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Three essays on technology adoption in emerging markets

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For my grandparents, whose presence I miss everyday, and whose love I feel everyday.

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Abstract: English Version

This thesis studies technology adoption in an emerging market, taking the example of India. In chapter I, I study the adoption of smartphones in India. Smartphones have become the primary device through which people in developing countries can access the benefits of widespread digitization. However, most mobile phone users in developing countries continue to use low-quality feature phones. This chapter 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 and changes in income distribution 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. Chapter II focuses on digital financial services. The use of digital financial services (DFS) in developing countries can be a tool for financial inclusion, curbing tax evasion, and facilitating the efficient delivery of public services. Using a unique event – an un-announced and large scale demonetization process that took place in 2016 in India that increased the short-term costs of holding and transacting in cash, this chapter studies the uptake of a specific form of DFS, namely mobile payments, in India. We find that in states where the labour market was less formal, and where workers were more likely to be affected by the demonetisation process, this shock led to a larger increase in the use of platforms larger than in states where the labour market is more formal. The effect of this "forced experimentation" was, however, short lived. At the individual level, people who were more exposed to the shock were more likely to adopt mobile payments and this effect persists over the next two years. Strikingly, the marginal effects of the shock for high-exposure women was almost twice as high as for high-exposure men. Our results contribute to understanding user behaviour and persistence of habits, with important implications for

the design of policies aimed at increasing the uptake of digital payment technologies. In the final chapter of this thesis, I (with a co-author) study firms' adoption of a new technology in their product portfolio. In particular, we attempt to understand the value of an easily imitable technology in an emerging market context. We study the introduction of dual SIM handsets in the Indian mobile phone market and quantify the value of this technology for consumers. We also quantify the impact on market outcomes of the quick imitation of this technology by competing firms. We find that the introduction of dual SIM handsets led to an increase in the consumer surplus of 3.1% to 8.9%, and an expansion in the total size of the market by 1.8% to 3.3%. We also find that while imitation reduced the innovator's profit substantially, it also made the technology much more affordable. In the absence of imitation, consumer prices would have been 22% higher. Finally, we provide a lower-bound on the innovator's cost of protecting intellectual property in an emerging market. We find this lower bound to be as high as 12% of the innovator's observed profits ($ 29.5 million).

Abstract: French Version

Cette thèse étudie l'adoption de technologies dans les pays en développement, en prenant l'exemple de l'Inde. Dans le chapitre I, j'étudie l'adoption des smartphones en Inde. Les smartphones sont devenus le principal appareil grâce auquel les habitants des pays en développement peuvent accéder aux avantages d'une numérisation généralisée. Cependant, la plupart des utilisateurs de téléphones mobiles dans les pays en développement continuent d'utiliser des téléphones basiques de faible qualité. Ce chapitre développe un modèle structurel de la demande des consommateurs et de l'offre des entreprises pour comprendre les principaux moteurs de l'adoption des smartphones. Il utilise ensuite l'estimation du modèle pour étudier les politiques qui peuvent accélérer l'adoption des smartphones. Je trouve que les gains en qualité des téléphones mobiles et les changements de revenus dans la population sont les principaux facteurs de la croissance des ventes de smartphones en Inde. Compte tenu du rôle central du revenu dans l'adoption de cette technologie, je simule l'impact de subventions ciblées pour les smartphones. Je trouve que, comparées à des réductions d'impôts ad valorem ou à des subventions uniformes, les subventions ciblées sont les moins coûteuses pour le gouvernement et sont les plus efficaces pour la redistribution, étant (presque) entièrement appropriées par les consommateurs. Le chapitre II porte sur les services financiers numériques. L'utilisation des services financiers numériques (SFN) dans les pays en développement peut être un outil d'inclusion financière, de lutte contre l'évasion fiscale et de facilitation de la prestation efficace des services publics. En utilisant un événement unique – un processus de démonétisation non annoncé et à grande échelle qui a eu lieu en 2016 en Inde et qui a augmenté les coûts à court terme de la détention d'espèces et de leurs transactions – ce chapitre étudie l'adoption d'une forme spécifique de SFN, à savoir les paiements mobiles, en Inde. Nous constatons que dans les régions où le marché du travail était moins formel, et où les travailleurs étaient plus susceptibles d'être touchés par le processus de démonétisation, ce choc a conduit à une augmentation plus importante de l'utilisation de plateformes mobiles que dans les États où le marché du travail est plus

formel. L'effet de cette "expérimentation forcée" fut cependant de courte durée. Au niveau individuel, les personnes les plus exposées au choc étaient plus susceptibles d'adopter les paiements mobiles et cet effet persiste au cours des deux années suivantes. Étonnamment, les effets marginaux du choc pour les femmes fortement exposées étaient presque deux fois plus élevés que pour les hommes fortement exposés. Nos résultats contribuent à comprendre le comportement des utilisateurs et la persistance des habitudes, avec des implications importantes pour la conception de politiques visant à accroître l'adoption des technologies de paiement numérique. Dans le dernier chapitre de cette thèse, j'étudie (avec un co-auteur) l'adoption par les entreprises d'une nouvelle technologie dans leur menu de produits. En particulier, nous essayons de comprendre la valeur d'une technologie facilement imitable dans un contexte de marché émergent. Nous étudions l'introduction des portables double SIM sur le marché indien et quantifions la valeur de cette technologie pour les consommateurs. Nous quantifions également l'impact sur les résultats du marché de l'imitation rapide de cette technologie par des entreprises concurrentes. Nous constatons que l'introduction de cette technologie a entraîné une augmentation du surplus du consommateur de 3,1% à 8,9%, et une expansion de la taille totale du marché de 1,8% à 3,3%. Nous constatons également que si l'imitation réduit considérablement le profit de l'innovateur, elle rend également la technologie beaucoup plus abordable pour les consommateurs. En l'absence d'imitation, les prix à la consommation auraient été supérieurs de 22%. Enfin, nous fournissons une borne inférieure du coût pour l'innovateur de la protection de la propriété intellectuelle dans un marché émergent. Nous constatons que cette borne inférieure atteint 12% des bénéfices observés de l'innovateur ($29,5 millions).

Contents

Chapter 1

Explaining Smartphone Adoption in India

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[1] I thank the Indian Council for Research on International Economic Relations for making the required data available to me.

1.1 Introduction

In the last decade, 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 etc.). As the developing world makes the transition to internet-based digitisation, insufficient smartphone adoption is one key challenge facing policy makers. Countries in East Africa and South Asia lag behind the developed world in smartphone penetration, as well as behind the world average (GSMA, 2017).[2] Moreover, the existing adoption of smartphones in developing countries is usually concentrated among the richest people.

Fostering smartphone adoption in developing countries 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. 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 digitisation. 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 of the problem of insufficient adoption has been brought to light in the ongoing Covid-19 pandemic.[3] A large proportion of the population in developing countries has had no access to online schooling, public and citizen-led health initiatives due to limited smartphone penetration.[4,5] Thus, to realize all the potential benefits of digital technologies in developing countries, the pace of smartphone adoption needs to be faster.

In this paper, I consider the case of India to draw lessons for smartphone adoption in the developing world. 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 in India? ii) Which policies can be effective to encourage adoption of smartphones? India is now the second largest market in the world for mobile telephony as well as internet services.[6] The smartphone market in India has seen important changes over the last decade: decreasing prices, increasing quality of products, entry of Chinese firms, as well as a sub-

[2] Accelerating Affordable Smartphone Ownership, GSMA, 2017; accessed on 26.08.2021
[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.
[6] List of countries by number of Internet users

stantial 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.

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

To overcome these challenges, 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 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.

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 development question, 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, this 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 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. This is especially relevant for studying digitisation since policy is often outpaced by rapid technological change.

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 do not allow for 3G and 4G network coverage 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) 8% if market competition is fixed at the baseline level; iv) 6% if 3G and 4G network coverage expansion did not take place; 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 calculating 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. 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

[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.

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 assumptions and including observed consumer heterogeneity.

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.

1.2 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

[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

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.

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.

1.3 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.

1.3.1 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 1.1). The market can be segmented into two groups - smartphones and feature phones. Feature phones are basic handsets that run

[11] World Bank Open Data last accessed on 14.10.2021
[12] World Inequality Database last accessed on 16.10.2020
[13] I thank David Salant and Daniel Ershov for making this data available to me

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 1.9 and table 1.10). 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]

Table 1.1: 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

Sales

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.[16] 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, 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

[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.

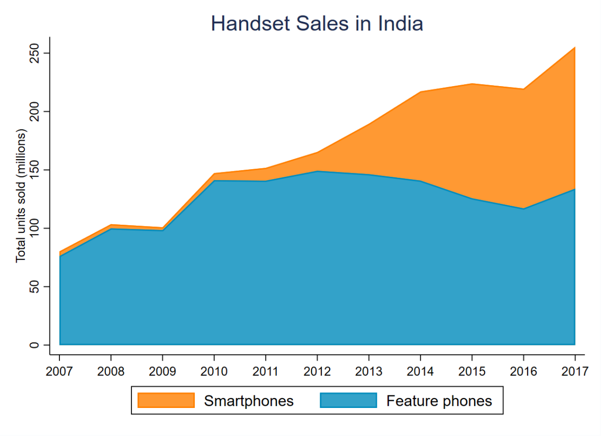

Figure 1.1: Volume of sales of handsets

accounted for over 50% of the market (see Figure 1.1). 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]

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

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 1.2 and Table 1.11).

[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.

[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

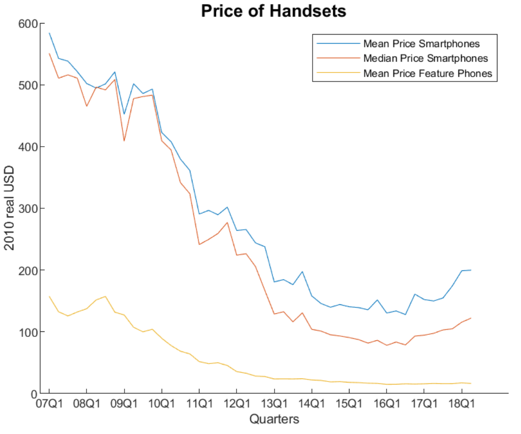

Figure 1.2: Price of Handsets (2010 real USD)

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.

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 1.3). 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

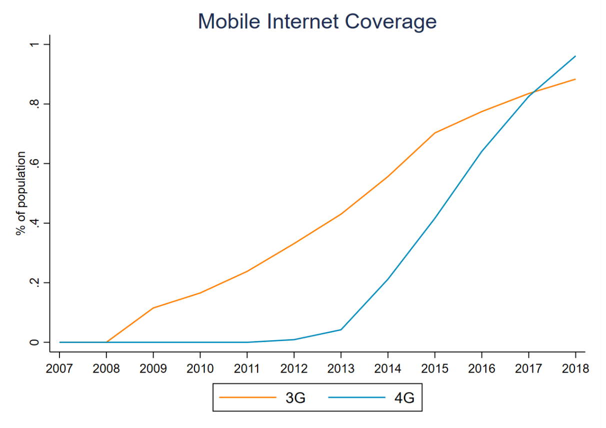

Figure 1.3: Network coverage over time

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.

Income and Affordability

The income of individuals has been increasing over the time period of consideration but so has the inequality (see Figure 1.4). 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 1.5, 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.

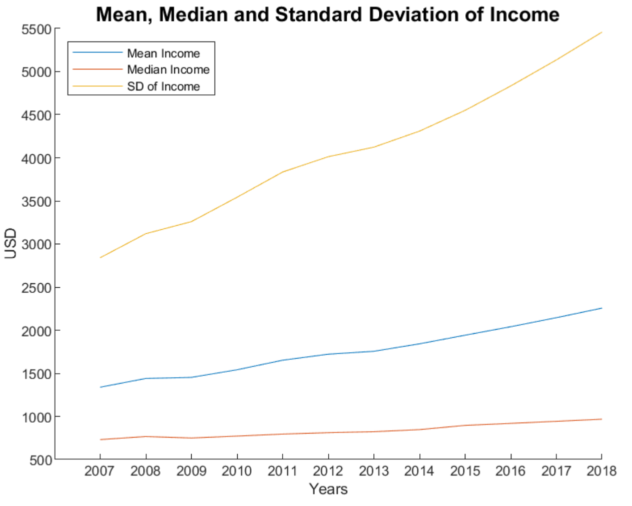

Figure 1.4: Income and Income Inequality in India

1.4 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.

1.4.1 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}:

[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).

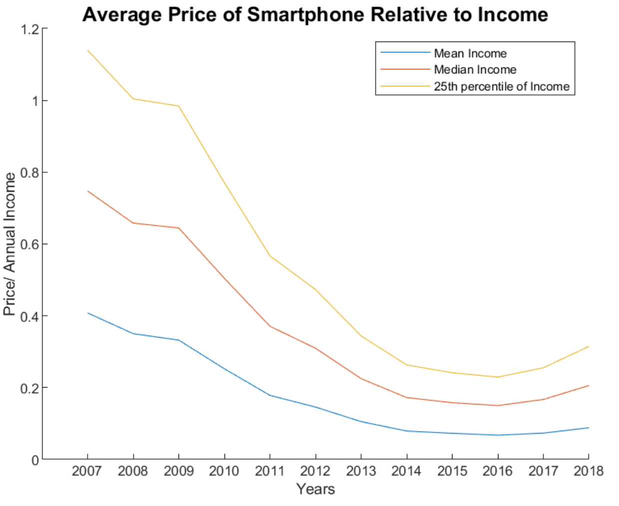

Figure 1.5: Affordability of smartphones

$$u_{ijt} = \beta x_{jt} + \alpha_i p_{jt} + \gamma c_{jt} + \xi_{jt} + \lambda_f + \lambda_t + \bar{\epsilon}_{ijt}, \tag{1.1}$$

where,

$$\alpha_i = \frac{\sigma}{Y_{it}}, \tag{1.2}$$

and

$$\bar{\epsilon}_{ijt} = \zeta_{igt} + (1-\rho)\epsilon_{ijt}. \tag{1.3}$$

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.

[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.

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 $(1-\rho)\epsilon_{ijt}$:

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + (1-\rho)\epsilon_{ijt} + \zeta_{igt}, \tag{1.4}$$

where

$$\delta_{jt} = \beta x_{jt} + \gamma c_{jt} + \lambda_f + \lambda_t + \xi_{jt}, \tag{1.5}$$

and

$$\mu_{ijt} = \frac{\sigma}{Y_{it}} p_{jt}. \tag{1.6}$$

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:

$$\pi_{ijt} = \frac{\exp(\frac{\delta_{jt}+\mu_{ijt}}{1-\rho})}{\exp(\frac{I_{igt}}{1-\rho})} \times \frac{\exp(I_{igt})}{\exp(I_{it})} \tag{1.7}$$

where

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

[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.

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:

$$s_{jt}(x_t, p_t, \xi_t; \theta) = \int_{\tilde{Y}_t} \pi_{ijt} dP_Y(Y_t) \tag{1.8}$$

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

1.4.2 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:

$$\mathbf{c} = \mathbf{p}^* - \Delta(\mathbf{p}^*)^{-1} s(\mathbf{p}^*) \tag{1.9}$$

1.5 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 (3.10). 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.

1.5.1 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 (3.7)). In the next step, for a given set of initial values of the non linear parameters, I find a unique δ_{jt} (equation (3.5)) 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 (3.5)). 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

1.5.2 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.

1.5.3 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.

1.5.4 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.

[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 %.

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:

$$\min_{\theta} \xi_j(\theta)' h(z_j) \Omega h(z_j) \xi_j(\theta) \tag{1.10}$$

1.5.5 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 (3.6), 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 (3.5), the idiosyncratic error term $(1-\rho)\epsilon_{ijt}$ is assumed to follow an extreme value type I distribution.

1.5.6 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 3.5.3 and using the variation in the income distribution of consumers. Formally, the identification assumption can be written as:

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

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

1.5.7 Marginal Costs

Once the demand is estimated, I use the firm's profit maximization condition (equation (3.11)) to obtain the marginal cost of each product. In equation (3.11), 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 1.7).

1.6 Results

The main results of the demand estimation are provided in Table 1.2. 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 1.2 and the full results of the demand estimation can be found in the appendix (Table 3.4).

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 ($\frac{\sigma}{\bar{Y}_t}$) 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.

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 1.2, 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.

Table 1.2: 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

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 3.4). 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 1.11 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 (3.11) 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

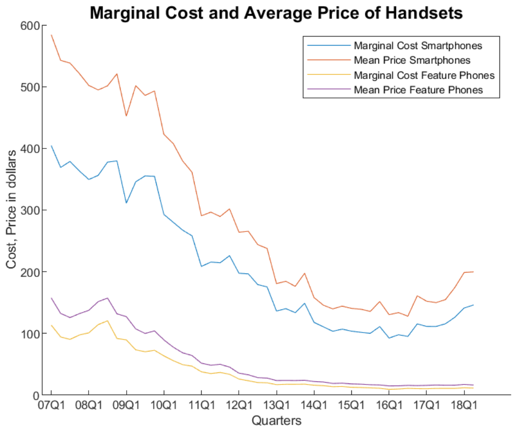

Figure 1.6: Marginal Cost and Average Price in 2010 real USD

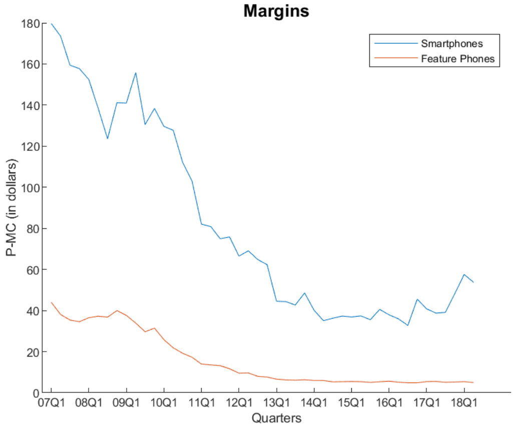

Figure 1.7: Margins over time in 2010 real USD

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 1.6). 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 1.7).

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).

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

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.

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 1.3). 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 1.3: 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

1.7 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.

1.7.1 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.

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 1.4. 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 1.8.

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 1.2). 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.

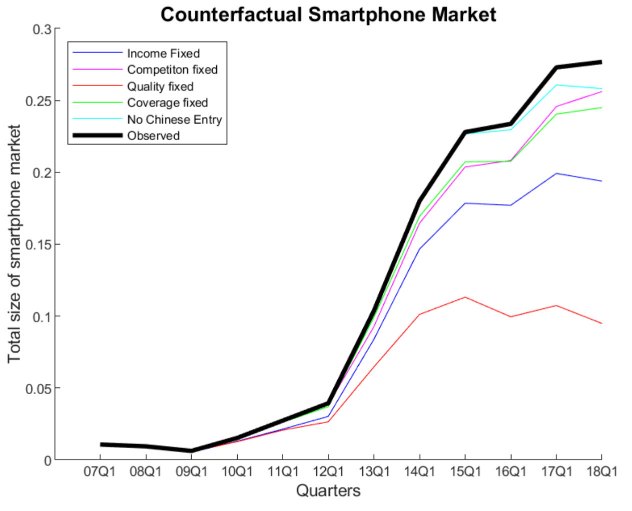

Figure 1.8: Smartphone market under counterfactual assumptions

In this counterfactual policy simulation, 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 re-simulate market outcomes. I find that in the absence of 3G and 4G network, the smartphone market would have contracted by 6% on average. This contraction is as large as 12% 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 1.4% on average, implying that smartphone users would have substituted to feature phones in the absence of network expansion of 3G and 4G.

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 1.1). 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 are still allowed to upgrade or diversify their product offerings in the counterfactual.[25]

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.

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 1.9, 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.

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 1.14). 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.

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

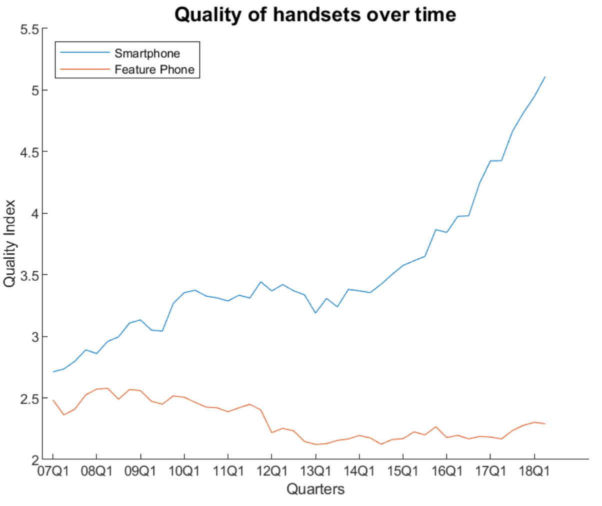

Figure 1.9: Decomposition of smartphone adoption

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.

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.[26] 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

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

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 1.8).

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.[27]

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 1.8, 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%.

[27] 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.

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.

1.7.2 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.

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 1.10), 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.

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 percentage points (from 12% to 3%). This tax reduction would lead to a contraction in the size of the feature phone market by 5%.

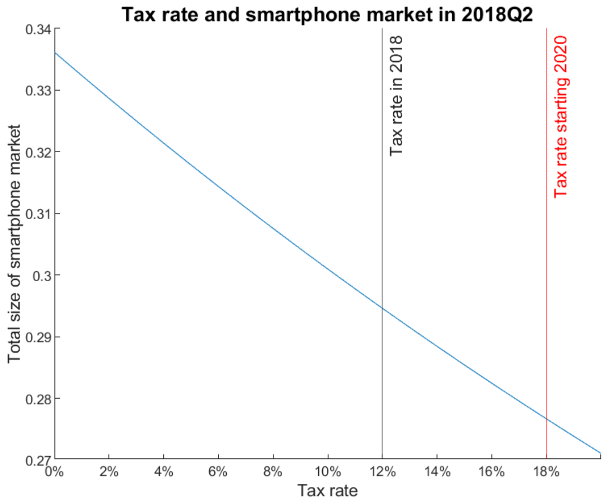

Figure 1.10: GST rate and smartphone market

Table 1.4: Pass through of taxes and subsidies in 2018 Q2

Policy	**△ Govt. Revenue***	**△ Consumer Price**	**△ 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.

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.[28] I find that the average pass through for budget smartphones is close to 1: consumers capture 98% of the tax reduction (Table 1.4).

[28] 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.

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.[29]

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 this.[30] 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 1.4). 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 1.5). The result on pass-through is consistent with industry expectations of the effect of the policy on consumer prices.[31] Industry experts claim that the tax hike and supply shocks will especially hurt the affordability of budget smartphones that cost less than \$ 200.[32]

1.7.3 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 sub-

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

[30] 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.

[31] Ibid.

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

Table 1.5: 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

sidy 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.

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 1.4). 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).

Table 1.6: 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

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 1.6).

1.7.4 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.[33] This infrastructure is

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

already in use for the rural employment guarantee subsidy scheme (MNREGA) in India.

Table 1.7: 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.

1.8 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 and changes in the income distribution over time. This is followed by increasing market competition, expansion of 3G and 4G network coverage and the entry of 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.

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Table 1.8: 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 1.9: 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

1.9 Appendix

1.9.1 Background of Industry

1.9.2 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 1.10: 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 1.11: 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

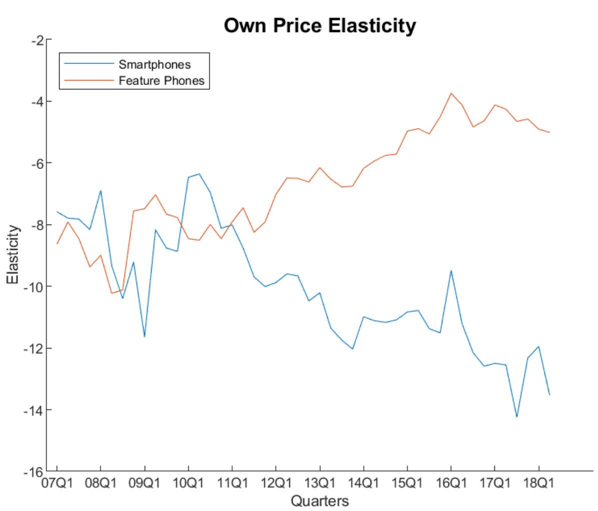

Figure 1.11: Price Elasticity of Handsets (2010 real USD)

Table 1.12: 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
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.9.3 Taxes

Table 1.15: 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.

1.9.4 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 t

Table 1.13: 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 1.14: 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
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

estimate the demand model with unobserved heterogeneity that follows a standard normal distribution. In this case, equation (3.2) is modified as follows:

$$\alpha_i = \frac{\sigma}{Y_{it}} + \eta \nu_{it}, \tag{1.11}$$

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

Table 1.16: 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 1.16). 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.

Chapter 2

Short Term Cost of Cash and Mobile Financial Services: Evidence from a natural experiment in India

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2.1 Introduction

Digital financial services (DFS), that include mobile payment, banking and finance, are increasingly valuable to further financial inclusion and simplify the delivery of public services in developing countries. A large proportion of the unbanked population in these countries has access to mobile phones (Donovan, 2012), and mobile based solutions are often quicker and cheaper alternatives than expanding traditional banking infrastructure. Additionally, governments in developing countries are interested in the substitution from cash to mobile financial services not just for the motive of financial inclusion but also to address tax evasion (Immordino and Russo, 2018). In this paper, we study a unique natural experiment carried out in India in 2016 that increased the short term costs of holding and transacting in cash. In particular, we examine if this short term inconvenience in using cash led to a sustained uptake of mobile financial services among individuals. We do this in two separate ways. First, we take an aggregate view and analyze the impact of this currency shock on the inclination to use DFS platforms at the state level using monthly data from Google Trends between 2014 and 2020. Second, we use a novel annual household survey to dig deeper and evaluate the impact of this shock on the individual probability of adopting mobile based DFS between 2014 and 2018.

On the evening of November 8 2016, without prior notice, the Prime Minister of India announced that the two highest denomination currency notes (Rs. 1000 and Rs. 500) were to be demonetized with immediate effect.[4] New currency was to be issued in the denominations of Rs 2000 and Rs 500. People had until 31 December 2016 to either exchange their old currency for the new notes, or deposit the old currency in their bank accounts. The total value of currency that could be exchanged or deposited had strict limits. As a result, 86.9% of the value and 75% of the volume of the currency in circulation was wiped out. For a largely informal economy with cash used for over 95% of transactions, this shock, henceforth called demonetization, translated into a decrease in the year on year growth rate in 2016Q4 by 2 percentage points(Chodorow-Reich et al. 2019). There was also a corresponding decline in employment by 2 percentage points (Chodorow-Reich et al. 2019). However, output declined relatively less than the decline in currency circulation which suggests that at least some individuals substituted from cash to electronic forms of payment.

[4]Approximately equal to \$16 and \$8 respectively.

The focus of this paper is this substitution from cash to electronic payment platforms and DFS resulting from the short term currency contraction caused by demonetization. Specifically, we are interested in the following three questions: 1) Did demonetisation lead to an aggregate change in the inclination to use platforms (measured by the total hits of specific keywords on Google search) across different Indian states ? 2) Did demonetisation have an impact on the individual probability of adopting mobile based DFS and did this impact persist over time ? 3) Did men and women respond differently to the shock ?

Note that we do not evaluate whether or not the demonetization policy achieved its objectives, nor do we compute welfare effects of this shock. Demonetization affected all sectors of the economy and the computation of overall welfare effects is outside the scope of this paper. Instead, the focus of the paper is on understanding the impact of this "forced experimentation", that temporarily increased the cost of cash transactions, on the probability of using mobile transactions.

We answer our research questions using a difference in differences framework. The main empirical challenge in this exercise is that demonetization was a shock that affected all the individuals in the economy at the same time. To address this, following recent literature (Chodorow-Reich et al. 2019), we construct measures of exposure to the shock that differ across states and individuals. For the aggregate analysis focused on the inclination to use digital platforms (measured by the total number of web hits on relevant keywords), we classify states by the degree of formality of their labour force. To measure formality, we use the state-wise proportion of workers receiving paid leaves- the fewer the proportion of workers receiving paid leaves, the more informal the state is said to be. We use a report published in 2013 by the Ministry of Labour and Employment, Government of India to obtain the data on workers.This implies that we assume that states have the same ranking of informality in our period of analysis (2014-18) that they did in 2013. We hypothesize that the more informal a state, the more it is exposed to demonetization, since it is likely that informal states are more cash dependent. We then compare more exposed states to less exposed states before and after the shock.

To understand the impact of the shock at the individual level, and answer questions 2) and 3), we use detailed survey data published by Financial Inclusion Insights (FII). In the same spirit as the previous exercise, we build a measure of individual exposure to demonetisation based on the observed distance of individuals from their nearest bank branch. In the aftermath of the shock, the only way old currency notes could be deposited or exchanged was at bank branches. Hence, distance from the bank branch is likely to be a good measure of exposure to the shock. Our hypothesis in this case is that the further away an individual lives from a bank branch, the more exposed they are to demonetisation and ceterus paribus, the more likely they are to adopt DFS and payment platforms. We thus compare the difference in adoption of mobile based payments and DFS of individuals living further from bank branches to those living closer before and after the shock.

From the aggregate analysis at the state level, we find that in the quarter of demonetization, the more informal the state, the greater the inclination to use digital platforms. However, this effect does not persist over time. For the individual level analysis, we find that conditional on individual demographics, people that were more exposed to the demonetisation shock were more likely to use their mobile phones for financial transactions in the year of the shock. Unlike at the state level, we find that this effect also persisted in 2017 and 2018. Note, however, that the magnitude of these effects are relatively small. On average, for individuals with high-exposure to demonetisation, the probability of using mobile based transactions increased by 2.9% in 2016, 1.3% in 2017 and 2.6% in 2018 (relative to low-exposure individuals). We also conduct this analysis separately for men and women. We find that the effects of demonetization on the probability of using mobile transactions is positive for both men and women, though the estimates are less precise for women. Notably, conditional on individual characteristics, the marginal effects for women in the high-exposure group are larger than men in the high-exposure group. It would be useful to understand the mechanisms driving this difference, however, our current data limitations do not allow us to do so.

There is a small but growing literature analysing the demonetization episode. Our paper is closest in spirit to Chodorow-Reich et al (2019). They build a theoretical model for cash holdings, and test the predictions of the model using a cross section of data at the district level. Contrary to this, we use cross-sectional data over 5 years at the individual level to study the impact of this shock on individual outcomes. We also differ in the main identifying assumption: we do not rely on assumptions about the behaviour of the central bank to construct a measure of exposure to the shock, instead using the distance from the nearest bank branch (which cannot change in response to the shock in the short run). Crouzet et al (2020) look at coordination failures in technology adoption on the merchant side of digital payments and use the demonetisation shock to study if these failures were overcome by a short-term cash shortage. Kisat and Phan (2020) investigate whether the demonetization shock propogates through the input-output networks. Agarwal et al (2021) study the relationship between consumer spending and digital payments, using demonetization as a source of exogenous variation.

We proceed as follows: section 2 discusses the institutional details of demonetization, section 3 describes the details of the data, section 4 provides the empirical model and results for the aggregate analysis, section 5 provides the empirical model and results for the individual level analysis, and section 6 concludes.

2.2 Demonetisation

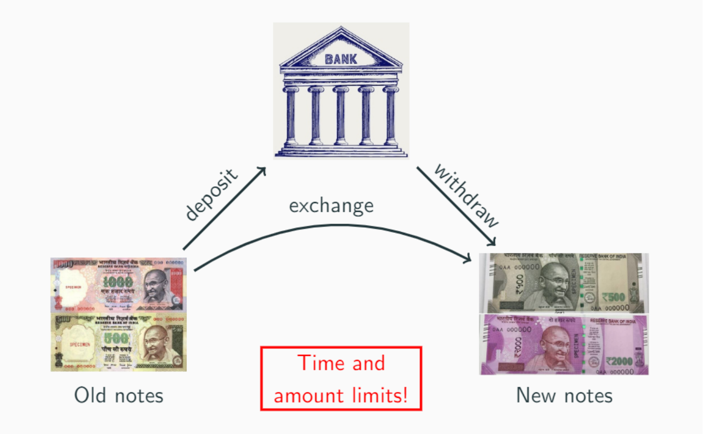
In this paper, demonetisation refers to the unexpected macroeconomic liquidity shock that happened in India in November 2016. Even though it wasn't the first time currency was demonetized in India or elsewhere, it was a unique episode as it happened in an otherwise economically stable environment (Lahiri, 2020). On the evening of November 8 2016, without prior notice, the Prime Minister of India announced that the two highest denomination currency notes (Rs. 1000 and Rs. 500) were to be demonetized with immediate effect.[5] This amounted to 86% of the value of the currency in circulation being wiped out with no prior notice to households, businesses or banks. The volume of cash in circulation fell by 75% and there was a corresponding increase in bank deposits (Figure 2). Demonetized currency could be deposited in banks or exchanged, with a daily limit for new denominations of 500 and 2000 rupees until December 31st 2016 (Figure 1).[6] Households with bank accounts could access funds using cheques, transfers, debit and credit card and the main difficulty was in using cash for transactions ((Chodorow-Reich et al. 2019).

The motivation for the policy was threefold. First, it aimed to target corruption and tax evasion through undeclared income held in cash. It also attempted to address the issue of counterfeit currency circulating in the economy. Lastly, as a more long-term objective, it hoped to steer the heavily cash dependent Indian economy towards a more formalized system of digital payments. The remonetization of the economy was not a smooth process-caught off-guard by the abruptness of the policy, both the Reserve Bank of India and com-

[5] Using 2016 USD-INR exchange rates, the value of the demonetized notes corresponded to $ 8 and $ 16.

[6] A daily limit of Rs. 4000 was imposed initially, which was then increased Rs 4500 and subsequently reduced to Rs 2000. Weekly limits on the amount that could be exchanged were also put in place. Additionally, for bank deposits of demonetized currency, taxpayer identification number had to be provided for deposits above 50,000 rupees.

Figure 2.1: Remonetization process



mercial banks struggled to stock automatic teller machines (ATMs) with cash. Moreover, there was a relative excess of 2000-rupee bills, which were less useful for low value daily transactions (Lahiri, 2020). Thus, in the days following demonetization, the cost of cash relative to other methods of payments increased substantially. This translated into a significant substitution towards digital platforms and electronic payments. As observed in figure 3, there was a sizeable jump in the volume of transactions taking place by debit cards and payment platforms. In the two months immediately following demonetization, the volume of debit card usage grew by an average of 72% per month, and the volume of platform transactions grew by nearly 47 %. At the same time, on the side of merchants there was a corresponding increase in the number of point of service terminals for electronic payments as well.

Figure 2.2: Demonetisation and cash in circulation

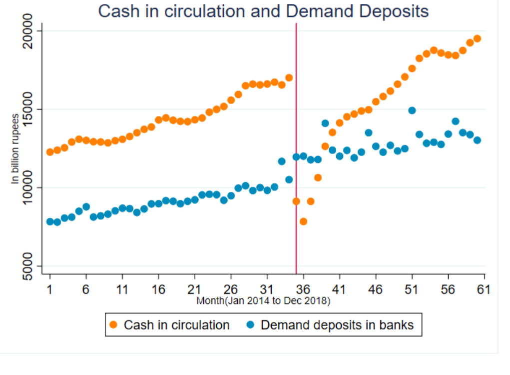
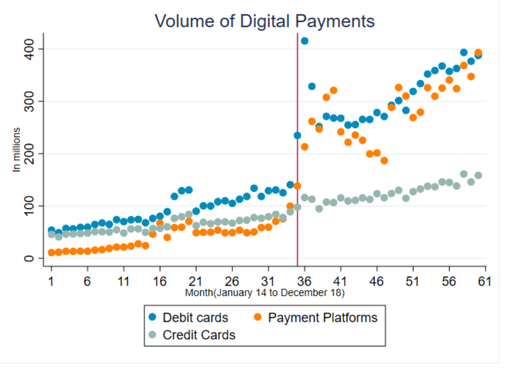


Figure 2.3: Demonetisation and electronic payments



Two noteworthy caveats emerge from figures 2 and 3. First, the demonetisation shock was short term - from figure 2.2, we can see that cash in circulation is restored to its pre-demonetisation levels in six months after the shock. In fact, by the end of the period of analysis, the cash in circulation was higher than pre-demonetisation levels. Additionally, although figure 2.2 points to an increase in volume of transactions, it is unclear if this increase happened because more individuals started transacting digitally or if existing users were transacting more.

2.3 Data

2.3.1 Google Trends

In our final data set obtained from Google Trends, we observe state wise monthly hits of keywords linked to 126 unique electronic payments platforms. The period of analysis is January 2014 to November 2020. Although we observe a total of 36 states and union territories, to be consistent with the geographical scope of the individual level analysis, we restrict our sample to the 21 states that are also present in the household survey data. We add the total platform hits by state and month, to end up with 2241 unique combinations of total state hits-state-month.

2.3.2 Data on formality of states

Our aggregate analysis rests on formality of the workforce as a measure of exposure to the demonetisation shock. We obtain the data on this from the report on Employment in Informal Sector and Conditions of Informal Employment published by the Ministry of Labour

Figure 2.4: Combined monthly hits of all platforms

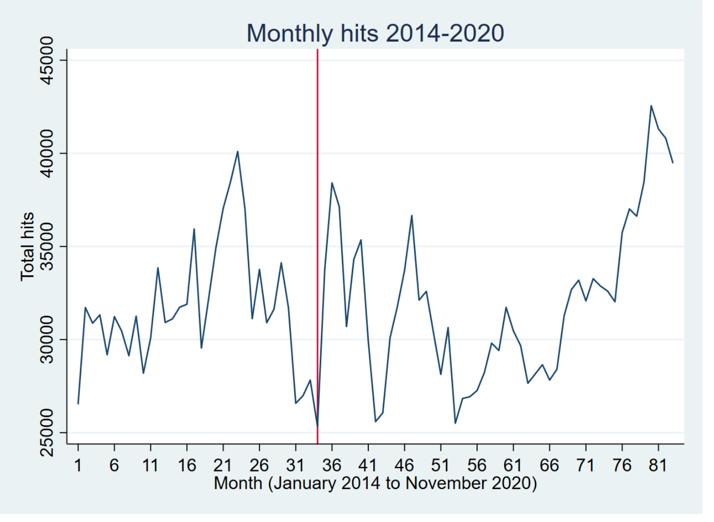


Figure 2.5: Digitisation in India

and Employment, Government of India in 2013. The measure of formality is defined as the number of workers per thousand that receive paid leaves in a given state. This means that this measure varies between 0 and 1000. A state which has a higher proportion of workers getting paid leave is said to be more formal than a state that has a lower proportion of workers getting paid leave. This enables us to have a continuous measure of formality of states. Since we use data from 2013 (before the start of our period of analysis) and no subsequent data is available for this indicator, we assume that the measure of formality of states remains constant over time.

Table 2.1: Number of workers/1000 receiving paid leave across states in 2013-14

PL workers/1000	No. of states
< 100	1
Between 100 & 200	4
Between 200 & 300	8
Between 300 & 400	3
Between 400 & 500	3
Between 500 & 600	3
< 700	2

2.3.3 Household Survey Data

To provide preliminary evidence on the effects of demonetisation on the individual probability of platform usage, we use 5 rounds of new household survey data between 2014 and

2018. This nationally representative data is collected by Financial Inclusion Insights, and samples approximately 45 thousand households and individuals per year. However, the data doesn't follow the same individuals over time and contains repeated cross-sections instead. In addition to information on household financial behaviour, the survey also provides a rich set of demographic variables.

Table 2.2: Year wise sample size

Year	Households
2014	45,087
2015	45,036
2016	45,540
2017	47,132
2018	48, 027

Digitisation in India

Descriptive evidence from the survey shows a swiftly changing digital landscape in India. The proportion of individuals that own a mobile phone has increased consistently over the period 2014 to 2018 (Figure 2.6). Similarly, the proportion of adults browsing the internet, using mobile phones to make transactions, as well as using payment platforms has increased substantially between 2014 and 2018 (Figure 2.7).

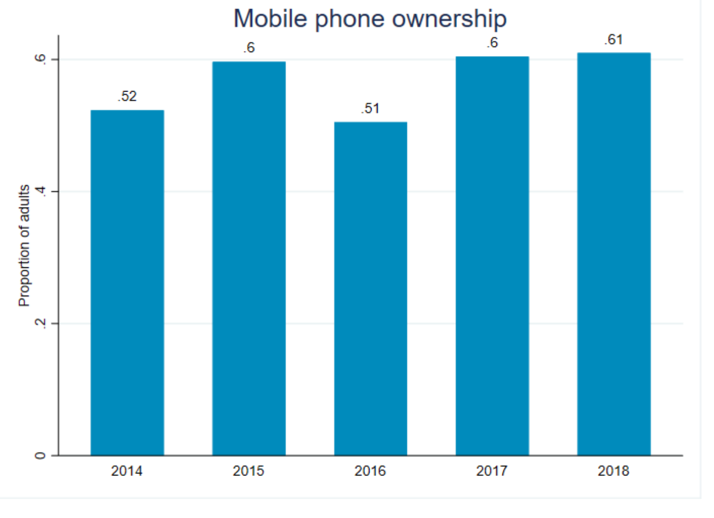


Figure 2.6: Mobile Ownership in India

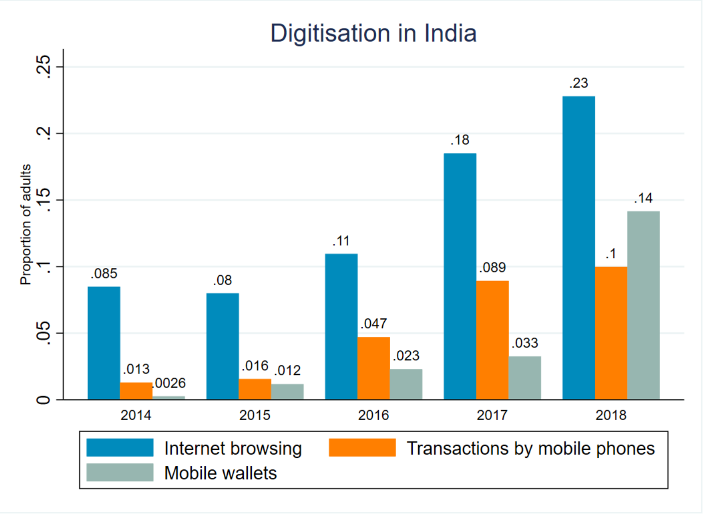


Figure 2.7: Digitisation in India

Bank Accounts and Savings

The proportion of the population having bank accounts increased from 55% in 2014 to 77% in 2018. However, the proportion of active users of bank accounts was significantly lower, though increasing, over the same period (Figure 2.8). At the same time, the proportion of people having any type of savings (formal, cash, gold, informal) declined substantially over this period (Figure 2.9). This was particularly true for the proportion of people having savings in cash: before demonetisation, in 2015, 71% of the population held some savings in cash, this decreased to 10% in 2017 (Figure 2.9). This was not compensated by an increase in savings in formal institutions, which declined as well during this period. By the end of the period, even though the proportion of people saving in formal institutions did not go back to the pre-shock levels, the proportion saving in cash did, reaching 60% in 2018.

2.4 State-level analysis

In this section, we provide an empirical model of the effect of demonetisation on the inclination to use platforms among different Indian states across different months. We proxy the inclination to use platforms in a particular state by the total hits of relevant keywords. We assign a level of formality to states based on the share of the labour force receiving paid leaves. The states that have a larger share of workers receiving paid leave are said to be more formal. In order to classify states based on their exposure to demonetisation, we argue that states with a more informal labour force are more exposed to the shock. Workers in the

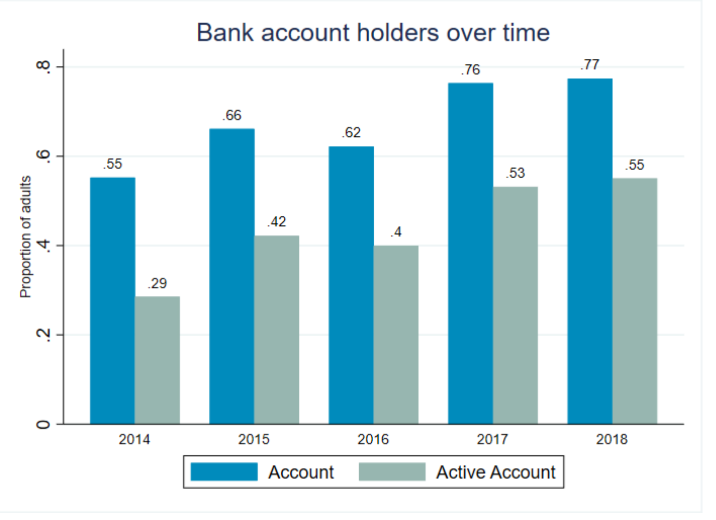


Figure 2.8: Bank Account Penetration

informal labour force are likely to be more cash dependent than formal workers, especially since the former are predominantly paid wages in cash.

We estimate the following model using OLS:

$$TH_{sm} = \beta Formality_s \times \mathbb{1}_{m>34} + \lambda_m + \lambda_q \times \lambda_s + \epsilon_{sm} \tag{2.1}$$

The indices m, q and s denote month, quarter and state respectively. The dependent variable is total hits of relevant keywords in state s, in month m. $Formality_s$ measures the share of workers in state s receiving paid leaves. The main variable of interest is $Formality_s \times \mathbb{1}_{m>34}$ which measures the exposure of the state to the demonetization shock. Demonetization took place in month number 34 of the period of analysis and $\mathbb{1}_{m>34}$ is an indicator for the months after the shock. The main parameter of interest β then measures the change in total hits after the shock for a 1 unit change in the formality variable. A negative estimate of β would mean a higher inclination to use platforms after the shock for informal states relative to formal states. We control for time varying heterogeneity by including month fixed effects λ_m and state specific time varying heterogeneity by including state-quarter fixed effects $\lambda_q \times \lambda_s$. The latter helps us control for changes in economic outcomes (for example, GDP) that vary across state and quarters.

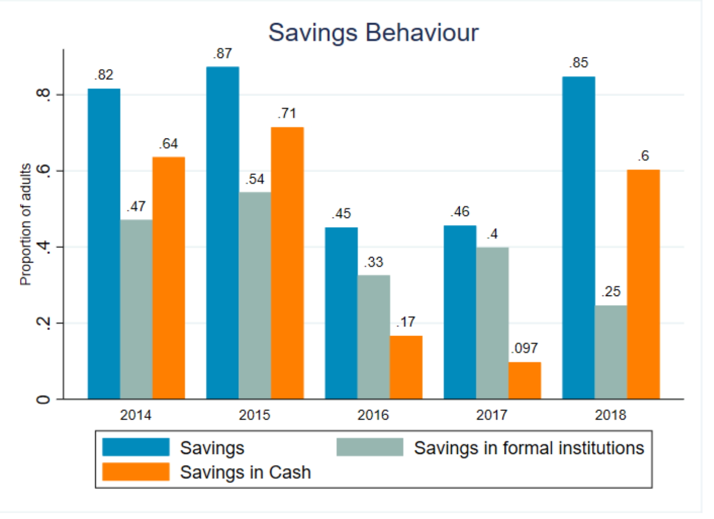


Figure 2.9: Proportion of Adults Saving

2.4.1 Persistence

In order to study the persistence in the effects of the shock on the inclination to use platforms, we decompose the econometric model in equation (1) as follows:

$$TH_{sm} = \sum_{i=0}^{i=9} \beta_i Formality_s \times \mathbb{1}_{q0_i} + \beta_{10} Formality_s \times \mathbb{1}_{m>61} \lambda_m + \lambda_q \times \lambda_s + \epsilon_{sm} \qquad (2.2)$$

The dependent variable and the fixed effects remain the same as in equation (1). However, instead of having one variable that captures the average effect on total hits for all the months after the shock place, we decompose this to allow for the effect to vary with quarters. Specifically, $q0_i$ refers to quarters after the shock with i going from 0 (the quarter of demonetisation: November to January 2016) to 9 (November to January 2019). $\mathbb{1}_{m>61}$ is an indicator for all the months after January 2019. The main parameters of interest then are β_i.

2.4.2 Results

As mentioned in the previous section, we use two specifications for our analysis. In the first (column 1 of table 2.3), we look at the average impact of the shock on the total state hits after the month of demonetisation. We find that the main parameter of interest on our exposure variable (the interaction of formality with the months after demonetisation) has a negative sign and is significantly estimated at 99% level of confidence. This means that after the shock, the more informal the state, the higher the total hits of the relevant keywords, and thus, the higher the inclination to use platforms. This result is consistent with economic intuition - in states which are more exposed to the shock, individuals have a greater incentive to switch to electronic payments and transactions through platforms.

Table 2.3: Aggregate Analysis Results

	(1) Total State Hits	(2) Total State Hits
Formality × After November 2016	-1.224**	
	(0.523)	
Formality × Nov'16-Jan'17		-1.224**
		(0.524)
Formality × Feb'17-Apr'17		-0.372
		(0.600)
Formality × May'17-Jul'17		1.447
		(0.742)
Formality × Aug'17-Oct'17		0.970
		(0.863)
Formality × Nov'17-Jan'18		0.408
		(1.144)
Formality × Feb'18-Apr'18		0.919
		(1.168)
Formality × May'18-Jul'18		1.786
		(1.235)
Formality × Aug'18-Oct'18		1.864
		(1.249)
Formality × Nov'18-Jan'19		2.094
		(1.291)
Formality × After Jan'19		2.642*
		(1.304)
Constant	720.3***	720.3***
	(88.17)	(88.42)
Month FE	yes	yes
State × Quarter FE	yes	yes
N	2241	2241
adj. R^2	0.950	0.951

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

However, as we see in column (2) of table 2.3, the relative effect of demonetisation on informal states is very short lived. The parameter of interest is negative and significant only for the month of demonetisation and the two months thereafter (November 2016 to January 2017). We find no significant relative effects of the shock after this. This finding is consistent with what the literature has found for adoption of electronic payments (by merchants) in India as a result of the shock (Crouzet et al, 2019). With a large extent of the remonetisation process occurring in the six months after demonetization, these authors conclude that the effects of this shock on merchants was short term.

2.5 Individual level analysis

In this section, we turn to individual level effects of demonetization and employ household survey data. The main dependent variable that we consider is the individual's probability of using their mobile phone to carry out a financial transaction. As mentioned earlier, since demonetization was a shock that affected all individuals in the country, we create a measure of exposure to the shock that classifies individuals into low-exposure and high-exposure groups.

2.5.1 Individual level exposure to demonetization

We use the distance of the individual from their nearest bank branch as a measure of exposure to the shock. In the aftermath of demonetisation, the only way for individuals to get rid of old bills was to either deposit it in their bank accounts or exchange it for new notes at the bank branch. Given individual level demographics, the further away an individual lives from the bank, the more exposed they were likely to be to the shock and the greater the incentive they have to switch to electronic payments.

In the survey, we do not observe individual's distance from the nearest bank branch as a continuous variable. We observe a categorical variable with 4 categories: i) bank branch located within 0.5km of residence; ii) bank branch located between 0.5 km and 1 km of residence; iii) bank branch between 1km and 5km of residence; iv) bank branch located at more than 5km of residence. In terms of demographic characteristics of individuals in these groups, we find that groups i) and ii) are more similar to each other than they are to groups iii) and iv) (Section 2.8.2). The same holds for groups iii) and iv). Hence, for the empirical analysis, we collapse these 4 categories into two: Near ($<$ 1km) and far ($>$ 1km).

2.5.2 Distance to bank and demographics

To check that the individual's nearest bank branch is not entirely explained by observed demographic and economic variables, we regress distance on age, gender, education level, income score, bank account ownership, urban-rural classification, mobile phone ownership, smartphone ownership, employment status and internet usage (results table in appendix).

Table 2.4: Number of individuals in each distance bin

Year	< 0.5km	0.5 to 1km	1 to 5km	> 5km	Missing
2014	4058	4492	6830	5354	24353
2015	10371	8320	12998	10532	2815
2016	6242	9107	15243	9650	5298
2017	9193	9060	15957	10238	2684
2018	5749	7738	19939	12802	1799
Total	39773	42335	77140	53502	63096

Table 2.5: Distance regressed on demographics

	Far
Age	-0.00435***
	(0.000486)
Gender	0.141***
	(0.0162)
Education	-0.0290**
	(0.00890)
Income score	0.000651
	(0.000333)
Bank Account	0.0260
	(0.0161)
Urban	-2.361***
	(0.0235)
Mobile	-0.0765***
	(0.0156)
Smartphone	0.0336
	(0.0269)
Employed	0.164***
	(0.0157)
Internet	-0.0546*
	(0.0267)
Pseudo R^2	**0.123**

We find that the distance to the nearest bank branch is not deterministic in individual level covariates of interest (Table 2.5).

2.5.3 Econometric specification

For an individual i in year t:

$$Y_{it} = \bar{\alpha} + \beta X_{it} + \gamma_1 Far_t + \gamma_{2t} \mathbb{1}_t + \gamma_{3t}(\mathbb{1}_t \times Far_t) + \epsilon_{it} \tag{2.3}$$

Y_{it} is a binary variable which records whether the individual uses their mobile phone for financial transactions.[7] X is a vector of demographic variables including gender, age, em-

[7] The precise question in the survey is: Have you ever used your mobile phone to carry out a financial transaction?

ployment status, whether the individual has a high school diploma, whether the individual lives in an urban or rural area and fixed effects for the state in which the individual resides in. Far_t is an indicator variable that denotes that individual lives in a high exposure area (nearest bank branch at more than 1 km away). $\mathbb{1}_t$ is an indicator variable for year fixed effects. The main variables of interest $\mathbb{1}_t \times Far_t$ capture the interaction between individuals in high exposure areas and the year.

2.5.4 Identification

In order to identify the effect of the shock on the individual probability of using mobile financial transactions, parallel trends need to hold. This would require that the high-exposure group and low-exposure groups have similar trends in adoption of mobile transactions before the shock. Moreover, we have to assume that the demonetization shock itself did not have an impact on our measure of exposure to the shock. This means that we assume that demonetization did not affect the geographical location of bank branches. It is reasonable to expect that banks did not take the costly (sometimes infeasible) decision of building more bank branches (or closing them) in response to the shock. The other factor that would affects the measure of exposure to the shock is if individuals migrated to be closer to bank branches as a result of demonetization. Given individual characteristics (which we explicitly control for) and the fact that demonetization was a temporary shock, we assume that this was not the case.

The main parameters of interest are γ_{3t}: capturing the relative probability of using mobile financial transactions for high exposure individuals in every year of the analysis. We expect the estimates for these parameters to be insignificant in the years before the shock. This would verify the parallel trend assumption. A positive sign of any of the γ_{3t} means that, controlling for other individual characteristics, high exposure individuals have a higher probability of using platforms/mobile phones for transactions.

2.5.5 Results

Table 2.6 provides the results of the logistic regression specified in section 4.3. We find that parallel trends hold: the coefficient on the interaction of the year before demonetization (2015) and the high-exposure group (Far) is not statistically significant. We find a positive and statistically significant effect of the shock on the probability of using mobile transactions for the high exposure group in the year of the shock (2016). This effect persists in 2017 and 2018, though the estimate for 2017 is less precise than the other years. The parameter estimates of the control variables have expected signs and are precisely estimated. A higher probability of using mobile phones for financial transactions is associated with younger individuals, men, individuals with high school diplomas, individuals living in urban areas and individuals that are employed.

Table 2.7 provides the average marginal effects of the shock on the probability of using mobile transactions for 2016, 2017 and 2018. Even though the effects are positive and statistically significant, their magnitude is relatively small. For instance, on average, for high-exposure individuals, the probability of using mobile phones for financial transactions increased by 2.9% in 2016, 1.3% in 2017 and 2.6% in 2018.

2.6 Heterogeneity Analysis: Gender

In this section, we examine the heterogeneous effects of this shock across men and women. The existence of a gender digital divide is now well-documented, especially in developing countries (Antoine and Tuffley, 2014). The individual level survey data for India also demonstrates this gender digital divide. Figure **??** clearly shows the gap in mobile phone ownership between men and women: in 2014, 68% of all men but only 34% of all women owned a mobile phone. In 2018, 76% of all men owned a mobile phone as opposed to 45% of all women. The gender gap in mobile phone ownership stayed roughly the same: in 2014 and in 2018, nearly 2 times as many men owned mobile phones as women. Figure **??** shows the gender gap in the proportion of people that access/browse the internet. In 2014, nearly 4 times as many men accessed the internet as women. Even in 2018, the gender gap persisted (though declined) and 2 times as many men accessed the internet as women. Figure 2.12 highlights the gender gap in the main variable of interest: the proportion of people using their mobile phones to make financial transactions. In 2014, 3 times as many men used mobile transactions as women. The gap between men and women reduced slightly by the end of the period and in 2018, twice as many men were using mobile transactions as women. In the rest of this section, we focus on the gender differences in the response (of the probability of using mobile transactions) to the demonetization shock. We estimate the regression specified in Equation 3 separately for the sample of men and women.

Table 2.8 summarizes the results of the estimation. Parallel trends hold for both the samples. For the sample of women, the demonetization shock has a positive impact on the

Table 2.6: Ever-use of mobile for financial transactions

	Mobile Transaction Indicator
Far	-0.539***
	(0.111)
Far × 2015	0.126
	(0.144)
Far × 2016	0.541***
	(0.120)
Far × 2017	0.267*
	(0.116)
Far × 2018	0.519***
	(0.115)
Age	-0.023***
	(0.0008)
Men	0.44***
	(0.025)
High School Diploma	1.220***
	(0.022)
Urban	0.675***
	(0.022)
Employed	0.731***
	(0.026)
Time FE	Yes
State FE	Yes
N	205825
pseudo R^2	0.200

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: Average Marginal Effects

Far × 2016	0.029***
	(0.007)
Far × 2017	0.013*
	(0.006)
Far × 2018	0.026**
	(0.006)

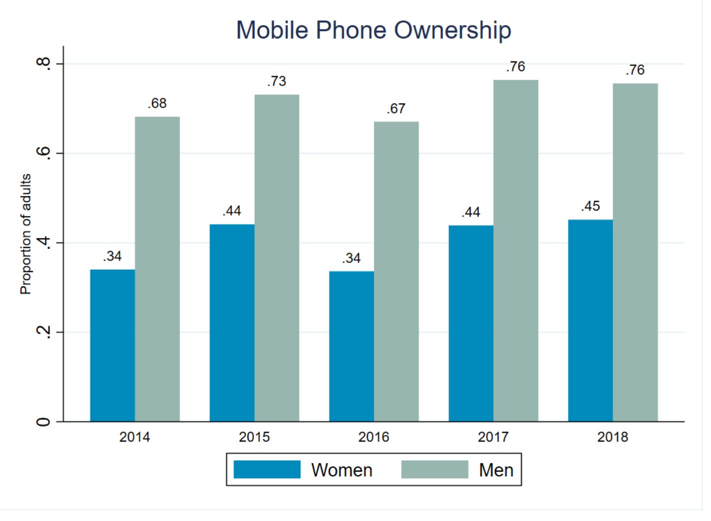


Figure 2.10: Mobile phone ownership by gender

probability of using mobile transactions for the high-exposure group relative to the low-exposure group. Estimates from the sample of men also show a positive effect of the shock on the dependent variable, however, the estimates are much less precise than for women. Strikingly, conditional on individual characteristics, the marginal effects for women in the high-exposure group are larger than men in the high-exposure group (Table 2.9). For example, in 2016, the probability of using mobile phones for transactions increased by nearly 5% for women, compared to only 2.4% for men.

2.7 Conclusion

In this paper, we focus on an un-announced and large scale natural experiment that took place in India in 2016 that increased the short-term costs of holding and transacting in cash. As mentioned previously, we do not evaluate the welfare effects of this policy or whether the policy met its intended objectives. Instead, we focus on how this temporary cash shortage affected the uptake of a specific form of DFS, mobile based payments/transactions. Using

Table 2.8: Ever-use of mobile for financial transactions

	Women	**Men**
	Mob. Transaction	Mob. Transaction
Far	-1.140***	-0.331***
	(0.233)	(0.128)
Far × 2015	0.557	0.0237
	(0.290)	(0.167)
Far × 2016	1.100***	0.340**
	(0.248)	(0.141)
Far × 2017	0.888***	0.0606
	(0.240)	(0.136)
Far × 2018	1.188***	0.273**
	(0.239)	(0.135)
Age	-0.0182***	-0.0246***
	(0.00139)	(0.00100)
High School Diploma	1.162***	1.246***
	(0.0390)	(0.0268)
Urban	0.736***	0.653***
	(0.0377)	(0.0280)
Employed	1.173***	0.402***
	(0.0359)	(0.0319)
Time FE	Yes	Yes
State FE	Yes	Yes
N	110566	95259
pseudo R^2	0.196	0.180

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

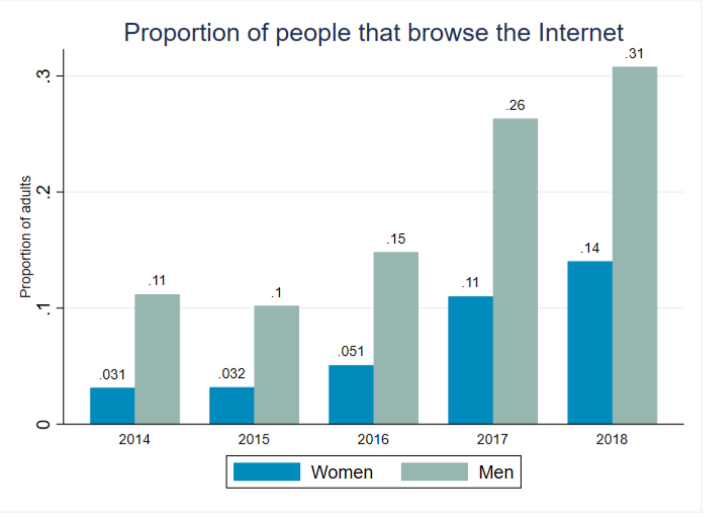


Figure 2.11: Internet browsing by gender

Table 2.9: Average Marginal Effects Across Gender

	Women	**Men**
Far × 2016	0.049***	0.024**
	(0.015)	(0.018)
Far × 2017	0.035***	0.003
	(0.012)	(0.009)
Far × 2018	0.049***	0.018**
	(0.013)	(0.009)

two new sources of data in a difference in differences framework, we conduct this analysis at the state level and also at the individual level. We build new measures of exposure to the shock, both at the state and the individual level. We find that in states where the labour market is less formal, and where workers were more likely to be affected by the demonetisation process, this shock led to a larger increase in the inclination to use mobile based payments than in states where the labour market is more formal. The effect of this "forced experimentation" was, however, short lived. At the individual level, people who were more exposed to the shock were more likely to use their mobile phones for transacting and we find that this effect persisted over the next two years. Strikingly, the marginal effects of the shock for high-exposure women was almost twice as high as for high-exposure men. However, the magnitude of all effects measured at the individual level was relatively small. Finally, ongoing work seeks to explore the mechanisms that explain the difference in marginal effects for men and women.

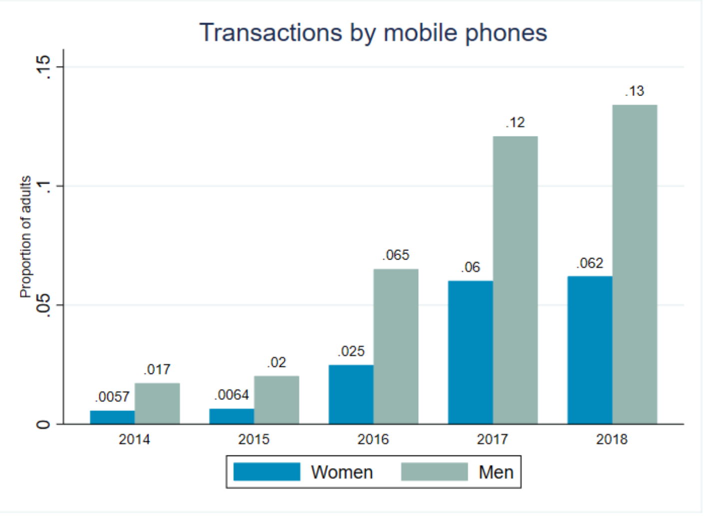


Figure 2.12: Mobile financial transactions by gender

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2.8 Appendix

2.8.1 Additional Descriptive Statistics

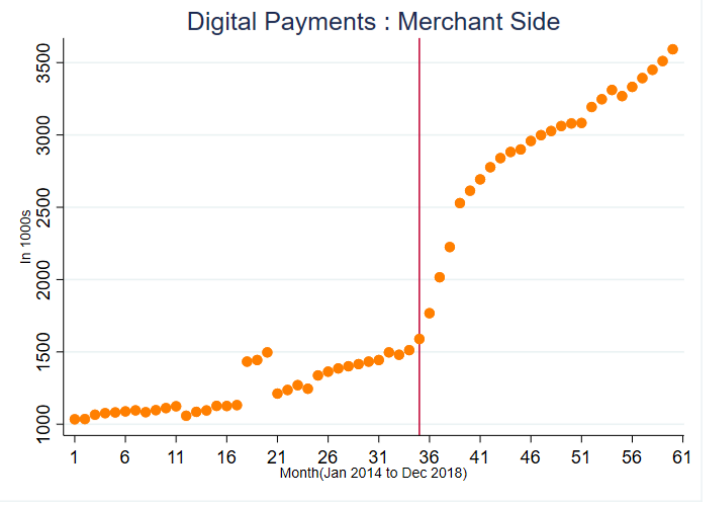

Figure 2.13: Number of Debit/Credit card terminals

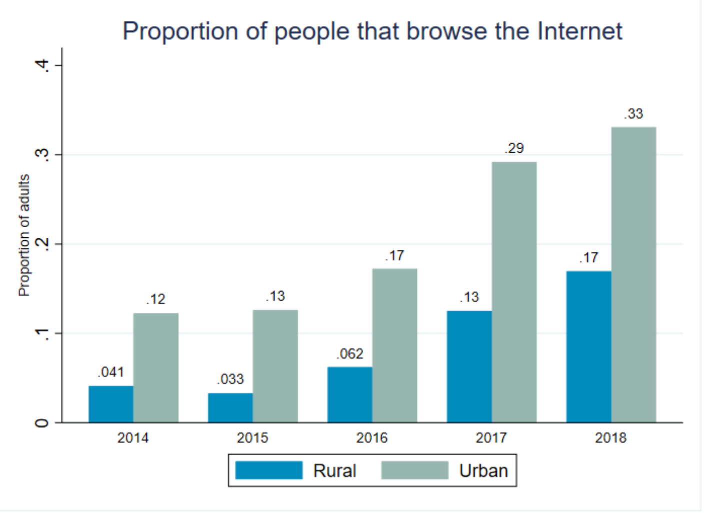

Figure 2.14: Internet browsing by region

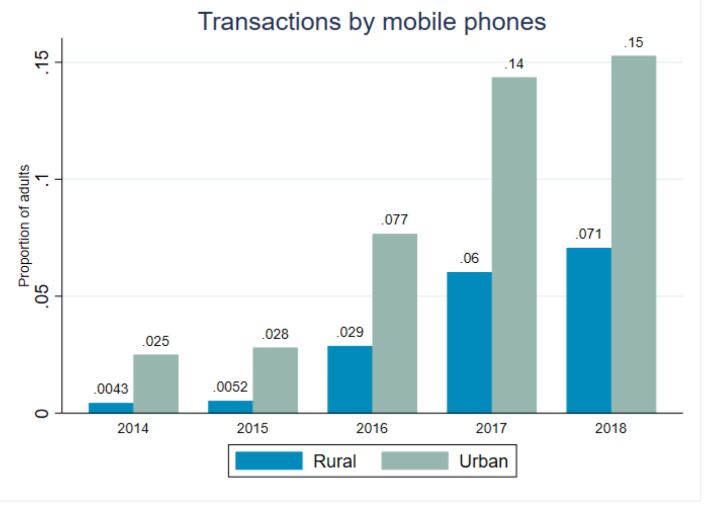

Figure 2.15: Mobile financial transactions by region

2.8.2 Distance Bin-Wise Demographics

The following graphs present key demographics classified into distance bins.

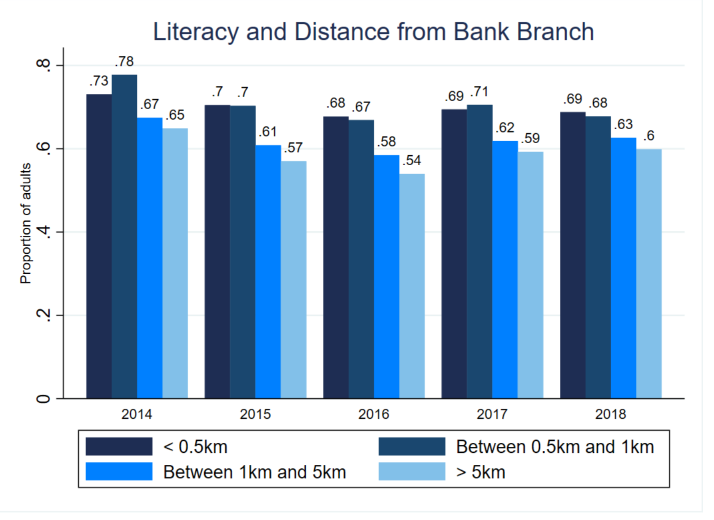

Figure 2.16: Literacy rates across distance bins

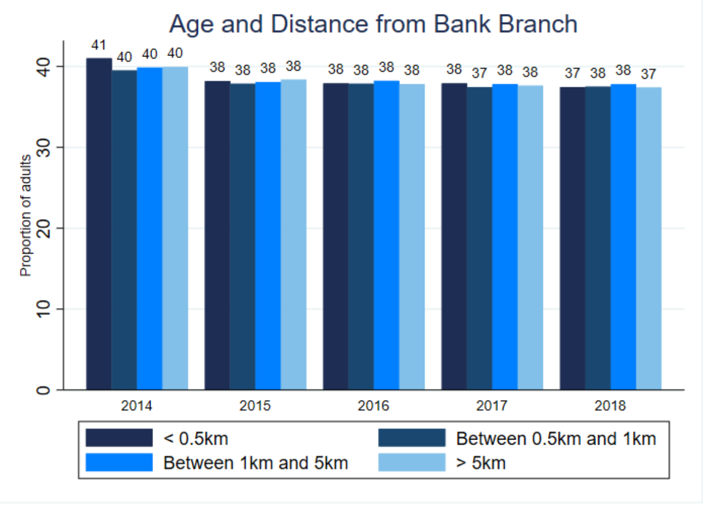

Figure 2.17: Mean age across distance bins

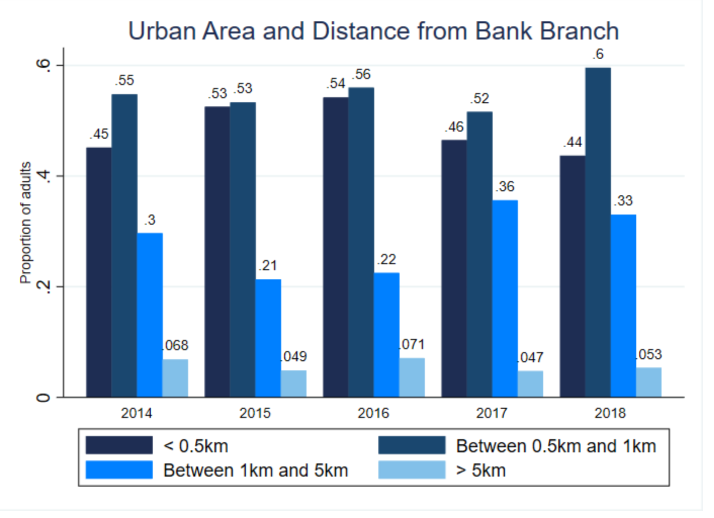

Figure 2.18: Proportion of people living in urban areas

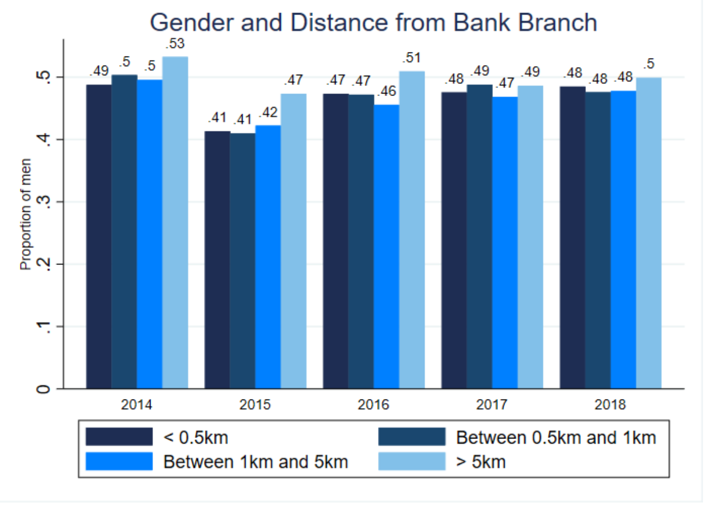

Figure 2.19: Proportion of men across distance bins

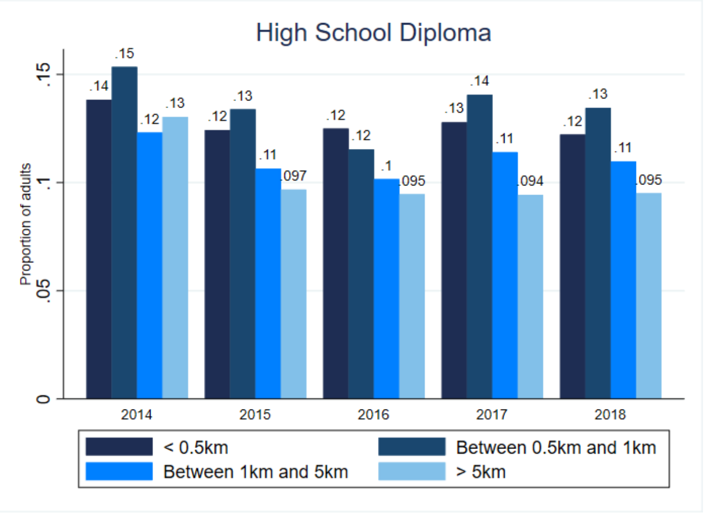

Figure 2.20: Proportion of high school diploma holders distance bins

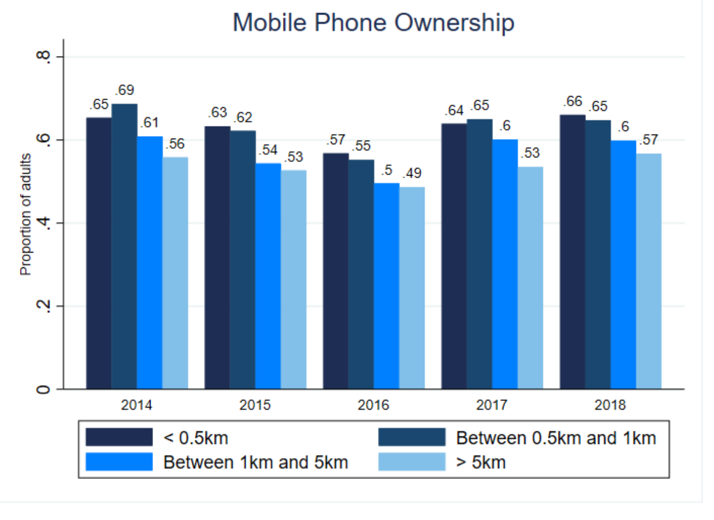

Figure 2.21: Mobile phone ownership across distance bins

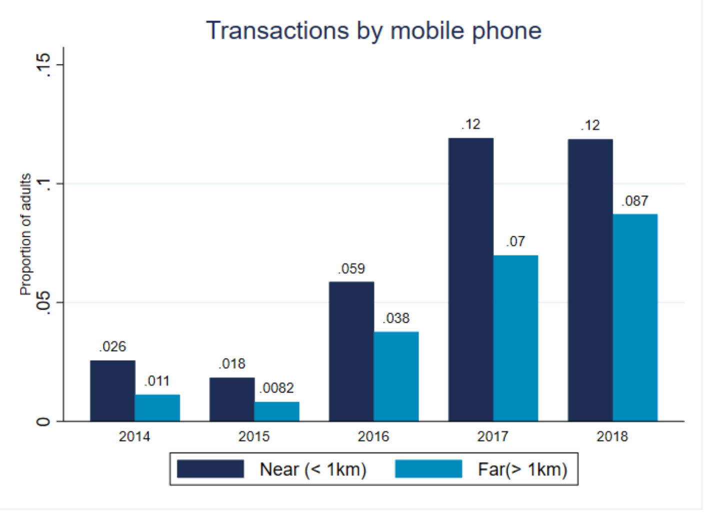

Figure 2.22: Mobile transactions across distance bins

Chapter 3

Imitation of product characteristics in the mobile handset market

Luise Eisfeld[1]
Vatsala Shreeti[2]

In this paper, we attempt to understand the value of an easily imitable technology in an emerging market context. We study the introduction of dual SIM handsets in the Indian mobile phone market and quantify the value of this technology for consumers. We also quantify the impact on market outcomes of the quick imitation of this technology by competing firms. We find that the introduction of dual SIM handsets led to an increase in the consumer surplus of 3.1% to 8.9%, and an expansion in the total size of the market by 1.8% to 3.3%. We also find that while imitation reduced the innovator's profit substantially, it also made the technology much more affordable. In the absence of imitation, consumer prices would have been 22% higher. Finally, we provide a lower-bound on the innovator's cost of protecting intellectual property in an emerging market. We find this lower bound to be as high as 12% of the innovator's observed profits ($ 29.5 million).

[1]Toulouse School of Economics
[2]Toulouse School of Economics

3.1 Introduction

In this chapter, we consider the introduction of a new technology in the mobile handset market and its subsequent adoption by firms. We focus on the introduction of dual SIM enabled handsets in the Indian market for mobile phones. With these handsets, consumers have the choice of switching between two different telecommunications operators. These devices became especially popular in emerging markets because they allowed consumers to optimize between the prices of different operators. While the technology was introduced by big multinational manufacturers like Samsung, local brands adopted it in their own product offerings relatively quickly. With this context, we seek to answer two questions: i) What was the value of this new technology for consumers? ii) What was the impact of imitation of this technology by smaller Indian companies on the handset market?

Dual SIM phones were first introduced in India in the third quarter of 2007. By 2016, they accounted for nearly 94% of the handset market by volume of sales and 44 out of 46 companies operating in the market offered dual SIM enabled handsets. Since these handsets were targeted at people with relatively lower incomes (who are likely to have a preference for optimizing over the price of two different connections), dual SIM handsets were on average cheaper than non-dual SIM handsets. By 2016, only premium handsets (such as the Apple iPhone) came without the dual SIM functionality. Among companies offering dual SIM handsets, there are significant differences in their characteristics. On one hand are large multinational companies like Samsung, LG Electronics etc that invest extensively in research and development, operate in several countries, and offer many consumer electronic goods. On the other hand are Indian companies that started off as resellers of unbranded handsets imported from China. A large majority of their operations are domestic and at least until recently, had limited R&D activity. In the context of the Indian dual SIM market, Samsung and one such Indian company (Spice) introduced the first dual SIM enabled handset in 2007. We consider Samsung to be the innovator as Spice did not have any R&D activities at this time. Shortly after the launch by Samsung, a host of Indian companies offered the same technology with their phones, and became very popular in the Indian market. Notably, Samsung did not enforce its dual SIM related patents in response to this.[3] for a full list of patent disputes in this market.

[3]This is unusual for the mobile handset market (especially the smartphone segment), which is ridden with patent disputes in several jurisdictions. See here

To answer our research questions, we estimate a structural model of demand and supply of mobile handsets. We use handset level quarterly data on sales, prices and device characteristics between 2007 and 2016. This is published by the International Data Corporation. On the demand side, we use the general framework of a mixed-logit model, allowing for rich horizontal product differentiation between handsets. Consumers are allowed to be heterogeneous in their sensitivity to the price of handsets, and this heterogeneity depends (non-parametrically) on their incomes. We recover the structural parameters of this model through GMM estimation and use them to compute the marginal cost of each handset in our data sets.

From this estimation exercise, we find that the parameter estimate for the dual SIM characteristic is positive and precisely estimated. This means that, on average, consumers obtain a positive utility from the dual SIM characteristic. We construct a quality index using the parameters of the demand model and find that on average dual SIM phones tend to have a lower overall quality than phones without dual SIM functionality. As mentioned before, it appears that dual SIM phones are targeted to people with lower incomes, and thus, on average these phones do not have premium/high-quality features. However, in the smartphone segment, we find that even though dual SIM phones have lower qualities, the quality itself is consistently increasing over time.

We use the demand estimates and marginal cost estimates to conduct counterfactual simulations. In the first counterfactual simulation, we seek to understand the value of the dual SIM technology for consumers. We simulate a counterfactual world where this technology did not exist. We let the choice set and other characteristics of handsets to be the same as in observed data. Firms are allowed to readjust their prices in the counterfactual world. We find that the consumer surplus would have been between 3.1% to 8.9% lower without the introduction of the dual SIM technology. Additionally, the overall market for mobile phones would have been between 1.8% to 3.3% smaller in the counterfactual world. Thus, the introduction of the dual SIM technology led to both an expansion in the size of the market and an increase in the consumer surplus.

Through the second counterfactual exercise, we study the impact of imitation of this technology by Indian firms on market outcomes, particularly prices and innovator profits. We simulate a counterfactual world where Samsung (and other dual SIM patent holding companies like Nokia, LG electronics etc) are able to prevent the imitation of this technology. We find that in the absence of imitation, Samsung's profits would have been significantly higher (for instance, 28.4% higher in 2016). However, we also find that imitation by Indian firms made a new technology more affordable. In the counterfactual world, the average price of a dual SIM enabled phone would have been significantly higher (22% higher in 2016). Finally, we also provide a lower bound on the costs of enforcing intellectual property rights in an emerging economy like India. In the absence of any frictions, it would be profit maximizing for Samsung to protect its intellectual property strongly and enjoy monopoly profits, at least for some years. The difference between Samsung's observed profits and its profit in the counterfactual world of no imitation then gives us the lower bound on the expected costs of protecting intellectual property in the Indian market. We find that on average, this lower bound is $ 29.5 million which is as high as 12% of its total observed profit.

Our work relates to several strands of literature in Economics and Management. The closest paper in terms of the methodology and the economic question is Thurk (2019) and Petrin (2002). This paper quantifies the returns to technological innovation in the automobile market, in the presence of imitation of product characteristics. The author finds that imitation increased product variety and decreased consumer prices. Additionally, even in the presence of imitation, the innovator's investment in the new technology was feasible. Thus, the author finds that innovation and imitation can go hand in hand in some industries. Petrin (2002) studies the minivan market and finds that the innovator of a new product was able to protect its profits despite imitation through product differentiation. Using data on firms, Mansfield et al (1981) find that imitating a new technology is significantly cheaper than the cost of developing the technology. In the digital music industry, Waldfogel (2012) finds that imitation in the digital music led to an overall increase in the quality of new music, and was more than offset by the fall in the cost of introducing new music on the market. In terms of the methodology, we follow the large literature on demand estimation in a differentiated product market that includes Berry, Levinsohn and Pakes (1995), Nevo (2002), and Grigolon and Verboven (2014). In particular, build on the random coefficients nested logit model proposed in Grigolon and Verboven (2014).

The rest of the section proceeds as follows: section 2 presents the data that we use to conduct our analysis, section 3 provides a background on the dual SIM technology and the market structure in the Indian market, section 4 presents the demand and supply model, section 5 discusses the estimation methods, section 6 presents the results of the estimation and section 7 presents the counterfactual simulations. As this is early stage work, section 8 provides some details of work-in-progress that would make our analysis economically richer. Section 9 concludes.

3.2 Data

Handset data As in Chapter 1, we use market level data published by the International Data Corporation (IDC). We observe sales, prices and characteristics of handsets of mobile handsets at a quarterly frequency between 2007 and the second quarter of 2018. An observation is a handset model-quarter combination, and there are a total of 27, 730 observations. A model is defined by its brand, screen size, operating system, communication technology (2G, 2.5G, 3G, or 4G), camera megapixels, dual SIM functionality, memory capacity, type of hardware (full touchscreen or not). We convert the prices given in this data set to real prices by using the IMF database on consumer price index. All prices are expressed in 2010 real dollars.

Data on income To incorporate consumer heterogeneity on the income dimension, we use data from the World Inequality Database. This provides the average income of each percentile of the population. To be consistent with the data on prices, we express the incomes in real 2010 dollars as well.

3.3 Market structure of handset market

By 2016, there were a total of 50 brands and 1850 distinct models of handsets being sold on the Indian market. The main segmentation in the market is between feature phones and smartphones. Feature phones, as mentioned in chapter 1 of this thesis, are handsets that can be used to send text messages, make voice calls and in rare cases, browse the internet at 2G speeds. As seen in chapter 1, the market has expanded over time, market concentration has reduced and average prices have decreased.

3.3.1 Dual SIM phones

Since their introduction in 2007, handsets enabled with dual SIM technology have become increasingly popular in the Indian market (Figure 3.1). A dual SIM device allows a consumer to switch between two separate connections (often with different telecom operators) on the same device. They were first introduced in the Indian market in the third quarter of 2007

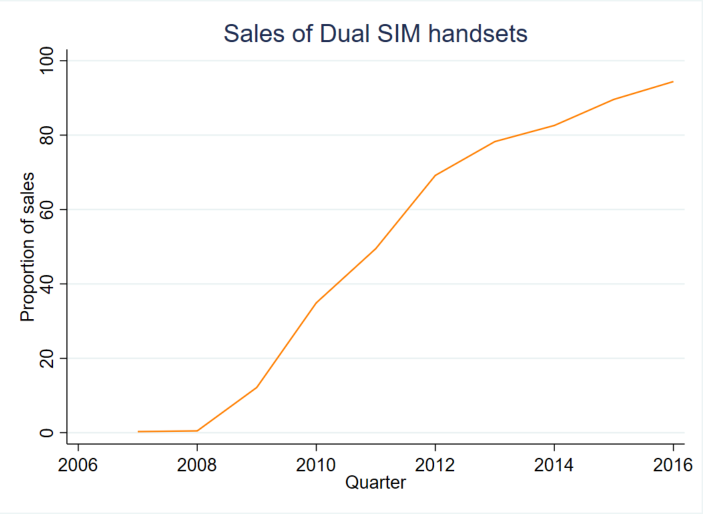

Figure 3.1: Proportion of phones sold that are Dual SIM enabled

by two companies simultaneously - Samsung, a Korean multinational firm, and Spice, an Indian firm. Both of these phones were feature phones and were priced above the average price for the quarter. By 2016, almost 94% of the phones sold in India were enabled with this technology, as opposed to only 3% in 2009 (Table 3.2). Dual SIM technology phones are popular in both categories – smartphones as well as feature phones (Table 3.2). As seen in Table 3.1, over time most companies adopt dual SIM phones in their product portfolio. By the end of the period of analysis, 44 out of 46 companies have dual SIM phones in their product offerings. Table 3.7 shows the top 5 companies by volume of sales of Dual SIM phones every year. Even though Samsung and Spice introduced dual SIM phones in the market, Samsung was much more successful in terms of volume of sales. Especially in the smartphone segment, Samsung is the most popular brand of dual SIM handsets (see Table 3.9). Apart from Samsung, however, most firms that offer this technology with their handsets are Indian firms (Spice, Micromax, Intex, Karbonn, Lava, Maxx; see Table 3.7).

Figure 3.2 shows a comparison between the average price of dual SIM enabled handsets and handsets that do not have this technology. From this, we see that dual SIM handsets have become cheaper over time, and that non-dual SIM handsets are typically more expensive than those with the dual SIM technology. This is because the premium segment of the market (for example, phones sold by Apple, or high-end phones sold by Samsung) did not come enabled with this technology. The dual SIM innovation was largely targeted at price-sensitive consumers who optimize between two plans of two operators to save money.[4] Note

[4] Dual SIM phones gaining popularity in India, PC World, last accessed on 16.04.2022

Table 3.1: Number of companies producing Dual SIM phones

Quarter	Total	Dual SIM
2007Q2	0	0
2008Q2	24	4
2009Q2	27	7
2010Q2	31	19
2011Q2	32	20
2012Q2	37	31
2013Q2	39	36
2014Q2	43	40
2015Q2	44	41
2016Q2	46	44
Total	**83**	**62**

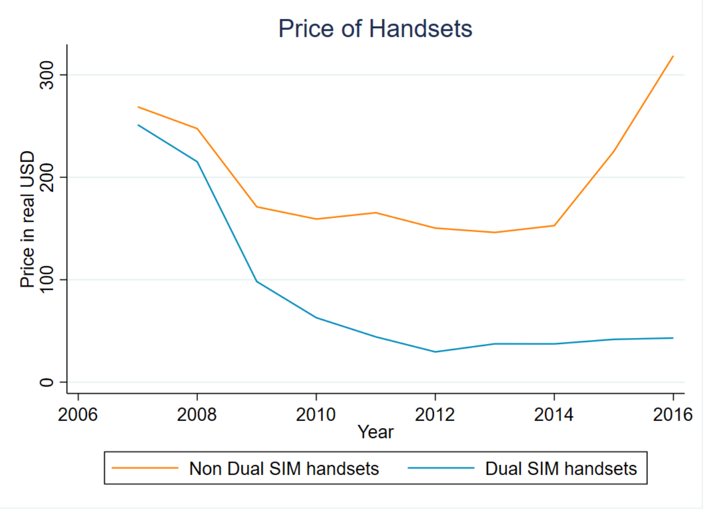

Figure 3.2: Price of Handsets

also that starting from 2014, non-dual SIM enabled handsets become much more expensive relative to dual SIM devices, reflecting both the latter's popularity and entry of premium handsets.

3.3.2 Characteristics of firms producing Dual SIM phones

Even though Samsung and Spice simultaneously introduced the first dual SIM phones in the third quarter of 2007, the two companies are very different in terms of characteristics. While Samsung is a large multinational company producing several types of phones (and other electronics) and selling its products across the world, Spice was an Indian company selling budget handsets only in India. Moreover, at least in the first half of the period of analysis, several Indian companies, including Spice, were importing unbranded handsets from China

Table 3.2: Dual SIM phones as proportion of total sales (in %)

Quarter	Total	Feature Phones	Smartphones
2007Q2	0	0	0
2008Q2	0.50	0.52	0
2009Q2	3.17	3,25	0.43
2010Q2	34.85	36.20	0
2011Q2	45.20	48.46	0.38
2012Q2	68.87	72.52	10.30
2013Q2	78.15	79.36	74.06
2014Q2	84.83	86.55	81.36
2015Q2	91.25	93.20	89.23
2016Q2	93.71	91.55	96.08

Table 3.3: Price of Samsung dual SIM phones versus Indian companies

Year	Samsung	Indian Companies
2007	$ 272	$ 304
2008	$ 325	$ 136
2009	$ 239	$ 87
2010	$ 160	$ 64
2011	$ 73	$ 44
2012	$ 69	$ 33
2013	$ 67	$ 40
2014	$ 65	$ 35
2015	$ 73	$ 44
2016	$ 113	$ 27

and selling them under their brand name in the Indian market.[5] These companies did not invest a lot in research and design, especially for the first half of the period of analysis. On the other hand, Samsung is not only an original equipment manufacturer, it is also an original design manufacturer, investing globally in research, design and development. This is also reflected in the differences in the patent holdings of Samsung and smaller Indian companies like Spice. While the dual SIM technology was first patented by Siemens in 1991, several other companies patented incremental or parallel innovations to introduce this technology with handsets. Among the top dual SIM companies operating in the Indian market, Samsung, Nokia, LG Electronics and Apple have registered patents related to this technology.[6] Based on these facts, we take the view that Samsung was the "innovator" of dual SIM handsets in the Indian market.

Even apart from differences in patent activity and R & D activities, Samsung differed substantially from the Indian companies. Samsung's dual SIM phones were on average

[5] How Nokia fell from dominance, The Economics Times, last accessed on 16.04.2022

[6] Mobile handsets now have a very high number of patents, a lot of which might be overlapping in their scope. For example, already as early as 2012, an average smartphone consisted of nearly 250,000 patented technologies. We conducted a search on Google Patents to find out if Indian companies like Spice patented any dual SIM related technology (in any jurisdiction) during the time dual SIM phones were launched in India, and do not find any. We used the key words "dual SIM" and "SIM switching".

more expensive than those offered by Indian companies (see Table 3.3).[7] This was true for both segments of the market, although for smartphones, the difference in the average price of a dual SIM enabled handset between Samsung and the Indian companies was much larger than for feature phones. By the end of the period of analysis in 2016, Samsung concentrated on the smartphone segment: it had more dual SIM enabled smartphones than feature phones (Table 3.12). On the other hand, Indian companies continued to produce more feature phones than smartphones (Table 3.13).

3.4 Model

The demand supply models closesly follow the models described in Chapter 1. We consider T markets defined as each quarter of the period 2007Q1-2018Q2 and define the potential market size of each market by M_t. Each consumer i decides between a handset j in segment g or the outside option of not buying a new phone. The following utility u_{ijt} is associated with the purchase of a handset:

$$u_{ijt} = \beta x_{jt} + \alpha_i p_{jt} + \gamma c_{jt} + \xi_{jt} + \lambda_f + \lambda_t + \bar{\epsilon}_{ijt}, \tag{3.1}$$

where,

$$\alpha_i = \frac{\sigma}{Y_{it}}, \tag{3.2}$$

and

$$\bar{\epsilon}_{ijt} = \zeta_{igt} + (1-\rho)\epsilon_{ijt}. \tag{3.3}$$

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.

The error term $\bar{\epsilon}_{ijt}$ allows products within each segment (g) 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. We classify the products into two segments - smartphones and feature phones.

[7] Indian companies include Micromax, Spice, Onida, Meridian Mobile, Lava, Karbonn, Intex and Maxx

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. We specify an outside option so that consumers have the choice to not buy a handset in a particular time period. We specify the outside option such that we assume that consumers have the choice to buy a new device or choose the outside option every two years.

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

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

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + (1-\rho)\epsilon_{ijt} + \zeta_{igt}, \tag{3.4}$$

where

$$\delta_{jt} = \beta x_{jt} + \gamma c_{jt} + \lambda_f + \lambda_t + \xi_{jt}, \tag{3.5}$$

and

$$\mu_{ijt} = \frac{\sigma}{Y_{it}} p_{jt}. \tag{3.6}$$

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:

$$\pi_{ijt} = \frac{\exp(\frac{\delta_{jt}+\mu_{ijt}}{1-\rho})}{\exp(\frac{I_{igt}}{1-\rho})} \times \frac{\exp(I_{igt})}{\exp(I_{it})} \tag{3.7}$$

where

$$I_{igt} = (1-p)\ln\left[\sum_{m=1}^{J_{gt}} \exp\left(\frac{\delta_{mt} + \mu_{imt}}{1-\rho}\right)\right] \tag{3.8}$$

and

$$I_{it} = \ln\left(1 + \sum_{g=1}^{G} \exp(I_{igt})\right) \tag{3.9}$$

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:

$$s_{jt}(x_t, p_t, \xi_t; \theta) = \int_{\tilde{Y}_t} \pi_{ijt} dP_Y(Y_t) \tag{3.10}$$

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

3.4.1 Supply

As in Chapter 1, we model the supply of handsets 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. Formally, the firm faces the following maximization problem:

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

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

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

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 from the following equation:

$$\mathbf{c} = \mathbf{p}^* - \Delta(\mathbf{p}^*)^{-1} s(\mathbf{p}^*) \tag{3.11}$$

3.5 Estimation

We construct aggregate market shares (s_{jt}) from the left hand side of equation (3.10) using the data on sales. To link heterogeneity among consumers with the aggregate data, we follow the vast literature on demand estimation with aggregate data (Berry, Levinhson and Pakes (1995), Nevo (2000) and Grigolon and Verboven (2014)). We use the same estimation algorithm as in Chapter 1.

3.5.1 Empirical Distribution of Income

We use data from the World Inequality Database to construct the empirical distribution of income. This data set provides us with the mean income of every percentile of the income distribution. At the time of analysis, this data was available only until 2015. We extrapolate from this data to obtain the empirical distribution for 2016, 2017 and 2018. The underlying assumption that we make is that the rate of growth of mean income between 2016-18 is constant.[8]

3.5.2 Market Size and outside option

We define the market size as $\frac{1}{8}$ of the total adult working population of that year. This implicitly assumes that consumers can choose between buying a new device and the outside option of no purchase every two years. We obtain data on the adult working population from the World Bank. This allows us to compute the market share of each product which is simply the total sales of the product divided by the market size.

3.5.3 Demand Moments and Instruments

Consumers and producers both observe the unobserved demand shocks ξ_{jt} but we do not. This leads to the endogeneity of prices to the demand system. To correct this, we use instruments for handset prices denoted by $h(z)$. We use own-product characteristics and the sum of other products' characteristics within each segment of the market. The economic intuition behind using other products' characteristics as instruments for price is that these characteristics are likely to affect the demand of the product, but only through its price. This implictly relies on the assumption that product characteristics are exogenous.In ongoing work, we attempt to relax this assumption and endogenize the dual SIM characteristic. We describe our proposed model in subsequent sections.

Using these instruments $h(z)$, we construct moments which are then minimized (by GMM) to obtain the structural parameters of the utility function. The objective function is then:

$$\min_{\theta} \xi_j(\theta)' h(z_j) \Omega h(z_j) \xi_j(\theta), \tag{3.12}$$

where θ is the vector of parameters, and Ω is the optimal weighting matrix.

[8] In ongoing work, as new data has become available, we relax this assumption and use the observed data.

3.5.4 Empirical Specification of the utility

We follow the same empirical specification of the utility as in Chapter 1.[9] Recall that in equation 3.5, 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. We include the following device characteristics: 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 (3.6), 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 (3.5), the idiosyncratic error term $(1-\rho)\epsilon_{ijt}$ is assumed to follow an extreme value type I distribution.

3.6 Results

We present results from the demand estimation in table 3.4. There are two main non-linear parameters of interest: σ on $\frac{p_{jt}}{Y_{it}}$ and the nest coefficient ρ. Both of these are precisely estimated and have the expected sign. The maginutde of the nesting parameter suggests that there are strong within-segment substitution between handsets, that is, smartphones are much closer substitutes of each other than they are of feature phones (and vice versa).

Dual SIM: The parameter estimate for the dual SIM characteristic is positive and precisely estimated. This implies that, on average, consumers prefer phones with dual SIM than phones without this technology. Figures 3.3 and 3.2 depict the quality of dual SIM phones over time. The measure of quality is constructed using the estimates of the demand model. Specifically, quality is defined as the weighted linear combination of product characteristics and their estimated preference coefficients. From figure 3.3, we observe that during the initial part of the sample, dual SIM feature phones were on average, of higher quality than non-dual SIM phones. This changed quickly and starting from 2009, on average, non-dual SIM feature phones were of higher quality. One potential explanation for this finding is that dual SIM phones were eventually marketed to relatively poorer consumers, the ones that were most likely to optimize between two different telecom connections. The same trend

[9] We discuss alternative specifications in subsequent sections.

holds for smartphones, with the difference that overall quality of both types of smartphones increases over time. The smartphones on the market which are not enabled with the dual SIM technology tend to be premium handsets target at relatively richer consumers.

Table 3.4: 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

3.7 Counterfactual Simulations

In order to answer the research questions posed in this paper, we conduct two counterfactual simulations. Through the first simulation, we aim to quantify the value of the introduction of the dual SIM technology through its effect on market outcomes and consumer surplus. Through the second counterfactual, we seek to understand the impact of widespread imitation of the dual SIM innovation by Indian companies.

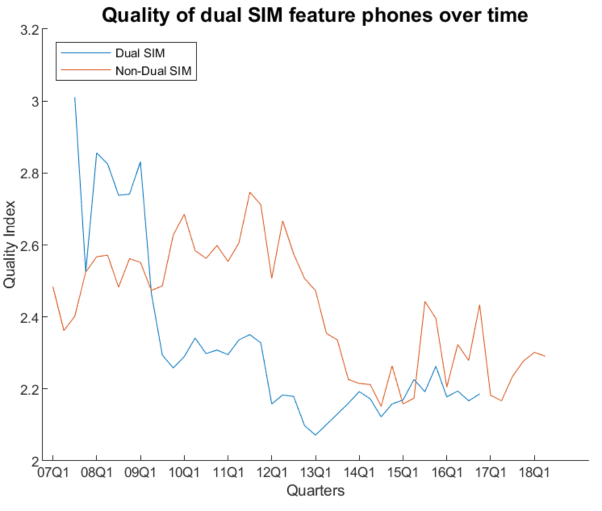

Figure 3.3: Quality of dual SIM feature phones

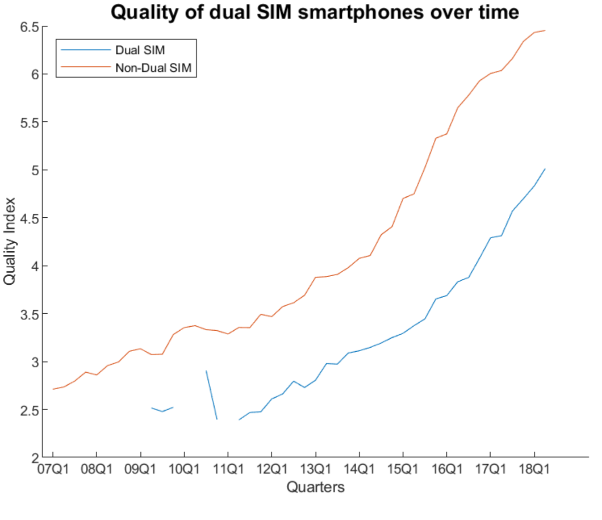

Figure 3.4: Quality of dual SIM smartphones

3.7.1 Value of dual SIM technology

To quantify the value of the dual SIM technology, in this counterfactual simulation, we simulate the market so that none of the devices are enabled with the dual SIM technology. Since the dual SIM characteristic enters the utility function of the consumer linearly, this effectively means simulating the market outcomes with a counterfactual mean utility of purchase. The counterfactual mean utility $\tilde{\delta_{jt}}$ is given by:

$$\tilde{\delta_{jt}} = \delta_{jt} - \beta_{ds} \times \mathbf{1}_{j \in dualSIM},$$

where β_{ds} is the preference parameter estimate for the dual SIM characteristic and $\mathbf{1}_{j \in dualSIM}$ is an indicator variable for phones that have the dual SIM characteristic enabled. Effectively, this means that the number of brands and products, and all other characteristics of a particular product stay the same in the counterfactual exercise. The only difference is that phones that had the dual SIM technology enabled in the observed world, do not have it in the counterfactual world. Using this counterfactual mean utility, we recompute the equilibrium prices and market shares. We denote the vector of counterfactual prices by $\tilde{\mathbf{p}}$ and the vector of counterfactual market shares by $\tilde{\mathbf{s}}$. We compute the change in consumer surplus between the observed and counterfactual worlds so as to quantify the value of the dual SIM technology for consumers.

For the random coefficients nested logit model, the individual level consumer surplus is given by the following equation:

$$CS_{it} = \left[\log(1 + \sum_{g=1}^{G} \exp I_{igt}) \middle/ \frac{-\partial I_{i1t}}{\partial p_{1t}}, \right]$$

where I_{igt} is given by equation 3.8.

Table 3.5: Counterfactual I: No dual SIM technology

Quarter	△ Consumer Surplus	△ Market Size
2015Q1	-3.5%	-2.5%
2015Q2	-3.6%	-2.4%
2015Q3	-8.4%	-1.8%
2015Q4	-4.7%	-2.1%
2016Q1	-3.1%	-3.3%
2016Q2	-4.3%	-2.3%
2016Q3	-8.9%	-1.8%
2016Q4	-4.7%	-2.3%

Table 3.6: Counterfactual II: No Imitation

Year	△ Price of Dual SIM	△ Samsung Profit
2008	26.5%	-1.7%
2009	46.9%	8.7%
2010	-0.74%	17.8%
2011	2%	13.4%
2012	-5%	9.2%
2013	-4.25%	16.6%
2014	5.4%	32.6%
2015	21.3 %	26.5%
2016	28.4%	22%

Table 3.6 shows the main results of the counterfactual simulation for the last two years of the period of analysis. Column 2 of this table shows the change in consumer surplus if there were no dual SIM enabled phones, and column 2 shows the change in the total inside market size (sum of market shares of all phones sold) in the counterfactual. Not having the dual SIM technology leads to a loss in consumer surplus between 3.1% to 8.9% in the years 2015 and 2016. Without the dual SIM technology, the total market for phones would be between 1.8 % to 3.3% smaller in these years.

3.7.2 Impact of imitation of dual SIM technology

As mentioned before in section 3.3.2, the first dual SIM "innovator" on the Indian market was Samsung. This innovation was quickly adopted by Indian companies, that were at the time only importing unbranded handsets from India. Dual SIM enabled phones of the "imitating" companies were typically cheaper than those of Samsung. Notably, Samsung did not enforce any of its dual SIM related patents in the Indian market. The reasons for this are not clear. In the absence of frictions, it should be profit-maximizing for Samsung to enforce its patents and enjoy monopoly rights for at least a part of the period of analysis. Two possible frictions that might arise in the process of enforcement are: i) high costs (litigation) for protecting intellectual property in India or ii) overlapping patents in the smartphone market.[10] In this counterfactual simulation, we quantify the impact of this quick imitation on market outcomes. We do so by re-simulating market outcomes without dual SIM products of 8 Indian companies (Micromax, Spice, Onida, Meridian Mobile, Lava, Karbonn, Intex, Maxx). Note that we still keep dual SIM phones of other companies (like Nokia, Apple etc) that had registered dual SIM related patents during our period of consideration.

Table 3.6 summarizes the main results of the counterfactual exercise. In the absence of imitation, on average, Samsung's profits would have been much higher, especially in the

[10] IP Protection: India among most challenging economies; National Herald, last accessed on 29.04.2022

last three years of the analysis (column 2 of table 3.6). On the other hand, the widespread imitation of the new dual SIM product had a substantial impact on the affordability of this new technology. In the counterfactual, without imitation, the average price of a dual SIM enabled phone would have been significantly higher, with the except of a few quarters. Thus, even though imitation leads to substantial loss in profits for the innovating company, it makes a new, useful technology more affordable.

Through the results of this counterfactual exercise, it is also possible to estimate a lower bound on the potential costs for Samsung for protecting its innovation. This lower bound is given by the difference between Samsung's observed profits in the data and its profit in the counterfactual world where it is able to prevent imitation of its product characteristics by Indian firms. We find that, on average, this lower bound is $ 29.5 million or around 12% of its total profit in the observed world.

3.8 Discussion

3.8.1 Endogenous product characteristics

The analysis presented so far does not take into account the firms' decision to offer dual SIM handsets or not. In the supply model, we consider the price of the handset as the only decision variable. In reality, it is likely that firms choose some of the product characteristics, especially ones that are innovative. In future iterations of this work, we will consider dual SIM as an endogenous characteristic and allow firms to choose whether or not to introduce handsets with this technology. While it is reasonable to assume that other phone characteristics (screensize, memory, camera etc) were exogenous in the Indian market since most of the research and development in this market takes place at the global level. However, the dual SIM functionality was meant specifically for emerging economies like India and thus is likely to be endogenous to the firms' decision problems. This leads to new challenges: with an endogenous product characteristic, not only the parameter estimate of the endogenous characteristic is biased, but all other parameter estimates are biased too (Crawford, 2012). To correct for this, we would require new instruments for the dual SIM characteristic.

3.8.2 Heterogeneity in preferences for dual SIM

It is also likely that consumer preferences for a dual SIM phone are heterogeneous. We attempted to estimate the model allowing for unobserved heterogeneity in the preference for this characteristic but the estimates were not precise. One reason for the imprecise estimates might be the aggregate nature of the data that we use for estimation. We plan to use survey data from Financial Inclusion Insights and LirneAsia to construct additional moments that might help us estimate this parameter with more precision. At the same time, there is likely to be heterogeneity in preferences for dual SIM phones based on individuals' income as well. However, this survey data does not record the income of individuals, so we cannot include income-based moments.

3.8.3 Telecom services market

One reason that the dual SIM market got traction in India was the increasing competition in the telecom operators market. The introduction of this technology coincided with a rapid decrease in telecom prices. Our analysis takes this into account only to the extent of including quarter fixed effects. It is likely that there are interlinkages between these two markets, for example, the popularity of dual SIM phones is likely to have affected telecom prices, which in turn would affect the market share of dual SIM phones. We leave this promising yet challenging aspect of research to future work.

3.9 Conclusion

In this preliminary work, we seek to understand the value of any easily imitable technology in the context of an emerging market. We consider the introduction of dual SIM enabled handsets in the Indian market. This technology was first introduced by Samsung and eventually adopted by several small Indian firms, with limited research and development activity of their own. We quantify the value of this new technology to consumers and the impact of imitation of this technology on market outcomes. We take a structural approach to do this - estimating a mixed-logit model of demand and supply using national level market data. Through counterfactual simulations we find that the introduction of the dual SIM technology led to an increase in consumer surplus of 3.1% to 8.9%. It also led to an expansion of 1.8% to 3.3% in the total size of the mobile phone market. We find that in the absence of Indian firms offering this technology, predictably the profits of Samsung would have been much higher but dual SIM phones would have been significantly more expensive (by 22% in 2016). We also find that the lower bound of the cost for Samsung to protect its intellectual property in the Indian market is as high as 12% of its total observed profit.

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3.10 Appendix

Table 3.7: Top 5 firms by volume of sales of Dual SIM phones

07Q3	08Q2	09Q2	10Q2	11Q2	12Q2	13Q2	14Q2	15Q2	16Q2
Samsung	Samsung	Micromax	G-Five	G-Five	Nokia	Samsung	Samsung	Samsung	Samsung
Spice	Spice	Karbonn	Micromax	Micromax	Samsung	Micromax	Micromax	Micromax	Micromax
	Meridian	Samsung*	Maxx	Samsung	Micromax	Karbonn	Nokia	Intex	Intex
	Onida	Maxx	Lava	Karbonn	Karbonn	Nokia	Karbonn	Lava	Lava
		Meridian	Karbonn	Nokia	Kenxinda	Lava	Lava	Karbonn	Karbonn

Table 3.8: Top 5 firms by volume of sales of Dual SIM feature phones

07Q3	08Q2	09Q2	10Q2	11Q2	12Q2	13Q2	14Q2	15Q2	16Q2
Samsung	Samsung	Micromax	G-Five	G-Five	Nokia	Nokia	Nokia	Samsung	Samsung
Spice	Spice	Karbonn	Micromax	Micromax	Samsung	Karbonn	Micromax	Intex	Intex
	Meridian	Samsung	Maxx	Samsung	Micromax	Micromax	Karbonn	Lava	Micromax
	Onida	Meridian	Lava	Karbonn	Karbonn	Samsung	Lava	Nokia	Lava
		Maxx	Karbonn	Nokia	Kenxinda	Lava	Samsung	Micromax	Karbonn

Table 3.9: Top 5 firms by volume of sales of Dual SIM smartphones

09Q2	10Q2	11Q2	12Q2	13Q2	14Q2	15Q2	16Q2
Spice	-	Micromax	Spice	Samsung	Samsung	Samsung	Samsung
Coolpad	-	Spice	Micromax	Micromax	Micromax	Micromax	Micromax
-	-	-	Celkon	Karbonn	Karbonn	Intex	Lenovo
-	-	-	HTC	Lava	Nokia	Lava	Intex
-	-	-	Karbonn	Intex	Lava	Lenovo	Reliance

Table 3.10: Number of companies and models with dual SIM: Feature Phones

Quarter	Companies	Models
2007Q1	0	0
2007Q2	0	0
2007Q3	2	2
2007Q4	2	2
2008Q1	3	3
2008Q2	4	6
2008Q3	4	6
2008Q4	5	8
2009Q1	2	7
2009Q2	5	23
2009Q3	11	48
2009Q4	13	96
2010Q1	17	174
2010Q2	19	212
2010Q3	21	233
2010Q4	23	305
2011Q1	20	209
2011Q2	20	238
2011Q3	24	336
2011Q4	23	302
2012Q1	30	465
2012Q2	30	362
2012Q3	30	441
2012Q4	30	667
2013Q1	31	529
2013Q2	32	514
2013Q3	32	451
2013Q4	31	464
2014Q1	31	464
2014Q2	31	588
2014Q3	31	684
2014Q4	27	584
2015Q1	24	498
2015Q2	25	443
2015Q3	24	460
2015Q4	21	372
2016Q1	15	349
2016Q2	24	397
2016Q3	21	460
2016Q4	20	399
Total	**45**	**3903**

Table 3.11: Number of companies and models with dual sim: Smartphones

Quarter	Companies	Models
2007	0	0
2008	0	0
2009Q1	0	0
2009Q2	2	2
2009Q2	3	3
2009Q3	1	1
2010Q1	0	0
2010Q2	0	0
2010Q3	1	1
2010Q4	1	1
2011Q1	0	0
2011Q2	2	2
2011Q3	4	5
2011Q4	3	5
2012Q1	7	13
2012Q2	8	19
2012Q3	11	33
2012Q4	18	62
2013Q1	22	135
2013Q2	23	153
2013Q3	25	194
2013Q4	26	187
2014Q1	29	209
2014Q2	31	305
2014Q3	33	356
2014Q4	37	369
2015Q1	36	380
2015Q2	39	417
2015Q3	39	545
2015Q4	373	454
2016Q1	35	403
2016Q2	37	508
2016Q3	34	480
2016Q4	33	418
2017Q1	37	395
2017Q2	35	395
2017Q3	34	389
2017Q4	25	366
2018Q1	34	322
2018Q2	34	330
Total	**70**	**3508**

Table 3.12: Number of Samsung dual SIM phones

Year	Smartphones	Feature Phones
2007	0	1
2008	0	3
2009	0	5
2010	0	8
2011	0	20
2012	7	23
2013	12	20
2014	17	20
2015	38	18
2016	37	6

Table 3.13: Number of Indian dual SIM phones

Year	**Smartphones**	**Feature Phones**
2007	0	1
2008	0	7
2009	1	82
2010	1	248
2011	8	296
2012	44	341
2013	161	301
2014	374	555
2015	473	497
2016	362	391