
Other charac.	yes
N	27,730

Expenditure and income in real 2010 USD

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 segmentation of the market into groups is not required. From table 3, the nesting parameter is estimated precisely at $\rho = 0.85$. 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.

Data expenditure parameters I use data expenditure as proxy for measuring usage of devices. From table 3, we see that the data expenditure parameters are significant and precisely estimated. As data expenditure is the product of data consumption (positively related to utility) and data prices (negatively related to utility), the sign of the parameter is ex-ante ambiguous. For smartphones, increasing data expenditure increases utility, presumably because the utility gains from higher data consumption outweigh the dis-utility arising from data prices. On the other hand, for feature phones, which have low data consumption, increasing data expenditure decreases utility, as the dis-utility of data prices outweighs the any utility gains from data consumption. As mentioned previously, currently data expenditure varies only by the technology type of device and over quarters. Ongoing work attempts to introduce heterogeneity in usage which can just as important as including heterogeneity in price sensitivities.

6 Counterfactual Policy Simulations[32]

I implement two sets of counterfactual exercises - the first set corresponds to the first research question and attempts to determine the key determinants of smartphone adoption in India. The second set of counterfactual policy simulations are normative and correspond to the second research question. These simulations aim to provide policy strategies that can be used to encourage smartphone adoption. In both of the cases, I provide results for simulations conducted in the first quarter of 2015.

6.1 Demand Decomposition

In this section, I use the estimated structural parameters of utility in order decompose the determinants of smartphone demand in India. This is done with the aim of identifying the key barriers to smartphone adoption in India. More specifically, I quantify the effect of the following factors on the adoption trajectory of smartphones : income, competition in the complementary telecom services market, product variety in the handset market **(ongoing)** and the entry of Chinese phones **(ongoing)**.

6.1.1 Income and Smartphone Adoption

Income and affordability of smartphones are arguably the most important determinants of the adoption trajectory. To disentangle the effect of income on smartphone adoption, I re-simulate the market equilibrium in 2015Q1 by setting the counterfactual income distribution to be that of the beginning of the period (2007Q1). The mean real annual income was $ 1338 in 2007 and $1941 in 2016. More precisely, this means recomputing the market equilibrium with the same choice set and data expenditure but with lower income (31% lower on average) and lower inequality of individuals. This implies that individual market shares are integrated over the counterfactual income distribution.

[32]This section is work in progress and results as well as the set up of the counterfactual simulations are continuously updated

Table 6: Income of 2007Q1 in 2015Q1

	Original	**Counterfactual**	**% change**
Sum of inside shares	0.4461	0.4438	-0.5%
Sum of SP shares	0.1888	0.1871	-0.9%
Sum of FP shares	0.2573	0.2567	-0.2%
Mean price SP	140.58	147.62	4.9%
Mean price FP	17.9	18.34	2.4%
Proportion of SP	42.3%	42.1%	-0.2%

I find that the reduction in income in 2015 to 2007 levels does not change market outcomes too much. The total size of the market decreases by 0.5%, the smartphone market decreases by 0.9%. Average price of smartphones increase by 4.9%.

6.1.2 Competition in complementary market

As mentioned previously, Reliance Jio entered the mobile internet market in 2016, and offered near zero tariffs for using mobile data on handsets. The average price per GB of data came down from USD 3.5 in 2015 to approximately USD 0.10 as of June 2018. In this counterfactual exercise, I try to capture the extent to which competition in the data services market affects smartphone adoption. I do this by allowing data expenditure in 2015Q1 to be equal to the post entry levels (thus, lower than observed). Effectively, this means simulating a scenario where the services market was more competitive in 2015 than actually observed.

Table 7: Data Expenditure of 2017Q1 in 2015Q1

	Original	**Counterfactual**	**% change**
Sum of inside shares	0.4461	0.5783	29.6%
Sum of SP shares	0.1888	0.3184	68.6%
Sum of FP shares	0.2573	0.2599	1%
Mean price SP	140.58	142.43	4.9%
Mean price FP	17.9	17.9	0%
Proportion of SP	42.3%	55%	12.7%

I find that increasing competitiveness of the data services market has a big impact on the handset market. In particular, setting the counterfactual data expenditure equal in 2015Q1 to the post-entry data expenditure leads to an expansion of the market by nearly 30% and expansion in the smartphone market by 68.6%. Smartphone adoption increases by 12.7%.

6.2 Policies to encourage smartphone adoption

In this section, I evaluate the types of policies that can be used to spur smartphone adoption. I consider a flat subsidy on all smartphones for all individuals, a targeted subsidy for smartphones for the bottom 30% of individuals **(ongoing** and a targeted subsidy conditional on the type of smartphone for the bottom 30% of individuals **(ongoing)**.

6.2.1 Flat subsidy on all smartphones

In this counterfactual, I evaluate a flat subsidy on all smartphones and find the required subsidy for 10 percentage point increase in smartphone adoption in 2015Q1. Providing a flat subsidy on all smartphones is mathematically equivalent to a reduction of marginal cost for firms producing smartphones. I recompute the market equilibrium with this reduction in marginal costs. I find that a subsidy of $ 16 per person per smartphone is required to have a 10 percentage point increase in smartphone adoption. Additionally, I find that the same subsidy amount leads to a larger percentage point increase in adoption in later periods. The gains from a $ 16 subsidy for every period after 2013 are between 8-10 percentage points. The gains from the same subsidy are between 0.76 to 4 percentage points before 2014. Thus, the timing of the subsidy might be an important factor to consider.

7 Ongoing work

In on going work, I am using micro data to incorporate heterogeneity in data expenditure based on income. This will allow me to identify the sensitivity of demand to data expenditure more precisely, as well as have more robust counterfactual results. Additionally, I am looking at evaluating the impact of Chinese entry and product variety on the smartphone adoption trajectory in the first set of counterfactual simulations. Finally, for the second set of counterfactual simulations, I am working on evaluating subsidies targeted to the bottom 30% of the income distribution and subsidies conditional on the type of smartphone to avoid subsidizing high end products like iPhones.

8 Conclusion

To conclude, in this paper, I study the patterns of smartphone adoption in India using rich aggregate data between 2007 and 2018. I use a structural model of demand in the random coefficients nested logit framework to estimate the structural parameters of consumer utility of buying mobile devices. Using these parameters, I conduct counterfactual simulations focused on finding out the key determinants of smartphone adoption in India, and the types of policies that can be used to spur smartphone adoption. According to preliminary results, I find that competition in the services market had an important role to play in increasing smartphone demand. In particular, increasing competition in the services market in 2015Q1 (and thus reducing data expenditures) led to a 12.7 percentage point increase in smartphone adoption. As a preliminary answer to the second research question, I find that in order to have a 10 percentage point increase in smartphone adoption, a subsidy of $ 16 is required. Crucially, the gains from the same level of subsidy are higher in later periods.

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Appendix

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

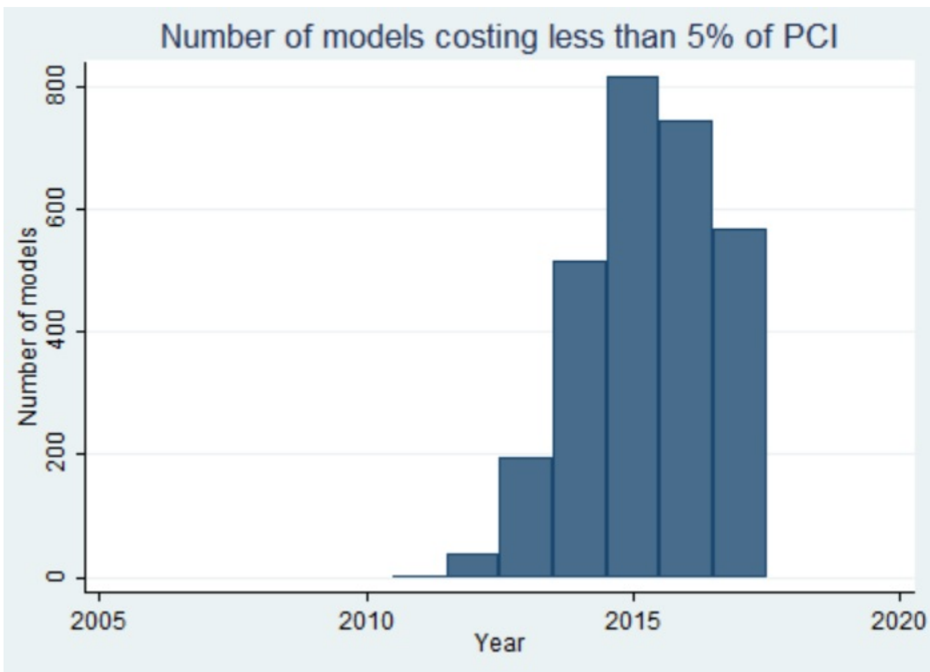

Figure 7: Number of models that cost < 5% of PCI

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

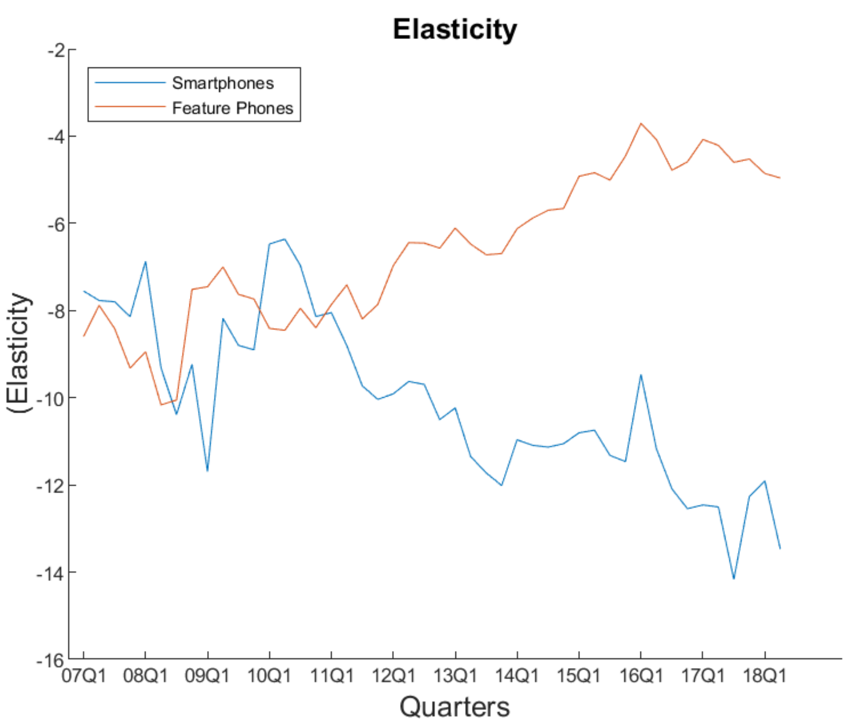

Figure 8: Price Elasticity of Handsets (2010 real USD)

Table 12: OLS: Expenditure and demographics

	(1) Data expenditure	(2) Total telecom expenditure
Disposable Income	0.00763*	0.0134***
	(0.00320)	(0.00284)
Years of schooling	4.983***	5.871**
	(0.776)	(2.135)
Gender	6.076	-29.24*
	(10.64)	(12.62)
Age	0.0775	0.776
	(0.297)	(0.938)
Work experience	0.558	-0.283
	(0.304)	(0.676)
Smartphone	76.80***	61.67***
	(10.05)	(13.05)
Years since 1st phone	1.029	2.871*
	(0.662)	(1.223)
No. of SIM	7.159	-1.251
	(6.398)	(7.552)
Urban	16.28*	30.60*
	(7.247)	(12.39)
NE phone	-4.688**	2.307
	(1.649)	(3.885)
NE social media	-0.0995	-0.223*
	(0.0616)	(0.113)
Operator FE	yes	yes
_cons	-28.80	32.73
	(21.49)	(32.67)
N	2002	2071
adj. R^2	0.242	0.168

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

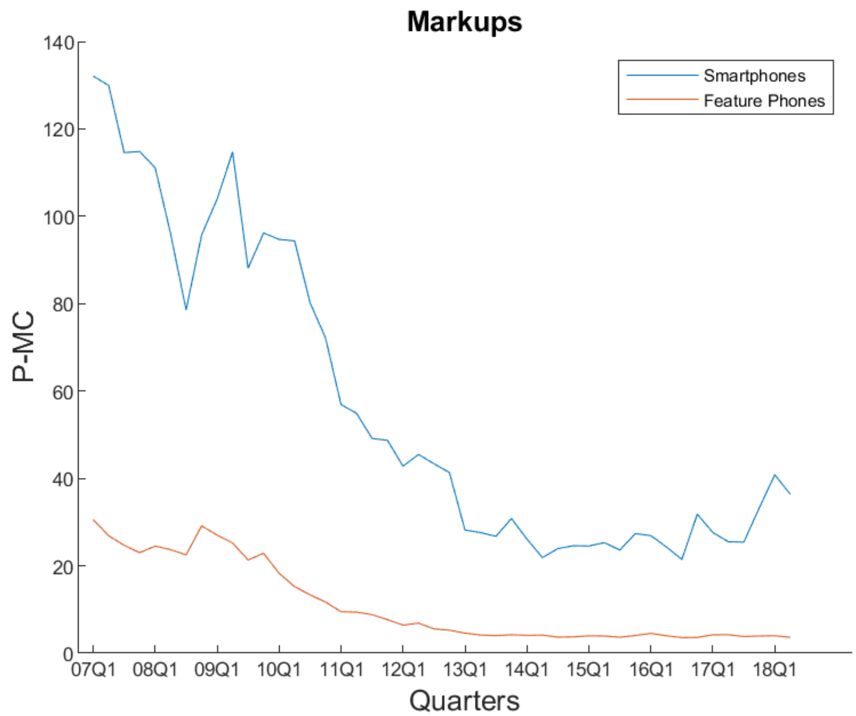

Figure 9: Markup of Handsets (2010 real USD)